Department of Civil and Environmental Engineering

University of Strathclyde

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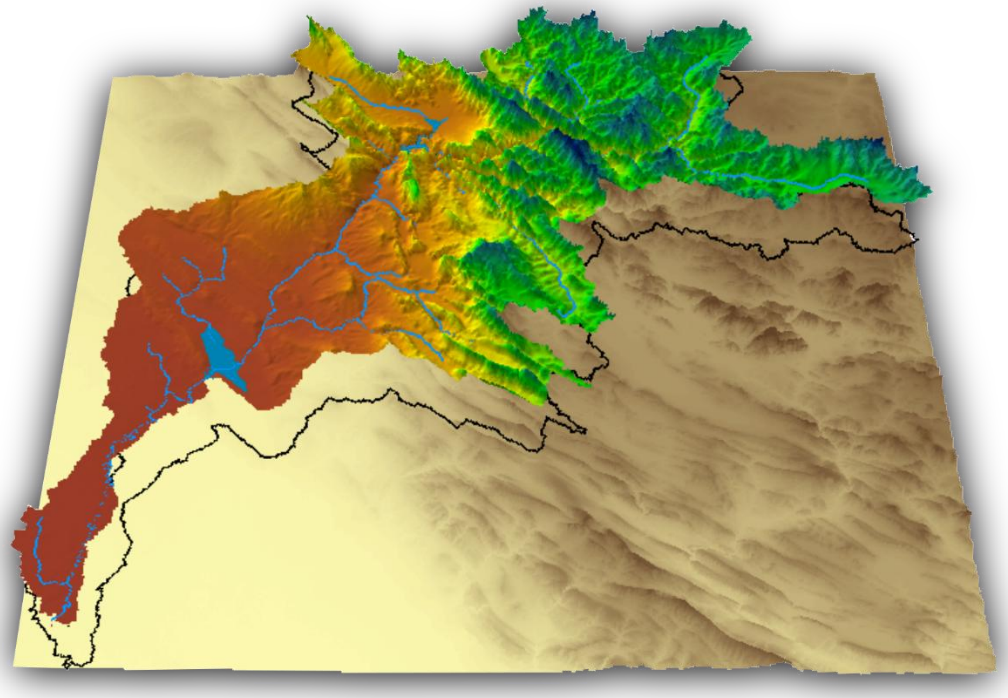

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By

JAFAR YAHYA SALEH AL-JAWAD

Thesis submitted in fulfilment of the requirement for the degree of

DOCTOR OF PHILOSOPHY

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DECLARATION

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A Comprehensive Optimum Integrated Water Resources Management Approach at a River Basin Level: Application at Diyala River Basin in Iraq

Jafar Y. Al-Jawad

ABSTRACT

Integrated Water Resources Management (IWRM) was broadly adopted, however nature's complexity, multidisciplinary stakeholders' demands, legislation policy, etc. restrained the success of holistic integration. Recently, Multi-Objectives Evolutionary Algorithms (MOEAs) were presented as a powerful decision making tool to generate a trade-off (or Pareto-front) for complex problems. Even so, problematics may develop in MOEAs for high-dimension problems. Thus, a new MOEA is developed and employed with a novel optimum comprehensive IWRM (OP-IWRM) approach to assemble: water demands, water resources and water control infrastructures for decision making trade-off production. To evaluate the approach pragmatically, Diyala River basin is selected, which has an area about 17000 km^2 in central Iraq and two multipurpose dams: Derbendikhan in the north, and Himren in the middle part of the basin.

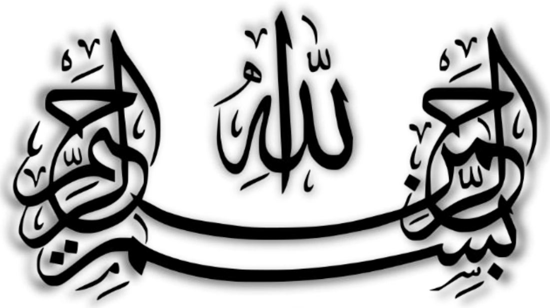
A new methodology of "*Epsilon-Dominance-Driven Self-Adaptive Evolutionary Algorithm for Many-Objective Optimization*" (ε-DSEA) to address MOEAs' dilemmas is first presented. Three operational management targets are modelled for Derbendikhan dam for initial algorithm's performance assessment in comparison with the state-of-the-art optimization algorithm Borg MOEA. Competitive results achieved by ε-DSEA for the considered problem. Then, long-term groundwater exploitation in the middle part of the basin is modelled by three operational management targets with two alternatives of irrigation system, open

furrows and drip. The results show sustainable management could be achieved when farms' water demands are reduced by at least 45%. Further, ε-DSEA outperforms Borg MOEA an almost all proposed alternatives.

A novel socio-environmental management approach is then developed to improve Himren downstream river environment. Nine multi-sectors' operational targets subjected to two inflows alternatives are formulated. An improvement is evident in downstream river environment, however dam's upstream shed needs to be integrated with the model, including groundwater. The ε-DSEA competitive performance is also endorsed.

Finally, a holistic approach including seventeen management targets combining surface and groundwater basin system with more than 1500 decision variables is developed to assess future climate's change, and water monopolizing in upstream region impacts at the river basin environment. The results demonstrate significant crises of upstream development projects on all river basin sectors and environment, even with the use of both surface and groundwater resources. Thus, the government needs to adopt future policy: to set an international agreement for water sharing with Iran for the current River basin, to adopt new irrigation techniques for the existing farms, and to rehabilitate the current water conveyance infrastructures to reduce water losses.

This approach could be a gateway to develop a comprehensive sustainable development plan at a country-scale to improve the 17th goals announced by the United Nations, since only limited approaches were developed previously.



القرآن الكريم: سورة الانبياء، آية 30

In the Name of God, the Merciful, the Compassionate

..We Have Made from Water Every Living Think

The Holy Quran: Surah Al-Anbiyaa, sector 30

DEDICATION

To my Imam and Lord, Al-Mahdi, who inspire me all the time

To my Mother and Father, who praying for me all the time

To my Wife, who supporting me all the time

To my Daughters, who filling my life with happiness all the time

Jafar Al-Jawad

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Jafar Al-Jawad

PREFACE

The main core of this thesis was developed as a series of five papers to be published in peer-review journals. Each chapter has its own abstract, introduction, methods, results, discussion, and conclusions. Also, a bridge text between these chapters was written to maintain the connections and harmony between the chapters. The following papers were published and submitted to the corresponding journals

Chapter 4

- Al-Jawad, J.Y., Tanyimboh, T.T., 2017a. Assessment of evolutionary algorithm for reservoir operation. Water Util. J. 15, 45–51
- Al-Jawad, J.Y., Tanyimboh, T.T., 2017b. Reservoir operation using a robust evolutionary optimization algorithm. J. Environ. Manage. 197, 275–286. https://doi.org/10.1016/j.jenvman.2017.03.081

Chapter 5

- Al-Jawad, J.Y., Tanyimboh, T.T., 2018. Epsilon-Dominance-Driven Self-Adaptive Evolutionary Algorithm For Many-Objective Optimization. Swarm Evol. Comput. In review.

Chapter 6

- Al-Jawad, J.Y., Al-Jawad, S.B., Tanyimboh, T.T., Kalin, R.M., 2018a. Comprehensive Evolutionary Algorithms Performance Assessment Using a Multi-Objectives Water Resources Management Problem. Water Resour. Manag. In review.

Chapter 7

- Al-Jawad, J.Y., Alsaffar, H.M., Bertram, D., Kalin, R.M., 2018b. Optimum Socio-Environmental Flows Approach for Reservoir Operation Strategy Using Many-Objectives Evolutionary Optimization Algorithm. Sci. Total Environ. published.

Chapter 8

- Al-Jawad, J.Y., Alsaffar, H.M., Bertram, D., Kalin, R.M., 2018c. A Comprehensive Optimum Integrated Water Resources Management Approach for Multidisciplinary Water Resources Management Problems. J. Environ. Manage. Under revi.

NOVELTY OF THE RESEARCH

This thesis has many global and local novel approaches developed during the research project. These are:

1- Global Novelty:

- Evolutionary algorithm (ε-DSEA) based on novel self-adaptive approach of recombination operators' parameters control in evolutionary optimization algorithm.
- Socio-environmental flow regime approach of reservoir operation strategy using many-objectives optimization algorithm.
- Auto-adaptive penalty factor methodology to overcome computational complexity problems in evolutionary algorithm.
- Comprehensive optimum integrated water resources management approach at a river-basin level using many-objectives evolutionary optimization algorithm.

2- Local Novelty:

- Regional 3D groundwater model using MODFLOW-2005 for the middle part of Diyala River Basin
- Groundwater management optimization approach for the middle part of Diyala River Basin using evolutionary algorithm.
- Reservoir management optimization approach for Himren reservoir using evolutionary algorithm.
- Reservoirs management optimization approach for Himren and Derbendikhan dam in Diyala River Basin using evolutionary algorithm.
- Surface-groundwater optimization approach for the entire Diyala River Basin using evolutionary algorithm.

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NOTATION

Symbol	**Description**
IWRM	Integrated Water Resources Management
MOEA	Multi-Objectives Evolutionary Algorithm
EA	Evolutionary Algorithm
GA	Genetic Algorithm
ES	Evolutionary Strategies
EP	Evolutionary Programming
X	Decision variables space
$\boldsymbol{x}$	Decision variables vector
$\boldsymbol{x}^L$	Decision variables lower limit
$\boldsymbol{x}^U$	Decision variables upper limit
Z	Objective space feasible region
M	Number of objective functions
$g_i(x)$	The i^{th} of n_g inequality constraints functions
$h_j(x)$	The j^{th} for n_h equality constraints functions
n_g	Number of inequality constraints
n_h	Number of equality constraints
PS	Pareto-optimum set
PF	Pareto Front
S_t	Reservoir storage at time *t*
S_{min}	Reservoir minimum storage (dead storage)
S_{max}	Reservoir maximum storage
R_t	Reservoir releases at time *t*
R_{min}	Reservoir minimum storage
R_{max}	Reservoir maximum storage
S_1	Reservoir storage at time t = 1 (initial storage)
S_{13}	reservoir storage in the first month of the next year
I_t	Reduced reservoir inflow at time *t*
I'_t	Original reservoir inflow at time *t*
SD_t, σ_t	Reservoir inflows' standard deviation at time *t*
f	Objective function
D_t	Downstream water demand at time *t*
S_{t+1}	Reservoir storage at time t+1
E_t	Reservoir evaporation losses at time *t*
C	Violation penalty factor
NC	Number of constraints

ε	Dimension of hyper-boxes in the objective space (or objective space resolution)
L	Number of decision variables
SBX	Simulated binary crossover recombination operators
DE	Differential evolution recombination operators
PCX	Parent-centric crossover recombination operators
UNDX	Unimodal normal distribution crossover recombination operators
SPX	Simplex crossover recombination operators
UM	Uniform mutation recombination operators
PM	Polynomial mutation recombination operators
CR	Probability of crossover for DE operator
F	Step size for DE operator
λ	expansion rate for SPX operator
σ_η, σ_ξ, σ_ζ	Variance parameters for the PCX and UNDX operators
e	Any integer number larger than zero
A	Constraint function's coefficient
NOP	Number of parents
P	Population size
$\mathcal{P}_i^{NDS}$	probability of i^{th} recombination operator
NDS	Number of dominance solutions in the dominance archive
NDS_i	Number of solutions in the archive contributed by the i^{th} recombination operator
NRO	Number of recombination operators
N_r	random integer $\in \mathbb{N}^+$
NFE_{max}	Maximum number of function evaluation
E_r	reset interval
ADS	Archive dominance solutions
$\sum NDS_{SBX}$	Sum of No. of dominance solutions generated by SBX operator
$\sum NDS_{DE}$	Sum of No. of dominance solutions generated by DE operator
$\sum NDS_{SPX}$	Sum of No. of dominance solutions generated by SPX operator
$\sum NDS_{UNDX}$	Sum of No. of dominance solutions generated by UNDX operator
$\sum NDS_{PCX}$	Sum of No. of dominance solutions generated by PCX operator
NFE	Number of function evaluation
NOP_1	Number of parents selected from the main population
NOP_2	Number of parents selected from the dominance archive
I_r	Number of function evaluations where the resetting occurs
δ_{PF}	Convergence error
$\mathbf{x}_M$	Decision variables vector for DTLZ test functions

$\mathbf{g}(\mathbf{x}_M)$	Function of $\mathbf{x}_M$
$\mathbf{x}_M^*$	Decision variables Pareto-front vector for DTLZ test functions
S_{t+1}^D	Reservoir storage for Derbendikhan dam at time t+1
S_t^D	Reservoir storage for Derbendikhan dam at time t
I_t^D	Reservoir inflows for Derbendikhan dam at time t
R_t^D	Reservoir releases for Derbendikhan dam at time t
E_t^D	Reservoir evaporation losses for Derbendikhan dam at time t
P_t^D	Direct precipitation on Derbendikhan dam reservoir at time t
SE_t^D	Seepage losses from Derbendikhan dam reservoir at time t
GR_t^D	Groundwater recharges to the Derbendikhan dam reservoir at time t
T	Total time
$\boldsymbol{F}_D$	Objective vector function for Derbendikhan dam operation strategy
$f_{winterD}$	Winter storage function for Derbendikhan dam
$f_{summerD}$	Summer storage function for Derbendikhan dam
f_{powerD}	Hydropower generation function for Derbendikhan dam
S_{max}^D	Maximum reservoir storage for Derbendikhan dam
C_P	Penalty factor includes all the violations of the model
T_W	Winter operation period
S_{minp}^D	Minimum allowable reservoir storage for hydropower generation for Derbendikhan dam
T_S	Summer operation period
Pw_{max}^D	maximum hydropower generation for Derbendikhan dam
Pw_t^D	hydropower generation for Derbendikhan dam at time t
η_e^D	Efficiency of Derbendikhan dam power plant
γ_w	Water density
Q_t^{tuD}	Derbendikhan dam power plant turbine discharge
H_t^{nD}	Net head between reservoir level and the tail water after the power plant at Derbendikhan dam
X_{dv}	Decision variables vector
P_r	Average precipitation
RO	Average surface runoff
ET_0	Reference evapotranspiration
Q_{av}	Average aquifer pumping discharge
TR_0	Groundwater recharge
K	Aquifer hydraulic conductivity
I	Hydraulic (groundwater) gradient
A_{Sec}	Boundary section area
Δh	Difference between the water table head at the recharge and

	discharge zones of the specified aquifer
Δl	Separation distance between recharge and discharge zones
Nw_t	Number of pumping wells at time *t*
PD_t	Projects' water demands
PD_{max}	Maximum projects' water demands
G_t	Groundwater withdrawal
C	Penalty factor
SM_t	Soil moisture content at time *t*
SM_{t+1}	Soil moisture content at time *t*+1
$maxSM$	Maximum soil moisture content
P_t	Precipitation at time *t*
IR_t	Irrigation water at time *t*
ET_t	Evapotranspiration at time *t*
RO_t	Surface runoff at time *t*
DP_t	Deep percolation at time *t*
S_{st}	Static groundwater storage
$S_{aq,t}$	Aquifer storage at time *t*
$S_{aq,t+1}$	Aquifer storage at time *t*+1
TR_t	Total aquifers water recharges at time *t*
f_{Del-SW}	Surface water delivery function
f_{WL}	Water losses function
f_{mining}	Mining function
k	Total number of parents
k_1	Number of parents selected from the main population
k_2	Number of parents selected from the dominance archive
OSEF	Optimum Socio-Environmental Flows
AAC	Auto-Adaptive Constraints
R_t^H	Reservoir releases for Himren dam at time *t*
DD_t^H	Water demands after Himren dam at time *t*
DD_{max}^H	Maximum water demands after Himren dam
PN	Number of penalty function
S_t^H	Reservoir storage for Himren dam at time *t*
S_{t+1}^H	Reservoir storage for Himren dam at time *t*+1
S_{max}^H	Maximum reservoir storage for Himren dam
S_{minp}^H	Minimum allowable reservoir storage for hydropower generation for Himren dam
I_t^H	Reservoir inflows for Himren dam at time *t*
R_t^H	Reservoir releases for Himren dam at time *t*

E_t^H	Reservoir evaporation losses for Himren dam at time t
P_t^H	Direct precipitation on Himren dam reservoir at time t
SE_t^H	Seepage losses from Himren dam reservoir at time t
GR_t^H	Groundwater recharges to the Himren dam reservoir at time t
Pw_{max}^H	maximum hydropower generation for Himren dam
Pw_t^H	hydropower generation for Himren dam at time t
η_e^H	Efficiency of Himren dam power plant
Q_t^{tuH}	Himren dam power plant turbine discharge
H_t^{nH}	Net head between reservoir level and the tail water after the power plant at Himren dam
Q_t^r	Diyala river discharge at time t
Q_{t+1}^r	Diyala river discharge at time t+1
Q_{max}^r	Maximum Diyala river discharge
Q_t^{r1}	Diyala river discharge before the WWTP at time t
Q_t^{r2}	Diyala river discharge after the WWTP at time t
Q_t^{r3}	Tigris river discharge at time t
Q_t^{PS}	Wastewater treatment plant discharge at time t
TDS	Total dissolve solids
TDS_t^{r1}	Total dissolved solids for Diyala river before the WWTP at time t
TDS_t^{r2}	Total dissolved solids for Diyala river after the WWTP at time t
TDS_t^{r3}	Total dissolved solids for Tigris river before the confluence at time t
TDS_t^{PS}	Total dissolved solids for WWTP at time t
TDS_t^R	Total dissolved solids for Tigris river after the confluence at time t
TDS_{max}	Maximum total dissolved solids for Tigris river
$BL_{i,t=0}$	Initial bed river level
$BL_{i,t=T}$	Final Bed river level
ΔBL_{max}	Maximum allowable river bed changes
$BL_{i,t}$, $BL_{i,t+1}$	Bed river level at section i at time t and t+1, respectively
$BD_{i,t}$, $BD_{i+1,t}$, $BD_{i-1,t}$	Bed river sediment discharge at time t for section i, i+1 and i-1, respectively
ΔT_t	Time interval
γ_m	Density of water-solid mixture
W_i	River bed width at section i
$L_{u,t}$, $L_{d,t}$	Length of river section between the current section and the upstream and downstream sections, respectively
$q_{i,t}^r$	River discharge per unit width
$q_{i,t}^c$	Critical discharge per unit width
$HG_{i,t}$	River hydraulic gradient at section i and time t
d_s	Diameter size of bed river

n	Manning coefficient
$A_{i,t}$	Wet cross-section area of the river at section *i* and time *t*
$HR_{i,t}$	Wet hydraulic radius for the river at section *i* and time *t*
NS	Number of river cross sections
DU_t^M	Domestic use water requirement at time *t*
ROF_t^M	Runoff rate at time *t*
QST_t^M	Seasonal stream discharge at time *t*
Ar_t^H, Ar_t^D	Himren and Derbendikhan reservoir surface area, respectively
$f_{demandsH}$	Water demands function for Himren dam
$f_{winterH}$	Winter storage function for Himren dam
$f_{summerH}$	Summer storage function for Himren dam
f_{powerH}	Hydropower generation function for Himren dam
f_{riverB}	Diyala river discharge function after the Barrage
f_{TDS-DY}	TDS concentration function for Diyala river
f_{DY-BCH}	Bedriver changes function for Diyala river
f_{TDS-TR}	TDS concentration function for Tigris river
$f_{Del-SW-GW}$	Surface + groundwater deliver function
f_{phy-M}	Physical model violation function for Himren dam
f_{MD}	Total model violation function
C_{D-H-Ph}	Physical model penalty function for Himren dam
DSSs	Decision Support Systems
OP-IWRM	Optimum integrated water resources management
$\boldsymbol{F}_{comp.}$	Vector for comprehensive model functions
$\boldsymbol{F}_{simple}$	Vector for simple model functions
$\Delta\boldsymbol{F}$	Differences between the comprehensive and simple models
Δ_{C2-C1}	Gross differences between case 1 and case 2
Δ_{S2-S1}	Gross difference between scenario-1 and scenario-2

SBX operator detail symbols

β	Spread factor
c_1, c_2	Offspring decision variable
p_1, p_2	Corresponding parents for c_1, c_2
β'	Factor
r	Random number from the uniform distribution in the interval [0,1]
$\mathcal{P}(\beta)$	Probability to generate new offspring

DE operator detail symbols

NP	Population size
G	Maximum number of generations

j	Number of parameters
$x_{j,i,G}$	Random vector
$b_{j.U}$	upper bounds
$b_{j,L}$	lower bounds
$v_{i,G+1}$	Mutant vector
r_1, r_2, r_3	random integer indices $\in \{1, 2, 3, \ldots, NP\}$
$\mathbf{u}_{i,G}$	Trial vector
$rand_j$	Random number $\in [0, 1]$
D	Dimension of the decision variable vector

UNDX operator detail symbols

μ	Number of parents
$\boldsymbol{\mathcal{P}}$	Mean vector
$\boldsymbol{d}^i$	Difference vector for the i^{th} parent
$\boldsymbol{e}^i$	Direction cosines vector for the i^{th} parent
D	length between the two vectors which is orthogonal to all $\boldsymbol{e}^i$
$\boldsymbol{x}^c$	New offspring
$\boldsymbol{e}^j$	Orthonormal basis vector of the subspace, which is orthogonal to the subspace spanned by all $\boldsymbol{e}^i$. ($j = \mu, \ldots, n$, where n is the size of the decision variable vector $\boldsymbol{x}$)
ω_i, ν_j	Random variables which follow a normal distribution having zero mean

SPX operator detail symbols

n	Number of parameters in the search space
X_k	Vector of parameters
O	Centre of mass of selected vectors
v_k	Factor
u	Uniform random number $u \in [0, 1]$
Y_k	Expansion vector
C_k	Factor
Y_n	expansion vector at $k = n$
C_n	Factor at $k = n$

PCX operator detail symbols

$\boldsymbol{x}^p$	Parent for mean vector $\boldsymbol{\mathcal{P}}$
$\boldsymbol{d}^p$	Direction vector
D_i	Perpendicular distance for the i^{th} parent
$\overline{D}$	Average distance
$\boldsymbol{y}$	New offspring

UM operator detail symbols

$\boldsymbol{x}$	Parent
$\boldsymbol{x}'$	New offspring
x_k	Random element
L	Lower bounds of the element
U	Upper bounds of the element

PM operator detail symbols

c	New solution
x	Parent
x_L, x_U	lower and upper bounds, respectively
u	Random number $\in [0,1]$
δ_q	Factor

CHAPTER ONE

INTRODUCTION

1.1 Introduction

The worldwide development in different sectors like agriculture, municipality and industry has increase the exploitation of fresh water. However, the impact of climate change, water pollutant, dispute on water sharing between riparian countries, etc. is restraining the availability of fresh water resources, especially in arid and semi-arid environments. To fulfil stakeholders' demands in multidisciplinary sectors (social, environmental, economic), decision makers are facing high challenges to set sustainable water resources management strategies. Many literatures (details are in the next chapters) developed variant management approaches to help the decision makers in their strategies using different decision support tools like optimization techniques, and system dynamic model. However, the common developed approaches were formulated to enhance specific objective or a few objectives in a river basin system, while other objectives remain embedded as system constraints or unconsidered. For example, improving hydropower generation and agriculture revenues were the main concern in broad literature.

Integrated Water Resources Management (IWRM) is another approach adopted to improve regional environment and economy by developing a collaborating relationship between all the stakeholders and the available resources within a sustainable framework. Even so, literature that implemented IWRM approach (details are in the next chapter) shows that only selected objectives from different disciplinary and resources were integrated. Examples of different proposed integration are: surface and groundwater, water quality and quantity, agriculture and industry, domestic and navigation, etc.

The above argument demonstrates the absence of a holistic water resources management approach, which is capable to conceptualize and combine all the objectives in a river system. The holistic approach will help decision makers to set long-term water resources management strategies under a sustainable development framework.

In order to develop and evaluate the proposed approach, a challenging case study in Iraq was selected. Iraq has an arid environment with mean annual rainfall less than 150 mm (IPCC, 2007), and has two big rivers, Tigris and Euphrates, which originated from neighbour countries: Turkey, Syria, and Iran. Diyala River is a major Tigris River tributary originated from high mountains in Northwest of Iran. The river extends 445 km towards its confluence with the main river at south of Baghdad City, the capital of Iraq. Two big dams were constructed on the river for multipurpose services, Derbendikhan in the north, and Himren in the central part of the basin. River watershed covers an area of about 32,600 km^2, of which 46% is inside Iraq and 54% in Iran. According to the literature (details are in the next chapter), the River basin is facing different multidisciplinary challenges in social, environmental and economic sectors, which are mainly due to: unset water sharing agreement with Iran, land use development expansion, population evolution, and expected impact of climate change.

1.2 Research's Aim

The aim of the research is to develop a holistic or comprehensive water resources management approach for a river system. Optimization techniques and IWRM principles will be employed to generate long-term flow regime strategy under sustainable development framework. Hence, the approach integrates all the common sectors (e.g.: society, environment and economy) with the available water resources (e.g.; surface water, groundwater and reused water) over water-control systems (e.g., dams, barrages, pipes, and pumps). The proposed approach will support decision makers' agenda for future sustainable development plans.

1.3 Research's Objectives

In order to achieve the research aim, the following objectives are adopted in this research:

- To carry out a review of the state-of-the-art multi-objectives optimization algorithms used recently to solve complex water resources management problems, as well as their potential drawbacks, to select a competitive algorithm.
- To utilize performance assessment to evaluate the nominated algorithm's achievement under different problems environments using reservoir operation problem from the literature, five test benchmark functions, and reservoir operation problem from the current case study (Derbendikhan dam). Modification or development of a new methodology may be employed to improve algorithm's achievement.

- To carry out a review of existing literature, database, maps, and models achieved for the study area to demonstrate problems identification and target objectives to be formulated in the proposed approach.
- To develop a groundwater management model for the middle region in the basin to evaluate sustainable use of aquifer storage by: creating a 3D MODFLOW model to estimate aquifer boundary recharges based on the historical database, and developing an optimization management model for long-term pumping for agriculture use.
- To develop optimum flow regime management strategy for the middle reservoir (Himren dam) considering social and environmental objectives, to enhance downstream region environment under different inflows scenarios.
- To develop the comprehensive approach for multidisciplinary water resource management problem using IWRM principles coupled with optimization algorithm to improve river basin environment and revenues. Implement different alternatives and scenarios to represent different possible potential risks like climate change, political and legislation impacts.

1.4 Thesis Structure

This thesis describes the development of a holistic management approach at a river basin level with application on Diyala River basin in Iraq. This was done by employing many-objectives optimization algorithm to achieve IWRM principles. Following the current chapter, eight chapters are developed as follow:

- Chapter 2 presents a historical background on IWRM definition, its implementation and challenges, and the relation to sustainable development goals. Reviews of recent optimization algorithms used in water resources management are also carried out, as well as some potential problematics in solving complex problems. The review also demonstrates the potential problems in a real-world river basin management, which was adopted to evaluate the proposed approach.

- Chapter 3 demonstrates research methods to address the knowledge gaps. The key elements of the holistic approach are presented, as well as the multi-objectives optimization algorithm. All target decision variables, objectives, and constraints are identified, which cover the current and unforeseen events management strategy. Optimization algorithms' difficulties are also discussed and addressed.
- Chapter 4 presents performance assessment for Borg MOEA using real-world reservoir operation problem from the literature. Detailed behaviour of Borg MOEA during objective function evaluation was presented and discussed.
- Chapter 5 demonstrates a detailed description of new evolutionary optimization algorithm entitled "Epsilon-Dominance-Driven Self-Adaptive Evolutionary Algorithm for Many-Objective Optimization (ε-DSEA)". A brief comparative assessment with Borg MOEA was achieved using five test benchmark functions for up to 8 objectives functions, and a real-world reservoir operation management problem (Derbendikhan dam).
- Chapter 6 illustrates long-term pumping impact on aquifer storage in the middle part of the basin. A 3D static groundwater flow model was achieved using MODFLOW-2005 software to estimate aquifer recharge. The aquifer recharge was employed with long-term groundwater optimization management model to assess the sustainability use of aquifer storage for farms irrigation. Open furrows

and drip irrigation systems were utilized as alternatives for farms' water delivery. Comprehensive algorithms' performance assessment for ε-DSEA and Borg MOEA was presented and discussed.

- Chapter 7 presents a novel Optimum Socio-Environmental Flows approach (OSEF) for reservoir management strategy. The approach ensemble all common river basin social and environmental objectives using many-objectives optimization algorithm. Further, a novel Auto-Adaptive Constraints approach (AAC) was developed to boost optimization algorithm convergence. The OSEF-AAC approach was implemented on Himren dam project to evaluate its robustness in improving downstream region environment and revenues under two inflows scenarios. Further ε-DSEA assessment results were presented and discussed, in comparison with Borg MOEA.
- Chapter 8 presents a novel comprehensive optimum integrated water resources management approach (OP-IWRM). The approach combines and employs all river basin common social, environmental, and economic objectives, and all available water resources, respectively, using many-objectives optimization algorithm. The entire Diyala River basin system was employed to evaluate the approach's effectiveness and robustness under different challenges including climate change and political impacts. Detailed results were presented and discussed for the proposed alternatives.
- Chapter 9 demonstrates research outputs and recommendations for future policies and works.

The above structure was conceptualized in a schematic diagram presented in Figure 1, which shows the adopted research methodology to achieve the research aim.

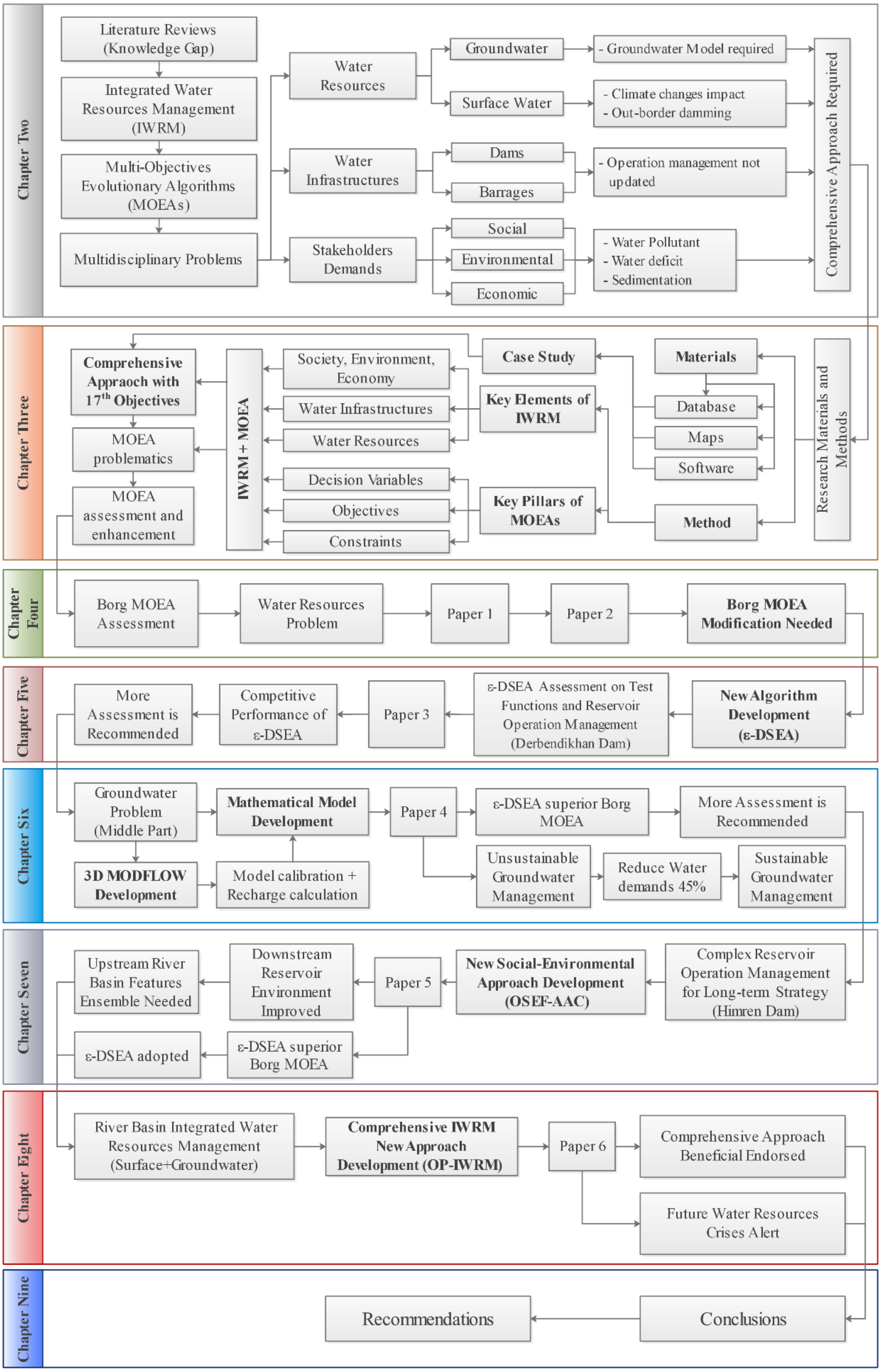
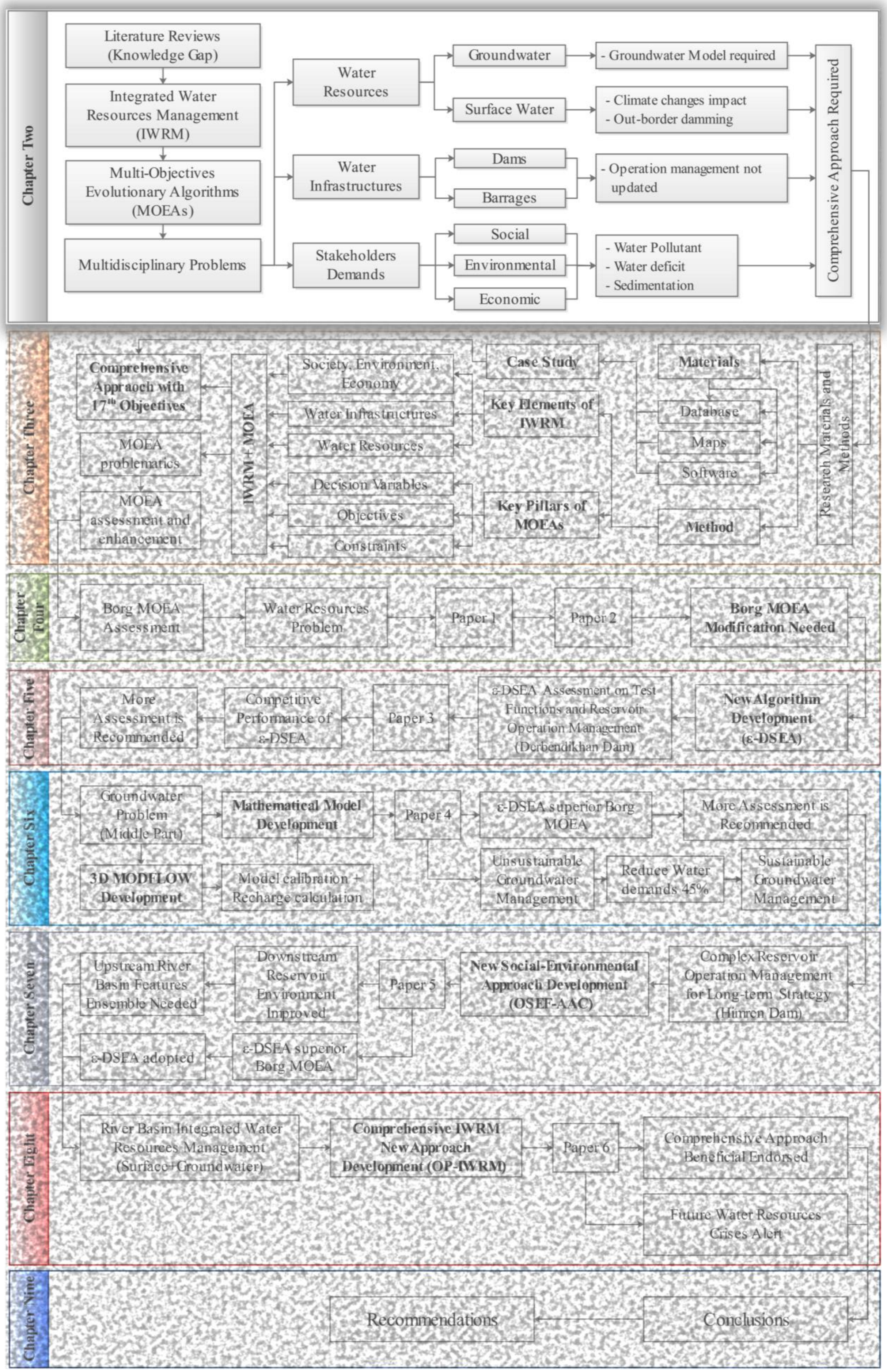


Figure 1. Research methodology schematic diagram



Chapter Two
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CHAPTER TWO
GENERAL LITERATURE REVIEW

2.1 Introduction

The current chapter presents general literature relevant to the research's aim, as the knowledge gap is demonstrated. After defining integrated water resources management (IWRM) term, challenges facing its implementation are reviewed. The consistent relation of IWRM with sustainable development goals (SDGs) is demonstrated. The optimization techniques are introduced and their utilization in water resources management are cited. Examples of some problematics in optimizing real-world complex problems are highlighted. Finally, a real-word case study challenges and problems are demonstrated, as a complex example to be solve.

2.2 Integrated Water Resources Management (IWRM)

2.2.1 Background

Different definitions of IWRM were presented by many worldwide organizations (Cardwell et al., 2006), however the most common one produced by the Global Water Partnership (GWP) as, "*IWRM is a process which promotes the co-ordinated development and management of water, land and related resources, in order to maximize the resultant economic and social welfare in an equitable manner without compromising the sustainability of vital ecosystems*" (GWP, 2000). A consistent definition of IWRM was adopted by the American Water Resources Association

(AWRA), as "*coordinated planning, development, protection and management of water, land and related resources in a manner that fosters sustainable economic activity, improves or sustains environmental quality, ensures public health and safety, and provides for the sustainability of communities and ecosystems*" (AWRA, 2011).

In other words, IWRM is a holistic approach for sharing water with all sectors and avoids using isolated approaches to improve a specific sector, or sectors (Giordano and Shah, 2014). Accordingly, the IWRM is a correlation process between water supply and water demand subjected to different situations and purposes, as shown in Figure 1 (Grigg, 2016).

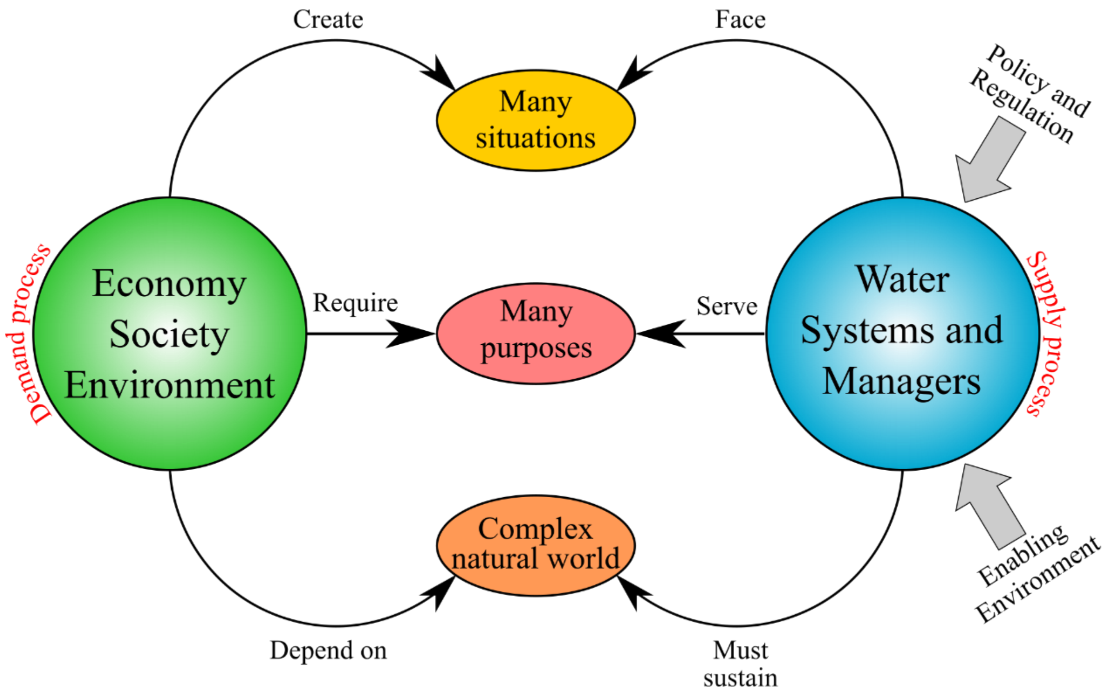


Figure 1. Schematic diagram for multi-sectors interrelation in IWRM (adapted from Grigg, (2016))

The Figure illustrates the demand process nexus (economy, society, and environment) with water systems and managers over many situations and purposes. The development process toward IWRM follows three steps (or levels) (Grigg, 2016):

- Technical level: the use of different infrastructures and equipment to carriage water, which is called "*water resources engineering*"
- Management level; water allocation by the decision makers using water infrastructure, which is called "*water resources management*"
- Integrative level: linking between the decision makers and the related water sectors, which is called "*Integrated Water Resources management*"

Hence, in order to achieve effective IWRM the manager should carry out; efficient water infrastructure systems and management programs, and secure their reliability to fulfil water-sectors' demands (Grigg, 2016).

Insight view of IWRM process and impact factors at a river basin level is presented in Figure 2, which demonstrates the collaborative interconnection between: the resources, the demands, and the external impacts.

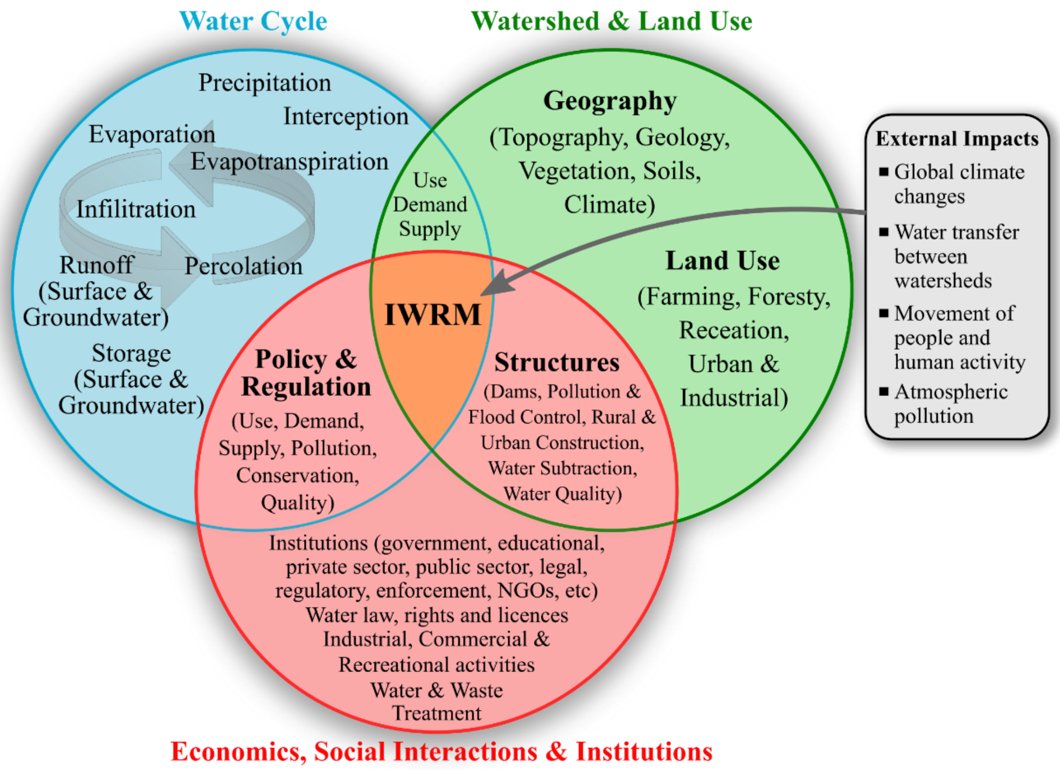


Figure 2. IWRM process and impact factors (adapted from Muste and Mocanu, (2016))

2.2.2 Challenges of IWRM implementation

Developing a plan for IWRM implementation on the river basin system scale has many challenges, which needs robust methods to tackle the complexity of water system management from one side (due to its nonlinearity, dynamic properties, conflict objectives, and constraints (Haimes and Hall, 1977; Yeh, 1985; Maier et al., 2014)), and the stakeholders' demands, governmental legislation, and environmental aspects (and others), on the other side (Grigg, 2016). The conflicts and interrelationship problems between the multidisciplinary sectors for IWRM implementation for larger-scale regions were observed by Biswas (2008), Hering and Ingold (2012), and Mohtar and Lawford (2016). Authors and institutes adopt different water management concepts due to the generalization in IWRM definition (Biswas, 2008). The latter author demonstrated 41 variant possible explanations for the term "integrated". Some examples are: water supply and water demands: surface water and groundwater, water quantity and water quality, urban and rural water issues, government and NGOs (nongovernmental organization). Moreover, "*... But by now we all know how complex water resources management is and that ideally it should be managed holistically, considering efficiency, equity and the environment. But we should also know by now that holistic management is costly and politically difficult, or impossible"* (Giordano and Shah, 2014). The latter authors reviewed examples of using simple alternatives to solve water resources problems for transboundary river basins, rather than implementing a complex IWRM approach.

Many recent studies investigate the impact of IWRM implementation on different river basins to improve its environmental and economic benefits using several tools and methods. Among these tools, System Dynamics Simulation (SDS) was used widely as a Decision Support Tool (DST) in the field of IWRM implementation. System Dynamics is a method to simplify the correlations' identification that joins variant interdependent subsystems, which controls system's behaviour (Sterman, 2000; Mirchi et al., 2012). However, the SD model is capable to solve a specific goal (or objective) of a certain problem (Sharawat et al., 2014), and they have spatial data inertia processing (Nikolic and Simonovic, 2015). Other studies adopt different tools for IWRM implementation. Weng et al., (2010) present an integrated scenario-based multi-criteria decision support system (SMC-DSS) for water resources planning and management in a Haihe river basin in China. The tool combines a multi-objective optimization algorithm, multi-criteria analysis and decision support system to assess the impact of multi policy management on the socio-economic and environmental sectors. The evidence shows that different results can be obtained when using different policies. Coelho et al., (2012) present and assess a multiple criteria decision support system as a tool for supporting IWRM in Tocantins-Araguaia river basin in Brazil. The authors combined GIS processing, fuzzy set theory, and dynamic programing algorithm to obtain optimum solution depending on user criteria selections. Nikolic, (2015) presents Agent-Based simulation coupled with system dynamic simulation to achieved IWRM in Upper Thames River basin in Canada. The results demonstrate the interaction between different regional resources and activities. Moreover, Klinger et al., (2015) produced IWRM tools for the Lower Jordan Rift Valley. The authors used multi-objective optimization algorithm to improve three sectors in the region. Safavi et al., (2016) present Expert knowledge based modelling for IWRM in Zayandehrud River Basin in Iran using WEAP software. The results show that the river basin management policy needs to be improved to avoid future water crises in the basin.

Bullet-1

To this extent, none of these studies (and others) achieved a holistic IWRM approach capable to integrate all water-supply and demands processes.

2.3 IWRM and Sustainable Development Goals (SDGs)

Sustainable development means "*development that meets the needs of the present without compromising the ability of future generations to meet their own needs",* defined by the World Commission on Environment and Development report (WCED) and published by United Nations (UN, 1987). The report's sustainability fundamentals are based on: economic growth, environmental protection, and social equality, thus it is an integral of these fundamentals. Clearly, these fundamentals are consistent with IWRM principles, in fact, IWRM is one of the supportive tools of sustainable development (Tejada-Guibert et al., 2015).

In 2015, the United Nations announced the 17 goals of 2030 agenda for sustainable development with 169 targets (UN, 2015), as in Figure 3. These goals set for countries' agenda toward national sustainable development. However, governments may face difficulties to select and achieve pragmatic targets due to SDGs' universal extent. Likewise, decision makers should be able to evaluate the long-term integral impacts of economy, society, environment strategies (Allen et al., 2016). Recent literatures demonstrate the gap toward holistic SDGs' achievement. Allen et al., (2016) analysed 80 models achieved to implement SDGs at national development planning scale, as only one model address all 17 goals (named "International Futures" produced by Frederick S. Pardee Center for International Futures, University of Denver). However, this model experienced limited variables for many goals.

Statement-1

Thus, the need to develop a holistic approach to achieved all SDGs goals and targets is evidenced (Allen et al., 2016). The current research focuses on developing a holistic IWRM approach, as it is a pathway towards the holistic SDGs approach.

Figure 3. The 17 Sustainable Development Goals (SDGs) (UN, 2018)

2.4 Optimization Techniques in Water Resources management

2.4.1 Background

Recent studies demonstrate the robustness of optimization algorithms as a decision support tool in water resources management problems (Maier et al., 2014; Horne et al., 2016; Horne et al., 2017; Barbour et al., 2016). The early paradigms of optimization algorithms to solve different types of problems are: linear programming, non-linear programming and dynamic programming (Horne et al., 2016; Tayfur, 2017). However, the aforementioned methods in general are incapable to solve complex problems that water resources management have (Haimes and Hall, 1977).

Recently, Evolutionary Algorithms (EAs) were widely used to solve complex problems in different fields of engineering and science (Coello Coello et al., 2007; Chiong et al., 2012), which were inspired from evolution process of genes (Nicklow et al., 2010; Back et al., 2000). Early computational paradigms of EA's are: genetic algorithm (GA) (Holland, 1975), evolutionary strategies (ES) (Schwefel, 1981), evolutionary programming (EP) (Fogel et al., 1966), and genetic programming (GP) (Koza, 1992). Figure 4 shows the EAs paradigms in the optimization search techniques taxonomy (Simon, 2013). These Algorithms can solve multiple objective problems simultaneously to generate a set of non-dominated solutions front (Pareto-front) in a single run (Deb, 2001; Coello et al., 2007).

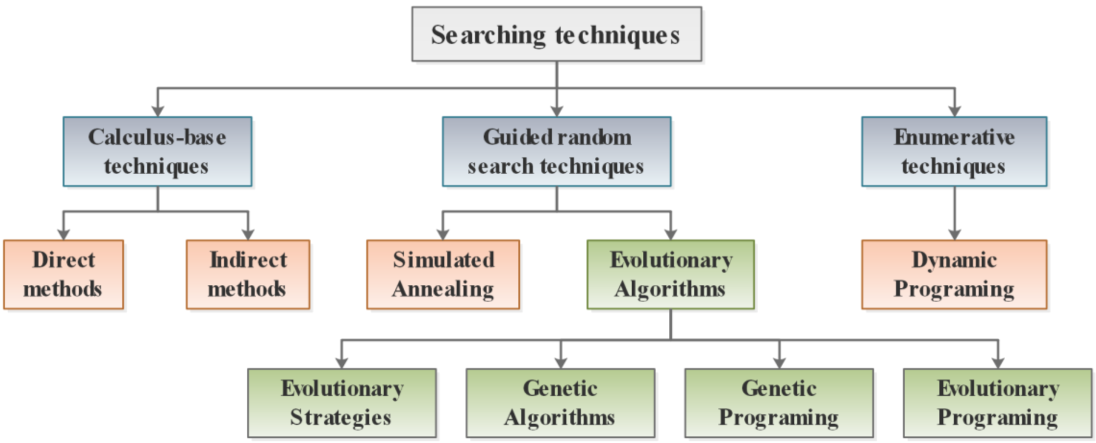


Figure 4. Search techniques taxonomy (adapted from Simon (2013))

Examples of MOEAs' implementation in water resources management include: Javadi et al. (2015) used non-dominated sorting genetic algorithm (NSGA-II) to optimize seawater intrusion in a coastal aquifer; Sidiropoulos et al. (2016) used simulation-optimization for groundwater management; Oxley and Mays (2016) applied a genetic algorithm (GA) for long-term planning and sustainable water resources management; Tigkas et al. (2016) investigated the efficiency of EAs for the calibration of a conceptual hydrologic model; Sreekanth et al. (2016) implemented the NSGA-II algorithm to maximize aquifer water injection and to minimize the variance in aquifer water levels; and Sadeghi-Tabas et al. (2017) coupled a multi-algorithm, genetically adaptive, multi-objective (AMALGAM) optimization algorithm and simulation model to minimize the deficit in water demands, shortage index, and drawdown in the water table. More MOEAs' types and application in water resources may be found in Tayfur (2017). However, the growing need to solve even more complex engineering problems, having four objectives or more, gives the motivation to improve further the capabilities of MOEAs. Deb and Jain (2013) upgraded NSGA-II to NSGA-III, while Seada and Deb (2015) proposed a new version of NSGA-III named U-NSGA-III. Hadka and Reed (2013) developed Borg MOEA with auto-adaptive recombination operators, while Roy et al., (2015) introduced an evolutionary path control strategy (EPCS). Zhang et al., (2015) produced Knee Point-Driven Evolutionary Algorithm, and Li et al., (2015) proposed MOEA/DD, for many-objective problems. Recently, Yuan et al., (2016) proposed an evolutionary algorithm for many objective optimization (θ-DEA) based on a new dominance relation. A brief list of many-objectives optimization algorithms can be found in B. Li et al. (2015) and Bechikh et al. (2017).

Statement-2

Based on competitive results achieved on benchmark test functions and real-word problems (Hadka and Reed, 2012; Hadka et al., 2012; Hadka and Reed, 2013;

Woodruff et al., 2015; Salazar et al., 2016), Borg MOEA met or outperform recent common state-of-the-art evolutionary optimization algorithms. It has many novel techniques to generate optimum solutions and avoid local optima stagnation.

2.4.2 MOEAs' Challenges in Water Resources Management Problems

Although real-world water resources problems have many conflicting objectives, recent studies have utilized up to three objectives to avoid the computational efficiency, high-dimension challenges and water resources system complexity for more than three objectives (Maier et al., 2014). Notably from Table 1, only three of nineteen studies consider more than five objectives in reservoir operation strategy (multiple publications used in the same case study are considered as one study). Moreover, some studies merge objectives to simplify the multiple dam system problems, and hydropower generation and water supply (for domestic and irrigation) were the dominant objectives adopted in these studies. While, few recent studies adopted many-objectives (more than three objectives) optimization water resources management problems.

Environmental objectives are seldom adopted in reservoir management, in a recent review of studies between 1980 and 2015, by Horne et al. (2016) found only 42 studies adopt environmental releases in reservoir management as decision variables.

Recently, Horne et al. (2017) presented Conditional Probability Networks (CPNs) approaches combined with Mixed Integer Programing (MIP) optimizer for environmental flow regimes. Poff et al. (2016) proposed a framework approach for eco-engineering decision scaling using performance indices, and Acreman et al.

(2014) show that environmental flows need a “designer” approach for considering ecosystem objectives in water control infrastructure, rather than a “natural” approach.

Bullet-2

Consequently, these studies (and others) rarely adopted combined multidisciplinary problem for river basin management (e.g. Social, Environmental, and Economic) (Horne et al., 2016; Horne et al.,2017; Poff et al., 2016).

Table 1. Summary of literatures that used evolutionary algorithms to optimize multi-objective reservoir operation strategy

Author	**Method**	**Objective No.**	**Subject**	**No. of dams**
Kim et al., (2008)	NSGA-II	2	Water shortage index + hydropower	1
Chang and Chang, (2009)	NSGA-II	2	Water shortage index for two dams	2
Dittmann et al., (2009)	MOES	5	Inundation + overtopping for three dams + releases	3
Reddy and Kumar, (2009)	MOPSO	2	hydropower + irrigation	1
Regulwar, (2009)	MOGA	2	hydropower + irrigation	5
Hakimi-Asiabar et al., (2010)	SLGA	3	hydropower + water supply + water quality	3
Wang et al., (2011)	MIGA	2	long term operation for water demand and storage	1
Malekmohammadi et al., (2011)	NSGA-II	2	Flood + water demands	2
Schardong et al., (2013)	MODE	3	Water demands + water quality + pumping cost	5
Kasprzyk et al., (2013)	ε-NSGA-II	6	Two cost + Three reliability + Market use	1
Giacomoni et al., (2013), Giuliani et al., (2014a)	Fitted Q-iteration	5	Two Recreation + sedimentation + water deficit + Temperature differences	1
Giuliani et al., (2014b), Giuliani et al., (2016), Zatarain Salazar et al., (2016) Zatarain Salazar et al., (2017)	Borg MOEA	6	Three water supply + hydropower + recreation + environment	1
Ahmadianfar et al., (2015)	MOEA/D	2	Flow demands + agriculture demands	3
Li and Qiu, (2015)	NSGA-II	2	Hydropower + firm power	1
Crookston and Tullis, (2016)	NSGA-II	2	Water quality + water temperature	1

Hurford et al., (2014)	ε-NSGA-II	10	Four agriculture water deficit + water losses + Hydropower + Land availability + Two Flow alteration	3
Qi et al., (2016)	MOEA/D	2	Water level + releases	1
Chen et al., (2016)	NSGA-II	5	Water supply + hydropower + flow alternation in two rivers + water quality	1
Dai et al., (2017)	NSGA-II	2	Hydropower + water alternation	2

2.4.3 The Decision Makers and MOEAs

Generally, water resources management models provide information to the decision makers, rather than the decision itself (Loucks, 2012). There are pre- and post-optimization implementation approaches for incorporating decision-maker criteria within a multi-aspects problems (Maier et al., 2014; Coello et al., 2007). One of the pre-criteria approach drawbacks is the dissatisfaction (or lack of trust) of decision makers toward model results that emerged depending on their criteria set, and they may change these criteria to generate new results (Loucks, 2012). Hence the model needs to be re-executed until they get satisfaction. The second approach is computationally challenging and has potential difficulties to find the Pareto-front for optimum solutions set, which recently tackles by using multi-objective (or many-objective for more than three objectives) optimization algorithms (Maier et al., 2014).

However, MOEAs' optimum achievement varies over different problems (Ishibuchi et al. 2015; Ishibuchi et al. 2017). For example, Reed et al. (2013) assess the performance of ten MOEAs to solve four benchmark problems and show the outperformance of Borg MOEA over other algorithms. Conversely, Borg MOEA exhibited a lower performance on a standard water distribution system benchmark problem and failed to approach the true Pareto-front (Qi et al. 2015; Zheng et al. 2016).

Salazar et al. (2016), however demonstrated consistent performance with other MOEAs on a real-world reservoir operation management problem.

Bullet-3

Hence, multiple algorithms may be required when solving real-world problems to achieve robust results and effective underpinning of decision making (Maier et al., 2014).

The MOEAs use many parameters such as population size, mutation and crossover rate, which have direct impact on their performance. Hence, these parameters (especially mutation and crossover rates) should be carefully selected and tested within the defined problem environment (Maier et al. 2014; Karafotias et al. 2015). The optimal performance of MOEAs is evaluated on benchmark test functions (e.g. DTLZ series, ZDT series, etc.), which consider easy and forward problems recognising that real-word problems have more complexity and challenges (Maier et al., 2014). The MOEAs' effectiveness is commonly measured using metrics like the hypervolume metric (Zitzler, 1999), which evaluates the non-dominated solutions' hypervolume, and generational distance metric (Van Veldhuizen and Lamont, 1998), which measures the average distance between the dominance solutions and the closer Pareto-front set. However, these metrics (and others) may provide misguiding results and most of their design principles depends on the true Pareto-front, which is unknown in real-world water resources management problems (Maier et al., 2014). Details of relevant parameters' (and other) problematics in MOEAs are presented in chapter 5 of the current research.

Bullet-4

Accordingly, performance and achievement of MOEAs require further assessment, especially when solving real-world problems (Maier et al., 2014).

Further, developing a penalty functions formula is a type of constraints approach paradigm (Coello Coello, 2002; Simon, 2013) to represent decision makers' policy or criteria (Maier et al., 2014) and to exaggerate the unfeasible solution to guide algorithm exploration towards feasible solutions. However, these functions should be carefully developed and tested for each problem to avoid premature or delay of algorithm convergence towards optimum solutions (Deb and Datta, 2013).

The initial random seeding of decision variables' population generates feasible and unfeasible candidates in the decision variables design space. Then these candidates subjected to mutation and crossover evolving process to produce new generations until evaluation process ends (Deb, 2001; Abraham et al., 2005), which is sensitive to objective achievement to produce non-dominated solutions. Therefore, the initial evaluation stages produce large penalized values due to numerous decision variables violations, which restrains the convergence process, or may cause stagnation in local optima (Deb and Datta, 2013).

Bullet-5

As a result, dynamic penalty function sensitive to model violation is evident to boost algorithm convergence.

2.5 Case Study

2.5.1 Background

Iraq may be considered a fortunate country in water resources compared to other countries of the arid and semiarid Middle East. Two important rivers, the Tigris and the Euphrates, though they originate in the heights of neighbouring Turkey and Iran, flow ultimately through its territory before joining and discharging in the Gulf. Moreover, Iraq possesses groundwater resources of some potential, which are not yet totally accounted. Nevertheless, Iraq may face a shortage in usable water resources in the near future because of: the steadily increase of water demands in the region, the unsettled dispute among the riparian countries on the sharing of the resources of the two rivers, and the on-going traditional methods of water resources management. Hence, agreements with neighbour's countries need to settle the share of water resources, and advanced methods of water resources management need to be adopted for optimum and sustainable exploitation of these resources.

Figure 5 shows the Tigris and Euphrates River catchment areas and the relevant water resources supply percentage. About 91% of the resources are from neighbours' country, and only 9% from internal catchment areas (GRID-Geneva, 2000; Adamo et al., 2018).

Priority of Iraqi water resources management may be forwarded to the Tigris River basin, which virtually aliments the northern and the eastern part of the country, including the capital Baghdad. Tigris is joined inside Iraq by five main tributaries, one of which is the Diyala River (Sub-basin No. 8 in Figure 5).

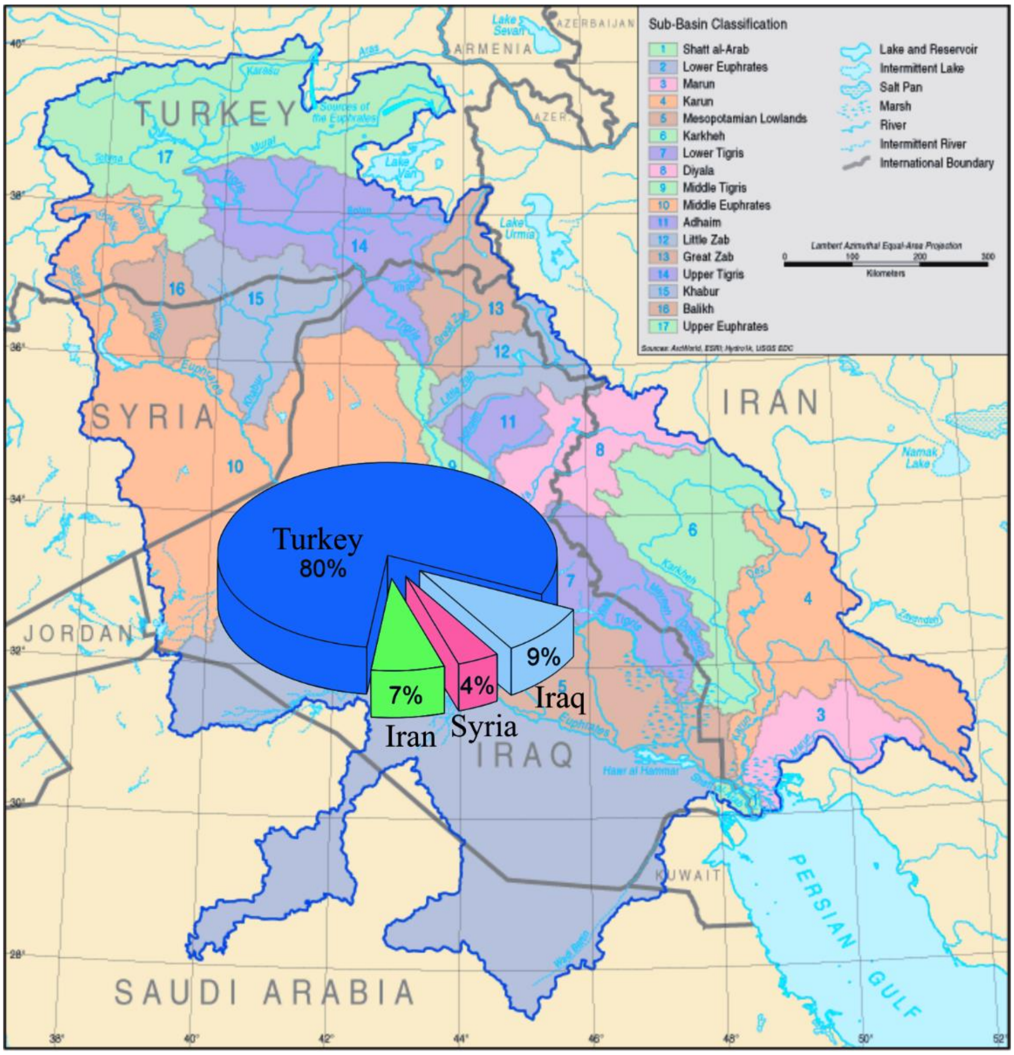


Figure 5. Iraqis' Tigris and Euphrates River catchment areas and its water resources supply quantities (adapted from (GRID-Geneva, 2000; Adamo et al., 2018))

2.5.2 Diyala River Basin Identification

The Diyala River originates in the Iranian heights, passes just south of the provisional town of Sulaymania in Kurdstan, and joins Tigris just south of Baghdad (Figure 6). The total area of the Diyala river basin inside Iraq is nearly 17000 km^2. It can be divided into three zones; upper, middle, and lower. The river flow is controlled at present by two dams: the Derbendi-khan dam located at the boundary between the upper and the middle zones, and the Hemrin dam located at the boundary between the middle and the lower zones.

The middle zone of the Diyala River basin has potential groundwater resources that can play an important role in water management. Several cities and towns benefit of the river water resources as well as several agricultural projects that cover an area of $693{\times}10^3$ hectares particularly in the middle and lower zones (SGI et al., 2014).

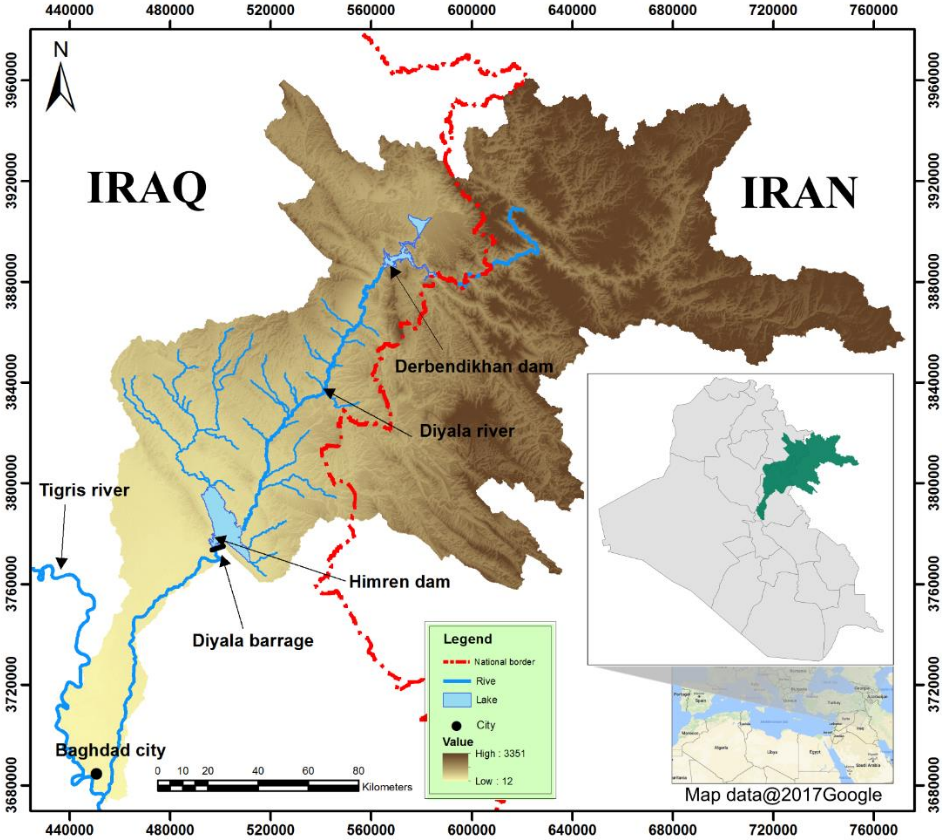


Figure 6. Location map of Diyala River Basin in Iraq

2.5.3 Hydrological regime of Diyala River Basin

The natural flow regime of Diyala River before the construction of Derbndi-khan dam appears in the feasibility study of the dam carried out by Harza and Binnie (1963). The Iraqi national water resources master plan prepared by the Russians (Soyuzgiprovodkhoz, 1982) contains a conclusion of hydrological background information and analysis of all Iraqi rivers. Other hydrological studies on the Diyala

River catchments (including its upper part inside Iran) was fully exposed by Al-Jibory (1991). The study concentrated on water quality and sediment transport in the river system. Further, Al-Sunawai (1985) exposed detailed water quality analysis of the lower Diyala region. Recently, Mohamad, (2010) diagnosed possible water crisis problems in Diyala province, among these: river flow scarcity, traditional irrigation system, water system infrastructures' maintenance limitation. Al-Ansari (2013) and Al-Ansari et al. (2014) present an assessment for the water resources in the country and future prediction for these resources. The studies refer to future water scarcity in the water resources in Iraq due to climate impact change and unsettled dispute in water sharing, including the Diyala River basin, which were endorsed by Al-Faraj and Scholz, (2014, 2015). A reduction of about 50% in mean monthly river flow was observed from 2004 to 2013 in summer season due to upstream projects development plans. The Iraqi Ministry of Water Resources has recently accomplished the "Strategy for Water & Land Resources in Iraq" study, prepared by SGI et al., (2014), which also altered future water resource scarcity at national scale.

Bullet-6

Thus, evidences of Diyala River basin water resources scarcity are endorsed.

2.5.4 Diyala River Morphology

The early study covering sediments discharge in Diyala River was achieved by Assad, (1978) (as in Ezz-Aldeen et al., (2018)), which was before Himren dam project's construction in 1981. Then a study was achieved by Al-Ansari et al., (1983), which concentrated on deposition in Himren dam reservoir. Another study observed sediment transport in Diyala River was accomplished by Al-Jibory, (1991). A recent study focus on river bed deposits in the middle part of Diyala River was prepared by Al-khaldy and Al-askari (2015).

Bullet-7

From the above, studies and models of Diyal River sediment transport were rarely developed and achieved.

2.5.5 Hydrogeological Assessment of Diyala River Basin

The first general groundwater resources assessment of Iraq was accomplished by Parsons (1957) (Engineering Company). Aquifer identification was based on the geological setting, some bore holing, and water point inventory. Due to lack of local basic data for renewable groundwater resources assessment, a rough estimate was made by relating the local water balance components to the components of an area elsewhere similar in physiographic features where data is available. This study as well as the General Scheme of Water Resources and Land Development in Iraq accomplished by Soyuzgiprovodkhoz (1982) did not refer to Diyala river basin as one unit. In the later study, moreover different reaches of the river fall within the different so called hydrogeological modulus that represent specific aquifer productivity and water quality. Studies that contain additional local field data were produced separately by several authors on parts of the basin. Part of the lower basin zone to the east and south of Hamrin reservoir was the focus of a study carried out by Khalil and Ridha (1993). Potential groundwater utilization for agriculture and the influence of Hamrin reservoir on the local groundwater regime was assessed. The upper zone around the lake of Derbendi-khan is included in a study prepared by FAO (2004) on the hydrogeology of the northern states published in 2004. Moreover, the middle part and the most promising zone as far as groundwater resources are concerned were thoroughly investigated by Ahmed et al., (2005). Furthermore, Al-Tamimi (2007) present an assessment for the Diyala River Basin with focusing on the middle part of the basin.

Groundwater abstraction from the different zones of the basin is not developed to the point where an interfering measure has become necessary. The present total abstraction from the middle zone was estimated by Ahmed et al. (2005) to be in the order of 13% of the zone renewable resources.

The water quality suitability in upper aquifer for agriculture uses for the middle part of the basin is within the permissible zone according to SGI et al. (2014) depending on four parameters: Electrical Conductivity (EC, μmohs/cm), Sodium (Na %), Chloride (Cl, ppm), Sulphate (SO4, epm), Soil Adsorption Rate (SAR, unit less), as shown in Figure 7.

Bullet-8

On the other hand, references do not indicate that there was an attempt to simulate numerically or analytically the effect of abstraction on groundwater or the river regimes. This could become the focus of the present or future studies if water management should set a more important role to groundwater in the water resources exploitation scheme of the river basin (Al-Tamimi, 2007; SGI et al., 2014)

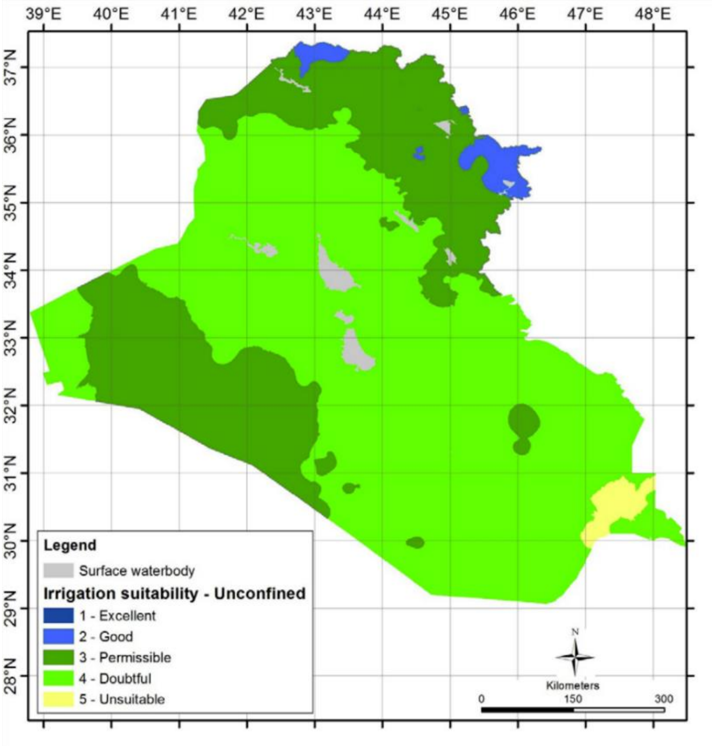


Figure 7. Groundwater suitability use for agriculture in unconfined aquifers (SGI et al., 2014)

2.5.6 Reservoirs Operation Management of Diyala River Basin

Reservoir operation has been the interest of many investigators of the Diyala River basin with emphasis on optimization techniques. Hameed (1986) and Naji (1989) used Discrete Differential Dynamic Programming or (DDDP) to optimize Derbndi-khan and Hamrin dams system. The first author found that the system is safe against flood, but it is inadequate during drought period. While Naji (1989) found that to improve Diyala River water quality by maintaining a fix monthly release discharge ends with a reduction in water supplies during the next period. Additionally, Al-Delewy (1995) developed a DDDP model for the Diyala River reservoirs in order to solve the monthly operation problem of multi-reservoirs system for multi-purpose operation. The objective was flood and pollution control while maintaining irrigation and electric power generation requirements. Moreover, Muhsun (2002) applied the DDDP model in order to reach to the optimum operation policy of all Tigris reservoirs, including those under construction (Bekhma and Mkhool). The optimum operation rule curve driven from the result of the optimization solution was used to develop a monthly simulation model in order to determine the real time monthly operation plan for the system with and without the dams under construction.

Bullet-9

References did not highlight any recent attempt to upgrade reservoirs operation rules using advance optimization techniques (Alsaffar, 2017a).

2.5.7 Current and Expansion of Water Demands

Water demands normally fall in three categories: agricultural or irrigation requirement, public or municipal needs, and industrial water demands. Presently these three components of water demands have sharp rising trends with time in a country like Iraq which is still in the path of development. The most important water user in Iraq is agriculture which consumes nearly 85% of the water resources of the country. Growing population and urbanization are boosting the municipal water needs as well.

Water requirements and water demand were part of the General Scheme of water Resources and Land Development in Iraq prepared by Soyuzgiprovodkhoz, (1982). The scheme which evaluated the national water demands in year 1982 presented a projection till the year 2000. A recent estimation of the demands to the year 2035 was made by (SGI et al., 2014). Accordingly, the expected national demands in year 2035 from both Tigris and Euphrates will reach the figure of 70.8 billion cubic meters (10^9 m^3), and the total fresh water available will be 56.52 billion cubic meters in end of the next three decades due to Turkish, Syrian, and Iranian projects, and the climate changes impacts. This will create a water deficit of about 15 billion cubic meters in year 2035 (SGI et al., 2014), as shown in Figure 8.

Bullet-10

As a result, future deficit is expected in Diyala River basin's water resources due to land use developing and expansion plans.

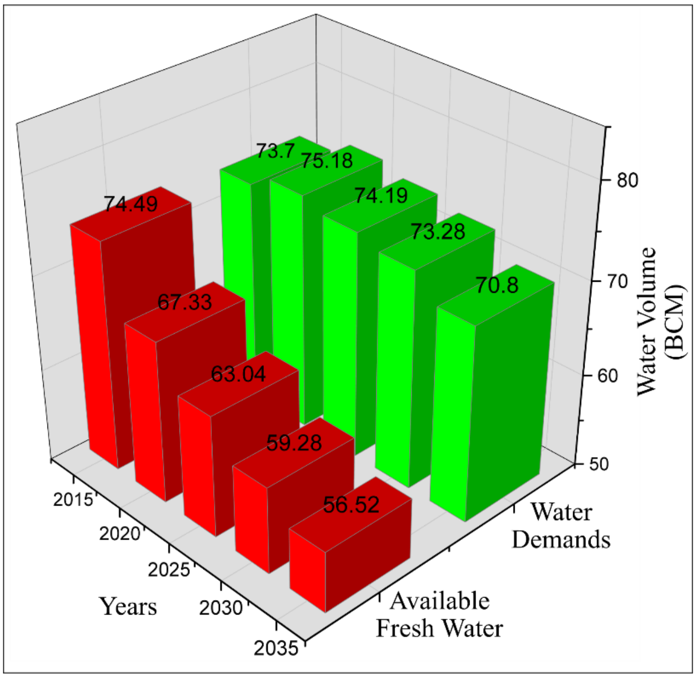


Figure 8. Future prediction of available fresh water and water demands in Iraq (adapted from SGI et al. (2014))

2.5.8 River Basin Problems and Challenges

Based on previous studies, the basic Diyala River basin management problems and challenges are:

1- Climate changes impact: the mean temperature may increase approximately 3 degrees Celsius and the annual rainfall may deplete by 21% for the next half-century (Abbas et al., 2016; Lelieveld et al., 2016)
2- Political impact: Iran built four dams on the river's source streams and a big water conveyance tunnel under construction were observed by Abdulrahman, (2017); Al-Faraj and Scholz, (2014) which divert water from catchment area.
3- Pollutant impact: the impact of Al-Rustamiya wastewater treatment plant discharges (470,000 m3/day, with 5000 mg/l of TDS) to the Diyala river, observed by many studies (Kubba et al., 2014; Aenab and Singh, 2014; Evan et al., 2012; WCC, 2006; CEB, 2011). This plant is located just before river confluence with the Tigris River, in the south of Baghdad city which has large density of population approaching seven million peoples and this is one of the primary treatment works for the city.
4- Leeching drains impact: two leeching drains from agriculture projects are discharging to the Diyala river, which increases the deterioration of the river environment (Soyuzgiprovodkhoz, 1982; SGI et al., 2014).
5- Water allocation losses impact: the use and impacts of traditional irrigation techniques by large agriculture projects in the downstream basin were observed by SGI et al., (2014), Al-Ansari, (2013), and Al-Ansari et al., (2014).
6- Future development plan impact: additional quantities of water will be needed for a number of planned but undeveloped agriculture projects the government intended for future investment in the basin (SGI et al., 2014).
7- Management impact: the absence of regional groundwater flow and management model (Al-Tamimi, 2007), and the current classical surface water management

strategy (Alsaffar, 2017b) are evident, which may cause misleading results in river basin water resources management strategy.

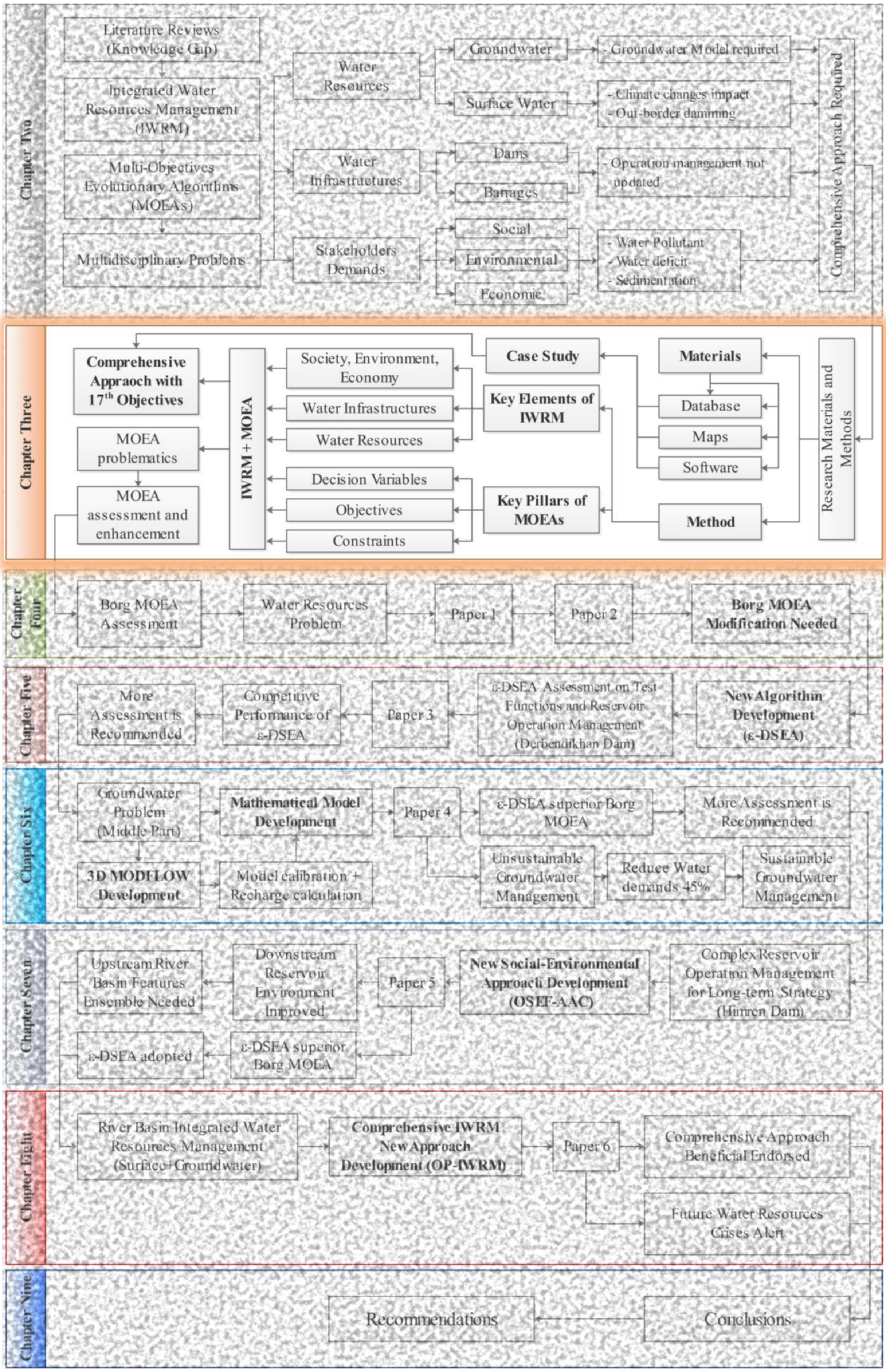
8- Bank slide impact: to avoid the hazard of the right dam bank sliding of Derbendikhan dam, the operation control rule should maintain reservoir water level above 455 m.a.s.l (World Bank, 2006).

2.6 Summary

This chapter demonstrates the principles of Integrated Water Resources Management (IWRM) implementation and the collaborative interconnections of supply and demands processes, based on literature. Economy, society, and environment are the main pillars governing IWRM development process. Literatures show potential gap in holistically IWRM implementation, which carried out on different river basins, while others highlight the end of IWRM implementation.

Also, the reviews carried out on Multi-Objectives Evolutionary Algorithms (MOEAs), since they widely used in water resources management problems as a powerful decision support tool. Even though, problematics observed in MOEAs' achievement as: number of objectives increase to more than three, and algorithms' adaptation with variant problems' environments.

Reviews the common studies on Diayla River basin, as a case study, was also presented. The transboundary river basin facing multidisciplinary crises including: water quantity and quality, operation management, possible future climate change impact, and upstream developing projects plans. Further, decision makers did not employ regional groundwater exploitation in their management strategy, as it has key values in river basin's water cycle. Based on the aforementioned potential problems, Diyala River basin is adopted as a complex example that need a holistic management approach to improve its environment.


Chapter Two
Literature Reviews (Knowledge Gap)
Integrated Water Resources Management (IWRM)
Multi-Objectives Evolutionary Algorithms (MOEAs)
Multidisciplinary Problems
Water Resources
Water Infrastructures
Stakeholders Demands
Groundwater
Surface Water
Dams
Barrages
Social
Environmental
Economic
- Groundwater Model required
- Climate changes impact
- Out-border damming
- Operation management not updated
- Water Pollutant
- Water deficit
- Sedimentation
Comprehensive Approach Required
Chapter Three
Comprehensive Appraoch with 17th Objectives
MOEA problematics
MOEA assessment and enhancement
IWRM + MOEA
Society, Environment, Economy
Water Infrastructures
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Key Elements of IWRM
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Paper 1
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3D MODFLOW Development
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Model calibration + Recharge calculation
Paper 4
ε-DSEA superior Borg MOEA
More Assessment is Recommended
Unsustainable Groundwater Management
Reduce Water demands 45%
Sustainable Groundwater Management
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Upstream River Basin Features Ensemble Needed
ε-DSEA adopted
Downstream Reservoir Environment Improved
ε-DSEA superior Borg MOEA
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New Social-Environmental Approach Development (OSEF-AAC)
Complex Reservoir Operation Management for Long-term Strategy (Himren Dam)
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River Basin Integrated Water Resources Management (Surface+Groundwater)
Comprehensive IWRM New Approach Development (OP-IWRM)
Paper 6
Comprehensive Approach Beneficial Endorsed
Future Water Resources Crises Alert
Chapter Nine
Recommendations
Conclusions

CHAPTER THREE

MATERIALS AND METHODS

3.1 Introduction

In the previous chapter, the knowledge gaps in IWRM and MOEAs implementation are highlighted over five bullet points (1 to 5). In general, the real-world system complexity and computational problematics restrain comprehensive IWRM implementation. Thus, developing a comprehensive approach capable to tackle these problems is the main focus of the current research.

To evaluate and assess such approach, a real-word case study in Iraq, the Diyala River basin, is selected. Review relevant to Diyala River basin was carried out, and potential problems are underlined (bullet points 6 to 10). Based on potential and external impacts, multidisciplinary dilemma is evident, including water scarcity crisis.

In this chapter, after identification of research materials, a research method is presented. A generous explanation of evolutionary algorithm is deployed, as well as the general expression of multi-objectives optimization algorithm.

3.2 Research Materials

3.2.1 Surface and Groundwater Data Source

All relevant information of Diyala river basin was provided by the Iraqi Ministry of Water Resources (IMWR), as they are the key stakeholders of research results. These are:

- Derbendikhan and Himren reservoirs monthly inflows and releases from 1981 to 2012.
- Topographic maps, scale 1:100,000;
- Geological maps, scale 1:100,000;
- Drilled wells database covering years from 1981 to 2012 which includes: discharge rates, water table level, permeability, transmissivity, and chemical analysis;
- Meteorological monthly database from 1981 to 2012, which includes: rainfall, evapotranspiration, and temperatures;
- Diyala riverbed cross sections for the Lower part of the basin; and
- Hydropower turbines graphs (head-discharge relationship).

3.2.2 Software and Codes

- GMS software v.9.2 (Groundwater Modelling Software) license to IMWR, produced by Aquaveo company (https://www.aquaveo.com), for groundwater flow modelling. The software has many powerful tools like: borehole log, fence diagram, 3D solid diagram, 3D analysis and visualization of groundwater flow model, etc.
- ArcGIS 10.2.2 license to University of Strathclyde, produced by ESRI company (https://www.esri.com/en-us/home) for: mapping, spatial analysis, vector and raster processing, etc.
- ArcSWAT v2012.10_2 license ESRI company (free download) is an ArcGIS-ArcView extension and graphical user input interface for SWAT (Soil and Water Assessment Tool) model. The SWAT Model is a public domain model

developed by a group of scientists from the USDA-Agricultural Research Service; USDA-Natural Resources Conservation Service, and Texas A&M University. It is "*a sophisticated basin-scale computer model that predicts impacts of weather, soils, land use and land management on water supplies and pollution as well as soil erosion, fertility and crop production*" (Scopel, 2012).

- Borg MOEA source code in C language licensed to Pennsylvania State University, USA (Hadka and Reed, 2013) (http://borgmoea.org) . Borg MOEA is an optimization algorithm for multi and many-objectives optimization problems.

3.3 Research Methods

3.3.1 Comprehensive IWRM approach

Based on IWRM definition, principles, and challenges described in section 2.2 in Chapter two, a comprehensive approach combines all water supply and demands processes is proposed using multi-objectives evolutionary optimization algorithm.

Briefly, the nexus of water demands (social, environmental, economic), water system infrastructure (dams, barrages), water cycle (surface water, groundwater, reused water), and nature complexity (physical and environmental barriers) are developed using MOEA. Figure 1 illustrates the comprehensive IWRM model's schematic diagram proposed at a river basin level. Hence, this approach address *bullet points 1 and 2* in Chapter two. As MOEA driving the nexus between approach features, a generous descriptive is deployed to identify its model key pillars.

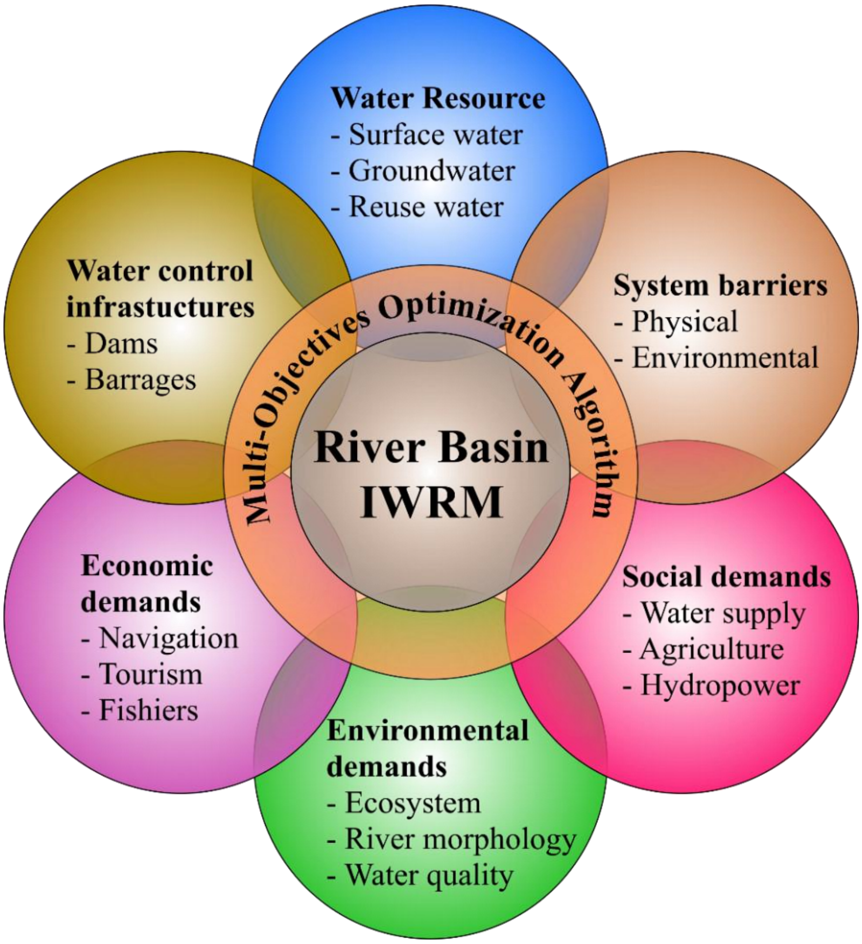


Figure 1. Comprehensive IWRM approach schematic diagram at a river basin level

3.3.2 Multi-Objectives Optimization Problems Identification

The main components of the evolved process in EAs are population, chromosome, and gene, as illustrated in Figure 2. The process of generating new gens (solutions) in evolutionary algorithms depends on the following characteristics (Simon, 2013):

1- Representation: refer how define the individual, which could be binary or real-value.

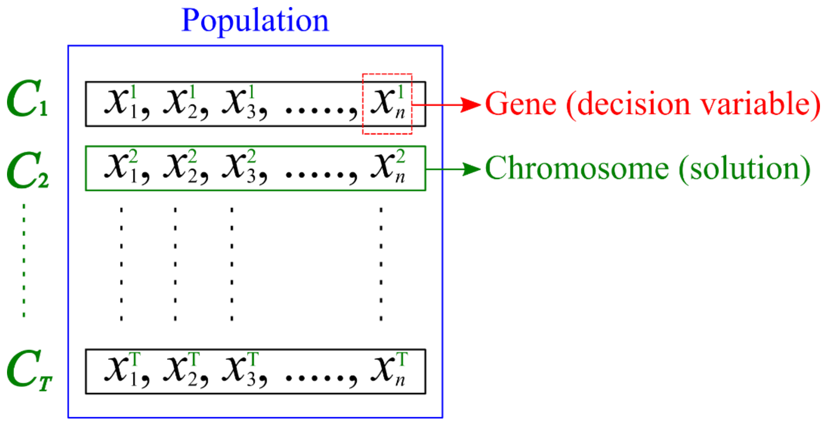


Figure 2. Evolutionary algorithms main evolve components

2- Selection: refer to the techniques to use parents in the next generation. Some of these are Truncation selection, Roulette wheel selection, Tournament selection, and Neighborhood selection.

3- Recombination: refer to the method to combines gens of the selected parents, which depend on the type of the representation (bits or value of gene).

4- Mutation: refer to the method of the change on a single gene of the parent. It has two types: switching bits, or updating the value of the gene, which depend on the type of representation.

5- Fitness function: refer to the intuition about the quality of the individual

6- Survivor decision: refer to the survival of the best individuals, which is about Elitism process.

Figure 3 shows the general flowchart for generating new solutions by EA, which represents the aforementioned six steps. While Figure 4 illustrates detail of crossover and mutation mechanism in EA to produce new solutions. Literature deployed many types of mutation and crossover operators used in EA (Geetha and Kumaran, 2013). Detail of a brief list is out of the scope of the current research, as the focus will be on those used by the candidate EA in chapter 5.

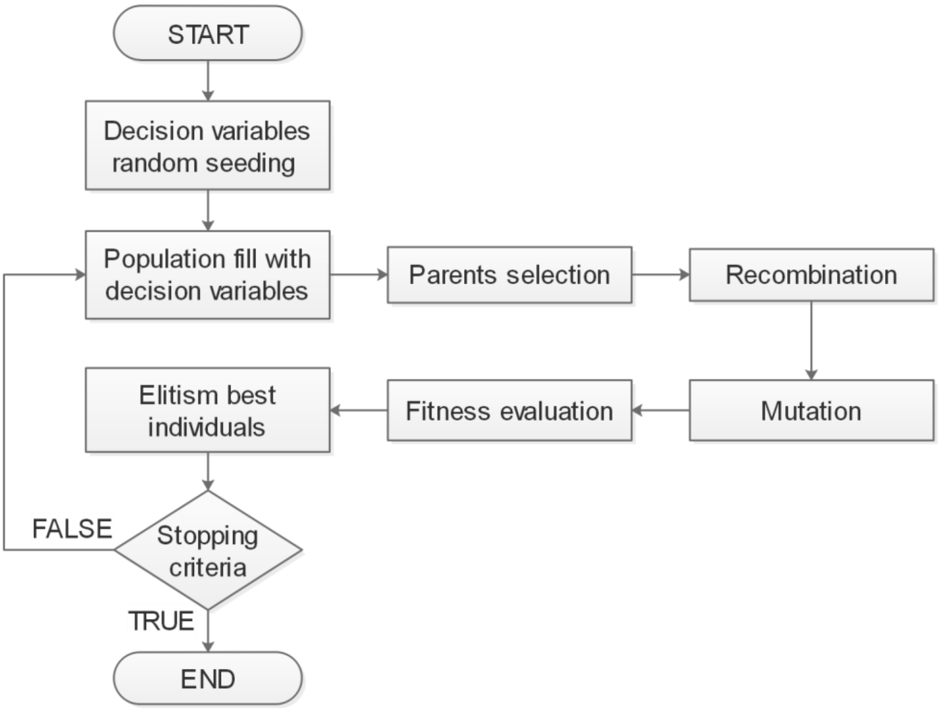


Figure 3. EA's flowchart for generating new solutions

The evolution mechanism needs many parameters to set, which differ from one type to another, however the main parameters are (Deb, 2001; Simon, 2013):

1- Population size (number of chromosome)
2- Maximum number of generation
3- Elitism factor
4- Mutation rate
5- Cross-over rate

More details of evolutionary algorithms types, characteristics, and parameters can be found in Simon (2013).

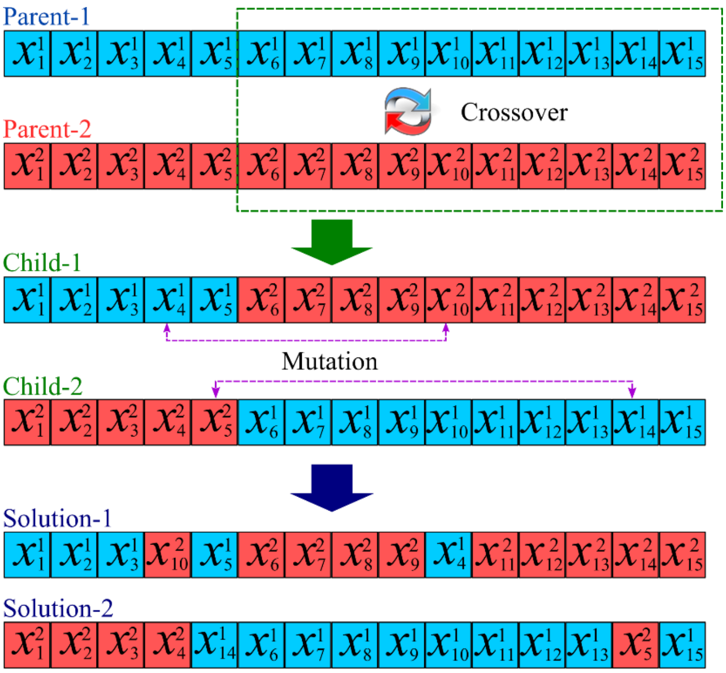


Figure 4. Evolution process to produce new generations (solutions) in evolutionary algorithms (adapted from Deb, (2001); Simon, (2013))

Commonly, real-word optimization problems have multiple objectives. A brief explanation of some of the key concepts associated with multi-objective optimization problem may be described as follows.

$$\text{Minimize: } \boldsymbol{F}(\mathbf{x}) = [f_1(\mathbf{x}), \ldots, f_M(\mathbf{x})]^T \quad (1)$$

$$\text{Subject to: } g_i(x) \geq 0, \forall i \in n_g$$

$$h_j(x) = 0, \forall j \in n_h$$

$$\boldsymbol{x} \in X$$

$X \in R^n$ is the decision space, i.e., $X = [\mathbf{x}^L, \mathbf{x}^U]$ where $\boldsymbol{x} = [x_1, x_2, \ldots, x_n]^T$ is the decision variable vector of dimension n; and $\mathbf{x}^L$ and $\mathbf{x}^U$ are the vectors of the lower and upper bounds on $\mathbf{x}$, respectively. $\boldsymbol{F}(\mathbf{x})$ consists of M objective functions $f_i : X \rightarrow Z \in R^M$, where $i = 1, \ldots, M$, and Z is the objective space feasible region containing all decision variables in X that satisfy all constraints. The $g_i(x)$ and $h_j(x)$ represents the i^{th} of n_g

and j^{th} for n_h inequality and equality constraints, respectively. For unconstraint problems, $n_g = n_h = \emptyset$, and $Z = X$.

In multi-objective optimization problems, there is more than one optimum solution hence a consistent approach is required to determine the solutions that are superior, and the concept of Pareto-optimal dominance is used widely (Stadler 1979, Miettinen 1999, Deb 2001). Superior solutions are said to dominate inferior solutions, and briefly:

1- In a minimization problem, a vector $\mathbf{u} = (u_1, \ . \ . \ . \ , u_M)^T$ is said to dominate another vector $\mathbf{v} = (v_1, \ . \ . \ . \ , v_M)^T$ if $u_i \leq v_i$ for $i = 1, \ . \ . \ . \ , M$ and $u \neq v$. This property may be denoted as $\mathbf{u} \prec \mathbf{v}$.

2- A feasible solution $\mathbf{x} \in X$ is called a Pareto-optimal solution, if there is no alternative solution $\mathbf{y} \in X$ such that $\mathbf{F}(\mathbf{y}) \prec \mathbf{F}(\mathbf{x})$.

3- The Pareto-optimal set, *PS*, is the union of all Pareto-optimal solutions, and may be defined as $PS = \{\mathbf{x} \in X : \nexists \mathbf{y} \in X, \mathbf{F(y)} \prec \mathbf{F(x)}\}$.

4- The Pareto-optimal front, *PF*, is the set comprising the Pareto-optimal solutions in the objective space in a multi-objective optimization problem. It may be expressed as $PF = \{\mathbf{F(x)} | \mathbf{x} \in PS\}$.

Figure 5 illustrates the solution space (X), objective space (Z), Pareto-optimal set (*PS*) and Pareto-optimal front (*PF*).

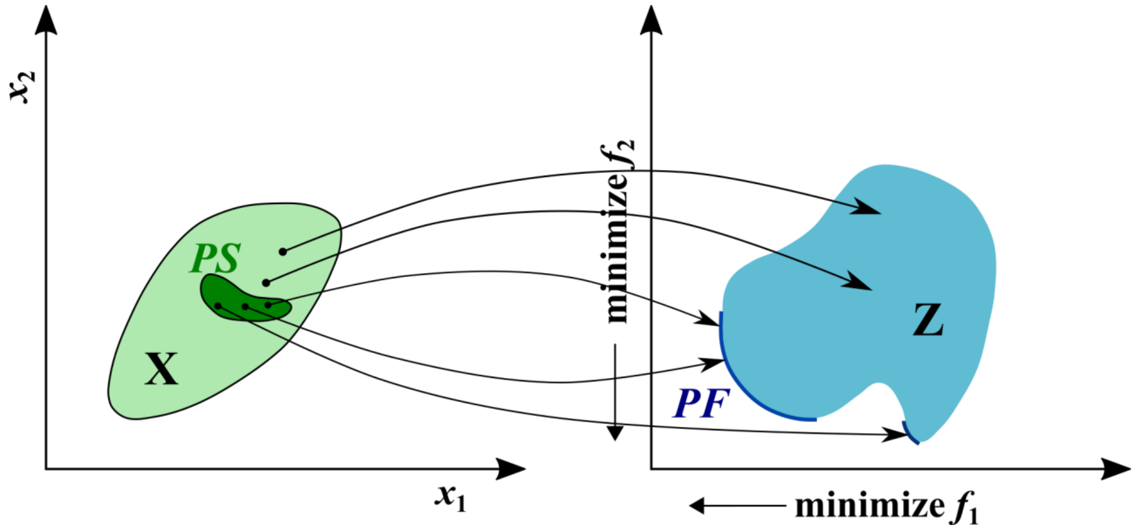


Figure 5. Illustration of Pareto-optimality. X is the solution space and Z is the objective functions space (adapted from Deb, (2001)).

The same above principles are applicable for many-objectives optimization problems, as the number of objectives is larger than 3 ($M > 3$) (Maier et al., 2014; Li et al., 2015). The above argument demonstrates three MOEA problem's key pillars; objective function, decision variables, and constraints (for constraint problem).

3.3.3 MOEA Problem's Pillars identification

The MOEA problem's model development requires identification of relevant decision variables, objectives functions, and constraints that essentially depends on decision makers' decision and system barriers (Maier et al., 2014). Thus, based on the adopted case study, adopted objectives and decision variables are shown in Table 1. In addition to the above, water resources management has many potential uncertainties, which leads to different risk severity, including climate change, political, social, economic, future water demands, and urbanization development components (Kong et al., 2017; Maier et al., 2014).

Table 1. illustrates the adopted decision variables and objectives of Diyala River basin based on decision makers' decisions (Alsaffar, 2017)

System infrastructure	Source of water	Demand type	Decision variable	Not.*	Objective	Not.*
Derbendikhan dam	Surface	- Hydropower	Reservoir releases	x_1	- Hydropower - Releases	f_{powerD} $f_{releasesD}$
Wells	Ground	- Agriculture - Sustainable use	No. of pumping wells	x_3	- Water deficit - Water losses - Storage mining	$f_{Del-SW-GW}$ f_{WL} f_{mining}
Himren dam	Surface	- Water supply - Agriculture - Hydropower	Reservoir releases	x_2	- Water deficit - Hydropower	$f_{demandsH}$ f_{powerH}
Diyala Barrage	Surface	- Agriculture	-		- Regulation	f_{riverB}

* *Notation*

In order to evaluate risk priority, a risk assessment matrix has been proposed widely in literature, which illustrates the relationship between the activity frequency (or likelihood) and its impact, as in Figure 6. The "Risk", or the "Risk priority", is equal to the product of the Likelihood by the Impact level *(Risk = Likelihood × Impact)* (Anthony Cox, 2008).

For Diyala River basin management strategy, Table 2 illustrates the possible major risks that may develop in the basin with its likelihood, impacts, degree, and proposed methods for addressing these risks (Alsaffar, 2017; Horne et al., 2016; Maier et al., 2014).

The possible future climate change risk (or impact) in Diyala River basin was investigated by Abbas et al. (2016) using Three General Circulation Model (GCM) A2, A1B and B1. The study shows moderate impact may occur for the next half century. This impact is directly affecting River basin water resources, which can be addressed using predicted reservoir inflows or sometimes called scenarios inflows (Maier et al., 2014; Maier et al., 2016; Alsaffar, 2017).

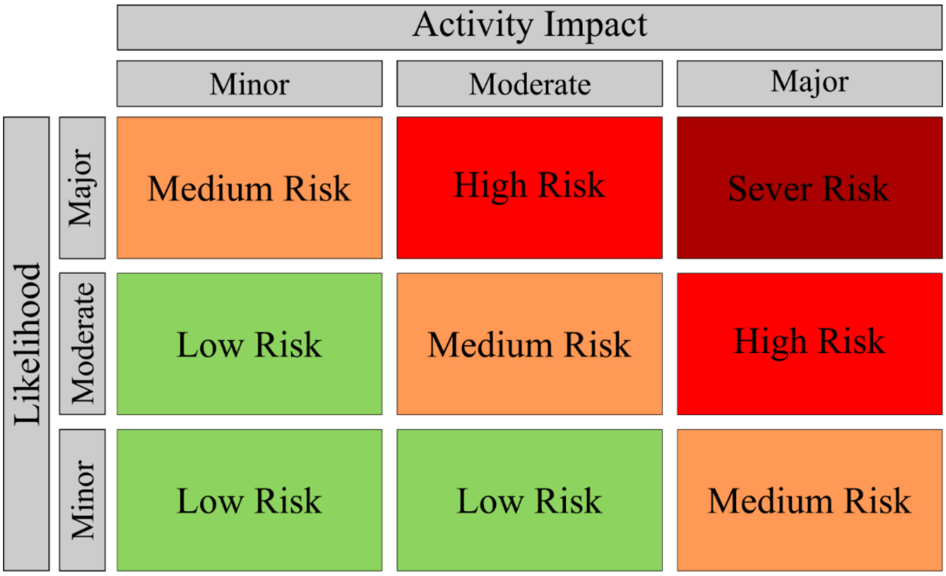


Figure 6. Simple (3×3) risk assessment matrix showing the impact - likelihood relationship to demonstrate risk priority

Table 2. Diyala River basin possible major risks and their priority (according to the risk assessment matrix in Figure 6)

Risk type	**Likelihood**	**Reason**	**Risk Impact**	**Risk degree**	**Risk address**
Climate change	Moderate	According to GCMs models[1]	Moderate[1]	Medium	Inflows prediction
Political	Moderate	dispute water sharing[2]	Major[4]	High	Inflows prediction
Flood	Minor	Arid and semi-arid environment[3]+ two multipurpose dams[4]	Major[4]	Medium	Objective
Unauthorized water use	Moderate	Regional-scale + legislation[4]	Moderate[4]	Medium	Decision variables
Water pollutant	Moderate	Wastewater treatment plant[4]	Major[5]	High	Objective
River Morphology	Minor	Controlled River flow[4]	Moderate[4]	Low	Objective

[1] (Abbas et al., 2016); [2] (Abdulrahman, 2017); [3] (IPCC, 2007); [4] (Alsaffar, 2017); [5] (Kubba et al., 2014; Aenab and Singh, 2014)

Consistency, projects development plan in out boarder upstream (in Iran) was alter as a major impact (Alsaffar, 2017) due to unsettled agreements for water sharing between the two countries (Abdulrahman, 2017). This impact can also be conceptualized as predicted inflows (Maier et al., 2016).

The flood probability in Diyala River is minor due to low rate of precipitation (arid environment (IPCC, 2007)) and the presence of two large multipurpose dams, which flood protection is one of its operation objectives (Alsaffar, 2017). However, its impact is high on communities in downstream regions.

Another major risk facing Diyala river basin is the pollutant source from the large wastewater treatment plant (Al-Rustumiya), which discharges heavily polluted water to the river just before its confluence with Tigris River (Kubba et al., 2014; Aenab and Singh, 2014). However, pollutant levels are likely changed (or moderate) due to: seasonal time-scale and treatment performance of Al-Rustumiya plant (Aenab and Singh, 2014).

Further, the risk of riverbed changes (degradation and aggregation) is minor since the river discharge is controlled by two dams (Alsaffar, 2017), which mitigate sever or dramatic changes in riverbed due to large discharge in flood time. However, moderate impact could be assigned for sediment aggregation in the river, which may reduce river flow capacity and cause navigation problems (Alsaffar, 2017).

According to the previous studies, the last three risks: flood, water pollutant, and river morphology can be addressed as objectives in an optimization management model (Horne et al., 2016).

Unauthorized water consumption for irrigation process is another risk observed recently in the river basin due legislations changes and political issues. However, moderate likelihood and impact is assigned for the current risk since new legislations may be approved to restrict unauthorized consumption; and it occurs in certain regions (regional-scale) in the river basin (Alsaffar, 2017). Since water consumption for irrigation is a time-scale during the year and there is no information about its quantity, this can be conceptualized as decision variables ($\boldsymbol{x_4}$) (as water delivery) in the optimization management model (Maier et al., 2016).

The real-world water resources management systems are restrained by physical and environmental barriers (or constraints) (Horne et al., 2016). Physical constraints are relevant to water control infrastructures like dams and barrages, as they have limited storage, power generation, and discharges. Other issues like ecosystem life, water quality, and river morphology are relevant to environmental constrains, as they are a decision making dependent (Maier et al., 2014; Horne et al., 2016). Accordingly, two objectives are proposed to handle system constraints: f_{phy-M} for physical constrains, f_{MD} for combination of both constraints.

As a result, the 17 Objectives are proposed to represent the comprehensive IWRM approach of Diyala River basin, as illustrated in Table 3 with their description. Figure 7 demonstrates the comprehensive IWRM approach objectives of Diyala River basin, based on Table 3. The right side illustrates the actual system of Diyala River basin, while the left side illustrates the relevant conceptual physical model features with their target objectives.

In addition to the mentions objectives, two inflows scenarios are presented to represent the impacts of climate change and politics, as proposed in Table 2. The historical dataset is analysed, reformed, and projected for the next decades to conceptualized uncertainties of future events. The details are in Chapters seven and Eight, as they address *bullet point 6* in Chapter two.

Table 3. Comprehensive IWRM approach of Diyala river basin showing adoptive objectives and their description

No.	Objective	Description
1	$f_{winterD}$	Maximize Derbindikhan reservoir storage in winter
2	$f_{summerD}$	Minimize Derbindikhan reservoir storage in summer
3	f_{powerD}	Maximize Derbindikhan power generation
4	$f_{releasesD}$	Maximize Derbindikhan releases
5	$f_{Del-SW-GW}$	Minimize water deficit after Derbindikhan dam (surface + groundwater)
6	f_{WL}	Minimize infiltration water losses
7	f_{mining}	Minimizing groundwater storage mining
8	$f_{demandsH}$	Minimize water deficit after Himren dam
9	$f_{winterH}$	Maximize Himren reservoir storage in winter
10	$f_{summerH}$	Minimize Himren reservoir storage in summer
11	f_{powerH}	Maximize Himren power generation
12	f_{riverB}	Minimize discharge fluctuation after Diyala Barrage
13	f_{TDS-DY}	Minimize pollutant in Diyala river
14	f_{TDS-TR}	Minimizing pollutant in Tigris river
15	f_{DY-BCH}	Minimizing riverbed changes in Diyala river
16	f_{phy-M}	Minimizing physical model violation
17	f_{MD}	Minimizing total model violation

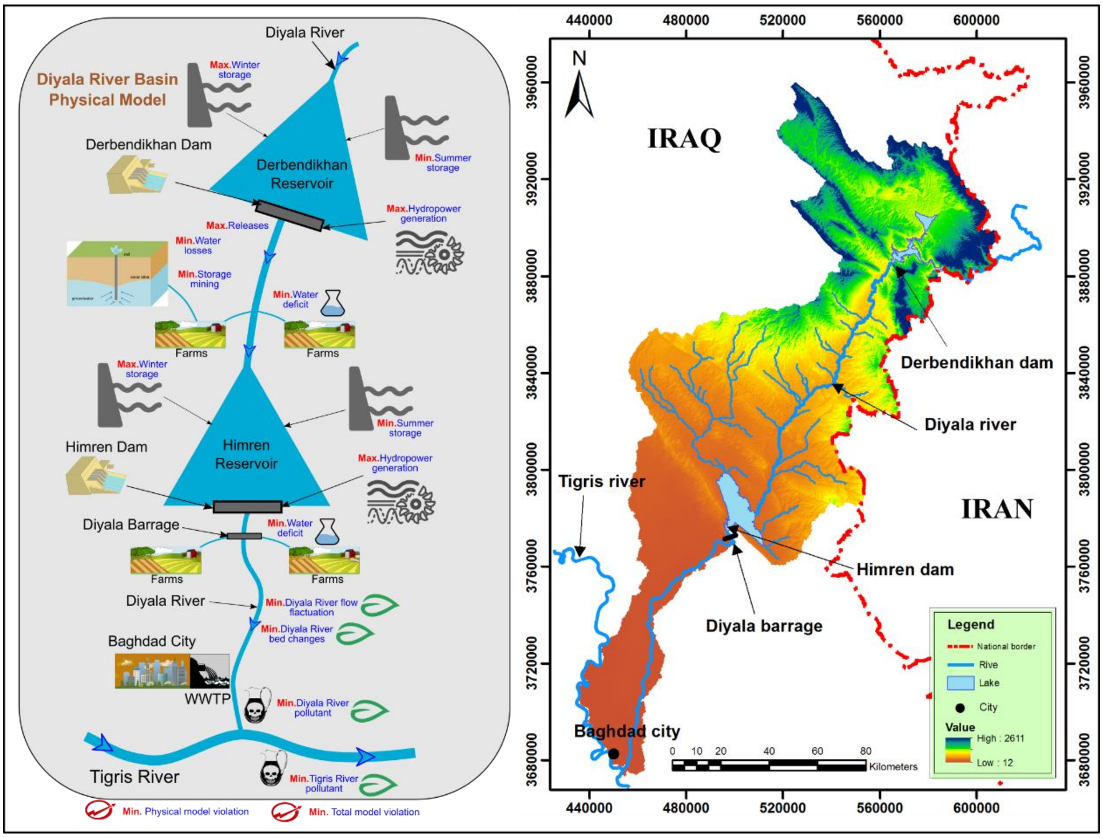


Figure 7. The Comprehensive IWRM objective’s approach of Diyala River basin

To mitigate river basin water scarcity, agriculture water exploitation reduction is a key factor. Hence, replacing the traditional open furrows water delivery system with drip system (as an alternative) is assessed in the middle part of the river basin. The current option address *bullet point10* in Chapter two. The details are presented in Chapter five.

3.3.4 Groundwater Numerical Model

Although three objectives are adopted to conceptualize groundwater management model, a numerical model is evident for boundary recharge estimation, as highlighted in *bullet point 8* in Chapter two. Thus, 3D groundwater flow is modelled using MODFLOW-2005 in GMS v9.2 software (Groundwater Modelling Software). A complete model details are presented in Chapter five.

Statement-2

To this extend, the proposed comprehensive IWRM approach and their objectives address the *bullet points 1, 2, 6 to 10,* with reference to Chapter two.

3.3.5 MOEA’s Problematics Addressing

The literature describes performance and parameterize problematics in MOEA, as highlighted in *bullet points 3, 4 and 5* in Chapter two. Thus, based on Statement-2 in Chapter two, Borg MOEA’s achievement and methodology will be analysed and assess. First of all, a brief description is presented to identify Borg MOEA potentially novel techniques.

3.3.5.1 Borg MOEA Identification

Hadka and Reed (2013) introduced Borg MOEA for many-objective optimization problems, with many features to overcome the weaknesses of other algorithms such as the following:

- Preservation of the best solutions found and diversity to overcome the deterioration phenomenon that MOEA suffers in many-objective optimization problems (Hanne 1999). This phenomenon occurs when one or more solutions found by the MOEA at time t_2 are dominated by solutions found at an earlier time t_1, where $t_1 < t_2$. This occurs because the number of non-dominated solutions increases with increasing number of objectives and the difficulties of comparison in the high-dimensional space (Wang et al., 2015).
- Assessment of stagnation and search progress to avoid premature convergence to local optima (Hadka and Reed 2013).
- Restart feature with adaptive population size to preserve search variety on highly multimodal problems (Tang et al., 2006).
- Improved search progress and efficiency using six recombination operators combined with auto-adaptive operator selection aimed at deploying the most appropriate combination of operators when solving real-world problems (Vrugt et al., 2009).

These features are described briefly in the following paragraphs.

1- ***Non-domination and Algorithm Progress:*** Borg MOEA uses an active population of solutions and an external archive that stores dominant solutions, and the population size is proportional to the archive size. Initially, the archive is empty;

hence an initial population size is required. Subsequently, the population size changes as follows (Hadka and Reed, 2013):

$$Ratio_{PA} = \frac{Population\ size}{Archive\ size} \qquad ratio_{PA} \geq 1 \qquad (2)$$

Where $Ratio_{PA}$ is the ratio of the population size to the archive size. Hadka and Reed (2013) suggested $Ratio_{PA}$ = 4.

The objective space in Borg MOEA is divided into hyper-boxes whose dimensions are equal to ε (Laumanns et al., 2002). The concept of the ε-box index vector is used to assess the dominance of alternative solutions instead of the objective function values. The algorithm calculates this index by dividing the values of the objective functions by ε and setting the result as the next integer. If two or more solutions are in the same ε-box, the dominant solution among these is the one which is nearest to the lower left corner of the ϵ-box in the case of a minimization problem. Usually, the ε value is predefined by the user, depending on the problem complexity and on the required accuracy of the results.

The concept of ε-progress is employed also, to measures the improvements while searching for new solutions. If the algorithm finds new dominant solutions in a new unoccupied ε-box, in other words, if the new dominant solutions have different ε-box indices, it means that there is improvement. On the other hand, if the new dominant solutions are located at previously occupied hyper-boxes, i.e. if they have the same ε-box indices for a certain number of evaluations, a revival process will occur to escape from any local optima.

A restart procedure is used to revive the algorithm, to escape from any local optima. The restart involves emptying the population and re-populating based on the population to archive ratio (Equation 2). The population is refilled using all solutions in the archive. Any remaining empty slots in the population are filled with solutions created by uniform mutation of solutions that are selected randomly from the archive. The trigger for the revival process depends on any of the following three conditions:

- If there is no change in the archive size for a certain number of evaluations;
- If there is no improvement indicated by the ϵ-progress indicator; and
- If the current population to archive ratio exceeds 1.25×$Ratio_{PA}$.

2- ***Recombination Operators:*** The recombination process or crossover depends on chromosomes taken from parents to generate new chromosomes. Geetha and Kumaran (2013) reviewed several types of crossover operators used in evolutionary algorithms; but, only the operators used in Borg MOEA are considered here. In Borg, six recombination operators are used, as follows:

a. Simulated binary crossover (SBX) (Deb and Agrawal 1994)
b. Differential evolution (DE) (Storn and Price 1997)
c. Parent-centric crossover (PCX) (Deb et al., 2002)
d. Unimodal normal distribution crossover (UNDX) (Kita et al., 1999)
e. Simplex crossover (SPX) (Tsutsui et al., 1999)
f. Uniform mutation (UM) (Michalewicz et al., 1994)

Furthermore, the polynomial mutation (PM) (Deb and Agrawal 1999) is applied to the offspring produced by all operators except for the UM. An overview of the above-mentioned operators is provided in the supplementary data in Chapter five.

3- ***Self-adaptive Operator Selection:*** Borg-MOEA employs a framework in which the deployment of recombination operators depends on the search environment, stage of the optimization process and relative success of each operator. The mechanism for selecting the operators is as follows. The algorithm calculates the probability $\mathcal{P}_i^{NDS}$ for each operator based on the number of dominance solutions NDS_i produced by that operator in the archive.

$$\mathcal{P}_i^{NDS} = \frac{NDS_i + \tau}{\sum_{j=1}^{NRO}\left(NDS_j + \tau\right)} \qquad i, j = 1,2, \dots NRO \qquad (3)$$

where NRO is the number of recombination operators and $\tau = 1.0$ is a constant used to avoid zero probabilities. The algorithm updates the probabilities periodically using Equation 3.

After the initial random seeding, the algorithm selects one operator at random at the start of the algorithm when all NDS_i are zero and selects one parent randomly from the archive. If the number of parents required is *k*, the remaining (*k*-1) parents are selected from the population using tournament selection to generate a new offspring, as shown in Figure 8. Hadka *et al.* (2012) observed that after certain number of function evaluations, the algorithm tends to use one recombination operator until the end of the optimization partly due to Equation 3. More details are available in Hadka and Reed (2013).

3.3.5.2 Borg MOEA Assessment

A real-world reservoir management problem is selected from Chenari et al. (2014) to assess algorithm's achievement and behaviour, since MOEA achievement may vary with different problems environments, as highlighted in Chapter two. The assessment details are presented in Chapter four, as two published papers. Borg MOEA show compete results in compare with Genetic Algorithm (GA), however problematics in operators' auto-adaptive techniques are observed (Equation 3).

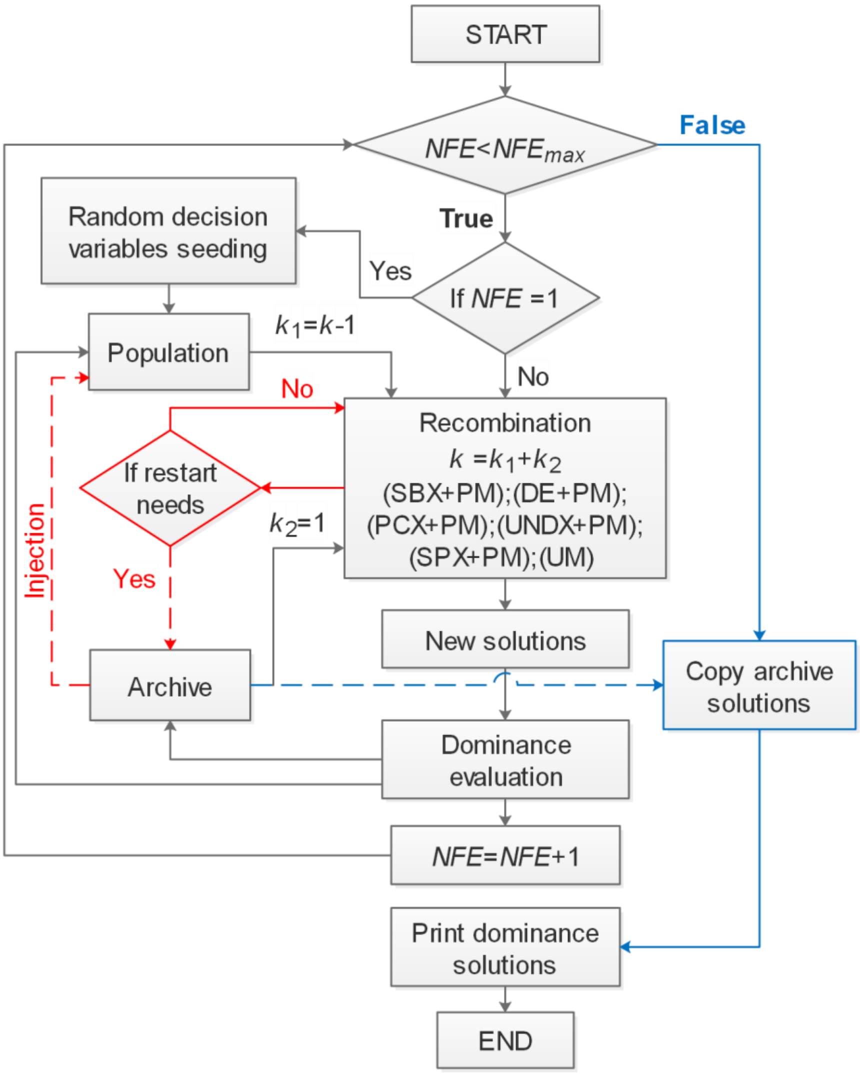


Figure 8. Overview of Borg MOEA flowcharts. k_1 and k_2 are the number of parents selected from the main population and dominance archive, respectively, while k is the total number of parents needed by adopted operator. *NFE* is the number of function evaluations with maximum value = NFE_{max} (adapted from Hadka and Reed (2013))

Further, based on insight experimental investigation on benchmark functions (DTLZ series), insufficient behaviour of key techniques is observed. For example, restart technique may lead exploration toward local optima pitfall and/or restrain algorithm convergence, as it recycles archive's dominance solutions periodically. Accordingly, failure to achieve global or near global optimum may occur. In the same context, the algorithm follows random sequence to select candidates from the population to produce new generations (solutions) (Figure 8). Hence, not all population members are employed which reduce exploitation and exploration of design search space at initial stage. This may tend delay in algorithm convergence or loss optimality achievement (Zecchin et al., 2012, Zheng et al., 2016). Thus, modification and/or advance methodology is evident.

3.3.5.3 New MOEA's Algorithm Development

New Evolutionary algorithm is developed entitle "Epsilon-Dominance-Driven Self-adaptive Evolutionary Algorithm" (ε-DSEA) to address Borg MOEA and other MOEA weakness techniques that highlighted in *bullet-4* in chapter two. The ε-DSEA approach comprises many novel features including: *(i) Diversity expansion*; *(ii) Self-adaptation of the control parameters of recombination operators*; *(iii) Exploration extension*; and *(iv) Virtual dominance archive*. The algorithm's details and performance achievement are demonstrated in chapter five. Accordingly, the algorithm is adopted to implement the comprehensive IWRM approach. Comparative analyses of ε-DSEA with Borg MOEA are carried out from Chapters five to seven to address *bullet point 3* in Chapter two.

3.3.5.4 MOEA's Convergence Booster

Based on *bullet point 5* in Chapter two, a convergence booster is developed named "Auto-Adaptive Constraints" (AAC). The AAC methodology is based on combining the penalty formula and model violations with dynamic nexus, which releases the chain of constraints gradually when large values of violation observed, then reinforces these chains at small values when decision variable values approaching feasible region, as shown in Figure 9. Details of AAC formula is presented in Chapter seven.

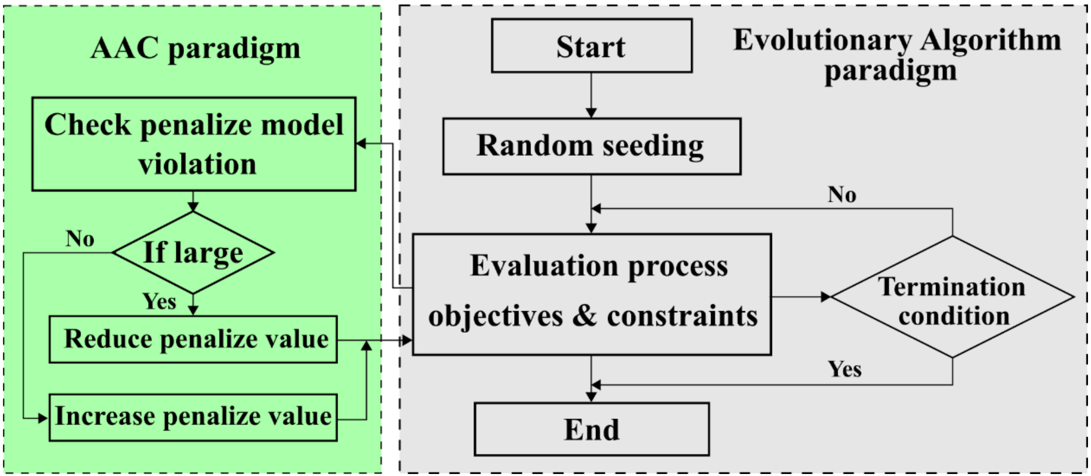


Figure 9. Auto-Adaptive Constraints (ACC) methodology to boost MOEAs' convergence

Statement-3

> As a result, the adopted methods succeed to achieve all the *10 bullet points* highlighted in Chapter two.

3.3.6 IWRM Approach's Mathematical Expressions Identification

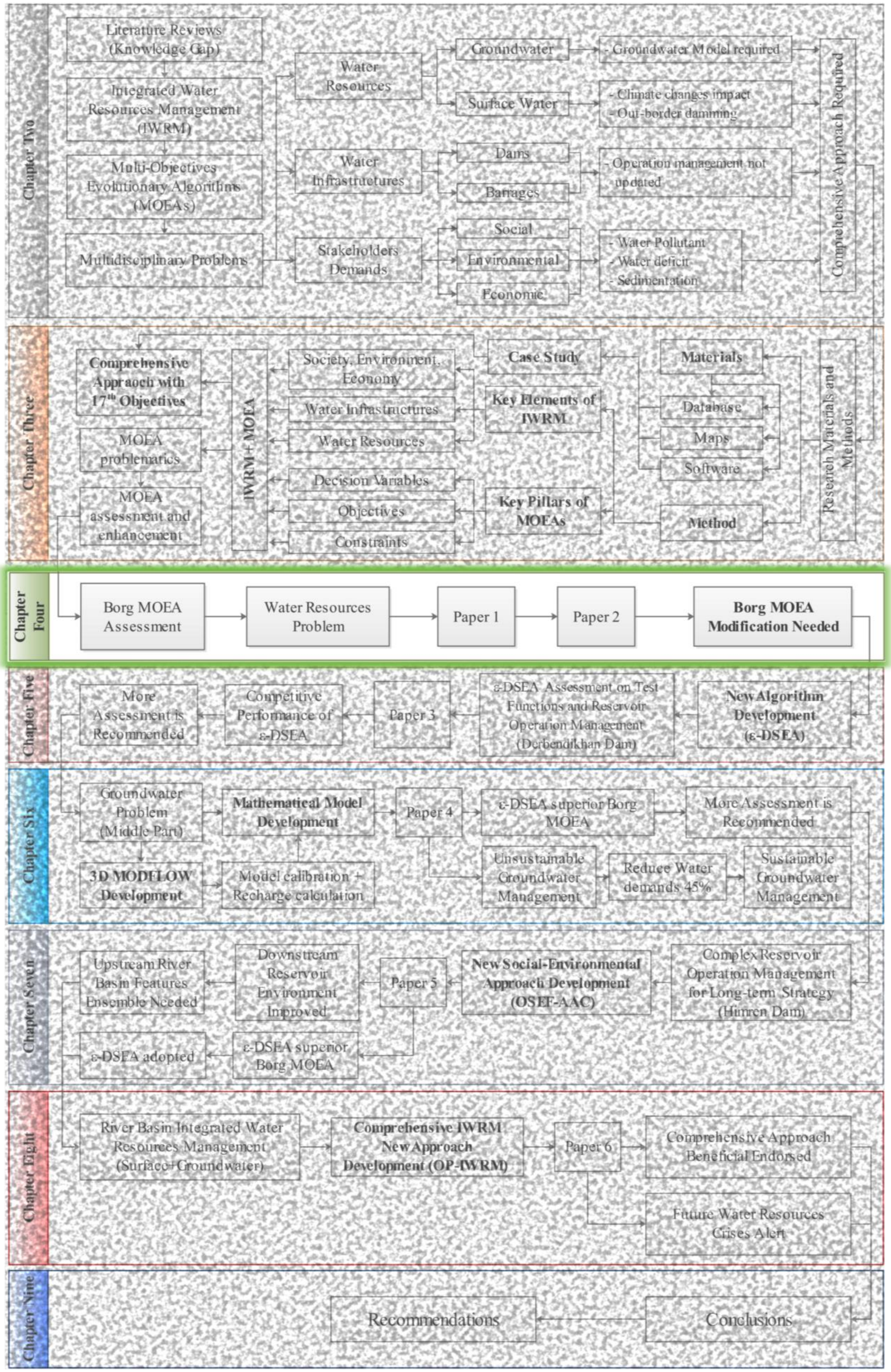
The mathematical expressions are developed in sequence starting from Derbendikhan dam in the north, towards river confluence with Tigris River in the south of Diyala River basin. Detailed objectives and constraints' expressions are delivered in the next chapters as papers submitted for publishing in well-known, high Impact Factor journals, as follows:

- Derbendikhan dam management model: Chapter five
- Groundwater management model: Chapter six
- Himren dam management model: Chapter seven
- Entire Diyala River basin management model: Chapter eight

A C language code is developed to conceptualize all mathematical expressions of Diyala River basin management models.

3.4 Summary

Research's materials and methods are presented in this Chapter to address the 10 bullet points highlighted in Chapter two. Sources of all database and maps used are described, as well as the software. Research methods are presented based on comprehensive IWRM approach layout. The approach interconnects; social, environmental, and economic demands with water control infrastructures using multi-objective evolutionary algorithm (MOEA). Thus, MOEA formulation was presented, and their main pillars are demonstrated as: decision variables, objectives, and constraints, on which mainly decision makers' depend. A brief identification of current Diyala River basin pillars is achieved based on decision makers' expertise. Additional pillars are proposed to address possible uncertainties and risks derived from the literature and the decision makers. Consistency, a 3D groundwater flow model is developed to address management bullet. In order to address MOEA's dilemmas, the nominated optimization algorithm Borg MOEA novel techniques is identify, as well as its achievement in solving real-wold reservoir management problem. Potential weakness is observed, hence new MOEA is developed (ε-DSEA) to tackle these issues. A novel methodology to reduce the convergence time of MOEAs is proposed to tackle the pitfall of penalization in constraints handling. To this extent, all 10 bullet points are addressed to underpin the path to a comprehensive IWRM approach, as their pillars' mathematical expressions are illustrated in the next chapters.


Chapter Two
Literature Reviews (Knowledge Gap)
Integrated Water Resources Management (IWRM)
Multi-Objectives Evolutionary Algorithms (MOEAs)
Multidisciplinary Problems
Water Resources
Water Infrastructures
Stakeholders Demands
Groundwater
Surface Water
Dams
Barrages
Social
Environmental
Economic
- Groundwater Model required
- Climate changes impact
- Out-border damming
- Operation management not updated
- Water Pollutant
- Water deficit
- Sedimentation
Comprehensive Approach Required
Chapter Three
Comprehensive Approach with 17th Objectives
MOEA problematics
MOEA assessment and enhancement
IWRM + MOEA
Society, Environment, Economy
Water Infrastructures
Water Resources
Decision Variables
Objectives
Constraints
Case Study
Key Elements of IWRM
Key Pillars of MOEAs
Materials
Database
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Chapter Four
Borg MOEA Assessment
Water Resources Problem
Paper 1
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Chapter Five
More Assessment is Recommended
Competitive Performance of ε-DSEA
Paper 3
ε-DSEA Assessment on Test Functions and Reservoir Operation Management (Derbendikhan Dam)
New Algorithm Development (ε-DSEA)
Chapter Six
Groundwater Problem (Middle Part)
3D MODFLOW Development
Mathematical Model Development
Model calibration + Recharge calculation
Paper 4
ε-DSEA superior Borg MOEA
More Assessment is Recommended
Unsustainable Groundwater Management
Reduce Water demands 45%
Sustainable Groundwater Management
Chapter Seven
Upstream River Basin Features Ensemble Needed
ε-DSEA adopted
Downstream Reservoir Environment Improved
ε-DSEA superior Borg MOEA
Paper 5
New Social-Environmental Approach Development (OSEF-AAC)
Complex Reservoir Operation Management for Long-term Strategy (Himren Dam)
Chapter Eight
River Basin Integrated Water Resources Management (Surface+Groundwater)
Comprehensive IWRM New Approach Development (OP-IWRM)
Paper 6
Comprehensive Approach Beneficial Endorsed
Future Water Resources Crises Alert
Chapter Nine
Recommendations
Conclusions

CHAPTER FOUR

ASSESSMENT OF EVOLUTIONARY OPTIMIZATION ALGORITHM

4.1 Introduction

The previous chapter illustrates research's materials and methods. One of the methods' key element is the assessment of the nominated optimization algorithm Borg MOEA. References show that drawbacks may occur in algorithms' results over different problem environments, as well as high-dimension computational complexity problems.

In order to assess Borg MOEA achievement in water resources management problems, an illustrative example of a real-world reservoir management problem was selected from the literature, as its operation rule was developed using Genetic Algorithm (GA). The reservoir is location in Iran, the western neighbor of Iraq, having consistent regional weather conditions. The assessment was accomplished as two papers published in peer review journals. The first paper (conference version) was published in Water Utility journal, and the second paper published in Journal of Environmental Management, as follows:

- Al-Jawad, J.Y., Tanyimboh, T.T., 2017a. Assessment of evolutionary algorithm for reservoir operation. Water Util. J. 15, 45–51.
- Al-Jawad, J.Y., Tanyimboh, T.T., 2017b. Reservoir operation using a robust evolutionary optimization algorithm. J. Environ. Manage. 197, 275–286. https://doi.org/10.1016/j.jenvman.2017.03.081.

“The following work represents my efforts, such as: theoretical formalism development, analytic calculations and numerical simulations, writing the manuscript. Dr. Tanyimboh, T.T., was the project supervisors, and provided assistance and support when required”

4.2 Paper 1

Al-Jawad, J.Y., Tanyimboh, T.T., 2017a. Assessment of evolutionary algorithm for reservoir operation. Water Util. J. 15, 45–51.[1]

Assessment of Evolutionary Algorithm for Reservoir Operation

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Abstract

The complexity of water resources management problems, especially for multipurpose reservoirs, increases the motivation to find a robust method to overcome this challenge. Evolutionary optimization algorithms are used widely to handle reservoir management problems. In this research, one of the competitive methods of optimization named Borg MOEA was used to achieve reservoir operation control. A case study from the literature was used to test the algorithm's performance on this type of problems. The objective was to reduce the difference between reservoir releases and water demands and also to maintain a suitable amount of storage in the reservoir. The adopted method produced competitive solutions by improving the objective function value significantly when compared with the result in the literature. In addition, the quantity of water stored in the reservoir was increased.

Keywords: Evolutionary optimization algorithm, Borg MOEA, reservoir operation, multipurpose reservoir system.

[1] Journal policy enable to share published papers without embargo period

1. INTRODUCTION

In recent decades, significant demands on water exploitation were observed. This raises the difficulties to manage and allocate water in a sustainable way. Reservoirs are essential for water resources management in a river basin which needs a powerful method for optimum operation strategies (Jothiprakash and Shanthi 2006).

Multipurpose reservoirs are widely used to serve many demands for domestic, industrial, irrigation, environment, hydropower production and flood control to satisfy the mentioned demands and maximize the economic benefits. These types of problems are complex because of nonlinear storage-inflow relationship, conflicting objectives, dynamic properties, constraints, etc. (Haimes and Hall 1977). Many methods for optimization were found to solve complex problem such as linear programming, non-linear programming, and dynamic programming. But these methods are generally not suitable for multipurpose reservoirs as Yeh (1985) observed.

To solve these types of problems, a new approach has been found based on evolutionary algorithms (EAs). EAs use a set of solutions as population, rather than one solution in every iteration (Deb, 2001). Many researchers adopted EAs to solve complex problems in different fields of science and engineering (Coello *et al.* 2007). In the field of water management, Javadi *et al.* (2015) used non-dominated sorting genetic algorithm (NSGA-II) to optimize seawater intrusion in coastal aquifer. Seyoum *et al.* (2016) used a penalty-free approach in water distribution network design. Sidiropoulos *et al.* (2016) used simulation-optimization for groundwater management. Additionally, Oxley and Mays (2016) applied a genetic algorithm (GA) for long-term planning and sustainable water resources management. Tigkas *et al.* (2016) investigated the efficiency of evolutionary algorithms for the calibration of a conceptual hydrologic model. In the area of integrated urban wastewater management, Rathnayake and Tanyimboh (2015) developed a methodology to control combined sewer overflows that combined a multi-objective algorithm and the storm water management model (SWMM 5.0) (US Environmental Protection Agency) (Rossman, 2009).

For reservoir operation and management, Ahmad *et al.* (2014) reviewed common optimization algorithms used in this field. In addition, Choong and El-Shafie (2015) compared different optimization algorithms used in reservoir management. Noori *et al.* (2013) used a GA to solve a multi-reservoir problem to maximize both hydropower production and flood protection. Chenari *et al.* (2014) also used a GA to assess the operation of a reservoir. Pianosi *et al.* (2011) combined an artificial neural network and a multi-objective GA (MOGA) for reservoir management. Zou and Wu (2012) applied MOGA to maximize both power generation and irrigation benefits. Scola *et al.* (2014) used NSGA-II, Hosseini-Moghari *et al.* (2015) applied two optimization algorithms, and Tayebiyan *et al.* (2016) applied a GA to optimize hydropower generation. Azizipour *et al.* (2016), implemented a weed optimization algorithm for hydropower production. Furthermore, Qi *et al.* (2016) proposed a multi-objective immune optimization algorithm for flood control. Chen *et al.* (2016) proposed a parallel strategy for NSGA-II to optimize reservoir operation.

In this study, a recently introduced algorithm, Borg MOEA, was selected to solve a reservoir operation problem. The aim of the current study was to test the performance of the above-mentioned algorithm on a real-word reservoir operation problem, based on a case study from the literature.

Hadka and Reed (2013) introduced Borg MOEA for many-objective and multimodal optimization problems. Some of the features in Borg MOEA include (a) diversity preservation; (b) tracking of the optimization progress and stagnation; and (c) restart to move away from any local optima. The algorithm uses six recombination operators to improve the search process.

To preserve diversity, the objective space is divided into hyper-boxes whose dimensions are equal to ϵ; the value of ϵ is specified by the user. The ϵ-index vector is used for dominance evaluation instead of the objective function values. The algorithm calculates this index by dividing the objective function value by ϵ, and the result is taken as the next integer number. If two or more solutions are in the same ϵ-box, the dominant solution among these is the one which is nearest to the lower-left corner of the ϵ-box in the case of a minimization problem.

To detect stagnation, Hadka and Reed (2013) employed ϵ-progress, which measures progress while searching for new solutions. If the algorithm finds new solutions in a new previously unoccupied ϵ-box, it means that there is progress and the algorithm is allowed to continue. On the other hand, if there is no improvement found based on ϵ-progress for a certain number of function evaluations, a revive procedure occurs, to search for additional solutions and escape from the local optima. The details of the revive procedure are available in Hadka and Reed (2013).

Finally, the algorithm depends on six recombination operators to produce offspring. In fact, in Borg MOEA, the selection of the recombination operators is competitive, and evolves depending on the environment of the problem. These operators are: Simulated Binary Crossover (SBX) (Deb and Agrawal 1994), Differential Evolution (DE) (Storn and Price 1997), Parent-Centric Crossover (PCX)

(Deb *et al.* 2002), Unimodal Normal Distribution Crossover (UNDX) (Kita *et al.* 1999), Simplex Crossover (SPX) (Tsutsui *et al.* 1999) and Uniform Mutation (UM) (Michalewicz *et al.* 1994). Furthermore, the Polynomial Mutation (PM) operator (Deb and Agrawal 1999) is applied to the offspring produced by all operators except for UM.

2. RESERVOIR OPTIMIZATION MODEL

Usually, multipurpose reservoirs serve many goals, like hydropower generation, domestic water supply, agricultural water supply, flood protection and other environmental management issues. In this study, the reservoir system consists of a single multipurpose dam constructed to control water discharge in the river for irrigation, domestic water supply, flood control and hydropower generation purposes. This type of dams has many economic benefits.

In the proposed model, three types of constraints were adopted for the operation and control of the reservoir system as follows.

The volume of storage in the reservoir is limited between the dead storage and the maximum capacity of the reservoir and can be expressed as

$$S_{min} \leq S_t \leq S_{max};\ t = 1, \ldots, 12 \tag{1}$$

where S_t is the initial storage at the beginning of month t, $t = 1 \ldots 12$; S_{min} is the dead storage of the reservoir; and S_{max} is the maximum storage of the reservoir.

The releases from the reservoir should be between the minimum and maximum values, i.e.

$$R_{min} \leq R_t \leq R_{max};\ t = 1, \ldots, 12 \tag{2}$$

where R_t is the mean monthly water release for the month t; R_{max} is the maximum release of the reservoir; and R_{min} is the minimum releases of the reservoir.

To ensure reservoir storage sustainability, another constraint was adopted in this study, which ensures that the amount of storage in the first month of the next year will be equal to or greater than the initial storage. This constraint can be expressed as

$$S_{13} \geq S_1 \tag{3}$$

where S_1 is the initial storage at the start of the first month and S_{13} is the reservoir storage in the first month of the next year.

A drought condition was considered, to test the algorithm's ability to find near-optimal solutions in such critical conditions. To simulate this condition, 50% of the standard deviation of the monthly average inflow for many years was subtracted from the origin inflow as follows.

$$I_t = I_t' - \frac{SD_t}{2}; \quad t = 1, \ldots, 12 \tag{4}$$

where, for month *t*, I_t is the reduced reservoir inflow; I_t' is the original reservoir inflow; and SD_t is the standard deviation of the reservoir inflow for month *t*.

The fitness function, that is to be minimized, for the reservoir operation can be expressed as

$$Minimize\ f = \left[\sum_{t=1}^{12}(R_t - D_t)^2 + \sum_{t=1}^{12}(S_t + I_t - S_{t+1} - R_t - E_t)^2\right](1 + C) \tag{5}$$

D_t is the mean monthly downstream water demand for the month *t*. S_t is the initial storage, i.e. the storage at the beginning of month *t*, where t = 1, …, 12, while S_{t+1} is the final storage at the end of month *t*. E_t is the mean monthly evaporation from the reservoir during the month *t* and *C* is a penalty for constraint violations. The first term in the (square) brackets in Equation 5 represents the sum of the squares of the differences between the reservoir releases and the demands. The second term in the (square) brackets represents the sum of the squares of the errors in the flow continuity equation; this term should be zero, to satisfy the principle of conservation of mass.

The penalty function used is

$$C = \sum_{t=1}^{12} \sum_{j=1}^{NC} g_{tj}(S_t) \tag{6}$$

where $NC = 4$ is the number of constraint functions. The function g_{tj}, with $j = 1$ to 4 and $t = 1$ to 12, is defined for the various reservoir conditions as follows.

$$g_{t1}(S_t) = (S_{min} - S_t) \times 100, \text{ for } S_t < S_{min};\ t = 1, \ldots, 12 \tag{7}$$

$$g_{t2}(S_t) = (S_t - S_{max}) \times 100, \text{ for } S_t > S_{max};\ t = 1, \ldots, 12 \tag{8}$$

$$g_{t3}(S_t) = (S_1 - S_{13}) \times 100, \text{ for } S_{13} < S_1 \tag{9}$$

$$g_{t4}(S_t) = 0, \text{ for } S_{min} \le S_t \le S_{max};\ t = 1, \ldots, 12 \tag{10}$$

The penalty function method has some disadvantages regarding the convergence of evolutionary algorithms. The convergence rate is directly affected by the penalty function values. In general, the user specifies the penalty function after performing some trials. In addition, the performance of the penalty function may differ from a problem to another. Therefore, this function must be chosen carefully for each problem (Siew and Tanyimboh 2010).

The mathematical model developed has some limitations. For example, very briefly, the period of operation considered is one year and seepage from the reservoir and other operational losses are neglected, as in Chenari *et al.* (2014).

3. RESULTS AND DISCUSSIONS

A case study based on a real-world reservoir system in the literature (Chenari *et al.* 2014) was considered. Chenari *et al.* (2014) employed a Genetic Algorithm (GA) to optimize the reservoir operation for Mahabad dam in Iran. The aim was to minimize the deficits in the monthly water releases. The dam is located in the northwest of Iran and has an approximate watershed area of 807 km^2. It is a cold semi-arid area with average annual rainfall of 542.58 mm. There is rainfall during the three months from February to April. The live storage and dead storage are 180 million m^3 and 40 million m^3 respectively. The minimum release was taken as zero, while the maximum release was 51.48 million m^3 per month for the first six months of the year and 53.57 million m^3 per month for the second six months of the year. Data for 32 years, from 1975 to 2006, were used in Chenari *et al.* (2014) to obtain the average monthly inflows to the reservoir. More details about the study area and the data can be found in Chenari *et al.* (2014).

We wrote a computer program in the C language to solve the optimization problem in Equations 1 through 10. The algorithm has many coefficients and parameters as summarised in Table 1 (Hadka and Reed 2013).

The algorithm was executed 10 times with 200,000 function evaluations in each run. Figure 1a shows the monthly reservoir releases and storage achieved by the GA in Chenari *et al.* (2014) while Figure 1b shows the results achieved by Borg MOEA. The value of the fitness function, Equation 5, using the GA was 185.3×10^6 m^3 (Chenari *et al.* 2014) and for Borg MOEA it was 23.0135×10^6 m^3.

Table 1. Default parameter values used in Borg MOEA

Parameter	**Value**	**Parameter**	**Value**
Initial population size	100	SPX parents	10
Tournament selection size	2	SPX offspring	2
Epsilon, $\boldsymbol{\epsilon}$	0.01	SPX epsilon	2.0
SBX crossover rate	1.0	UNDX parents	10
SBX distribution index	15.0	UNDX offspring	2
DE crossover rate	1.0	UNDX σ_ξ	0.5
DE step size	3.0	UNDX σ_η	$0.35/\sqrt{L}$
PCX parents	10	UM mutation rate	$1/L$
PCX offspring	2	PM mutation rate	$1/L$
PCX $\boldsymbol{\sigma_\eta}$	0.1	PM distribution index	20
PCX $\boldsymbol{\sigma_\zeta}$	0.1		

*$\boldsymbol{\epsilon}$ is the dimension of the hyper-boxes in the objective space; $\boldsymbol{\sigma_\eta}$, $\boldsymbol{\sigma_\zeta}$ **and** $\boldsymbol{\sigma_\xi}$ are parameters of variance; and L is the number of decision variables.*

There were some deficits in the monthly releases, especially in the first two months (September and October). Also, the effect of the sustainability constraint on the releases is observed especially in the last five months from April to August, which causes some deficits in the releases in order to satisfy the requirement.

For the algorithm itself, Figure 2 shows the convergence characteristics. It can be seen that the algorithm began to converge around 25,000 function evaluations. At 25,000 function evaluations, the value of fitness function was about 65×10^6 m^3, i.e. less than the best value found using the GA in Chenari *et al.* (2014). Then, after 40,000 function evaluations, the algorithm approached the best solution with a stable trend. The number of function evaluations for the GA (Chenari *et al.* 2014) was 525,000.

Figure 2 also illustrates the effects of the penalty on the fitness function. It can be seen that the initial values were far away from the final solution. This observation seems to reflect the algorithm's ability to converge early in the environment provided by the dynamic penalty function in Equation 6.

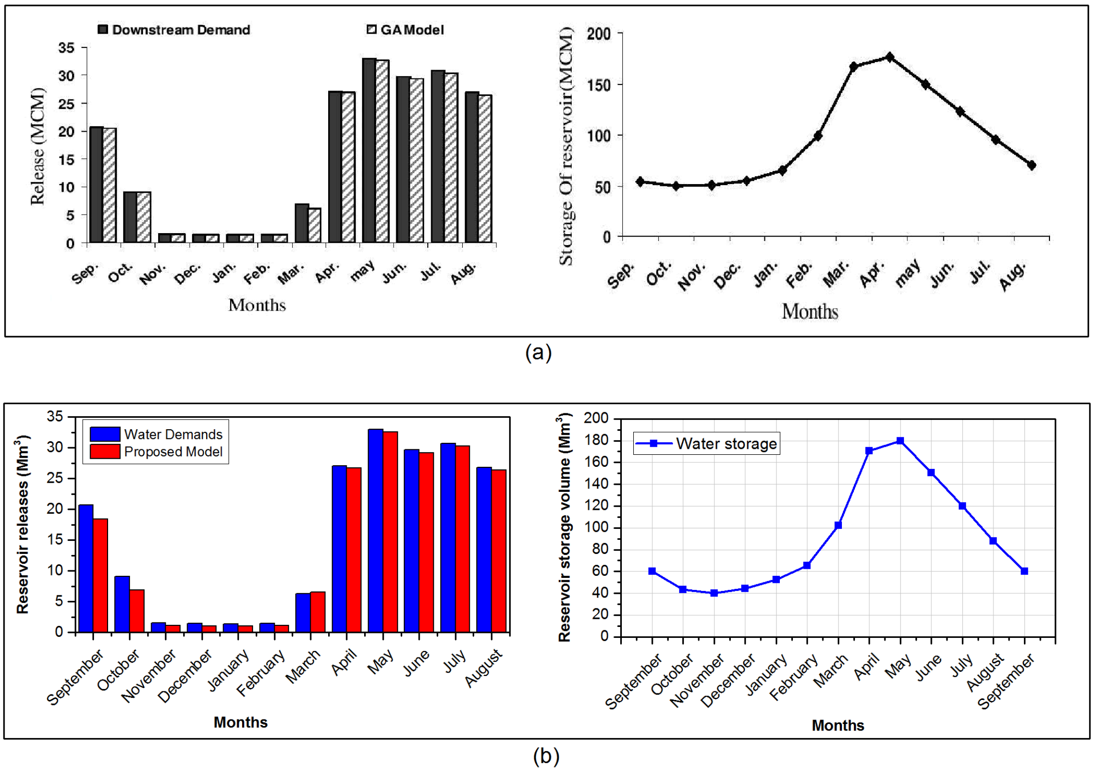

Figure 1. Reservoir operation results (a) Chenari et al. (2014) (b) Present approach

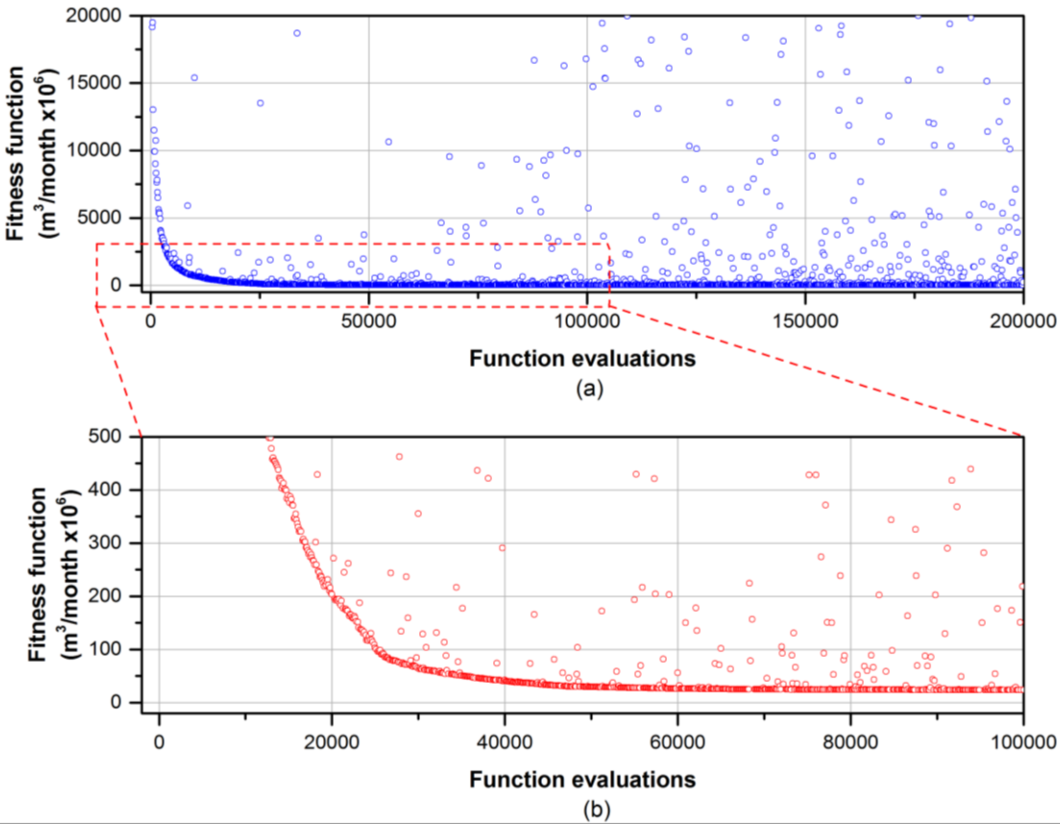

Figure 2. Convergence characteristics of the fitness function using Borg MOEA

The execution of the algorithm took only a few seconds, i.e. fast outputs could be achieved repeatedly. The research outcomes could help the relevant planning authorities and decision makers to improve the economic benefits of reservoir projects. Furthermore, the results strengthen the motivation for future work to solve more complex water management problems in the real-world.

4. CONCLUSIONS

An evolutionary optimization algorithm was used in this study to solve a real-world scenario reservoir operation and management problem. The state-of-the-art Borg MOEA optimization algorithm was selected to solve a multipurpose reservoir operation problem. A case study based on a reservoir system in the literature was selected to test the algorithm's performance and reliability. The early results are encouraging. The fitness function was improved by 87.6%, from 185.3×10^6 m^3 to 23.0135×10^6 m^3. The convergence was relatively quick. Furthermore, the results strengthen the motivation for future work to solve more complex water management problems in the real-world.

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REFERENCES

Ahmad, A., El-Shafie, A., Razali, S.F.M., Mohamad, Z.S., 2014. Reservoir Optimization in Water Resources: a Review. Water Resour. Manag. 28, 3391–3405. doi:10.1007/s11269-014-0700-5

Azizipour, M., Ghalenoei, V., Afshar, M.H., Solis, S.S., 2016. Optimal Operation of Hydropower Reservoir Systems Using Weed Optimization Algorithm. Water Resour. Manag. 30, 3995–4009. doi:10.1007/s11269-016-1407-6

Chen, D., Chen, Q., Leon, A.S., Li, R., 2016. A Genetic Algorithm Parallel Strategy for Optimizing the Operation of Reservoir with Multiple Eco-environmental Objectives. Water Resour. Manag. 30, 2127–2142. doi:10.1007/s11269-016-1274-1

Chenari, K., Ghaderi, M., Reza, M., 2014. Improved adaptive genetic algorithm and its application in short-term optimal operation of water resources system. Agric. Environ. Mana gement 3, 209–217.

Choong, S.-M., El-Shafie, A., 2015. State-of-the-Art for Modelling Reservoir Inflows and Management Optimization. Water Resour. Manag. 29, 1267–1282. doi:10.1007/s11269-014-0872-z

Coello, C.A.C., Lamont, G.L., van Veldhuizen, D.A., 2007. Evolutionary Algorithms for Solving Multi-Objective Problems, 2nd ed, Genetic and Evolutionary Computation. Springer, Berlin, Heidelberg. doi:10.1007/978-0-387-36797-2

Deb, K., 2001. Multi-Objective Optimixation using Evolutionary Algorithm, 1st editio. ed. John Wiley & Sons Ltd.

Deb, K., Agrawal, R.B., 1994. Simulated Binary Crossover for Continuous Search Space, Complex Systems. doi:10.1.1.26.8485Cached

Deb, K., Agrawal, S., 1999. A Niched-Penalty Approach for Constraint Handling in Genetic Algorithms, in: ProcInternational Conference on Artificial Neural Network and Genetic Algorithms. pp. 235–243. doi:10.1007/978-3-7091-6384-9_40

Deb, K., Joshi, D., Anand, A., 2002. Real-coded evolutionary algorithms with parent-centric recombination. Proc. 2002 Congr. Evol. Comput. CEC 2002 1, 61–66. doi:10.1109/CEC.2002.1006210

Hadka, D., Reed, P., 2013. Borg: An Auto-Adaptive Many-Objective Evolutionary Computing Framework. Evol. Comput. 21, 1–30. doi:10.1162/EVCO_a_00075

Haimes, Y.Y., Hall, W.A., 1977. Sensitivity, responsivity, stability and irreversibility as multiple objectives in civil systems. Adv. Water Resour. 1, 71–81. doi:10.1016/0309-1708(77)90025-2

Hosseini-Moghari, S.-M., Morovati, R., Moghadas, M., Araghinejad, S., 2015. Optimum Operation of Reservoir Using Two Evolutionary Algorithms: Imperialist Competitive Algorithm (ICA) and Cuckoo Optimization Algorithm (COA). Water Resour. Manag. 29, 3749–3769. doi:10.1007/s11269-015-1027-6

Javadi, A., Hussain, M., Sherif, M., Farmani, R., 2015. Multi-objective Optimization of Different Management Scenarios to Control Seawater Intrusion in Coastal Aquifers. Water Resour. Manag. 29, 1843–1857. doi:10.1007/s11269-015-0914-1

Jothiprakash, V., Shanthi, G., 2006. Single Reservoir Operating Policies Using Genetic Algorithm. Water Resour. Manag. 20, 917–929. doi:10.1007/s11269-005-9014-y

Kita, H., Ono, I., Kobayashi, S., 1999. Multi-parental extension of the unimodal normal distribution crossover for real-coded genetic algorithms. Proc. 1999 Congr. Evol. Comput. 1581–1587. doi:10.1109/CEC.1999.782672

Michalewicz, Z., Logan, T., Swaminathan, S., 1994. Evolutionary operators for continuous convex parameter spaces. Proc. 3rd Annu. Conf. Evol. Program. 84–97.

Noori, M., Othman, F., Sharifi, M., M, H., 2013. A New Flocculant-Coagulant with Potential Use for Industrial Wastewater Treatment. 2nd Int. Conf. Environ. Energy Biotechnol. 51, 139–142. doi:10.7763/IPCBEE.

Oxley, R.L., Mays, L.W., 2016. Application of an Optimization Model for the Sustainable Water Resource Management of River Basins. Water Resour. Manag. 30, 4883–4898. doi:10.1007/s11269-016-1459-7

Pianosi, F., Thi, X.Q., Soncini-Sessa, R., 2011. Artificial Neural Networks and Multi Objective Genetic Algorithms for water resources management: An application to the Hoabinh reservoir in Vietnam. IFAC Proc. Vol. 18, 10579–10584. doi:10.3182/20110828-6-IT-1002.02208

Qi, Y., Bao, L., Sun, Y., Luo, J., Miao, Q., 2016. A Memetic Multi-objective Immune Algorithm for Reservoir Flood Control Operation. Water Resour. Manag. 30, 2957–2977. doi:10.1007/s11269-016-1317-7

Rathnayake, U.S., Tanyimboh, T.T., 2015. Evolutionary Multi-Objective Optimal Control of Combined Sewer Overflows. Water Resour. Manag. 29, 2715–2731. doi:10.1007/s11269-015-0965-3

Rossman, L.A., 2009. SWMM 5.0 User’s Manual EPA/600/R-05/040. Water Supply and Water Resources Division, National Risk Management Research Laboratory, Cincinnati.

Scola, L.A., Takahashi, R.H.C., Cerqueira, S.A.A.G., 2014. Multipurpose Water Reservoir Management: An Evolutionary Multiobjective Optimization Approach. Math. Probl. Eng. 2014, 14. doi:10.1155/2014/638259

Seyoum, A.G., Tanyimboh, T.T., Siew, C., 2016. Practical Application of Penalty-Free Evolutionary Multi-Objective Optimisation of Water Distribution Systems. Water Util. J. 49–55.

Sidiropoulos, P., Mylopoulos, N., Loukas, A., 2016. Reservoir-aquifer combined optimization for groundwater restoration : The case of Lake Karla watershed , Greece. Water Util. J. 17–26.

Siew, C., Tanyimboh, T., 2010. Penalty-Free Multi-Objective Evolutionary Optimization of Water Distribution Systems. Water Distrib. Syst. Anal. 2010 41203, 764–770. doi:doi:10.1061/41203(425)71

Storn, R., Price, K., 1997. Differential evolution–a simple and efficient heuristic for global optimization over continuous spaces. J. Glob. Optim. 341–359. doi:10.1023/A:1008202821328

Tayebiyan, A., Mohammed Ali, T.A., Ghazali, A.H., Malek, M.A., 2016. Optimization of Exclusive Release Policies for Hydropower Reservoir Operation by Using Genetic Algorithm. Water Resour. Manag. 30, 1203–1216. doi:10.1007/s11269-015-1221-6

Tigkas, D., Christelis, V., Tsakiris, G., 2016. Comparative Study of Evolutionary Algorithms for the Automatic Calibration of the Medbasin-D Conceptual Hydrological Model. Environ. Process. 3, 629–644. doi:10.1007/s40710-016-0147-1

Tsutsui, S., Yamamura, M., Higuchi, T., 1999. Multi-parent recombination with simplex crossover in real coded genetic algorithms. Proc. 1999 Genet. Evol. Comput. Conf. 657–664.

Wu, Y.G., Zou, J., 2012. An Advanced Multi-Objective Genetic Algorithm Based on Borda Number, in: Progress in Industrial and Civil Engineering, Applied Mechanics and Materials. Trans Tech Publications, pp. 4909–4915. doi:10.4028/www.scientific.net/AMM.204-208.4909

Yeh, W.W., 1985. Reservoir Management and Operations Models: A State-of-the-Art Review. Water Resour. Res. 21, 1797–1818.

4.5 Paper 2

Al-Jawad, J.Y., Tanyimboh, T.T., 2017b. Reservoir operation using a robust evolutionary optimization algorithm. J. Environ. Manage. 197, 275–286. https://doi.org/10.1016/j.jenvman.2017.03.081.[2]

OPTIMIZING RESERVOIR OPERATION USING ROBUST EVOLUTIONARY ALGORITHM

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Abstract

In this research, a significant improvement in reservoir operation was achieved using a state-of-the-art evolutionary algorithm named Borg MOEA. A real-world multipurpose dam was used to test the algorithm's performance, and the target of the reservoir operation policy was to fulfil downstream water demands in drought condition while maintaining a sustainable quantity of water in the reservoir for the next year. The reservoir's performance was improved by increasing the maximum reservoir storage by 14.83 million m^3. Furthermore, sustainable water storage in the reservoir was achieved for the next year, for the simulated low flow condition considered, while the total annual imbalance between the monthly reservoir releases and water demands was reduced by 64.7%. The algorithm converged quickly and reliably, and consistently good results were obtained. The methodology and results will be useful to decision makers and water managers for setting the policy to manage the reservoir efficiently and sustainably.

Keywords: Evolutionary optimization algorithm, reservoir operation policy, multipurpose reservoir system, reservoir drawdown limits, self-adaptive recombination, environmental water management

[2] Journal policy have embargo period of two years to share published papers

1. INTRODUCTION

Multipurpose reservoirs are widely used to serve multiple demands for domestic, industrial, irrigation, environment, hydropower production and flood control, to maximize the economic benefits. These types of systems are complex because of the nonlinear storage-inflow relationship, conflicting objectives, dynamic properties, nonlinear constraints, etc. (Haimes and Hall 1977). In the field of water resources management, significant demands on water exploitation were observed in recent decades. This raises the challenge to manage and allocate water in a sustainable way, and reservoirs are essential for water resources management in a river basin (Jothiprakash and Shanthi 2006, Horne *et al.* 2016) .

Many methods for optimization were found to solve different types of problems such as linear programming, non-linear programming and dynamic programming, etc. (Horne *et al.* 2016). However, the classical optimization methods are generally not suitable for such complex problems for a number of reasons. For example, typically, they provide a single local optimum solution. Evolutionary algorithms on the other hand, use a population of solutions rather than one solution in every iteration (Deb 2001). In recent decades, evolutionary optimization algorithms were widely used in different fields of engineering and science to solve real-world problems (Coello *et al*. 2007).

Regarding engineering applications, Formiga *et al.* (2003) used the Non-dominated Sorting Genetic Algorithm (NSGA II) to solve water distribution network problems. Régnier *et al.* (2005) applied NSGA II in electromechanical system design. In structural design, Tract (1997) used a genetic algorithm (GA) with Pareto ranking in truss design. Deb and Tiwari (2005) used NSGA II for design in the field of mechanical engineering. In the field of civil engineering, Feng *et al*. (1999) used a GA with Pareto ranking to optimize building construction planning.

To achieve effective operational management policies for water resources management problems, many researchers used different optimization approaches (Horne *et al.* 2016). Sharif and Wardlaw (2000) used a GA to maximize the hydropower production while allowing deficits to occur in irrigation supplies. Chenari *et al.* (2014) also used a GA to determine the releases from a reservoir. Furthermore, Tilmant *et al*. (2002) used fuzzy stochastic dynamic program to optimize the control rules for a multipurpose reservoir. Kim and Heo (2006) used MOGA (multi-objective genetic algorithm) to solve a multi-reservoir multi-objective problem. Wu and Zou (2012) applied MOGA to maximize both power generation and irrigation benefits. Scola *et al*. (2014) applied NSGA II to maximize power generation. Cancelliere *et al*. (2003) used a multi-objective optimization method to reduce the deficit in the releases for irrigation and improve municipal volumetric reliability.

Borg MOEA is a recent optimization algorithm that was introduced by Hadka and Reed (2013). In this research, Borg MOEA was used to solve a reservoir operation problem. These types of problems need a powerful algorithm to handle the complexity of the inflow-storage relationship. The Borg MOEA algorithm has six operators that compete to create offspring in each generation. The effectiveness of the algorithm is maintained throughout the optimization by deploying the most suitable combination of operators for crossover. In addition, Borg MOEA is able to detect stagnation and escape from local optima by reviving the search process.

The aim of the current study was to investigate the robustness and performance of the algorithm on a reservoir operation problem. A drought condition and an additional reservoir drawdown constraint were considered in order to test the algorithm's ability to find good solutions consistently in such critical conditions. In reservoir management, it is difficult to control the releases over the entire year in order to fulfil the downstream demands and to maintain the same or higher initial water storage in the reservoir for the next year in drought conditions. Hence, the influence of the extra drawdown constraint imposed was investigated.

2. OVERVIEW OF THE OPTIMIZATION APPROACH

Hadka and Reed (2013) introduced Borg MOEA for many-objective optimization problems. Some of the features in Borg MOEA include (a) diversity preservation; (b) measurement of search progress and stagnation; (c) restart to move away from local optima; (d) multiple recombination operators that compete to produce offspring; and (e) use of a dominance archive. The algorithm uses six operators in the recombination process to improve the search progress and a dominance archive to store all the non-dominated solutions.

To preserve diversity, the objective space is divided into hyper-boxes whose dimensions are all equal to ϵ, as in Figure 1. Thus the ϵ-box index vector is used to find the dominant solutions instead of the objective function values. The algorithm calculates this index by dividing the objective function value by ϵ, and then sets the result as the succeeding integer value. If two or more solutions are in the same ϵ-box, the dominant solution is the one which is nearest to the lower-left corner of the ϵ-box, in the case of a minimization problem.

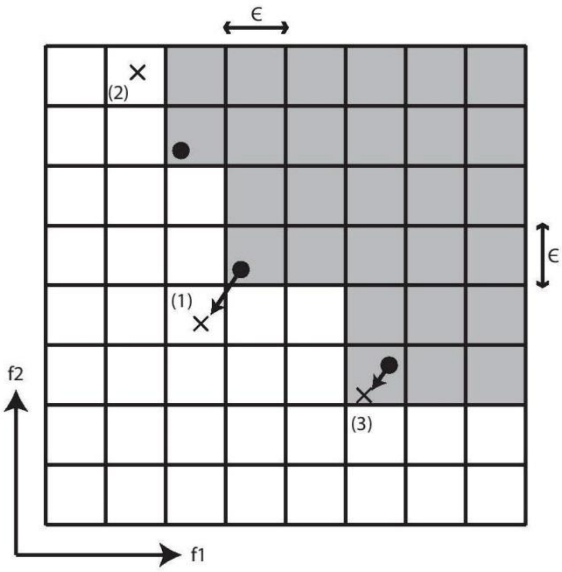

Figure 1. Graphical representation of ε-progress concept in a minimization problem with two objectives. Solutions (1) and (2) are new solutions in unoccupied boxes and thus represent improvements. Solution (3) is not considered as an improvement because it resides in a previously occupied box. The shaded boxes were previously occupied while unshaded boxes were not previously occupied (Hadka and Reed 2013).

For stagnation measurement, ϵ-progress was introduced, which measures the improvement while searching for new solutions. If the algorithm finds new solutions in a new unoccupied ϵ-box, it means that there is progress and the algorithm is allowed to continue. This can be observed more clearly in Figure 1. On the other hand, if there is no improvement based on ϵ-progress for a certain number of evaluations, a revival process is triggered, to escape from any local optima. The details of the restart procedure are available in Hadka and Reed (2013). The algorithm maintains the population size as a certain ratio of the archive size during the optimization process. This feature was adopted from ϵ-NSGA II (Kollat and Reed 2006) and is called the injection rate.

The algorithm employs multiple recombination operators to produce offspring. In fact, Borg MOEA provides a framework in which the selection of the recombination operators adjusts depending on the dynamic properties of the objective and solution spaces of the optimization problem, including the make-up and diversity of the candidate solutions, and the landscape of the objectives. The recombination operators in Borg MOEA are:

(a) simulated binary crossover (SBX) (Deb and Agrawal 1994);

(b) differential evolution (DE) (Storn and Price 1997);

(c) parent-centric crossover (PCX) (Deb *et al.* 2002);

(d) unimodal normal distribution crossover (UNDX) Kita *et al.* (2000);

(e) simplex crossover (SPX) (Tsutsui *et al.* 1999); and

(f) uniform mutation (UM) (Michalewicz *et al.* 1994).

Also, the polynomial mutation (PM) (Deb and Agrawal 1994) is applied to the offspring produced by all the operators except for UM.

The probability of choosing a particular recombination operator to produce offspring depends on its ability to contribute nondominated solutions in the dominance archive, compared to the other operators; hence the operator selection probabilities are proportional to their effectiveness and respective contributions.

The values of the decision variables in the offspring generated lie within the upper and lower bounds of the decision variables. The algorithm has many coefficients and parameters as summarised in Table 1 (Hadka and Reed 2013) in which L represents the number of decision variables, ϵ is the dimension of the hyper-box in the objective space, and σ_η, σ_ξ and σ_ζ represent the variance parameters that control the spatial distribution of the resulting offspring for the PCX and UNDX operators.

The values of the paramters shown in Table 1 are the recommended empirical values from the literature, based on extensive testing that included complex real-world problems (Hadka *et al.* 2012, Reed *et al.* 2013). The values have been used widely in subsequent studies also (Zheng *et al.* 2016). Further improvement through fine tuning on a case-specific basis may be possible; however this issue is complex (Lobo *et al.* 2007) and is not the main focus of the present research.

Hadka and Reed (2012) presented comparisons of eight state-of-the-art evolutionary algorithms based on their performance on eight test functions. Furthermore, Reed *et al.* (2013) compared the performance of Borg MOEA on real-world water resources problems with ten competitive algorithms. Both studies concluded that Borg MOEA outperformed the other algorithms on the problems considered.

Table 1. Default values of the parameters used in Borg MOEA

Parameter	Value	Parameter	Value
Initial population size	100	SPX parents	10
Tournament selection size	2	SPX offspring	2
Epsilon, $\boldsymbol{\epsilon}$	0.01	SPX epsilon	2.0
SBX rate	1.0	UNDX parents	10
SBX distribution index	15.0	UNDX offspring	2
DE crossover rate	1.0	UNDX σ_ξ	0.5
DE step size	3.0	UNDX σ_η	$0.35/\sqrt{L}$
PCX parents	10	UM rate	$1/L$
PCX offspring	2	PM rate	$1/L$
PCX $\boldsymbol{\sigma_\eta}$	0.1	PM distribution index	20
PCX $\boldsymbol{\sigma_\zeta}$	0.1		

ϵ is the dimension of hyper-boxes in objective space; L is the number of decision variables; and the various σ symbols are variance parameters.

The criteria used in the comparisons included the hypervolume, generational distance and additive ϵ-indicator metrics (Knowles and Corne 2002). For a set of nondominated solutions, the hypervolume represents the fraction of the objective space that the solutions dominate. It increases as: the solutions approach the Pareto-optimal front; their range increases; and their distribution becomes more even. The generational distance calculates the average distance between the resulting nondominated front and the Pareto-front. The additive ϵ-indicator measures the smallest factor by which the resulting approximation set achieved must be translated in the objective space in order weakly to dominate the reference set. Based on these criteria, the main conclusion was that Borg MOEA showed significant advantages over the other algorithms.

The algorithms considered by Hadka and Reed (2013) in their comparative study are listed below, with additional details in Deb *et al.* (2003), Zhang *et al.* (2009), Sierra and Coello Coello (2005), Kollat and Reed (2006), etc.

a. ϵ-MOEA
b. MOEA/D (multi-objective evolutionary algorithm based on decomposition))
c. GBE3 (generalized differential evolution, version 3)
d. OMOPSO (multi-objective particle swarm optimization)
e. IBEA (indicator-based evolutionary algorithm)
f. ϵ-NSGA II

In another study, in addition to the previous algorithms, Reed *et al*. (2013) compared Borg MOEA based on four test problems with NSGA II (Deb *et al.* 2002), SPEA2 (Zitzler *et al.* 2002) and AMALGAM (Vrugt and Robinson 2007). The authors concluded that Borg MOEA was the best among the nine algorithms, including a. to f. in the preceding list.

3. RESERVOIR OPTIMIZATION MODEL

Usually, multipurpose reservoirs serve many goals like hydropower generation, domestic water supply, agricultural water supply, flood protection, and other environmental goals. In this study, the reservoir system consists of a single multipurpose dam constructed to control water discharge in the river for irrigation and domestic use, flood control and hydropower generation. This type of dam has many economic benefits. In this model, three types of constraints were considered. A drought condition was considered in order to test the algorithm's ability to find an optimum solution in such critical conditions without violating the reservoir drawdown limit imposed.

3.1 Reservoir Storage Constraints

The volume of storage in the reservoir is limited between the dead storage and the maximum capacity of the reservoir. The dead storage constraint, which is the minimum allowable storage in the reservoir, is

$$C_1(t) = S_t - S_{min} \geq 0;\ \forall t \tag{1}$$

where $S_t \geq 0$ is the initial storage at the beginning of the month t, $t = 1, \ldots, 12$; S_{min} is the dead storage of the reservoir. The maximum storage constraint, which is the maximum storage capacity of the reservoir, is

$$C_2(t) = S_{max} - S_t \geq 0;\ \forall t \tag{2}$$

where S_{max} is the maximum normal storage in the reservoir.

3.2 Reservoir Release Constraints

The releases from the reservoir should be bounded between the minimum and maximum releases. The minimum release constraint, for the minimum amount of water to be released from the reservoir, is

$$C_3(t) = R_t - R_{min} \geq 0;\ \forall t \tag{3}$$

where $R_t \geq 0$ is the mean monthly water release for month t. R_{min} is the minimum allowable water releases from the reservoir. The maximum allowable amount of water released from the reservoir should not exceed e.g. the spillway or downstream channel capacity. Thus

$$C_4(t) = R_{max} - R_t \geq 0;\ \forall t \tag{4}$$

where R_{max} is the maximum allowable release from the reservoir.

3.3 Constraint on Annual Reservoir Drawdown

To ensure reservoir storage sustainability, an extra constraint was introduced in this study so that the amount of storage in the first month of the next year will equal or exceed the initial storage of the first month. This constraint can be expressed as

$$C_5(13) = S_{13} - S_1 \geq 0$$

(5)

where S_1 is the initial storage in the first month and S_{13} is the reservoir storage at the start of the first month of the next year.

3.4 Low Reservoir Inflow Condition

A drought condition was considered in order to test the algorithm's ability to find good solutions quickly and consistently in such critical conditions. To calculate this condition, 50% of the standard deviation of the monthly average inflow for many years was subtracted from the original inflow (Reddy and Kumar 2006).

$$I_t = I_t' - 0.5\sigma_t$$

(6)

where I_t is the reduced reservoir inflow for month *t;* I_t' is the original reservoir inflow for month *t;* and σ_t is the standard deviation of the reservoir inflow for month *t.*

3.5. Fitness Function

The monthly flow continuity equation is

$$S_t + I_t - S_{t+1} - R_t - E_t = 0 \qquad (7)$$

where S_{t+1} is the final storage at the end of month t and E_t is the mean monthly evaporation from the reservoir during the month t.

The fitness function for reservoir operation that should be minimized can be expressed as

$$f = \left[\sum_{t=1}^{12}(R_t - D_t)^2 + \sum_{t=1}^{12}(S_t - S_{t+1} + I_t - R_t - E_t)^2\right](1 + C)^e \qquad (8)$$

where D_t is the mean monthly downstream water demand for the month t; C is a penalty for constraint violations; and the value of the exponent, e, is 2. The first part of Equation 8 aims to minimize the differences between the monthly reservoir releases and the demands, subject to the flow continuity equation in Eq. 7. The second part is a quadratic penalty function to address constraint violations. At the solution, the continuity equation in Eq. 7 is equal to zero. Also, the constraint violation penalty C is zero for feasible solutions.

Thus the fitness function, Eq. 8, aims to minimize the total annual imbalance between the monthly reservoir releases and water demands, including deficits and surpluses. Self-evidently a deficit implies a shortfall in the supply, while a surplus is to be avoided if possible, as a water conservation measure during periods with low reservoir inflows.

In general, the convergence rate and optimality of the solutions achieved are influenced by the penalty function employed, and the effects differ from a problem to another. Therefore, this function should be chosen carefully for each problem (Dridi *et al.* 2008, Siew and Tanyimboh 2012, Deb and Datta 2013, Siew *et al.* 2014, Saleh and Tanyimboh 2013, 2014, 2016). The problem of formulating and calibrating penalty functions is complex (Coello Coello 2002, Chang *et al.* 2010, Deb and Datta 2013). A review of constraint handling in evolutionary algorithms is available in Coello Coello (2002).

The constraint violation penalty adopted here is

$$C = A(g_1 + g_2 + g_3) \tag{9}$$

where A is a coefficient that was taken as 100, and g_1, g_2, and g_3 represent the penalties for the minimum, maximum, and sustainable storage constraints, respectively.

The values of the penalty factor *A* and exponent *e* were determined empirically, to apply an appropriate amount of selection pressure that would not render all the infeasible solutions including those with relatively small constraint violations totally uncompetitive (Yang and Soh 1997, Dridi *et al.* 2008, Tanyimboh and Seyoum 2016). Indeed, evolutionary algorithms that include nondominated or competitive infeasible solutions in the optimization process generally achieve better results than those that fail to exploit any infeasible solutions generated (Yang and Soh 1997, Woldesenbet *et al.* 2009, Eskandar *et al.* 2012, Barlow and Tanyimboh 2014, Siew *et al.* 2016).

On the other hand, an algorithm's convergence rate may be too slow if the selection pressure is insufficient. For example, Siew and Tanyimboh (2012) compared two versions of a performance function that represents the fitness. They adopted the version with more selection pressure and significantly faster convergence.

The penalties for violating the minimum, maximum, and sustainable storage constraints, respectively, are as follows.

$$g_1 = \sum_{t=1}^{12} Max[0, (S_{min} - S_t)] \quad (10)$$

$$g_2 = \sum_{t=1}^{12} Max[0, (S_t - S_{max})] \quad (11)$$

$$g_3 = Max[0, (S_1 - S_{13})] \quad (12)$$

The form of fitness function adopted in Eq. 8 has the advantages that it allows simultaneous minimization of both the objective and penalty functions. The penalty function is dynamic and reflects the degree of constraint violation. This allows promising infeasible solutions to contribute essential genetic material to the gene pool. The quadratic form of the penalty function adjusts the selection pressure on the infeasible solutions gradually as the optimization progresses (Yang and Soh 1997), thus shifting the emphasis of the search progressively away from more exploration at the start to more exploitation at the end.

The formulation of the penalty function aims to exploit all the solutions generated fully, including virtually feasible solutions that promote exploration and exploitation around the active constraint boundaries. In this way, the whole solution space is searched effectively. The infeasible solutions enhance diversity, promote active boundary search, help avoid a purely interior search and premature convergence, and improve the overall effectiveness of the algorithm (Yang and Soh 1997, Siew and Tanyimboh 2012).

The total number of decision variables is 25, i.e. 12 for the monthly releases and 13 for the storages as shown in Figure 2b and 2c, in which the 13 month represents the first month of the following year. We wrote a computer program in C++ language to solve the optimization problem in Equations 1 through 12 using Borg MOEA. The algorithm was executed ten times with 200,000 function evaluations allowed in each run, with an initial population of 100, for each scenario of the optimization problem.

The period of operation considered was one year. For long-term planning, the number of decision variables and dimensionality of the problem may increase and/or longer time steps may be used. Monthly rather weekly values were considered in the model as the focus of the research is to assist with the development of an efficient seasonal operating policy, rather than daily operational control (Horne *et al.* 2016). Environmental water management decisions may relate to a range of spatial and temporal scales, from sub-daily to multi-year and a single location to the river basin, respectively. Horne et al. (2016) mentioned the importance of the relationships between the various scales and provided examples of the strategies used such as nested and hierarchical models, and stochastic programming.

In addition, seepage from the reservoir and other operational losses were neglected, based on the problem specification in Chenari et al. (2014). These issues are not the main focus of the present investigation; a simulation model that provides the relevant properties of the system (i.e. inflow, evaporation, etc.) could be used instead if necessary. Hence the losses may be incorporated, with additional case-specific data.

4. ILLUSTRATIVE EXAMPLE

A real-world case study from the literature was adapted in this study. Chenari *et al.* (2014) employed a GA to optimize the reservoir operation for Mahabad dam in Iran. The aim was to minimize the deficit in water demands. The dam, located in the northwest of Iran, has an approximate watershed area of 807 km^2. It is in a cold semi-arid area with average annual rainfall of 542.58 mm. There is rainfall during the three months from February to April. The live storage and dead storage are 180 million m^3 and 40 million m^3, respectively. The minimum release was taken as zero and the maximum release was taken as 51.48 million m^3 per month for the first six months of the year and 53.57 million m^3 per month for the second six months of the year. Data for 32 years, from 1975 to 2006, were used by Chenari *et al.* (2014) to obtain the average monthly inflows to the reservoir. Table 2 presents the values of inflows and water demands in the case study area.

Table 2 Reservoir inflows and water demands (Chenari *et al.* 2014)

Month	Average inflow (10^6 m^3)	Standard deviation (10^6 m^3)	Drought season inflow (10^6 m^3)	Water demand (10^6 m^3)	Maximum release (10^6 m^3)
September	1.340	1.450	0.615	20.67	51.84
October	7.850	11.86	1.920	9.110	51.84
November	11.03	11.33	5.365	1.530	51.84
December	16.28	15.30	8.630	1.430	51.84
January	20.98	14.36	13.80	1.400	51.84
February	54.00	33.26	37.37	1.440	51.84
March	97.13	43.28	75.49	6.290	53.57
April	55.88	37.70	37.03	27.04	53.57
May	10.90	10.80	5.500	33.01	53.57
June	2.470	1.870	1.535	29.64	53.57
July	1.140	0.940	0.670	30.74	53.57
August	0.900	0.920	0.440	26.80	53.57

More details and data can be found in Chenari *et al.* (2014) that used a population size of 350 and 1500 generations, i.e. 525,000 function evaluations. The final value of the objective function in Chenari *et al.* (2014) was 185.3×10^6 m^3. The minimum and maximum storage in the reservoir were 49.99 million and 165.17 million m^3, respectively.

5. RESULTS AND DISCUSSION

5.1 Reservoir Storage and Release

Figure 2a illustrates the monthly reservoir releases and storage reported by Chenari *et al.* (2014) while Figure 2b and 2c show the corresponding results achieved in this study. The initial storage in the reservoir was insufficient; hence some deficits occurred especially in the first two months (September and October). Also, the effect of the water sustainability constraint on the releases is observed especially in the last five months (April to August), which causes some deficits in the releases due to this constraint (Figure 2b).

The sustainability constraint was not considered in the original formulation of the problem in Chenari *et al.* (2014), and Figure 2c shows the results achieved in this study for the original problem specifications in Chenari *et al.* (2014). In Figure 2a, the first six months (September to February) show a good match between the releases and demands. However, these results do not match the reservoir storage shown in the storage graph.

Moreover, Figure 2a shows that the initial storage in September is about 60 million m^3, and the releases from the reservoir in the same month is about 20 million m^3, and inflow is 0.615×10^6 m^3 (Table 2). It means that in the next month the water storage in the reservoir will be approximately equal to the dead storage, i.e. 40 million m^3. Then, the release in the next month is 9.11 million m^3 and the inflow is 1.92 million m^3 (Table 2). This means that the storage in the reservoir will be less than the dead storage. Consequently, there should be deficits in the releases for the first two months to maintain the water storage limits in the reservoir as observed in Figure 2b and 2c.

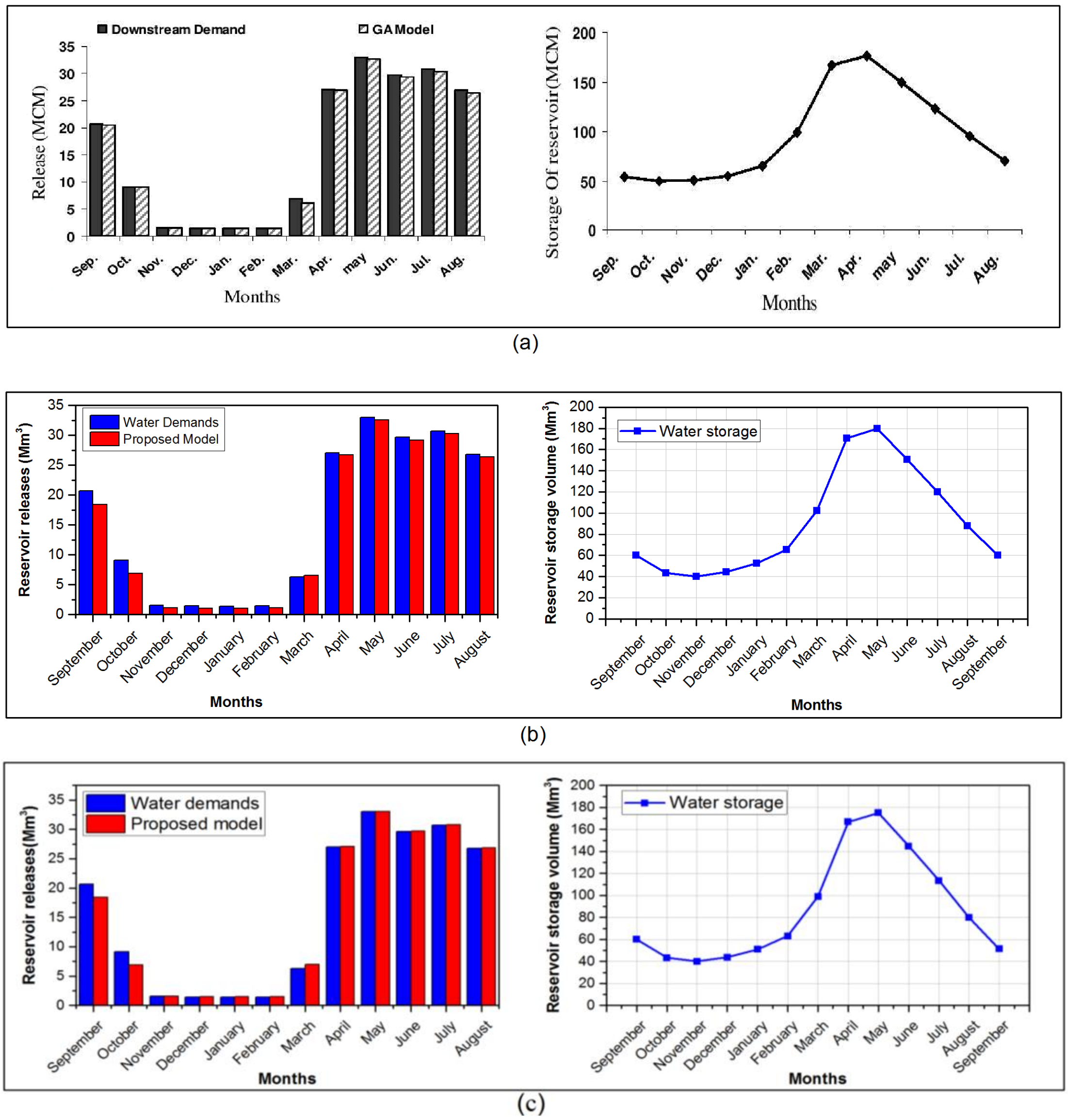

Figure 2. Reservoir releases and storage (a) Chenari *et al.* (2014) (b) Present formulation with sustainability constraint (c) Present formulation without sustainability constraint

5.2. Decision Variable Values Achieved

Table 3 summarises the reservoir release, deficit and storage for each month based on ten runs of the optimization algorithm. The maximum standard deviation of the releases was 0.151 million m^3 in November and the minimum was 0.004 million m^3 in September. There were deficits in all months except for March. The deficits arose because the amount of water in the reservoir and the inflows could not fulfil the water demands and evaporation losses.

The deficit over the entire year occurs because of the sustainability constraint adopted in this research. This constraint ensures the storage in the beginning of the next year will be equal or larger than the initial storage in the current year. For planning and operational purposes, more sophistication of the reservoir depletion constraint may be required to optimise the benefits further as, in practice, short-term drawdown of the reservoir would likely be acceptable. For example, Kim and Heo (2006) used smaller ranges of upper and lower storage limits than the original limits for the next year. Chang *et al.* (2010) allowed depletion between the initial and next year's storage of 10%. The effect of the sustainability constraint is examined further in Subsection 5.5 based on the original problem specifications in Chenari *et al.* (2014).

Table 3 Reservoir operation based on ten optimization runs

Month	Release ($m^3 \times 10^6$)			Deficit ($m^3 \times 10^6$)		Storage ($m^3 \times 10^6$)		
	Minimum	Mean	Std.	Minimum	Mean	Minimum	Mean	Std.
September	18.431	18.439	0.004	2.224	2.231	60.000	60.000	0.000
October	6.839	6.875	0.013	2.215	2.235	43.184	43.202	0.011
November	1.132	1.270	0.151	0.007	0.260	40.000	40.000	0.000
December	1.040	1.164	0.131	0.076	0.266	43.874	44.363	0.288
January	1.031	1.115	0.095	0.117	0.285	51.258	52.102	0.538
February	1.092	1.129	0.040	0.251	0.311	63.89	65.078	0.719
March	6.548	6.582	0.023	(**0.325**)	(**0.292**)	100.29	101.63	0.806
April	26.575	26.671	0.056	0.307	0.368	168.96	170.23	0.801
May	32.451	32.538	0.041	0.427	0.472	178.22	179.45	0.693
June	28.996	29.131	0.082	0.430	0.509	149.08	150.13	0.625
July	29.985	30.203	0.111	0.442	0.537	118.97	119.82	0.480
August	26.019	26.246	0.135	0.429	0.554	87.258	87.678	0.266
September	-	-	-	-	-	60.000	60.000	0.000

Std. denotes the standard deviation. The initial storage is a set value. Surpluses are in bold in parentheses.

The minimum storage was 40 million m^3 in November, and the maximum storage occurred in May. Comparing these results with Chenari *et al.* (2014), the maximum water storage was increased by about 14.83 million m^3 and the minimum storage decreased by 9.99 million m^3. The average standard deviation (i.e. the ratio of the standard deviation to the mean) of the storage for the year (excluding the set or constrained values in September and November) was 0.006, which suggests a very high degree consistency in the results achieved. The sustainability constraint succeeded to guide the algorithm to find solutions that store enough water over the entire year to maintain the required initial storage for the next year. This is observed clearly in the first and 13^{th} month (September).

5.3 Fitness Function Values

The best fitness function value was 23.01×10^6 m^3. At the solution, the value of the constraint violation penalty *C* was zero. The fitness function value of 23.01×10^6 m^3 is a significant improvement (87.6%) relative to the previous value of 185.3×10^6 m^3 in Chenari *et al.* (2014). In other words, based on these results, the total annual imbalance between the releases and demands has been reduced by 64.7%, from $f^{1/2} = 13.61\times10^6$ m^3 to $f^{1/2} = 4.80\times10^6$ m^3. The average number of restarts to escape stagnation of the algorithm and/or improve the results of the search (as explained in Section 2) per optimization run was 320.

Each run of the optimization algorithm took a few seconds on a personal computer (Linux, Dell OptiPlex 780, Core Duo 2, E8400 @ 2 × 3.0 GHz, 8.0 GB RAM). Figure 3a illustrates the convergence of the fitness function. It can be seen that the fitness function converged within 25,000 function evaluations approximately. The algorithm's convergence is fast, which is beneficial for rapid updating of the policy of reservoir operation. The convergence point in Chenari *et al.* (2014) was 525,000 function evaluations.

As stated previously, the values of the penalty factor, $A = 100$, and exponent, $e = 2$, were determined empirically. The best alternative fitness function value was achieved with a penalty factor A of 1,000 i.e. 23.01×10^6 m^3, based on 10 optimization runs, with $e = 2$. A safe value of 100 was therefore selected for the penalty factor A, to strike a balance that reduces the risk of premature convergence due to selection pressure; ultimately, $A = 100$ and $A = 1{,}000$ gave essentially the same solution, with an exponent value of $e = 2$.

Other combinations of the penalty factor, A, and exponent, including $e = 1$ and $e = 4$, gave slightly larger values of the fitness function. However, due to the effectiveness of methodology employed, consistently good results were achieved. The mean value of the fitness function, based on 10 optimization runs, ranged from 23.2×10^6 m^3 to 23.7×10^6 m^3 while the minimum ranged from 23.01×10^6 m^3 to 23.04×10^6 m^3.

Table 4 and Figure 3b provide a summary of the results of the sensitivity analysis. These results demonstrate that the formulation used is effective, stable, robust, and not overly sensitive to the values of the parameters A and e of the penalty function. It can be seen also that the parameter-free version of the penalty function, with both A and e set to unity, i.e. $A = e = 1$, is also satisfactory, albeit with a slightly lower consistency based on the standard deviation of 0.905×10^6 m^3. Indeed, it is interesting to note that the median and minimum values of the fitness function were effectively virtually identical.

Table 4 Sensitivity of the fitness function to the parameters of the penalty function

A	10^0	10^1	10^2	10^3	10^4	10^2	10^0
e	2	2	2	2	2	4	1
	Fitness function ($m^3 \times 10^6$)						
Min.	23.020	23.014	23.013	23.013	23.023	23.012	23.016
Median	23.037	23.038	23.024	23.039	23.041	23.042	23.037
Mean	23.383	23.725	23.381	23.186	23.558	23.451	23.454
Max.	25.333	27.368	24.319	23.978	27.884	26.943	26.281
Std.	0.682	1.368	0.475	0.309	1.522	1.166	0.905

The constraint violation *C* at the solution was zero; Std. denotes the standard deviation.

Overall, the parameter combination (A, e) = (100, 2) and (1000, 2) gave the best results in terms of accuracy and consistency, as can be seen in Figure 3b, with the smallest standard deviations of 0.475×10^6 m^3 and 0.309×10^6 m^3, respectively, in Table 4. These results (Figure 3b and Table 4) suggest that A is efficient between 100 and 1000. The present fitness function values may be compared to 185.3×10^6 m^3 in Chenari *et al.* (2014). The results achieved here are thus a significant improvement.

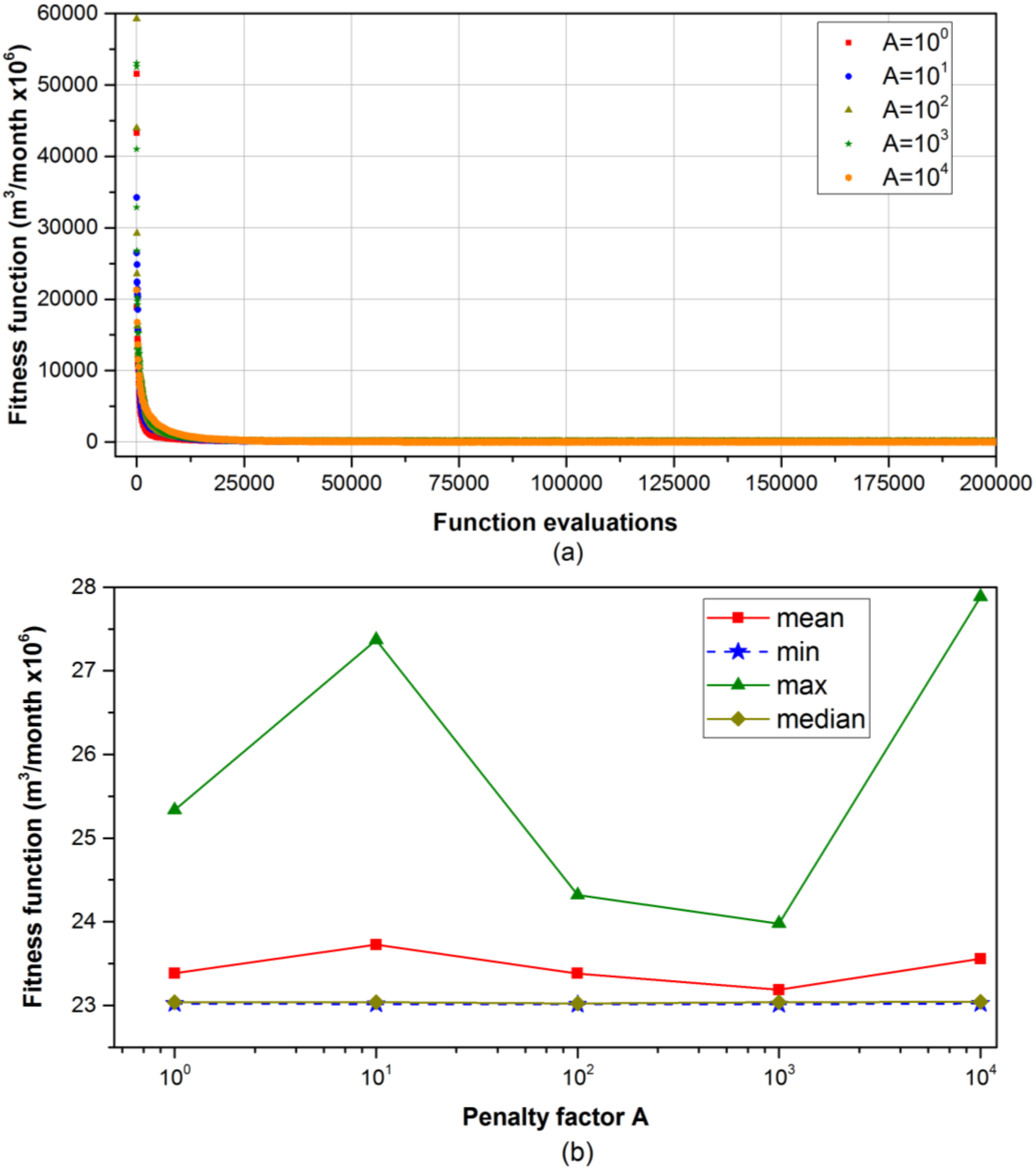

Figure 3. Properties of the fitness function. (a) Convergence characteristics (b) Accuracy and consistency. The lines in (b) are to aide visualization. The value of the exponent in Equation 8 is 2.

5.4 Observations on the Optimization Algorithm

Figure 4 illustrates the typical development of the decision variables of releases and storages toward the best solution during the optimization. Starting with an initial random population, it can be seen that rapid convergence was achieved within 25,000 function evaluations approximately, and the values remained stable thereafter.

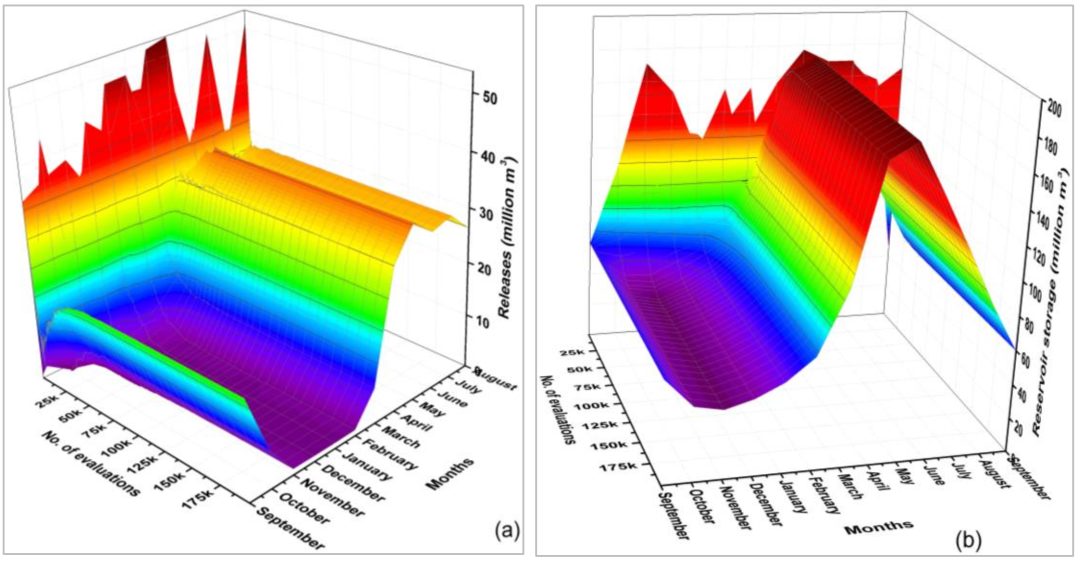

Figure 4. Evolution of the decision variables. (a) Water release (b) Reservoir storage. The irregular patterns at the far ends, at zero function evaluations, depict the initial random seeds.

Figure 5a shows the calculated percentages of the solutions in the archive, based on the respective selection probabilities of the recombination operators. PCX and UNDX were, apparently, the most successful operators, with averages of 28% and 29%, respectively. SPX and SBX had averages of 21% and 18%, respectively. The DE operator had an average of 8%. The UM operator rarely succeeded to generate dominant solutions for the archive, with an average of 0.16%.

On the other hand, Figure 5b shows the actual contributions of the various operators. All the percentages ranged between 14% and 19%. UM was the least successful operator while the most successful were PCX and UNDX followed by SPX. It can be seen that the contributions of the six recombination operators were roughly comparable.

To investigate further the relative merits of the recombination operators, Figure 6 shows heat maps of their selection probabilities for the entire optimization run. PCX generated dominant offspring in all the runs, with more solutions generated after

80,000 function evaluations. UNDX performed well in the early stages, especially before 80,000 evaluations. Then its ability to generate dominant solutions decreased slowly until the end.

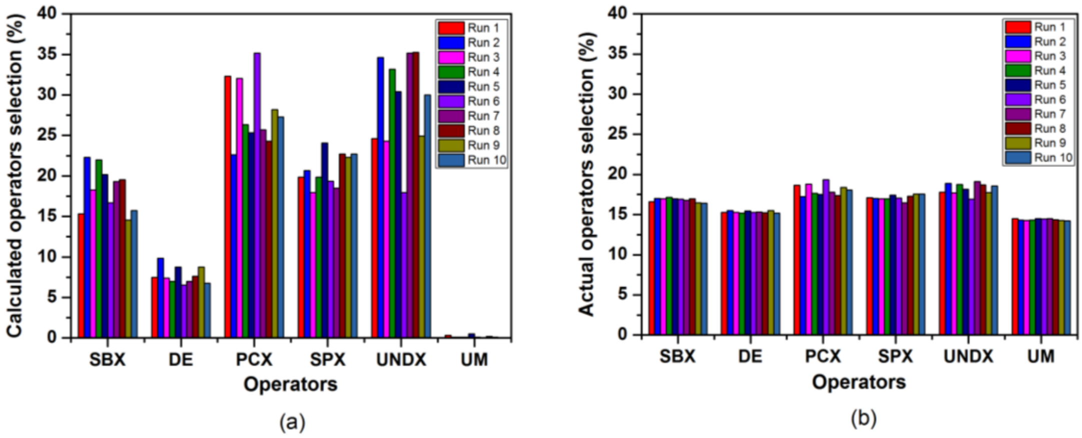

Figure 5. Relative contributions of the recombination operators (a) Calculated operator selection probabilities (b) Actual operator selection frequencies achieved

The difference between the calculated and actual operator selection probabilities may be due to the operator selection mechanism used in Borg MOEA (Hadka and Reed, 2013), i.e.

$$Q_i = \frac{C_i + \alpha}{\sum_{i=1}^{K}(C_i + \alpha)}\ ; \qquad i = 1, \dots, K \tag{13}$$

where K is the number of operators; Q_i is the probability of selecting operator i; C_i is the number of solutions produced by the ith operator in the archive; and $\alpha = 1$ is a constant used to avoid probability values of zero.

The algorithm initially sets a uniform probability of $1/K$ for all the operators. Then, the probability is updated periodically throughout the optimization. In the case of a single-objective optimization problem, the probability Q_i may remain in a limited range with no operator dominating the others because there is only one dominant solution in the archive. Therefore, the algorithm almost randomly selects the operators.

On the other hand, for multi-objective problems, the algorithm generates a population of solutions in the dominance archive, and the value of Q_i changes according to Equation 13.

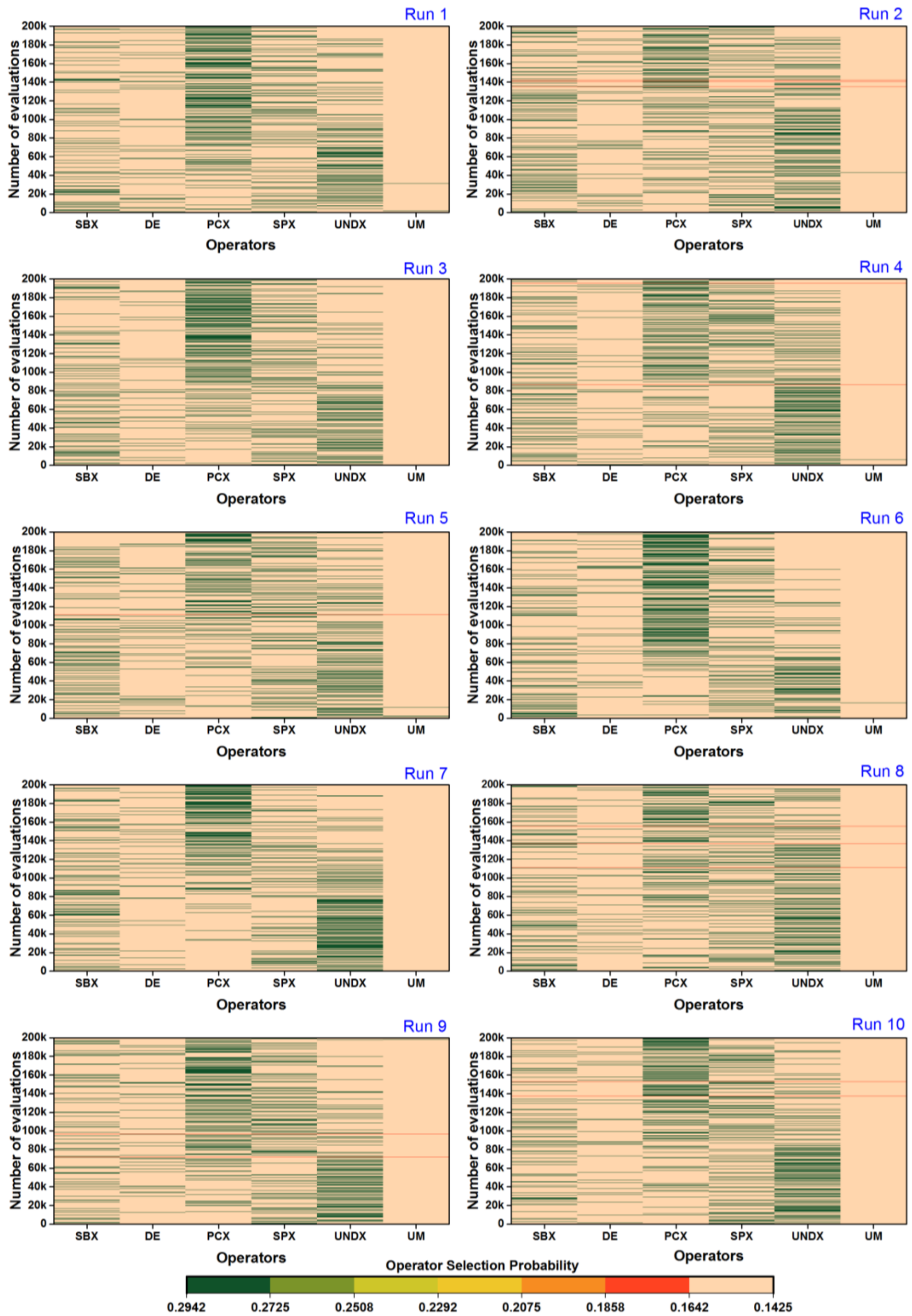

Figure 6. Selection probabilities for the recombination operators

5.5 Influence of the Reservoir Storage Sustainability Constraint

To understand the effects of the sustainability constraint, the optimization problem was also solved without the constraint on the annual reservoir drawdown, as specified originally in Chenari *et al.* (2014). The objective function value obtained was 19.97×10^6 m^3, with mean, median and standard deviation of 20.60×10^6 m^3, 20.63×10^6 m^3 and 0.53×10^6 m^3, based on 10 optimization runs. The convergence, for the best run, was achieved at 30,000 function evaluations approximately, with 399 restarts to escape from local minima and/or improve the results, subject to the total number of function evaluations allocated. The improvement achieved by reducing the value of the objective function was thus 89.2%, while the improvement achieved with the sustainability constraint in force was 87.6% (Subsection 5.3).

The results achieved are summarised in Table 5.

Table 5 Reservoir operation results without the storage sustainability constraint

	Reservoir Release (10^6 m^3)			Storage (10^6 m^3)		
Month	Min.	Mean	Std.	Min.	Mean	Std.
September	18.437	18.443	0.007	60.000	60.000	0.000
October	6.863	6.876	0.009	43.184	43.203	0.010
November	1.140	1.463	0.266	40.000	40.000	0.000
December	1.035	1.374	0.255	43.070	43.965	0.529
January	1.031	1.351	0.240	49.503	51.278	1.035
February	1.104	1.401	0.211	61.190	63.775	1.507
March	6.631	6.884	0.196	96.490	99.779	1.927
April	26.797	27.014	0.160	163.94	167.83	2.306
May	32.813	33.000	0.129	171.91	176.30	2.617
June	29.465	29.628	0.096	141.22	146.07	2.875
July	30.633	30.733	0.058	109.65	114.78	3.063
August	26.754	26.798	0.022	76.282	81.575	3.174
September	-	-	-	47.458	52.797	3.215

Std. denotes the standard deviation.

The total annual imbalance between the releases and demands was reduced by 67.2%, from $f^{1/2} = 13.61\times10^6$ m^3 to $f^{1/2} = 4.47\times10^6$ m^3, compared to 64.7% with the sustainability constraint. Table 5 shows the reservoir operation results, without the annual reservoir storage sustainability constraint. The maximum standard deviation of the releases was 0.266×10^6 m^3 in November, while the smallest was 0.007×10^6 m^3. The average coefficient of variation of the storage for the year (excluding September and November with set or constrained values) was 0.023 that demonstrates a high level of consistency in the results achieved.

6. CONCLUSIONS

A state-of-the-art evolutionary optimization algorithm (Borg MOEA) was investigated and used to solve a reservoir operation problem. The objectives of the optimization were to manage the reservoir drawdown and water releases to satisfy the requirements downstream.

The algorithm converged rapidly and reliably. For the reservoir system considered, convergence was achieved within approximately 25,000 function evaluations compared to 525,000 for a previous genetic algorithm in the literature (Chenari *et al.* 2014). The quantity of water stored in the reservoir was improved by increasing the maximum storage by 14.83 million m^3. This has the potential to increase the economic and environmental benefits of the reservoir. The total annual imbalance between the monthly reservoir releases and water demands was reduced by 64.7%, from 13.61×10^6 m^3 to 4.80×10^6 m^3.

Moreover, the reservoir drawdown constraint was satisfied strictly. In other words, the required amount of water was retained in the reservoir for the next year. On the other hand, when the storage sustainability constraint was removed to conform to the original specifications of the problem considered in Chenari *et al.* (2014), the annual imbalance between the demands and releases was reduced further from

13.61×10^6 m^3 to 4.47×10^6 m^3 (i.e. 67.2%).

Borg MOEA deploys multiple recombination operators self-adaptively, which contributes to its effectiveness, versatility and robustness. The algorithm's performance was reliable and stable, and good results were achieved consistently and quickly, which shows, also, that the optimization model used was effective. However, for the problem considered in this study, the algorithm seemingly did not adapt the selection of the recombination operators based on the solutions achieved by each operator. It seems the algorithm randomly selected operators to generate solutions. Additional investigation on this is thus indicated.

This research is in progress and the results achieved provide encouragement to solve even more complex real-world reservoir management problems in the future. This research could assist water managers and decision makers, and help to maximize the potential environmental and economic benefits of reservoir systems (Horne *et al.* 2016). It is vitally

important to maximize the socio-economic and environmental benefits of long-term capital-intensive infrastructure such as reservoirs, at all stages including planning, design, operation, management, rehabilitation and/or upgrading. Optimization based studies can help to achieve this objective. The study provides an indicative example of the improvements that could be gained potentially by optimizing complex systems, and helps to enhance the knowledge and understanding of the dynamic properties of the system under consideration.

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REFERENCES

Barlow, E., Tanyimboh, T.T., 2014. Multiobjective Memetic Algorithm Applied to the Optimisation of Water Distribution Systems. Water Resour. Manag. 28, 2229–2242. doi:10.1007/s11269-014-0608-0

Cancelliere, A., Giuliano, G., Nicolosi, V., Rossi, G., 2003. Optimal short-term operation of a multipurpose reservoir system under limited water supply. Water Resour. Syst. Risk Manag. Dev. 200–207.

Chang, L.C., Chang, F.J., Wang, K.W., Dai, S.Y., 2010. Constrained genetic algorithms for optimizing multi-use reservoir operation. J. Hydrol. 390, 66–74. doi:10.1016/j.jhydrol.2010.06.031

Chenari, K., Ghaderi, M., Reza, M., 2014. Improved adaptive genetic algorithm and its application in short-term optimal operation of water resources system. Agric. Environ. Mana gement 3, 209–217.

Coello, C.A.C., Lamont, G.L., van Veldhuizen, D.A., 2007. Evolutionary Algorithms for Solving Multi-Objective Problems, 2nd ed, Genetic and Evolutionary Computation. Springer, Berlin, Heidelberg. doi:10.1007/978-0-387-36797-2

Coello Coello, C.A., 2002. Theoretical and numerical constraint-handling techniques used with evolutionary algorithms: a survey of the state of the art. Comput. Methods Appl. Mech. Eng. 191, 1245–1287. doi:http://dx.doi.org/10.1016/S0045-7825(01)00323-1

Deb, K., 2001. Multi-Objective Optimixation using Evolutionary Algorithm, 1st editio. ed. John Wiley & Sons Ltd.

Deb, K., Agrawal, R.B., 1994. Simulated Binary Crossover for Continuous Search Space, Complex Systems. doi:10.1.1.26.8485Cached

Deb, K., Datta, R., 2013. A bi-objective constrained optimization algorithm using a hybrid evolutionary and penalty function approach. Eng. Optim. 45, 503–527. doi:10.1080/0305215X.2012.685074

Deb, K., Joshi, D., Anand, A., 2002. Real-coded evolutionary algorithms with parent-centric recombination. Proc. 2002 Congr. Evol. Comput. CEC 2002 1, 61–66. doi:10.1109/CEC.2002.1006210

Deb, K., Manikanth, M., Shikhar, M., 2003. A Fast Multi-objective Evolutionary Algorithm for Finding Well-Spread Pareto-Optimal Solutions. KanGAL Technical Report No.2003002, IIT, Kanpur, India.

Deb, K., Pratap, A., Agarwal, S., Meyarivan, T., 2002. A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Trans. Evol. Comput. 6, 182–197. doi:10.1109/4235.996017

Deb, K., Tiwari, S., 2005. Multi-objective optimization of a leg mechanism using genetic algorithms. Eng. Optim. 37, 325–350. doi:10.1080/03052150500066695

Dridi, L., Parizeau, M., Mailhot, A., Villeneuve, J.P., 2008. Using evolutionary optimization techniques for scheduling water pipe renewal considering a short planning horizon. Comput. Civ. Infrastruct. Eng. 23, 625–635. doi:10.1111/j.1467-8667.2008.00564.x

Eskandar, H., Sadollah, A., Bahreininejad, A., Hamdi, M., 2012. Water cycle algorithm – A novel metaheuristic optimization method for solving constrained engineering optimization problems. Comput. Struct. 110–111, 151–166. doi:http://dx.doi.org/10.1016/j.compstruc.2012.07.010

Feng, B.C., Liu, L., Member, A., 1999. Using Genetic Algorithms to Solve Construction Time-Cost Trade-off Problems. Comput. Civ. Eng. 10, 184–189.

Formiga, K.T.M., Chaudhry, F.H., Cheung, P.B., Reis, L.F.R., 2003. Optimal Design of Water Distribution System by Multiobjective Evolutionary Methods, in: Fonseca, C.M., Fleming, P.J., Zitzler, E., Thiele, L., Deb, K. (Eds.), Evolutionary Multi-Criterion Optimization: Second International Conference, EMO 2003, Faro, Portugal, April 8--11, 2003. Proceedings. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 677–691. doi:10.1007/3-540-36970-8_48

Hadka, D., Reed, P., 2013. Borg: An Auto-Adaptive Many-Objective Evolutionary Computing Framework. Evol. Comput. 21, 1–30. doi:10.1162/EVCO_a_00075

Hadka, D., Reed, P., 2012. Diagnostic Assessment of Search Controls and Failure Modes in Many-Objective Evolutionary Optimization. Evol. Comput. 20, 423–452. doi:10.1162/EVCO_a_00053

Hadka, D., Reed, P.M., Simpson, T.W., 2012. Diagnostic assessment of the borg MOEA for many-objective product family design problems, in: 2012 IEEE Congress on Evolutionary Computation, CEC 2012. pp. 10–15. doi:10.1109/CEC.2012.6256466

Haimes, Y.Y., Hall, W.A., 1977. Sensitivity, responsivity, stability and irreversibility as multiple objectives in civil systems. Adv. Water Resour. 1, 71–81. doi:10.1016/0309-1708(77)90025-2

Horne, A., Szemis, J.M., Kaur, S., Webb, J.A., Stewardson, M.J., Costa, A., Boland, N., 2016. Optimization tools for environmental water decisions: A review of strengths, weaknesses, and opportunities to improve adoption. Environ. Model. Softw. 84, 326–338. doi:10.1016/j.envsoft.2016.06.028

Jothiprakash, V., Shanthi, G., 2006. Single Reservoir Operating Policies Using Genetic Algorithm. Water Resour. Manag. 20, 917–929. doi:10.1007/s11269-

005-9014-y

Kim, T., Heo, J.-H., 2006. Multireservoir system optimization in the Han River basin using multi-objective genetic algorithms. Hydrol. Process. 20, 2057–2075. doi:10.1007/BF02830091

Kita, H., Ono, I., Kobayashi, S., 2000. Multi-Parental Extension of the Unimodal Normal Distribution Crossover for Real-Coded Genetic Algorithms. Trans. Soc. Instrum. Control Eng. 36, 875–883. doi:10.9746/sicetr1965.36.875

Knowles, J., Corne, D., 2002. On metrics for comparing nondominated sets, in: Evolutionary Computation, 2002. CEC '02. Proceedings of the 2002 Congress on. pp. 711–716. doi:10.1109/CEC.2002.1007013

Kollat, J.B., Reed, P.M., 2006. Comparing state-of-the-art evolutionary multi-objective algorithms for long-term groundwater monitoring design. Adv. Water Resour. 29, 792–807. doi:10.1016/j.advwatres.2005.07.010

Lobo, F.G., Lima, C.F., Michalewicz, Z., 2007. Parameter Setting in Evolutionary Algorithms, 1st ed. Springer Publishing Company, Incorporated.

Michalewicz, Z., Logan, T., Swaminathan, S., 1994. Evolutionary operators for continuous convex parameter spaces. Proc. 3rd Annu. Conf. Evol. Program. 84–97.

Reddy, M.J., Kumar, D.N., 2006. Optimal reservoir operation using multi-objective evolutionary algorithm. Water Resour. Manag. 20, 861–878. doi:10.1007/s11269-005-9011-1

Reed, P.M., Hadka, D., Herman, J.D., Kasprzyk, J.R., Kollat, J.B., 2013. Evolutionary multiobjective optimization in water resources: The past, present, and future. Adv. Water Resour. 51, 438–456. doi:10.1016/j.advwatres.2012.01.005

Régnier, J., Sareni, B., Roboam, X., 2005. System optimization by multiobjective genetic algorithms and analysis of the coupling between variables, constraints and objectives. COMPEL - Int. J. Comput. Math. Electr. Electron. Eng. 24, 805–820. doi:10.1108/03321640510598157

Saleh, S., Tanyimboh, T.T., 2016. Multi-Directional Maximum-Entropy Approach to the Evolutionary Design Optimization of Water Distribution Systems. Water Resour. Manag. 30, 1885–1901. doi:10.1007/s11269-016-1253-6

Saleh, S.H.A., Tanyimboh, T.T., 2014. Optimal Design of Water Distribution Systems Based on Entropy and Topology. Water Resour. Manag. 28, 3555–3575. doi:10.1007/s11269-014-0687-y

Saleh, S.H.A., Tanyimboh, T.T., 2013. Coupled Topology and Pipe Size Optimization of Water Distribution Systems. Water Resour. Manag. 27, 4795–4814. doi:10.1007/s11269-013-0439-4

Scola, L.A., Takahashi, R.H.C., Cerqueira, S.A.A.G., 2014. Multipurpose Water Reservoir Management: An Evolutionary Multiobjective Optimization Approach. Math. Probl. Eng. 2014, 14. doi:10.1155/2014/638259

Sharif, M., Wardlaw, R., 2000. Multireservoir Systems Optimization Using Genetic Algorithms: Case Study. J. Comput. Civ. Eng. 14, 255–263.

Sierra, M.R., Coello Coello, C.A., 2005. Improving PSO-Based Multi-objective Optimization Using Crowding, Mutation and ∈-Dominance, in: Coello Coello, C.A., Hernández Aguirre, A., Zitzler, E. (Eds.), Evolutionary Multi-Criterion Optimization: Third International Conference, EMO 2005, Guanajuato, Mexico, March 9-11, 2005. Proceedings. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 505–519. doi:10.1007/978-3-540-31880-4_35

Siew, C., Tanyimboh, T.T., 2012. Penalty-Free Feasibility Boundary Convergent Multi-Objective Evolutionary Algorithm for the Optimization of Water Distribution Systems. Water Resour. Manag. 26, 4485–4507. doi:10.1007/s11269-012-0158-2

Siew, C., Tanyimboh, T.T., Seyoum, A.G., 2016. Penalty-Free Multi-Objective Evolutionary Approach to Optimization of Anytown Water Distribution Network. Water Resour. Manag. 30, 3671–3688. doi:10.1007/s11269-016-1371-1

Siew, C., Tanyimboh, T.T., Seyoum, A.G., 2014. Assessment of Penalty-Free Multi-Objective Evolutionary Optimization Approach for the Design and Rehabilitation of Water Distribution Systems. Water Resour. Manag. 28, 373–389. doi:10.1007/s11269-013-0488-8

Storn, R., Price, K., 1997. Differential Evolution -- A Simple and Efficient Heuristic for global Optimization over Continuous Spaces. J. Glob. Optim. 11, 341–359. doi:10.1023/A:1008202821328

Tanyimboh, T.T., Seyoum, A.G., 2016. Multiobjective evolutionary optimization of water distribution systems: Exploiting diversity with infeasible solutions. J. Environ. Manage. 183, Part, 133–141. doi:http://dx.doi.org/10.1016/j.jenvman.2016.08.048

Tilmant, a., Fortemps, P., Vanclooster, M., 2002. Effect of averaging operators in fuzzy optimization of reservoir operation. Water Resour. Manag. 16, 1–22. doi:10.1023/A:1015523901205

Tract, A.B., 1997. Multiobjective optimization design with pareto genetic algorithm. Struct. Eng. 123, 1252–1261.

Tsutsui, S., Yamamura, M., Higuchi, T., 1999. Multi-parent recombination with simplex crossover in real coded genetic algorithms, in: Proceedings of the 1st Annual Conference on Genetic and Evolutionary Computation-Volume 1. pp. 657–664.

Vrugt, J. a, Robinson, B. a, 2007. Improved evolutionary optimization from genetically adaptive multimethod search. Proc. Natl. Acad. Sci. 104, 708–711. doi:10.1073/pnas.0610471104

Woldesenbet, Y.G., Yen, G.G., Tessema, B.G., 2009. Constraint Handling in Multiobjective Evolutionary Optimization. IEEE Trans. Evol. Comput. 13, 514–525. doi:10.1109/TEVC.2008.2009032

Wu, Y.G., Zou, J., 2012. An Advanced Multi-Objective Genetic Algorithm Based on Borda Number, in: Progress in Industrial and Civil Engineering, Applied Mechanics and Materials. Trans Tech Publications, pp. 4909–4915. doi:10.4028/www.scientific.net/AMM.204-208.4909

Yang, J., Soh, C.K., 1997. Structural Optimization by Genetic Algorithms with Tournament Selection. J. Comput. Civ. Eng. 11, 195–200. doi:10.1061/(ASCE)0887-3801(1997)11:3(195)

Zhang, Q., Liu, W., Li, H., 2009. The performance of a new version of MOEA/D on CEC09 unconstrained MOP test instances, in: 2009 IEEE Congress on Evolutionary Computation. pp. 203–208. doi:10.1109/CEC.2009.4982949

Zhang, Q., Liu, W., Li, H., 2009. The Performance of a New Version of {MOEA/D} on {CEC09} Unconstrained {MOP} Test Instances.

Zheng, F., Simpson, A.R., Zecchin, A.C., Maier, H.R., Feifei, Zh., 2016. Comparison of the Searching Behavior of NSGA-II, SAMODE, and Borg MOEAs Applied to

Water Distribution System Design Problems. J. Water Resour. Plan. Manag. 142. doi:10.1061/(ASCE)WR.1943-5452.0000650

Zitzler, E., Laumanns, M., Thiele, L., 2002. SPEA2: Improving the Strength Pareto Evolutionary Algorithm for Multiobjective Optimization, in: Evolutionary Methods for Design, Optimisation, and Control. CIMNE, Barcelona, Spain, pp. 95–100.

4.6 Further Discussion

Insight investigation of Borg MOEA code was carried out to diagnose the disorder operations' selection behavior. The accumulated sum of operator's selection probabilities (Q_i) was compared with a random real number between [0,1]. This can be expressed by the following code:

Code 1 Mechanism of selection operator in Borg MOEA

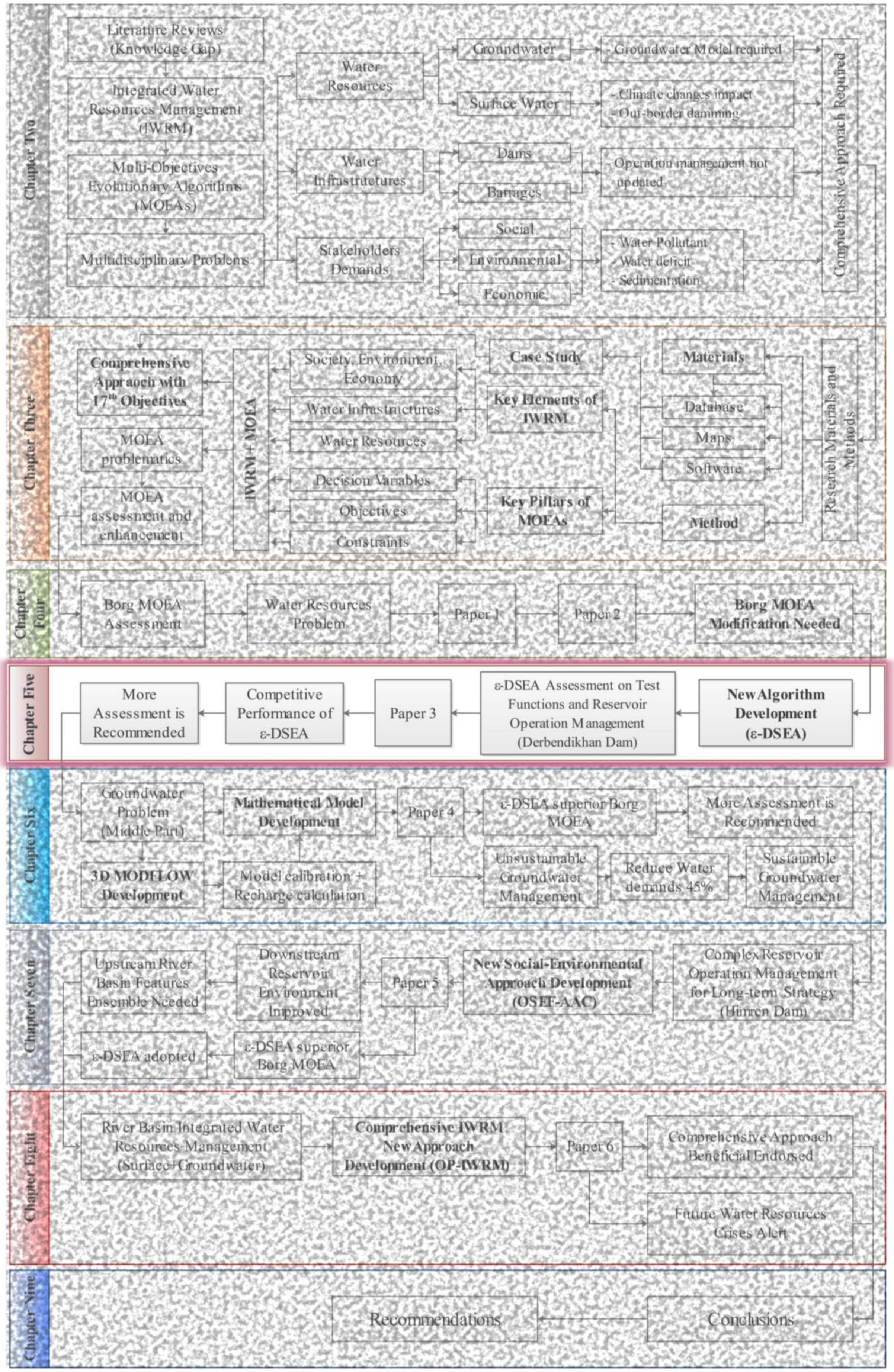
```
rand = real number random [0,1]
for i = 1 to K (where K is the Number of operators)
        sum = ∑_{i=1}^{K} Q_i
                If sum > rand
        return i
else next i
```

Hence, in case of a single objective problem, Equation 13 delivers misleading operators' achievement as long as only one dominance solution kept in the archive over the evaluation process. As a result, Q_i will have a unique value of (1/*K*) for all operators. Thus, this pitfall is dominated in the early stage of feasible space exploration in a constraint multi-objectives optimization problems. Briefly, constraints handling reduces feasible region in the design search space, hence while in infeasible region, there is only one solution periodically refreshed in the archive, as its technique designed to eliminate any dominated solutions from the archive.

As a result, more investigation is needed to address this drawback to accelerate convergence process.

4.7 Conclusions

This chapter demonstrates Borg MOEA assessment using real-word reservoir operation problem, in comparison with GA. Two papers were developed and published in peer-reviewed journals. The outperformance of Borg MOEA is evident in generating better sustainable reservoir management. However, one of the algorithm key element techniques show misleading behavior, as it follows random sequence of operators' selection, rather than adapting the most optimum productive operator. This drawback will also restrain early convergence of a constraint multi-objectives optimization problem. Hence, further assessment and insight investigation are needed to enhance and /or develop an advance MOEA's methodology to address any potential drawbacks, which is achieved in the next chapter.



Chapter Two
Literature Reviews (Knowledge Gap)
Integrated Water Resources Management (IWRM)
Multi-Objectives Evolutionary Algorithms (MOEAs)
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Stakeholders Demands
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CHAPTER FIVE

EVOLUTIONARY OPTIMIZATION ALGORITHM'S ENHANCEMENT

5.1 Introduction

In the previous chapter, Borg MOEA was assessed using an illustrative example in water resources management problems. The operation reservoir rule curve achieved by Borg MOEA has better sustainable management, in comparison with Genetic Algorithm (GA). Conversely, irregular algorithm's behaviour in recombination operators' auto-adaptive technique was observed during the evaluation process, which may cause convergence problematics in advance complex problems. Hence, solving this problem will accelerate algorithm convergence and reduce execution time. Further, adapting with problem environment may enhance exploration and exploitation processes, which improve optimality achievement.

As a result, the potential MOEAs' drawback enhancement is beneficial to improve algorithm's diversity, convergence, and adaptation, as these will improve algorithm's performance.

Accordingly, new methodologies are proposed to address the aforementioned and other MOEAs' drawbacks (bullet point 4 in Chapter two), after intensive diagnosis and assessment using benchmark test functions and a real-world water resources problem. A paper is developed and submitted to Swarm and Evolutionary Computation journal, as:

- Al-Jawad, J.Y., Tanyimboh, T.T., 2018. Epsilon-Dominance-Driven Self-Adaptive Evolutionary Algorithm For Many-Objective Optimization. Swarm Evol. Comput. In review.

"The following work represents my efforts, such as: theoretical formalism development, analytic calculations and numerical simulations, writing the manuscript. Dr. Tanyimboh, T.T., was the project supervisors, and provided assistance and support when required"

5.2 Paper:

Al-Jawad, J.Y., Tanyimboh, T.T., 2018. Epsilon-Dominance-Driven Self-Adaptive Evolutionary Algorithm For Many-Objective Optimization. Swarm Evol. Comput. In review.[1]

EPSILON-DOMINANCE-DRIVEN SELF-ADAPTIVE EVOLUTIONARY ALGORITHM FOR MANY-OBJECTIVE OPTIMIZATION

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Abstract

Self-adaptation of the values of control parameters and selection of candidate recombination operators in evolutionary algorithms was investigated in this research, considering diversity in the initial population and revival following stagnation or premature convergence. The algorithm developed is called ε-DSEA (ε-dominance-driven self-adaptive evolutionary algorithm). The methodology was demonstrated and assessed by an extensive comparison with Borg MOEA, a recent state-of-the-art evolutionary algorithm for many-objective optimization, based on a suite of test functions with a range of objectives selected from the literature, and a real-word case study. The early results are very encouraging, and they demonstrate that the methodology proposed is highly competitive. Consistently good results were obtained, based on the reliability, robustness, effectiveness and efficiency of the solutions achieved. The ε-DSEA highly adaptive with different problems environments towards

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optimum solutions. The effect of parameters tuning during evaluation process were observed on the optimality achievement for the considered test problems. The values of these parameters varied, depending on the number of objectives, the stage of the optimization and the properties of the optimization problem. The methodology proposed therefore lends itself to further research on the calibration and self-adaptation of control parameters and solution of real-world optimization problems with many objectives.

Keywords: Parameter tuning and adaptation, Many-objective hybrid evolutionary optimization algorithm, Borg MOEA, Adaptive operator selection, Epsilon dominance, Recombination operators

1 INTRODUCTION

Inspired by evolution and natural selection, evolutionary algorithms (EAs) are used widely to solve real-word optimization problems (Holland 1975, Schaffer 1985). Many EAs have been proposed by researchers, for example, the Non-dominated Sorting Genetic Algorithm (NSGA II) (Deb *et al.* 2002), Multi-objective Evolutionary Algorithm based on Decomposition (MOEA/D) (Zhang and Li 2007), Indicator-Based Evolutionary Algorithm (IBEA) (Zitzler and Simon 2004) and Differential Evolution (DE) (Storn and Price 1997). Furthermore, approaches based on swarm intelligence include Particle Swarm Optimization (PSO) (Eberhart and Kennedy 1995) and Ant Colony Optimization (ACO) (Dorigo and Stützle 2004) while the annealing process in metallurgy inspired Simulated Annealing (SA) (Scott *et al.* 1983). A review of EAs and other metaheuristic algorithms and their applications can be found in Zhou *et al.* (2011). These algorithms are widely used in different fields of science and engineering (Coello *et al.* 2007).

However, the growing need to solve even more complex engineering problems having four objectives or more gives the motivation to improve further the capabilities of MOEAs. Deb and Jain (2013) upgraded NSGA-II to NSGA-III, while Seada and Deb (2015) proposed a new version of NSGA-III named U-NSGA-III. Hadka and Reed (2013) developed Borg MOEA with auto-adaptive recombination operators, while Roy *et al.* (2015) introduced an evolutionary path control strategy (EPCS). Zhang *et al.* (2015) produced Knee Point-Driven Evolutionary Algorithm, and Li *et al.* (2015) proposed MOEA/DD, for many-objective problems. Recently, Yuan *et al.* (2016) proposed an evolutionary algorithm for many objective optimization (θ-DEA) based on a new dominance relation.

The algorithms often have many parameters that require calibration (Goldberg 1989, De Jong 2007). Karafotias *et al.* (2015) presented a review of the approaches for the calibration and control of the parameters. There are two types of EA parameter setting problems that may be categorised as (a) parameter tuning and (b) parameter control. The first problem called parameter tuning relates to the initial values of some parameters that should be set before executing the algorithm. The second problem that is called parameter control involves adjusting some of the values during the run time, in situations in which some parameter values may need to be adjusted to generate better results (Eiben *et al.* 1999).

The first problem of parameter tuning that relates to parameters such as the population size, mutation and crossover rate, etc., has been discussed widely in the literature and recommended values have been proposed (Karafotias *et al.* 2015). However, some of the parameters can vary widely and generally need extensive trials to find suitable values for a particular problem. For example, the distribution index for the Simulated Binary Crossover (SBX) operator may vary between 0 and 500 (Deb and Agrawal 1994). Similarly, Reynoso-Meza *et al.* (2011) concluded from experimental studies on multi-objective optimization problems that the value of the step size for the Differential Evolution (DE) operator is case sensitive. Consequently, it is extremely difficult to set default values for all problems.

With regard to the performance of algorithms, Stephens *et al.* (1998) stated that parameter control is more important than parameter tuning in genetic algorithms. Eiben *et al.* (1999) classified parameter control problems into three categories depending on the way the parameter variation is accomplished: (a) deterministic, (b) adaptive, and (c) self-adaptive. Deterministic control is based on rules that are specified *a priori* (Hesser and Männer 1991, Aleti 2012). In self-adaptive control, the parameters may be encoded to evolve in the genotype such that, for example, mutation and recombination are applied to the parameter also (Deb and Beyer 2001, Farmani and Wright 2003). The approach extends the search space to cover the parameter values, which consumes more time during the optimization processes (Eiben *et al.* 1999). The adaptive method of parameter control depends on feedback from the optimization process that is used to adjust the parameter values as the optimization progresses (Eiben *et al.* 1999, Giger *et al.* 2007), and is considered more effective in solving complex problems.

There have been many attempts to develop and incorporate adaptive parameter control mechanisms in evolutionary algorithms. For example, Hadka and Reed (2013) used an adaptive population size that was proportional to the archive size. Kaveh and Shahrouzi (2008) used an adaptive approach for selection. Vafaee and Nelson (2010) suggested an adaptive mutation mechanism. Vrugt and Robinson (2007) and Vrugt *et* *al.* (2009) introduced an adaptive multi-operator approach to help deploy the most effective operators.

Karafotias *et al.* (2015) showed that the recombination parameters have received the most attention while other parameters have received less consideration in the literature. They identified a gap in the area of parameter control where more research is required. Also, in addition to an extensive literature review of parameter setting in EAs, Aleti (2012) presented an adaptive approach for parameter control that used a feedback loop to adjust the values of the parameters. Additional reviews are available in Eiben and Smit (2011) and Smit (2012).

The above challenges provide the motivation for the present research focused on adaptive parameter control in many-objective evolutionary algorithms. The aim of the research was to develop and demonstrate the effectiveness of parameter control's self-adaptive methodology in many-objective evolutionary algorithms. In this article, a novel approach named ε-DSEA (Epsilon-Dominance-driven Self-adaptive Evolutionary Algorithm) is proposed. Additionally, the importance of active fine tuning of the control parameters during the optimization process is demonstrated.

The ε-DSEA approach comprises many novel features including: *(i) Diversity expansion*; *(ii) Self-adaptation of the control parameters of recombination operators*; *(iii) Exploration extension*; and *(iv) Virtual dominance archive*. The algorithm's performance was investigated extensively using unconstrained test problems from the literature and a constrained real-world regional water management problem. A comparative analysis of ε-DSEA and Borg MOEA was carried out based on the DTLZ test functions (1 to 4 and 7) and a multi-objectives reservoir management in the Middle

East. Borg MOEA is a state-of-the-art evolutionary algorithm that has many key computational and evolutionary properties. Hadka and Reed (2012) presented performance comparisons of Borg MOEA with eight state-of the-art algorithms based on 8 test functions in the literature while Reed *et al.* (2013) compared Borg MOEA with ten competitive algorithms on real-world water resources problems. The authors concluded that Borg MOEA performed better than the other algorithms considered.

The performance assessment in this article addressed the following properties: (i) *Reliability*, which refers to the replication and consistency of the best solutions achieved (Marchi et al., 2014) (ii); *Robustness*, which relates the algorithms dependable performance in different problem environments (Maier et al., 2014); (iii) *Computational efficiency*, i.e. the algorithm's speed of convergence to the non-dominated solutions (Silver, 2004); and (iv) *Effectiveness*, which refers to the closeness of the solutions achieved to the true Pareto-front and their distribution; and dominance front extension in objective space (Zitzler et al., 2000).

2 ADOPTED MULTI-OBJECTIVE OPTIMIZATION APPROACH

Commonly, real-word optimization problems have multiple objectives. A brief explanation of some of the key concepts associated with multi-objective optimization is provided here. An constrained multi-objective optimization problem may be described briefly as follows (Deb, 2001)

$$\text{Minimize: } \boldsymbol{F}(\boldsymbol{x}) = [f_1(\boldsymbol{x}), \ldots, f_M(\boldsymbol{x})]^T \quad (1)$$

$$\text{Subject to: } g_i(x) \geq 0, \forall i \in n_g$$

$$h_j(x) = 0, \forall j \in n_h$$

$$\boldsymbol{x} \in X$$

$X \in R^n$ is the decision space, i.e. $X = [\mathbf{x}^L, \mathbf{x}^U]$ where $\boldsymbol{x} = [x_1, x_2, \ldots, x_n]^T$ is the decision variable vector of dimension n; and $\boldsymbol{x}^L$ and $\boldsymbol{x}^U$ are the vectors of the lower and upper bounds on $\boldsymbol{x}$, respectively. $\boldsymbol{F(x)}$ consists of M objective functions $f_i : X \rightarrow Z \in R^M$, where $i = 1, \ldots, M$, and Z is the objective space feasible region containing all decision variables in X that satisfy all constraints. The $g_i(x)$ and $h_j(x)$ represents the i^{th} of n_g and j^{th} for n_h inequality and equality constraints, respectively. For unconstraint problems, $n_g = n_h = \emptyset$, and $Z = X$.

The concept of Pareto-dominance (Stadler 1979, Miettinen 1999, Deb 2001) is used widely to characterise the solutions of multi-objective optimization problems, and superior solutions are said to dominate inferior solutions. Thus:

1- In a minimization problem, a vector $\mathbf{u} = (u_1, \ldots, u_M)^T$ is said to dominate another vector $\mathbf{v} = (v_1, \ldots, v_M)^T$ if $u_i \leq v_i$ for $i = 1, \ldots, M$ and $u \neq v$. This property may be denoted as $\mathbf{u} \prec \mathbf{v}$.

2- A feasible solution $\mathbf{x} \in X$ is called a Pareto-optimal solution, if there is no alternative solution $\mathbf{y} \in X$ such that $\mathbf{F}(\mathbf{y}) \prec \mathbf{F}(\mathbf{x})$.

3- The Pareto-optimal set, PS, is the union of all Pareto-optimal solutions, and may be defined as $PS = \{\mathbf{x} \in X : \nexists \mathbf{y} \in X, \mathbf{F(y)} \prec \mathbf{F(x)}\}$.

4- The Pareto-optimal front, PF, is the set comprising the Pareto-optimal solutions in the objective space. It may be expressed as $PF = \{\mathbf{F(x)} | \mathbf{x} \in PS\}$.

2.1 Details of the Algorithm Developed (ε-DSEA)

The algorithm developed is based on the main principles of multi-objective evolutionary algorithms (MOEAs) e.g. recombination, mutation and dominance sorting. However, many novel techniques are included to enhance the algorithm's ability to handle the complexities of different problem environments. These techniques are:

1- Diversity expansion to increase decision variables search space exploitation
2- Self-adaptive operators' parameters for parameters in process tuning
3- Exploration extension for algorithm revival and stagnation coping
4- Virtual dominance archive to improve diversity and convergence.

The details of the algorithm's key features are presented in the following sections.

2.1.1 Recombination Operators

The recombination process or crossover depends on chromosomes taken from parents to generate new chromosomes. The algorithm employs a combination of six recombination operators having different evolving techniques, namely: Simulated binary crossover (SBX) (Deb and Agrawal 1994); Differential evolution (DE) (Storn and Price 1997); Parent-centric crossover (PCX) (Deb *et al.* 2002); Unimodal normal distribution crossover (UNDX) (Kita *et al.* 1999); Simplex crossover (SPX) (Tsutsui *et al.* 1999); Uniform mutation (UM) (Michalewicz *et al.* 1994). Furthermore, the polynomial mutation (PM) (Deb and Agrawal 1999) is applied to the offspring produced by all operators except for the UM. An overview of the above-mentioned operators is provided in the supplementary data while Geetha and Kumaran (2013) reviewed several types of crossover operators used in evolutionary algorithms.

2.1.2 Diversity Expansion

The search procedure in an optimization algorithm has two main components, namely, exploration and exploitation. Evidence in the literature indicates the best results are achieved if exploration and exploitation are deployed preferentially in the early and latter stages of the search, respectively (Zecchin *et al.* 2012, Zheng *et al.* 2016). Accordingly, a procedure that safeguards diversity in the population at the start is incorporated in the proposed algorithm.

A procedure is proposed to increase the diversity of the initial population using all the available recombination operators. After the initial random seeding, the algorithm uses each recombination operator to generate new offspring, selecting parents from the entire population. If more parents are needed (e.g. in case of odd number of parents), they are selected from the population using a binary tournament selection. Figure 1 illustrates the procedure by which the parents are selected.

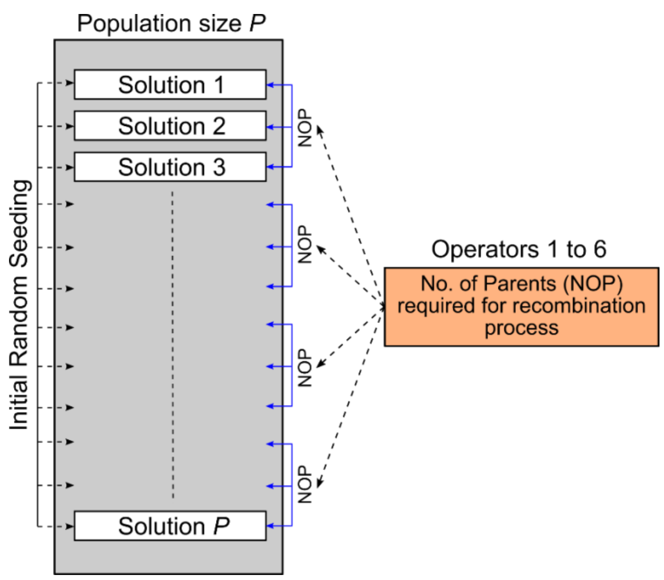

Figure 1. Illustrates operators' parents selection from the entire population candidates after the initial random seeding at the begining of the evaluation process

2.1.3 ε-dominance Archive

The objective space is divided into hyper-boxes whose dimensions are equal to ε (Laumanns *et al.* 2002). The concept of the ε-box index vector was used to assess the dominance of alternative solutions in the objective space instead of the objective function values. The algorithm calculates this index by dividing the values of the objective functions by ϵ and setting the result as the next integer (Hadka and Reed, 2013). Figure 2 illustrates the ε-dominance concept. The concept of ε-dominance archive was used in ε-MOEA (Deb et al., 2003) and ε-NSGA-II (Kollat and Reed, 2007). The archive is used to elitism and store non-dominated solutions during the evaluation process. Usually, the ε value is predefined by the user, depending on the problem complexity and on the required accuracy of the results. More details are presented in the aforementioned references.

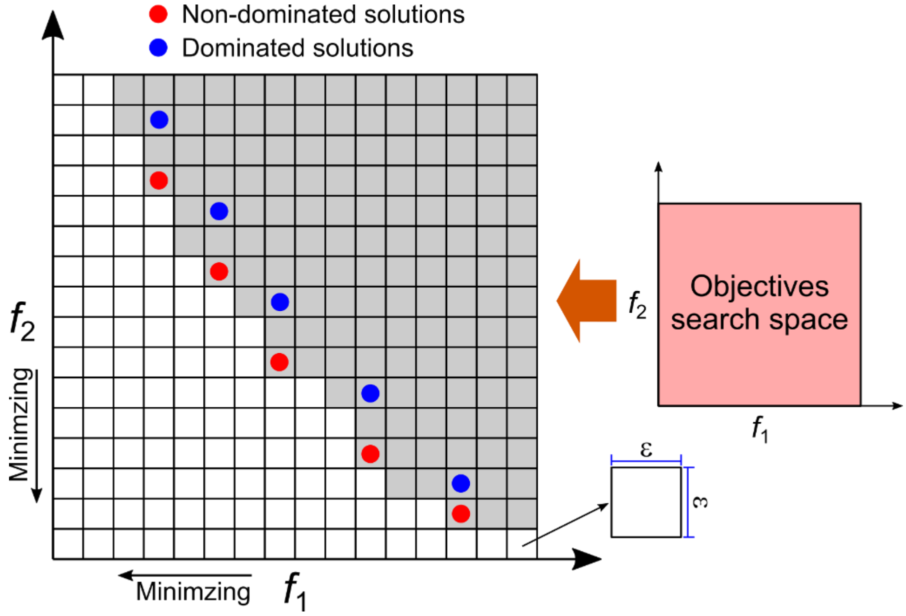

Figure 2. Illustration of ε-dominance concept

2.1.4 Dynamic Selection of Recombination Operators

In each generation, the recombination operators are selected on a competitive basis, according to the proportion of dominance solutions in the archive (*NDS*) contributed by each operator. Thus, the selection probabilities for the recombination operators are obtained as follows (Vrugt and Robinson, 2007; Hadka and Reed, 2013).

$$\mathcal{P}_i^{NDS} = \frac{NDS_i + 1}{\sum_{j=1}^{NRO}(NDS_j + 1)} \qquad i, j = 1,2, \dots NRO \qquad (2)$$

where $\mathcal{P}_i^{NDS}$ is the probability of ith recombination operator, *NDS*$_i$ is the number of solutions in the archive contributed by the i^{th} recombination operator NRO is the number of recombination operators; . The constant 1.0 is used to avoid probability values of zero.

2.1.5 Self-Adaptive Mechanism and Formulae

The success of any operator depends on the chosen values of the parameters that directly affect its performance. Any operator may lead an algorithm to suboptimal solutions because of unsatisfactory parameter calibration. However, parameter calibration is extremely challenging. This difficulty provided the motivation for establishing a dynamic relationship between the values of the control parameters of the recombination operators and their relative effectiveness, to obviate the need for fine tuning. The efficiency of the optimization algorithm is thus improved by continuously seeking to improve the collective effectiveness of the recombination operators. In other words, the formulation developed herein allows the values of the control parameters of each recombination operator to improve adaptively based on the success of the recombination operator compared to the rest of the recombination operators.

Table 1 shows the lower and upper bounds of the operator control parameters. If an operator's ability to contribute offspring to the dominance archive is decreased, its selection probability $\mathcal{P}_i^{NDS}$ will decrease according to Equation 2. In turn, the values of the relevant control parameter decrease and, consequently, the recombination operator's ability to contribute new offspring to the archive will improve.

It is worth noting that, initially, all the recombination operators have an equal selection probability ($\mathcal{P}_i^{NDS}$) of 1/*NRO*. During the evaluation process the $\mathcal{P}_i^{NDS}$ value for any recombination operator changed along with its control parameters, according to its contribution in the dominance archive. If any recombination operator is relatively unsuccessful, its selection probability ($\mathcal{P}_i^{NDS}$) and parameters controls will decrease. If, subsequently, the effectiveness of another recombination operator decreases, then the selection probabilities of some or all the other recombination operators will increase along with the values of their control parameters. In this way a dynamic equilibrium is maintained among the operators' selection probabilities, which in turn regulates the operator control parameters.

The initial values of the control parameters were set to the default or recommended values in the literature. After experimentation, the proposed ranges for the control parameters were set as follows. Distribution index η for SBX: [0,100]; probability of crossover *CR* for DE: [0.1,1.0]; step size *F* for DE: [0.5, 1.0] (Storn and Price 1997); expansion rate λ for SPX: [2.5, 3.5]; standard deviations σ_η and σ_ζ for PCX: [0.1, 0.3]; and variation factors σ_ζ and σ_η, respectively, for UNDX: [0.4, 0.6] and [$0.1/\sqrt{L}$, $0.35/\sqrt{L}$], where L is the number of decision variables. The functions used to adjust the values of the control parameters are summarised in Table 1.

Figure 3a illustrates the relationships between operators' dominance attainment and their control parameters values. It shows how operators' parameters auto-tuned according to the operator successful to produce non-dominated solutions in the dominance archive.

Table 1. Parameters control formulae in ε-DSEA

Operator	Parameters	Adaptation Functions	Comments
SBX	η	$\lfloor \mathcal{P}_i^{NDS} \times 100 \rfloor$	Distribution index
DE	CR	$Max\ (0.1, \mathcal{P}_i^{NDS}{}_i\ )$	Crossover probability
	F	$0.5 + (\mathcal{P}_i^{NDS}/2)$	Step size
SPX	λ	$2.5\ + \mathcal{P}_i^{NDS}$	Expansion rate
PCX	σ_η	$0.1\ + (\mathcal{P}_i^{NDS}/5)$	These parameters (standard deviations) control the spatial distribution of the offspring for PCX and UNDX
	σ_ζ	$0.1\ + (\mathcal{P}_i^{NDS}/5)$	
UNDX	σ_ζ	$0.4\ + (\mathcal{P}_i^{NDS}/5)$	
	σ_η	$[0.1\ + (\mathcal{P}_i^{NDS}/3)]/\sqrt{L}$	

2.1.6 Exploration Extension Mechanism

This mechanism based on initializing (resetting) all operators' selection probabilities $\mathcal{P}_i^{NDS}$ uniformly to$1/NRO$. This aims to provide an equal opportunity for all the operators, by assessing the performance best on the most recent results. Otherwise, the previously successful operators with more solutions in the archive would continue to dominate based on past performance as dictated by Equation 2.

The number of resets depends on a random integer N_r such that $N_r \in \mathbb{N}^+ \in [1, 3]$. When the algorithm starts, an N_r value is selected at random and the maximum permissible number of function evaluations NFE_{max} is divided by $N_r + 1$ to determine the reset interval E_r. For example, if NFE_{max} = 300,000 and N_r = 2, the reset occurs at every E_r = 100,000 function evaluations. Hence, in this case, two resets occur during the entire optimization. Formally,

$$E_r = \frac{NFE_{max}}{N_r + 1}; \quad N_r \in \mathbb{N}^+ \in [1,3] \tag{3}$$

where E_r is the reset interval.

Figure 3b shows an example of the resetting process and its relation with self-adaptive mechanism to extend algorithm explorations and escaping from possible local optima.

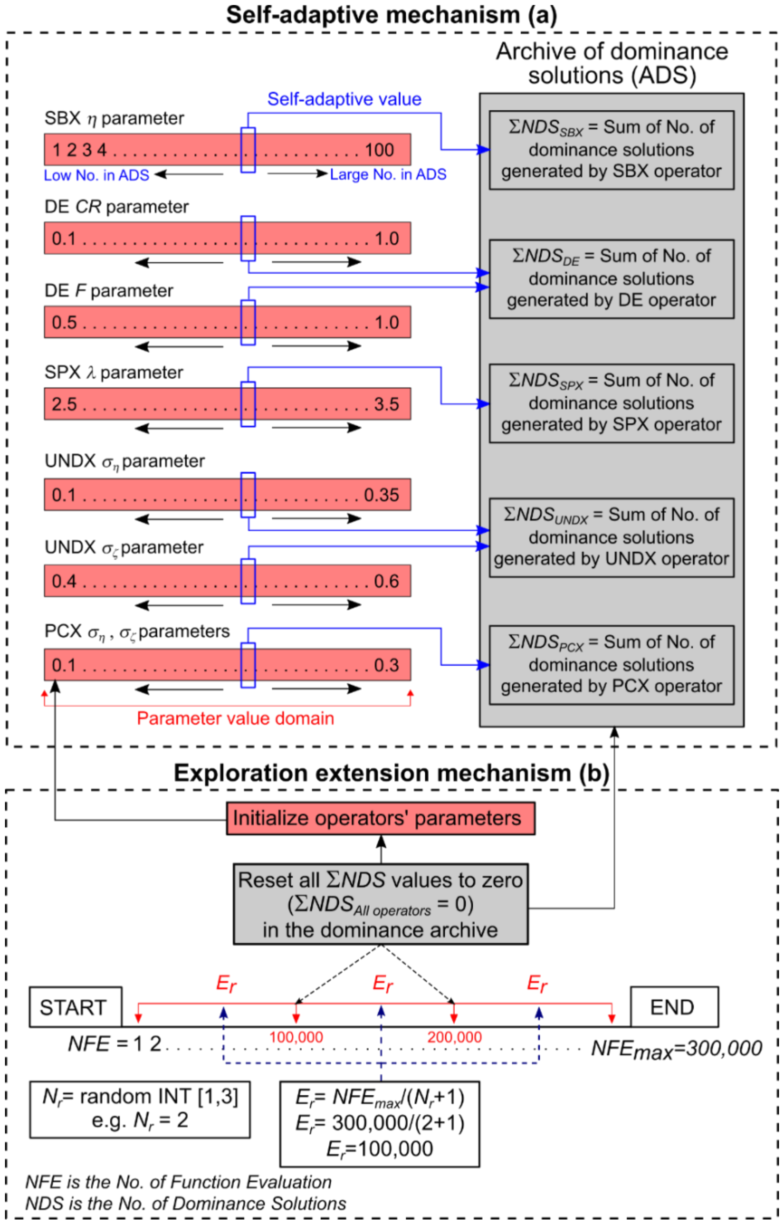

Figure 3. Illustrates the Self-adaptive mechanism (a) and exploration extension (b) used by ε-DSEA

2.1.7 Virtual Dominance Archive

In early stages of evaluation process for constraints problems with enormous decision variables, the ε-dominance archive techniques (section 2.1.3) tend to maintain only the non-dominated solutions in the dominance archive. Experimental tests on such problems show only one non-dominated solution maintain in the archive while exploring the design space for feasible solutions. Hence, the operators' parameters will be on its minimum values during this stage in the evaluation process using the proposed self-adaptive mechanism. To overcome this issue, a virtual dominance archive was developed by randomly generate virtual number of the dominance solutions for the selected operator to preserve diversity and early convergence exploration for feasible solutions using the entire parameter's domain.

2.1.8 Population Injection

The base work of injection is presented by Goldberg (1989b) and Srivastava (2002) and developed by Kollat and Reed (2006) and Hadka and Reed (2013). The early version frequently refilling the population with new random seeding solutions after emptying the population while holding the best solutions for the next generation. The second version refilling the population from dominance archive, instead of new random solutions. If archive members less than population slots, random solutions used to fill these slots. The recent version of injection depends on emptying the population and refilled using all solutions in the archive. Any remaining empty slots in the population are filled with solutions created by uniform mutation of solutions that are selected randomly from the archive.

The last version was adopted for ε-DSEA, however the injection trigger is only implement after two process, the diversity expansion and exploration extension, which is differ from other aforementioned literatures mechanism, which periodically employ injection during the evaluation process which is computation time consuming and my cause regenerating local optima solutions rather than advance exploration for possible global optima (Zheng et al., 2016).

2.1.9 The ε-DSEA Methodology

The previous sections explore the main algorithm's mechanisms and techniques used to enhance exploration and exploitation. A flowchart for ε-DSEA is presented in Figure 4.

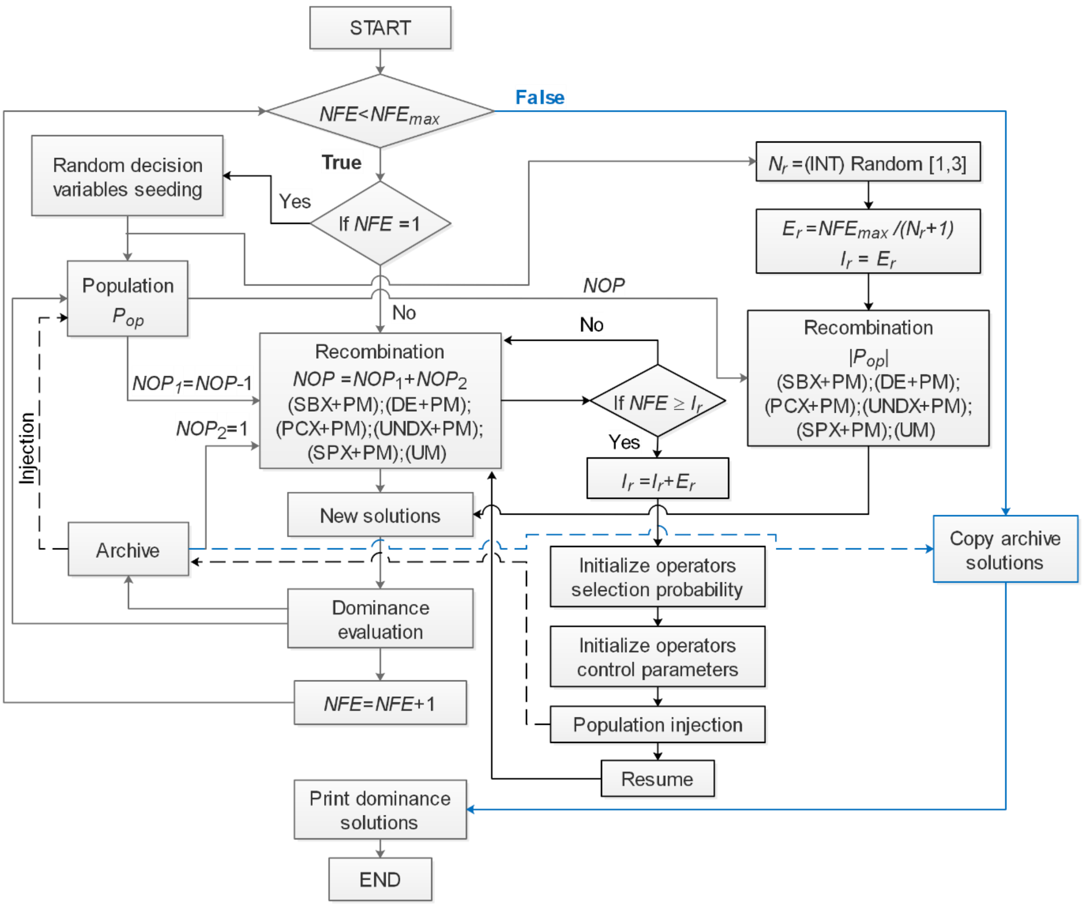

Figure 4. Overview of ε-DSEA flowcharts. NOP_1 and NOP_2 are the number of parents selected from the main population and dominance archive, respectively, while NOP is the total number of parents needed by adopted operator. NFE is the number of function evaluations with maximum value = NFE_{max}. E_r is the reset interval, and I_r is the number of function evaluations where the resetting occurs.

2.2 Comparative Paradigms

There are many types of MOEAs' paradigms introduced in the literatures (Zhou et al., 2011). Many recent algorithms are basically based on previous design principles like; ε-MOEA (Deb et al., 2003) and ε-NSGA-II (Kollat and Reed, 2006) which employ the ε-dominance sorting proposed by Laumanns et al., 2002, on the original version of MOEA (Goldberg, 1989a) and NSGA-II (Deb et al., 2002b); MOEA/D (Zhang and Li, 2007) also employ decomposition on the origin MOEA. Here, Borg MOEA (Hadka and Reed, 2013) was adopted in this research for comparative purposes for many reasons. The algorithm employ also many MOEAs design principles adopted from previous works like; recombination, mutation, and dominance sorting. But the authors present many novel techniques including: ε-progress indicator for stagnation and improvement exploring, population expansion to preserve diversity exploration, and multiple recombination operators for search variations. Additionally, a competitive assessment for Borg MOEA in compare with other state-of-the-art evolutionary algorithms (ε-MOEA, ε-NSGA-II, MOEA/D, GBE3, OMOPSO, IBEA, NSGA-II, AMALGAM) was utilized using multi-objectives problems, through which it outperforms or met these algorithms (Hadka and Reed, 2012; Hadka et al., 2012; Hadka and Reed, 2013; Woodruff et al., 2015; Zatarain Salazar et al., 2016). More details on Borg MOEA are presented in the aforementioned literatures.

3 IDENTIFICATION OF EXPERIMENTAL TEST PROBLEMS

3.1 Unconstraint Test Problems

Five well-known test functions, namely DTLZ1, DTLZ2, DTLZ3, DTLZ4, and DTLZ7 (Deb *et al.* 2001) were chosen from the literature. They have special challenging properties and have been investigated extensively in the literature (Zhu *et al.* 2016). Additional details on the functions are presented in Table A2 in the supplementary data. The algorithms were evaluated and compared extensively herein, based on the effectiveness, efficiency, reliability, and robustness.

The accuracy of the optimization results was assessed in terms of the difference between the solution achieved and the known Pareto-optimal front (Tagawa and Imamura 2013). Accordingly, the convergence errors were evaluated as follows.

For DTLZ1: $\delta_{PF} = \sum_{i=1}^{M} f_i - 0.5$ (4)

For DTLZ2, DTLZ3 and DTLZ4: $\delta_{PF} = \sum_{i=1}^{M} f_i^2 - 1$ (5)

For DTLZ7: $\delta_{PF} = \mathbf{g}(\mathbf{x}_M) - 1$ (6)

δ_{PF} is the convergence error, M is the number of objective functions and f_i is the value of the i^{th} objective function. Briefly, the vector $\mathbf{x}_M$ comprises the decision variables that do not belong to the union of the independent decision variables of $(f_1, f_2, \ldots, f_M)^{\mathrm{T}}$. $\mathbf{g}(\mathbf{x}_M)$ is a function of $\mathbf{x}_M$ only. The supplementary data has more information while Deb *et al.* (2001) has the details.

DTLZ1 has a linear Pareto-optimal front with $\sum_{i=1}^{M} f_i^* - 0.5 = 0$ and $\mathbf{x}_M^* = 0.5$. DTLZ2, DTLZ3 and DTLZ4 have non-linear Pareto-optimal fronts with $\sum_{i=1}^{M} (f_i^*)^2 - 1 = 0$ and $\mathbf{x}_M^* = 0.5$. For DTLZ7, $\mathbf{x}_M^* = 0.5$ and $g(\mathbf{x}_M^*) = 0$ (Deb *et al.* 2001). $\mathbf{x}_M^*$ and f_i^* represent the optimal values. At the solution, δ_{PF} is zero for DTLZ1, DTLZ2, DTLZ3, DTLZ4 and DTLZ7. Herein, δ_{PF} was used to assess the effectiveness and reliability of the solutions.

3.2 Constraint Test Problem

A case study in Iraq's Diyala river basin was adopted for a real-world constraints problem which has more complexity than previous test functions (Maier et al., 2014). The Iraqi government construct two multipurpose dams on the river, Derbendikhan just at the international border in Sulaymaniya governorate, and Himren in the middle part of the basin inside the country in Diyala governorate (Figure 5). Here, the Derbendikhan dam operation management is adopted using a historical monthly inflows data from 1981 to 2012 (thirty-three years) to generate future operation strategy. Hence, reservoir releases are representing the decision variables for the next 396 months.

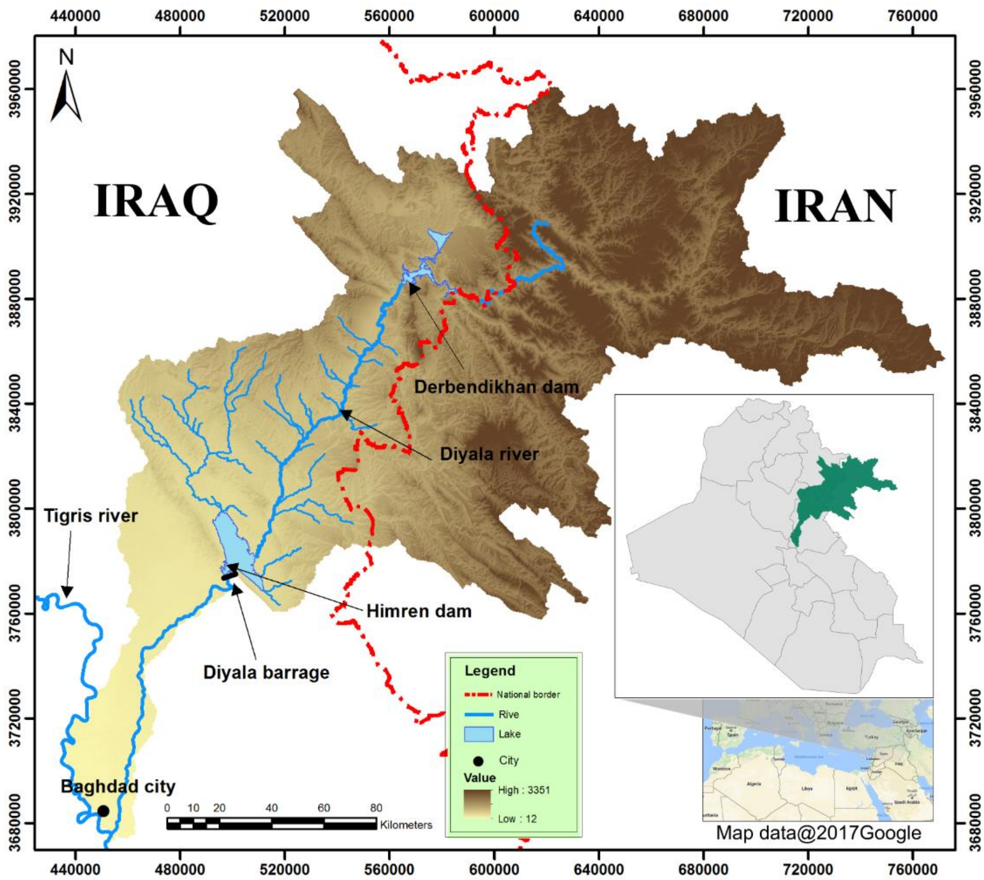

Figure 5. Catchment area of the transboundary Diyala river basin in Iraq

3.2.1 Objectives Functions Formulae

The reservoir water budget is governing by the water balance equation, as:

$$S_{t+1}^{D} = S_t^D + I_t^D - R_t^D - E_t^D + P_t^D - SE_t^D + GR_t^D \qquad , t = 1, 2,..\ T \tag{7}$$

where S_t^D and S_{t+1}^D are the reservoir storage at time t and t+1, I_t^D and R_t^D are reservoir inflows and releases, respectively. E_t^D is the evaporation losses from reservoir surface, P_t^D is the direct rainfall on the reservoir. While, SE_t^D and GR_t^D are seepage losses and groundwater recharges from the reservoir, respectively.

The reservoir operation strategy ($\boldsymbol{F}_D$) is represented by the following formula:

$$min\ \boldsymbol{F}_D = (f_{winterD}\ , f_{summerD}, f_{powerD}) \tag{8}$$

where

$f_{winterD}$ is for maximizing winter storage to fulfil summer demands

$f_{summerD}$ is for minimizing summer storage to absorb expected flood wave in the next season

f_{powerD} is for maximizing hydropower generation

The details of the three objectives functions are as follows:

$$min\, f_{winterD} = \sum_{t=1}^{Tw} \left(\frac{S_{max}^D - S_t^D}{S_{max}^D} \right)^2 + C_P \qquad , t = 1, 2,..\ T_W \tag{9}$$

$$min\, f_{summerD} = \sum_{t=1}^{Ts} \left(\frac{S_t^D - S_{minp}^D}{S_{max}^D} \right)^2 + C_P \qquad , t = 1, 2, ..\ T_S \tag{10}$$

$$min\, f_{powerD} = \sum_{t=1}^{T} \left(\frac{Pw_{max}^D - Pw_t^D}{Pw_{max}^D} \right)^2 + C_P \qquad , t = 1, 2,..T \tag{11}$$

$$C_P = A.\sum_{i=1}^{NC} g_i\,;\;\; A \geq 1 \qquad , i = 1, 2, ..\, NC \tag{12}$$

Where:

S^D_{max} = maximum allowable reservoir storage

S^D_{minp}= minimum allowable reservoir storage for hydropower generation

T_W, T_S *and* T = winter, summer and total operation periods, respectively.

Pw^D_t= hydropower generation at time t

Pw^D_{max}= maximum hydropower generation

C_P = penalty factor includes all the violations of the model

NC = number of constraints

g_i = penalty function for the (i^{th}) constraint

A = a positive real number

The hydropower generation can be expressed as:

$$Pw^D_t = \eta^D_e . \gamma_w . Q^{tuD}_t . H^{nD}_t \tag{13}$$

Where (Q^{tuD}_t) is the turbine discharge, (H^{nD}_t) is the net head between reservoir level and the tail water after the power plant, (η^D_e) is the efficiency of power plant, and (γ_w) is the water density.

3.2.2 Reservoir System Constraints

The reservoir storage is limited between the minimum and maximum allowable storage, $283.48 \leq S^D_t \leq 2572.0$ (million cubic meters), the water level head (H^D_t) should be ≥ 434.0 m.a.s.l, the power generation must be less than 249000 KW and greater than 16000 KW, and the release between $51.84 \leq R^D_t \leq 878.6$ MCM. Hence, the penalty functions (g_i) can be expressed as:

$$g_1 = \sum_{t=1}^{T} Max[0, (S_t^D - 283.48)] \tag{14}$$

$$g_2 = \sum_{t=1}^{T} Max[0, (2572.0 - S_t^D)] \tag{15}$$

$$g_3 = \sum_{t=1}^{T} Max[0, (H_t^D - 434.0)] \tag{16}$$

$$g_4 = \sum_{t=1}^{T} Max[0, (Pw_t^D - 16000)] \tag{17}$$

$$g_5 = \sum_{t=1}^{T} Max[0, (249000 - Pw_t^D)] \tag{18}$$

$$g_6 = \sum_{t=1}^{T} Max[0, (R_t^D - 51.84)] \tag{19}$$

$$g_7 = \sum_{t=1}^{T} Max[0, (878.6 - R_t^D)] \tag{20}$$

3.3 Computational Implementation

The properties of the unconstrained test problems are summarised in Table 2 using computational budgets of 50,000 and 100,000 function evaluations. For the case study problem, 2.0×10^6 function evaluation and $\varepsilon = 0.1$ were used for both algorithms. For each DTLZ test and case study problem, 10 and 20 optimization runs were carried out, respectively. The minimum population size was 100 while the maximum was 1000. A Dell OptiPlex 780 computer was used (Core Duo 2 E8400, 2 × 3.0 GHz, 8.0 GB RAM, Ubuntu 16.04 operating system). Table 3 shows the parameter values used for both algorithms. A program in C language was developed to implement all test problems.

Table 2. Properties of the test problems used to investigate the algorithms

Problem	Number of objectives (M)	Number of decision variables	Features of optimization problems	ε values for the respective values of M
DTLZ1	2, 4, 6 and 8	M+4	Multimodal and separable	0.01, 0.02, 0.02 and 0.03
DTLZ2	2, 4, 6 and 8	M+9	Concave and separable	0.01, 0.05, 0.1 and 0.15
DTLZ3	2, 4, 6 and 8	M+9	Multimodal, concave and separable	0.01, 0.05, 0.1 and 0.35
DTLZ4	2, 4, 6 and 8	M+9	Concave and separable	0.01, 0.05, 0.1 and 0.35
DTLZ7	2, 4, 6 and 8	M+19	Discontinuous and separable	0.01, 0.05, 0.1 and 0.35

Table 3. Parameter values used in the optimization algorithms

Parameters	Borg	ε-DSEA[a]	Parameters	Borg	ε-DSEA
Initial population size	100	100	SPX parents	10	3
Tournament selection size	2	2	SPX offspring	2	2
SBX crossover rate	1.0	1.0	SPX expansion rate λ	3	[2.5, 3.5]
SBX distribution index η	15.0	[0, 100]	UNDX parents	10	10
DE crossover rate *CR*	0.1	[0.1, 1.0]	UNDX offspring	2	2
DE step size *F*	0.5	[0.5, 1.0]	UNDX σ_ζ	0.5	[0.4, 0.6]
PCX parents	10	10	UNDX σ_η	$0.35/\sqrt{L}$	$[0.1, 0.35]/\sqrt{L}$
PCX offspring	2	2	UM mutation rate	$1/L$	$1/L$
PCX σ_η	0.1	[0.1, 0.3]	PM mutation rate	$1/L$	$1/L$
PCX σ_ζ	0.1	[0.1, 0.3]	PM distribution index η_m	20	20

L is the number of decision variables. The permissible range for dynamic parameters is shown in brackets. The parameters σ_η and σ_ζ are defined in Section 2.1.5. [a]The initial values of dynamic parameters used in ε-DSEA are as shown for Borg MOEA.

4 RESULTS AND DISCUSSION

4.1 Unconstraint Test Problems

4.1.1 The Effectiveness and Reliability of the Solutions Found

Table 4 shows the values of the error δ_{PF} for DTLZ1and DTLZ2. For DTLZ1, Borg MOEA has better results in the case of two objectives with 50,000 and 100,000 function evaluations. However, ε-DSEA has better performance than Borg MOEA in all the other cases, especially on 8 objectives. For DTLZ2, the results suggest that ε-DSEA is competitive, especially in terms of the maximum and standard deviation values in all cases, thus indicating that the ε-DSEA results are more consistent.

Table 4. Convergence errors (δ_{PF}) for DTLZ1 and DTLZ2 based on 10 optimization runs

	Borg MOEA					**ε-DSEA**				
Obj.	Min.	Max.	Mean	Median	Std.	Min.	Max.	Mean	Median	Std.
DTLZ1	50,000 function evaluation									
2D	**1.022E-08**	**1.760E-06**	**1.393E-07**	**9.661E-08**	2.693E-07	1.743E-06	2.600E-06	2.059E-06	1.955E-06	**2.475E-07**
4D	7.571E-04	4.375E-02	9.609E-03	8.602E-03	5.238E-03	**2.521E-04**	**1.984E-02**	**3.307E-03**	**2.886E-03**	**2.055E-03**
6D	2.340E-01	2.592E+00	8.326E-01	8.141E-01	2.698E-01	**9.630E-04**	**1.422E-01**	**3.333E-02**	**2.991E-02**	**1.876E-02**
8D	4.004E+00	3.149E+02	3.842E+01	2.916E+01	3.127E+01	**1.907E+00**	**5.266E+01**	**9.598E+00**	**9.152E+00**	**3.633E+00**
	100,000 function evaluation									
2D	**2.421E-09**	**2.757E-09**	**2.496E-09**	**2.481E-09**	**7.060E-11**	5.987E-06	6.020E-06	6.011E-06	6.012E-06	5.344E-09
4D	2.482E-04	2.007E-02	2.893E-03	2.453E-03	1.839E-03	**9.170E-05**	**1.148E-02**	**1.704E-03**	**1.455E-03**	**1.235E-03**
6D	7.782E-04	1.402E-01	2.660E-02	2.329E-02	1.609E-02	**2.512E-04**	**8.318E-02**	**1.665E-02**	**1.489E-02**	**9.763E-03**
8D	1.067E+00	1.342E+02	1.008E+01	7.409E+00	1.014E+01	**1.271E-03**	**1.634E-01**	**3.736E-02**	**3.324E-02**	**2.182E-02**
DTLZ2	50,000 function evaluation									
2D	4.220E-07	1.820E-05	1.840E-06	1.380E-06	2.520E-06	**7.615E-08**	**1.410E-06**	**2.650E-07**	**2.170E-07**	**2.100E-07**
4D	**1.076E-03**	2.169E-01	1.211E-02	**9.923E-03**	1.128E-02	1.392E-03	**4.797E-02**	**1.164E-02**	1.044E-02	**6.060E-03**
6D	**3.443E-03**	7.492E-01	**5.014E-02**	**4.157E-02**	3.783E-02	4.817E-03	**2.164E-01**	5.510E-02	5.033E-02	**2.742E-02**
8D	**6.080E-03**	1.157E+00	**7.974E-02**	**6.974E-02**	5.147E-02	8.635E-03	**4.180E-01**	9.594E-02	8.839E-02	**4.647E-02**
	100,000 function evaluation									
2D	1.980E-09	5.120E-07	1.650E-08	5.890E-09	6.990E-08	**2.600E-10**	**1.830E-08**	**1.100E-09**	**7.240E-10**	**2.420E-09**
4D	6.630E-04	3.131E-02	6.226E-03	5.487E-03	3.510E-03	**5.160E-04**	**2.725E-02**	**4.955E-03**	**4.276E-03**	**2.973E-03**
6D	**2.402E-03**	3.853E-01	**2.940E-02**	**2.593E-02**	1.829E-02	2.845E-03	**1.158E-01**	2.949E-02	2.676E-02	**1.484E-02**
8D	**4.184E-03**	2.495E-01	**4.809E-02**	4.310E-02	2.589E-02	4.965E-03	**1.966E-01**	5.160E-02	**4.732E-02**	**2.518E-02**

In the case of DTLZ3, DTLZ4 and DTLZ7, the ε-DSEA performance is better than Borg MOEA in almost all cases and scenarios as shown in Table 5. Taken together, these results indicate that on average ε-DSEA outperforms Borg MOEA on these problems. In the comparison tables that follow, the preferred values are highlighted in grey and bold.

Furthermore, Table A3 in the supplementary data shows the number of restarts (population injection) for Borg MOEA. An interesting observation is that, except for DTLZ4, the number of restarts in Borg MOEA decreased on average as the number of objectives increased, with significantly more restarts for two and four objectives. Also, there are more restarts for 100,000 function evaluations than for 50,000. Therefore, these results suggest that, effectively, Borg MOEA solved the problem repeatedly, to exhaust the available computations budget. For example, Borg MOEA's overall performance on two objectives is superior; it can be seen also, that the two-objective instances had the largest number of restarts overall. Furthermore, by comparison, given the limited restarts employed in ε-DSEA (Figure 3), these results lend support to the idea that new ε-DSEA framework proposed is highly effective and competitive.

Table A4 in the supplementary data shows the number of ε-progress improvements for both algorithms, for all test functions. While the values are generally comparable, collectively, the values for ε-DSEA are slightly higher (by almost 5% approximately). Given the very considerable extent of the investigations carried out, these results indicate that, on average, ε-DSEA outperforms Borg MOEA on the problems considered. Although the ε-DSEA does not employ any stagnation indicators such as the ε-progress indicator used in Borg MOEA, the comparison in table A4 was included here for completeness.

Table 5. Convergence errors (δ_{PF}) for DTLZ3, DTLZ4 and DTLZ7 based on 10 optimization runs

	Borg MOEA					**ε-DSEA**				
Obj.	Min.	Max.	Mean	Median	Std.	Min.	Max.	Mean	Median	Std.
DTLZ3	50,000 function evaluation									
2D	1.412E+00	1.423E+00	1.415E+00	1.415E+00	1.926E-03	**2.030E-04**	**3.780E-04**	**2.490E-04**	**2.420E-04**	**3.130E-05**
4D	1.973E+00	8.214E+00	4.873E+00	4.930E+00	8.469E-01	**2.523E-02**	**4.749E-01**	**3.601E-01**	**3.628E-01**	**5.804E-02**
6D	1.735E+03	9.154E+04	1.283E+04	1.017E+04	1.018E+04	**1.576E+02**	**9.555E+02**	**4.295E+02**	**4.238E+02**	**1.152E+02**
8D	1.224E+04	8.817E+05	1.204E+05	9.558E+04	8.923E+04	**2.303E+02**	**2.965E+04**	**1.164E+03**	**8.273E+02**	**1.727E+03**
	100,000 function evaluation									
2D	7.990E-05	1.400E-04	9.570E-05	9.550E-05	1.100E-05	**2.970E-05**	**3.120E-05**	**3.050E-05**	**3.050E-05**	**2.800E-07**
4D	9.167E-02	8.685E-01	6.905E-01	6.870E-01	3.055E-02	**4.222E-03**	**5.670E-02**	**1.880E-02**	**1.768E-02**	**7.248E-03**
6D	6.835E+00	6.790E+01	1.908E+01	1.825E+01	6.520E+00	**1.167E-02**	**2.085E-01**	**6.813E-02**	**6.477E-02**	**2.496E-02**
8D	3.865E+03	4.256E+05	4.370E+04	3.401E+04	3.685E+04	**2.588E+03**	**2.047E+04**	**8.557E+03**	**8.397E+03**	**1.895E+03**
DTLZ4	50,000 function evaluation									
2D	2.034E-07	1.510E-05	1.130E-06	7.670E-07	2.070E-06	**7.252E-08**	**1.900E-06**	**3.540E-07**	**2.990E-07**	**2.900E-07**
4D	1.162E-03	4.229E-02	9.616E-03	8.526E-03	5.328E-03	**1.808E-04**	**4.311E-03**	**4.700E-04**	**3.900E-04**	**2.910E-04**
6D	3.295E-03	1.271E-01	3.017E-02	2.720E-02	1.509E-02	**2.908E-03**	**1.127E-01**	**2.618E-02**	**2.340E-02**	**1.384E-02**
8D	**7.919E-07**	6.850E-04	3.890E-05	**4.610E-06**	1.250E-04	1.988E-06	**2.820E-04**	**2.850E-05**	1.120E-05	**5.410E-05**
	100,000 function evaluation									
2D	3.130E-09	1.270E-07	1.000E-08	7.590E-09	1.650E-08	**1.800E-10**	**4.580E-09**	**5.640E-10**	**4.610E-10**	**6.350E-10**
4D	4.650E-04	2.588E-02	4.966E-03	4.282E-03	2.919E-03	**1.050E-04**	**6.787E-03**	**7.660E-04**	**6.670E-04**	**4.650E-04**
6D	2.128E-03	9.860E-02	2.123E-02	1.904E-02	1.112E-02	**2.075E-03**	**8.888E-02**	**1.859E-02**	**1.651E-02**	**1.006E-02**
8D	**7.560E-09**	**1.500E-04**	**4.870E-06**	**2.670E-08**	**2.520E-05**	1.570E-08	3.610E-04	1.140E-05	1.150E-07	5.950E-05
DTLZ7	50,000 function evaluation									
2D	1.097E-07	2.760E-06	2.600E-07	1.960E-07	4.060E-07	**1.140E-09**	**4.190E-09**	**2.350E-09**	**2.300E-09**	**6.290E-10**
4D	6.591E-03	4.174E-02	1.763E-02	1.687E-02	5.147E-03	**1.104E-03**	**1.906E-02**	**3.697E-03**	**3.321E-03**	**1.768E-03**
6D	2.601E-02	1.598E-01	7.113E-02	6.939E-02	1.836E-02	**3.315E-03**	**8.679E-02**	**2.097E-02**	**1.906E-02**	**1.020E-02**
8D	1.181E-02	8.047E-02	3.239E-02	3.113E-02	9.188E-03	**1.809E-03**	**4.723E-02**	**8.119E-03**	**7.091E-03**	**4.472E-03**
	100,000 function evaluation									
2D	1.400E-10	3.420E-06	7.480E-08	4.060E-10	4.990E-07	**1.380E-11**	**3.900E-10**	**1.020E-10**	**8.050E-11**	**7.950E-11**
4D	2.824E-03	2.215E-02	7.559E-03	7.212E-03	2.292E-03	**2.810E-04**	**6.724E-03**	**9.950E-04**	**9.030E-04**	**5.460E-04**
6D	1.627E-02	1.128E-01	4.728E-02	4.590E-02	1.250E-02	**2.439E-03**	**5.248E-02**	**1.166E-02**	**1.051E-02**	**5.570E-03**
8D	5.802E-03	5.152E-02	1.708E-02	1.628E-02	5.238E-03	**1.082E-03**	**2.811E-02**	**4.102E-03**	**3.628E-03**	**2.343E-03**

4.1.2 Algorithms' Robustness

Figure 6 shows the operator selection probabilities for 100,000 function evaluations. The graphs are based on the best results for each algorithm as shown in Tables 4, for 8 objectives. The selection probabilities had similar trends for both algorithms with mostly the SBX operator being employed, followed by SPX and DE. Also, in ε-DSEA, the effects of resetting the probabilities as proposed here can be observed clearly. In DTLZ1, DTLZ2 and DTLZ3 in particular, the last resetting event enabled other operators to take part in the search process

Generally, many evolutionary algorithms use fixed values of the control parameters of the evolutionary operators. In general, the values are set *a priori* by experimentation or trial and error. The procedures involved are generally time consuming and extremely challenging. The default values of the control parameters used are shown in Table 3. Figure 7 shows adaptation of the control parameter values in ε-DSEA, thus helping to achieve the optimal and near-optimal solutions without undue reliance on the restarts. At the reset point, both the operator selection probabilities and their respective control parameters are re-initialized. The effectiveness of the proposed methodology can be seen clearly in the graphs.

In general, the parameters make steady progress towards the best values (within the given range) and different 'best' values often apply in different phases of the optimization. Indeed, these results may be used to aid calibration efforts in the future, and to adjust the ranges and/or initial values used if necessary. As stated previously, the reset feature adjusts the trajectory of the population make-up and, rather like mutation, improves convergence by helping the algorithm to escape from local optima.

Table A5 in the supplementary data shows the values of the control parameters. There is some variation in the values for the test problem considered, especially SBX. On the other hand, some of the parameters are quite stable (DE, PCX, SPX and UNDX). The UNDX parameters changed only slightly because of its low selection probability, due to the dominance of the other operators. In general, the respective modal values of the control parameters, i.e. those that occurred most frequently, tended to be different from the default values in Borg MOEA (Table 3). It is hoped that these results and self-adaptive capability will provide additional insights on the control parameters in the future.

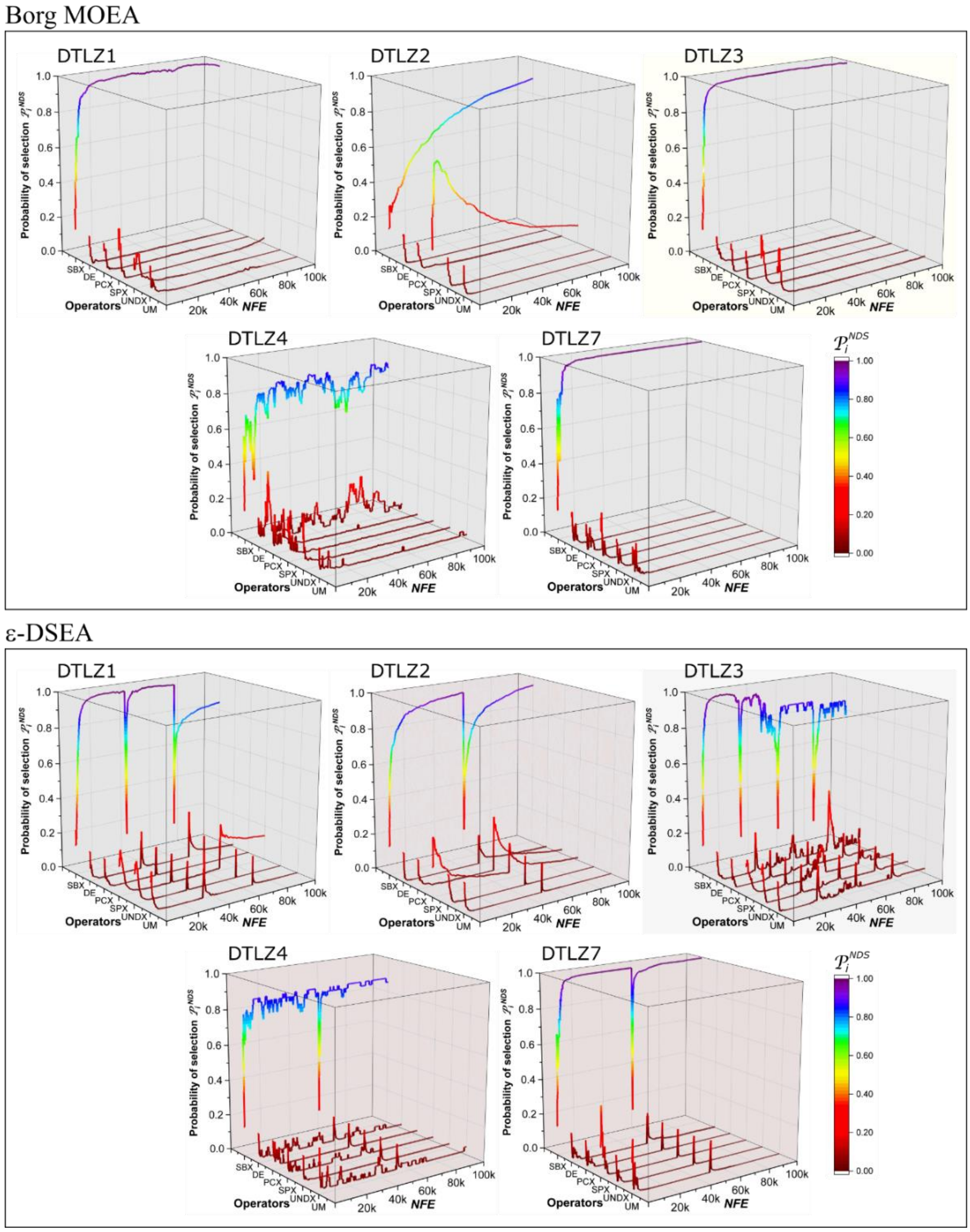

Figure 6. Selection probabilities of the recombination operators for both algorithms with 8 objectives and 100,000 function evaluations

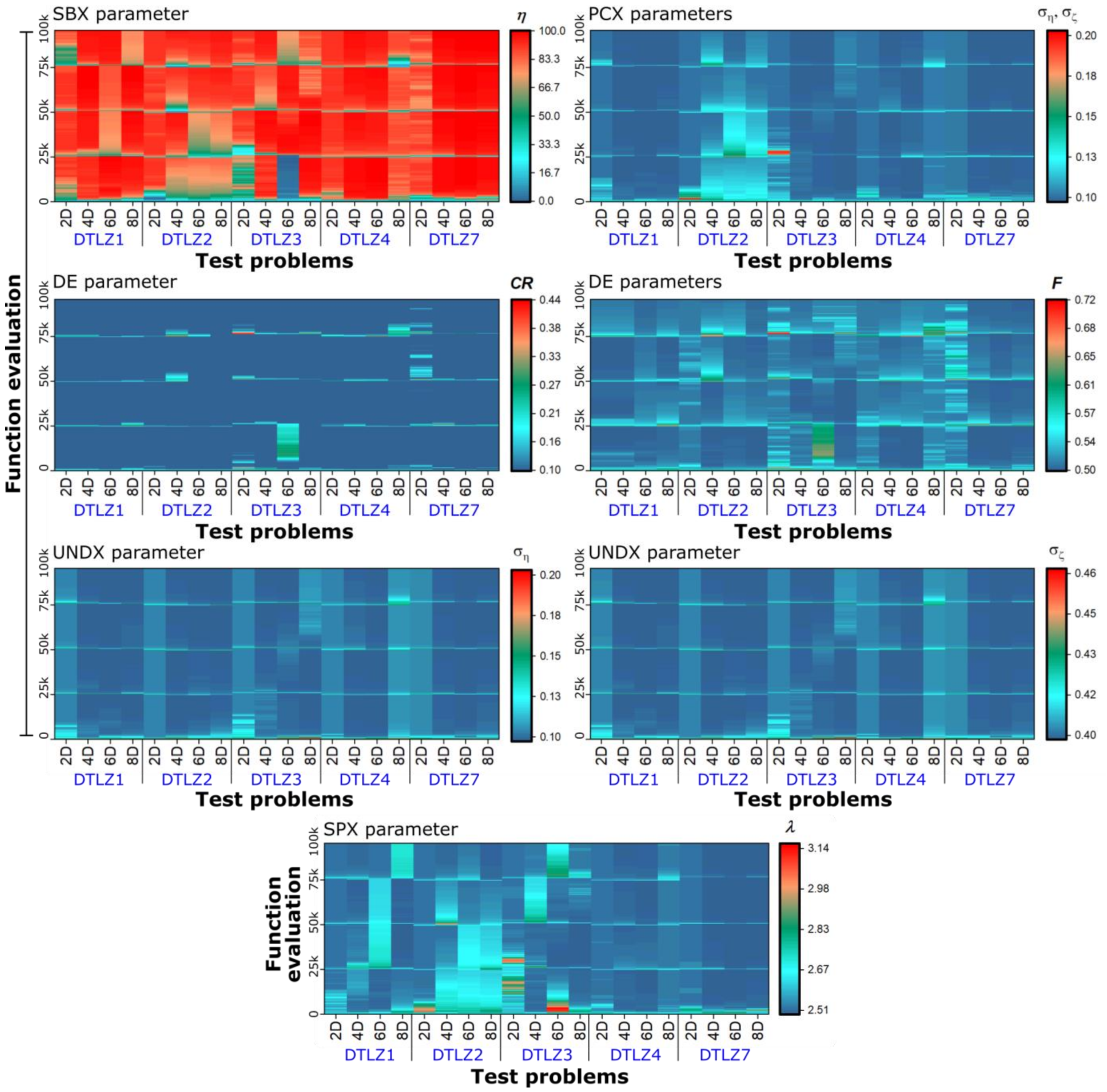

Figure 7. Values of control parameters of recombination operators in ε-DSEA with 100,000 function evaluations on all alternatives test problems

4.1.3 Algorithms' Computational Efficiency

Figure 8 illustrates the progress of decision variables for both algorithms. It can be seen clearly that ε-DSEA converged significantly faster than Borg MOEA on DTLZ1, DTLZ3, and DTLZ7. For DTLZ2 and DTLZ4, the ε-DSEA results is very competitive to those of Borg MOEA. This reflects the adaptive robustness of ε-DSEA with different problems environments.

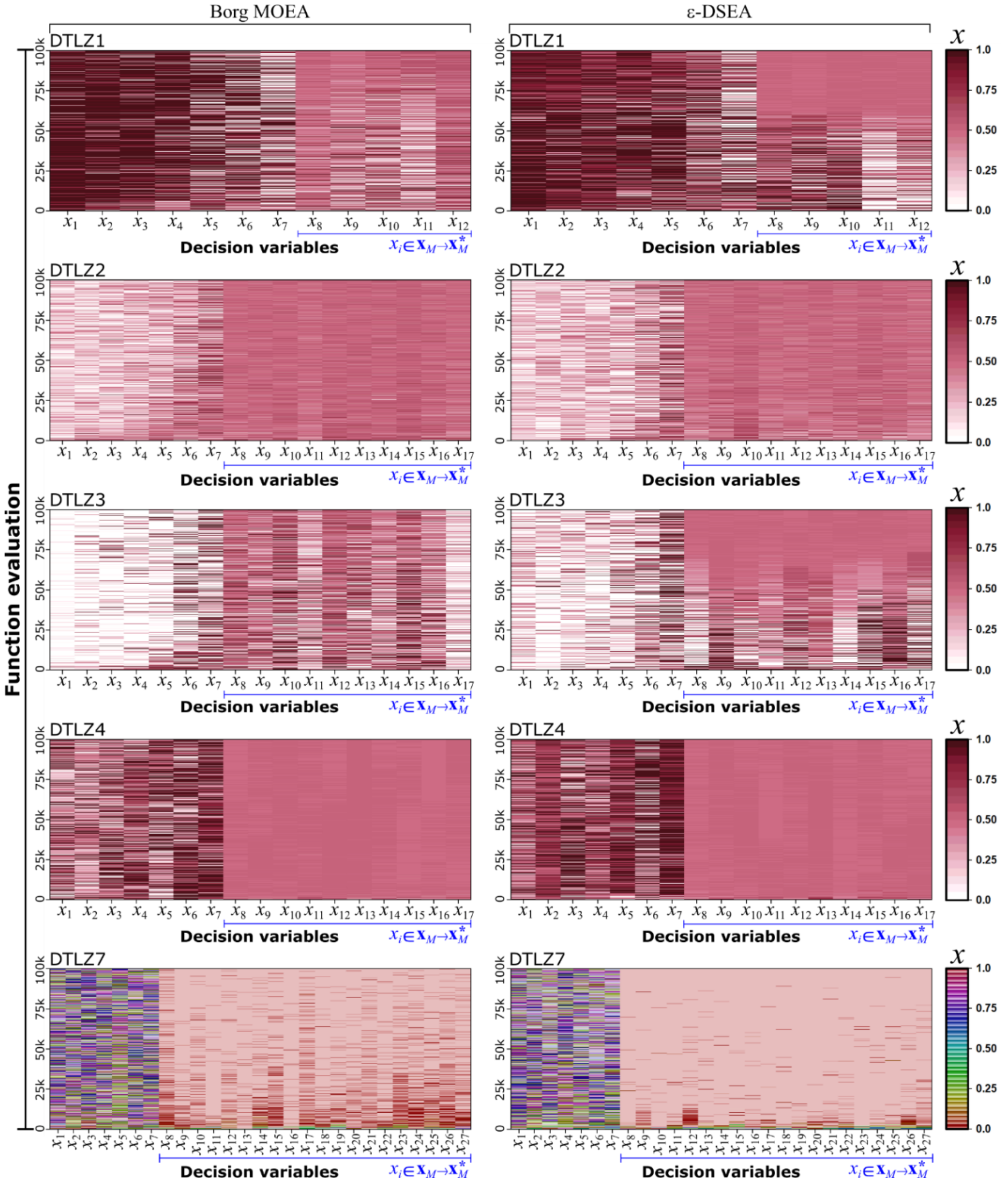

Figure 8. Decision variables convergence based on the best results for the 8-objective problems for DTLZ1 to DTLZ4 and DTLZ7.

4.2 Constraint Test Problem

Figure 9 illustrates the Pareto-front for 20 replicated random runs for the case study benchmark problem for both algorithms. The ε-DSEA reliability is obvious by approaching the possible optimum solutions in all trials. Conversely, Borg MOEA fails in four trials to converge and to generate a Pareto-front, and in two trials in approaching to the optimum front. This is because Borg MOEA tend to adapt with one operator after finding possible feasible solutions. Here, the SBX operator was adopted in the early stage of evaluation process, then PCX operator adopted to the end. Zheng *et al.* (2016) observed that, for two-objective problems, Borg MOEA tended to converge prematurely and population diversity decreased relatively rapidly. This arises because Borg MOEA does not maintain a separate transient sub-population of offspring as in NSGA-II for example. Instead, any offspring that dominates any of its parents immediately replaces one of the parents; the choice of the parent that is replaced is random. As new fitter solutions are introduced, the selection pressure on less competitive solutions increases, due to the binary tournament selection used for crossover. Fitter solutions have a higher probability of selection for crossover, leading to more exploitation and less exploration and thus less diversity. Secondly, the injection trigger which depends mainly on ε-progress indicators, did not always succeed to reflect stagnation occurrences during the evaluation process. Thirdly, PCX operator produces offspring in the vicinity of the parents. If the PCX operator creates solutions around the best solutions found, the PCX-generated solutions quickly dominate the archive, leading to more exploitation, less exploration and consequently relatively rapid loss of diversity. As stated previously the recombination operators are deployed in proportion to the number of offspring they contributed in the archive.

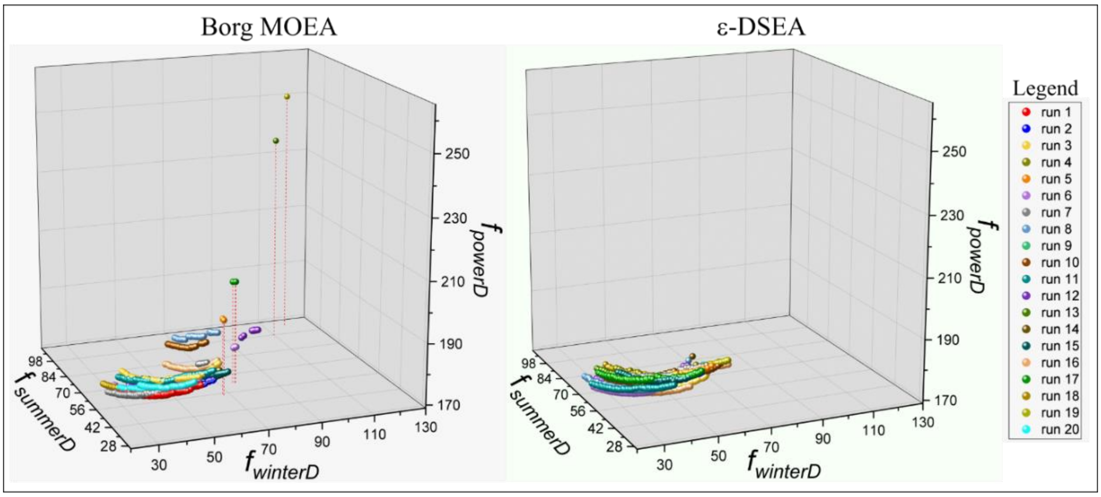

Figure 9. Pareto-fronts for twenty random runs achieved by both algorithms

In ε-DSEA, operators' adaptation and their parameters are connected by the non-dominated attainments in the archive. Figure 10a illustrates the self-adaptive operators' parameter tuning behaviour of ε-DSEA during the evaluation process. The most effective operators adopted to generate dominance solutions for the best trial are SBX, PCX, and SPX. Initially the virtual dominance archive mechanism tuned operator's parameters when only one solution is kept in the dominance archive. Then SBX operator adopted until the first resetting trigger at $5.0{\times}10^5$ function evaluation. The PCX operator then involve by increasing the variation parameters (σ_η and σ_ζ) to about 0.15. The SPX operator is also involving in the same time when its parameter (λ) changed to about 2.7. Both PCX and SPX operators compete to explore dominance solutions until the third resetting trigger, after that SPX operator start to generate more dominance solutions in the dominance archive. Increasing PCX and SPX parameters will generate new offspring farther away from their original parents, which will increase algorithm exploration in the design search space.

In Borg MOEA the operators that produce more successful (i.e. non-dominated) offspring will be deployed more frequently. However, as the search progresses and the balance between exploration and exploitation shifts gradually, it is desirable that the operators be deployed based on the current status of the search rather than their previous performances or cumulative successes. In other words, the selection of the operators should recognize the current performance also. Hence, the proposed performance assessment of the operators relies on the results from the current phase of the search rather than the cumulative performance to date.

Hence, the proposed mechanism provides advance diversity and balancing between exploration and exploitation process toward possible Pareto-front set.

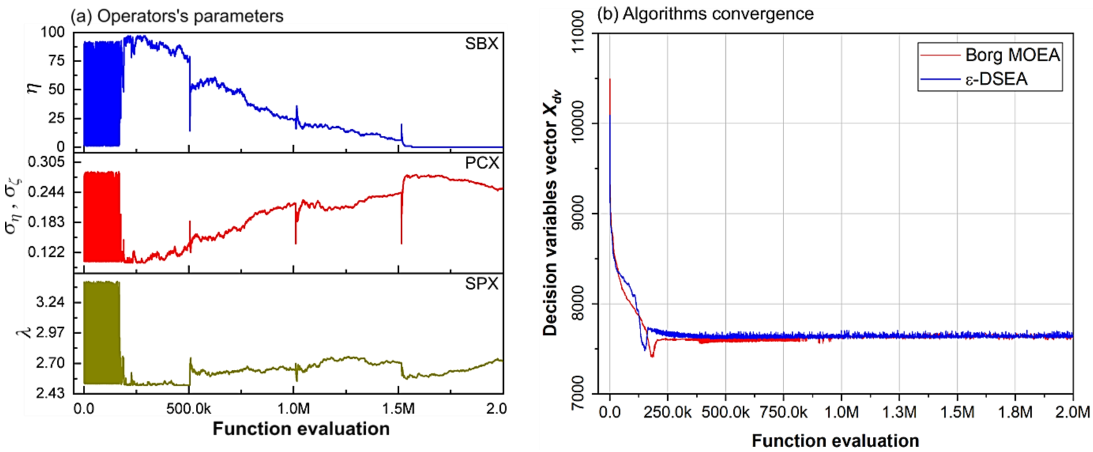

Figure 10. Parameters self-adaptation of the most effective operators for the best solution achieved (a), and algorithm convergence (b) to generate dominance solutions during the evaluation process.

The algorithms convergence (efficiency) was also investigated using the decision variables vector (X_{dv}) development in the dominance archive during the evaluation process. The X_{dv} is equal to $\sqrt{x_1^2 + x_2^2 + x_3^2 + \cdots + x_n^2}$, where x_1 to x_n are the decision variables. Figure 10b shows early convergence of ε-DSEA in compare with Borg MOEA for the best solution achieved. Hence, the ε-DSEA is more efficient than Borg MOEA for the proposed test problem.

5 CONCLUSIONS

Self-adaptation of the values of control parameters and selection of candidate recombination operators in evolutionary algorithms were investigated in this research, considering the diversity of the initial population and revival of the algorithm following stagnation or premature convergence. The methodology developed was demonstrated and assessed by an extensive comparison with Borg MOEA, a state-of-the-art evolutionary algorithm introduced recently for many-objective optimization. The basis of the comparison was a suite of five test functions selected from the literature, with a range of objectives from two to eight and two computational budgets. A constrained real-world case study with three objectives and 396 decision variables was investigated also.

The selected test problems in the literature with various properties were considered to assess the proposed algorithm. The results are very encouraging. They revealed that the methodology proposed is highly competitive. Consistently good results were achieved, based on the computational efficiency and quality of the solutions found. On the problems considered, the SBX (simulated binary crossover) operator was used the most, followed by SPX (simplex crossover) and DE (differential evolution). Also, the values of some of the control parameters varied/deviated from the recommended default values, depending on the number of objectives, the stage of the optimization and the particular test problem under consideration. The methodology proposed therefore lends itself to parameter calibration, which may be an interesting area for further research in the future.

Furthermore, the results on a benchmark real-world case study with constraints clearly demonstrated the reliability and robustness of the proposed methodology by consistently yielding near-optimal solutions in all random trials, and outperforming Borg MOEA significantly. The adaptive operators sequence changing during the evaluation stages, starting by SBX operator and ending with PCX and SPX operators in parallel. New range of operators' parameters was present to consider for consistent real-word problems. The research is in progress and, in addition to trials involving other more complex real-world problems that may be computationally expensive, more verification would be likely yield additional insights.

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REFERENCES

Aleti, A., 2012. An Adaptive Approach to Controlling Parameters of Evolutionary Algorithms. PhD. Thesis, Swinburne University of Technology, Australia.

Coello, C.A.C., Lamont, G.L., van Veldhuizen, D.A., 2007. Evolutionary Algorithms for Solving Multi-Objective Problems, 2nd ed, Genetic and Evolutionary Computation. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-0-387-36797-2

De Jong, K., 2007. Parameter Setting in EAs: a 30 Year Perspective, in: Lobo, F.G., Lima, C.F., Michalewicz, Z. (Eds.), Parameter Setting in Evolutionary Algorithms. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 1–18. https://doi.org/10.1007/978-3-540-69432-8_1

Deb, K., 2001. Multi-Objective Optimization using Evolutionary Algorithms, 1st ed, Wiley-Interscience Series in Systems and Optimization. John Wiley & Sons, Chichester.

Deb, K., Agrawal, R.B., 1994. Simulated Binary Crossover for Continuous Search Space, Complex Systems. https://doi.org/10.1.1.26.8485Cached

Deb, K., Agrawal, S., 1999. A Niched-Penalty Approach for Constraint Handling in Genetic Algorithms, in: ProcInternational Conference on Artificial Neural Network and Genetic Algorithms. pp. 235–243. https://doi.org/10.1007/978-3-7091-6384-9_40

Deb, K., Beyer, H.G., 2001. Self-adaptive genetic algorithms with simulated binary crossover. Evol. Comput. 9, 197–221.

https://doi.org/10.1162/106365601750190406

Deb, K., Jain, H., 2013. An Evolutionary Many-Objective Optimization Algorithm Using Reference-point Based Non-dominated Sorting Approach, Part I: Solving Problems with Box Constraints. Ieeexplore.Ieee.Org 18, 1–1. https://doi.org/10.1109/TEVC.2013.2281534

Deb, K., Joshi, D., Anand, A., 2002a. Real-coded evolutionary algorithms with parent-centric recombination. Proc. 2002 Congr. Evol. Comput. CEC 2002 1, 61–66. https://doi.org/10.1109/CEC.2002.1006210

Deb, K., Manikanth, M., Shikhar, M., 2003. A Fast Multi-objective Evolutionary Algorithm for Finding Well-Spread Pareto-Optimal Solutions. KanGAL Technical Report No.2003002, IIT, Kanpur, India.

Deb, K., Pratap, A., Agarwal, S., Meyarivan, T., 2002b. A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Trans. Evol. Comput. 6, 182–197. https://doi.org/10.1109/4235.996017

Deb, K., Thiele, L., Laumanns, M., Zitzler, E., Abraham, A., Jain, L., Goldberg, R., 2001. Scalable test problems for evolutionary multiobjective optimization, Computer Engineering and Networks Laboratory (TIK). https://doi.org/10.1007/1-84628-137-7

Dorigo, M., Stützle, T., 2004. Ant Colony Optimization. Bradford Company, Scituate, MA, USA.

Eberhart, R., Kennedy, J., 1995. A new optimizer using particle swarm theory. MHS'95. Proc. Sixth Int. Symp. Micro Mach. Hum. Sci. 39–43.

https://doi.org/10.1109/MHS.1995.494215

Eiben, A.E., Michalewicz, Z., Schoenauer, M., Smith, J.E., 1999. Parameter control in evolutionary algorithms. Stud. Comput. Intell. 54, 19–46. https://doi.org/10.1007/978-3-540-69432-8_2

Eiben, A.E., Smit, S.K., 2011. Parameter tuning for configuring and analyzing evolutionary algorithms. Swarm Evol. Comput. 1, 19–31. https://doi.org/10.1016/j.swevo.2011.02.001

Farmani, R., Wright, J.A., 2003. Self-adaptive fitness formulation for constrained optimization. IEEE Trans. Evol. Comput. 7, 445–455. https://doi.org/10.1109/TEVC.2003.817236

Geetha, T., Kumaran, K.M., 2013. Article: An Observational Analysis of Genetic Operators. Int. J. Comput. Appl. 63, 24–34.

Giger, M., Keller, D., Ermanni, P., 2007. AORCEA – An adaptive operator rate controlled evolutionary algorithm. Comput. Struct. 85, 1547–1561. https://doi.org/http://dx.doi.org/10.1016/j.compstruc.2006.12.002

Goldberg, D.E., 1989a. Genetic Algorithms in Search, Optimization and Machine Learning, 1st ed. Addison-Wesley Longman Publishing Co., Inc., Boston, MA, USA.

Goldberg, D.E., 1989b. Sizing Populations for Serial and Parallel Genetic Algorithms, in: Proceedings of the 3rd International Conference on Genetic Algorithms. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, pp. 70–79.

Hadka, D., Reed, P., 2013. Borg: An Auto-Adaptive Many-Objective Evolutionary Computing Framework. Evol. Comput. 21, 1–30. https://doi.org/10.1162/EVCO_a_00075

Hadka, D., Reed, P., 2012. Diagnostic Assessment of Search Controls and Failure Modes in Many-Objective Evolutionary Optimization. Evol. Comput. 20, 423–452. https://doi.org/10.1162/EVCO_a_00053

Hadka, D., Reed, P.M., Simpson, T.W., 2012. Diagnostic assessment of the borg MOEA for many-objective product family design problems, in: 2012 IEEE Congress on Evolutionary Computation, CEC 2012. pp. 10–15. https://doi.org/10.1109/CEC.2012.6256466

Hesser, J., Männer, R., 1991. Towards an optimal mutation probability for genetic algorithms, in: Schwefel, H.-P., Männer, R. (Eds.), Parallel Problem Solving from Nature: 1st Workshop, PPSN I Dortmund, FRG, October 1-3, 1990 Proceedings. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 23–32. https://doi.org/10.1007/BFb0029727

Holland, J.H., 1975. Adaptation in natural and artificial systems : an introductory analysis with applications to biology, control, and artificial intelligence. University of Michigan Press, Ann Arbor.

Karafotias, G., Hoogendoorn, M., Eiben, A.E., 2015. Parameter Control in Evolutionary Algorithms: Trends and Challenges. IEEE Trans. Evol. Comput. 19, 167–187. https://doi.org/10.1109/TEVC.2014.2308294

Kaveh, A., Shahrouzi, M., 2008. Dynamic selective pressure using hybrid evolutionary and ant system strategies for structural optimization. Int. J. Numer. Methods Eng. 73, 544–563. https://doi.org/10.1002/nme.2088

Kita, H., Ono, I., Kobayashi, S., 1999. Multi-parental extension of the unimodal normal distribution crossover for real-coded genetic algorithms. Proc. 1999 Congr. Evol. Comput. 1581–1587. https://doi.org/10.1109/CEC.1999.782672

Kollat, J.B., Reed, P.M., 2007. A computational scaling analysis of multiobjective evolutionary algorithms in long-term groundwater monitoring applications. Adv. Water Resour. 30, 408–419. https://doi.org/10.1016/j.advwatres.2006.05.009

Kollat, J.B., Reed, P.M., 2006. Comparing state-of-the-art evolutionary multi-objective algorithms for long-term groundwater monitoring design. Adv. Water Resour. 29, 792–807. https://doi.org/10.1016/j.advwatres.2005.07.010

Kukkonen, S., Lampinen, J., 2005. GDE3: the third evolution step of generalized differential evolution. 2005 IEEE Congr. Evol. Comput. 1, 443–450. https://doi.org/10.1109/CEC.2005.1554717

Laumanns, M., Thiele, L., Deb, K., Zitzler, E., 2002. Combining convergence and diversity in evolutionary multiobjective optimization. Evol. Comput. 10, 263–282. https://doi.org/10.1162/106365602760234108

Li, K., Deb, K., Zhang, Q., Kwong, S., 2015. An Evolutionary Many-Objective Optimization Algorithm Based on Dominance and Decomposition. IEEE Trans. Evol. Comput. 19, 694–716. https://doi.org/10.1109/TEVC.2014.2373386

Maier, H.R., Kapelan, Z., Kasprzyk, J., Kollat, J., Matott, L.S., Cunha, M.C., Dandy, G.C., Gibbs, M.S., Keedwell, E., Marchi, A., Ostfeld, A., Savic, D., Solomatine, D.P., Vrugt, J.A., Zecchin, A.C., Minsker, B.S., Barbour, E.J., Kuczera, G., Pasha, F., Castelletti, A., Giuliani, M., Reed, P.M., 2014. Evolutionary algorithms and other metaheuristics in water resources: Current status, research challenges and future directions. Environ. Model. Softw. 62, 271–299. https://doi.org/10.1016/j.envsoft.2014.09.013

Marchi, A., Dandy, G., Wilkins, A., Rohrlach, H., 2014. Methodology for Comparing Evolutionary Algorithms for Optimization of Water Distribution Systems. J. Water Resour. Plan. Manag. 140, 22–31. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000321

Michalewicz, Z., Logan, T., Swaminathan, S., 1994. Evolutionary operators for continuous convex parameter spaces. Proc. 3rd Annu. Conf. Evol. Program. 84–97.

Miettinen, K., 1999. Nonlinear multiobjective optimization. Boston : Kluwer Academic Publishers.

Price, K., Storn, R.M., Lampinen, J.A., 2005. Differential Evolution: A Practical Approach to Global Optimization (Natural Computing Series). Springer-Verlag New York, Inc., Secaucus, NJ, USA.

Reed, P.M., Hadka, D., Herman, J.D., Kasprzyk, J.R., Kollat, J.B., 2013. Evolutionary multiobjective optimization in water resources: The past, present, and future. Adv. Water Resour. 51, 438–456. https://doi.org/10.1016/j.advwatres.2012.01.005

Reynoso-Meza, G., Sanchis, J., Blasco, X., Martínez, M., 2011. An empirical study on parameter selection for multiobjective optimization algorithms using Differential Evolution, in: Differential Evolution (SDE), 2011 IEEE Symposium on. pp. 1–7. https://doi.org/10.1109/SDE.2011.5952055

Roy, P.C., Islam, M.M., Murase, K., Yao, X., 2015. Evolutionary Path Control Strategy for Solving Many-Objective Optimization Problem. IEEE Trans. Cybern. 45, 702–715. https://doi.org/10.1109/TCYB.2014.2334632

Salazar, J.Z., Reed, P.M., Herman, J.D., Giuliani, M., Castelletti, A., 2016. A diagnostic assessment of evolutionary algorithms for multi-objective surface water reservoir control. Adv. Water Resour. 92, 172–185. https://doi.org/10.1016/j.advwatres.2016.04.006

Schaffer, J.D., 1985. Multiple objective optimization with vector evaluated genetic algorithms, in: The 1st International Conference on Genetic Algorithms. pp. 93–100.

Scott, K., Gelatt, C.D., Vecchi, M.P., 1983. Optimization by simulated annealing. Science (80-.). 220, 671–680. https://doi.org/10.1126/science.220.4598.671

Seada, H., Deb, K., 2015. U-NSGA-III: A Unified Evolutionary Optimization Procedure for Single, Multiple, and Many Objectives: Proof-of-Principle Results, in: Gaspar-Cunha, A., Henggeler Antunes, C., Coello, C.C. (Eds.), Evolutionary Multi-Criterion Optimization: 8th International Conference, EMO 2015, Guimar{ã}es, Portugal, March 29 --April 1, 2015. Proceedings, Part II. Springer International Publishing, Cham, pp. 34–49. https://doi.org/10.1007/978-3-319-15892-1_3

Silver, E.A., 2004. An overview of heuristic solution methods. J. Oper. Res. Soc. 55, 936–956. https://doi.org/10.1057/palgrave.jors.2601758

Smit, S.K., 2012. Parameter Tuning and Scientific Testing in Evolutionary Algorithms. Department of Computer Science, PhD Thesis, VU University Amesterdam, Amsterdam, Netherland.

Srivastava, R.P., 2002. Time continuation in genetic algorithms. Technical report, Illinois Genetic Algorithm Laboratory. Storn,.

Stadler, W., 1979. A survey of multicriteria optimization or the vector maximum problem, part I: 1776-1960. J. Optim. Theory Appl. 29, 1–52. https://doi.org/10.1007/BF00932634

Stephens, C.R., Garcia Olmedo, I., Mora Vargas, J., Waelbroeck, H., 1998. Self-adaptation in evolving systems. Artif. Life 4, 183–201.

Storn, R., Price, K., 1997. Differential Evolution : A Simple and Efficient Heuristic for global Optimization over Continuous Spaces. J. Glob. Optim. 11, 341–359. https://doi.org/10.1023/A:1008202821328

Tagawa, K., Imamura, A., 2013. Many-hard-objective optimization using differential evolution based on two-stage constraint-handling. Proceeding fifteenth Annu. Conf. Genet. Evol. Comput. Conf. - GECCO '13 671. https://doi.org/10.1145/2463372.2463446

Tsutsui, S., Yamamura, M., Higuchi, T., 1999. Multi-parent recombination with simplex crossover in real coded genetic algorithms, in: Proceedings of the 1st Annual Conference on Genetic and Evolutionary Computation-Volume 1. pp.

657–664.

Vafaee, F., Nelson, P.C., 2010. An explorative and exploitative mutation scheme. 2010 IEEE World Congr. Comput. Intell. WCCI 2010 - 2010 IEEE Congr. Evol. Comput. CEC 2010. https://doi.org/10.1109/CEC.2010.5586142

Vrugt, J.A., Robinson, B.A., Hyman, J.M., 2009. Self-adaptive multimethod search for global optimization in real-parameter spaces. IEEE Trans. Evol. Comput. 13, 243–259. https://doi.org/10.1109/TEVC.2008.924428

Vrugt, J. a, Robinson, B. a, 2007. Improved evolutionary optimization from genetically adaptive multimethod search. Proc. Natl. Acad. Sci. 104, 708–711. https://doi.org/10.1073/pnas.0610471104

Woodruff, M.J., Simpson, T.W., Reed, P.M., 2015. Multi-Objective Evolutionary Algorithms' Performance in a Support Role, in: ASME 2015 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference. p. 12.

Yuan, Y., Xu, H., Wang, B., Yao, X., 2016. A New Dominance Relation-Based Evolutionary Algorithm for Many-Objective Optimization. IEEE Trans. Evol. Comput. 20, 16–37. https://doi.org/10.1109/TEVC.2015.2420112

Zecchin, A.C., Simpson, A.R., Maier, H.R., Marchi, A., Nixon, J.B., 2012. Improved understanding of the searching behavior of ant colony optimization algorithms applied to the water distribution design problem. Water Resour. Res. 48. https://doi.org/10.1029/2011WR011652

Zhang, Q., Li, H., 2007. MOEA/D: A Multiobjective Evolutionary Algorithm Based on Decomposition. IEEE Trans. Evol. Comput. 11, 712–731. https://doi.org/10.1109/TEVC.2007.892759

Zhang, Q., Liu, W., Li, H., 2009. The performance of a new version of MOEA/D on CEC09 unconstrained MOP test instances, in: 2009 IEEE Congress on Evolutionary Computation. pp. 203–208. https://doi.org/10.1109/CEC.2009.4982949

Zhang, X., Tian, Y., Jin, Y., 2015. A Knee Point-Driven Evolutionary Algorithm for Many-Objective Optimization. IEEE Trans. Evol. Comput. 19, 761–776. https://doi.org/10.1109/TEVC.2014.2378512

Zheng, F., Simpson, A.R., Zecchin, A.C., Maier, H.R., Feifei, Zh., 2016. Comparison of the Searching Behavior of NSGA-II, SAMODE, and Borg MOEAs Applied to Water Distribution System Design Problems. J. Water Resour. Plan. Manag. 142. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000650

Zhou, A., Qu, B.-Y., Li, H., Zhao, S.-Z., Suganthan, P.N., Zhang, Q., 2011. Multiobjective evolutionary algorithms: A survey of the state of the art. Swarm Evol. Comput. 1, 32–49. https://doi.org/10.1016/j.swevo.2011.03.001

Zhu, C., Xu, L., Goodman, E.D., 2016. Generalization of Pareto-Optimality for Many-Objective Evolutionary Optimization. IEEE Trans. Evol. Comput. 20, 299–315. https://doi.org/10.1109/TEVC.2015.2457245

Zitzler, E., Laumanns, M., Thiele, L., 2002. SPEA2: Improving the Strength Pareto Evolutionary Algorithm for Multiobjective Optimization, in: Evolutionary Methods for Design, Optimisation, and Control. CIMNE, Barcelona, Spain, pp.

95–100.

Zitzler, E., Lothar, T., Kalyanmoy, D., 2000. Comparison of Multiobjective Evolutionary Algorithms: Empirical Results. Evol.\ Comput. 8, 173–195.

Zitzler, E., Simon, K., 2004. Indicator-Based Selection in Multiobjective Search. 8th Int. Conf. Parallel Probl. Solving from Nat. (PPSN VIII) 3242, 832–842. https://doi.org/10.1007/b100601

5.3 Supplementary Data

1. Recombination Operators

Figure A1 shows the essential properties of the operators. The algorithms in Table A1 are widely used in different fields of science and engineering (Zhou et al. 2011) and their respective recombination operators are indicated also.

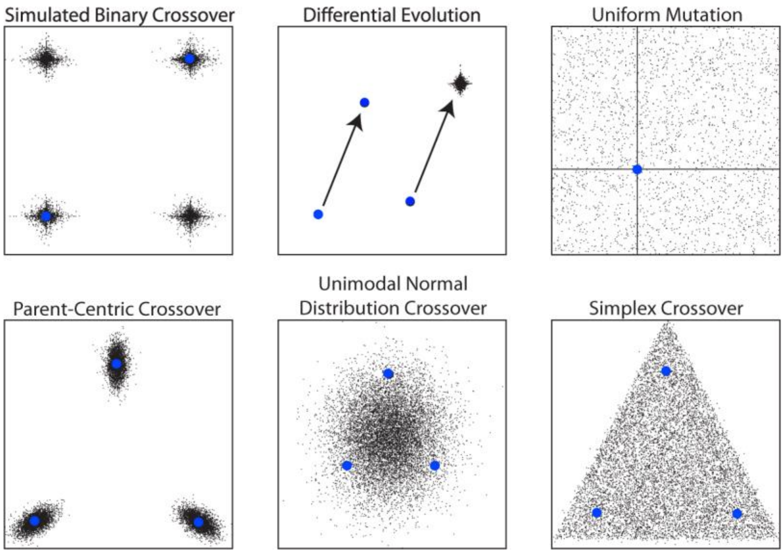


Figure A1. Spatial distributions of offspring from different recombination operators. The blue points indicate the parents while black dots refer to offspring (Hadka and Reed 2013).

Table A1. Recombination operators in common evolutionary algorithms (Reed *et al.* 2013)

Recombination Operators	Evolutionary Algorithms
Simulated Binary Crossover (SBX)	Borg, AMALGAM[1], IBEA[2], ε-MOEA[3], ε-NSGA-II[4], SPEA2[5], NSGA-II[6]
Differential Evolution (DE)	Borg, AMALGAM, IBEA, GDE3[7], MOEA/D[8]
Unimodal normal distribution crossover (UNDX)	Borg
Simplex crossover (SPX)	Borg
Parent-centric Crossover (PCX)	Borg
Uniform Mutation (UM)	Borg
Polynomial Mutation (PM)	Borg, AMALGAM, IBEA, ε-MOEA, ε-NSGA-II, SPEA2, NSGA-II, MOEA/D

[1](Vrugt and Robinson 2007), [2] (Zitzler and Simon 2004), [3](Laumanns *et al.* 2002),

[4](Kollat and Reed 2006), [5](Zitzler *et al.* 2002), [6](Deb *et al.* 2002), [7](Kukkonen and Lampinen 2005), [8](Zhang *et al.* 2009).

1.1 Simulated Binary Crossover (SBX)

This operator uses two parents to generate two offspring by applying a single-point crossover. It generates offspring evenly distributed near the parents as follows (Deb and Agrawal 1994).

a. Calculate the factor β.

$$\beta = \begin{cases} (2r)^{\frac{1}{(\eta+1)}} & if\ r \leq 0.5 \\ \left(\frac{1}{2(1-r)}\right)^{\frac{1}{(\eta+1)}} & if\ r > 0.5 \end{cases} \tag{A1}$$

where r is a random number from the uniform distribution in the interval [0,1], and η is the distribution index, a nonnegative real number. A small value of η produces a high probability to generate offspring far away from the parents, through which diversity in the search process will increase while large values yield offspring near the parents. In other words, small values promote diversity and greater exploration while large values intensify the search, which leads to greater exploitation.

b. Calculate the β' based on the probability to generate new offspring, $\mathcal{P}(\beta)$.

$$\beta' \approx \mathcal{P}(\beta) = \begin{cases} 0.5(\eta+1)\beta^{\eta} & if\ \beta \leq 1 \\ 0.5(\eta+1)\frac{1}{\beta^{\eta+2}} & otherwise \end{cases} \tag{A2}$$

c. Calculate the new offspring values (c_1, c_2) from parents (p_1, p_2) as follows.

$$c_1 = 0.5[(1+\beta')p_1 + (1-\beta')p_2] \tag{A3}$$

$$c_2 = 0.5[(1-\beta')p_1 + (1+\beta')p_2] \tag{A4}$$

1.2 Differential Evolution (DE)

Differential Evolution is a global optimization approach for real-coded optimization algorithms. This operator uses the weighted difference direction vector for two parents along with a third parent to generate new offspring. The general procedure for DE is as follows (Storn and Price 1997, Price *et al.* 2005), where $NP \geq 4$ is the population size, G is the maximum number of generations, and j is the number of parameters.

a. Generate a random vector $x_{j,i,G}$ using the following formula.

$$x_{j,i,G} = rand(0,1)_j.\left(b_{j.U} - b_{j,L}\right) + b_{j,L} \tag{A5}$$

$0 \leq rand(0,1)_j < 1$; $b_{j.U}$ *and* $b_{j,L}$ are the upper and lower bounds respectively.

b. Generate a mutant vector $v_{i,G+1}$ for each $x_{i,G}$.

$$\mathbf{v}_{i,G+1} = \mathbf{x}_{r1,G} + F.(\mathbf{x}_{r2,G} - \mathbf{x}_{r3,G}) \tag{A6}$$

where $r_1, r_2, r_3 \in \{1,2,3,\dots,NP\}$ are random integer indices and the factor F $\in$ [0, 2] is a real number called step size.

c. A trial vector $\mathbf{u}_{i,G} = (u_{j,i,G}, u_{j,i,G}, \dots.., u_{D,i,G})$ is formed using the crossover process to increase the diversity according to the following relation

$$u_{j,i,G} = \begin{cases} v_{j,i,G} & if\ (rand_j \leq CR)\ or\ (j = j_{rand}) \\ x_{j,i,G} & otherwise \end{cases} \tag{A7}$$

where $rand_j \in [0,1]$ is a random number, CR $\in [0,1]$ is the crossover rate defined by the user, $j_{rand} \in [1, D]$ is a random integer and D is the dimension of the decision variable vector, i.e. the number of decision variables.

d. To preserve a constant population size, a selection between vectors for the next generation (G + 1) is utilized to decide the surviving vector as follows.

$$\mathbf{x}_{i,G+1} = \begin{cases} \mathbf{u}_{i,G} & if\ f(\mathbf{u}_{i,G}) \leq f(\mathbf{x}_{i,G}) \\ \mathbf{x}_{i,G} & otherwise \end{cases} \tag{A8}$$

where $f(\mathbf{x})$ is the minimizing objective function. The authors suggested that an initial value of F = 0.5 would be suitable, and if the algorithm converges early, this values should be increased while values of F less than 0.4 or greater than 1.0 are rarely used. For CR, for the initial trials, 0.9 or 1.0 may be used to achieve rapid the convergence. Subsequently the value may be reduced to 0.1.

1.3 Unimodal Normal Distribution Crossover (UNDX)

This operator generates offspring around the centre of mass of three or more parents, known as mean-centric recombination approach, as follows (Kita *et al.* 1999).

a. Randomly select (μ -1) parents $(\boldsymbol{x}^1, \dots, \boldsymbol{x}^{\mu-1})$ from the population, where μ is the number of parents.

b. Calculate the mean vector $\boldsymbol{\mathcal{P}}$ for these parents.

c. Calculate $\boldsymbol{d}^i$, i.e. the difference vector between $\boldsymbol{x}^i$ and $\boldsymbol{\mathcal{P}}$: $\boldsymbol{d}^i = \boldsymbol{x}^i - \boldsymbol{\mathcal{P}}$, i = 1, …, μ.

d. Find the direction cosines vector: $\boldsymbol{e}^i = \frac{\boldsymbol{d}^i}{|\boldsymbol{d}^i|}$; i = 1, …, μ.

e. Randomly select parent $\boldsymbol{x}^\mu$ and calculate the length, D, between the two vectors $\boldsymbol{x}^\mu$ and $\boldsymbol{\mathcal{P}}$ which is orthogonal to all $\boldsymbol{e}^i$.

f. The new offspring $\boldsymbol{x}^c$ is generated as follows.

$$\boldsymbol{x}^c = \boldsymbol{\mathcal{P}} + \sum_{\boldsymbol{i=1}}^{\boldsymbol{\mu-1}} \omega_i . \left|\boldsymbol{d}^i\right| . \boldsymbol{e}^i + \sum_{j=\mu}^{n} \nu_j . D . \boldsymbol{e}^j \tag{A9}$$

where $\boldsymbol{e}^j$ ($j = \mu, \ldots, n$, where n is the size of the decision variable vector $\boldsymbol{x}$) is the orthonormal basis vector of the subspace, which is orthogonal to the subspace spanned by all $\boldsymbol{e}^i$. ω_i and ν_j are random variables which follow a normal distribution having zero mean, with variances σ_ζ^2 and σ_η^2 respectively. The authors suggested $\sigma_\zeta = 1/\sqrt{\mu-2}$ and $\sigma_\eta = 0.35/\sqrt{n-\mu-2}$.

1.4 Simplex Crossover (SPX)

This is a multi-parent operator that uses the mean-centric recombination approach. It restricts the generation of the new offspring in a region called simplex around the parents' centre of mass using the uniform distribution. The operator uses three parents or more to generate offspring. Let n represent the number of parameters in the search space with vectors X_k, $k = 0, 1, \ldots, n$. The offspring is obtained as follows (Tsutsui *et al.* 1999).

a. Select (n+1) parental vectors X_k randomly and calculate their centre of mass O using

$$O = \frac{1}{n+1}\sum_{k=0}^{n} X_k \tag{A10}$$

b. Calculate v_k, i.e.

$$v_k = u^{\left(\frac{1}{k+1}\right)},\ u \in [0, 1] \tag{A11}$$

where u is a uniform random number.

c. Calculate the expansion vector $Y_k = O + \lambda(X_k - O)$, where λ is the expansion rate that is a control parameter.

d. Calculate the factor $C_k = \begin{cases} 0 & if\ k = 0 \\ v_{k-1}(Y_{k-1} - Y_k + C_{k-1}) & if\ k > 0 \end{cases}$ (A12)

e. Generate the new offspring at $C = Y_n + C_n$, where Y_n and C_n are the expansion vector and factor at *k* = *n*, respectively.

The authors suggested a value of $\lambda = \sqrt{\mu + 2}$, where μ is the number of parents.

1.5 Parent Centric Crossover (PCX)

This operator is derived from the UNDX operator with some modifications. In this operator, the mean vector $\boldsymbol{\mathcal{P}}$ is generated for μ parents rather than $(\mu - 1)$ as in the UNDX. Then one parent $\boldsymbol{x}^p$ is chosen with equal probability, and the direction vector $\boldsymbol{d}^p = \boldsymbol{x}^p - \boldsymbol{\mathcal{P}}$ is calculated. The perpendicular distance D_i, $(i = 1, \dots, \mu - 1)$ to the line $\boldsymbol{d}^p$ is calculated for the other $(\mu - 1)$ parents, and their average distance $\overline{D}$ is used to generate the new offspring as follows (Deb *et al.* 2002).

$$\boldsymbol{y} = \boldsymbol{x}^p + \omega_\zeta . |\boldsymbol{d}^p| + \textstyle\sum_{i=1, i \neq p}^{\mu} v_\eta . \overline{D} . \boldsymbol{e}^i \tag{A13}$$

where the $\boldsymbol{e}^i$ represent the $(\mu - 1)$ orthonormal bases spanning the subspace perpendicular to $\boldsymbol{d}^p$, while ω_ζ and v_η have the same definition as ω_i and v_j in UNDX with variance σ_ζ^2 and σ_η^2 respectively. The authors proposed values for σ_ζ and σ_η of 0.1. The operator has similar properties to UNDX and SPX except that the new offspring is not generated around the centre mass of the parents. Instead, the new offspring are generated around the parents.

1.6 Uniform Mutation (UM)

This operator generates single offspring $\boldsymbol{x}'$ from single parent $\boldsymbol{x}$. A random element x_k is selected from the vector $\boldsymbol{x} = (x_1, \dots, x_k, .., x_n)$, where $k \in \{1, \dots, n\}$ to generate the new vector $\boldsymbol{x}' = (x_1, \dots, x_k', .., x_n)$, where $x_k' \in [x_k^L, x_k^U]$ and *L* and *U* refer to the upper and lower bounds of the element. This operator is allowed to search freely in the search space which is useful in the early stages of the EA (Michalewicz *et al.* 1994).

1.7 Polynomial Mutation (PM)

This operator uses a polynomial distribution to generate a new offspring near the parent, and is widely used in the recent evolutionary algorithms (Reed et al. 2013). The procedure to generate the new solution c from a solution $x \in [x_L, x_U]$ where x_L and x_U denote the lower and upper bounds, respectively, is as follows (Deb and Agrawal 1999).

a. Generate a random number $u \in [0,1]$.

b. Calculate the factor δ_q using the following equation

$$\delta_q = \begin{cases} [2u + (1-2u)(1-\delta)^{\eta_m+1}]^{\frac{1}{\eta_m+1}} - 1 & if\ u \leq 0.5 \\ 1 - [2(1-u) + 2(u-0.5)(1-\delta)^{\eta_m+1}]^{\frac{1}{\eta_m+1}} & Otherwise \end{cases} \quad \text{(A14)}$$

where η_m is the distribution index for mutation that may take any non-negative value and $\delta = \min[(x - x_L), (x_U - x)] / (x_U - x_L)$.

c. Generate the new solution: $c = x + \delta_q (x_U - x_L)$.

2. Details of Test Functions Used For Comparative Analyses

Table A2. Details of the optimization test functions (Deb *et al.* 2001)

Test functions	Details
DTLZ1	Minimize: $$f_1(\mathbf{x}) = 0.5x_1x_2 \ldots x_{M-1}\big(1+g(\mathbf{x}_M)\big)$$ $$f_2(\mathbf{x}) = 0.5x_1x_2 \ldots (1-x_{M-1})\big(1+g(\mathbf{x}_M)\big)$$ $$\vdots \qquad \vdots$$ $$f_{M-1}(\mathbf{x}) = 0.5x_1(1-x_2)\big(1+g(\mathbf{x}_M)\big)$$ $$f_M(\mathbf{x}) = 0.5(1-x_1)\big(1+g(\mathbf{x}_M)\big)$$ Subjected to $0 \le x_i \le 1$ $\forall i = 1,2,\ldots,L$ (L is the number of variables) Where $g(\mathbf{x}_M) = 100\big[\lvert\mathbf{x}_M\rvert + \sum_{x_i \in \mathbf{x}_M}(x_i-0.5)^2 - \cos\big(20\pi(x_i - 0.5)\big)\big]$
DTLZ2	Minimize: $$f_1(\mathbf{x}) = \big(1+g(\mathbf{x}_M)\big)\cos(x_1\pi/2)\cos(x_2\pi/2)\ldots\cos(x_{M-2}\pi/2)\cos(x_{M-1}\pi/2)$$ $$f_2(\mathbf{x}) = \big(1+g(\mathbf{x}_M)\big)\cos(x_1\pi/2)\cos(x_2\pi/2)\ldots\cos(x_{M-2}\pi/2)\sin(x_{M-1}\pi/2)$$ $$f_3(\mathbf{x}) = \big(1+g(\mathbf{x}_M)\big)\cos(x_1\pi/2)\cos(x_2\pi/2)\ldots\sin(x_{M-2}\pi/2)$$ $$\vdots \qquad \vdots$$ $$f_{M-1}(\mathbf{x}) = \big(1+g(\mathbf{x}_M)\big)\cos(x_1\pi/2)\sin(x_2\pi/2)$$ $$f_M(\mathbf{x}) = \big(1+g(\mathbf{x}_M)\big)\sin(x_1\pi/2)$$ Subjected to: $0 \le x_i \le 1$; $\forall i = 1,2,\ldots,L$ (L is the number of variables) Where $g(\mathbf{x}_M) = \sum_{x_i \in \mathbf{x}_M}(x_i-0.5)^2$
DTLZ3	Minimize: $$f_1(\mathbf{x}) = \big(1+g(\mathbf{x}_M)\big)\cos(x_1\pi/2)\cos(x_2\pi/2)\ldots\cos(x_{M-2}\pi/2)\cos(x_{M-1}\pi/2)$$ $$f_2(\mathbf{x}) = \big(1+g(\mathbf{x}_M)\big)\cos(x_1\pi/2)\cos(x_2\pi/2)\ldots\cos(x_{M-2}\pi/2)\sin(x_{M-1}\pi/2)$$ $$f_3(\mathbf{x}) = \big(1+g(\mathbf{x}_M)\big)\cos(x_1\pi/2)\cos(x_2\pi/2)\ldots\sin(x_{M-2}\pi/2)$$ $$\vdots \qquad \vdots$$ $$f_{M-1}(\mathbf{x}) = \big(1+g(\mathbf{x}_M)\big)\cos(x_1\pi/2)\sin(x_2\pi/2)$$ $$f_M(\mathbf{x}) = \big(1+g(\mathbf{x}_M)\big)\sin(x_1\pi/2)$$ Subjected to: $0 \le x_i \le 1$; $\forall i = 1,2,\ldots,L$ (L is the number of variables) Where $g(\mathbf{x}_M) = 100\big[\lvert\mathbf{x}_M\rvert + \sum_{x_i \in \mathbf{x}_M}(x_i-0.5)^2 - \cos\big(20\pi(x_i - 0.5)\big)\big]$
DTLZ4	Minimize: $$f_1(\mathbf{x}) = \big(1+g(\mathbf{x}_M)\big)\cos(x_1^\alpha\pi/2)\cos(x_2^\alpha\pi/2)\ldots\cos(x_{M-2}^\alpha\pi/2)\cos(x_{M-1}^\alpha\pi/2)$$

	$f_2(\mathbf{x}) = \left(1+g(\mathbf{x}_M)\right)\cos(x_1^{\alpha}\pi/2)\cos(x_2^{\alpha}\pi/2)\ldots\cos(x_{M-2}^{\alpha}\pi/2)\sin(x_{M-1}^{\alpha}\pi/2)$ $f_3(\mathbf{x}) = \left(1+g(\mathbf{x}_M)\right)\cos(x_1^{\alpha}\pi/2)\cos(x_2^{\alpha}\pi/2)\ldots\sin(x_{M-2}^{\alpha}\pi/2)$ $\vdots \qquad \vdots$ $f_{M-1}(\mathbf{x}) = \left(1+g(\mathbf{x}_M)\right)\cos(x_1^{\alpha}\pi/2)\sin(x_2^{\alpha}\pi/2)$ $f_M(\mathbf{x}) = \left(1+g(\mathbf{x}_M)\right)\sin(x_1^{\alpha}\pi/2)$ Subjected to: $0 \le x_i \le 1;\ \forall i = 1,2,\ldots,L$ (L is the number of variables) Where $g(\mathbf{x}_M) = \sum_{x_i\in\mathbf{x}_M}(x_i-0.5)^2;\ \alpha = 100$
DTLZ7	Minimize: $f_1(\mathbf{x}) = x_1$ $f_2(\mathbf{x}) = x_2$ $\vdots \qquad \vdots$ $f_{M-1}(\mathbf{x}) = x_{M-1}$ $f_M(\mathbf{x}) = \left(1+g(\mathbf{x}_M)\right)h(f_1,f_2,\ldots,f_{M-1},g)$ Subjected to: $0 \le x_i \le 1;\ \forall i = 1,2,\ldots,L$ (L is the number of variables) Where $g(\mathbf{x}_M) = 1+\frac{9}{\lvert\mathbf{x}_M\rvert}\sum_{x_i\in\mathbf{x}_M}x_i$ $h(f_1,f_2,\ldots,f_{M-1},g) = M-\sum_{i=1}^{M-1}\left[\frac{f_i}{1+g}\left(1+\sin(3\pi f_i)\right)\right]$

3. Comparison Of Restarts And ε-Index Improvements

Table A3. Average number of restart per optimization run (Borg MOEA)

Objectives	DTLZ1	DTLZ2	DTLZ3	DTLZ4	DTLZ7
			50,000 function evaluations		
2D	110	113	33	113	111
4D	16	6	22	7	9
6D	7	5	7	7	11
8D	6	6	6	141	11
			100,000 function evaluations		
2D	260	247	149	246	258
4D	20	13	31	20	13
6D	9	7	18	9	13
8D	7	7	8	304	14

ε-DSEA employs no more than three restarts (population injection).

Table A4. Average number of improvement per optimization run (Borg MOEA and ε-DSEA)

	Borg MOEA					ε-DSEA				
Function	2D	4D	6D	8D	Totals	2D	4D	6D	8D	Totals
					50,000 function evaluations					
DTLZ1	756	7104	8846	12258	28964	734	6139	14454	16871	38198
DTLZ2	439	6662	13030	13518	33649	457	6187	12237	13995	32876
DTLZ3	2397	6593	5601	9891	24482	1836	6701	9720	11480	29737
DTLZ4	303	3893	5652	99	9947	318	3954	6149	112	10533
DTLZ7	779	7148	14684	5128	27739	645	5409	13166	4647	23867
Totals					124781					**135211**
					100,000 function evaluations					
DTLZ1	633	9349	24512	21178	55672	676	8516	28985	33045	71222
DTLZ2	424	7657	17995	19618	45694	456	7028	16380	18519	42383
DTLZ3	2570	12238	12840	15908	43556	1850	10136	15286	16617	43889
DTLZ4	280	4509	7911	99	12799	291	4070	8321	107	12789
DTLZ7	755	8532	23336	6270	38893	619	5562	19773	5296	31250
Totals					196614					**201533**
Grand Total					321395					**336744**

4. Control Parameters of Evolutionary Operators In ε-DSEA

Table A5a. ε-DSEA values of control parameters of evolutionary operators on DTLZ1

Parameters	Objectives	Mean	Std.	Minimum	Median	Maximum
η (SBX)	2D	79.650	15.953	16.000	89.000	91.000
	4D	92.103	11.579	14.000	95.000	99.000
	6D	86.295	12.296	16.000	86.000	99.000
	8D	87.349	14.816	16.000	95.000	99.000
CR, F (DE)	CR-2D	0.102	0.013	0.100	0.100	0.267
	F-2D	0.510	0.016	0.500	0.503	0.633
	CR-4D	0.102	0.013	0.100	0.100	0.267
	F-4D	0.510	0.016	0.500	0.503	0.633
	CR-6D	0.101	0.008	0.100	0.100	0.188
	F-6D	0.510	0.012	0.500	0.507	0.594
	CR-8D	0.104	0.022	0.100	0.100	0.333
	F-8D	0.514	0.021	0.500	0.507	0.667
σ_η, σ_ζ (PCX)	2D	0.106	0.006	0.104	0.104	0.140
	4D	0.101	0.003	0.100	0.100	0.133
	6D	0.101	0.003	0.100	0.100	0.133
	8D	0.101	0.004	0.100	0.100	0.133
λ (SPX)	2D	2.533	0.034	2.518	2.518	2.700
	4D	2.537	0.050	2.502	2.525	2.858
	6D	2.596	0.084	2.503	2.620	2.823
	8D	2.571	0.093	2.502	2.519	2.831
σ_η, σ_ζ (UNDX)	σ_ζ -2D	0.405	0.004	0.404	0.404	0.433
	σ_η -2D	0.109	0.007	0.106	0.106	0.156
	σ_ζ -4D	0.401	0.003	0.400	0.400	0.433
	σ_η -4D	0.102	0.005	0.100	0.100	0.156
	σ_ζ -6D	0.401	0.003	0.400	0.400	0.433
	σ_η -6D	0.101	0.006	0.100	0.100	0.156
	σ_ζ -8D	0.401	0.004	0.400	0.400	0.433
	σ_η -8D	0.102	0.006	0.100	0.100	0.156

Table A5b. ε-DSEA values of control parameters of evolutionary operators on DTLZ2

Parameters	Objectives	Mean	Std.	Minimum	Median	Maximum
η (SBX)	2D	84.844	18.500	1.000	91.000	92.000
	4D	77.901	18.893	5.000	84.000	97.000
	6D	77.344	15.180	16.000	79.000	95.000
	8D	80.233	15.060	16.000	82.000	96.000
CR, F (DE)	CR-2D	0.101	0.009	0.100	0.100	0.238
	F-2D	0.514	0.013	0.507	0.508	0.619
	CR-4D	0.109	0.030	0.100	0.100	0.321
	F-4D	0.519	0.028	0.501	0.508	0.661
	CR-6D	0.101	0.012	0.100	0.100	0.300
	F-6D	0.513	0.015	0.501	0.509	0.650
	CR-8D	0.101	0.005	0.100	0.100	0.167
	F-8D	0.507	0.010	0.501	0.504	0.583
σ_η, σ_ζ (PCX)	2D	0.107	0.013	0.103	0.103	0.206
	4D	0.114	0.012	0.102	0.110	0.159
	6D	0.116	0.013	0.101	0.114	0.168
	8D	0.114	0.009	0.103	0.113	0.143
λ (SPX)	2D	2.545	0.094	2.515	2.515	3.026
	4D	2.594	0.086	2.507	2.564	3.024
	6D	2.602	0.071	2.520	2.622	2.783
	8D	2.595	0.077	2.503	2.607	2.838
σ_η, σ_ζ (UNDX)	σ_ζ -2D	0.404	0.003	0.403	0.403	0.433
	σ_η -2D	0.106	0.005	0.105	0.105	0.156
	σ_ζ -4D	0.401	0.004	0.400	0.400	0.437
	σ_η -4D	0.102	0.007	0.100	0.100	0.162
	σ_ζ -6D	0.401	0.003	0.400	0.400	0.433
	σ_η -6D	0.102	0.006	0.100	0.100	0.156
	σ_ζ -8D	0.401	0.004	0.400	0.400	0.433
	σ_η -8D	0.102	0.006	0.100	0.100	0.156

Table A5c. ε-DSEA values of control parameters of evolutionary operators on DTLZ3

Parameters	Objectives	Mean	Std.	Minimum	Median	Maximum
η	2D	74.598	21.430	11.000	87.000	92.000
(SBX)	4D	86.904	13.419	16.000	91.000	98.000
	6D	64.035	38.118	0.000	77.000	98.000
	8D	87.378	14.274	16.000	91.000	99.000
CR, F	CR-2D	0.111	0.041	0.100	0.100	0.438
(DE)	F-2D	0.526	0.031	0.507	0.515	0.719
	CR-4D	0.104	0.020	0.100	0.100	0.308
	F-4D	0.513	0.020	0.501	0.507	0.654
	CR-6D	0.134	0.059	0.100	0.100	0.285
	F-6D	0.537	0.048	0.501	0.508	0.643
	CR-8D	0.103	0.018	0.100	0.100	0.333
	F-8D	0.513	0.019	0.500	0.506	0.667
σ_η, σ_ζ	2D	0.109	0.015	0.103	0.103	0.207
(PCX)	4D	0.102	0.003	0.100	0.101	0.133
	6D	0.102	0.004	0.100	0.101	0.133
	8D	0.103	0.004	0.100	0.102	0.133
λ	2D	2.599	0.133	2.515	2.531	3.056
(SPX)	4D	2.573	0.087	2.508	2.527	2.900
	6D	2.616	0.151	2.502	2.527	3.155
	8D	2.534	0.056	2.501	2.521	2.828
σ_η, σ_ζ	σ_ζ -2D	0.405	0.005	0.403	0.403	0.433
(UNDX)	σ_η -2D	0.108	0.008	0.105	0.105	0.156
	σ_ζ -4D	0.401	0.003	0.400	0.400	0.433
	σ_η -4D	0.102	0.005	0.100	0.101	0.156
	σ_ζ -6D	0.402	0.005	0.400	0.401	0.452
	σ_η -6D	0.103	0.008	0.100	0.101	0.187
	σ_ζ -8D	0.403	0.006	0.400	0.401	0.462
	σ_η -8D	0.106	0.010	0.100	0.102	0.203

Table A5d. ε-DSEA values of control parameters of evolutionary operators on DTLZ4

Parameters	Objectives	Mean	Std.	Minimum	Median	Maximum
η (SBX)	2D	87.965	9.973	16.000	92.000	92.000
	4D	93.183	10.509	16.000	97.000	98.000
	6D	93.001	10.893	16.000	96.000	99.000
	8D	79.712	16.659	12.000	85.000	88.000
CR, F (DE)	CR-2D	0.102	0.013	0.100	0.100	0.250
	F-2D	0.514	0.015	0.507	0.508	0.625
	CR-4D	0.103	0.015	0.100	0.100	0.278
	F-4D	0.513	0.018	0.500	0.508	0.639
	CR-6D	0.103	0.018	0.100	0.100	0.333
	F-6D	0.515	0.018	0.500	0.512	0.667
	CR-8D	0.109	0.031	0.100	0.100	0.300
	F-8D	0.525	0.026	0.512	0.512	0.650
σ_η, σ_ζ (PCX)	2D	0.105	0.006	0.103	0.103	0.149
	4D	0.102	0.005	0.100	0.101	0.144
	6D	0.102	0.004	0.100	0.101	0.133
	8D	0.107	0.005	0.105	0.105	0.133
λ (SPX)	2D	2.525	0.033	2.515	2.515	2.786
	4D	2.515	0.025	2.502	2.508	2.714
	6D	2.512	0.026	2.501	2.505	2.778
	8D	2.534	0.027	2.524	2.524	2.700
σ_η, σ_ζ (UNDX)	σ_ζ -2D	0.404	0.003	0.403	0.403	0.433
	σ_η -2D	0.106	0.005	0.105	0.105	0.156
	σ_ζ -4D	0.401	0.003	0.400	0.400	0.433
	σ_η -4D	0.102	0.006	0.100	0.101	0.156
	σ_ζ -6D	0.401	0.004	0.400	0.400	0.433
	σ_η -6D	0.101	0.006	0.100	0.100	0.156
	σ_ζ -8D	0.407	0.005	0.405	0.405	0.446
	σ_η -8D	0.111	0.008	0.108	0.108	0.177

Table A5e. ε-DSEA values of control parameters of evolutionary operators on DTLZ7

Parameters	Objectives	Mean	Std.	Minimum	Median	Maximum
η (SBX)	2D	82.469	12.917	7.000	86.000	90.000
	4D	94.137	12.317	13.000	98.000	99.000
	6D	96.288	9.627	16.000	99.000	99.000
	8D	95.045	10.940	16.000	98.000	99.000
CR, F (DE)	CR-2D	0.112	0.032	0.100	0.100	0.355
	F-2D	0.533	0.028	0.510	0.520	0.677
	CR-4D	0.103	0.021	0.100	0.100	0.368
	F-4D	0.511	0.020	0.501	0.505	0.684
	CR-6D	0.101	0.011	0.100	0.100	0.273
	F-6D	0.505	0.012	0.500	0.502	0.636
	CR-8D	0.101	0.013	0.100	0.100	0.250
	F-8D	0.508	0.014	0.501	0.503	0.625
σ_η, σ_ζ (PCX)	2D	0.105	0.005	0.104	0.104	0.136
	4D	0.102	0.006	0.100	0.100	0.157
	6D	0.101	0.004	0.100	0.100	0.146
	8D	0.101	0.003	0.100	0.100	0.133
λ (SPX)	2D	2.532	0.048	2.519	2.519	2.890
	4D	2.510	0.035	2.501	2.502	2.857
	6D	2.508	0.039	2.500	2.501	2.897
	8D	2.510	0.043	2.501	2.501	2.974
σ_η, σ_ζ (UNDX)	σ_ζ -2D	0.405	0.003	0.404	0.404	0.433
	σ_η -2D	0.108	0.006	0.106	0.106	0.156
	σ_ζ -4D	0.401	0.004	0.400	0.400	0.433
	σ_η -4D	0.102	0.006	0.100	0.101	0.156
	σ_ζ -6D	0.401	0.002	0.400	0.400	0.433
	σ_η -6D	0.101	0.004	0.100	0.100	0.156
	σ_ζ -8D	0.401	0.003	0.400	0.400	0.433
	σ_η -8D	0.102	0.005	0.100	0.100	0.156

5.4 Further Discussion

Regarding real-world benchmark problem, the total number of optimum solutions generated by ε-DSEA over the 20 runs was 6935, while it was 4848 for Borg MOEA, which reflects algorithm's diversity robustness to exploit and explore the decision variables design space. Hence, more reservoir operation management will deliver to the decision makes as alternatives.

The average and median gross reservoir releases, storage, and power generation achieved by ε-DSEA for the best solution were: 133.7×10^9 m^3; 133.6×10^9 m^3; 641.8×10^9 m^3; 650.4×10^9 m^3; 36.8 GW; 37 GW, respectively. For Borg MOEA, they were: 133.9×10^9 m^3; 133.9×10^9 m^3; 612.2×10^9 m^3; 619.7×10^9 m^3; 36.7 GW; 37 GW, respectively. Hydropower generation achieved by both algorithms are consistent, however better storage sustainable management is achieved by ε-DSEA over reducing the releases. Thus, quality of optimum solutions achieved by ε-DSEA is endorsed, not only the quantity. This is a key benefit in arid and semi-arid environment since it has limited water resources to store in winter for summer season demands.

5.5 Conclusions

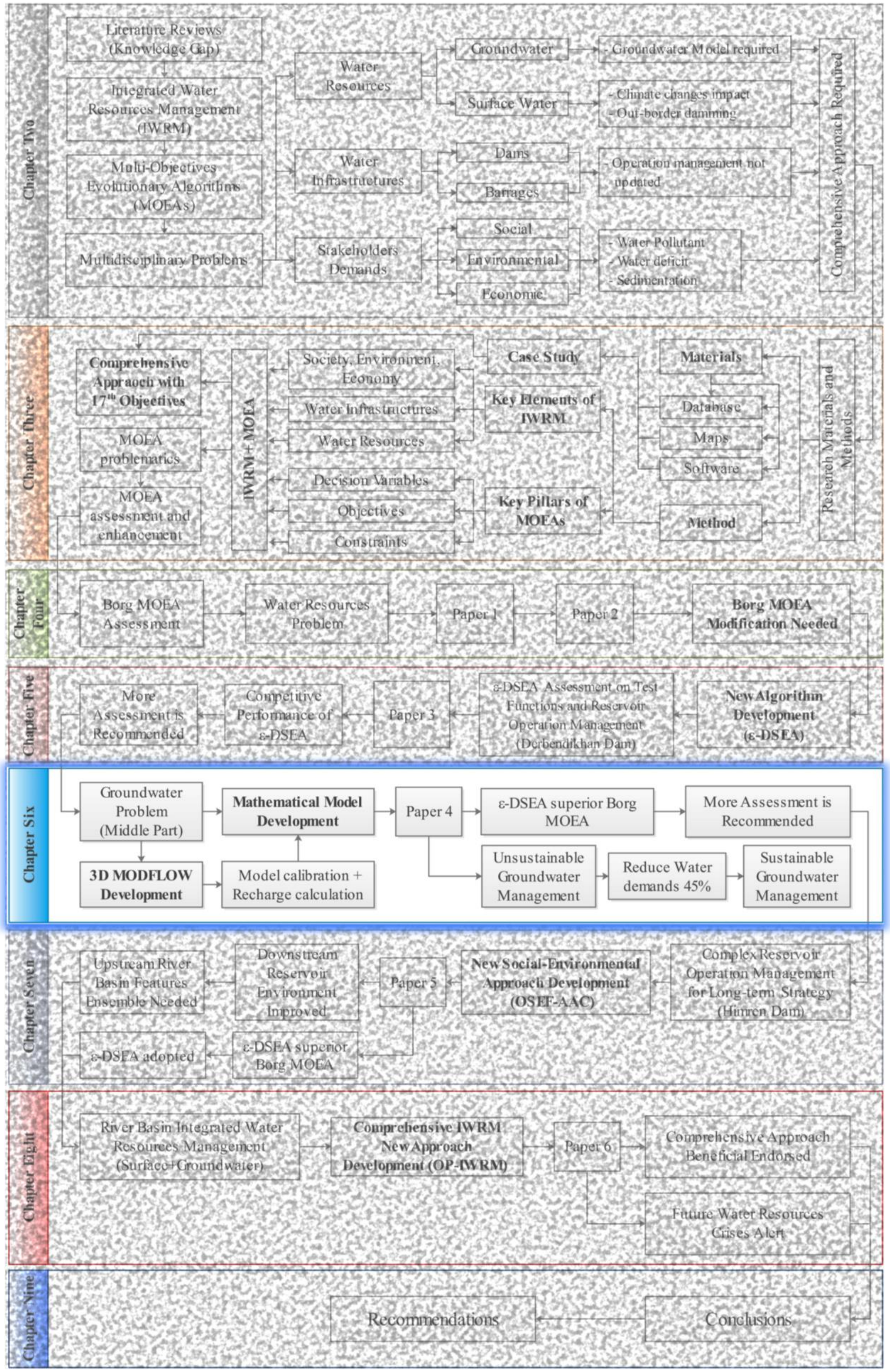
In this chapter, a new evolutionary algorithm is presented entitled "Epsilon-Driven Self-Adaptive Evolutionary Algorithm" (ε-DSEA), which has many novel methodologies to improve the diversity, convergence and adaptation of optimization algorithm. Initial diversity exploration achieved by multiple recombination operators (for crossover evolve process) uses all population candidates to produce new generations. New recombination operators' parameters tuning technique is developed for dynamic adaptation with operator's optimality achievement. Moreover, random operators' parameters resetting is also developed to escape from local optima pitfall.

The ε-DSEA is assessed intensively in comparison with the state-of-the-art Borg MOEA using a set of commonly implemented benchmark test function with two computational budgets, and a real-word reservoir management problem. The results are very encouraging. They revealed that the methodology proposed is highly competitive. Consistently good results were achieved, based on the computational efficiency and quality of the solutions found. On the problems considered, the SBX (simulated binary crossover) operator was used the most, followed by SPX (simplex crossover) and DE (differential evolution). Also, the values of some of the control parameters varied/deviated from the recommended default values, depending on the number of objectives, the stage of the optimization and the particular test problem under consideration. The methodology proposed therefore lends itself to parameter calibration, which may be an interesting area for further research in the future.

Furthermore, the results on a benchmark real-world case study with constraints clearly demonstrated the reliability and robustness of the proposed methodology by consistently yielding near-optimal solutions in all random trials, and outperforming

Borg MOEA significantly. The adaptive operators sequence changing during the evaluation stages, starting by SBX operator and ending with PCX and SPX operators in parallel. New range of operators' parameters was present to consider for consistent real-word problems. The research is in progress and, in addition to trials involving other more complex real-world problems that may be computationally expensive, more verification would be likely yield additional insights.

Hence, in the next chapter, a long-term groundwater pumping management problem is used to assess MOEAs' performance based on reliability, robustness, efficiency, and effectiveness indices, as it has different types of decision variables, objectives, and constraints.



Chapter Two
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CHAPTER SIX

GROUNDWATER MANAGEMENT ASSESSMENT

6.1 Introduction

The proposed self-adaptive methodology was investigated in the previous chapter using benchmark test functions and a real-world reservoir management strategy. The primary results show encouraging results with ε-DSEA in comparison with Borg MOEA in almost all considered test problems. However, further assessment was recommended using a different problems environment, as in *bullet point 4* in Chapter two. Thus, the ε-DSEA is subjected to solve different problem environment, which has different types of variables, targets, and barriers. Borg MOEA is also implemented for confidence and robustness of results, as highlighted in *bullet point 3* in Chapter two (applying more than one algorithm).

The potential groundwater storage in the middle part of Diyala river basin, which highlighted by *bullet point 8* in Chapter two, can participate in fulfilling water consumption use in this part. Hence sustainable management strategy assessment is needed for long-term water exploitation, since only simple water balance models were previously implemented. This problem is adopted as a case study to evaluate algorithms' performance, and to demonstrate the aquifers' productivity in this region.

A paper is developed and submitted at *Water Resources Management* journal (2018) as:

- Al-Jawad, J.Y., Al-Jawad, S.B., Tanyimboh, T.T., Kalin, R.M., 2018a. Comprehensive Evolutionary Algorithms Performance Assessment Using a Multi-Objectives Water Resources Management Problem. Water Resour. Manag. Under review.

“The following work represents my efforts, such as: theoretical formalism development, analytic calculations and numerical simulations, writing the manuscript. Dr. Tanyimboh, T.T. and Dr. Kalin, R.M., were the project supervisors, and provided assistance and support when required. Al-Jawad, S.B. was a governmental key stackeholder, provided assistance and support when required”

6.2 Paper:

Al-Jawad, J.Y., Al-Jawad, S.B., Tanyimboh, T.T., Kalin, R.M., 2018a. Comprehensive Evolutionary Algorithms Performance Assessment Using a Multi-Objectives Water Resources Management Problem. Water Resour. Manag. Under review.[1]

COMPREHENSIVE EVOLUTIONARY ALGORITHMS PERFORMANCE ASSESSMENT USING A MULTI-OBJECTIVES WATER RESOURCES MANAGEMENT PROBLEM

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COMPREHENSIVE EVOLUTIONARY ALGORITHMS PERFORMANCE ASSESSMENT USING A MULTI-OBJECTIVES WATER RESOURCES MANAGEMENT PROBLEM

Abstract

Multi-Objectives Evolutionary Algorithms' (MOEAs) ability to attain optimal solutions is directly affected by a consistency of evolutionary parameters within the problem environment, and stagnation sensitivity that fails to produce dominant solutions. Competitive MOEAs were here subjected to a comprehensive performance assessment using Iraq's Diyala River basin as case study to evaluate optimization potential. The Borg MOEA and ε-DSEA were applied to optimize a three-objective groundwater management problem involving farms irrigation covering a half-century over five discrete periods contrasting open furrows and drip irrigation systems. The results show superiority of ε-DSEA in all categories (reliability, robustness, efficiency and effectiveness) with new evolve parameters; the potential of ε-DSEA techniques are hence endorsed. The Diyala case results demonstrate unsustainable groundwater use for either delivery system due to recharge scarcity. Predictive simulations indicate future policy should reduce water consumption by 45%, or consider conjunctive surface water use to augment long-term sustainable aquifer resource management.

Keywords: Evolutionary Algorithms, Multi-Objectives Optimization, Borg MOEA, ε-DSEA, Performance Assessment, groundwater management

1 INTRODUCTION

Ever increasing pressures of population growth, food production and energy needs require that decision makers adopt robust water resources management strategies to fulfil demands (Yang et al. 2001; Maier et al. 2014; Horne et al. 2016). Optimization algorithms represent a key management tool in solving a variety of water resources management and planning challenges (Coello et al. 2007; Nicklow et al. 2010). The continual development of optimization methods has generated many different approaches based on linear, non-linear and dynamic programming (Horne et al. 2016). The evolutionary algorithm (EA) approach of Holland (1975) inspired from natural evolution has been widely used to solve real-word multi-objectives problems (Schaffer 1985). Such algorithms generate population of solutions rather than a single solution in a single run (Deb 2001) with many types of EAs now available (Zhou et al., 2011).

Multi-Objectives Evolutionary Algorithms (MOEAs) have been widely used to overcome the conflicts, non-linearity and dynamic characteristics typically present in water resources systems management (Maier et al., 2014). Examples of MOEAs' implementation include: Javadi et al. (2015) used non-dominated sorting genetic algorithm (NSGA-II) to optimize seawater intrusion in a coastal aquifer. Sidiropoulos et al. (2016) used simulation-optimization for groundwater management. Oxley and Mays (2016) applied a genetic algorithm (GA) for long-term planning and sustainable water resources management. Tigkas et al. (2016) investigated the efficiency of EAs for the calibration of a conceptual hydrologic model. Sreekanth et al. (2016) implemented the NSGA-II algorithm to maximize aquifer water injection and to minimize the variance in aquifer water levels. Sadeghi-Tabas et al. (2017) coupled a multi-algorithm, genetically adaptive, multi-objective (AMALGAM) optimization algorithm and simulation model to minimize the deficit in water demands, shortage index, and drawdown in the water table. More MOEAs' types and application in water resources may be found in Tayfur (2017).

However, MOEAs' optimum achievement varies over different problems (Ishibuchi et al. 2015; Ishibuchi et al. 2017). For example, Reed et al. (2013) assess the performance of ten MOEAs to solve four benchmark problems and show the outperformance of Borg MOEA over other algorithms. Conversely, Borg MOEA exhibited a lower performance on a standard water distribution system benchmark problem and failed to approach the true Pareto-front (Qi et al. 2015; Zheng et al. 2016). Salazar et al. (2016), however it demonstrated consistent performance with other MOEAs on a real-world reservoir operation management problem. Hence, multiple algorithms may be required when solving real-world problems to achieve robust results and effective underpinning of decision making (Maier et al., 2014).

The MOEAs use many parameters such as population size, mutation and crossover rate, which have direct impact on their performance. Hence, these parameters (especially mutation and crossover rates) should be carefully selected and tested within the defined problem environment (Maier et al. 2014; Karafotias et al. 2015). The optimal performance of MOEAs is evaluated on benchmark test functions (e.g. DTLZ series, ZDT series, etc.) which consider easy and forward problems recognising real-word problems have more complexity and challenges (Maier et al., 2014). The MOEAs' effectiveness is commonly measured using metrics like the hypervolume metric (Zitzler, 1999) which evaluate the non-dominated solutions' hypervolume, and generational distance metric (Van Veldhuizen and Lamont, 1998) which measure the average distance between the dominance solutions and the closer Pareto-front set. However, these metrics (and others) may provide misguiding results and most of their design principles depends on the true Pareto-front, which is unknown in real-world water resources management problems (Maier et al., 2014). Accordingly, behaviours and performance of MOEAs and methodologies require further assessment of their performance, especially when solving real-world problems (Maier et al., 2014).

The above challenges motivated our research to assess the performance of two competitive MOEAs. The state-of-the-art auto-adaptive Borg MOEA (Hadka and Reed, 2013) and the resent new Epsilon-Dominance-Driven Self-Adaptive Evolutionary Algorithm (ε-DSEA) (Al-Jawad and Tanyimboh, manuscript submitted 2018) were used. They both employ common EA operators, but use different solution methodologies. The assessment covers (i) *reliability*, which refers to the replication of the best solutions finding (Marchi et al., 2014) (ii) *robustness*, which indicates the evolve parameters' consistency with different problems environment (Maier et al., 2014) (iii) *efficiency*, which reflects algorithm's optimality convergence speed (Silver, 2004) and (iv) *effectiveness*, which refers to: how far the generated optimum solutions from the true Pareto-front; diversity; and dominance front rang in objective space (Zitzler et al., 2000).

The analysis focused on solving a challenging real-world groundwater resources management problem that involved long-term multi-objectives groundwater management using many alternatives. The large scale Diyala River basin in Iraq is suffering from climate change influence and trans-boundary water resource demands irrigation projects in both Iraq and Iran (Abbas et al. 2016; Al-Faraj and Scholz 2014;

Abdulrahman 2017). The existing potential groundwater storage in the basin may play an important role for regional land use future investment and water crisis mitigation. A previous regional water resources management model had no obvious solutions when using a simple water balance model (Al-Tamimi 2007; SGI et al. 2014).

2 BENCHMARK REGIONAL IDENTIFICATION

The case study area is located between longitude E 44º 30' – 45º 48', and Latitude N 33º 57' – 34º 58' in northeast of Iraq (Figure 1). It comprises the central part of the Dyiala river basin within Iraq. It is bounded by two multipurpose dams; Derbindikhan located in the north, and Himren in the south, and covers an area of about 7360 km^2. The land surface elevation ranges between 1809 and 88 m.a.s.l. The average annual rainfall and mean temperature (T_{mean}) are 285 mm and 24^{o}C, respectively (SGI et al., 2014).

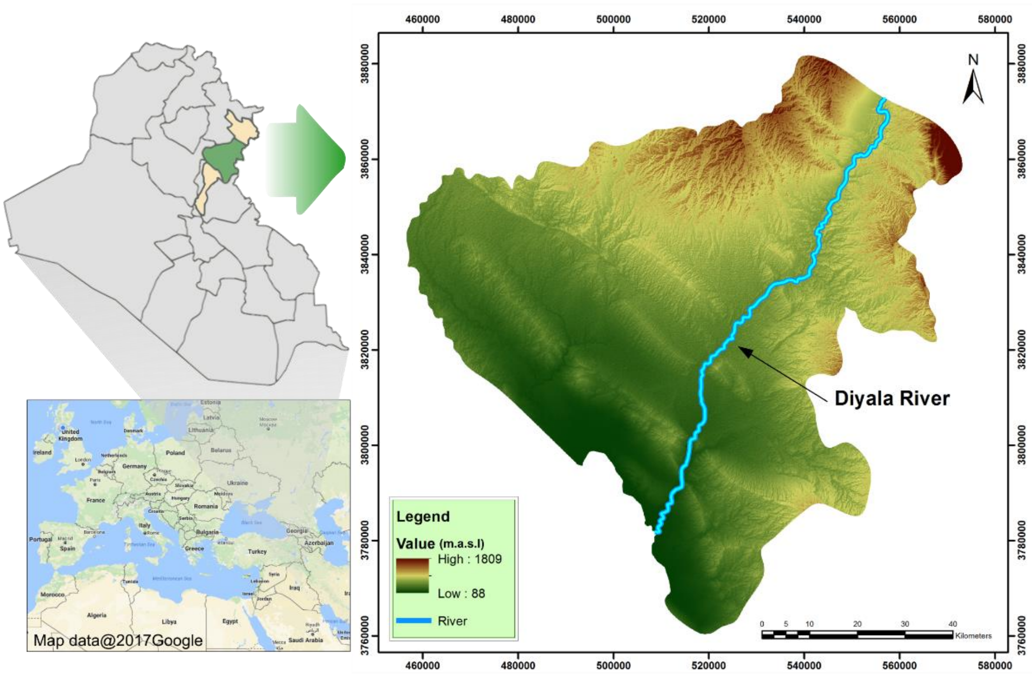


Figure 1. Location and topography of Diyala River Basin in Iraq (UTM coordinate system)

The area is located on a low-angle folded zone, which extends from the northeast foothill areas of Iraq (Jassim and Goff, 2006). The Tertiary sediments present range between middle-late Eocene, represented by Gercus formation, to late Pliocene represented by Bai-Hassan formation. The Quaternary sediments are of late Pliocene-Pleistocene age manifested by Bammu Conglomerate, and ending with Valley fill deposit of the Holocene. The stratification is illustrated in Figure 2a.

Groundwater generally flows from the north to the south of the basin, following the topographic surface elevation decline (Figure 1). The main units of hydrogeological significance with aquifer resource potential are the Mukdadiya, Bai-Hassan, and Quaternary deposits. The Quaternary deposits cover a wide portion of the study area with a thickness from 5 to 25 m. It is composed mainly of gravel, sand, and rock fragment. The Bai-Hassan and Mukdadiya formations are considered to be the two major aquifer of this region. The Bai-Hassan formation outcrops at different locations in the study area, while Mukdadiya appears at other parts of the area (Figure 2a). The Mukdadiya formation is composed of fining upward cycles of gravely sandstone, sandstone and mudstone, while Bai-Hassan is composed of conglomerates with beds of mudstone, siltstone and sandstone. Their thickness range from 500 to 1000 m (Jassim and Goff, 2006). These layers overlay Injana formation, which is composed mainly of sandstone, and claystone. The average hydraulic conductivity for both upper aquifers is 4.88 m/day (SGI et al., 2014). Groundwater quality as characterized by salinity varies; the total dissolved salts (TDS) ranged between 182 and 5500 mg/l for the upper aquifer (with c. 1000 mg/l being the brackish taste threshold. The estimated aquifer water storage is about 9×10^9 m^3, with storage coefficient for the upper and lower aquifer estimated at 3.5% and 0.14 %, respectively

(Al-Tamimi, 2007). The central part of Diyala river basin has many cities, villages, and farms. Since 1980s, about 1800 wells were drilled (SGI et al., 2014) in the area due to urban and rural development and associated regional water exploitation increase. Moreover, the government intends to develop and invest in six irrigation projects covering a total area of 647.4×10^6 m^2 (Soyuzgiprovodkhoz 1982, SGI *et al.* 2014). The average aquifer pumping discharge (Q_{Av}) within projects areas is about 778 m^3/day, which is calculated using spatial analysis in ArcGIS 10.2 depending on wells' discharges available in the historical database (SGI et al., 2014) (Figure 2b).

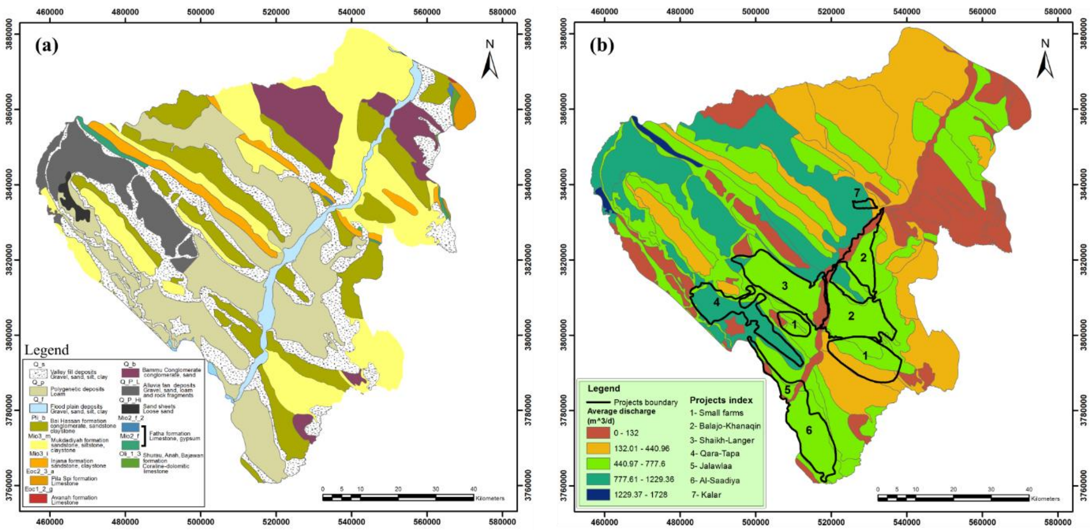


Figure 2. Geological and average aquifers discharge maps of the study area. (a) is the geological map (GEOSURV, 1993), while (b) is the average aquifers discharges map extracted from the historical wells logs dataset and ArcGIS spatial analysis (UTM coordinate system)

The annual design crop plan pattern exploits 100% of the arable land for winter crops, and 20% for summer crops. The project's water demands are based upon open furrow with an irrigation efficiency equal to 65%, hence 35% loss of the delivered water consisting of conveyance, evaporation, on farm allocation and infiltration losses. Sprinklers techniques have consistently high evaporative water losses due to the semi-arid environment (Soyuzgiprovodkhoz, 1982). Hence, drip irrigation was proposed in this study as an alternative technique to reduce water allocation losses. This has normal irrigation efficiency of about 90%, an efficiency of 85% was modelled as a conservative option. The total agricultural project's annual water demand is 567×10^6 m^3 (Soyuzgiprovodkhoz 1982; SGI et al. 2014). This is set within the context of thirty years' average meteorological data (precipitation and evapotranspiration) from 1981-2010 presented in Table 1 (SGI et al., 2014). The maximum field capacity according to SOGREAH (1983) in Al-Tamimi (2007), is equal to 115 mm, with the surface runoff being equal to 7% of the direct rainfall (Ahmad et al. 2005). The expected future gross total benefit is about 160 million USD per year. Hence, the decision makers will require a robust water resources management strategy to enable basin economic benefits to be realised without jeopardising the sustainability of the water resource.

Table 1. Average monthly meteorological data from 1981-2010 within the central part of Diayal river basin (mm) (SGI et al., 2014)

Month	**Rainfall** P_r	**Surface runoff** RO	**Reference Evapo-transpiration** ET_o	**Total water balance** $P_r - RO - ET_0$
October	14	0.98	131	-117.98
November	37	2.59	67	-32.59
December	46	3.22	38	4.78
January	61	4.27	36	20.73
February	44	3.08	48	-7.08
March	41.5	2.905	84	-45.41
April	33	2.31	122	-91.31
May	8	0.56	183	-175.56
June	0.5	0.035	229	-228.54
July	0	0	253	-253
August	0	0	234	-234
September	0	0	176	-176
Annual	*285*	*19.95*	*1600*	*-1334.95*

3 REGIONAL PROBLEM FORMULAE

3.1 Natural Recharge Identification

Generally, regional groundwater resources are from; the local rainfall recharge, and from the boundaries of the system: exchange with neighbouring aquifers and water bodies like river, lake, or even sea. The aquifer boundary recharges can be calculated using Darcy's law, as follows:

$$TR_0 = K.I.A_{Sec} \tag{1}$$

where TR_0 is the groundwater recharge across a boundary section area A_{Sec}, the aquifer permeability is K *is the aquifer hydraulic conductivity*, and I is the hydraulic (groundwater) gradient where $I = \Delta h/\Delta l$, with Δh being the difference between the water table head at the recharge and discharge zones of the specified aquifer, and Δl is the separation distance. These parameters can be calculated using MODFLOW-2005 and GIS techniques. A regional groundwater model had not previously been developed and hence a complete regional 3D MODFLOW-2005 model was built for recharge estimation, the details of which are presented in the *supplementary data S1*. The initial boundary head levels and wells parameters were extracted from wells log database and maps archive available in the Iraq's Ministry of Water Resources and SGI et al. (2014). The regional water balance in Table 1 shows scarcity in water recharges from the rainfall due to high evapotranspiration rates ($ET_o > P_r$), hence zero recharge from rainfall was considered for the simulation model (Jalut et al., 2018). Although minor recharges achieved in December and January (Table 1), zero recharge condition is dominated since these values less than soil maximum field capacity (115 mm). The simulation model achieved for static flow for parameter calibration. The model consists of four layers, the first two layers; Bai-Hassan and Mukdadiya formation since the two formations are composed of course sediments and are hydraulically connected. The last two layers represent the Injana aquifer system, which composed of alternation of clay and sand beds. The average thickness of the two system is 2000 m. The calibrated K value is about 2.67 m/day and 0.01 m/day for the upper and lower aquifers, respectively, while the upper aquifer boundary recharge (TR_0) is about 4.88×10^6 m^3/month.

3.2 Regional Management Model Identification

The regional water management strategy aims to fulfil the projects' water demands with sustainable groundwater exploitation, hence aquifer storage mining and infiltration losses should be also considered. Accordingly, decision variables, objectives, and constraints are developed for the optimization approach. Here, the decision variables (Nw_t) for the conceptual model are the numbers of monthly pumping wells to fulfil projects' monthly water demands over the operation period. Table 2 shows the adopted scenarios and operation periods (the number of decision variables) for the model.

Table 2. Alternative irrigation methods and operation periods

Methods of irrigation	**Operation periods (months) = Nw_t**				
Open furrows irrigation (scenario-1)	12	60	120	300	600
Drip irrigation (scenario- 2)	12	60	120	300	600

To evaluate management strategies for competing groundwater demands in the study area, the first objective is minimizing water deficit between projects' water demands (PD_t) and the total groundwater withdrawal (G_t) at time t with respect to maximum projects' demands (PD_{max}) over the entire considered period (T), which can be expressed by the following formula:

$$min\, f_{Del-GW} = \sum_{t=1}^{T} \left(\frac{PD_t - G_t}{PD_{max}}\right)^2 + C \quad (2)$$

$$G_t = Nw_t \times Q_{av} \quad , Nw_t = 1, 2, ..Nw_{max} \, , Nw_t \in \mathbb{N}^+ \quad (3)$$

where Nw_{max} is the design maximum wells' number, and C is a penalty factor that includes all models violations, which can be formulated as (Chang et al. 2010; Al-Jawad and Tanyimboh 2017):

$$C = A. \sum_{i=1}^{NC} g_i \, ; \;\; A \geq 1 \quad (4)$$

where A is a coefficient, NC is the number of constraint violation functions, and g_i represents constraint violations functions and their formulas' details are presented in Equations 12 to 15.

Usually A is found empirically, which depends on several replications of trials and error (Chang et al. 2010, Al-Jawad and Tanyimboh 2017). This value should be selected carefully to preserve suitable selection pressure to accelerate the algorithm convergence to the near-optimum solutions (Deb and Datta, 2013). Here, a value of $A = 10^4$ was selected to exploit all feasible solutions and avoid rendering infeasible solutions at the constraints threshold, especially those with small violation values.

The groundwater recharges at any time t (DP_t) occurs due to water infiltration from rainfall (P_t) or irrigation (IR_t), when soil moisture (SM_t) and the crop evapotranspiration (ET_t) requirements are fully satisfied. The general soil-water balance equation to calculate the infiltrating amount of water to groundwater in the time period t+1 can be expressed as:

$$SM_{t+1} = SM_t + P_t + IR_t - ET_t - RO_t - DP_t \qquad (5)$$

where SM_{t+1} is the soil moisture content at time t+1; and RO_t is the surface runoff at time t.

Regional future projection for rainfall was achieved by Abbas et al. (2016) using SWAT model (Soil and Water Associated Tool) and GCM (General Circulation Model) to predict climate change impacts for a half-century for the entire basin. The average annual rainfall reduction at the end of the half-century was about 21%, hence the monthly reduction will be 0.035%. The monthly aquifer rainfall at time t (P_t) can be estimated as:

$$P_t = P_r \times (1 - (0.035\%) \times t) \qquad , t = 1, 2, ..T \qquad (6)$$

When soil moisture content exceeds the maximum soil field capacity (*maxSM*), deep percolation occurs (Allen et al., 1998), hence the deep percolation, in case of $SM_{t+1} > maxSM$, can be found as follows:

$$DP_t = SM_{t+1} - maxSM \qquad (7)$$

The second objective is minimizing infiltration losses due to water allocation at time t (DP_t) with respect to maximum soil field capacity ($maxSM$) over the considered period of time (T), which can be expressed as:

$$min\, f_{WL} = \sum_{t=1}^{T} \left(\frac{DP_t}{maxSM}\right)^2 + C^2 \qquad (8)$$

Finally, minimizing the mining from static groundwater storage (S_{st}) in the aquifers during the extracting process at time t can be expressed as:

$$min\, f_{mining} = \sum_{t=1}^{T} \left(\frac{S_{st}}{S_{aq,t}} \right)^2 + C^2 \qquad (9)$$

where S_{aq} is the aquifer storage calculated from the water balance equation as:

$$S_{aq,t+1} = S_{aq,t} + TR_t - G_t \qquad (10)$$

where TR_t is the total water recharges to the aquifers at time *t*

Abbas et al. (2016) also estimates the average annual groundwater recharge depletion after a half-century for the entire basin about 35%, hence the monthly recharge reduction will be 0.058%. The monthly aquifer boundary recharge at time *t* (TR_t) can be estimated as:

$$TR_t = TR_0 \times (1 - (0.058\%) \times t) \qquad , t = 1, 2, ..T \qquad (11)$$

The groundwater management model has multiple operational and environmental constraints, which were illustrated in Table 3. The monthly groundwater pumping discharge (G_t) is equal or less than maximum projects' water demands. While, the monthly number of operated wells (Nw_t) should not exceed the maximum design number (Nw_{max}). Also, the monthly soil moisture content (SM_t) should be greater than 50% of maximum soil moisture content ($maxSM$) to avoid reaching wilting point, in which the plant will die, nor the value of ($maxSM$) to avoid water deep percolation.

Table 3. Groundwater management constraints in the central part of Diyala river basin

Parameter	**Limitations**
Pumping discharge (m^3/month $\times 10^6$)	$0 < G_t \leq 74.27$ (open furrow)
	$0 < G_t \leq 56.79$ (Drip)
Number of wells (per month)	$1 \leq Nw_t \leq 3183.0$
Soil moisture content (mm/month)	$57.5 \leq SM_t \leq 115.0$

From the above, the constraints functions g_i can be expressed as:

$$g_1 = \sum_{t=1}^{T} Max[0, (D_t - G_t)] \quad (12)$$

$$g_2 = \sum_{t=1}^{T} Max[0, (Nw_{max} - Nw_t)] \quad (13)$$

$$g_3 = \sum_{t=1}^{T} Max[0, (SM_t - 0.5 \times maxSM)] \quad (14)$$

$$g_4 = \sum_{t=1}^{T} Max[0, (maxSM - SM_t)] \quad (15)$$

4 MOEA METHOD IDENTIFICATION

The Multi-Objectives Evolutionary Algorithm (MOEA) was used to solve the optimization problem to minimize $\boldsymbol{F(x)} = (f_1(\boldsymbol{x}), \ldots, f_m(\boldsymbol{x}))^T$; subjected to: $\boldsymbol{x} \in \Omega$, Ω is the decision space and $\boldsymbol{x} \in \Omega$ is a decision vector. $\boldsymbol{F(x)}$ consists of m objective functions $f_i : \Omega \rightarrow R^m$, $i = 1, \ldots, m$, where R^m is the objective space.

The multi-objective optimisation problem needs a strategy to compare and select solutions, because there is more than one optimum solution in the decision variables space that dominates other solutions. Stadler (1979) define the Pareto-optimal dominance relation concepts, which is widely used to describe the dominance solutions (Miettinen 1999, Deb 2001). In a minimisation problem, a vector $\mathbf{u} = (u_1, \ldots, u_m)^T$ is said to dominate another vector $\mathbf{v} = (v_1, \ldots, v_m)^T$ if $u_i \leq v_i$ for $i = 1, \ldots, m$ and $u \neq v$. This can be defined as $\mathbf{u} \prec \mathbf{v}$. Also, a feasible solution $\mathbf{x} \in \Omega$ is called a Pareto-optimal solution, if there is no alternative solution $\mathbf{y} \in \Omega$ such that $\mathbf{F}(\mathbf{y}) \prec \mathbf{F}(\mathbf{x})$. Then, the Pareto-optimal set, *PS*, is the union of all Pareto-optimal solutions, and may be defined as: $PS = \{\mathbf{x} \in \Omega : \nexists \mathbf{y} \in \Omega, \mathbf{F(y)} \prec \mathbf{F(x)}\}$. The Pareto-optimal front (*PF*) is the set comprising the Pareto-optimal solutions in the objective space in a multi-objective optimisation problem, and is expressed as: $PF = \{\mathbf{F(x)} | \mathbf{x} \in PS\}$.

4.1 ε-DSEA

Recently, Al-Jawad and Tanyimboh (2018) presented the "Epsilon-Dominance-Driven Self-adaptive Evolutionary Algorithm" (ε-DSEA), with auto-adaptive recombination operators, ε-box resolution search space, and dominance archive to maintain Pareto-front set. The algorithm has novel methodology to improve the diversity and the convergence to an optimal solution. The diversity enhanced by implementing multiple operators produces new offspring after an initial random seeding of population. These operators are: simulated binary crossover (SBX) (Deb and Agrawal 1994), differential evolution (DE) (Storn and Price 1997), parent-centric crossover (PCX) (Deb et al. 2002), unimodal normal distribution crossover (UNDX) (Kita et al., 2000), simplex crossover (SPX) (Tsutsui et al. 1999), and uniform mutation (UM) (Michalewicz et al. 1994). Also, the polynomial mutation (PM) (Deb and Agrawal 1994) is applied to the offspring produced by all the operators except for UM.

Moreover, it has novel methodology to control parameters tuning over the evaluation process for the operators, through which operators' parameters connected with its performances to produce dominance solutions in the dominance archive. These parameters adjust dynamically within specified ranged depending on the number of dominance solutions produced by each operator.

4.2 Borg MOEA

Hadka and Reed (2013) presents Borg MOEA for many-objectives optimization problems which has many novel concepts to produce optimum solutions and overcome high-dimension complexity. It has dominance archive to maintain the non-dominated solutions to preserve diversity and convergence. Also, the search space is divided into hyper-boxes, which has dimensions equal to ε and represent the search resolution. Moreover, the algorithm has an improvement indicator for stagnation monitoring (ε-progress), which monitors the solutions in the dominance archive periodically to check stagnation on local optima. Hence, the algorithm adopts a restart mechanism to revive the search. Furthermore, it has multi recombination operators to generate new solutions, and adapt with the one who generates non-dominated solutions in the dominance archive. More details could be found in (Hadka and Reed 2013).

A competitive assessment for Borg MOEA in compare with other state-of-the-art evolutionary algorithms was utilized using multi-objectives problems, through which it outperforms or met these algorithms (Hadka and Reed 2012; Hadka et al. 2012; Hadka and Reed 2013; Woodruff et al. 2015; Zatarain Salazar et al. 2016).

The parameters and flowcharts used for both algorithms are illustrated in Table 4 and Figure 3, respectively. The red lines and boxes in ε-DSEA flowchart refer to the new methodology for diversity and parameter initializing during the evaluation process, and the reviving trigger in Borg MOEA.

Table 4. Parameter values used in the optimisation algorithms

Parameters	Borg	ε-DSEA[a]	Parameters	Borg	ε-DSEA
Initial population size	100	100	SPX parents	10	3
Tournament selection size	2	2	SPX offspring	2	2
SBX crossover rate	1.0	1.0	SPX expansion rate λ	3	[2.5, 3.5]
SBX distribution index η	15.0	[0, 100]	UNDX parents	10	10
DE crossover rate *CR*	0.1	[0.1, 1.0]	UNDX offspring	2	2
DE step size *F*	0.5	[0.5, 1.0]	UNDX σ_ζ	0.5	[0.4, 0.6]
PCX parents	10	10	UNDX σ_η	$0.35/\sqrt{L}$	$[0.1, 0.35]/\sqrt{L}$
PCX offspring	2	2	UM mutation rate	1/L	1/L
PCX σ_η	0.1	[0.1, 0.3]	PM mutation rate	1/L	1/L
PCX σ_ζ	0.1	[0.1, 0.3]	PM distribution index η_m	20	20

L is the number of decision variables. The permissible range for dynamic parameters is shown in brackets. The parameters σ_η and σ_ζ are defined in Section 2. [a]The initial values of dynamic parameters used in ε-DSEA are as shown for Borg MOEA.

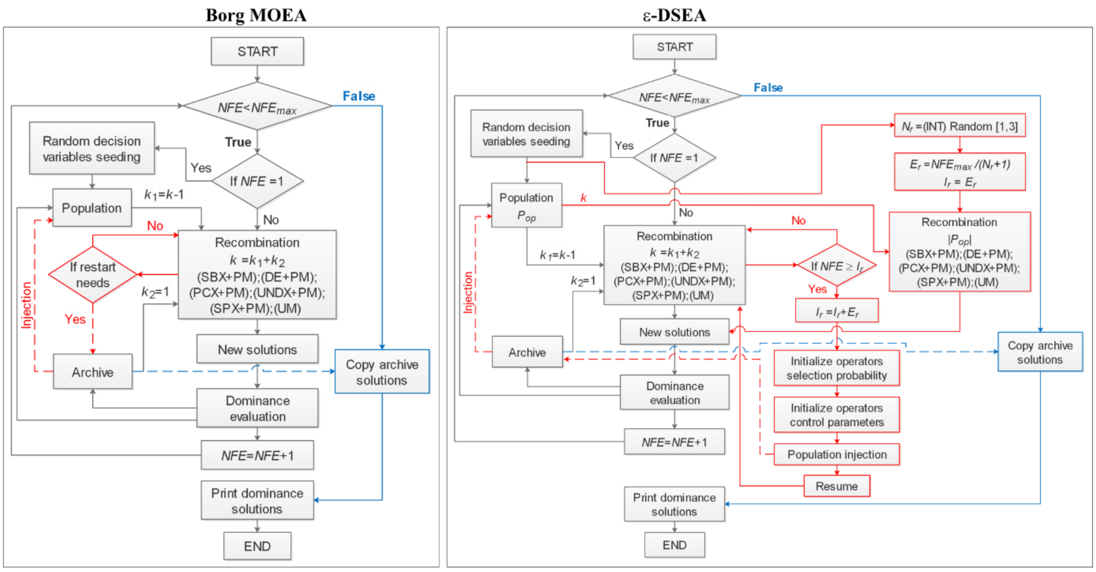


Figure 3. Overview of Borg MOEA and ε-DSEA flowcharts. k_1 and k_2 are the number of parents selected from the main population and dominance archive, respectively, while k is the total number of parents needed by adopted operator. *NFE* is the number of function evaluations with maximum value = NFE_{max}. E_r is the reset interval, and I_r is the number of function evaluations where the resetting occurs. The details are available in Hadka and Reed (2013) and Al-Jawad and Tanyimboh (2018).

4.3 Model Computational Implementation

A program was written in C language to represents Equations 2 to 15. Ten runs were executed for each case, using each of the two scenarios, hence the total runs were 200 for the entire scenarios and periods using a desktop PC with Ubuntu 16.04 OS (Core i7-6700 CPU @ 3.4 GHz, 16 GB RAM). The ε values, which is the hyper-box dimension, which represent the resolution of the objective function search space, ranged between 0.001 and 0.5 for Equations 1, 0.01 to 0.5 for Equation 2, and from 0.001 to 0.1 for Equation 3. While, the number of function evaluations ranged between 0.5×10^6 to 1.2×10^6 in both scenarios.

5 RESULTS AND DISCUSSION

5.1 Evolutionary Algorithms Performance Assessment

5.1.1 *Reliability and effectiveness*

Both optimization algorithms were utilized to generate optimum solutions for the groundwater regional management. The algorithms objectives functions' best median achievement summary for all alternatives are presented in Table 5. The best achievement are highlighted in bold, which clearly shows the ε-DSEA out performs the Borg MOEA in most alternatives (as a result of ε-DSEA reliability to generate optimum solutions over execution replication). Both results show excessive groundwater mining of the estimated aquifer storage (9.0×10^9 m^3) after forty years, hence the fifty years' alternative (600 months) is not presented. Detail results are available in the *supplementary data Table A1 and A5*.

Table 5. Median summary's best achievement for both algorithms under two irrigation alternative scenarios. The superior results in Bold style (smallest values for minimum and largest values for maximum).

		Borg MOEA				**ε-DSEA**			
Months		***12***	***60***	***120***	***300***	***12***	***60***	***120***	***300***
Min. $f_{Del\text{-}GW}$	**Scenario-1**	**0.005**	**0.916**	2.952	10.183	0.006	1.057	**2.490**	**7.988**
Max. $f_{Del\text{-}GW}$		1.192	5.362	7.599	15.988	**1.244**	**6.248**	**9.371**	**18.922**
Min. f_{WL}		0.274	2.05	6.387	19.934	**0.161**	**1.476**	**4.329**	**12.839**
Max. f_{WL}		**7.547**	**11.606**	18.121	34.877	7.426	10.758	**18.420**	**37.521**
Min. f_{mining}		12.145	65.077	143.648	544.399	**12.142**	**65.05**	**143.169**	**528.478**
Max. f_{mining}		12.257	67.656	153.438	649.679	**12.256**	**67.973**	**158.254**	**765.451**
Min. $f_{Del\text{-}GW}$	**Scenario-2**	**0.002**	**0.348**	0.889	3.241	0.003	0.436	**0.729**	**2.453**
Max. $f_{Del\text{-}GW}$		0.528	**3.668**	3.997	6.837	**0.531**	3.159	**4.040**	**8.063**
Min. f_{WL}		0.149	1.067	3.758	12.311	**0.146**	**1.074**	**3.430**	**9.864**
Max. f_{WL}		2.066	**4.481**	**8.079**	16.522	**2.149**	4.006	8.053	**17.027**
Min. f_{mining}		12.121	**64.599**	141.408	516.02	**12.120**	64.607	**141.288**	**506.564**
Max. f_{mining}		**12.200**	66.233	148.191	571.196	**12.200**	**66.730**	**149.655**	**601.931**

The median range solutions were selected and presented in Figure 4 to illustrate the Pareto-front optimality achieved for two irrigation scenarios using both optimization algorithms. The ε-DSEA outperforms the Borg MOEA in almost all cases.

The Pareto-fronts achieved by ε-DSEA are wider than those for Borg MOEA especially when decision variables evolve (e.g. 120 and 300 for ten the twenty five years alternatives, respectively) for both scenarios. This reflects algorithm's effectiveness to generate wider Pareto-front in the objective search space.

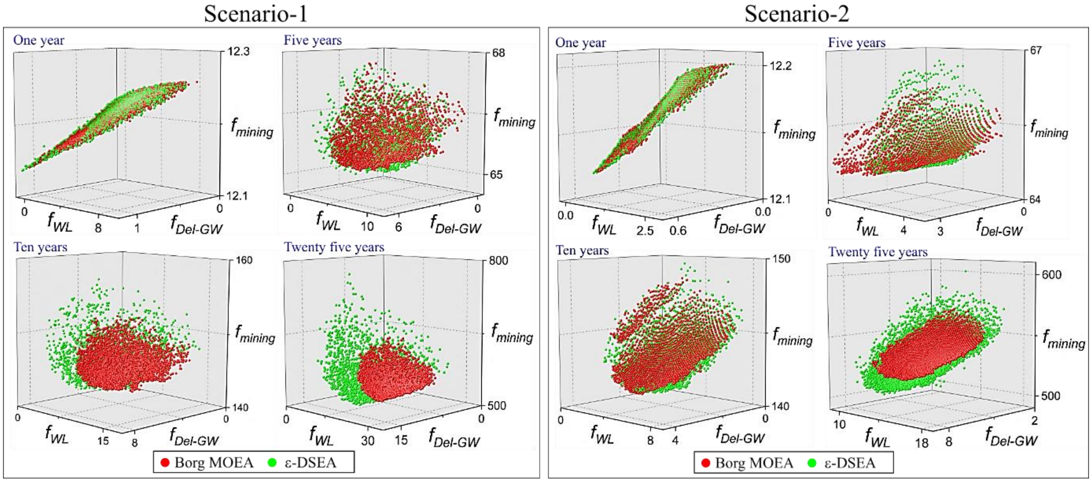


Figure 4. Optimum solution Pareto-front for both irrigation alternative scenarios using Borg MOEA and ε-DSEA algorithms. f_{Del-GW} , f_{WL}, and f_{mining} refer to groundwater delivery, water losses, and mining objectives functions, respectively

5.1.2 Robustness

Figure 5 illustrates the auto-adapted and the self-adaptive mechanism for Borg MOEA and ε-DSEA in all alternatives. Borg MOEA adapted with PCX recombination operator in all periods in both scenarios. Hadka et al. (2012) observed the behaviour and mechanism of Borg MOEA to adapt with one operator after certain evaluation process. This phenomena was also observed and discussed by Zheng et al. (2016). When Borg MOEA adapted with PCX operator, the new offspring generated in the vicinity and around the selected parents, which may cause the stagnation of the algorithm.

Conversely, ε-DSEA is adapted with both PCX and SPX operators in parallel to generate optimum solutions. The resetting methodology in ε-DSEA succeeds in changing the operators' adaptation to escape from local optima which remains clear in all operation periods. In scenario-1, the ε-DSEA was initially adapted with SBX operator during the first year of operation, then adapted with PCX and SPX operators after the first resetting triggered.

The same behaviour was observed for the other cases, but with involvement of the PCX operator with the SPX. For scenario-2, ε-DSEA adapted with SBX operators for one and five years, and with PCX and SPX operators for ten and twenty-five years. This shows the robustness of the ε-DSEA methodologies to adapt rapidly with different environment problems and escape from local optima.

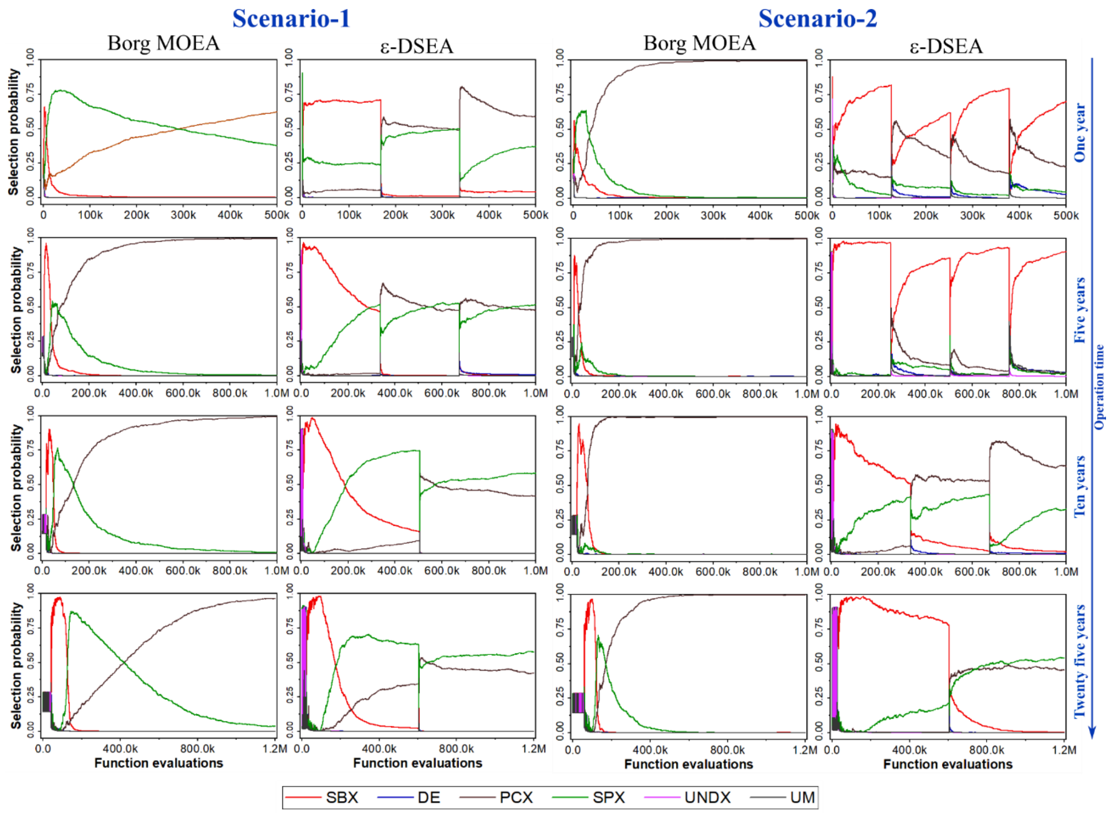


Figure 5. Operators' selection probability comparison between both algorithms for four adopted operating periods under selected irrigation alternatives scenarios. All x-axis represents number of function evaluation, and all y-axis are operator's selection probability.

The robustness of the parameters self-adaptive methodology of ε-DSEA is apparent in Table 6, which illustrates the median evolve operators' parameters achieved for the median optimum solutions for all alternatives. Almost all parameters adopt different values than their initial setting, to adapt with problem environment; this fails to be the case for the Borg MOEA. Hence ε-DSEA eliminates parameter tuning exploration time in finding suitable values applicable to the problem environment and produce best optimum solutions (Maier et al., 2014). Details summary for parameters achievement for all alternatives are presented in the *supplementary data Table A4 and A8.*

Table 6. Median evolve operators' parameters achieved by ε-DSEA for the median solutions for all alternatives

	Operator	**Parameter**	**Initial value**	**Operation periods (years)**			
				1	**5**	**10**	**25**
Open furrows system	SBX	η	15.0	69	75	65	82
	DE	*CR*	0.1	0.1	0.1	0.222	0.125
		F	0.5	0.503	0.507	0.611	0.563
	PCX	$\sigma_\eta, \sigma_\zeta$	0.1	0.218	0.202	0.192	0.189
	SPX	λ	3.0	2.867	2.979	3.076	3.066
	UNDX	σ_ζ	0.5	0.401	0.408	0.432	0.557
		σ_η	0.35	0.101	0.113	0.153	0.361
Drip system	SBX	η	15.0	67	88	65	87
	DE	*CR*	0.1	0.1	0.1	0.1	0.444
		F	0.5	0.529	0.523	0.507	0.722
	PCX	$\sigma_\eta, \sigma_\zeta$	0.1	0.165	0.122	0.228	0.193
	SPX	λ	3.0	2.58	2.567	2.834	3.003
	UNDX	σ_ζ	0.5	0.402	0.402	0.413	0.55
		σ_η	0.35	0.103	0.103	0.121	0.35

Table 7 shows the gross parameter performance to generate optimum solutions. The results shows that ε-DSEA generates more optimum solutions in the archive with

2.45×10^5, in comparison with 1.94×10^5 for the Borg MOEA. Conversely, the number of improvements (which refers to the number of new dominance solutions generated in new hyper-box) registered in the Borg MOEA is larger than for the ε-DSEA in both scenarios. The total number of improvement is equal to 2.79×10^6 and 1.38×10^6 using 2202 and 9427 restart triggers compared to 2.48×10^6 and 1.02×10^6 in ε-DSEA with only 120 and 116 trigger for restart respectively, which is randomly trigged. However, ε-DSEA generates more, and better, optimality solutions in all cases depending on the methodology for parameter tuning and diversity employed.

As a result, the Borg MOEA improvement index did not reflect the real algorithm's performance to generate new dominance solution toward possible optimum front. This may be due to the large number of restarts in the Borg MOEA, with essentially the same solutions being counted repeatedly. However, the total computational time (CPU time) needed for function evaluations used in ε-DSEA is less than Borg MOEA. The total CPU time in ε-DSEA is about 2.1 and 1.8 hours compared to 3.1 and 3.0 hours in Borg MOEA. Hence the computational methodology of ε-DSEA is more efficient. Detail performance parameters achievement are presented in the *supplementary data Tables A2, A3, A6, and A7*.

Table 7. Gross performance parameters for both algorithms under two alternatives irrigation scenarios

	Borg MOEA		**ε-DSEA**	
	Scenario-1	**Scenario-2**	**Scenario-1**	**Scenario-2**
Archive size	1.94×10^5	0.68×10^5	$\mathbf{2.45\times10^5}$	$\mathbf{0.8\times10^5}$
Improvement	$\mathbf{2.79\times10^6}$	$\mathbf{1.38\times10^6}$	2.48×10^6	1.02×10^6
Restart	2202	9427	**120**	**116**
CPU time (hr)	3.1	3.0	**2.1**	**1.8**

5.1.3 Efficiency

The decision variables vector (X_{dv}) development occurring during the evaluation process is presented in Figure 6 for all alternatives. The X_{dv} is equal to $\sqrt{x_1^2 + x_2^2 + x_3^2 + \cdots + x_n^2}$, where x_1 to x_n are the decision variables. A smoothed averaged vector of X_{dv} for each generation (100 function evaluation) was also generated to ascertain decision variables convergence and development during the evaluation process. Early stage convergence for both algorithms is observed with outperform of ε-DSEA on Borg MOEA in ten and twenty-five years operation time for both scenarios. The ε-DSEA self-adaptive mechanism effectiveness can be observed during the evaluation process to generate dominance solutions by changing the X_{dv} values when resetting process activated, (e.g., at ten and twenty-five years operation time in scenario-2).

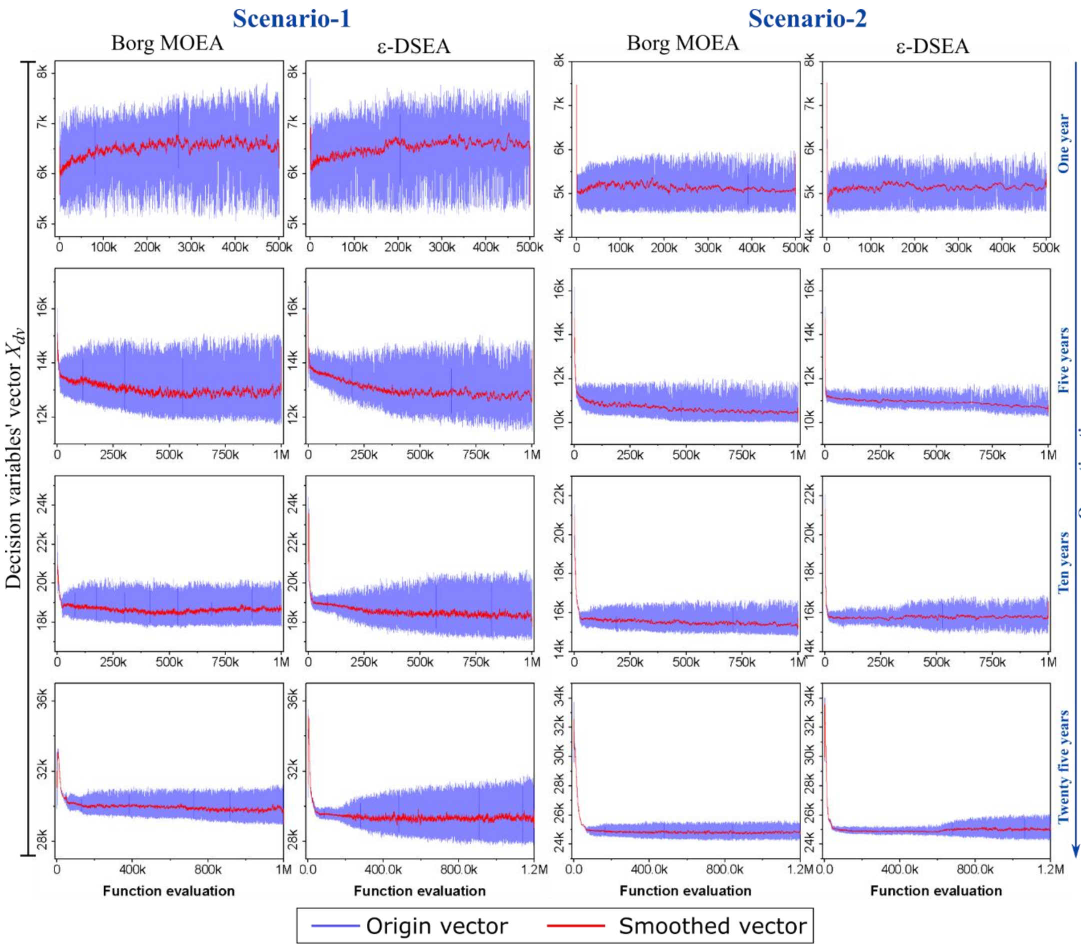


Figure 6. Decision variables development comparison between both algorithms for four adopted operating periods under selected irrigation alternatives scenarios. All x-axis represents number of function evaluation, and all y-axis are the decision variables' vectors (X_{dv}).

In ten years, the X_{dv} value trend changed twice during the function evaluation process by the resetting trigger (at 35×10^4 and 70×10^4 of function evaluation, Figure 5), which also occurs for twenty-five years at 50×10^4 function evaluation. This emerge the powerful of adapting two recombination operators in parallel to generate dominance solutions, in compare with Borg MOEA mechanism which adapt with only one operator.

5.2 Groundwater Optimum Management

The evolutionary algorithms performance assessment shows more robust performance of the ε-DSEA when compared to the Borg MOEA in nearly all alternatives. Its results are hence adopted to evaluate likely groundwater management options. Figure 7 presents a monthly summary of operating wells (the decision variables) and the deficit in water farms delivery for both scenarios. The average optimum number of wells used in open furrow system ranged from 1100 to 2000 for one year of pumping compared to 1300 to 1600 for other pumping periods. However, the drip system achievements were 1000 to 1500 for one year pumping and 1000 to 1300 for other pumping periods. Furthermore, the median values were about 1400 in drip system for all periods, while the range was from 1500 to 1850 in the open furrows system. Generally, the drip system results show less deficit in water delivery to the farms. The average value for the drip system was 15×10^6 m^3/month, and it ranged from 15×10^6 to 20×10^6 m^3/month for open furrows system.

The effect of water exploitation on groundwater storage is illustrated in Figure 8, which shows the final lowest storage achieved for different pumping periods for both water delivery alternatives. Groundwater storage depletion is obvious for medium and long-term pumping, while drip system mitigates the impact on aquifer storage. For one year pumping, the depletion was 4%, while for five and ten years pumping was about 12%, and 25% respectively, for both irrigation system alternatives. Details are illustrated in the *supplementary data Figure A4*.

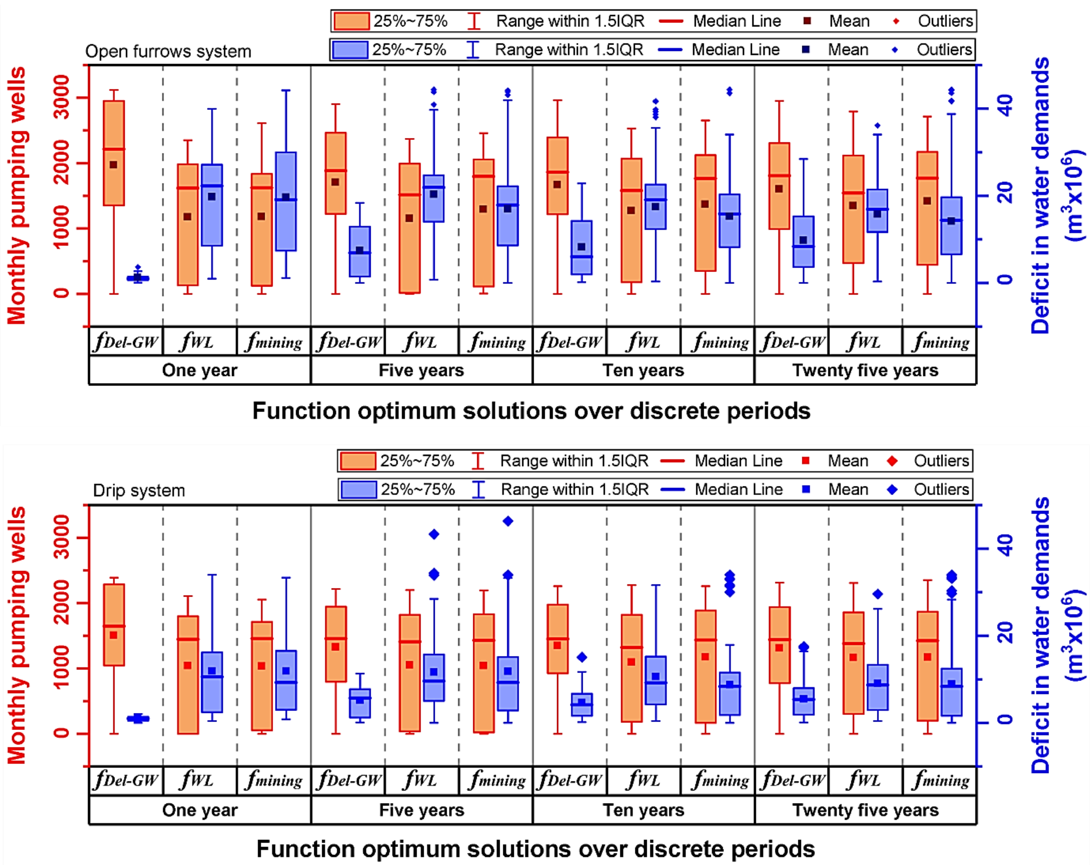


Figure 7. Number of wells and deficit in water demands achieved for both scenarios for discrete periods using optimization model. f_{Del-GW} , f_{WL}, and f_{mining} refer to groundwater delivery, water losses, and storage mining objective functions, respectively

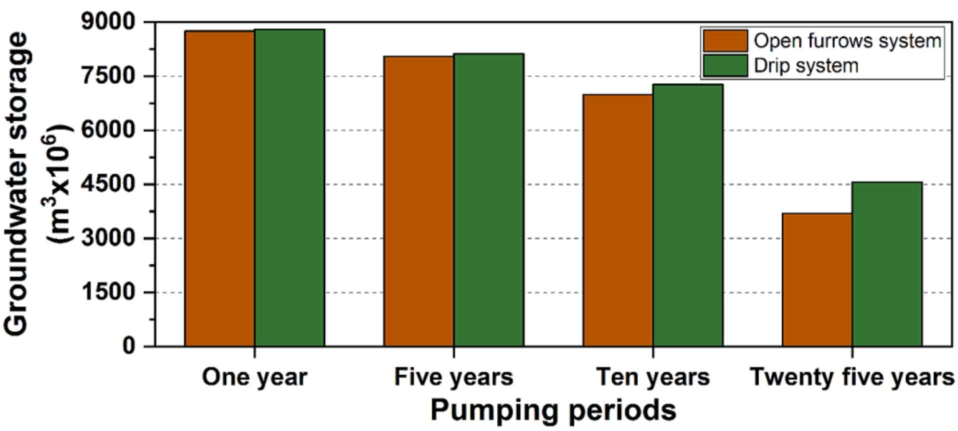


Figure 8. Final groundwater storage achieved by optimization model for open furrows and drip irrigation system over the adopted discrete periods

The final storage depletions were 61% and 55% for open furrows and drip system for twenty-five years pumping, respectively. All alternatives show unsustainability in groundwater storage management due to scarcity in aquifers' water recharges as shown in Table 8, which illustrates the pumping discharge and aquifer recharge summary for the best objectives functions' achievement.

The results show significant differences between the groundwater exploitation and the aquifer recharges over the adopted pumping scenarios. The depletion in the recharges ranged between 50% to 80% for mean values, and between 60% to 100% for the median values, in comparison with the pumping discharges.

Table 8. Summery of pumping discharges and aquifer recharges for the optimum solution achieved by each objective function over considered periods using open furrows and drip irrigation system (m^3/month×10^6).

	Operating periods (years)		f_{Del-GW}	f_{WL}	f_{mining}	f_{Del-GW}	f_{WL}	f_{mining}
				Mean			**Median**	
Open furrows system	One	Pumping discharge	45.95	27.48	27.56	51.67	37.78	37.96
	Five		39.81	26.93	30.24	44.00	35.44	42.00
	Ten		38.97	29.75	31.94	43.51	36.87	41.15
	Twenty five		37.43	31.44	33.06	42.22	35.99	41.32
	One	groundwater recharge	18.31	3.34	3.99	16.46	0.00	0.00
	Five		18.20	5.42	11.62	8.08	0.00	2.11
	Ten		17.91	7.60	13.26	7.78	0.00	2.46
	Twenty five		16.15	8.79	14.06	7.79	1.17	3.88
Drip system	One	Pumping discharge	35.12	24.24	24.20	38.45	33.73	33.95
	Five		30.94	24.46	24.28	34.02	32.89	33.40
	Ten		31.49	25.56	27.39	33.88	30.79	33.46
	Twenty five		30.61	27.11	27.26	33.63	32.23	33.24
	One	groundwater recharge	11.63	3.14	3.32	6.80	0.00	0.00
	Five		11.36	4.21	6.79	5.02	0.00	0.00
	Ten		11.91	5.85	9.80	5.11	0.00	1.23
	Twenty five		10.88	7.81	9.24	5.04	0.99	1.43

f_{Del-GW} , f_{WL}, and f_{mining} refer to groundwater delivery, water losses, and storage mining objective functions, respectively

The results show unsustainable regional groundwater resource for all alternatives due to the projects' high water demands and aquifers' recharge scarcity in the semi-arid environment. Hence, other alternatives may seek to reduce water demands by either reducing the areas irrigated or changing to less water demanding crop types.

A sustainable groundwater management resource budget is forward modelled for the next half-century considering these. Sustainability is may achieved when the projects' water demands are reduced by 45% as a minimum for both irrigation alternatives (Figure 9). The use of an open furrows system maintains aquifer storage for about twenty-five years compared to the drip system of about thirty-three years. The average final storage depletions in both alternatives is about 22% and 16%, respectively. Hence, using drip irrigation system in this region is beneficial for longer and may represent a more sustainable groundwater management.

Based on the results of this modelling, the decision makers (the Iraqi's government) should consider a future policy to reduce projects' water demands in this region. In addition, other alternatives are required including; conjunctive use with surface water, aquifer storage and recovery (ASR) initiatives, as well as the rehabilitation of leaky water conveyance infrastructure.

The results provide a prediction of future groundwater management alternatives for decision makers to consider within future policies for strategic sustainable water resources management for the investigated study area with potential for wider implementation in other regions with comparable scenarios.

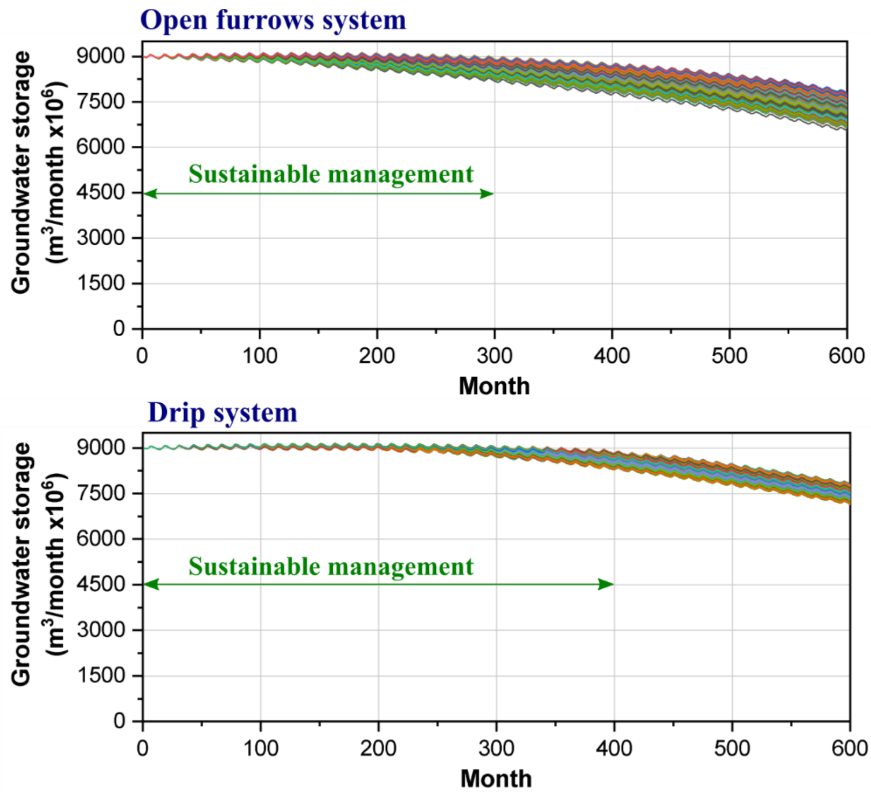


Figure 9. Illustrates the sustainable groundwater management periods achieved for 50 years for both irrigation systems using ε-DSEA

6 CONCLUSIONS AND RECOMMENDATIONS

Multi-Objectives Evolutionary Algorithms (MOEAs) behaviour and performance may vary according to problem formulation and environment and evolutionary parameters needs to be tuned to adapt to the problem at hand. A performance assessment (reliability, robustness, efficiency, effectiveness) comparing MOEAs attainment application with respect to a real-world problem was successfully. The auto-adaptive Borg MOEA (Hadka and Reed, 2013) and the self-adaptive ε-DSEA (Epsilon-Dominance-Driven Self-Adaptive Evolutionary Algorithm) (Al-Jawad and Tanyimboh 2018) were intensively evaluated using many parameters within the context of a rigorous evaluation of a potentially pressing regional groundwater sustainable management problem in the Middle East. The optimization problem was formulated for long-term farm irrigation with three objective function for five discrete periods with up to 600 decision variables using two water delivery alternatives. The study utilized a developed and calibrated groundwater simulation model built in MODFLOW-2005 GMS software (Groundwater Modelling System). Both algorithms were executed ten random seeding for each alternative leading to the following conclusions:

- *Evolutionary algorithms performance assessment:* the ε-DSEA provided more robust results when compared to the Borg MOEA for almost all alternatives. The ε-DSEA approaches' main advantage over the Borg MOEA is reliability, it repeatedly produced optimum solutions over computational budget replication. The Pareto-front extent wider and has better optimality in the objective search space, which emerge the effectiveness of ε-DSEA. Its robustness is evident, adapting with different problem environment using dynamic evolve parameters during the evaluation process. New parameters domain was produced for the commonly used recombination operators, which can be beneficial for comparative water resources problems. Other parameters like number of optimum solutions, restart replication, and CPU time also show the superiority of ε-DSEA on Borg MOEA in all alternatives. The decision variables convergence and development was competitive and superior especially for long-term operation, which emerge ε-DSEA efficiency outperformance. The mechanism of auto-adaptive in Borg MOEA may cause stagnation in local optima and injection repetition may regenerate solutions nearby local optima. Although ε-DSEA outperformance Borg MOEA in almost all alternates, further analysis and assessment may consider for other real-word problems with higher complexity.

- *Groundwater Management achievement:* Although both algorithms results demonstrate unsustainability in groundwater resource management for both irrigation systems, the computational results illustrate results from the ε-DSEA were more robust. Hence, the ε-DSEA results should be used to consider groundwater resource management for the case study area. The storage depletion was 25% for ten years' water exploitation, which increase to about 60% for twenty-five years. The aquifer storage was completely exhausted after forty years in both alternatives due to low aquifer recharge, which caused by low rainfall and high evapotranspiration rates (semi-arid zone). The introduction of drip irrigation mitigates the impact on the aquifer storage over the discrete periods, especially for long-term water exploitation. The probability of sustainable groundwater resource management was scenario modelled for the next half-century by reducing water delivery demands. The results show possible sustainable storage budget using open furrows system can be achieved for the next twenty-five years, and thirty-three years for drip system with 45% demand's yield for both. Hence, the decision makers (the Iraqi government) should consider future policy to reduce water demands by either changing crops types, or reducing farms areas. Also, the use of drip system for water allocation should be considered in the policy since it has less impacts on groundwater yields. However, crop yield and productivity should consider over the alternatives. Conjunctive use with surface water and water harvesting may consider also to mitigate groundwater depletion and maintain its sustainability.

REFERENCES

Abbas, N., Wasimi, S.A., Al-Ansari, N., 2016. Impacts of Climate Change on Water Resources in Diyala River Basin, Iraq. J. Civ. Eng. Archit. 10, 1059–1074.

Abdulrahman, S.A., 2017. Failure to securitise environmental problems in Iraq: the case of the Alwand and Sirwan Rivers. Int. J. Environ. Stud. 74, 540–557. https://doi.org/10.1080/00207233.2017.1330493

Ahmad, A.M., Abdul Razak, M.I., Dawood, K.S., 2005. Hydrogeological study of upper Diyala River Basin. Technical Report (in Arabic). The General Directorate for Water Resources Management, Ministry of Water Resources, Government of Iraq.

Al-Faraj, F.A.M., Scholz, M., 2014. Assessment of temporal hydrologic anomalies coupled with drought impact for a transboundary river flow regime: The Diyala watershed case study. J. Hydrol. 517, 64–73. https://doi.org/10.1016/j.jhydrol.2014.05.021

Al-Jawad, J.Y., Tanyimboh, T.T., 2017. Reservoir operation using a robust evolutionary optimization algorithm. J. Environ. Manage. 197, 275–286. https://doi.org/10.1016/j.jenvman.2017.03.081

Al-khaldy, M.A.T., Al-askari, A.J.H., 2015. Analysis of Physical characteristics of Fluvial Deposits in the Diyala Middle Basin (in Arabic). J. Res. Diyala Humanit. 1–24.

Al-Tamimi, O.S., 2007. Water resources evaluation in Diyala River basin – Middle part. PhD Thesis (in Arabic). College of Science,University of Baghdad, Iraq.

Allen, R.G., Pereira, L.S., Raes, D., Smith, M., 1998. Crop evapotranspiration - Guidelines for computing crop water requirements. FAO Irrigation and drainage paper 56.

Chang, L.C., Chang, F.J., Wang, K.W., Dai, S.Y., 2010. Constrained genetic algorithms for optimizing multi-use reservoir operation. J. Hydrol. 390, 66–74. https://doi.org/10.1016/j.jhydrol.2010.06.031

Coello, C.A.C., Lamont, G.L., van Veldhuizen, D.A., 2007. Evolutionary Algorithms for Solving Multi-Objective Problems, 2nd ed, Genetic and Evolutionary Computation. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-0-387-36797-2

Deb, K., 2001. Multi-Objective Optimization using Evolutionary Algorithms, 1st ed, Wiley-Interscience Series in Systems and Optimization. John Wiley & Sons, Chichester.

Deb, K., Agrawal, R.B., 1994. Simulated Binary Crossover for Continuous Search Space, Complex Systems. https://doi.org/10.1.1.26.8485Cached

Deb, K., Datta, R., 2013. A bi-objective constrained optimization algorithm using a hybrid evolutionary and penalty function approach. Eng. Optim. 45, 503–527. https://doi.org/10.1080/0305215X.2012.685074

Deb, K., Joshi, D., Anand, A., 2002. Real-coded evolutionary algorithms with parent-centric recombination. Proc. 2002 Congr. Evol. Comput. CEC 2002 1, 61–66. https://doi.org/10.1109/CEC.2002.1006210

GEOSURV, (State Company of Geological Survey and Mining), 1993. Geological maps of Iraq. Series of geological maps of Iraq, Ministry of Industry and Minerals, Baghdad, Iraq.

Hadka, D., Reed, P., 2013. Borg: An Auto-Adaptive Many-Objective Evolutionary Computing Framework. Evol. Comput. 21, 1–30.

https://doi.org/10.1162/EVCO_a_00075

Hadka, D., Reed, P., 2012. Diagnostic Assessment of Search Controls and Failure Modes in Many-Objective Evolutionary Optimization. Evol. Comput. 20, 423–452. https://doi.org/10.1162/EVCO_a_00053

Hadka, D., Reed, P.M., Simpson, T.W., 2012. Diagnostic assessment of the borg MOEA for many-objective product family design problems, in: 2012 IEEE Congress on Evolutionary Computation, CEC 2012. pp. 10–15. https://doi.org/10.1109/CEC.2012.6256466

Harbaugh, A., McDonald, M., 1996. User's documentation for MODFLOW-96, an update to the U.S. Geological Survey modular finite-difference groundwater flow model. Open file report 96–485,U.S. Geological Survey.

Harbaugh, A.W., 2005. MODFLOW-2005, The U.S. Geological Survey Modular Ground-Water Model—the Ground-Water Flow Process. U.S. Geological Survey Techniques and Methods 6-A16.

Holland, J.H., 1975. Adaptation in natural and artificial systems : an introductory analysis with applications to biology, control, and artificial intelligence. University of Michigan Press, Ann Arbor.

Horne, A., Szemis, J.M., Kaur, S., Webb, J.A., Stewardson, M.J., Costa, A., Boland, N., 2016. Optimization tools for environmental water decisions: A review of strengths, weaknesses, and opportunities to improve adoption. Environ. Model. Softw. 84, 326–338. https://doi.org/10.1016/j.envsoft.2016.06.028

Ishibuchi, H., Akedo, N., Nojima, Y., 2015. Behavior of Multiobjective Evolutionary Algorithms on Many-Objective Knapsack Problems. IEEE Trans. Evol. Comput. 19, 264–283. https://doi.org/10.1109/TEVC.2014.2315442

Ishibuchi, H., Setoguchi, Y., Masuda, H., Nojima, Y., 2017. Performance of Decomposition-Based Many-Objective Algorithms Strongly Depends on Pareto Front Shapes. IEEE Trans. Evol. Comput. 21, 169–190. https://doi.org/10.1109/TEVC.2016.2587749

Jalut, Q.H., Abbas, N.L., Mohammad, A.T., 2018. Management of groundwater resources in the Al-Mansourieh zone in the Diyala River Basin in Eastern Iraq. Groundw. Sustain. Dev. 6, 79–86. https://doi.org/10.1016/j.gsd.2017.11.004

Jassim, S.Z., Goff, J.C., 2006. Geology of Iraq, First. ed. , Dolin, Prague and Moravian Museum, Brno, Czech Republic.

Javadi, A., Hussain, M., Sherif, M., Farmani, R., 2015. Multi-objective Optimization of Different Management Scenarios to Control Seawater Intrusion in Coastal Aquifers. Water Resour. Manag. 29, 1843–1857. https://doi.org/10.1007/s11269-015-0914-1

Karafotias, G., Hoogendoorn, M., Eiben, A.E., 2015. Parameter Control in Evolutionary Algorithms: Trends and Challenges. IEEE Trans. Evol. Comput. 19, 167–187. https://doi.org/10.1109/TEVC.2014.2308294

Kita, H., Ono, I., Kobayashi, S., 2000. Multi-Parental Extension of the Unimodal Normal Distribution Crossover for Real-Coded Genetic Algorithms. Trans. Soc. Instrum. Control Eng. 36, 875–883. https://doi.org/10.9746/sicetr1965.36.875

Maier, H.R., Kapelan, Z., Kasprzyk, J., Kollat, J., Matott, L.S., Cunha, M.C., Dandy, G.C., Gibbs, M.S., Keedwell, E., Marchi, A., Ostfeld, A., Savic, D., Solomatine, D.P., Vrugt, J.A., Zecchin, A.C., Minsker, B.S., Barbour, E.J., Kuczera, G., Pasha, F., Castelletti, A., Giuliani, M., Reed, P.M., 2014. Evolutionary algorithms and other metaheuristics in water resources: Current status, research challenges and future directions. Environ. Model. Softw. 62, 271–299. https://doi.org/10.1016/j.envsoft.2014.09.013

Marchi, A., Dandy, G., Wilkins, A., Rohrlach, H., 2014. Methodology for Comparing Evolutionary Algorithms for Optimization of Water Distribution Systems. J. Water Resour. Plan. Manag. 140, 22–31. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000321

Michalewicz, Z., Logan, T., Swaminathan, S., 1994. Evolutionary operators for continuous convex parameter spaces. Proc. 3rd Annu. Conf. Evol. Program. 84–97.

Miettinen, K., 1999. Nonlinear multiobjective optimization. Boston : Kluwer Academic Publishers.

Nicklow, J., Reed, P., Savic, D., Dessalegne, T., Harrell, L., Chan-Hilton, A., Karamouz, M., Minsker, B., Ostfeld, A., Singh, A., Zechman, E., 2010. State of the art for genetic algorithms and beyond in water resources planning and management. J. Water Resour. Plann. Manag. 136, 412–432.

Oxley, R.L., Mays, L.W., 2016. Application of an Optimization Model for the Sustainable Water Resource Management of River Basins. Water Resour. Manag. 30, 4883–4898. https://doi.org/10.1007/s11269-016-1459-7

Qi, W., Michele, G., Dragan, S., Zoran, K., 2015. Two-Objective Design of Benchmark Problems of a Water Distribution System via MOEAs: Towards the Best-Known Approximation of the True Pareto Front. J. Water Resour. Plan. Manag. 141, 4014060. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000460

Reed, P.M., Hadka, D., Herman, J.D., Kasprzyk, J.R., Kollat, J.B., 2013. Evolutionary multiobjective optimization in water resources: The past, present, and future.

Adv. Water Resour. 51, 438–456. https://doi.org/10.1016/j.advwatres.2012.01.005

Sadeghi-Tabas, S., Zahra Samadi, S., Akbarpour, A., Pourreza-Bilondi, M., 2017. Sustainable groundwater modeling using single- and multi-objective optimization algorithms. J. Hydroinformatics 19, 97–114.

Salazar, J.Z., Reed, P.M., Herman, J.D., Giuliani, M., Castelletti, A., 2016. A diagnostic assessment of evolutionary algorithms for multi-objective surface water reservoir control. Adv. Water Resour. 92, 172–185. https://doi.org/10.1016/j.advwatres.2016.04.006

Schaffer, J.D., 1985. Multiple objective optimization with vector evaluated genetic algorithms, in: The 1st International Conference on Genetic Algorithms. pp. 93–100.

SGI, (Studio Galli Ingegneria S.p.A.), MED, (INGEGNERIA S.r.l.), EL CONCORDE, (Construction LLC), 2014. The Strategic Study for Water and Land Resources in Iraq. Technical Study (unpublished), Accomplished for the General Directorate for Water Resources Management, Ministry of water resources, Baghdad, Iraq.

Sidiropoulos, P., Mylopoulos, N., Loukas, A., 2016. Reservoir-aquifer combined optimization for groundwater restoration : The case of Lake Karla watershed , Greece. Water Util. J. 17–26.

Silver, E.A., 2004. An overview of heuristic solution methods. J. Oper. Res. Soc. 55, 936–956. https://doi.org/10.1057/palgrave.jors.2601758

SOGREAH, 1983. Upper Adhaim Dams Project. Appendix(I), Republic of Iraq, Ministry of Irrigation, State Organization for Dams.

Soyuzgiprovodkhoz, 1982. General Scheme of Water Resources and Land Development in Iraq. Technical Study (unpublished), Ministry of Water Resources, Iraq.

Sreekanth, J., Moore, C., Wolf, L., 2016. Pareto-based efficient stochastic simulation–optimization for robust and reliable groundwater management. J. Hydrol. 533, 180–190. https://doi.org/http://dx.doi.org/10.1016/j.jhydrol.2015.12.001

Stadler, W., 1979. A survey of multicriteria optimization or the vector maximum problem, part I: 1776-1960. J. Optim. Theory Appl. 29, 1–52. https://doi.org/10.1007/BF00932634

Storn, R., Price, K., 1997. Differential Evolution -- A Simple and Efficient Heuristic for global Optimization over Continuous Spaces. J. Glob. Optim. 11, 341–359. https://doi.org/10.1023/A:1008202821328

Tayfur, G., 2017. Modern Optimization Methods in Water Resources Planning, Engineering and Management. Water Resour. Manag. 31, 3205–3233. https://doi.org/10.1007/s11269-017-1694-6

Tigkas, D., Christelis, V., Tsakiris, G., 2016. Comparative Study of Evolutionary Algorithms for the Automatic Calibration of the Medbasin-D Conceptual Hydrological Model. Environ. Process. 3, 629–644. https://doi.org/10.1007/s40710-016-0147-1

Tsutsui, S., Yamamura, M., Higuchi, T., 1999. Multi-parent recombination with simplex crossover in real coded genetic algorithms, in: Proceedings of the 1st Annual Conference on Genetic and Evolutionary Computation-Volume 1. pp. 657–664.

Van Veldhuizen, D. a, Lamont, G.B., 1998. Evolutionary Computation and

Convergence to a Pareto Front. Late Break. Pap. Genet. Program. 1998 Conf. 221–228.

Woodruff, M.J., Simpson, T.W., Reed, P.M., 2015. Multi-Objective Evolutionary Algorithms' Performance in a Support Role, in: ASME 2015 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference. p. 12.

Yang, Y.S., Kalin, R.M., Zhang, Y., Lin, X., Zou, L., 2001. Multi-objective optimization for sustainable groundwater resource management in a semiarid catchment. Hydrol. Sci. J. 46, 55–72. https://doi.org/10.1080/02626660109492800

Zheng, F., Simpson, A.R., Zecchin, A.C., Maier, H.R., Feifei, Zh., 2016. Comparison of the Searching Behavior of NSGA-II, SAMODE, and Borg MOEAs Applied to Water Distribution System Design Problems. J. Water Resour. Plan. Manag. 142. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000650

Zhou, A., Qu, B.-Y., Li, H., Zhao, S.-Z., Suganthan, P.N., Zhang, Q., 2011. Multiobjective evolutionary algorithms: A survey of the state of the art. Swarm Evol. Comput. 1, 32–49. https://doi.org/10.1016/j.swevo.2011.03.001

Zitzler, E., 1999. Evolutionary Algorithms for Multiobjective Optimization: Methods and Applications.

Zitzler, E., Lothar, T., Kalyanmoy, D., 2000. Comparison of Multiobjective Evolutionary Algorithms: Empirical Results. Evol.\ Comput. 8, 173–195.

6.3 Supplementary Data

1. GROUNDWATER MODEL OVERVIEW

1.1. Identification of Groundwater Flow Model

The three-dimensional groundwater flow through an aquifer can be expressed by the following finite-difference equation as in Harbaugh and McDonald (1996)

$$\frac{\partial}{\partial x}\left(K_{xx}\frac{\partial h}{\partial x}\right)+\frac{\partial}{\partial y}\left(K_{yy}\frac{\partial h}{\partial y}\right)+\frac{\partial}{\partial z}\left(K_{zz}\frac{\partial h}{\partial z}\right)\pm W=S_S\frac{\partial h}{\partial t} \quad \text{(A1)}$$

where K_{xx}, K_{yy}, and K_{zz} are the hydraulic conductivities of the media in x, y, and z direction respectively. *W* is a source or sink of water, S_s is the specific storage of the aquifer, *h* and *t* represent the groundwater level and time, respectively. Harbaugh and McDonald (1996) present MODFLOW-96 package as a groundwater model solver for steady and unsteady flow. An updated version for MODFLOW-2005 was presented by Harbaugh (2005).

1.2. Aquifer Parameters and Recharges

A three dimensional solid model was created and converted to a MODFLOW finite difference model using Groundwater Model System (GMS) v.9.2, as shown in Figure A1. The model consists of four layers, the first two layers; Bai-Hassan and Mukdadiya formation since the two formations are composed of course sediments and are hydraulically connected. The last two layers represent the Injana aquifer system, which composed of alternation of clay and sand beds. The average thickness of the two system is 2000 m. Since the presence of two dams located in the north and south of the basin, a changing head boundary condition was assigned to these boundaries. River boundary conditions were assigned to the Diyala River across the basin.

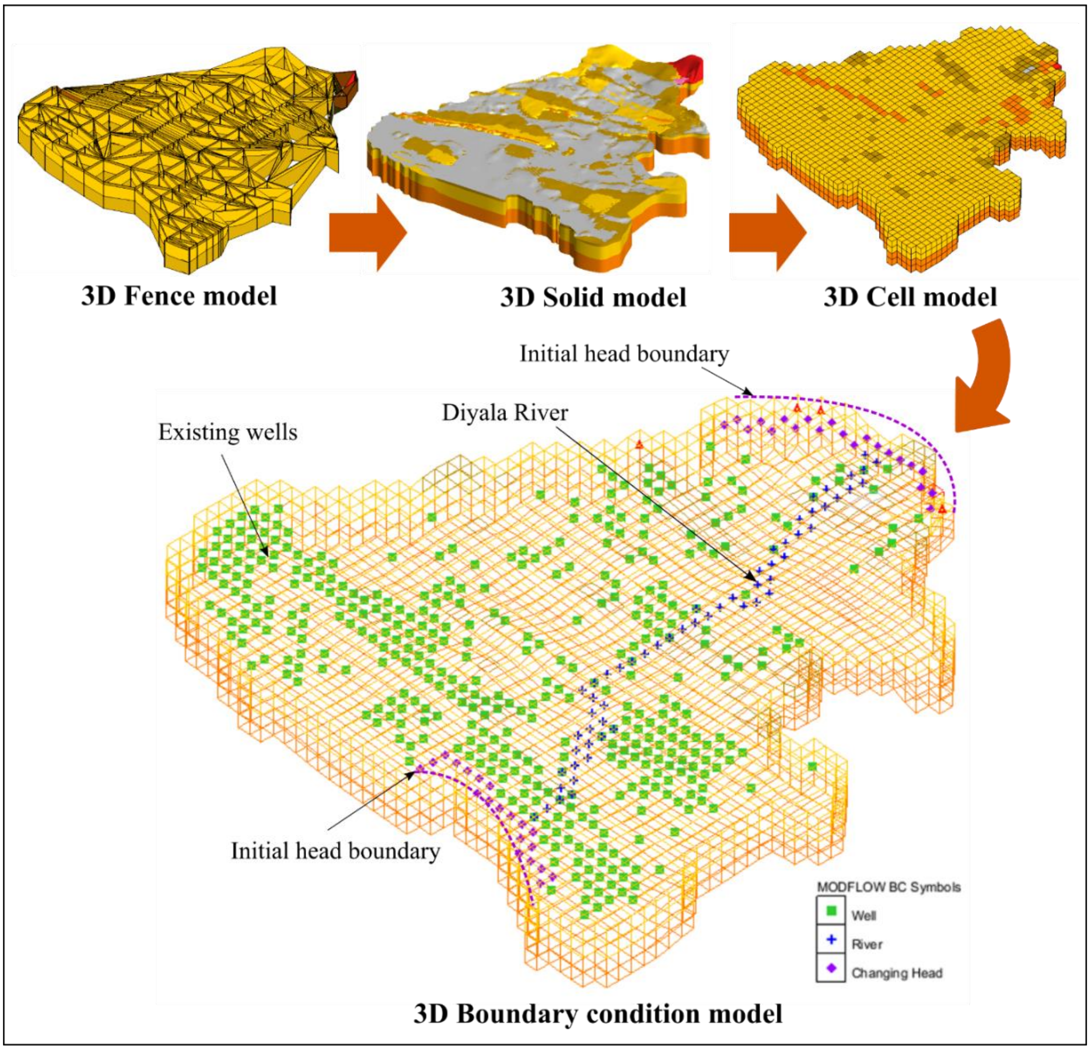
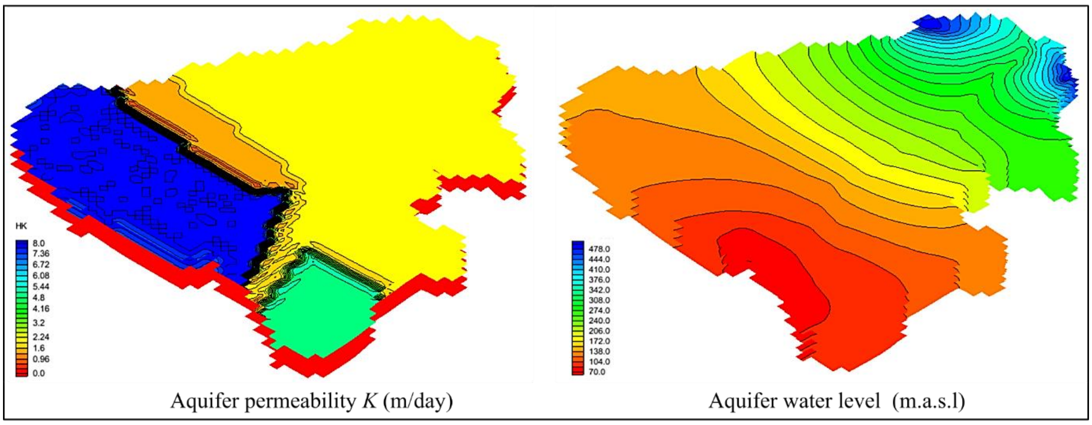


Figure A1. illustrates MODFLOW conceptual model development from 3D fence, 3D sold, 3D cell, and 3D boundary conditions models using GMS software.

To calculate aquifer groundwater recharge, a calibration for aquifer parameter *K* was achieved using parameter estimation procedures using MODFLOW-2005. The *K* value for Bai-Hassan and Mukdadiya formation ranges between 1.5 and 8.0 m/day with an average about 2.67 m/day, while for the Injana formation is about 0.01 m/day, as shown in Figure A2. These results were consistence to the range of field tests available in the database (Figure A2), hence they adopted to calculate the aquifer groundwater recharges.

Generated parameters



Database parameters

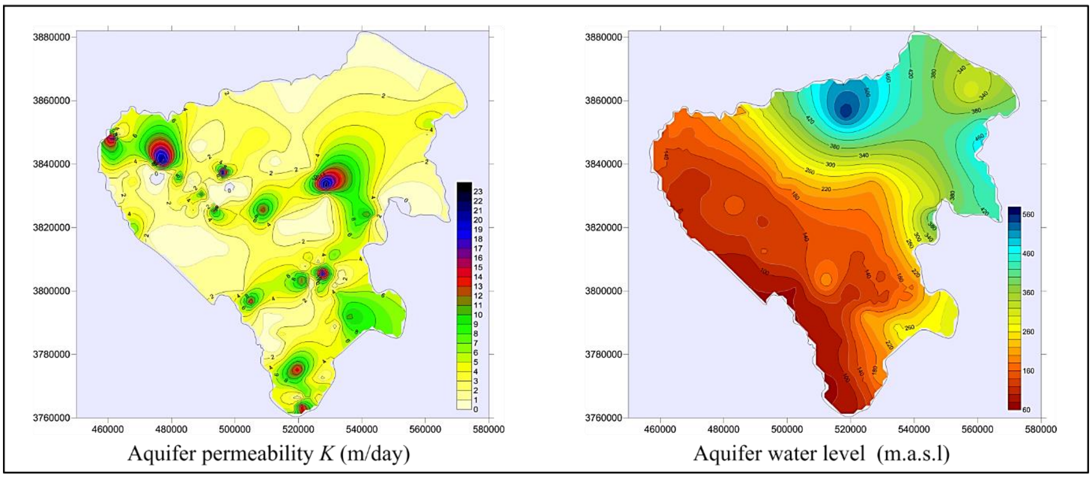


Figure A2. Generated parameters from MODFLOW model implementation in compare with the database parameters for the aquifer permeability in meters/day and groundwater level in meters (above sea level), respectively.

It is obvious from Figure A2 that Diyala River drains groundwater from the northern part of the basin, with that condition reversing gradually to the south. The relation between the groundwater and surface water depends on the riverbed sediments and the water level. In the upper part of the basin, the river bounded between high-level lands (Figure 1) with coarse bed sediment. This condition change gradually toward the lower part of the basin, in which the riverbed is higher than the groundwater level with finer bed sediment (Al-khaldy and Al-askari, 2015).

Moreover, Figure A2 show clustering in database parameters' values, which is according to irregular locations and clustering of wells in the basin, which cause divergence values of K and water levels. Additionally, these datasets represent wells and aquifer parameters' distribution were drilled during the last 25 years, hence it adopted as a general guide for these parameters. Figure A3 illustrates regional groundwater depth based on SGI et al. (2014) database.

The calibrated K value used to calculate the monthly groundwater recharge using Equation 1 (Darcy's law), as follows:

A = width × depth = 34904.65 m ×(350 + 532)/2 m (calculated from the MODFLOW model, and DEM map using GIS)

Δh = 500 – 80 = 420 m (calculated from the MODFLOW model, water level)

Δl = 103264.48 m (calculated from the DEM map using GIS)

K = 2.67 m/day (calculated from MODFLOW model)

$\therefore\ TR_0 = 4.88 \times 10^6\ m^3/month$

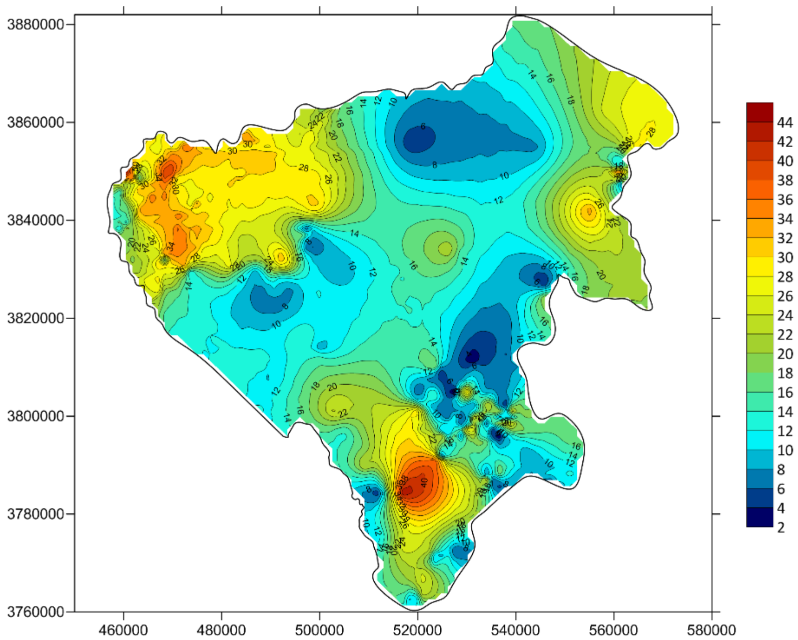


Figure A3. Groundwater depth (m) in the study area based on SGI et al. (2014) database

2. ALGORITHMS PERFORMANCE ASSESSMENT

2.1. Open Furrows Irrigation System

Tables A1 to A4 illustrate the summary of fitness functions, performance parameter properties, and evolve parameters achieved by both algorithms, for 10 runs each for open furrows system. ε-DSEA performance is clearly better than Borg MOEA in almost all cases.

Table A1. Results summary of open furrows system for 10 optimisation runs

	Borg MOEA				ε-DSEA			
	Best	Mean	Median	Std.	Best	Mean	Median	Std.
	12 months (one year)							
Min. $f_{Del\text{-}GW}$	**0.002**	**0.006**	**0.005**	0.006	0.003	0.007	0.006	**0.003**
Max. $f_{Del\text{-}GW}$	1.275	1.184	1.192	0.071	**1.335**	**1.258**	**1.244**	**0.054**
Min. f_{WL}	0.168	0.248	0.274	0.057	**0.147**	**0.176**	**0.161**	**0.032**
Max. f_{WL}	**7.870**	7.430	**7.547**	0.456	7.814	**7.446**	7.426	**0.244**
Min. f_{mining}	12.141	12.145	12.145	0.003	**12.138**	**12.141**	**12.142**	**0.002**
Max. f_{mining}	12.258	**12.256**	12.257	0.002	**12.257**	**12.256**	**12.256**	**0.001**
	60 months (5 years)							
Min. $f_{Del\text{-}GW}$	**0.795**	**0.952**	**0.916**	0.145	0.884	1.057	1.057	**0.094**
Max. $f_{Del\text{-}GW}$	6.746	5.366	5.362	0.614	**7.238**	**6.242**	**6.248**	**0.425**
Min. f_{WL}	1.627	2.085	2.050	0.314	**1.142**	**1.433**	**1.476**	**0.117**
Max. f_{WL}	13.278	**11.512**	**11.606**	1.356	**13.253**	11.125	10.758	**1.153**
Min. f_{mining}	65.034	65.083	65.077	0.038	**65.021**	**65.055**	**65.050**	**0.023**
Max. f_{mining}	68.173	67.671	67.656	0.282	**68.288**	**67.998**	**67.973**	**0.199**
	120 months (10 years)							
Min. $f_{Del\text{-}GW}$	2.479	3.052	2.952	0.566	**2.157**	**2.492**	**2.490**	**0.237**
Max. $f_{Del\text{-}GW}$	8.760	7.553	7.599	0.628	**10.504**	**9.410**	**9.371**	**0.539**
Min. f_{WL}	5.973	6.690	6.387	0.811	**4.071**	**4.341**	**4.329**	**0.222**
Max. f_{WL}	**21.836**	17.949	18.121	2.609	20.579	**18.483**	**18.420**	**1.391**
Min. f_{mining}	143.075	143.640	143.648	0.486	**142.701**	**143.186**	**143.169**	**0.240**
Max. f_{mining}	155.345	153.585	153.438	1.231	**159.340**	**158.315**	**158.254**	**0.591**
	300 months (25 years)							
Min. $f_{Del\text{-}GW}$	8.895	10.167	10.183	0.796	**7.094**	**8.032**	**7.988**	**0.560**
Max. $f_{Del\text{-}GW}$	18.724	16.263	15.988	1.009	**21.303**	**19.354**	**18.922**	**0.982**
Min. f_{WL}	18.884	20.358	19.934	1.218	**11.699**	**12.854**	**12.839**	**0.783**
Max. f_{WL}	37.172	34.345	34.877	**2.011**	**42.627**	**37.768**	**37.521**	2.385
Min. f_{mining}	532.802	545.671	544.399	8.624	**523.548**	**529.385**	**528.478**	**4.084**
Max. f_{mining}	675.967	649.098	649.679	**13.436**	**798.476**	**766.563**	**765.451**	15.453

Table A2. parameters performance properties for Borg MOEA achieved in open furrows system

		1 year	5 years	10 years	25 years	Total
Sum.	Archive size	**66963**	**37556**	54725	34797	194041
Min.		**6320**	3038	3885	2371	
Max.		**7032**	**4317**	7080	4648	
Mean		**6696**	**3756**	5473	3480	
Median		**6701**	**3780**	5478	3343	
Std.		204.141	361.439	971.917	795.836	
Sum.	Improvement	**371101**	**585729**	**978840**	859199	**2794869**
Min.		**30944**	**51872**	**78789**	65581	
Max.		**43826**	**66420**	**118202**	105095	
Mean		**37110**	**58573**	**97884**	85920	
Median		**37342**	**58382**	**98057**	84265	
Std.		3557.913	4908.233	10043.333	13661.385	
Sum.	Restart	310	591	581	720	2202
Min.		29	55	55	68	
Max.		33	67	65	77	
Mean		31	59	58	72	
Median		31	59	58	72	
Std.		1.183	3.807	2.587	2.408	
Sum.	CPU time (sec)	568.265	877.378	1469.572	8209.707	11124.922
Min.		53.377	79.134	126.409	734.016	
Max.		59.240	93.327	167.043	871.391	
Mean		56.826	87.738	146.957	820.971	
Median		57.180	88.593	149.110	830.377	
Std.		2.148	**4.532**	16.263	**46.260**	

Table A3. parameters performance properties for ε-DSEA achieved in open furrows system

		1 year	5 years	10 years	25 years	Total
Sum.	Archive size	53169	36567	**79807**	**76095**	**245638**
Min.		5158	**3283**	**7152**	**6848**	
Max.		5429	4267	**8461**	**8547**	
Mean		5317	3657	**7981**	**7610**	
Median		5370	3684	**8013**	**7495**	
Std.		**108.093**	**284.286**	**372.909**	**456.591**	
Sum.	Improvement	234578	352912	768156	**1125810**	2481456
Min.		22447	31548	71432	**101135**	
Max.		24532	38994	81593	**122042**	
Mean		23458	35291	76816	**112581**	
Median		23343	35422	76689	**114350**	
Std.		**696.266**	**2105.599**	**3061.316**	**6723.207**	
Sum.	Restart	**30**	**29**	**29**	**32**	**120**
Min.		**2**	**2**	**2**	**2**	
Max.		**4**	**4**	**4**	**4**	
Mean		**3**	**3**	**3**	**3**	
Median		**3**	**3**	**3**	**4**	
Std.		**0.775**	**0.831**	**0.700**	**0.872**	
Sum.	CPU time (sec)	**288.528**	**617.214**	**1167.547**	**5642.663**	**7715.952**
Min.		**27.041**	**54.741**	**107.833**	**497.632**	
Max.		**31.604**	**71.502**	**124.593**	**662.459**	
Mean		**28.853**	**61.721**	**116.755**	**564.266**	
Median		**28.672**	**62.169**	**116.255**	**562.720**	
Std.		**1.318**	5.026	**5.070**	51.423	

Table A4. Summary of ε-DSEA evolved parameters achieved in open furrows system

Parameters	No. of years	Minimum	Maximum	Mean	Median	Std.
η	1	0	70.000	63.931	69.000	17.400
(SBX)	5	0	96.000	71.591	75.000	19.025
	10	0	98.000	60.574	65.000	28.033
	25	0	98.000	68.359	82.000	30.824
CR, F	CR-1	0.100	0.167	0.105	0.100	0.015
(DE)	F-1	0.500	0.583	0.515	0.503	0.023
	CR-5	0.100	0.737	0.117	0.100	0.098
	F-5	0.500	0.868	0.521	0.507	0.057
	CR-10	0.100	0.907	0.440	0.222	0.362
	F-10	0.500	0.954	0.704	0.611	0.196
	CR-25	0.100	0.904	0.465	0.125	0.378
	F-25	0.500	0.952	0.718	0.563	0.204
σ_η, σ_ζ	1	0.100	0.268	0.215	0.218	0.028
(PCX)	5	0.100	0.274	0.203	0.202	0.014
	10	0.100	0.278	0.186	0.192	0.025
	25	0.100	0.282	0.181	0.189	0.021
λ	1	2.532	3.406	2.871	2.867	0.103
(SPX)	5	2.505	3.115	2.952	2.979	0.082
	10	2.502	3.398	3.087	3.076	0.119
	25	2.503	3.412	3.086	3.066	0.089
σ_η, σ_ζ	σ_ζ -1	0.400	0.500	0.406	0.401	0.010
(UNDX)	σ_η -1	0.100	0.350	0.110	0.101	0.018
	σ_ζ -5	0.400	0.582	0.455	0.408	0.077
	σ_η -5	0.100	0.404	0.192	0.113	0.129
	σ_ζ -10	0.400	0.581	0.479	0.432	0.076
	σ_η -10	0.100	0.402	0.231	0.153	0.126
	σ_ζ -25	0.400	0.581	0.505	0.557	0.078
	σ_η -25	0.100	0.402	0.274	0.361	0.129

2.2. Drip Irrigation System

The results summary of drip irrigation system was presented in Tables A5 to A8. ε-DSEA performance is superior to Borg MOEA in almost all cases except for five years. However, the results are very close in that case. Hence, in general, ε-DSEA is outperform in this alternative and its results will be adopted.

Table A5. Results summary of the drip system for 10 optimisation runs

	Borg MOEA				ε-DSEA			
	Best	Mean	Median	Std.	Best	Mean	Median	Std.
12 months (one year)								
Min. $f_{Del\text{-}GW}$	**0.001**	**0.002**	**0.002**	**0.001**	0.002	0.003	0.003	**0.001**
Max. $f_{Del\text{-}GW}$	**0.547**	0.521	0.528	0.022	0.543	**0.531**	**0.531**	**0.006**
Min. f_{WL}	0.145	0.152	0.149	0.007	**0.144**	**0.146**	**0.146**	**0.001**
Max. f_{WL}	**2.308**	2.063	2.066	**0.104**	2.276	**2.119**	**2.149**	0.108
Min. f_{mining}	**12.119**	12.121	12.121	0.002	**12.119**	**12.120**	**12.120**	**0.001**
Max. f_{mining}	**12.201**	**12.200**	**12.200**	**0.001**	**12.201**	**12.200**	**12.200**	**0.001**
60 months (5 years)								
Min. $f_{Del\text{-}GW}$	**0.242**	**0.337**	**0.348**	**0.047**	0.293	0.436	0.436	0.099
Max. $f_{Del\text{-}GW}$	**3.948**	**3.615**	**3.668**	0.270	3.458	3.197	3.159	**0.148**
Min. f_{WL}	0.923	1.092	1.067	0.124	**0.885**	**1.041**	**1.074**	**0.098**
Max. f_{WL}	**5.532**	**4.541**	**4.481**	0.427	4.600	4.102	4.006	**0.343**
Min. f_{mining}	**64.567**	**64.599**	**64.599**	0.025	64.590	64.608	64.607	**0.013**
Max. f_{mining}	66.559	66.306	66.233	0.151	**66.879**	**66.717**	**66.730**	**0.128**
120 months (10 years)								
Min. $f_{Del\text{-}GW}$	0.739	0.872	0.889	**0.095**	**0.645**	**0.772**	**0.729**	0.154
Max. $f_{Del\text{-}GW}$	**5.419**	**4.146**	3.997	0.594	4.892	4.109	**4.040**	**0.337**
Min. f_{WL}	**3.182**	3.780	3.758	0.440	3.337	**3.471**	**3.430**	**0.127**
Max. f_{WL}	**9.020**	**8.157**	**8.079**	**0.442**	8.616	8.006	8.053	0.530
Min. f_{mining}	**141.124**	141.404	141.408	0.242	141.154	**141.305**	**141.288**	**0.107**
Max. f_{mining}	149.547	148.070	148.191	0.906	**151.313**	**149.825**	**149.655**	**0.877**
300 months (25 years)								
Min. $f_{Del\text{-}GW}$	2.731	3.213	3.241	**0.267**	**2.272**	**2.663**	**2.453**	0.525
Max. $f_{Del\text{-}GW}$	7.596	6.742	6.837	0.640	**8.594**	**8.096**	**8.063**	**0.335**
Min. f_{WL}	11.098	12.139	12.311	**0.418**	**9.129**	**9.794**	**9.864**	0.529
Max. f_{WL}	**17.906**	**16.705**	16.522	**0.596**	17.824	16.637	**17.027**	1.439
Min. f_{mining}	513.838	516.958	516.020	**3.258**	**499.751**	**506.268**	**506.564**	3.363
Max. f_{mining}	587.806	571.068	571.196	**8.700**	**632.234**	**602.036**	**601.931**	13.128

Table A6. parameters performance properties for Borg MOEA achieved in drip system

		1 year	5 years	10 years	25 years	Total
Sum.	Archive size	**15211**	**12097**	**17679**	22972	67959
Min.		**1444**	**1082**	1236	1739	
Max.		**1579**	**1307**	**2726**	2689	
Mean		**1521**	**1210**	**1768**	2297	
Median		**1520**	**1236**	**1723**	2274	
Std.		33.351	64.5136	391.814	**279.050**	
Sum.	Improvement	**113768**	**205090**	**349198**	**708199**	**1376255**
Min.		**9874**	**17998**	**30301**	**49690**	
Max.		**12793**	**23570**	**43664**	**82248**	
Mean		**11377**	**20509**	**34920**	**70820**	
Median		**11347**	**20128**	**33900**	**73724**	
Std.		860.136	1761.311	4117.949	9549.918	
Sum.	Restart	3795	3709	1142	781	9427
Min.		302	181	74	71	
Max.		439	499	199	108	
Mean		380	371	114	78	
Median		383	397	101	75	
Std.		44.996	85.098	39.296	10.492	
Sum.	CPU time(sec)	244.098	527.987	894.324	9097.121	10763.53
Min.		21.474	52.163	85.762	845.439	
Max.		25.688	53.770	94.312	975.618	
Mean		24.410	52.799	89.432	909.712	
Median		24.663	52.716	88.414	920.013	
Std.		1.386	**0.586**	**2.647**	**43.935**	

Table A7. parameters performance properties for ε-DSEA achieved in drip system

		1 year	5 years	10 years	25 years	Total
Sum.	Archive size	14911	11098	16776	**36925**	**79710**
Min.		1473	1038	**1430**	**2325**	
Max.		1508	1238	1933	**4897**	
Mean		1491	1110	1678	**3693**	
Median		1495	1101	1670	**3631**	
Std.		**9.741**	**56.377**	**150.899**	722.759	
Sum.	Improvement	86238	122893	220909	585776	1015816
Min.		7421	10960	19336	47654	
Max.		9139	13755	23949	67526	
Mean		8624	12289	22091	58578	
Median		8684	12461	22192	58848	
Std.		**455.375**	**901.671**	**1350.611**	**5671.934**	
Sum.	Restart	**31**	**31**	**28**	**26**	**116**
Min.		**2**	**2**	**2**	**2**	
Max.		**4**	**4**	**4**	**4**	
Mean		**3**	**3**	**3**	**3**	
Median		**4**	**4**	**3**	**2**	
Std.		**0.943**	**0.943**	**0.600**	**0.800**	
Sum.	CPU time(sec)	**161.632**	**385.008**	**657.451**	**5301.796**	**6505.887**
Min.		**15.138**	**35.791**	**57.993**	**480.954**	
Max.		**16.958**	**41.926**	**68.909**	**629.137**	
Mean		**16.163**	**38.501**	**65.745**	**530.180**	
Median		**16.282**	**39.127**	**67.506**	**508.391**	
Std.		**0.608**	2.136	3.643	50.410	

Table A8. Summary of ε-DSEA evolved parameters achieved in drip system

Parameters	No. of years	Minimum	Maximum	Mean	Median	Std.
η (SBX)	1	4.000	88.000	63.874	67.000	13.199
	5	1.000	98.000	85.929	88.000	10.950
	10	1.000	94.000	60.417	65.000	25.064
	25	0	98.000	84.232	87.000	18.433
CR, *F* (DE)	CR-1	0.100	0.300	0.104	0.100	0.019
	F-1	0.500	0.650	0.531	0.529	0.021
	CR-5	0.100	0.891	0.122	0.100	0.105
	F-5	0.500	0.946	0.537	0.523	0.059
	CR-10	0.100	0.912	0.203	0.100	0.250
	F-10	0.500	0.956	0.570	0.507	0.139
	CR-25	0.100	0.911	0.459	0.444	0.361
	F-25	0.500	0.955	0.714	0.722	0.197
σ_η, σ_ζ (PCX)	1	0.100	0.214	0.165	0.165	0.022
	5	0.100	0.264	0.130	0.122	0.023
	10	0.100	0.282	0.226	0.228	0.028
	25	0.100	0.282	0.192	0.193	0.015
λ (SPX)	1	2.521	3.000	2.609	2.580	0.079
	5	2.506	3.409	2.576	2.567	0.102
	10	2.508	3.407	2.832	2.834	0.089
	25	2.502	3.409	2.940	3.003	0.149
σ_η, σ_ζ (UNDX)	σ_ζ -1	0.400	0.544	0.408	0.402	0.017
	σ_η -1	0.100	0.350	0.114	0.103	0.029
	σ_ζ -5	0.400	0.581	0.434	0.402	0.062
	σ_η -5	0.100	0.401	0.157	0.103	0.104
	σ_ζ -10	0.400	0.580	0.470	0.413	0.082
	σ_η -10	0.100	0.401	0.217	0.121	0.137
	σ_ζ -25	0.400	0.582	0.501	0.550	0.080
	σ_η -25	0.100	0.404	0.269	0.350	0.133

2. GROUNDWATER STORAGE

Figure A3 illustrates the monthly groundwater storage achieved for different operating periods using ε-DSEA with both delivery system scenarios. The colour lines represent all optimum solutions achieved. These graphs show continues storage yields due to recharges' scarcity and high water demands in the region.

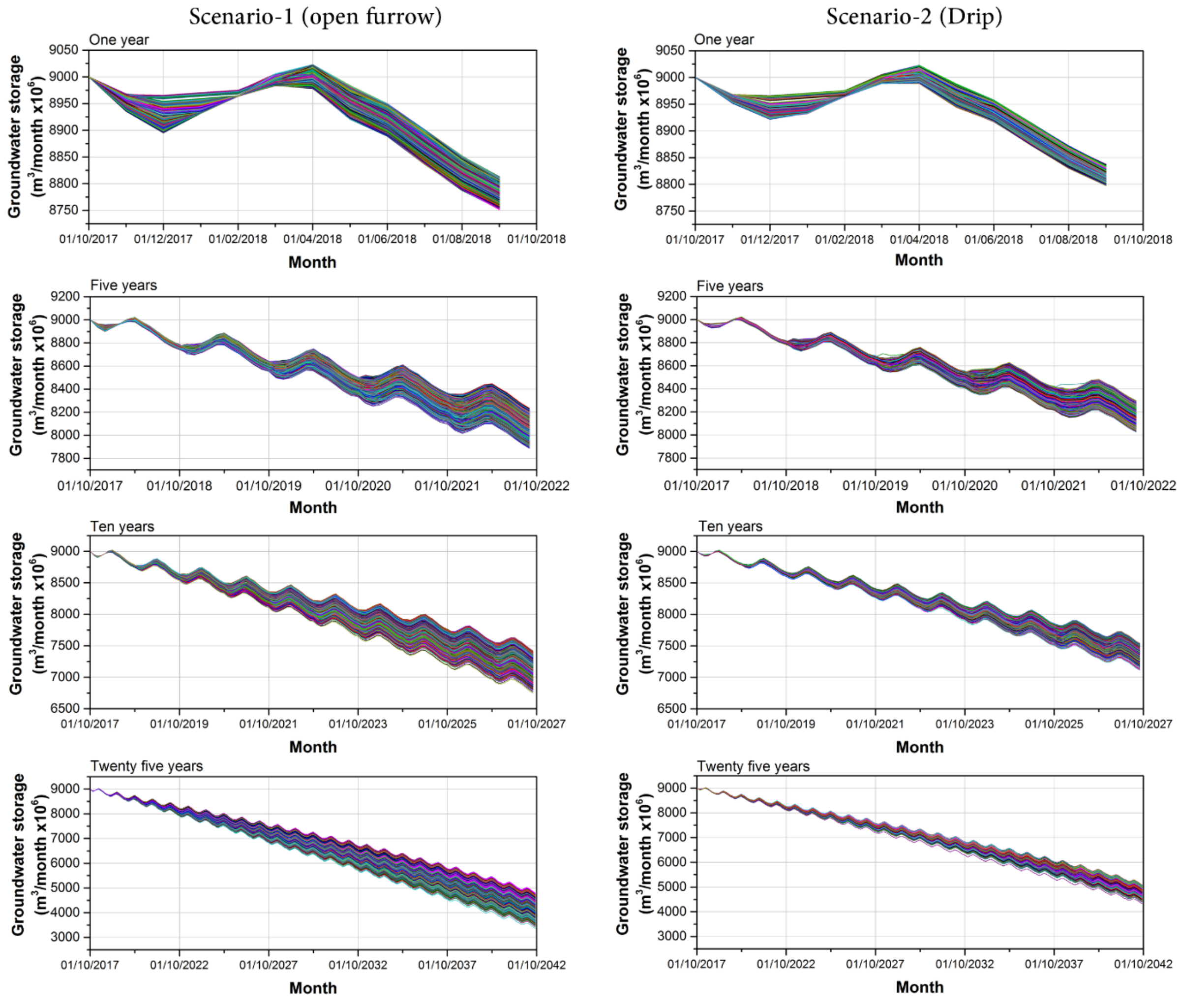


Figure A4. Details of groundwater storage achieved for both scenarios using ε-DSEA

6.4 Further Discussion

The average and median number of wells for the best sustainable management solution for drip and open furrow systems were 619 and 776; 748 and 939, respectively, as 45% of farms' water demands are reduced. Hence, economic revenues could be improved about 45% by reducing wells' infrastructure construction cost, as well as the relevant power consumption of pumps.

In the same context, the corresponding values of aquifers recharge of open furrows system are also reduced by 45% to about 10.0×10^6 and 3.0×10^6 m^3/month. However, minor reduction is observed for drip system since its' irrigation efficiency is higher. Thus, percolation from irrigation water (surface water) is the main source of aquifers' recharge in this region, which evident the scarcity of aquifers recharge from the boundary regions.

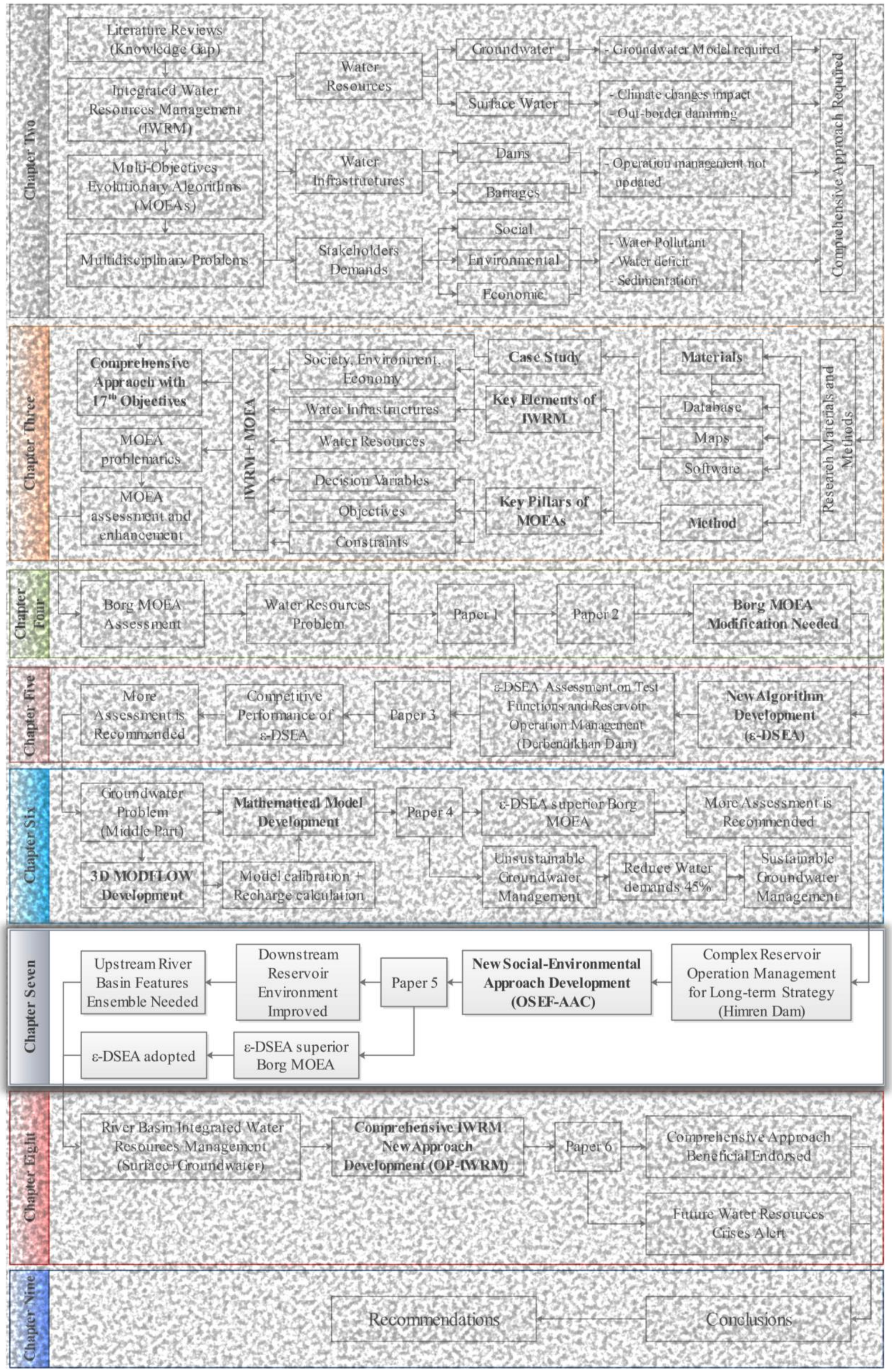
Furthermore, the average water deficit was reduced by 64% for drip system, and 53% for open system, hence crop production industries' revenues could also be improved, which reinforce the regional water-food-energy nexus.

6.5 Conclusion

The performance of ε-DSEA was assessed using real-world groundwater management problem, in comparison with Borg MOEA. The developed model minimizes: delivery water deficit, aquifer storage mining, and infiltration water losses. The management strategy mapped for five discrete periods up to half-century using open furrows and drip irrigation system alternatives. The ε-DSEA provided more robust results when compared to the Borg MOEA for almost every alternatives. The ε-DSEA approaches' main advantage over the Borg MOEA is reliability; it repeatedly produced optimum solutions over computational budget replication. The Pareto-front extends wider and has better optimality in the objective search space, which demonstrates the effectiveness of ε-DSEA. Its robustness is evident, adapting to different problem environments using dynamically evolved parameters during the evaluation process. New parameters domain was produced for the commonly used recombination operators, which can be beneficial for comparing water resources problems. Other parameters like number of optimum solutions, restart replication, and CPU time also show the superiority of ε-DSEA over Borg MOEA in all alternatives. The decision variables convergence and development was competitive and superior especially for long-term operation, which emerge ε-DSEA efficiency outperformance. The mechanism of auto-adaptive in Borg MOEA may cause stagnation in local optima, and injection repetition may regenerate solutions nearby local optima. Although ε-DSEA outperforms Borg MOEA in almost every cases, further analysis and assessment may consider for other real-world problems with higher complexity.

Although both algorithms' results demonstrate unsustainability in groundwater resource management for both irrigation systems, the computational evidence illustrate that results from the ε-DSEA were more robust. Hence, the ε-DSEA results should be used to consider groundwater resource management for the case study area. The storage depletion was 25% for ten years' water exploitation, which increase to about 60% for twenty-five years. The aquifer storage was completely exhausted after forty years in both alternatives due to low aquifer recharge, which is caused by low rainfall and high evapotranspiration rates (semi-arid zone). The introduction of drip irrigation mitigates the impact on the aquifer storage over the discrete periods, especially for long-term water exploitation. The probability of sustainable groundwater resource management was scenario modelled for the next half-century by reducing water delivery demands. The results show possible sustainable storage budget using open furrows system can be achieved for the next twenty-five years, and thirty-three years for drip system with 45% demand's yield for both. Hence, decision makers (the Iraqi government) should consider future policy to reduce water demands by either changing crops types, or reducing farms areas. Also, the use of drip system for water allocation should be considered in the policy since it has less impacts on groundwater yields. However, crop yield and productivity should consider over the alternatives. Conjunctive use with surface water and water harvesting may consider also to mitigate groundwater depletion and maintain its sustainability.

In the next chapter, a complex reservoir operation management scenario is selected with Many-objectives problem (more than three objectives). Both algorithms will be implemented to evaluate their performance.



Chapter Two
Literature Reviews (Knowledge Gap)
Integrated Water Resources Management (IWRM)
Multi-Objectives Evolutionary Algorithms (MOEAs)
Multidisciplinary Problems
Water Resources
Water Infrastructures
Stakeholders Demands
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Surface Water
Dams
Barrages
Social
Environmental
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- Climate changes impact
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- Operation management not updated
- Water Pollutant
- Water deficit
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Comprehensive Approach Required
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ε-DSEA Assessment on Test Functions and Reservoir Operation Management (Derbendikhan Dam)
New Algorithm Development (ε-DSEA)
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3D MODFLOW Development
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Model calibration + Recharge calculation
Paper 4
ε-DSEA superior Borg MOEA
More Assessment is Recommended
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Reduce Water demands 45%
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Chapter Seven
Upstream River Basin Features Ensemble Needed
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New Social-Environmental Approach Development (OSEF-AAC)
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Comprehensive Approach Beneficial Endorsed
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Chapter Nine
Recommendations
Conclusions

CHAPTER SEVEN

RESERVOIR OPERATION IMPROVEMENT APPROACH

7.1 Introduction

A performance assessment for ε-DSEA and Borg MOEA algorithms was implemented in the preceding chapter using groundwater management problem located in the middle part of Diyala river basin. The ε-DSEA outperformance was evident over almost all alternatives, which reflect algorithm's robustness to adapt with different problem environment, as its performance was also evident in previous problems. Hence its' management results were adopted. These results demonstrate future policy should be considered by the decision makers (The Iraqi government) to reduce water consumption by about 45% to achieve sustainable management for the next twenty-five and thirty-three years using open furrows and drip system, respectively.

However, problematics in MOEAs performance may develop while solving a high-dimension problem (more than three objectives), as highlighted in *bullet point 2* in Chapter two.

In the current chapter, Himren dam, located in the middle part of Diyala river basin, is selected as a complex reservoir management problem having social and environmental objectives to be optimized to improve its operation strategy. Both algorithms are implemented for further performance assessment and results' endorsement.

A paper is developed and submitted to the *Science of the Total Environment* journal (2018) as:

- Al-Jawad, J.Y., Alsaffar, H.M., Bertram, D., Kalin, R.M., 2018b. Optimum Socio-Environmental Flows Approach for Reservoir Operation Strategy Using Many-Objectives Evolutionary Optimization Algorithm. Sci. Total Environ. under review.

"The following work represents my efforts, such as: theoretical formalism development, analytic calculations and numerical simulations, writing the manuscript. Dr. Kalin, R.M., was the project supervisors, and provided assistance and support when required. Alsaffar, H.M., was a governmental key stackeholder and provided assistance and support when required. Dr. Bertram, D., provided technical support and assistance".

7.2 Paper:

Al-Jawad, J.Y., Alsaffar, H.M., Bertram, D., Kalin, R.M., 2018b. Optimum Socio-Environmental Flows Approach for Reservoir Operation Strategy Using Many-Objectives Evolutionary Optimization Algorithm. Sci. Total Environ. Under review.[1]

OPTIMUM SOCIO-ENVIRONMENTAL FLOWS APPROACH FOR RESERVOIR OPERATION STRATEGY USING MANY-OBJECTIVES EVOLUTIONARY OPTIMIZATION ALGORITHM

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Abstract

Water resource system complexity, high-dimension modelling dilemma and computational efficiency challenges often limit decision makers' strategies to combine environmental flow objectives (e.g. water quality, ecosystem) with social flow objectives (e.g. hydropower, water supply and agriculture). Hence, a novel Optimum Social-Environmental Flows (OSEF) with Auto-Adaptive Constraints (AAC) approach is introduced as a river basin management decision support tool which integrates Socio-Environmental (SE) objectives with convergence booster support to mitigate any computational challenges. The OSEF-AAC effectiveness was evaluated using Iraq's Diyala river basin. Nine SE objectives and 396 decision variables were modelled under two inflows scenarios. The results show there are decision support

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options that could improve river basin SE sectors revenues including hydropower, flood risk, agriculture, water quality and quantity, enhancing river basin economic benefits. However, advanced land use and water exploitation policy would need adoption to secure the basin's SE sectors.

Keywords: Environmental flows regime, Water resources management, Borg MOEA, ε-DSEA, auto-adaptive constraints, Diyala River basin

1 INTRODUCTION

The limitations of water resources often lead to the construction of dams in arid-environments to fulfil social and environmental demands such as flood wave absorption, water supply, agriculture projects, generating hydropower, tourist attraction, and other recreational purposes. These structures and their catchments need a robust management plan to handle their complexity in terms of: non-linearity, dynamic characteristics, conflicting objectives, multimodal, etc. (Haimes and Hall, 1977 in Reed et al., 2013).

In the last few decades optimization algorithms were developed and implemented in different scientific and engineering fields to solve complex problems (Coello et al., 2007); these problems include water resources management (Maier et al., 2014). Multiple optimization methods were used in reservoir system operation including linear and non-linear programing, dynamic programing and evolutionary algorithms (Ahmad et al., 2014; Rani and Moreira, 2010). Evolutionary algorithms (EA) are widely employed to tackle the intricacies of reservoir systems, inspired from evolutionary process of genes (Nicklow et al., 2010; Back et al., 2000). Studies involving multi-objective reservoir operation optimization using evolutionary algorithm are summarized in Table 1. Only three of nineteen studies consider more than five objectives in reservoir operation strategy (multiple publications used in the same case study are considered as one study). Moreover, some studies merge objectives to simplify the multiple dam system problems, and hydropower generation and water supply (for domestic and irrigation) were the dominant objectives adopted in these studies.

Environmental objectives are seldom adopted in reservoir management, in a recent review of studies between 1980 and 2015 by Horne et al., (2016) found only 42 studies adopt environmental releases in reservoir management as decision variables.

Recently Horne et al., (2017) presented conditional probability networks (CPNs) approaches combined with Mixed Integer Programing (MIP) optimizer for environmental flow regimes. Poff et al., (2016) propose a framework approach for eco-engineering decision scaling using performance indices, and Acreman et al., (2014) show that environmental flows need a “designer” approach for considering ecosystem objectives in water control infrastructure, rather than a “natural” approach.

Older studies do consider social objectives (hydropower, water supply, and flood protection) in their optimization models for reservoir operation strategy, and more recent studies consider environmental flow regimes. We propose to adopt a more holistic approach, where environmental flows from reservoir are combined with the social water needs to improve economic revenues reliant on the river basin system.

Table 1. Summary of literatures used evolutionary algorithms to optimize multi-objective reservoir operation strategy

Author	Method	Objective No.	Subject	No. of dams
Kim et al., (2008)	NSGA-II	2	Water shortage index + hydropower	1
Chang and Chang, (2009)	NSGA-II	2	Water shortage index for two dams	2
Dittmann et al., (2009)	MOES	5	Inundation + overtopping for three dams + releases	3
Reddy and Kumar, (2009)	MOPSO	2	hydropower + irrigation	1
Regulwar, (2009)	MOGA	2	hydropower + irrigation	5
Hakimi-Asiabar et al., (2010)	SLGA	3	hydropower + water supply + water quality	3
Wang et al., (2011)	MIGA	2	long term operation for water demand and storage	1
Malekmohammadi et al., (2011)	NSGA-II	2	Flood + water demands	2
Schardong et al., (2013)	MODE	3	Water demands + water quality + pumping cost	5
Kasprzyk et al., (2013)	ε-NSGA-II	6	Two cost + Three reliability + Market use	1
Giacomoni et al., (2013), Giuliani et al., (2014a)	Fitted Q-iteration	5	Two Recreation + sedimentation + water deficit + Temperature differences	1
Giuliani et al., (2014b), Giuliani et al., (2016), Zatarain Salazar et al., (2016) Zatarain Salazar et al., (2017)	Borg MOEA	6	Three water supply + hydropower + recreation + environment	1
Ahmadianfar et al., (2015)	MOEA/D	2	Flow demands + agriculture demands	3
Li and Qiu, (2015)	NSGA-II	2	Hydropower + firm power	1
Crookston and Tullis, (2016)	NSGA-II	2	Water quality + water temperature	1
Hurford et al., (2014)	ε-NSGA-II	10	Four agriculture water deficit + water losses + Hydropower + Land availability + Two Flow alteration	3
Qi et al., (2016)	MOEA/D	2	Water level + releases	1
Chen et al., (2016)	NSGA-II	5	Water supply + hydropower + flow alternation in two rivers + water quality	1
Dai et al., (2017)	NSGA-II	2	Hydropower + water alternation	2

Generally water resources management models provide information to the decision makers, rather than the decision itself (Loucks, 2012). There are pre- and post-optimization implementation approaches for incorporating decision maker criteria within a multi-aspects problems (Maier et al., 2014; Coello et al., 2007). One of the pre-criteria approach drawbacks is the dissatisfaction (or lack of trust) of decision makers toward model results that emerged depending on their criteria set, and they may change these criteria to generate new results (Loucks, 2012). Hence the model needs to be re-executed until they get satisfaction. The second approach is computationally challenging and has potential difficulties to find the Pareto-front for optimum solutions set, which recently tackles by using multi-objective (or many-objective for more than three objectives) optimization algorithms (Maier et al., 2014).

These holistic challenges motivate development of a novel approach to generate optimum river basin management strategies that combines both social and environmental objectives. Many-objective evolutionary optimization algorithm was adopted to conceptualise and analyse the multi-sector problem. Additionally, an auto-adaptive constraints approach was used to overcome system complexity and boost algorithm convergence. The approach effectiveness was evaluated using challenging water resources problem in a semi-arid region in Middle East. The approach achievement and robustness was supported by two evolutionary algorithms (Maier et al., 2014): the state-of-the-art Borg MOEA (Hadka and Reed, 2013) and the new ε-DSEA (Al-Jawad et al., 2018b). The findings are expected to improve the river basin system potential social and environmental sectors economic revenues. Also, the optimum water management strategy "trade-off" will provide the decision makers with a flexible flow regime management consistent with different time-scales for real-world IWRM.

2 METHODS AND TOOLS

2.1 Identification of OSEF-AAC Approach

This study presents the Optimum Socio-Environmental Flows (OSEF) approach which combines all social and environmental sectors (or objectives) together in one model using a many-objectives optimization algorithm approach.

Many-objectives model can solve more than three objectives problems (Maier et al., 2014; Li et al., 2015); however, the complexity increases exponentially when involving more objectives, which leads to challenges in computational efficiency (Lokman and Köksalan, 2013; Maier et al., 2014). Nevertheless, involving more objectives has minor or similar impact on the computational complexity of MOEAs' algorithms, since it's a function of; population size, number of objectives and number of generations (Curry and Dagli, 2014). The later study concluded that involving more objectives to an optimization problem will have minor or similar computational complexity impact. This was based on comparing two versions of MOEAs for multi and many-objectives optimization algorithms; NSGA-II (Deb et al., 2002) and NSGA-III (Deb and Jain, 2013); SPEA (Zitzler et al., 2002) and FD-SPEA2 (He et al., 2014). Also, they refer to the length of chromosome (number of decision variables) as a key-factor affecting on the computational complexity. Maier et al., (2014) explore computational efficiency challenges in water resources management models and the available methods to handle them, over the use of surrogate model (SM) or parallel computing. The SM approaches are used to reduce the difficulties (or the dimensions) and the authors reviewed several studies implementing the SM model, noting "*SMs are only an approximation and therefore subject to errors*" (Maier et al., 2014). While the parallel computing is not commonly available and highly expensive, another challenging aspect are the barriers (or constraints) that real-world water resources management problems have which limit the model feasible solutions region. For examples dam releases are restricted to the spillway gates' maximum discharge capacity, and power generation is limited to the maximum power plant turbine flows. Hence, to approach the actual conditions constraints should be assigned for unconstrained optimization algorithms like evolutionary algorithms (Deb, 2001; Abraham et al., 2005).

Developing a penalty functions formula is a type of constraints approach paradigm (Coello Coello, 2002; Simon, 2013) to represent decision makers policy or criteria (Maier et al., 2014) and to exaggerate the unfeasible solution to guide algorithm exploration towards feasible solutions. However these functions should be carefully developed and tested for each problem to avoid premature or delay of algorithm convergence towards optimum solutions (Deb and Datta, 2013). Hence, the new Auto-Adaptive Constraints (AAC) methodology was developed to overcome such challenges. The AAC was developed after intensive practical diagnosis and assessment of evolutionary algorithm behaviour on real-world many-objectives problem with large number of decision variables. The initial decision variables population random seeding generates feasible and unfeasible candidates in the decision variables design space. Then these candidates subjected to mutation and crossover evolving process to produce new generations until evaluation process ends (Deb, 2001; Abraham et al., 2005), which is sensitive to objective achievement to produce non-dominated solutions. Therefore, the initial evaluation stages produce large penalized values due to numerous decision variables violations which restrains the convergence process or may cause stagnation in local optima (Deb and Datta, 2013). To overcome this problem, the AAC methodology combined the penalty formula and model violations with dynamic nexus, which release the chain of constraints gradually when large values of violation observed, then reinforce these chains at small values when decision variable values approaching feasible region. Figures 1 illustrates the diagram of OSEF-AAC and AAC details approaches.

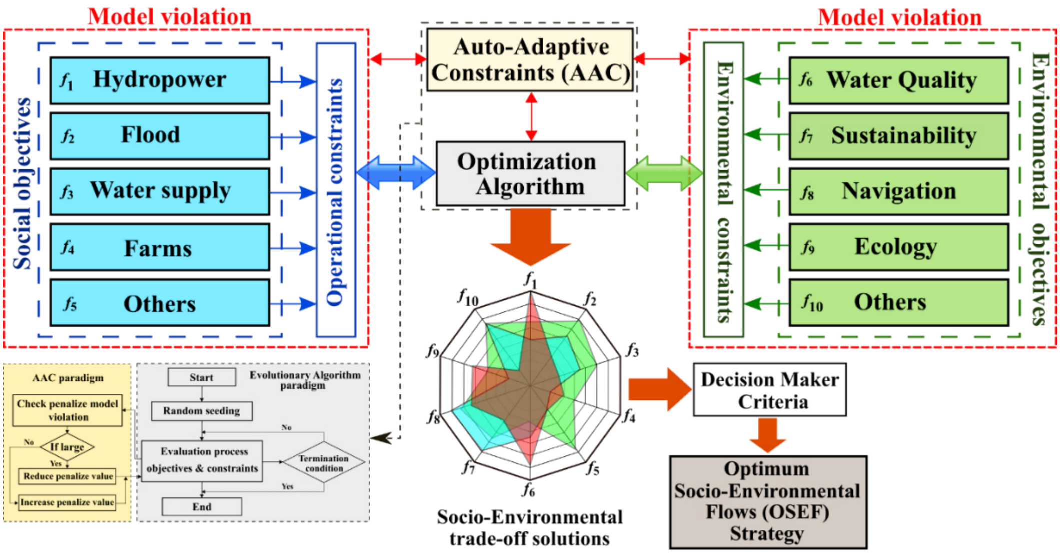

Figure 1. Schematic diagram of the developed OSEF-AAC diagram in the current research. OSEF refer to Optimum Socio-Environmental Flows, and AAC to Auto-Adapted Constraints approaches.

2.2 Identification of Many-Objectives Optimization Algorithms

Hadka and Reed (2013) present the state-of-the-art Borg MOEA for many-objectives optimization problem with auto-adaptive six recombination operators, ε-box techniques for dominance sorting, injection mechanism (Kollat and Reed, 2006) to avoid stagnation, and an archive for dominance solutions sorting. Comparative assessment studies of Borg MOEA achieved by Hadka and Reed (2012), Hadka et al. (2012), Reed et al., (2013), Woodruff et al. (2015), and Zatarain Salazar et al., (2016) on various problems with competitive evolutionary algorithms (like NSGA-II, AMALGAM, ε-MOEA, SPEA2, .. etc.) shows outperformance of Borg MOEA. Recently, Al-jawad and Tanyimboh (2017) assessed Borg MOEA to solve real-world reservoir operation; results show that Borg MOEA enhances the solution significantly.

New methodologies were proposed by in developing ε-DSEA to increase the diversity and enhance model convergence. ε-DSEA has self-adaptive operators' parameters control technique for auto-parameter-tuning, and random parameters resetting to avoid stagnation. The ε-DSEA were intensively tested on five benchmarks functions with up to 8-objectives, three objectives real-world reservoir operation problem, and a real-world groundwater long-term management (Al-Jawad and Tanyimboh, 2018; Al-Jawad et al., 2018). The results showed that ε-DSEA outperformed Borg MOEA in almost all adopted cases.

3 CASE STUDY DESCRIPTION

3.1 Regional Identification

The Himren dam system in Iraq was selected as a challenging water resources problem, located in the semi-arid region in the Middle East, which has many social and environmental management dilemmas. It is a rock fill multipurpose dam located in the Diyala governorate of Iraq at 34° 06' 45" N – 44° 58' 11" E, 120 km in the northeast from Baghdad city (Figure 2).

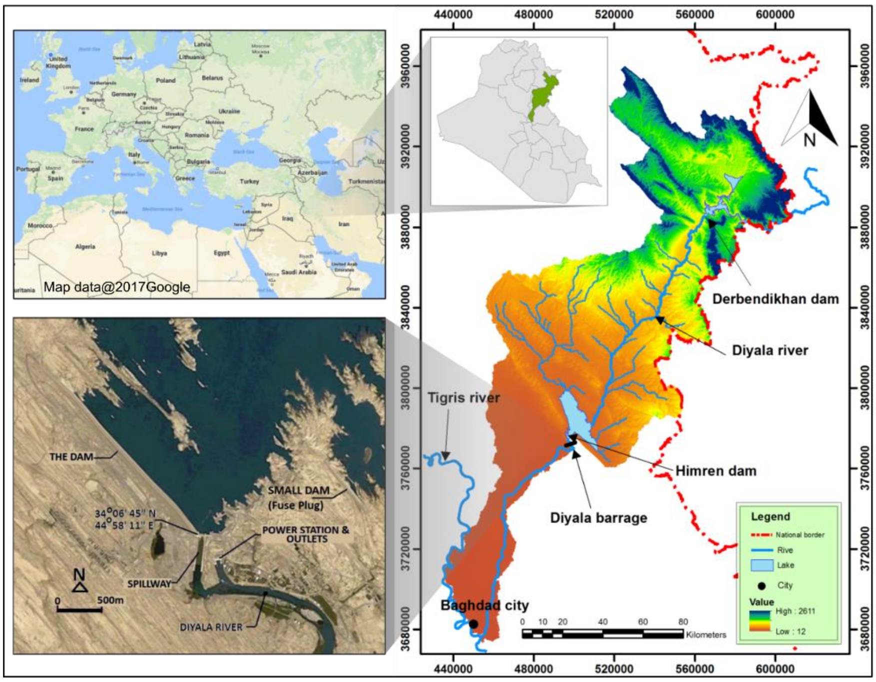

Figure 2. Diyala river basin and Himren dam location in Iraq
(adapted from (SGI et al., 2014))

The dam was built for hydropower production, flood control, agriculture and re-regulates river flows for downstream water exploitation. Table A2 and A3 in the *supplementary data* presents Himren dam characteristics details, and the average monthly meteorological data, precipitation, evaporation, river losses, and irrigation projects demands for the dam system, respectively. The Diyala river basin is facing crisis and deterioration in the sustainability of its water resources and environments. Details identification of the problem are illustrated in section 3 in the *supplementary data*.

3.2 Identification of Reservoir Management Objectives (OSEF-AAC approach)

In general, each river basin has its own operation objectives and constraints, hence mathematical models are developed for the adopted case study for OSEF-AAC approach implementation. Water resources management decisions may relate to a range of spatial and temporal scales, from sub-daily to multi-year and a single location to the river basin, respectively. However monthly rather weekly values were considered in the model as the focus of the research is to assist with the development of an efficient seasonal operating policy, rather than daily operational control (Horne et al., 2016). In order to clarify the model structure and the proposed objective functions for the reservoir operation management, Figure A1 in the *supplementary data* shows the physical model features together with the nine objective functions for Himren dam. The river basin management system was categorized in to two main groups, social and environmental.

3.2.1 Social Sector Objectives

This sector includes objectives addressing water demands, storage support, flood risk management, and power generation. To fulfil downstream water demands for domestic, industrial, and irrigation projects at time *t* (DD_t^H), the corresponding reservoir releases (R_t^H) should be managed to follow these demands over the time operation *T*, which can be formulated as:

$$min\, f_{demandsH} = \sum_{t=1}^{T} \left(\frac{R_t^H - DD_t^H}{DD_{max}^H} \right)^2 + C_P \quad , t = 1, 2, .. T \tag{1}$$

where DD_{max}^H is the maximum water demands, and C_P is the penalty value includes all the violations of the model, which could be expressed as:

$$C_P = \sum_{i=1}^{PN} C_i^e \quad , i = 1, 2, .. PN \tag{2}$$

where *PN* is the number of penalty functions, C_i is the penalty value for the (i^{th}) penalty function, and *e* is any positive integer number. More details of C_i are presented in equations 19 and 20 below.

In arid environments one of the main reasons for a dam is to support reservoir storage during rainy seasons (T_W), usually in winter, to fulfil water demands in hotter / dryer seasons. Hence the reservoir storage at time t (S_t^H) should be increased to the maximum reservoir storage (S_{max}^H). Therefore, the second social objective can be expressed as:

$$min\, f_{winterH} = \sum_{t=1}^{Tw} \left(\frac{S_{max}^H - S_t^H}{S_{max}^H} \right)^2 + C_P \quad , t = 1, 2,.. T_W \tag{3}$$

The reservoir water storage budget is affected by the quantity of reservoir inflows (I_t^H), the reservoir releases (R_t^H), reservoir lake evaporation (E_t^H), direct rainfall (P_t^H), reservoir seepage losses (SE_t^H), and reservoir groundwater recharge (GR_t^H). Hence, reservoir storage at time t+1 (S_{t+1}^H) could be expressed as:

$$S_{t+1}^H = S_t^H + I_t^H - R_t^H - E_t^H + P_t^H - SE_t^H + GR_t^H \quad , t = 1, 2,.. T \tag{4}$$

Reservoir area-storage and head-storage relationships are presented in the section 5 in the *supplementary data*. Flood risk management strategy should be considered in the operation policy to reduce inundation hazards, and can be managed by reducing reservoir storage during the summer season (T_S) before the next rainy season. While the minimum generating power (S_{minp}^H) need to be maintained during this period. Hence the third social objective can be formulated as:

$$min\, f_{summerH} = \sum_{t=1}^{Ts} \left(\frac{S_t^H - S_{minp}^H}{S_{max}^H} \right)^2 + C_P \quad , t = 1, 2, .. T_S \tag{5}$$

Generating power is one of the main economic purposes considered in dam operational design. Therefore, the fourth social objective is to maximize the power generation at time t (Pw_t^H) towards the maximum power plant capacity (Pw_{max}^H) over the operation time T to improve project revenues using the following formula:

$$min\, f_{powerH} = \sum_{t=1}^{T} \left(\frac{Pw_{max}^H - Pw_t^H}{Pw_{max}^H} \right)^2 + C_P \quad , t = 1, 2,..T \tag{6}$$

The general hydropower generation formula is as follows:

$$Pw_t^H = \eta_e^H . \gamma_w . Q_t^{tuH} . H_t^{nH} \tag{7}$$

where η_e^H is power plant efficiency, γ_w is water specific weight, Q_t^{tuH} is the turbine discharge, and H_t^{nH} is the net head in the reservoir measured between reservoir water surface level and the tail water level after the dam structure (after the hydropower turbine structure).

3.2.2 Environmental Sector Objectives

The objectives of this sector can be expressed as: controlling river discharges, river water quality, downstream water quality, and river morphology. The harmony in river flows is important for controlling river morphology, navigation and tourism in the region. Since the discharges are controlled by the Diyala barrage downstream of the dam, additional control considerations should be combined within the management model. A new Barrage operation policy is proposed to enhance river environment, which its details are in section 6 in the *supplementary data*. Hence the second environmental objective is to minimize the river discharge differences at time t (Q_t^r) and t+1 (Q_{t+1}^r) with respect to the maximum river discharge (Q_{max}^r) for the entire periods time T. The following formula was proposed:

$$min\, f_{riverB} = \sum_{t=1}^{T} \left(\frac{Q_t^r - Q_{t+1}^r}{Q_{max}^r} \right)^2 + C_P \quad , t = 1, 2,..T \tag{8}$$

The river water quality is important for ecosystem and anthropogenic needs; therefore, reservoir releases management should consider this issue. Where a pollutant source discharges to the river, the final concentration of total dissolved solids after the source point at time *t* (TDS_t^{r2}) depend on the mixed concentrations of pollutant source and the river (TDS_t^{PS}, TDS_t^{r1}) coupled with their discharges (Q_t^{PS}, Q_t^{r1}), respectively. Hence, the final concentration can be calculated using mass solute balance equation:

$$TDS_t^{r2} = \frac{TDS_t^{r1} \times Q_t^{r1} + TDS_t^{PS} \times Q_t^{PS}}{Q_t^{r1} + Q_t^{PS}} \quad , t = 1, 2,..T \tag{9}$$

From the above, the second environmental objective is to minimize river pollutant after the pollutant source over the operation time *T*, which can be expressed as:

$$min\, f_{TDS-DY} = \sum_{t=1}^{T} \left(\frac{TDS_t^{r2}}{TDS_t^{PS}} \right)^2 + C_P \quad , t = 1, 2,..T \tag{10}$$

Consistency, since the Diyala river is merging with Tigris river downstream, the mixing water should also be monitored. So, the mix concentration after the confluence (TDS_t^R) depends on both rivers quality and quantity TDS_t^{r2}, Q_t^{r2}, TDS_t^{r3}, Q_t^{r3}, respectively, which could be expressed as:

$$TDS_t^R = \frac{TDS_t^{r2} \times Q_t^{r2} + TDS_t^{r3} \times Q_t^{r3}}{Q_t^{r2} + Q_t^{r3}} \quad , t = 1, 2,..T \tag{11}$$

The third environmental objective is to minimize the final mixed concentration in Tigris river after the confluence With Diyala river with respect to the maximum allowable concentration of (TDS_{max}) over the operation period *T*, which can be formulated as:

$$min\, f_{TDS-TR} = \sum_{t=1}^{T} \left(\frac{TDS_t^R}{TDS_{max}} \right)^2 + C_P \quad , t = 1, 2,..T \qquad (12)$$

River morphology is another environmental aspect considered through degradation and aggregation in the riverbed at section *i* and time *t* according to the Schoklisch formula (1934) (Yang 1996 in Ali 2016) and it depends on river discharge per unit width ($q_{i,t}^r$), critical discharge per unit width ($q_{i,t}^c$), energy gradient of water ($HG_{i,t}$), and soil particle diameter (d_s). Hence, the riverbed sediment load discharge ($BD_{i,t}$) per unit width is:

$$BD_{i,t} = \frac{7000\, HG_{i,t}^{3/2}}{\sqrt{d_s}} . \left(q_{i,t}^r - q_{i,t}^c \right) \quad , t = 1, 2,..T, i = 1, 2, .. NS \qquad (13)$$

where *NS* is the number of considered sections along the river

$$q_{i,t}^c = \frac{1.944 \times 10^{-5} . d_s}{HG_{i,t}^{4/3}} \qquad (14)$$

The energy gradient at section *i* and time *t* could be calculated using Manning's formula, which depends on Manning's roughness coefficient (*n*), river discharge (Q_t^r), effective flow area ($A_{i,t}$), and hydraulic radius ($HR_{i,t}$) of the river section

$$HG_{i,t} = \frac{n^2 (Q_t^r)^2}{A_{i,t}^2 HR_{i,t}^{4/3}} \quad , t = 1, 2,..T, i = 1, 2, .. NS \qquad (15)$$

Carriaga and Mays (1995) and Nicklow and Mays (2001) proposed sediment routing formula in the river to calculate the bed level change at section *i* and time *t* ($BL_{i,t}$), and time *t*+1 ($BL_{i,t+1}$), respectively. Their formula depends on the difference between bed load discharge at section *i*-1 and *i*+1 ($BD_{i-1,t}$, $BD_{i+1,t}$), specific density of water-soil mixture (γ_m), river bed width (W_i), and the length between the considered section and the upstream section ($L_{u,t}$) and downstream section ($L_{d,t}$). Hence, the aggregation and degradation at *i* section in any time difference ΔT along riverbed could be calculated as follows:

$$BL_{i,t+1} = BL_{i,t} - \frac{\Delta T_t}{0.5\gamma_m W_i} \frac{\left(BD_{i-1,t} - BD_{i+1,t}\right)}{\left(L_{u,t} + L_{d,t}\right)} \quad , t = 1, 2, .. T, \; i = 1, 2, .. NS \qquad (16)$$

In order to minimize the changes in river bed levels over the operation time T, the following formula proposed:

$$min\, f_{DY-BCH} = \sum_{i=1}^{NS} \left(\frac{BL_{i,t=0} - BL_{i,t=T}}{\Delta BL_{max}}\right)^2 + C_P \quad , t = 1, 2, .. T \qquad (17)$$

where ΔBL_{max} is the maximum allowable river bed level changes

3.2.3 Model Violation Objective

The final objective function is to minimize the penalty function value (C_P) to force the optimization algorithm to search in the feasible space of the problem, as follows:

$$min\, f_{MD} = C_P \qquad (18)$$

When model system boundaries are violated over the evaluation process, the following formula was proposed for the entire model violation (Chang et al., 2010; Al-jawad and Tanyimboh, 2017):

$$C_i = A_i . \sum_{j=1}^{T} g_j \,; \;\; A_i \geq 1 \qquad (19)$$

where, (g_j) is the penalty function of (j^{th}) constraint. In this research, the AAC approach was adopted for the factor (A_i) for the environmental constraints. In reservoir releases management, these constraints are concerned with the ecosystem requirement such as river flow, river water quality, sediment transport, navigation …etc. The factor (A_i) was first set for an initial value, then these values were dynamically adapted with the corresponding penalty function (C_i) using the following formula during the evaluation process, which was developed by empirical practice:

$$A_i = \begin{Bmatrix} A_i - \left(\dfrac{1}{\sqrt{C_i}}\right) & if\ C_i \geq 1.0 \\ A_i + 1.0 & otherwise \end{Bmatrix}, A_i \geq 1.0 \qquad (20)$$

Two scenarios were adopted using a historical data from 1981 to 2012. Scenario-1 represents the projection of the historical data for the next future inflows. Scenario-2 reflects the predicted climate changes impacts on reservoir inflows for the next thirty-three years. Details of proposed scenarios are presented in section 7 in the *supplementary data*.

The reservoir system operational, environmental parameters, and constraints are shown in Table 2. The operational parameters include the physical limits of reservoir storage, releases, turbine and river discharges, while the environmental parameters include water quality limits, river morphology, and storage sustainability.

Details of constraints formulae (g_j) for the reservoir operation management are presented in the *supplementary data in section 7*

Table 2. Reservoir system operation parameters and constraints (SGI et al. 2014; Alsaffar, 2017)

Parameter	Value	Unit	Parameter	Value	Unit
S^H_{min}	20×10^6	m^3	Q^r_{max}	1000	m^3/s
S^H_{max}	2400×10^6	m^3	TDS^{r1}_t at Q^r_{min}	2220[1]	mg/l
S^H_{minp}	102×10^6	m^3	TDS^{PS}_t	5000[1]	mg/l
R^H_{min}	20	m^3/s	TDS^U	500[3]	mg/l
R^H_{max}	447	m^3/s	Q^{PS}_t	15[1]	m^3/s
Pw^H_{min}	50	MW	γ_m	1486[2]	kg/m^3
Pw^H_{max}	7.5	MW	W_i (mean)	80.0	m
η^H_e	88	%	ΔBL_{max}	2.0	m
γ_w	≈1000	KN/m^3	d_s	20.0 - 0.177	mm
Q^{tuH}_{min}	38	m^3/s	NS	41	-
Q^{tuH}_{max}	98.5	m^3/s	T_W	October – March	Month
$H^{nH}_{t,min}$	15.9	m	T_S	April - September	Month
$H^{nH}_{t,max}$	30.8	m	ΔT_t	1	Month
Q^r_{min}	10	m^3/s	S^H_{T+1}	$0.9\times S^H_{t=0}$	

[1] Kubba et al. (2014), [2] Nicklow and Mays (2001), [3] Saleh (2013)

3.3 Computational Model Implementation

Using in the programming language C, a model was developed to conceptualize all the objective functions and the corresponding constraints. For completeness, both the Borg MOEA and the ε-DSEA algorithms were replicated 20 times for each scenario, with the number of function evaluations equal to 500,000 and epsilon (ε) (ε is the resolution of the objective search space) equal to 0.5 for the nine objectives for both scenarios. The number of decision variables, 396, equals the number of monthly releases over the thirty-three years' data period. Additionally, other reservoir parameters system including storage, surface area, water level, and power generating were calculated by the model; hence the model solved 3564 variables in each run. The overall function evaluation total is 40 million, with total processing time about 80 hours CPU time. The optimization running process was made using PC desktop (Core i7-6700 CPU @ 3.4 GHz, 16 GB RAM) with Ubuntu 16.04 OS. The parameters used for both algorithms are shown in Table A1 in the supplementary data.

In the current study, a value of $A = 10^4$ was selected for the dam physical model constraints to exploit all feasible solutions and avoid rendering infeasible solutions at the constraints threshold, especially those with small violation values. While $A_i = 10^2$ (Al-Jawad and Tanyimboh, 2017) was selected as starting value for the environmental constraints, as described in section 3.3.

4 RESULTS AND DISCUSSION

4.1 Optimum Trade-off Achievement

The MOEAs' effectiveness is commonly measured using metrics like the hypervolume metric (Zitzler, 1999) which evaluate the non-dominated solutions' hypervolume, and generational distance metric (Van Veldhuizen and Lamont, 1998) which measure the average distance between the dominance solutions and the closer Pareto-front set. However, these metrics (and others) may provide misguiding results and most of their design principles depends on the true Pareto-front, which is unknown in real-world water resources management problems (Maier et al., 2014). Accordingly, qualitative and quantitative parameters were adopted for achievement assessment. The optimization results are shown in Figure 3, here the ε-DSEA outperforms Borg MOEA in both scenarios for the near median Pareto-front values achieved from the 20 runs for each scenario, since the range of objectives functions values achieved by ε-DSEA are lower than those in Borg MOEA.

The mean numbers of dominance solutions achieved by ε-DSEA and Borg MOEA in both scenarios were about 721, 406; 771, 368; and the median were 372, 286; 815, 273, respectively. While, the gross number of dominance solutions achieved by both algorithms for the adopted scenarios were 14410, 8118; 15415, 7363, respectively, hence the ε-DSEA has advance diversity than Borg MOEA. Convergence speed is another parameter chosen for performance assessment, which represents algorithm's efficiency. Figure 4 illustrates convergence development process for model objectives functions over the evaluation process for both algorithms and scenarios. It is clearly that ε-DSEA converge faster than Borg MOEA in both scenarios. Hence the ε-DSEA solutions were adopted for interpretation of the reservoir operation management. Detail competitive analysis results for both algorithms are presented in section 8 in the *supplementary data*.

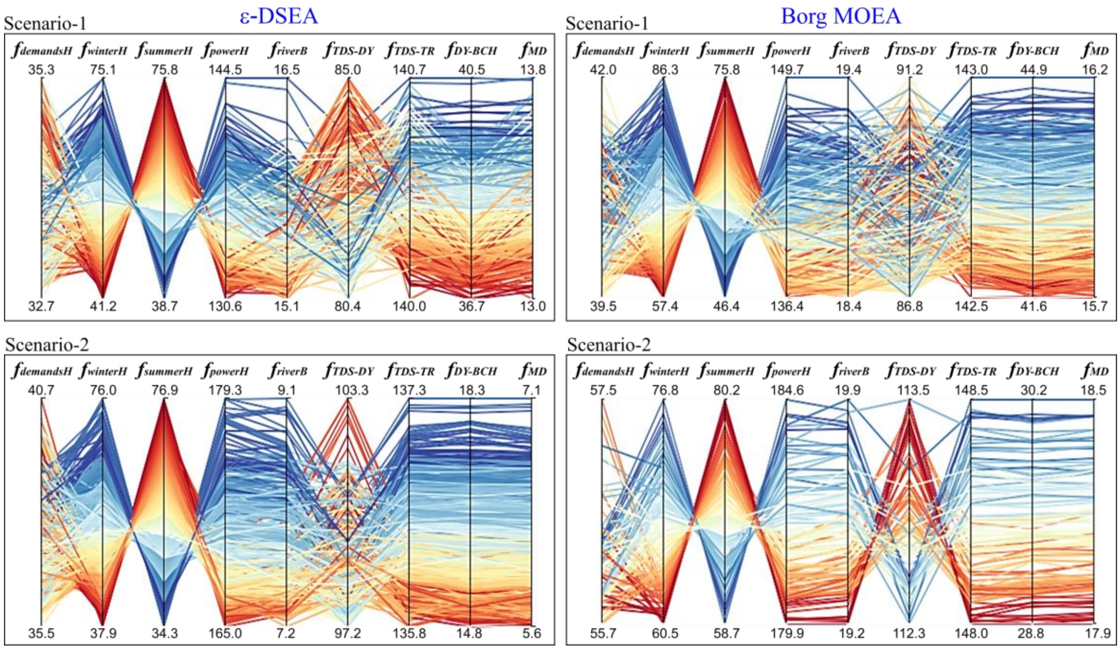

Figure 3. Pareto-front (trade-off) for the nine objective functions using Borg MOEA and ε-DSEA algorithms for Himren dam future management strategy scenarios.

The conflicts relationship between model objectives is obvious in both scenarios (Figure 3), except for f_{TDS-TR} and f_{DY-BCH}, but in fact there are slight conflicts for many solutions. The Diyala river bed changes are directly affected by the river discharge, and the concentration of TDS in the Tigris river is affected by both discharges and quality of Diyala river. Hence the relation between the two function is indirect, with lower level of conflicts than other objectives functions. Further, the degree of mutual influence between power generation objective (f_{power}) and river flow regulation objective (f_{riverB}) by Diyala Barrage is medium because the Barrage divert most of reservoir releases to the agriculture projects. The multi-objectives evolutionary algorithm's capability to solve conflicts objectives simultaneously by generating a set of optimum solutions (Deb, 2001) (trade-off) has a major advantage, through which decision makers can adopt a solution (or solutions) that consistent with their criteria.

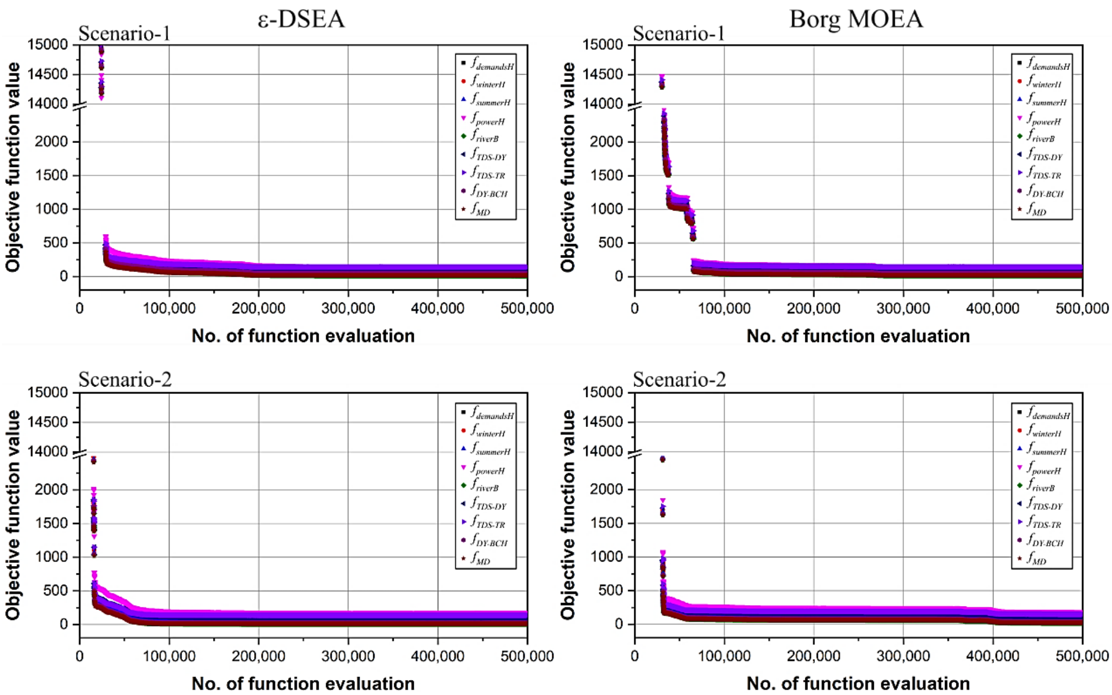

Figure 4. Illustrates objectives convergence speed over evaluation process for Borg MOEA and ε-DSEA with two inflows scenarios

Figure 3 also shows that the total model violation function is greater than one ($f_{MD} > 1.0$) in all cases, which refers to unfeasible solutions achievement in the objective search space. However, these solutions are located in both the feasible and unfeasible regions in the decision variables search space. Table 2 illustrates the summary of Himren dam system parameters achieved by ε-DSEA for both scenarios. The reservoir releases, storage, water level, surface area and hydropower generation did not violate its barriers, hence their objectives attainment were emerged from feasible decision variables. Also, the Diyala River discharges did not exceed river maximum capacity because they are controlled by the Himren dam and the Diyala Barrage. However, partial violations were observed in the Diyala river morphology and in the Tigris River water quality about their preferable limits (river bed changes ≤ 2.0, TDS ≤ 600 mg/l), which are specified requirements from the NCWRM (the decision makers). This refers to the reservoir releases inertia to satisfy these limits over the operation periods, hence some decision variables located in the unfeasible region of the decision variables space.

Table 2. Summary of optimum parameters achieved for Himren dam system using ε-DSEA for both scenarios

System parameter	**Scenario-1**		**Scenario-2**	
	Min.	**Max.**	**Min.**	**Max.**
Reservoir releases (MCM)	98.51	1158.62	98.52	1158.62
Reservoir storage (MCM)	101.55	2398.48	92.78	2399.97
Reservoir water level (m.a.s.l)	89.20	105.36	89.00	105.37
Reservoir Surface area (Km^2)	38.77	321.74	37.42	321.89
Hydropower generation (MW)	7.50	50.00	7.50	50.00
Diyala river discharge (MCM)	30.85	1108.84	30.85	1084.10
Absolute Diyala bed river changes (m)	0.00	4.62	0.00	3.00
Diyala river TDS before WWTP (mg/l)	540.21	2220.00	541.12	2220.00
Diyala river TDS after WWTP (mg/l)	599.73	3590.60	601.98	3590.58
Tigris river TDS (mg/l)	520.38	613.84	528.89	613.79

MCM=Million cubic meters/month; TDS=Total dissolved solids; WWTP=Wastewater treatment plant

Usually operation management priorities were set depending on stakeholders' demands. Here the operating priority is to satisfy domestic demands downstream

Himren dam, and other objectives considered within the secondary priorities. Although the potential violation in Tigris River quality for downstream regions, the model succeeds to maintain its quality < 620 mg/l in both scenarios over the entire period of operation, in compare with the range of 600 to 1200 mg/l in the previous recent records. However, the government needs to adopt advance remediation policy for the wastewater quality discharged from Al-Rustumiya plant to mitigate the impact of pollution in the downstream.

The above argument shows the importance of understanding reservoir management priorities in developing system objectives functions and constraints to represent these priorities. Furthermore, partial violated solutions in secondary priorities could be adopted for reservoir operation strategy.

4.2 AAC approach Achievement

The new AAC approach succeed to guide the optimization algorithm towards possible optimum solutions. Figure 5 shows the values of penalty factors (A_i) with the corresponding penalty function value (C_i) over the evaluation process for both scenarios. This Figure illustrates how A_i's values dynamically changed with the corresponding penalty function value (C_i) when $C_i \geq 1.0$. However, the riverbed changes penalty factor A_4 remains at minimum value ($A_4 = 1.0$) in both scenarios, since its penalty value C_4 is greater than one over the entire evaluation process. The riverbed changes, which includes aggregation and degradation, are mainly effected by water flow velocity and riverbed sediment grain size. The flow velocity is directly proportion with reservoir releases, hence inconsistent releases may cause changes in riverbed morphology, depending on bed sediment grain sizes. Here, because of lack data, the adopted riverbed changes mathematical model was simplified by averaging river bed width, and assuming water energy gradient equal to the river bed slop. Therefore, detail cross sections, bed sediment grain size, and other parameters are required to improve the control of river morphology changes.

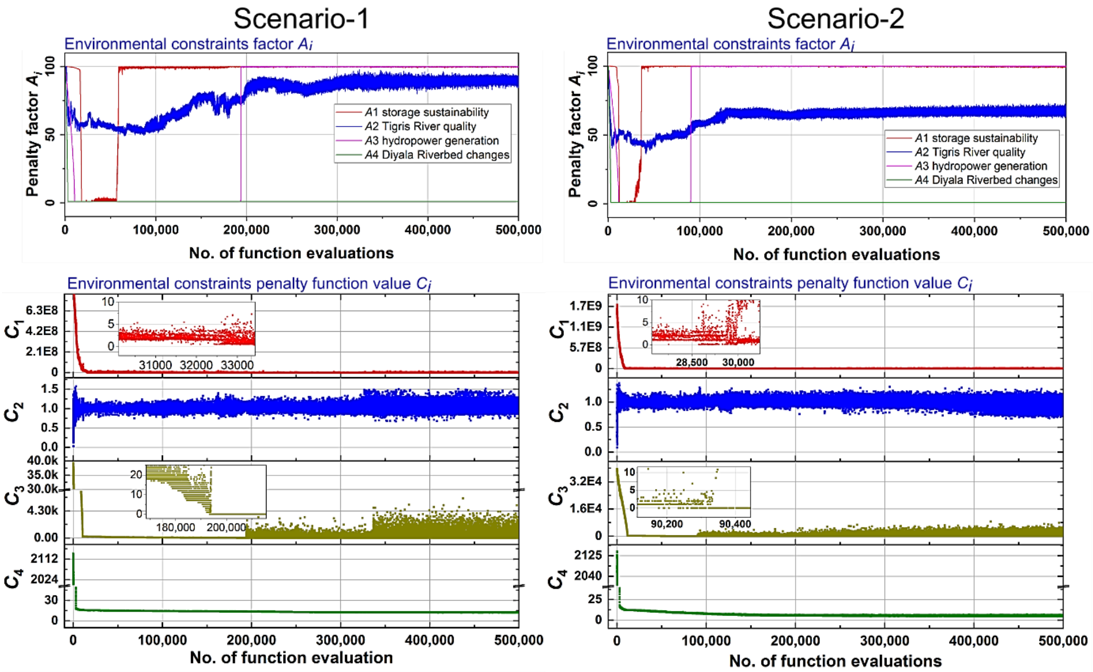

Figure 5. AAC approach for environmental constraints factors (A_i) and their corresponding penalty function values (C_i) over the evaluation process for the secondary priorities objectives for Himren dam operation policy. The magnified graphs show the region when C_i = 0.

4.3 Reservoir Operation Strategy

Although the decision of adopting any optimum solution depends on the decision makers' decision, we will propose a solution emerged from the best achievement of each objective, which could be beneficial for the decision makers to consider. The corresponding reservoir releases for optimum solutions are presented in Figure 6, (a) and (b) for both scenarios respectively. It clearly that these results are consistent, hence an average values for reservoir releases was generated, as shown in Figure 6 (c) and

(d) for both scenarios, respectively. The details of other corresponding variables of the system like: reservoir storage, surface area, hydropower generation, etc., for both scenarios were presented in section 9 in the *supplementary data*.

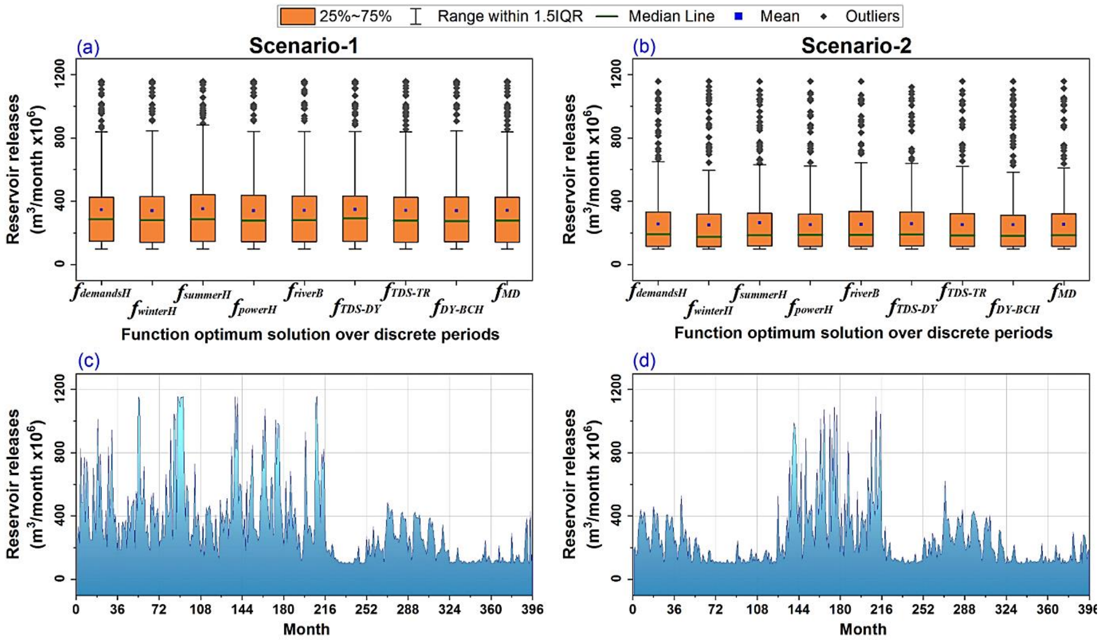

Figure 6. Optimum individual and average reservoir releases achieved by optimization model for the two scenarios. Where (a) and (b) are the releases achieved by each objective function optimum solution for scenario 1 and 2, respectively, while (c) and (d) represent the average releases for the nine objective functions optimum solutions.

The summary of the outcomes is illustrated in Tables 3; from this data there emerges an optimum socio-environmental flows regime for long-term reservoir system management strategy that could be adopted by the decision makers. Furthermore, improvements were achieved in different sectors in the river basin (e.g. hydropower generation, crop production, water industry, etc.). The mean hydropower generated in scenario-1 was about 26 MW over three decades with standard deviation about 14 MW, while in scenario-2, is about 21 MW and 12 MW, respectively. The mean agriculture water delivery for both scenarios were maintained between about 157 MCM and 137 MCM, respectively. However, these values show deficit in water delivery when compared with the actual design demands. Hence, the government should adopt future policy to assess other alternatives to reduce the water deficit, such as reducing crop patterns, changing crops types, using groundwater, changing irrigation method (e.g. sprinkles, drips), developing water conveyance infrastructure, etc.

Table 3. Summary results for the reservoir system parameters achieved using average optimum reservoir releases for the two adopted scenarios.

Parameter		**Min.**	**Max.**	**Mean**	**Median**	**Std.**
				Scenario-1		
Releases (MCM)*	Dam system	98.97	1158.47	343.46	280.047	249.60
Storage (MCM)	Dam system	326.85	2276.07	1332.75	1348.664	394.69
Surface area (km^2)	Dam system	72.58	309.496	204.08	207.795	47.78
Water level (m.a.s.l)	Dam system	93.08	104.662	100.00	100.237	2.13
Hydropower (MW)	Dam system	7.85	50.00	26.03	23.951	13.66
River discharge (MCM)	Downstream river system	30.87	1105.95	186.73	102.43	216.53
TDS** before WWTP*** (mg/l)	Downstream river system	540.31	2220.00	1243.36	1071.61	564.61
TDS after WWTP (mg/l)	Downstream river system	599.99	3589.43	1885.29	1705.26	912.91
Initial riverbed level (m.a.s.l)	Downstream river system	25.16	60.90	35.92	31.10	9.55
Final riverbed level (m.a.s.l)	Downstream river system	25.26	55.64	35.25	30.95	8.33
TDS in Tigris River (mg/l)	Downstream river system	520.39	612.89	565.87	563.16	21.31
Original farms water demands (MCM)	Downstream river system	30.46	313.34	191.00	200.13	87.45
Achieved farms water delivery (MCM)	Downstream river system	30.46	313.34	156.73	138.56	88.08
				Scenario-2		
Releases (MCM)	Dam system	98.69	1153.73	254.21	186.59	195.47
Storage (MCM)	Dam system	365.97	2327.52	1354.36	1371.04	431.26
Surface area (km^2)	Dam system	78.29	314.67	206.33	210.46	51.88
Water level (m.a.s.l)	Dam system	93.56	104.95	100.09	100.35	2.307
Hydropower (MW)	Dam system	7.82	50.00	20.63	16.48	12.44
River discharge (MCM)	Downstream river system	30.86	1012.03	116.96	55.94	158.05
TDS before WWTP (mg/l)	Downstream river system	544.05	2220.00	1474.89	1528.18	550.77
TDS after WWTP (mg/l)	Downstream river system	609.13	3585.63	2263.96	2420.52	868.08
Initial riverbed level (m.a.s.l)	Downstream river system	25.16	60.90	35.92	31.10	9.55
Final riverbed level (m.a.s.l)	Downstream river system	25.25	57.25	35.36	31.42	8.46
TDS in Tigris River (mg/l)	Downstream river system	529.31	612.99	573.27	575.45	20.30
Original farms water demands (MCM)	Downstream river system	30.46	313.34	191.00	200.13	87.45
Achieved farms water delivery (MCM)	Downstream river system	30.46	313.34	137.26	130.01	81.29

** is refer to million cubic meters per month.*
*** is refer to Total Dissolved Solids*
**** is refer to wastewater treatment plant*

Furthermore, the reservoir storage was also maintained with its limits with a mean value about 1.3×10^9 m^3/month for both scenarios. This provides suitable space when compared with the normal storage of 2.4×10^9 m^3/month, to absorb flood waves and reduce the possible flood risk impact on the community downstream the river. However, future government led policies should also consider flood alarm systems for advance flood control. Additionally, reservoir seepage losess and advanced data collection systems should be included in their policy for comprehensive water resources management.

With consistency, the proposed operation policy for the Diyala barrage maintains a minimum discharge about 30.8 MCM in both scenarios, which is equivalent to about 12 m^3/s; this is more than the minimum river discharge of 10 m^3/s. Also, the model predicts maintenance of the mean and median changes in river morphology less than one meter in both scenarios over the entire period, which mitigates the impact of load sediment transport on downstream projects. Sediment movement impacts navigation, water supply projects, and for river hydraulic infrastructures in the downstream, which raise maintenance costs to overcome these problems.

The impact of Diyala river environment improvement was also observed by maintaining Tigris water quality (TDS) less than 613 mg/l in both scenarios over the entire periods, predicted management would have a positive economic impact on the water supply projects, farming, and the industry in downstream cities and villages. However, river quality should be monitored in case of shortage in Tigris water resources to avoid any deterioration due to high TDS concentration in Diyala river discharges.

The model reliability was compared with the actual operating management criteria in which the median reservoir releases in scenario-2 show robust consistency, according to the (Alsaffar, 2017b).The proposed methodology in scenario-2 could be adopted to represent the impact of climate changes in other part of this region. Furthermore, the proposed approach succeeds to provide future prediction picture for the decision makers about the interaction between all considered features, including social and environmental objectives in the river basin. However, other inflows alternatives (scenarios), like out boarder upstream development projects impacts on downstream river basin system, could be implemented for further insight approach assessment.

The study outcomes also illustrate how the system is sensitive to the reservoir inflows, which are affected generally by the releases from the upstream reservoir (Derbindikhan dam reservoir), out-border tributaries, and upstream direct runoff and water exploitation. Hence, the government should consider future policies to restrict unauthorized water use in upstream region. Also they should consider developing water sharing agreement with Iran to avoid future water crisis in the basin. Therefore, the river basin needs further future management development to involve the above mentioned features (and others) for fully river basin management, which is known as integrated water resources management (IWRM). Finally, this study’s novel approach implementation illustrates how environmental features could be improved when they are considered in the reservoir operation management, and how they will promote the potential economic benefits for the entire system.

The current study presents an approach which its principle could be implemented for any reservoir operation problem (combining social with environmental objectives using many-objective optimization algorithm). While the proposed mathematical optimization model is correlated with current case study and /or similar problems, and can be modified for other region in the world.

However, the current model's temporal (regional extension) and special scale (No. of decision variables) is correlated to the adopted case study, which can be extended for other problems for future works.

5 CONCLUSIONS

In this research a novel Optimum Social-Environmental Flows approach with Auto-Adaptive Constraints (OSEF-AAC) was developed to improve the river basin management strategy which combines all social and environmental objectives in the river basin. The research used a many-objectives evolutionary optimization algorithm to generate a trade-off to the decision makers. This approach was developed to fill the gap of combined environmental flow regimes in the reservoir operation strategy (Horne et al., 2016; Horne et al., 2017), and to overcome the complexity and computational challenges of such models (Maier et al., 2014).

The OSEF-AAC was evaluated and assessed using a challenging case study in the Middle East. The Diyala river basin was modelled with nine social and environmental objectives using the state-of-the-art Borg MOEA and the new ε-DSEA optimization algorithms with 396 decision variables under two inflows scenarios to promote the operation strategy for Himren reservoir system. The algorithms computational analysis results show the ε-DSEA outperformed the Borg MOEA in almost all cases, hence the ε-DSEA results were adopted. Moreover, the AAC approach succeed to overcome the complexity of the problem, boosting algorithm convergence toward possible optimum solutions and avoiding algorithm stagnation in local optima.

The reservoir releases optimum trade-off emerged from the OSEF-AAC approach integrate all adopted social and environmental sectors in the river basin including hydropower generation, flood risk management, river quality, river sediment transport, reservoir storage control, agriculture water delivery, discharge regulation, and downstream water quality. More objectives could be embedded to the approach for comprehensive flows regime (e.g. fisheries, navigation and tourism). The decision makers can adjust the trade-offs and adopt those that fit their criteria.

However, to fully develop the potential achievement of the OSEF-AAC approach, an average optimum solution was generated using optimum solution achieved by each objective. The results show improvement in reservoir system environments in all sectors, as follows:

- *Environmental Sectors:* The Diyala river water quality (TDS) was improved after a pollutant source from about 2600 mg/l to about 2400 mg/l, which leads to improve the downstream water quality mean value of TDS from about 750 mg/l to 570 mg/l for both scenarios. This will decrease water remediation cost in downstream region. Additionally, the mean and median river morphology changes were maintained within one meters for both scenarios over the considered period. Hence, positive impacts on the maintenance cost for water supply and hydraulic structures in the river were achieved.
- *Social Sector:* The power revenues were improved over continues hydropower generating for the next three decades under two scenarios. Future investment opportunities plans could be set from the mean values 26 MW and 21 MW obtained

for both scenarios, respectively. Moreover, the storage control objectives were succeeded to preserve free mean reservoir storage about 1.0×10^9 m^3 for flood wave absorption, which mitigate the possible flood risk and reduce the cost of inundated indemnity for lands and properties. For crop production, the mean and median agriculture water deficit for both scenarios were maintained within the range of 18-28% and 30-35%, respectively, which robust crop investment revenues.

The adopted mathematical optimization model for the current case study considers only the common management objectives based on the available database. However, other issues like; water influent and affluent of Reservoir Lake, ecosystem and navigation objectives, etc. could be implemented for future works.

Finally, the OSEF-AAC approach can be adopted to solve any river basin management problems to generate optimum socio-environmental flows regime. These provide decision makers a trade-off for developing robust management strategy towards achieving better economic revenues for the water-energy-food nexus objectives of a river basin.

Recommendations for the decision makers to improve the lower Diyala river basin environment are presented in section 10 in the *supplementary data*.

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REFERENCES

Abbas, N., Wasimi, S.A., Al-Ansari, N., 2016. Impacts of Climate Change on Water Resources in Diyala River Basin, Iraq. J. Civ. Eng. Archit. 10, 1059–1074.

Abdulrahman, S.A., 2017. Failure to securitise environmental problems in Iraq: the case of the Alwand and Sirwan Rivers. Int. J. Environ. Stud. 74, 540–557. https://doi.org/10.1080/00207233.2017.1330493

Abraham, A., Jain, L., Robert, G. (Eds), 2005. Evolutionary Multiobjective Optimization, Evolutionary Multiobjective Optimization. Springer-Verlag London. https://doi.org/10.1007/1-84628-137-7

Acreman, M., Arthington, A.H., Colloff, M.J., Couch, C., Crossman, N.D., Dyer, F., Overton, I., Pollino, C.A., Stewardson, M.J., Young, W., 2014. Environmental flows for natural, hybrid, and novel riverine ecosystems in a changing world. Front. Ecol. Environ. 12, 466–473. https://doi.org/10.1890/130134

Aenab, A.M., Singh, S.K., 2014. Critical Assessment of River Water Quality and Wastewater Treatment Plant (WWTP). IOSR J. Environ. Sci. Toxicol. Food Technol. 8, 44–48.

Ahmad, A., El-Shafie, A., Razali, S.F.M., Mohamad, Z.S., 2014. Reservoir Optimization in Water Resources: a Review. Water Resour. Manag. 28, 3391–3405. https://doi.org/10.1007/s11269-014-0700-5

Ahmadianfar, I., Adib, A., Taghian, M., Faculty, E., Resources, N., 2015. a Multi-Objective Evolutionary Algorithm Using Decomposition (Moea/D) and Its Application in Multipurpose Multi-Reservoir Operations. Int. J. Optim. Civ. Eng. 5, 167–187.

Al-Ansari, N., Ali, A.A., Knutsson, S., 2014. Present Conditions and Future Challenges of Water Resources Problems in Iraq. J. Water Resour. Prot. 6, 1066–1098. https://doi.org/10.4236/jwarp.2014.612102

Al-Ansari, N.A., 2013. Management of Water Resources in Iraq: Perspectives and Prognoses. Engineering 05, 667–684. https://doi.org/10.4236/eng.2013.58080

Al-Faraj, F.A.M., Scholz, M., 2014. Assessment of temporal hydrologic anomalies coupled with drought impact for a transboundary river flow regime: The Diyala watershed case study. J. Hydrol. 517, 64–73. https://doi.org/10.1016/j.jhydrol.2014.05.021

Al-Jawad, J.Y., Al-Jawad, S.B., Tanyimboh, T.T., Kalin, R.M., 2018a. Comprehensive Evolutionary Algorithms Performance Assessment Using a Multi-Objectives Water Resources Management Problem. Water Resour. Manag. In review.

Al-Jawad, J.Y., Tanyimboh, T.T., 2017. Reservoir operation using a robust evolutionary optimization algorithm. J. Environ. Manage. 197, 275–286. https://doi.org/10.1016/j.jenvman.2017.03.081

Al-Jawad, J.Y., Tanyimboh, T.T., Kalin, R.M., 2018b. ε-DSEA: A Multi and Many-Objective Evolutionary Optimization Algorithm Based on Novel Self-Adaptive Technique. Appl. Soft Comput. In review.

Ali, A.A., 2016. Three Dimensional Hydro-Morphological Modeling of Tigris River. PhD. Thesis, Luleå University of Technology, Sweden.

Alsaffar, H.M., 2017a. Personal communication. , 15 July.

Alsaffar, H.M., 2017b. Personal communication. , 9 October.

Amirkhani, M., Bozorg-Haddad, O., Fallah-Mehdipour, E., Loáiciga, H.A., 2016. Multiobjective Reservoir Operation for Water Quality Optimization. J. Irrig. Drain. Eng. 142. https://doi.org/10.1061/(ASCE)IR.1943-4774

Back, T., Fogel, D.B., Michalewicz, Z. (Eds.), 2000. Handbook of Evolutionary Computation. IOP Publishing Ltd., Bristol, UK, UK.

Carriaga, C.C., Mays, L.W., 1995. Optimization Modeling For Sedimentation In Alluvial Rivers. J. WATER Resour. Plan. Manag. 121, 251–259.

CEB, (Consulting Engineering Bureau), 2011. Tigris and Euphrates Sampling. Unpublished report, University of Baghdad, Baghdad, Iraq.

Chang, L.C., Chang, F.J., 2009. Multi-objective evolutionary algorithm for operating parallel reservoir system. J. Hydrol. 377, 12–20. https://doi.org/10.1016/j.jhydrol.2009.07.061

Chang, L.C., Chang, F.J., Wang, K.W., Dai, S.Y., 2010. Constrained genetic algorithms for optimizing multi-use reservoir operation. J. Hydrol. 390, 66–74. https://doi.org/10.1016/j.jhydrol.2010.06.031

Chen, D., Chen, Q., Leon, A.S., Li, R., 2016. A Genetic Algorithm Parallel Strategy for Optimizing the Operation of Reservoir with Multiple Eco-environmental Objectives. Water Resour. Manag. 30, 2127–2142. https://doi.org/10.1007/s11269-016-1274-1

Coello, C.A.C., Lamont, G.L., van Veldhuizen, D.A., 2007. Evolutionary Algorithms for Solving Multi-Objective Problems, 2nd ed, Genetic and Evolutionary

Computation. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-0-387-36797-2

Coello Coello, C.A., 2002. Theoretical and numerical constraint-handling techniques used with evolutionary algorithms: a survey of the state of the art. Comput. Methods Appl. Mech. Eng. 191, 1245–1287. https://doi.org/http://dx.doi.org/10.1016/S0045-7825(01)00323-1

Curry, D.M., Dagli, C.H., 2014. Computational complexity measures for many-objective optimization problems. Procedia Comput. Sci. 36, 185–191. https://doi.org/10.1016/j.procs.2014.09.077

Dai, L., Zhang, P., Wang, Y., Jiang, D., Dai, H., Mao, J., Wang, M., 2017. Multi-objective optimization of cascade reservoirs using NSGA-II: A case study of the Three Gorges-Gezhouba cascade reservoirs in the middle Yangtze River, China. Hum. Ecol. Risk Assess. 23, 814–835. https://doi.org/10.1080/10807039.2017.1285692

Deb, K., 2001. Multi-Objective Optimization using Evolutionary Algorithms, 1st ed, Wiley-Interscience Series in Systems and Optimization. John Wiley & Sons, Chichester.

Deb, K., Datta, R., 2013. A bi-objective constrained optimization algorithm using a hybrid evolutionary and penalty function approach. Eng. Optim. 45, 503–527. https://doi.org/10.1080/0305215X.2012.685074

Deb, K., Jain, H., 2013. An Evolutionary Many-Objective Optimization Algorithm Using Reference-point Based Non-dominated Sorting Approach, Part I: Solving

Problems with Box Constraints. Ieeexplore.Ieee.Org 18, 577–601. https://doi.org/10.1109/TEVC.2013.2281534

Deb, K., Pratap, A., Agarwal, S., Meyarivan, T., 2002. A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Trans. Evol. Comput. 6, 182–197. https://doi.org/10.1109/4235.996017

Dittmann, R., Froehlich, F., Pohl, R., Ostrowski, M., 2009. Optimum multi-objective reservoir operation with emphasis on flood control and ecology. Nat. Hazards Earth Syst. Sci. 9, 1973–1980. https://doi.org/10.5194/nhess-9-1973-2009

Evan, R., Soppe, R., Saleh, R., Abbas, A., 2012. Report B1.4: Water and salt trends and balances for the Mesopotamian plain. Technical report No.6, ICARDA (International Center for Agricultural Research in the Dry Areas), Lebanon.

Giacomoni, M.H., Kanta, L., Zechman, E.M., 2013. Complex Adaptive Systems Apporach to Simulate the Sustainability of Water Resources and Urbanization. J. Water Resour. Plan. Manag. 139, 554–564. https://doi.org/10.1061/(ASCE)WR.1943-5452

Giuliani, M., Castelletti, A., Pianosi, F., Mason, E., Reed, P.M., 2016. Curses, Tradeoffs, and Scalable Management: Advancing Evolutionary Multiobjective Direct Policy Search to Improve Water Reservoir Operations. J. Water Resour. Plan. Manag. 142, 04015050. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000570

Giuliani, M., Galelli, S., Soncini-Sessa, R., 2014a. A dimensionality reduction approach for many-objective Markov Decision Processes: Application to a water reservoir operation problem. Environ. Model. Softw. 57, 101–114. https://doi.org/10.1016/j.envsoft.2014.02.011

Giuliani, M., Herman, J.D., Castelletti, A., Reed, P., 2014b. Many-objective reservoir policy identification and refinement to reduce policy inertia and myopia in water management. Water Resour. Res. 50, 3355–3377. https://doi.org/10.1002/2013WR014700

Hadka, D., Reed, P., 2013. Borg: An Auto-Adaptive Many-Objective Evolutionary Computing Framework. Evol. Comput. 21, 1–30. https://doi.org/10.1162/EVCO_a_00075

Hadka, D., Reed, P., 2012. Diagnostic Assessment of Search Controls and Failure Modes in Many-Objective Evolutionary Optimization. Evol. Comput. 20, 423–452. https://doi.org/10.1162/EVCO_a_00053

Hadka, D., Reed, P.M., Simpson, T.W., 2012. Diagnostic assessment of the borg MOEA for many-objective product family design problems, in: 2012 IEEE Congress on Evolutionary Computation, CEC 2012. pp. 10–15. https://doi.org/10.1109/CEC.2012.6256466

Haimes, Y.Y., Hall, W.A., 1977. Sensitivity, responsivity, stability and irreversibility as multiple objectives in civil systems. Adv. Water Resour. 1, 71–81. https://doi.org/10.1016/0309-1708(77)90025-2

Hakimi-Asiabar, M., Ghodsypour, S.H., Kerachian, R., 2010. Deriving operating policies for multi-objective reservoir systems: Application of Self-Learning Genetic Algorithm. Appl. Soft Comput. J. 10, 1151–1163.

https://doi.org/10.1016/j.asoc.2009.08.016

He, Z., Yen, G.G., Zhang, J., 2014. Fuzzy-based pareto optimality for many-objective evolutionary algorithms. IEEE Trans. Evol. Comput. 18, 269–285. https://doi.org/10.1109/TEVC.2013.2258025

Horne, A., Kaur, S., Szemis, J., Costa, A., Webb, J.A., Nathan, R., Stewardson, M., Lowe, L., Boland, N., 2017. Using optimization to develop a “designer” environmental flow regime. Environ. Model. Softw. 88, 188–199. https://doi.org/10.1016/j.envsoft.2016.11.020

Horne, A., Szemis, J.M., Kaur, S., Webb, J.A., Stewardson, M.J., Costa, A., Boland, N., 2016. Optimization tools for environmental water decisions: A review of strengths, weaknesses, and opportunities to improve adoption. Environ. Model. Softw. 84, 326–338. https://doi.org/10.1016/j.envsoft.2016.06.028

Hurford, A.P., Huskova, I., Harou, J.J., 2014. Using many-objective trade-off analysis to help dams promote economic development, protect the poor and enhance ecological health. Environ. Sci. Policy 38, 72–86. https://doi.org/10.1016/j.envsci.2013.10.003

IPCC, 2007. Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, M.L. Parry, O.F. Canziani, J.P. Palutikof, P.J. van der Linden and C. Hanson, Eds., Cambridge University Press, Cambridge, UK, 976pp.

Kasprzyk, J.R., Nataraj, S., Reed, P.M., Lempert, R.J., 2013. Many objective robust decision making for complex environmental systems undergoing change. Environ. Model. Softw. 42, 55–71. https://doi.org/10.1016/j.envsoft.2012.12.007

Kim, T., Heo, J.-H., Bae, D.-H., Kim, J.-H., 2008. Single-reservoir operating rules for a year using multiobjective genetic algorithm. J. Hydroinformatics 10, 163. https://doi.org/10.2166/hydro.2008.019

Kollat, J.B., Reed, P.M., 2006. Comparing state-of-the-art evolutionary multi-objective algorithms for long-term groundwater monitoring design. Adv. Water Resour. 29, 792–807. https://doi.org/10.1016/j.advwatres.2005.07.010

Kubba, F.A., Joodi, A.S., Al-Sudani, H.A.H., 2014. Two Dimensional Mathematical Model of Contamination Distribution in the Lower Reach. Int. J. Eng. Sci. Res. Technol. 3, 213–225.

Lelieveld, J., Proestos, Y., Hadjinicolaou, P., Tanarhte, M., Tyrlis, E., Zittis, G., 2016. Strongly increasing heat extremes in the Middle East and North Africa (MENA) in the 21st century. Clim. Change 137, 245–260. https://doi.org/10.1007/s10584-016-1665-6

Li, B., Li, J., Tang, K., Yao, X., 2015. Many-objective evolutionary algorithms: A survey. ACM Comput. Surv. 48, 35. https://doi.org/10.1145/2792984

Li, F.F., Qiu, J., 2015. Multi-objective reservoir optimization balancing energy generation and firm power. Energies 8, 6962–6976. https://doi.org/10.3390/en8076962

Lokman, B., Köksalan, M., 2013. Finding all nondominated points of multi-objective integer programs. J. Glob. Optim. 57, 347–365. https://doi.org/10.1007/s10898-

012-9955-7

Loucks, D.P., 2012. Water Resource Management Modeling in 2050. Towar. a Sustain. Water Futur. 341–349.

Maier, H.R., Kapelan, Z., Kasprzyk, J., Kollat, J., Matott, L.S., Cunha, M.C., Dandy, G.C., Gibbs, M.S., Keedwell, E., Marchi, A., Ostfeld, A., Savic, D., Solomatine, D.P., Vrugt, J.A., Zecchin, A.C., Minsker, B.S., Barbour, E.J., Kuczera, G., Pasha, F., Castelletti, A., Giuliani, M., Reed, P.M., 2014. Evolutionary algorithms and other metaheuristics in water resources: Current status, research challenges and future directions. Environ. Model. Softw. 62, 271–299. https://doi.org/10.1016/j.envsoft.2014.09.013

Malekmohammadi, B., Zahraie, B., Kerachian, R., 2011. Ranking solutions of multi-objective reservoir operation optimization models using multi-criteria decision analysis. Expert Syst. Appl. 38, 7851–7863. https://doi.org/10.1016/j.eswa.2010.12.119

Nicklow, J., Reed, P., Savic, D., Dessalegne, T., Harrell, L., Chan-Hilton, A., Karamouz, M., Minsker, B., Ostfeld, A., Singh, A., Zechman, E., 2010. State of the art for genetic algorithms and beyond in water resources planning and management. J. Water Resour. Plann. Manag. 136, 412–432.

Nicklow, J.W., Mays, L.W., 2001. Optimal control of reservoir releases to minimize sedimentation in rivers and reservoirs. J. Am. Water Resour. Assoc. 37, 197–211. https://doi.org/DOI 10.1111/j.1752-1688.2001.tb05486.x

Poff, N.L., Brown, C.M., Grantham, T.E., Matthews, J.H., Palmer, M.A., Spence, C.M., Wilby, R.L., Haasnoot, M., Mendoza, G.F., Dominique, K.C., Baeza, A., 2016. Sustainable water management under future uncertainty with eco-engineering decision scaling. Nat. Clim. Chang. 6, 25–34. https://doi.org/10.1038/nclimate2765

Qi, Y., Bao, L., Ma, X., Miao, Q., Li, X., 2016. Self-adaptive multi-objective evolutionary algorithm based on decomposition for large-scale problems: A case study on reservoir flood control operation. Inf. Sci. (Ny). 367–368, 529–549. https://doi.org/10.1016/j.ins.2016.06.005

Rani, D., Moreira, M.M., 2010. Simulation-optimization modeling: A survey and potential application in reservoir systems operation. Water Resour. Manag. 24, 1107–1138. https://doi.org/10.1007/s11269-009-9488-0

Reddy, M.J., Kumar, D.N., 2009. Performance evaluation of elitist-mutated multi-objective particle swarm optimization for integrated water resources management. J. Hydroinformatics 11, 79–88. https://doi.org/10.2166/hydro.2009.042

Reed, P.M., Hadka, D., Herman, J.D., Kasprzyk, J.R., Kollat, J.B., 2013. Evolutionary multiobjective optimization in water resources: The past, present, and future. Adv. Water Resour. 51, 438–456. https://doi.org/10.1016/j.advwatres.2012.01.005

Regulwar, D.G., 2009. Multi Objective Multireservoir Optimization in Fuzzy Environment for River Sub Basin Development and Management. J. Water Resour. Prot. 01, 271–280. https://doi.org/10.4236/jwarp.2009.14033

Salazar, J.Z., Reed, P.M., Herman, J.D., Giuliani, M., Castelletti, A., 2016. A diagnostic assessment of evolutionary algorithms for multi-objective surface water reservoir control. Adv. Water Resour. 92, 172–185. https://doi.org/10.1016/j.advwatres.2016.04.006

Salazar, J.Z., Reed, P.M., Quinn, J.D., Giuliani, M., Castelletti, A., 2017. Balancing exploration, uncertainty and computational demands in many objective reservoir optimization. Adv. Water Resour. 109, 196–210. https://doi.org/10.1016/j.advwatres.2017.09.014

Saleh, S.A.H., 2013. A Study of Himreen Reservoir Water Quality Using in Situ Measurement and Remote Sensing Techniques. J. Environ. Earth Sci. 3, 96–105.

Schardong, A., Ph, D., Simonovic, S.P., Asce, F., Vasan, A., 2013. Multiobjective Evolutionary Approach to Optimal Reservoir Operation. J. Comput. Civ. Eng. 27, 139–147. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000213.

SGI, (Studio Galli Ingegneria S.p.A.), MED, (INGEGNERIA S.r.l.), EL CONCORDE, (Construction LLC), 2014. The Strategic Study for Water and Land Resources in Iraq. Technical Study (unpublished), Accomplished for the General Directorate for Water Resources Management, Ministry of water resources, Baghdad, Iraq.

Simon, D., 2013. Evolutionary optimization algorithms: biologically-Inspired and population-based approaches to computer intelligence. Hoboken, New Jersey, John Wiley & Sons Inc. http://site.ebrary.com/id/10722521.

Soyuzgiprovodkhoz, 1982. General Scheme of Water Resources and Land

Development in Iraq. Technical Study (unpublished), Ministry of Water Resources, Iraq.

Van Veldhuizen, D. a, Lamont, G.B., 1998. Evolutionary Computation and Convergence to a Pareto Front. Late Break. Pap. Genet. Program. 1998 Conf. 221–228.

Wang, K.W., Chang, L.C., Chang, F.J., 2011. Multi-tier interactive genetic algorithms for the optimization of long-term reservoir operation. Adv. Water Resour. 34, 1343–1351. https://doi.org/10.1016/j.advwatres.2011.07.004

WCC, (Water Control Center), 2006. Technical Data for Dams, Reservoirs and Main Control Structures with Mean Monthly Flow Rates and Water Quality for Main Water Resources (1976-Sep 2005). General Directorate of Water Resources Management, Ministry of Water Resources, Baghdad, Iraq.

Woodruff, M.J., Simpson, T.W., Reed, P.M., 2015. Multi-Objective Evolutionary Algorithms' Performance in a Support Role, in: ASME 2015 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference. p. 12.

Yang, C.T., 1996. Sediment transport: theory and practice. McGraw-Hill Inc, USA.

Zhang, W., Liu, P., Wang, H., Chen, J., Lei, X., Feng, M., 2017. Reservoir adaptive operating rules based on both of historical streamflow and future projections. J. Hydrol. 553, 691–707. https://doi.org/10.1016/j.jhydrol.2017.08.031

Zitzler, E., 1999. Evolutionary Algorithms for Multiobjective Optimization: Methods and Applications.

Zitzler, E., Laumanns, M., Thiele, L., 2002. SPEA2: Improving the Strength Pareto Evolutionary Algorithm for Multiobjective Optimization, in: Evolutionary Methods for Design, Optimisation, and Control. CIMNE, Barcelona, Spain, pp. 95–100.

7.3 Supplementary Data

1. Reservoir Description

The Himren dam system features in the Diyala river basin in Iraq were presented in the following paragraphs. Table A1 present the characteristics of the dam structure and its physical boundary limitations. While Table A2 illustrate average monthly meteorological data, precipitation, evaporation, river losses, and irrigation projects demands for the dam system

Table A1. Characteristics of Himren dam system

Item	**Value**	**Unit**
Height	40	m
Length at crest	3360	m
Crest width at elevation 109.5 m.a.s.l	8	m
Normal operation elevation	104	m.a.s.l
Reservoir storage capacity at normal operation	2.4×10^{9}	m^3
Area of reservoir at normal operation	340	Km^2
Minimum dead storage level	84.1	m.a.s.l
Reservoir dead storage capacity	20×10^{6}	m^3
Max flood elevation	107.5	m.a.s.l
Reservoir flood storage capacity	3.56×10^{9}	m^3
Area of reservoir at flood elevation	450	Km^2
Minimum hydropower level	89	m.a.s.l

The spillway structure consists of five gates, each 10.6×12.5m with a maximum capacity discharge for each gate is 1360 m^3/s at flood elevation 107.5 m.a.s.l. There are two main flow tunnels in the dam, each 6.6 m in diameter. Each tunnel divides into three smaller tunnels, one is 5.0 m in diameter which connects to the hydroelectric power station and the other two tunnels are of diameter 3.0 m and connect to the irrigation outlet. There are two generator units in the hydroelectric power station with capacity of 25 MW for each.

The Diyala Barrage is a flow control dam located on the Diyala River 90 km northeast of Baghdad city and about 10 km downstream of the Himren dam. The main purpose of the barrage is to divert the outflow on the Diyala River to the Khalis and Sadr Al-Mushtarak canals for irrigation. The length of the barrage is about 400 m and it has 23 gates, each 12m×2m. The design discharge is 1200 m^3/s, while the operation discharge is 25 m^3/s.

Table A2. Average monthly meteorological data and water demands in the dam region (SGI et al. 2014; Alsaffar, 2017a)

	T_{min} (C°)	T_{max} (C°)	T_{mean} (C°)	P^1 (mm)	E^2 (mm)	River losses[3] (%)	ID[4] ($m^3 \times 10^6$)
October	18	34	27	13	166	10	193.54
November	11	24	18	42	86	5	130.45
December	6	18	12	48	51	0	30.46
January	5	16	10	56	49	0	49.39
February	6	18	12	45	70	5	138.56
March	10	22	16	50	123	20	232.00
April	15	29	23	29	185	30	297.82
May	21	37	30	5	272	35	206.71
June	25	42	35	0	328	50	276.76
July	27	45	37	0	363	50	313.34
August	27	45	36	0	336	35	250.33
September	22	40	33	0	238	20	172.69

[1] precipitation , [2] Evaporation from reservoir lake, [3] the losses between upstream and downstream of the river in the investigated area, [4] Irrigation water demands

2. Identification of River Basin Challenges and Current Management Strategy

According to the IPCC (IPCC, 2007) Iraq has an arid environment with less than 150mm annual rainfall. Iraq has two main rivers, Tigris and Euphrates, which originate from Turkey and Iran in the north and flow south east to the Arab Gulf. Hence, its sustainability depends mainly on upstream water resources. Originating in

Iran, the Diyala River is one of the main tributaries of the Tigris River. It is over 445 km long, draining an area about 32,600 km^2, of which 46% is inside Iraq and 54% in Iran (Soyuzgiprovodkhoz, 1982).The current challenges include:

1- Climate changes impact: the mean temperature may increase approximately 3 degrees Celsius and the annual rainfall may deplete by 21% for the next half-century (Abbas et al., 2016; Lelieveld et al., 2016)

2- Political impact: Iran built four dams on the river's source streams and a big water conveyance tunnel under construction, was observed by Abdulrahman, (2017); Al-Faraj and Scholz, (2014) which divert water from catchment area.

3- Pollutant impact: the impact of Al-Rustamiya wastewater treatment plant discharges (470,000 m3/day, with 5000 mg/l of TDS) to the Diyala river, observed by many studies (Kubba et al., 2014; Aenab and Singh, 2014; Evan et al., 2012; WCC, 2006; CEB, 2011). This plant is located just before river confluence with the Tigris River, in the south of Baghdad city which has large density of population approaching seven million people, and this is one of the primary treatment works for the city.

4- Leaching drains impact: two leaching drains from agriculture projects are discharging to the Diyala river, which increases the deterioration of the river environment (Soyuzgiprovodkhoz, 1982; SGI et al., 2014).

5- Water allocation losses impact: the use and impacts of traditional irrigation techniques by large agriculture projects in the downstream basin were observed by SGI et al., (2014), Al-Ansari, (2013), and Al-Ansari et al., (2014).

6- Future development plan impact: additional quantities of water will be needed for a number of planned, but undeveloped, agriculture projects the government intended for future investment in the basin (SGI et al., 2014).

Currently, releases from the dam system are drained through power penstocks to generate electric power. In flood events, all dam outlets including power, spillway and bottom outlets would be opened to drain excess water to avoid hazard damages to the dam structure. However, in the arid environments, the flashing flood wave usually last a matter of hours or a maximum few days and its effects dissipated when considering average monthly inflows dataset. Hence, any spillway operation was not considered in this study's model. The Diyala Barrage's current operational policy focuses on delivering water to the irrigation projects rather than enhancing river environment, and is included.

In water resources decision making, the scarcity of domestic demands is a priority, while other requirements like agriculture and hydropower generating will often be reduced or masked. Hence, this aspect of river basin management needs more attention from the decision makers (the Government of Iraq) to improve its environmental and economic benefits by employing innovate strategies.

3. Himren Dam Objectives Functions

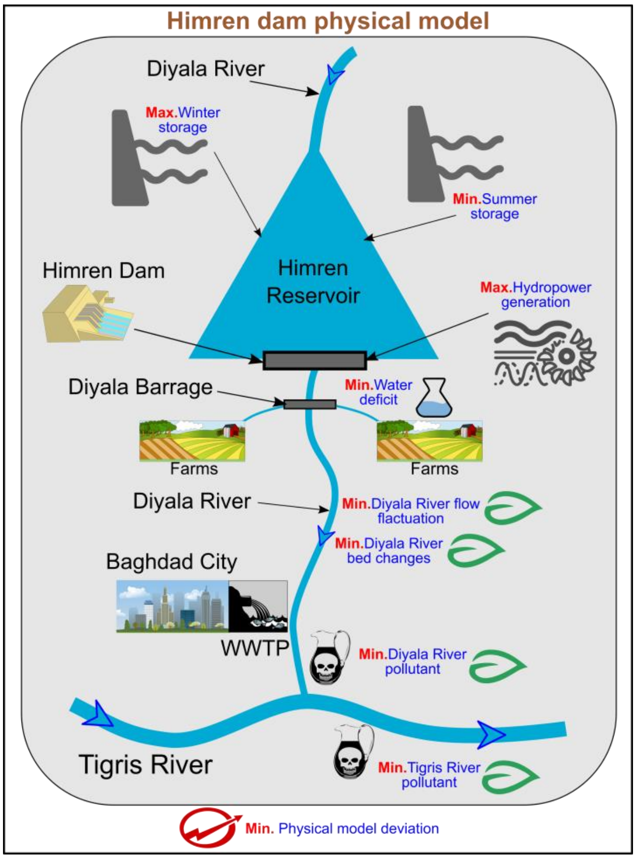


Figure A1. Himren dam physical model shows all the feature of the problem and the nine objective functions adopted in the model

4. Area-Storage and Head-Storage Relationships of Himren Dam

Polynomial equations (Equation A4 and A5) for the area-storage and head-storage relation were constructed depending on the design data available in the NCWRM. For Himren dam, the evaporation losses from the reservoir surface area at time t (Ar_t^H) in meter square, which can be expressed as follows, where the storage (S_t^H) in million cubic meters (MCM):

$$Ar_t^H = 2.3 \times 10^7 + 156915.48 \times S_t^H - 16.369 \times (S_t^H)^2 + 0.0012 \times (S_t^H)^3 \quad \text{(A1)}$$

Equation A2 is used to calculate the water head in the reservoir for hydropower generation, where (H_t^H) is Himren water level in meters (m) and (S_t) is reservoir storage in MCM:

$$\begin{aligned} H_t^H = 86.51 + 0.031 \times S_t^H - 4.37{\times}10^{-5} \times (S_t^H)^2 + 4.33{\times}10^{-8} \times (S_t^H)^3 \\ - 2.55{\times}10^{-11} \times (S_t^H)^4 + 8.63{\times}10^{-15} \times (S_t^H)^5 \\ - 1.54{\times}10^{-18} \times (S_t^H)^6 + 1.13{\times}10^{-22} \times (S_t^H)^7 \end{aligned} \quad \text{(A2)}$$

Equations A1 and A2 is valid at $S_{min}^H \leq S_t^H \leq S_{max}^H$

5. Promotion of Diyala Barrage Operation Policy

In order to enhance the river environment, a new operating policy was proposed for Diyala barrage. It provides priority to the river rather than irrigation projects. When the reservoir releases (R_t) is less than the half of the total demands ($R_t < 0.5 \times DD_t$), which include the irrigation demands (ID_t) and water supply demands (Q_{min}^r), the releases from the barrage will be

$$Q_t^r = Q_{min}^r + (5\% \times R_t) \quad \text{(A3)}$$

For example, if the release from the reservoir is 100 m^3/sec, and the total demands was 250 m^3/sec, then the river discharge will equal to 10+(0.05×100) = 15 m^3/sec, and the remaining discharge (85 m^3/sec) will delivered to the irrigation projects. In this case when the reservoir releases are between the half and total demands ($0.5 \times DD_t \leq R_t \leq DD_t$), the river discharge will be as follows, and the remaining will delivered to the irrigation projects

$$Q_t^r = Q_{min}^r + (10\% \times R_t) \quad \text{(A4)}$$

Otherwise ($R_t > DD_t$), the river discharge will be

$$Q_t^r = \begin{Bmatrix} R_t - ID_t \quad if \ R_t - ID_t > Q_{min}^r + (10\% \times R_t) \\ Q_{min}^r + (10\% \times R_t) \qquad\qquad\qquad otherwise \end{Bmatrix} \tag{A5}$$

6. Reservoir System Predicted Future Resources

A historical thirty-three year dataset from 1981 to 2013, provided by the Iraqi Ministry of Water Resources/National Centre for Water Resources Management (NCWRM) (Alsaffar, 2017a), was used to model reservoir inflows. These data were smoothed using Fast Fourier Transformation (FFT) to reduce any potential errors observed by NCWRM (Alsaffar, 2017a) such as reservoir seepage losses, unauthorized direct pumping from reservoir lake, recharges from neighbouring farms located on reservoir boundaries, etc., and smoothing out any flooding waves which directly affects the average monthly records. Figure A2a illustrates four smoothing options in which the 6-points cycle smoothing showing consistent behaviour with the original data, hence it is adopted for the model. The same smoothing option was also adopted for the Tigris river historical discharge (Alsaffar, 2017a).

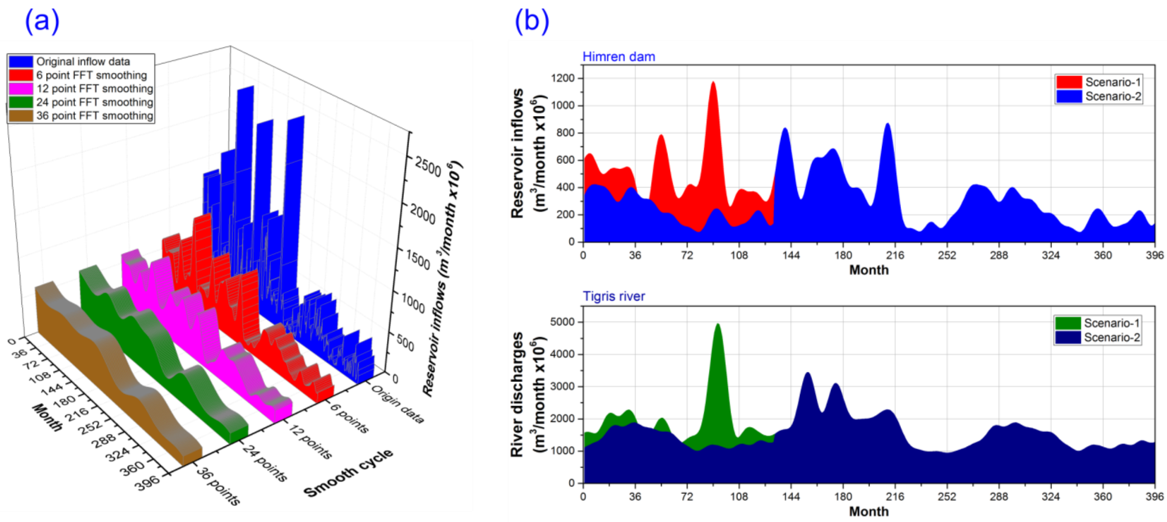


Figure A2. Himren reservoir inflows smoothing and scenarios, where (a) shows the smoothing options using Fast Fourier Transformation (FFT) for thirty-three years (1981-2013), and (b) shows the model scenarios for Himren dam and Tigris river for future projection for thirty-three years

Figure A2a also illustrates two hydrological periods, wet and dry. The wet period is from 1981 to 2000, and the dry is from 2000 to 2013 (from 0 to 240 and from 241 to 396 in Figure 4a, respectively). Hence the first scenario (scenario-1) is the projection of these cycles for the next thirty-three years to investigate the model performance and reliability. A second scenario (scenario-2) was adopted to adapt with possible future climate changes in the region (Abbas et al., 2016) by swapping the first eleven wet years by dry years. The same methodology was adopted for the Tigris river discharge. Figure A2b shows the two proposed model scenarios (Alsaffar, 2017; Zhang et al., 2017).

7. Reservoir System Constraints Formulae

The following equations are the details of the penalty functions (g_j) for the (j^{th}) model constraints for Himren dam system:

$$g_1 = \sum_{t=1}^{T} Max[0, (S_t - S_{min})] \tag{A6}$$

$$g_2 = \sum_{t=1}^{T} Max[0, (S_{max} - S_t)] \tag{A7}$$

$$g_3 = \sum_{t=1}^{T} Max[0, \mu_1(S_t)] \tag{A8}$$

$$\mu_1(S_t) = \begin{cases} 0 & S_t \geq 0.9 \times S_{T+1} \\ 0.5 \times (1 - cos\left(\frac{(S_t - S_{minp})}{(0.9 \times S_{T+1} - S_{minp})}\right) & S_{minp} < S_t < 0.9 \times S_{T+1} \\ 1.0 & S_t < S_{minp} \end{cases} \tag{A9}$$

$$g_4 = \sum_{t=1}^{T} \left\{ Max[0, 1] \middle| \begin{matrix} Pw_t < Pw_{min} \\ Pw_t > Pw_{max} \end{matrix} \right\} \tag{A10}$$

$$g_5 = \sum_{t=1}^{T} Max\left[0, (Q_t^{tu} - Q_{min}^{tu})\right] \tag{A11}$$

$$g_6 = \sum_{t=1}^{T} Max[0, (Q_{max}^{tu} - Q_t^{tu})] \tag{A12}$$

$$g_7 = \sum_{t=1}^{T} Max[0, (R_t - R_{min})] \tag{A13}$$

$$g_8 = \sum_{t=1}^{T} Max[0, (R_{max} - R_t)] \tag{A14}$$

$$g_9 = \sum_{t=1}^{T} Max[0, (Q_t^r - Q_{min}^r)] \tag{A15}$$

$$g_{10} = \sum_{t=1}^{T} Max[0, (Q_{max}^{r} - Q_{t}^{r})] \tag{A16}$$

$$g_{11} = \sum_{t=1}^{T} Max[0, \mu_2(TDS_t^R)] \tag{A17}$$

$$\mu_2(TDS_t^R) = \left\{ \begin{matrix} 0 \\ 0.5 \times (1 - cos\left(\frac{(TDS_t^{r3} - TDS^{max1})}{(TDS^{max2} - TDS^{max1})}\right) \\ 1.0 \end{matrix} \right| \left. \begin{matrix} TDS_t^R \leq TDS^{max1} \\ TDS^{max1} < TDS_t^R < TDS^{max2} \\ TDS_t^R \geq TDS^{max2} \end{matrix} \right\} \tag{A18}$$

$$g_{12} = \sum_{t=1}^{T} Max[0, \mu_3(\Delta BL_i)] \tag{A19}$$

$$\mu_3(\Delta BL_i) = \left\{ \begin{matrix} 0 \\ 0.5 \times (1 - cos\left(\frac{(\Delta BL_i - BL_{max1})}{(BL_{max2} - BL_{max1})}\right) \\ 1.0 \end{matrix} \right| \left. \begin{matrix} \Delta BL_i \leq BL_{max1} \\ BL_{max1} < \Delta BL_i < BL_{max2} \\ \Delta BL_i \geq BL_{max2} \end{matrix} \right\} \tag{A20}$$

$$\Delta BL_i = \left| BL_{i,t=1} - BL_{i,t=T} \right| \tag{A21}$$

8. Optimization Parameters and Comparative Results

Table A3 illustrates the algorithm parameters used to solve the many-objective problem. The ε-DSEA algorithm has an auto-adapt parameter mechanism, through which the operators parameters tuned dynamically to adapt with performance of the operator that generates dominance solutions. Hence, the operators’ parameter is tuned over the evaluation process. More details about Borg MOEA and ε-DSEA algorithms could be found in (Hadka and Reed, 2013) and (Al-Jawad et al., 2018b), respectively.

Table A3. Parameter values used in the optimisation algorithms

Parameters	Borg	ε-DSEA[a]	Parameters	Borg	ε-DSEA
Initial population size	100	100	SPX parents	10	3
Tournament selection size	2	2	SPX offspring	2	2
SBX crossover rate	1.0	1.0	SPX expansion rate λ	3	[2.5, 3.5]
SBX distribution index η	15.0	[0, 100]	UNDX parents	10	10
DE crossover rate *CR*	0.1	[0.1, 1.0]	UNDX offspring	2	2
DE step size *F*	0.5	[0.5, 1.0]	UNDX σ_ζ	0.5	[0.4, 0.6]
PCX parents	10	10	UNDX σ_η	$0.35/\sqrt{L}$	$[0.1, 0.35]/\sqrt{L}$
PCX offspring	2	2	UM mutation rate	$1/L$	$1/L$
PCX σ_η	0.1	[0.1, 0.3]	PM mutation rate	$1/L$	$1/L$
PCX σ_ζ	0.1	[0.1, 0.3]	PM distribution index η_m	20	20

L is the number of decision variables. The permissible range for dynamic parameters is shown in brackets. The parameters σ_η and σ_ζ are defined in Section 2.1.5. [a]The initial values of dynamic parameters used in ε-DSEA are as shown for Borg MOEA.

Table A4 illustrates the summary of the results for 20 random-seeding optimization runs for both algorithms and for both scenarios. It can be seen that the ε-DSEA outperforms Borg MOEA in almost all results for Scenario-1 and Scenario-2. Hence, its results were adopted for the river basin management.

Table A4. Results summary for Scenario-1 and Scenario-2 for 20 optimization runs. The best achievements are shaded with grey

	Scenario-1							
	Borg MOEA				ε-DSEA			
	Best	Mean	Median	Std	Best	Mean	Median	Std
$minf_{demandsH}$	31.483	45.532	43.555	13.723	30.799	38.779	32.446	16.362
$maxf_{demandsH}$	35.028	48.205	46.198	13.131	33.305	41.740	35.382	16.137
$minf_{winterH}$	39.237	59.837	62.126	16.956	38.996	48.065	41.455	16.783
$maxf_{winterH}$	74.582	87.206	85.561	9.811	71.422	82.576	77.842	13.989
$minf_{summerH}$	37.779	55.811	55.415	15.181	31.467	44.755	39.302	15.138
$maxf_{summerH}$	75.787	87.217	85.098	8.184	74.230	83.614	81.602	10.389
$minf_{powerH}$	125.131	146.963	143.848	20.257	127.656	139.384	130.290	22.529
$maxf_{powerH}$	138.206	157.092	154.250	17.092	140.850	153.159	144.683	21.148
$minf_{riverB}$	14.433	23.786	20.156	10.558	14.424	19.873	15.221	11.432
$maxf_{riverB}$	15.881	24.850	21.375	10.329	15.863	21.299	16.784	11.539
$minf_{TDS-DY}$	77.339	94.193	91.999	14.506	78.840	87.517	80.841	15.654
$maxf_{TDS-DY}$	82.034	97.840	94.596	13.457	82.740	92.507	86.808	14.829
$minf_{TDS-TR}$	139.827	147.364	143.712	9.722	139.781	143.919	140.024	10.095
$maxf_{TDS-TR}$	140.668	148.008	144.583	9.629	140.561	144.808	140.858	10.308
$minf_{DY-BCH}$	35.883	46.806	44.042	11.497	35.730	41.640	36.756	12.502
$maxf_{DY-BCH}$	40.058	49.948	47.518	10.861	39.419	45.493	40.782	12.314
$minf_{MD}$	12.823	20.521	16.934	9.806	12.747	16.970	13.019	10.239
$maxf_{MD}$	13.812	21.245	17.889	9.696	13.608	17.934	13.905	10.441
	Scenario-2							
$minf_{demandsH}$	35.883	63.251	69.580	24.169	34.427	42.533	35.712	28.531
$maxf_{demandsH}$	40.202	66.526	72.369	23.345	38.557	46.855	40.594	27.836
$minf_{winterH}$	37.596	69.865	77.860	26.836	34.571	45.621	38.851	28.756
$maxf_{winterH}$	70.836	95.529	93.795	21.432	65.572	78.562	74.404	23.762
$minf_{summerH}$	32.222	60.365	65.644	22.458	31.173	40.292	33.581	25.883
$maxf_{summerH}$	68.834	89.888	91.707	15.502	68.696	78.652	73.888	19.724
$minf_{powerH}$	161.468	194.588	202.797	29.139	163.025	173.334	165.069	35.040
$maxf_{powerH}$	174.369	204.068	210.633	27.399	174.001	185.377	178.131	33.059
$minf_{riverB}$	6.517	27.512	31.036	19.765	6.481	12.217	7.034	22.822
$maxf_{riverB}$	8.226	29.155	32.747	19.549	8.036	14.062	9.002	22.731
$minf_{TDS-DY}$	94.843	120.500	126.509	22.155	94.688	103.030	97.155	26.189
$maxf_{TDS-DY}$	99.422	123.679	129.047	21.350	98.643	107.835	102.250	25.378
$minf_{TDS-TR}$	135.976	155.721	158.387	18.986	135.732	140.843	135.954	21.657
$maxf_{TDS-TR}$	137.157	157.026	159.932	18.945	136.963	142.154	137.246	21.637
$minf_{DY-BCH}$	14.929	36.614	40.731	20.245	14.500	20.254	14.885	23.309
$maxf_{DY-BCH}$	18.062	39.423	43.187	19.802	17.392	23.374	18.187	22.993
$minf_{MD}$	5.712	25.651	28.443	19.125	5.437	10.586	5.658	21.809
$maxf_{MD}$	7.028	27.049	30.030	19.046	6.763	12.006	7.054	21.773

Table A5 presents the computational summary (CPU time) of the results for both algorithms and for both scenarios used to solve the optimization problem. ε-DSEA is clearly superior Borg MOEA in almost all cases.

Table A5. The summary of computational results of Scenario-1 and Scenario-2 for both algorithms using 20 runs. All results are in minutes and the best achievement are shaded with grey

	Scenario-1		Scenario-2	
	Borg MOEA	ε-DSEA	Borg MOEA	ε-DSEA
Min.	39.88	40.37	46.00	31.51
Max.	85.16	57.61	87.98	124.01
Mean	55.65	47.91	59.25	45.50
Median	54.15	46.62	57.05	42.45
Std.	11.24	5.70	9.75	19.76

The above results shows that ε-DSEA has better diversity and faster convergence than Borg MOEA, which refer to the stability and reliability of the algorithm to generate optimum solutions in fewer random seeding runs. Hence, ε-DSEA is computationally more economic than Borg MOEA.

9. Reservoir Optimization Model

Figures A3 and A4 illustrate the results from the average optimum reservoir releases utilization for both scenarios. It shows the impact of dry weather on the river basin model, which represented by Scenario-2. On the other hand, the sensitivity of system component was observed toward any changing in the system inflows.

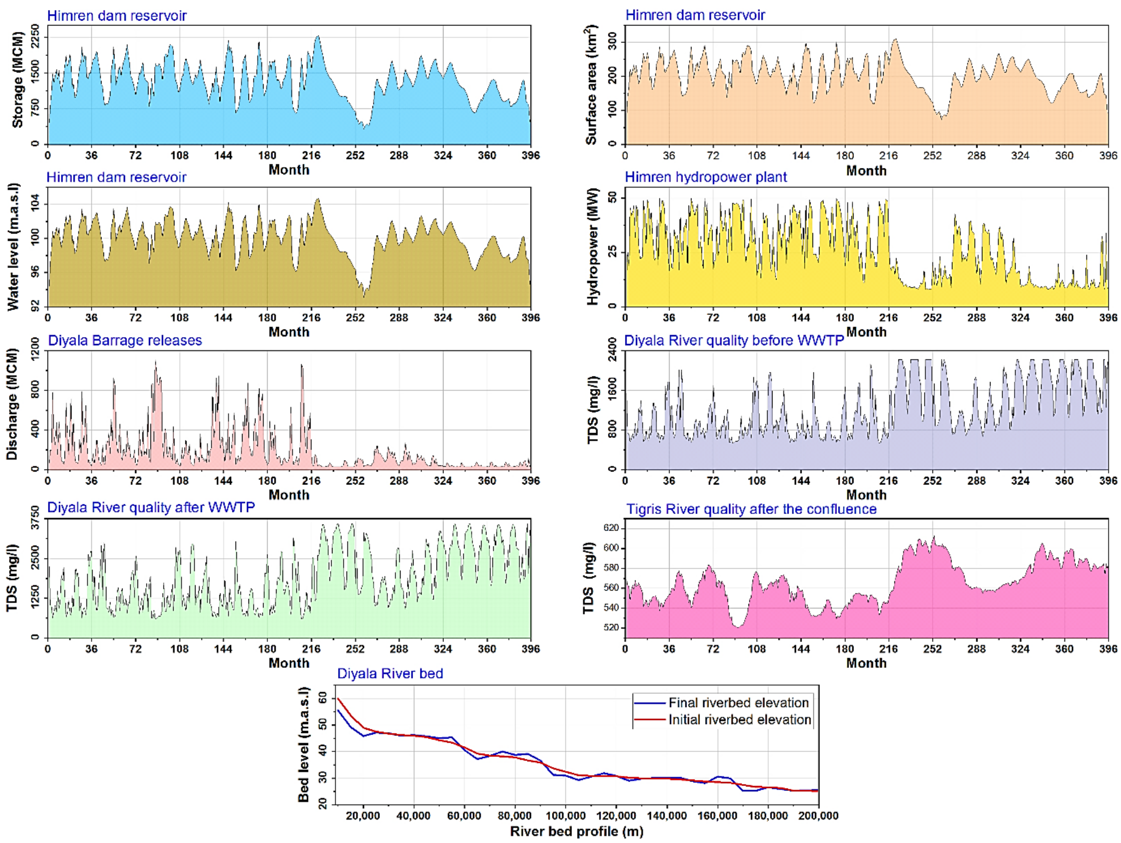


Figure A3. Reservoir system features achieved for Scenario-1 using the average optimum reservoir releases.

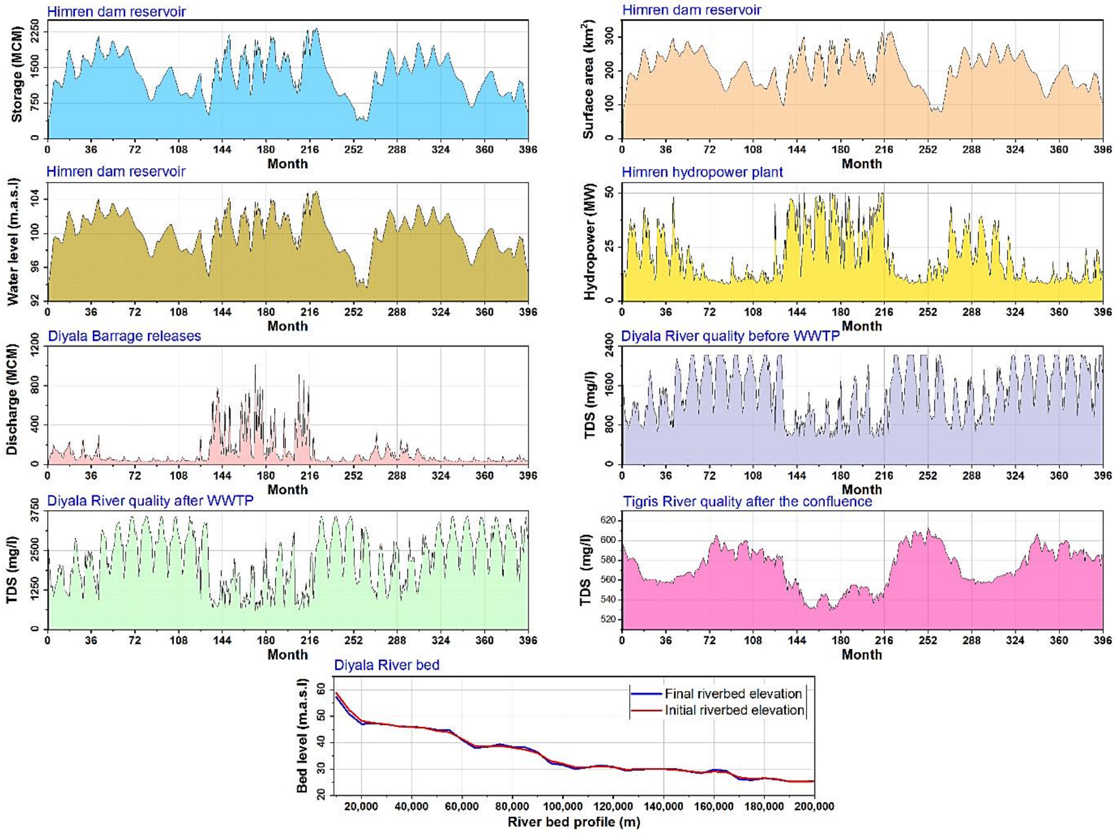


Figure A4. Reservoir system features achieved for Scenario-2 using the average optimum reservoir releases.

10. Recommendations

In order to improve the lower Diyala river basin environment, the following suggested policy changes should be considered for different sectors:

- *Environmental Sectors:* A monitoring and mitigation strategies must be developed to solve the high pollutant concentration from Al-Rustumiya wastewater treatment plan outflows, which increases both pollutant level in Diyala and Tigris Rivers water and remediation costs to downstream water supply projects. Moreover, detail hydrological study and field survey are needed to explore and control sediment transport in the river.
- *Social Sector:* Adopt developed irrigation techniques (e.g. sprinkles, drips) to reduce losses due to crop water allocations, evaporation and infiltration. Also, change summer crop types or reduce crop pattern to reduce water exploitation in summer for this part of the river basin. Further, rehabilitate water conveyance infrastructure (e.g. main channels, outlets, gates, etc.) and restrict water exploitation in the middle part of the river basin (upstream region of Himren dam) to mitigate water delivery losses and to robust water resource sustainability for the lower part of the basin. Other actions include to remove any unauthorized water exploitation pumps and develop a comprehensive seepage model from the Himren reservoir to improve accuracy of the actual water budget.

Additional to above, a policy for adopting advanced daily monitoring system for data collections and flood alarm system should be consider to improve water resources management and forecasts in the basin.

However, the middle part of the basin has significant effect on the considered reservoir system, which includes a multipurpose dam and potential groundwater storage. These could be integrated with the river basin model management by using integrated water resources management principles to improve understanding of the system. Finally, an International agreement with Iran should be sought for the Diyala River and its tributaries to maintain the long-term sustainability of river water resources.

7.4 Further Discussion

The parameters of recombination operators adopted by ε-DSEA for the two scenarios were consistent for all operators, in comparison with its initial values, except for the SBX operator. The average and median values are presented in Table 3. The optimum solutions were generated using $\eta > 70$ in both scenarios, which is higher than its commonly used value ($\eta = 15$). The larger value of η generate new offspring closer to their parents, and the smaller η is vice versa. Since the SBX operator is widely used in many evolutionary algorithms like: AMALGAM, IBEA, ε-MOEA, ε-NSGA-II, SPEA2, and NSGA-II, the current outcomes will be very beneficial in implementation of these algorithms to solve consistent real-world problems.

In the previous chapter, we notice how ε-DSEA adapted with different values of η in solving groundwater management problem, which ranged from 65 to 88 (in addition to other operators' parameters), hence the robustness of the proposed methodologies in ε-DSEA to adapt with different problem environment is endorsed.

Table 4. The mean and median parameters' values of recombination operators adopted by ε-DSEA for both scenarios

Operator	Parameter	Initial value	Scenario-1		Scenario-2	
			Mean	**Median**	**Mean**	**Median**
SBX	η	15.0	79.893	79.000	71.606	75.000
DE	CR	0.1	0.291	0.107	0.308	0.105
	F	0.5	0.633	0.554	0.640	0.553
PCX	σ_η, σ_ζ	0.1	0.149	0.123	0.154	0.122
SPX	λ	3.0	2.797	2.611	2.799	2.625
UNDX	σ_ζ	0.5	0.461	0.417	0.455	0.415
	σ_η	0.35	0.202	0.128	0.192	0.126

7.5 Conclusions

Improvement to reservoir operation strategy was presented in this chapter using optimization model. The competitive algorithms, ε-DSEA and Borg MOEA were implemented to explore trade-off solutions using nine socio-environmental objectives for the next thirty-three years under two inflows scenarios. The algorithms' computational analyses show that ε-DSEA outperformed the Borg MOEA in almost all cases, hence the ε-DSEA results were adopted. Moreover, the AAC approach succeed to overcome the complexity of the problem, boosting algorithm convergence toward possible optimum solutions and avoiding algorithm stagnation in local optima.

The optimum trade-off for reservoir releases emerged from the OSEF-AAC approach, integrate all adopted social and environmental sectors in the river basin including hydropower generation, flood risk management, river quality, river sediment transport, reservoir storage control, agriculture water delivery, discharge regulation, and downstream water quality. More objectives could be embedded to the approach for comprehensive flows regime (e.g., fisheries, navigation and tourism). Decision makers can adjust the trade-offs and adopt those that fit their criteria. However, to fully develop the potential achievement of the OSEF-AAC approach, an average optimum solution was generated using optimum solution achieved by each objective. The results show improvement in reservoir system environments in all sectors, as follows:

- *Environmental Sectors:* The Diyala river water quality (TDS) was improved after a pollutant source from about 2600 mg/l to about 2400 mg/l, which improves the downstream water quality mean value of TDS from about 750 mg/l to 570 mg/l for both scenarios. This will decrease water-remediation costs in downstream region. Additionally, the mean and median river morphology changes were maintained within one meter for both scenarios over the considered period. Hence, positive impacts on the maintenance cost for water supply and hydraulic structures in the river were achieved.

- *Social Sector:* The power revenues were improved over continues hydropower generating for the next three decades under two scenarios. Future investment plans could be set from the mean values 26 MW and 21 MW obtained for both scenarios, respectively. Moreover, the storage control objectives were succeeded to preserve free mean reservoir storage about 1.0×10^9 m^3 for flood wave absorption, which mitigate the possible flood risk and reduce the cost of inundated indemnity for lands and properties. For crop production, the mean and median agriculture water deficit for both scenarios were maintained within the range of 18-28% and 30-35%, respectively, which strengthen crop-investment revenues.

The adopted mathematical optimization model for the current case study considers only the common management objectives based on the available database. However, other issues like water influent and effluent of reservoir lake, ecosystem and navigation objectives, etc. could be implemented for future work.

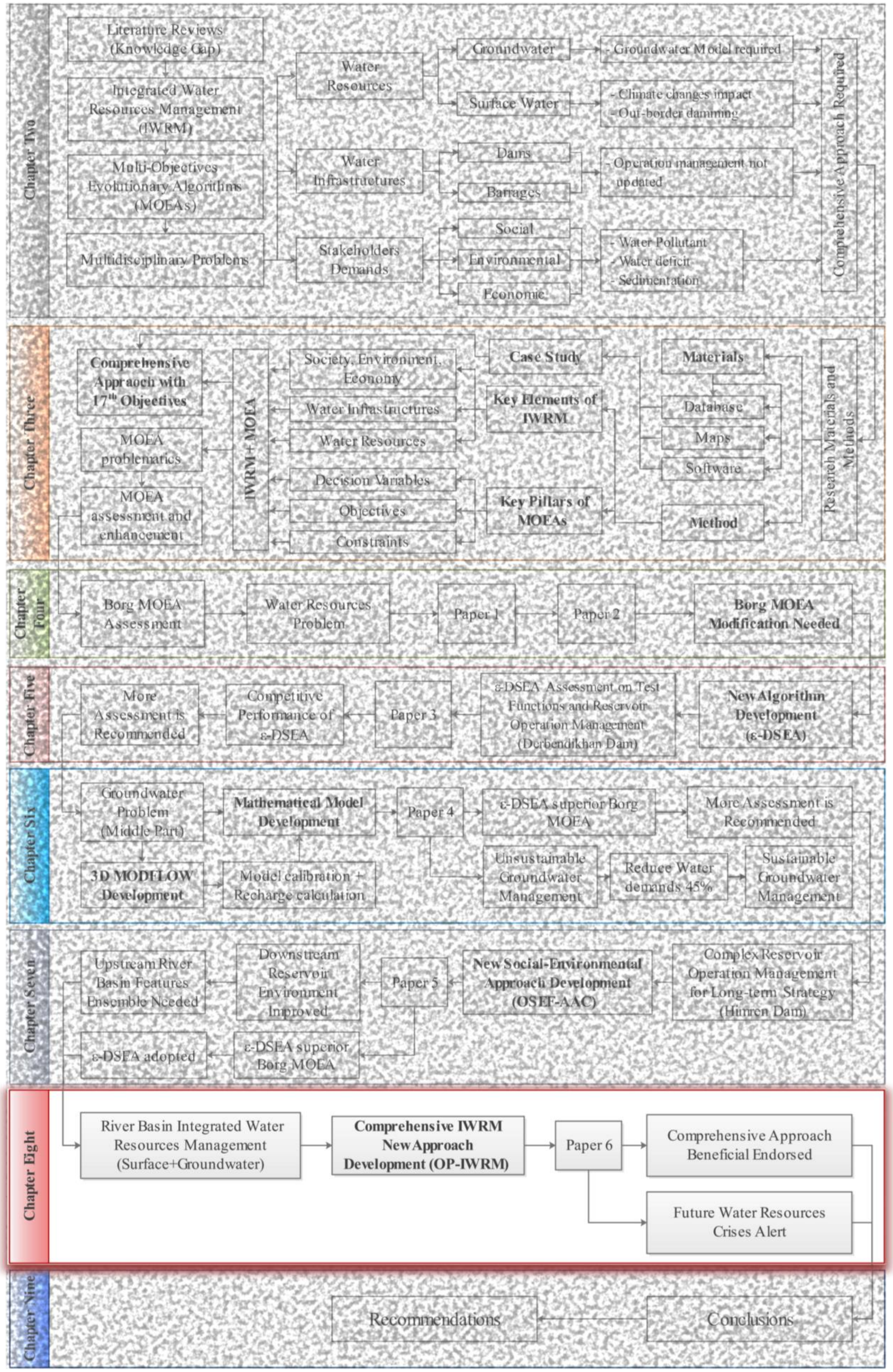
Finally, the OSEF-AAC approach can be adopted to solve any river basin management problems to generate optimum socio-environmental flows regime. These provide decision makers a trade-off for developing robust management strategies towards achieving better economic revenues for the water-energy-food nexus objectives of a river basin.

7.6 Recommendations

In order to improve the lower Diyala river basin environment, the following suggested policy changes should be considered for different sectors:

- *Environmental Sectors:* A monitoring and mitigation strategies must be developed to solve the high pollutant concentration from Al-Rustumiya wastewater treatment plan outflows, which increases both pollutant level in Diyala and Tigris Rivers water and remediation costs to downstream water supply projects. Moreover, detail hydrological study and field survey are needed to explore and control sediment transport in the river.
- *Social Sector:* Adopt developed irrigation techniques (e.g. sprinkles, drips) to reduce losses due to crop water allocations, evaporation and infiltration. Also, change summer crop types or reduce crop pattern to reduce water exploitation in summer for this part of the river basin. Further, rehabilitate water conveyance infrastructure (e.g. main channels, outlets, gates, etc.) and restrict water exploitation in the middle part of the river basin (upstream region of Himren dam) to mitigate water delivery losses and to robust water resource sustainability for the lower part of the basin. Other actions include to remove any unauthorized water exploitation pumps and develop a comprehensive seepage model from the Himren reservoir to improve accuracy of the actual water budget.

Additional to above, a policy for adopting advanced daily monitoring system for data collections and flood alarm system should be considered to improve water resources management and forecasts in the basin. However, the middle part of the basin has significant effect on the considered reservoir system, which includes a multipurpose dam and potential groundwater storage. These could be integrated with the river basin model management by using integrated water resources management principles to improve understanding of the system. Finally, an International agreement with Iran should be sought for the Diyala River and its tributaries to maintain the long-term sustainability of river water resources.


Chapter Two
Literature Reviews (Knowledge Gap)
Integrated Water Resources Management (IWRM)
Multi-Objectives Evolutionary Algorithms (MOEAs)
Multidisciplinary Problems
Water Resources
Water Infrastructures
Stakeholders Demands
Groundwater
Surface Water
Dams
Barrages
Social
Environmental
Economic
- Groundwater Model required
- Climate changes impact
- Out-border damming
- Operation management not updated
- Water Pollutant
- Water deficit
- Sedimentation
Comprehensive Approach Required
Chapter Three
Comprehensive Approach with 17th Objectives
MOEA problematics
MOEA assessment and enhancement
IWRM + MOEA
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Water Infrastructures
Water Resources
Decision Variables
Objectives
Constraints
Case Study
Key Elements of IWRM
Key Pillars of MOEAs
Materials
Database
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Software
Method
Research Materials and Methods
Chapter Four
Borg MOEA Assessment
Water Resources Problem
Paper 1
Paper 2
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Chapter Five
More Assessment is Recommended
Competitive Performance of ε-DSEA
Paper 3
ε-DSEA Assessment on Test Functions and Reservoir Operation Management (Derbendikhan Dam)
New Algorithm Development (ε-DSEA)
Chapter Six
Groundwater Problem (Middle Part)
Mathematical Model Development
Paper 4
ε-DSEA superior Borg MOEA
More Assessment is Recommended
3D MODFLOW Development
Model calibration + Recharge calculation
Unsustainable Groundwater Management
Reduce Water demands 45%
Sustainable Groundwater Management
Chapter Seven
Upstream River Basin Features Ensemble Needed
Downstream Reservoir Environment Improved
Paper 5
New Social-Environmental Approach Development (OSEF-AAC)
Complex Reservoir Operation Management for Long-term Strategy (Himren Dam)
ε-DSEA adopted
ε-DSEA superior Borg MOEA
Chapter Eight
River Basin Integrated Water Resources Management (Surface+Groundwater)
Comprehensive IWRM New Approach Development (OP-IWRM)
Paper 6
Comprehensive Approach Beneficial Endorsed
Future Water Resources Crises Alert
Chapter Nine
Recommendations
Conclusions

CHAPTER EIGHT

COMPREHENSIVE INTEGRATED WATER RESOURCES MANAGEMENT APPROACH

8.1 Introduction

Starting from Chapter four, the preceding chapters demonstrate fragment management models of Diyala River basin; Derbendikhan dam, middle region, and Himren dam. Although independent models' results are promising, they do not reflect the reality of the river basin's natural interaction. Thus, they will not extract the actual potential economic benefits and revenues of the entire river basin. Furthermore, the interaction nexuses that joining river basin system variables are difficult to formulate, since they are non-linear, dynamic and multimodal; in fact, they are complex multi-variable multi-objective problems (Maier et al., 2014).

As highlighted in Chapter two, section 2.2.2, in order to avoid system complexity, literature tend to join independent models' results by decision support tools for decision making, as in System Dynamics Models (SDMs), while others used multi-criteria analysis tools.

In the same context, although multi-system reservoirs management were achieved in many literature to improve specific targets, like maximizing power generation as noted in Table 1 in chapter seven, these models masked other targets in the river basin, as highlighted in *bullet point 2* in Chapter two.

Based on previous chapters' findings, the dependency of fragment models of Diyala River basin is evident. Himren dam system environment is directly affected by water exploitation in the intermediate region between the two dams, and by the amount of Derbendikhan dam releases. While, the amount of groundwater participation in irrigation process in the intermediate region will reduce surface water dependency in this region, which will provide more water to Himren dam system. Furthermore, Derbendikhan dam releases has direct impact on the whole downstream system, as it depends on upstream shed water resources at Iran. Thus, integration and management of all models simultaneously is significant to demonstrates a holistic social, environmental and economic improvement and revenues of a river basin system, which is a pathway towards a holistic sustainable development goals' plan at a country-scale, as in Statement-1 Chapter two.

Accordingly, this chapter presents a comprehensive optimum IWRM approach using many-objectives evolutionary optimization algorithm at a river basin level. The holistic approach's benefits will be demonstrated by a comparison with a simple approach. The previous fragment models of Diyala River basin are ensemble in a single model using the proposed approach. The ε-DSEA robustness are endorsed over different problems environments (from chapters four to seven), in comparison with Borg MOEA, which reinforce its methodology to generate better optimum qualitative and quantitative management solutions. Hence, the ε-DSEA is adopted for the current approach.

A paper was developed and submitted at *Journal of Environmental Management*, as:

- Al-Jawad, J.Y., Alsaffar, H.M., Bertram, D., Kalin, R.M., 2018c. A Comprehensive Optimum Integrated Water Resources Management Approach for Multidisciplinary Water Resources Management Problems. J. Environ. Manage. Under revi.

"The following work represents my efforts, such as: theoretical formalism development, analytic calculations and numerical simulations, writing the manuscript. Dr. Kalin, R.M., was the project supervisors, and provided assistance and support when required. Alsaffar, H.M., was a governmental key stackeholder and provided assistance and support when required. Dr. Bertram, D., provided technical support and assistance".

8.2 Paper:

Al-Jawad, J.Y., Alsaffar, H.M., Bertram, D., Kalin, R.M., 2018c. A Comprehensive Optimum Integrated Water Resources Management Approach for Multidisciplinary Water Resources Management Problems. J. Environ. Manage. Under revi.[1]

COMPREHENSIVE OPTIMUM INTEGRATED WATER RESOURCES MANAGEMENT APPROACH FOR MULTIDISCIPLINARY WATER RESOURCES MANAGEMENT PROBLEMS

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[1] This paper was submitted on 14/08/2018

A COMPREHENSIVE OPTIMUM INTEGRATED WATER RESOURCES MANAGEMENT APPROACH FOR MULTIDISCIPLINARY WATER RESOURCES MANAGEMENT PROBLEMS

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Abstract

A novel, comprehensive Optimum Integrated Water Resources Management (OP-IWRM) approach which combines common river basin multidisciplinary sectors using a many-objectives optimization algorithm is presented here. Two approaches having seventeen and five objectives respectively, were developed using the ε-DSEA optimization algorithm using more than 1500 decision variables. The large-scale Diyala river basin, Iraq, was evaluated using this approach. Results conclude that climate change and upstream development impacts are possible multidisciplinary crises in the basin, even with enhanced groundwater use. This holistic approach provides decision making confidence for complex integrated water resources management of large-scale regions.

Keywords: Integrated Water Resources Management (IWRM), ε-DSEA, holistic approach, Many-Objectives Optimization, Diyala River Basin

1. INTRODUCTION

Climate changes, populations evolve, crop industries increase water demands and water industry development all increase integrated water resources management (IWRM) challenges. GWP, (2000) (Global Water Partnership) defines the IWRM as "*IWRM is a process which promotes the co-ordinated development and management of water, land and related resources, in order to maximize the resultant economic and social welfare in an equitable manner without compromising the sustainability of vital ecosystems*". More definitions were presented by Cardwell et al., (2009).

However, IWRM implementation on the river basin system scale has many challenges. These need robust methods to tackle the complexity of water system management (due to its nonlinearity, dynamic properties, conflict objectives, and constraints (Haimes and Hall, 1977; Yeh, 1985; Maier et al., 2014)), and the stakeholders' demands, governmental legislation, and environmental aspects (and others) (Grigg, 2016). The conflicts and interrelationship problems between the multidisciplinary sectors for IWRM implementation for larger-scale regions were observed by Biswas (2008), Hering and Ingold (2012), and Mohtar and Lawford (2016). Authors and institutes adopt different water management concepts due to the generalization in IWRM definition (Biswas, 2008). The later author demonstrates 41 variant possible explanations for the term "integrated". Some examples are: water supply and water demands; surface water and groundwater; water quantity and water quality; urban and rural water issues; government and NGOs (nongovernmental organization). Moreover, "*... But by now we all know how complex water resources management is and that ideally it should be managed holistically, considering efficiency, equity and the environment. But we should also know by now that holistic* *management is costly and politically difficult, or impossible"* (Giordano and Shah, 2014). The later authors review examples of using simple alternatives to solve water resources problems for transboundary river basins, rather than implementing a complex IWRM approach.

Many recent studies investigate the impact of IWRM implementation on different river basins to improve its environmental and economic benefits using several tools and methods. Among these tools, System Dynamic Simulation (SDS) was used widely as a Decision Support Tool (DST) in the field of IWRM implementation, however they have spatial data inertia processing (Nikolic and Simonovic, 2015). Weng et al., (2010) present an integrated scenario-based multi-criteria decision support system (SMC-DSS) for water resources planning and management in a Haihe river basin in China. The tool combines a multi-objective optimization algorithm, multi-criteria analysis and decision support system to assess the impact of multi policy management on the socio-economic and environmental sectors. The evidence shows that different results can be obtained when using different policies. Coelho et al., (2012) present and assess a multiple criteria decision support system as a tool for supporting IWRM in Tocantins-Araguaia river basin in Brazil. The authors combine GIS processing, fuzzy set theory, and dynamic programing algorithm to obtain optimum solution depending on user criteria selections. Nikolic, (2015) presents Agent-Based simulation coupled with system dynamic simulation to achieved IWRM in Upper Thames River basin in Canada. The results demonstrate the interaction between different regional resources and activities. Moreover, Klinger et al., (2015) produced IWRM tools for the Lower Jordan Rift Valley. The authors used multi-objective optimization algorithm to improve three sectors in the region. Safavi et al.,

(2016) present Expert knowledge based modelling for IWRM in Zayandehrud River Basin in Iran using WEEP software. The results show that the river basin management policy needs to be improved to avoid future water crises in the basin. None of these examples (and others) adopt a holistic IWRM approach.

The process of using robust computational tools to solve complex problems have developed in recent decades. The multi-objectives optimization algorithms were presented recently as a tool to solve complex problems in variant engineering and sciences fields, including water resources management (Coello et al., 2007; Maier et al., 2014). Evolutionary Algorithms (EAs) are a meta-heuristics paradigm, which inspire from gene evolution (Nicklow et al., 2010; Back et al., 2000), were widely utilized to solve multiple conflict objectives optimization problems, through which a set of optimum solutions obtain in a single run (Deb et al., 2002). Recent studies have utilized up to three objectives to solve water resources management problems (Kim et al., 2008; Chang and Chang, 2009; Reddy and Kumar, 2009; Regulwar, 2009; Hakimi-Asiabar et al., 2010; Wang et al., 2011; Malekmohammadi et al., 2011; Schardong et al., 2013; Ahmadianfar et al., 2015; Li and Qiu, 2015; Crookston and Tullis, 2016; Qi et al., 2016; Dai et al., 2017) to avoid the computational efficiency, high-dimension challenges and water resources system complexity for more than three objectives (Maier et al., 2014). A few recent studies adopt many-objectives (more than three objectives) optimization water resources management problems (Dittmann et al., 2009; Kasprzyk et al., 2013; Giacomoni et al., 2013; Giuliani et al., 2014a; Giuliani et al., 2014b, Giuliani et al., 2016; Zatarain Salazar et al., 2016; Zatarain Salazar et al., 2017; Chen et al., 2016). However, these studies rarely adopted multidisciplinary problem combinations for river basin management (e.g. Social, Environmental, and Economic) (Horne et al., 2016; Horne et al.,2017; Poff et al., 2016).

Hence, there is a need to develop a holistic Optimum IWRM approach (OP-IWRM) which combine stakeholders' demands (e.g. Social, Environmental, and Economic) and river basin infrastructures, to generate optimum water resources management strategy by using many-objectives optimization algorithm. This OP-IWRM would then generate Socio-Enviro-Economic decision variable that provide a sustainable strategy for river basin management.

Iraqi's Diyala River basin with its semi-arid environment was adopted as a case study to evaluate the proposed approach. The basin has multidisciplinary problems including political, environmental, economic, and social. The sub-disciplinary sectors allow formulation of up to seventeen objective functions using the new ε-DSEA optimization algorithm (Al-Jawad and Tanyimboh, 2018) including; flood risk management, hydropower generation, crop production, water quality, river discharges, river morphology, groundwater sustainability, groundwater storage mining, and water losses due to infiltration process. The outcomes will support the possibility of implementing a holistic IWRM approach for large scale river basins, which can be developed for the entire country. Moreover, it can be used to help in setting international agreements between riparian countries.

2. IDENTIFICATION OF OP-IWRM APPROACH

Multi-objectives optimization models are one of the Decision Support Systems (DSSs) tools used in Integrated Water Resources Management (IWRM) implementation (Molina et al., 2010) which consider multidisciplinary sectors in the river basin. Hence, this study presents a novel Optimum IWRM (OP-IWRM) approach as a DSSs tool using many-objectives evolutionary optimization algorithm. The OP-IWRM approach combines all available river basin water resources (groundwater and surface water), and all stakeholder's demands (social, environmental, economic, and others). In order to overcome high-dimension computational challenges of many-objectives problems (Maier et al., 2014), the OP-IWRM approach employ the new Auto-Adaptive Constraints (AAC) approach proposed by Al-Jawad et al., (2018b). The ACC methodology depends on releasing constraints chains in the initial evaluation process stages and reinforced it when feasible solutions are achieved. Figure 1 illustrates the OP-IWRM approach details for comprehensive river basin water resources management strategy.

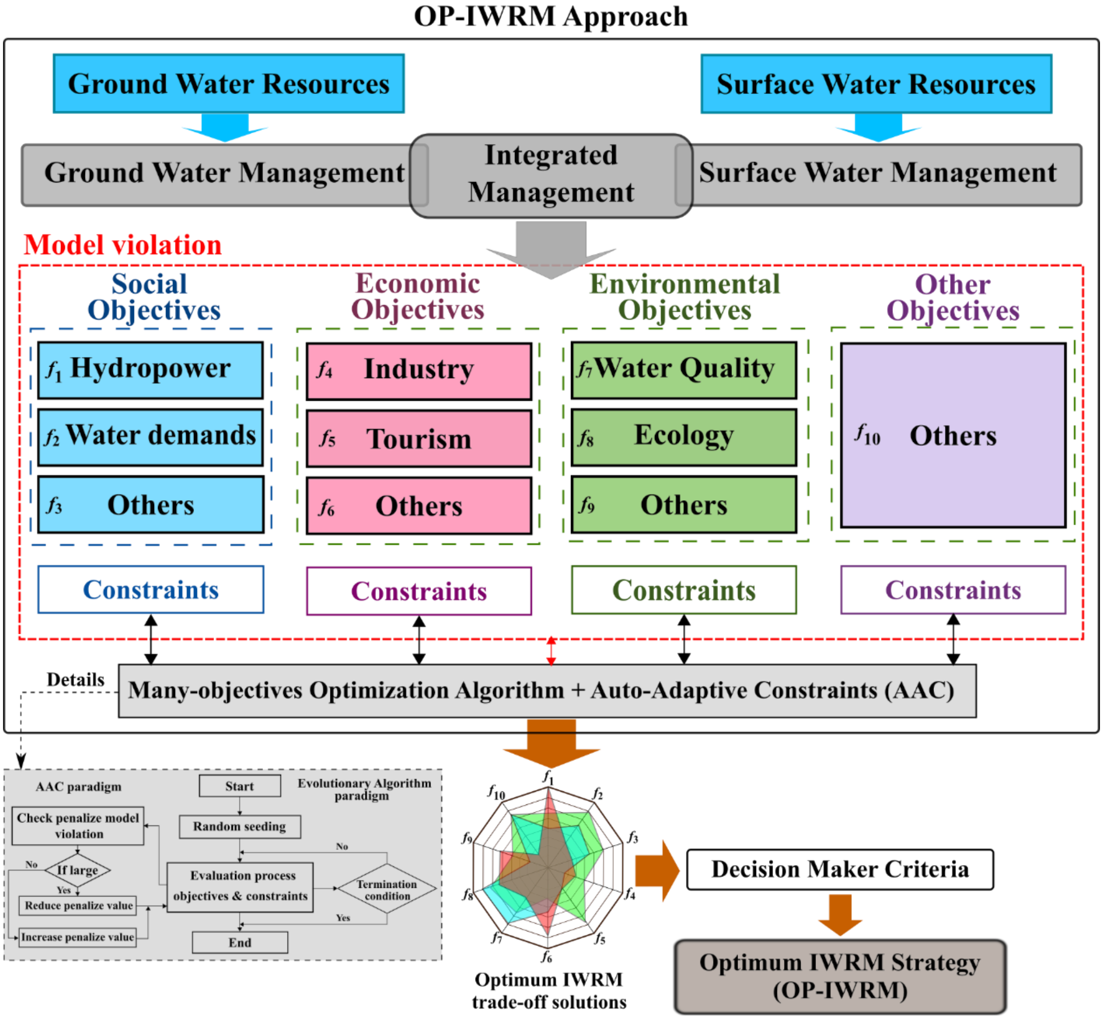

Figure 1. Illustration of Optimum Integrated Water Resources Management (OP-IWRM) approach for a comprehensive river basin management strategy. The Auto-Adaptive Constraints (AAC) approach details were also identified (Al-Jawad et al., 2018b).

In order to demonstrate the approach's advantages, the following steps are considered, as in Figure 2, below:

1- Comprehensive models ($\boldsymbol{F}_{comp.}$) are compared with simple models ($\boldsymbol{F}_{simple}$) using four alternatives to demonstrate the advantages and disadvantages of both models in water resources management problems.

2- The outperforming model results will be adopted for the water resources management strategy in the river basin.

3- Comparison between alternatives for the selected model.

4- The most sustainable management strategy will be adopted for the investigated problem.

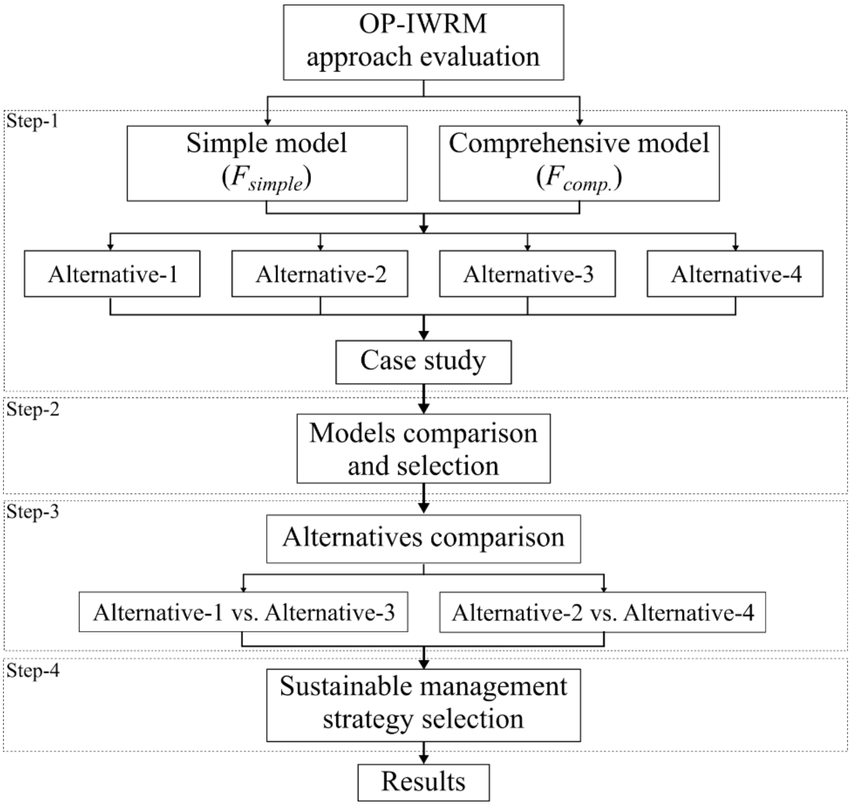

Figure 2. OP-IWRM approach evaluation steps

3. THE DIYALA RIVER BASIN

The Diyala River basin is a transboundary basin located the northeast of Iraq between 33.216° and 35.833°N, and 44.500° and 46.833°E, and originated from Zagrose Mountains in Iran, as shown in Figure 3. It is over 445 km long, draining an area about 32,600 km^2, in which 46% inside Iraq and 54% in Iran (Soyuzgiprovodkhoz, 1982). The Iraqi government constructed two multipurpose dams on the river, Derbendikhan just at the international border in Sulaymaniya governorate, and Himren in the middle part of the basin inside the Diyala governorate (Figure 3). Additionally, a barrage (the Diyala Barrage) was constructed about 10 km downstream Himren dam for water distribution control to downstream irrigation projects. The characteristics of these structures are illustrated in Table 1, while in Table 2, the monthly water demands for irrigation projects downstream the two dams were presented.

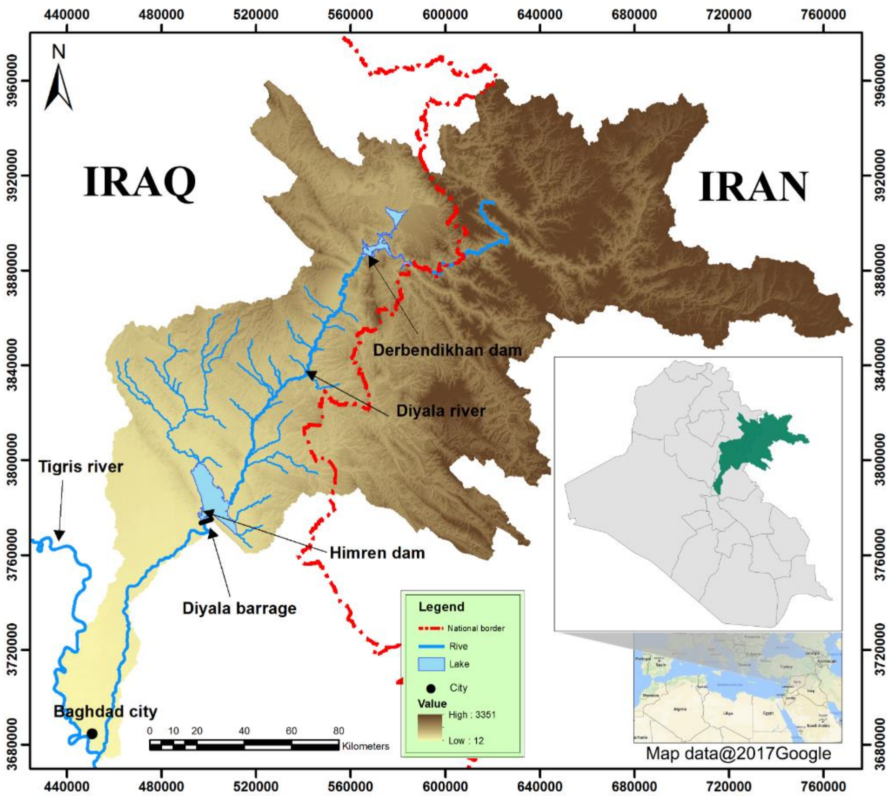

Figure 3. Catchment area of the transboundary Diyala river basin in Iraq and Iran

Table 1. Main characteristics of Diyala river basin water control structures (SGI et al., 2014)

Parameter	**Derbendikhan**	**Himren**	**Unit**
Height	128.0	40.0	m
Normal operation elevation	485.0	104.0	m.a.s.l
Reservoir storage capacity at normal operation	2.57×10^9	2.4×10^9	m^3
Area of reservoir at normal operation	114.0	340	Km^2
Minimum dead storage level	410.0	84.1	m.a.s.l
Reservoir dead storage capacity	500×10^6	20×10^6	m^3
Max flood elevation	493.5	107.5	m.a.s.l
Reservoir flood storage capacity	4.02×10^9	3.56×10^9	m^3

Area of reservoir at flood elevation	200.0	450	Km^2
Minimum hydropower level	434.0	89.0	m.a.s.l
	Diyala Barrage		
Length of barrage	400.0		m
No. of gates	23.0		-
Gate dimension	12.0×2.0		m
Maximum discharge	1200.0		m^3/s
Normal discharge	25.0		m^3/s

Table 2. Downstream monthly irrigation water demands for the two dams, Derbendikhan and Himren ($m^3 \times 10^6$) (Soyuzgiprovodkhoz, 1982; SGI et al., 2014)

	Oct.	**Nov.**	**Dec.**	**Jan.**	**Feb.**	**Mar.**	**Ap.**	**May**	**June**	**July**	**Aug.**	**Sep.**
Dam1	69.36	45.80	1.56	1.21	21.97	44.42	73.47	58.75	74.27	72.84	59.16	43.81
Dam2	193.54	130.45	30.46	49.39	138.56	232.00	297.82	206.71	276.76	313.34	250.33	172.69

Dam1 and Dam2 refer to Derbendikhan and Himren dams, respectively

3.1 Regional Groundwater Identification

The main groundwater storage region is located between the two dams, in the upper part of the river basin. The lower basin groundwater storage is inadequate for irrigation purposes because of its high salinity concentration (Al-Tamimi, 2007; SGI et al., 2014). The hydrogeological units consist of three aquifers, Mukdadiya, Bai-Hassan, and Quaternary deposits. The Quaternary deposits thickness ranged from 5 to 25m and cover a wide portion of the study area, which composed mainly of gravel, sand, and rock fragment. The Bai-Hassan and Mukdadiya formations are considered to be the two major aquifer of this area. The Bai-Hassan formation outcrops at different locations in the study area, while Mukdadiya appears at other parts of the area. The Mukdadiya formation is described to be composed of fining upward cycles of gravely sandstone, sandstone and mudstone, while Bai-Hassan is composed of conglomerates with beds of mudstone, siltstone and sandstone. Their thickness range from 500 to 1000 m (Jassim and Goff, 2006). These layers overlay Injana formation, which is composed mainly of sandstone, and claystone. The average hydraulic conductivity for both upper aquifers is 2.67 m/day (Al-Jawad et al., 2018a), and the range of total dissolved solids (TDS) is between 182 and 5500 mg/l for the upper aquifer. Furthermore, the estimated aquifer water storage is about 9×10^{9} m^{3}, with storage coefficient for the upper and lower aquifer equal to 3.5% and 0.14%, respectively (Al-Tamimi, 2007). The average aquifer pumping discharge for is about 778 m^{3}/day (Al-Jawad et al., 2018a). More details can be found in Al-Jawad et.al. (2018).

3.2 Identification of challenging river basin Management problem

Iraq is located in an arid zone (IPCC, 2007) and has three transboundary basins shared with Turkey, Syria and Iran. Although the country has two big rivers, the Tigris and Euphrates, it has recently suffered from water crisis due to; the impact of climate changes coupled with highly water demands, and water monopolizing from the upstream transboundary countries (Issa and Al-Ansari, 2014; Abdulrahman, 2017). Many dams were constructed on rivers up streams without considering the transboundary downstream water demands. This causes water resources’ scarcity in these rivers. Although the presence of international agreement regarding sharing water resources of Euphrates river with Turkey and Syria, partial commitments are noticed recently. For Tigris river, international agreement is absence with Iran regarding its tributaries (Abdulrahman, 2017). In order to overcome the first problem, the decision makers or the water managers needs to develop methods and techniques in water resources management to set robust strategies for long-term management. The second problem is a political issue and the government needs to adopt future policy to set international agreements with the riparian countries. (Al-Ansari, 2013, Al-Ansari et al., 2014).

Diyala River basin is one of the main tributaries of Tigris River, which suffers from both problems detailed above (Abbas et al., 2016; Lelieveld et al., 2016; Al-Faraj and Scholz, 2014; Abdulrahman, 2017). The river originates from high mountains in Iran and more than 50% of its catchment area is located in Iran (Soyuzgiprovodkhoz, 1982; SGI et al., 2014). The river crosses the Iraqi border at Al-Sulaymaniya governorate and continues its way to the confluence with Tigris River, south of Baghdad. The river basin has potential economic benefits with two multipurpose hydropower dams giving maximum power generation equal to 500 MW, and many irrigation projects distributed along the river shore. These projects exhaust significant amounts of water for crop production. In addition, many cities and villages are located along the river, which increase the pressure on river water resources.

Although the presence of suitable groundwater for crop farming in some parts of the basin (Al-Tamimi, 2007; SGI et al., 2014), people depends mainly on surface water from the river because it is easier, cheaper, and copiously than groundwater exploitation. Many recent studies explore different crisis in the country, including Diyala river basin. Al-Ansari, (2013), Al-Ansari et al., (2014), and Al-Faraj and Scholz, (2014) investigates water quantities and qualities crisis due to global climate changes and the impact of transboundary projects. They observe possible future scarcity in water resources, hence more developed methods in water management are needed and active cooperative with the transboundary countries should be adopted. Abbas et al., (2016) explore the impact of climate changes in the Diyala river basin using SWAT (The Soil and Water Assessment Tool) model for a century in advance.

The results show a scarcity in the precipitation and groundwater recharges in the basin. Moreover, Lelieveld et al., (2016) used Coupled Model Intercomparison Project Phase 5 (CMIP5) with two greenhouse gas emission model, RCP4.5 and RCP8.5 (Representative Concentration Pathways), to predict future temperature projection in MENA region, which include the current investigated region. The study shows increases in summer temperature for the next mid and end century to about four degrees, which increase the water demands and the evaporation losses from water bodies in the region. Furthermore, deterioration over the last decade in Tigris river water quality after the confluence with Diyala river was observed by Evan et al., (2012), WCC, (2006), and CEB, (2011). The total dissolved solids (TDS) concentration ranged between 600 to 1200 mg/l, compared with about 500 mg/l before the confluence.

In the same context, the Iraqi government intended to develop more lands in the basin for future investment (SGI et al., 2014). This has significant impacts on communities, the economy, crop production and industry. Recently, Al-Jawad et al., (2018a) assessed the storage sustainability of groundwater exploitation in the middle part of the basin for future regional development using optimization approach to minimize water deficit, water losses, and storage mining. The assessment covers a period of half-century using two irrigation methods, open furrows and drip methods. The results show that the aquifer storage will significantly exhausted after 40 years of water exploitation using both irrigation methods. However sustainable management could be achieved for 25 and 33 years using both irrigation alternatives by reducing 45% of water delivery, respectively. Hence a combined use of groundwater with surface water was one of the alternatives that was suggested to mitigate water deficit.

Furthermore, Al-Jawad et al., (2018b) used optimization model to promote the operation of Himren dam, located in the middle part of the basin, to remediate the river environments for the lower part of the basin before the confluence with Tigris river. The model succeeded to promote reservoir operation management to remediate river environment. Also, the results show sensitivity of the system to the inflows from the upper part of the basin, which dictate the quantity of releases from the upper dam (Derbindikhan), runoff from catchment area, and water exploitation in the middle part of the basin. Hence, river basin water resources management strategies should consider all basin features to overcome water and environment crisis challenges.

3.3 Objectives Functions

The operation strategy for the two multipurpose dams is to fulfil community, environment, and energy water requirements. Hence, the following formulas were proposed to represents these requirements (Al-Jawad and Tanyimboh, 2018; Al-Jawad et al., 2018a; Al-Jawad et al., 2018b). Table 4 illustrate the comprehensive mathematical formulae for the entire river basin. However, a simple model is also presented to demonstrate the significance of the OP-IWRM approach's implementation in river basin management strategy. Both models can be expressed as, with function reference to Table 3:

$$\boldsymbol{F}_{comp.}(\boldsymbol{x}) = (f_1, \dots \dots \dots, f_{18}) \qquad \forall\, \boldsymbol{x} \in \boldsymbol{\Omega} \tag{1}$$

$$\boldsymbol{F}_{simple}(\boldsymbol{x}) = (f_3, f_5, f_6, f_9, f_{17}, f_{18}) \qquad \forall\, \boldsymbol{x} \in \boldsymbol{\Omega} \tag{2}$$

where $\boldsymbol{F}_{comp.}$ refer to the comprehensive model and $\boldsymbol{F}_{simple}$ for the simple model, $\boldsymbol{x}$ is the decision variables' vector, and $\boldsymbol{\Omega}$ is the decision variables feasible search space. Details of both models are in Figure 4.

Here, two cases were adopted to investigate the system behaviour, Case 1 represents only two dams' optimization management model, and Case 2 combine groundwater management model with Case 1 to fully integrated water resources management problem. Hence, f_5 and f_6 are involve according to the above Cases. Details of objectives functions and its parameters are presented in the *supplementary data, Tables A1 to A6.*

Table 3. Comprehensive mathematical model for Diyala river basin

No.	Objective function	Description
1	$f_{winterD}$	Maximize Derbindikhan reservoir storage in winter
2	$f_{summerD}$	Minimize Derbindikhan reservoir storage in summer
3	f_{powerD}	Maximize Derbindikhan power generation
4	$f_{releasesD}$	Maximize Derbindikhan releases
5	f_{Del-SW}	Minimize water deficit after Derbindikhan dam (surface water)
6	$f_{Del-SW-GW}$	Minimize water deficit after Derbindikhan dam (surface+groundwater)
7	f_{WL}	Minimize infiltration water losses
8	f_{mining}	Minimizing groundwater storage
9	$f_{demandsH}$	Minimize water deficit after Himren dam
10	$f_{winterH}$	Maximize Himren reservoir storage in winter
11	$f_{summerH}$	Minimize Himren reservoir storage in summer
12	f_{powerH}	Maximize Himren power generation
13	f_{riverB}	Minimize discharge fluctuation after Diyala Barrage
14	f_{TDS-DY}	Minimize pollutant in Diyala river
15	f_{TDS-TR}	Minimizing pollutant in Tigris river
16	f_{DY-BCH}	Minimizing riverbed changes in Diyala river
17	f_{phy-M}	Minimizing physical model violation
18	f_{MD}	Minimizing total model violation

3.4 Decision Variables

The decision variables are divided in three sets for Case 1 and four sets for Case 2 to represent monthly base management strategy, these are:

1- Derbendikhan dam releases represented by set-1 ($\boldsymbol{x_1}$).

2- Himren dam releases are represented by set-2 ($\boldsymbol{x_2}$).

3- Groundwater exploitation management (number of wells) in the middle part are represented by set-3 ($\boldsymbol{x_3}$).

4- The uncertainty of water exploitation in the middle part of the basin are represented by set-4 ($\boldsymbol{x_4}$).

Each set of decision variables has its own upper and lower limits, depending on the corresponding problem boundaries.

Simple Model (F_{simple}) **Comprehensive Model ($F_{comp.}$)**

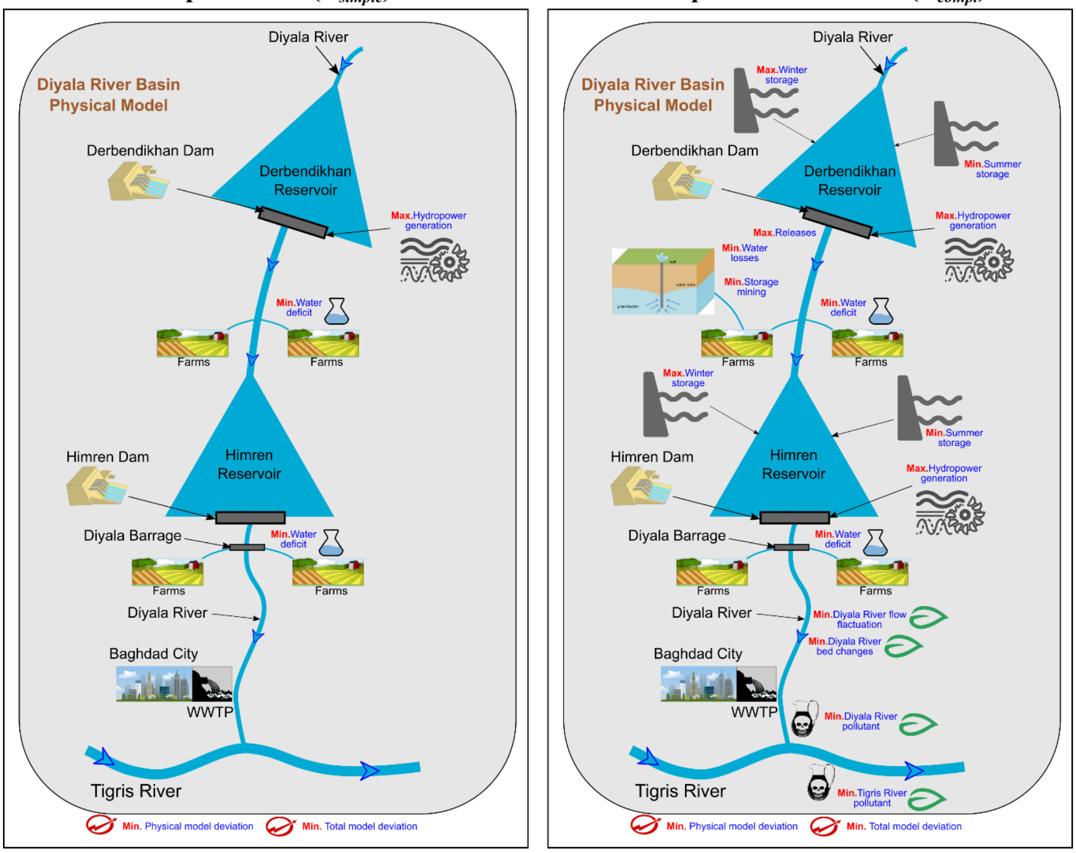

Figure 4. Proposed Diyala river basin management objectives' models.

3.5 River Basin System Limitations

The evolutionary algorithm is designed to solve unconstrained problems. However in real-world problems, constraints should be considered in the optimization model (Maier et al., 2014). The river basin system has many physical and environmental constraints. The physical constraints control the reservoirs physical barrier for storage, releases, and hydropower generation, while the environmental constraints are considered for storage sustainability, water quality, and river environment. Table 4 presents the river basin system constraints. Further model parameters are presented in the *supplementary data, Table 7.*

Table 4. Physical and environmental constraints for Diyala river basin system (SGI et al., 2014)

Parameter	**Physical Constraints**	**Environmental Constraints**
Derbindikhan dam		
Storage (S_t^D) (MCM)[1]	$283.48 \leq S_t^D \leq 2572.0$	$S_{t=next\ year}^D \leq 0.9 \times S_{t=0}^D$
Head (H_t^D) (m.a.s.l)	-	$H_t^D \geq 434.0$
Power (Pw_t^D) (KW)	$Pw_t^D \leq 249000$	$Pw_t^D \geq 16000$
Releases (R_t^D) (MCM)	$51.84 \leq R_t^D \leq 878.6$	
Between two dams (Middle part)		
Total Delivered water (Del_t^M) (MCM)	$Del_t^M \leq 74.27$	-
Aquifer storage $(S_{aq,t})$ (MCM)	-	$S_{aq,t} \geq 85\% S_{st}$
Soil moisture content (SM_t) (mm)	$SM_t \leq 115.0$	-
Himren dam		
Storage (S_t^H) (MCM)	$102.0 \leq S_t^H \leq 2400.0$	$S_{t=next\ year}^H \leq 0.9 \times S_{t=0}^H$
Head (H_t^H) (m)	-	$H_t^H \geq 89.0$
Power (Pw_t^H) (KW)	$Pw_t^H \leq 50000$	$Pw_t^H \geq 7500$
Releases (R_t^H) (MCM)	$51.84 \leq R_t^H \leq 510.6$	
Diyala river after Himren dam (Lower part)		
River discharge (MCM)	$25.92 \leq Q_{min}^r \leq 2592$	-
River bed changes (ΔBL_{max}) (m)	-	$1.0 \leq \Delta BL_{max} \leq 2.0$[2]
Tigris River quality (TDS_t^R) (mg/l)	-	$500.0 \leq TDS_t^R \leq 600.0$

[1]MCM = million cubic meters per month; [2](Alsaffar, 2017)

3.6 Predicted Future Water Resources Scenarios

In this research, a dataset of thirty-three years (from 1981 to 2013) was utilized in the proposed model for the Derbendikhan dam. The National Center of Water Resources management (NCWRM)/Ministry of water resources in Iraq adopted a 6-month smoothing in order to reduce the data noise and potential registrations errors. The dataset was projected for future management using two scenarios to overcome the uncertainty of inflows. Scenario1 was adopted to reflect the climate impact changes on the reservoir inflows by recycling the last eleven-years (dry years) to the beginning of the selected dataset (Alsaffar, 2017). The same methodology was adopted by Al-Jawad et al., (2018b) for Himren dam operation management. While scenario-2 reflects the out border influences on the inflows (damming the river streams in Iran) by recycling the drying periods for the entire dataset. Accordingly, the four alternatives proposed in section 2 will be:

- Alternative-1 = Scenario-1/Case 1
- Alternative-2 = Scenario-1/Case 2
- Alternative-3 = Scenario-2/Case 1
- Alternative-4 = Scenario-2/Case 2

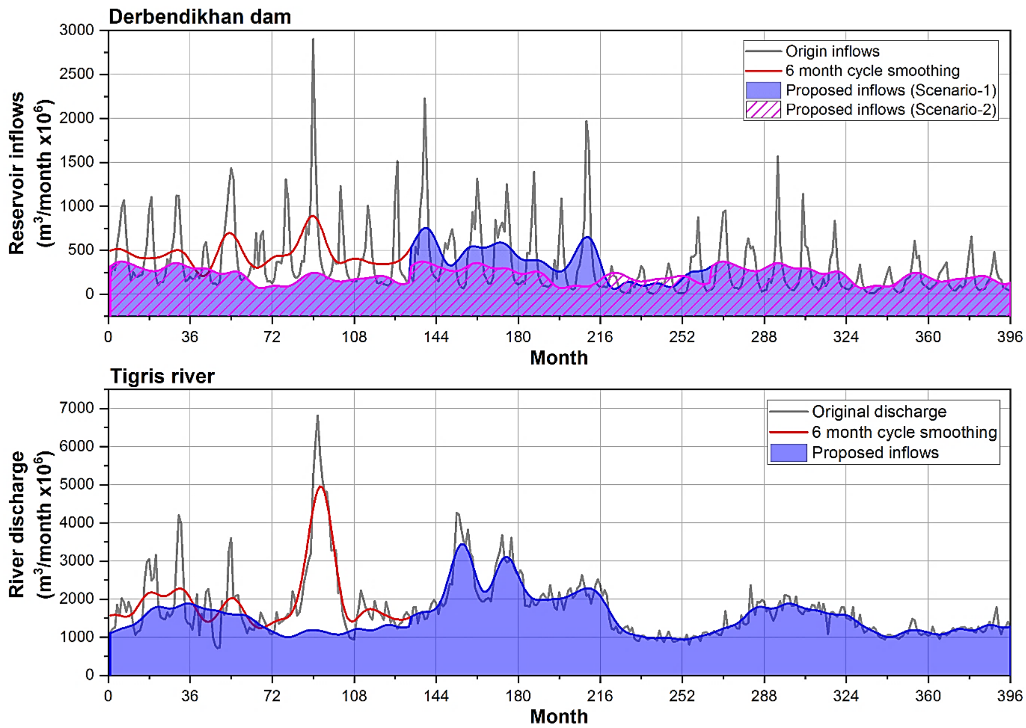

Figure 5. Illustrates the adopted scenarios from the historical dataset from 1981 to 2013 for Derbendikhan dam and Tigris river. Scenario-1 conceptualizes the climate change impact, and scenario-2 for out border damming process effects on reservoir inflows for Derbendikhan dam. The Tigris river discharge was conceptualized as in scenario-1 (Al-Jawad et al., 2018b).

The same data projection as in scenario-1 was adopted for the Tigris historical discharge (Alsaffar, 2017; Al-Jawad et al., 2018b). Figure 5 illustrates the adopted scenarios that extracted from the historical dataset for Derbendikhan dam and Tigris river, respectively.

3.7 Computational Model Utilization

In this research the self-adapted ε-DSEA optimization algorithm presented by Al-Jawad and Tanyimboh, (2018) was adopted. The algorithm has multi operators and auto-parameter tuning adapted with the quality of dominance solutions during the evaluation process. The ε-DSEA was assessed against the state-of-the-art Borg MOEA (Hadka and Reed, 2013) using multiple test functions and two real-world water resources management problems. The algorithm out competed the Borg MOEA in almost all adopted problems (Al-Jawad and Tanyimboh, 2018; Al-Jawad et al., 2018a; Al-Jawad et al., 2018b). Previously Borg was assessed against other state-of-the-art evolutionary algorithms using challenging multi-objectives problems, through which it outperforms or met these algorithms (Hadka and Reed, 2012; Hadka et al., 2012; Hadka and Reed, 2013; Woodruff et al., 2015; Zatarain Salazar et al., 2016). The ε-DSEA parameters are presented in Table 5.

In order to conceptualize the optimization river basin system model, a program in C language was created. The adopted optimization algorithm was executed 10 times for each scenario using 2.0×10^{6} functions evaluations in each run; hence the gross function evaluation was 1.6×10^{8}. The total number of decision variables for Case 1 is 1188, and 1584 for Case 2.

Table 5. Parameter values used in the optimisation algorithm (ε-DSEA) (Al-Jawad and Tanyimboh, 2018)

Parameters	**Values**	**Parameters**	**Value**
Initial population size	100	SPX parents	3
Tournament selection size	2	SPX offspring	2
SBX crossover rate	1.0	SPX expansion rate λ	[2.5, 3.5]
SBX distribution index η	[0, 100]	UNDX parents	10
DE crossover rate CR	[0.1, 1.0]	UNDX offspring	2
DE step size F	[0.5, 1.0]	UNDX σ_ζ	[0.4, 0.6]
PCX parents	10	UNDX σ_η	$[0.1, 0.35]/\sqrt{L}$
PCX offspring	2	UM mutation rate	1/L
PCX σ_η	[0.1, 0.3]	PM mutation rate	1/L
PCX σ_ζ	[0.1, 0.3]	PM distribution index η_m	20

L is the number of decision variables. The permissible range for dynamic parameters is shown in brackets. The parameters σ_η and σ_ζ are the decision variables' variation.

The resolution of objective function search space (ε) for all objective functions was set to 0.5 for the comprehensive model, and 0.1 for the simple model. Furthermore, the adopted model calculates other parameters for the system like: surface area, storage, water level, power generating for the reservoirs. While for the other parts, it calculates: groundwater storage, river discharge, riverbed level changes, and river quality before and after the confluence with the Tigris river. Totally, in each execution process, the number of calculated variables is 6732 for Case 1, and 7920 for Case 2. The execution process was implemented using PC desktop (Core i7-6700 CPU @ 3.4 GHz, 16 GB RAM) with Ubuntu 16.04 OS.

4. RESULTS AND DISCUSSION

4.1 Simple and Comprehensive Models Achievement

The best median solutions for f_{powerD} (f_1) and $f_{demandsH}$ (f_2) achieved by both models ($\boldsymbol{F}_{simple}$, $\boldsymbol{F}_{comp.}$) are selected for comparative assessment since they represent the main objectives management in the simple model. Figure 6 illustrates the differences between both models ($\Delta\boldsymbol{F} = \boldsymbol{F}_{simple} - \boldsymbol{F}_{comp.}$) for Derbendikhan dam system using all alternatives. Deficits in several alternatives are observed, except for water delivery from groundwater to the farms in dam downstream (Figure 6e). However, this leads to large depletion (about 60×10^9 m^3 in scenario-1 Case 1 and 2) in groundwater storage for the considered operation time (Figure 6f).

Figure 6 shows models' differences ($\Delta\boldsymbol{F}$) for Himren dam system for all alternatives. Similar results in the upper part system are notable except for reservoir releases (Figure 7d) and water delivery to the farms in dam downstream (Figure 7e). However, the achievement in water deliver cause depletions in river discharges (Figure 7f) may increase pollutant concentration in river downstream region.

For the whole system, the $\boldsymbol{F}_{comp.}$ model is better than the $\boldsymbol{F}_{simple}$ model in all sectors, as it produces more power, larger water surface storage, lower impact on groundwater storage, and more water flows in the upper and lower parts of the river. The computational analysis results are presented in Table 6. The interesting findings are in CPU time, which is almost the same in both models. Usually, combining more objectives to a problem formulation will increase its computational complexity, including the execution time (Maier et al., 2014).

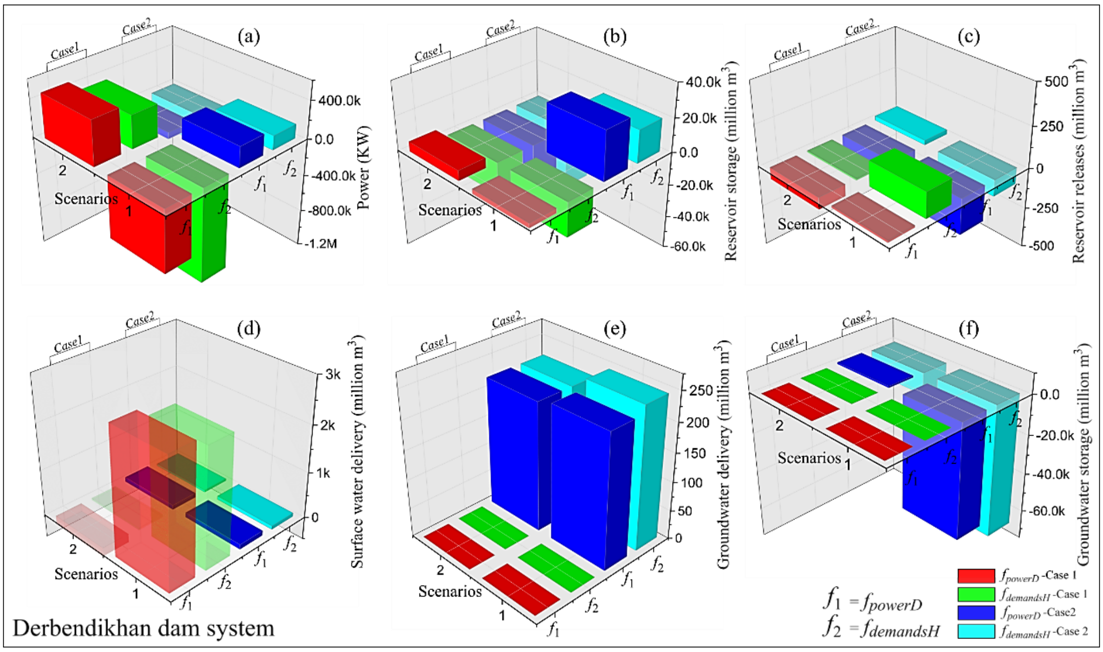

Figure 6. Differences between simple and comprehensive model ($\Delta\boldsymbol{F}$) for Denbendikhan dam system (upper part of Diyala river basin) for all alternatives

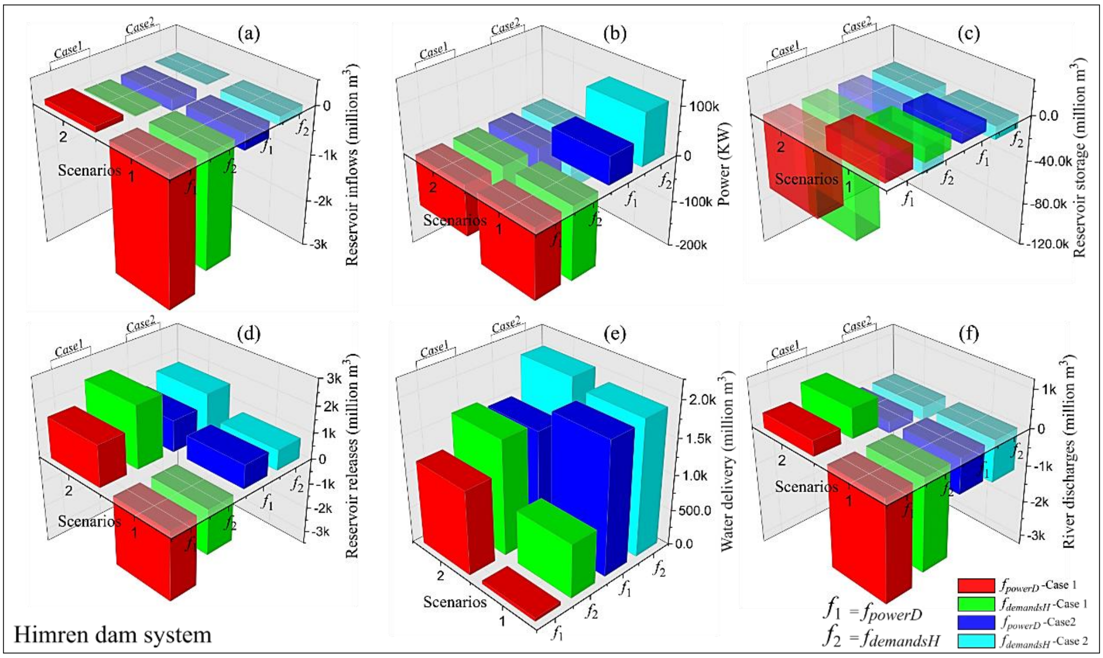

Figure 7. Differences between simple and comprehensive model ($\Delta\boldsymbol{F}$) for Himren dam system (lower part of Diyala river basin) for all alternatives

However, here using five or seventeen objectives has almost the same impact on problem's implementation time. The complexity of enormous decision variables (more than 1000) with different boundaries (here, three and four different boundaries adopted in Case 1 and 2, respectively) dominate objectives complexity.

Producing more dominance solutions is another advantage aspect of using comprehensive models. More than ten times solutions are generated using larger objectives search space resolutions (ε). Increasing decision search space using many objectives will involve additional search regions which may include possible global optimum solutions, conversely simple models may exclude these regions (Maier et al., 2014).

Table 6. General computational analysis comparison for simple and comprehensive models

Parameter	$\boldsymbol{F}_{simple}$	$\boldsymbol{F}_{comp.}$
Number of objectives functions	5	17
Objective search apace resolution (ε)	0.1	0.5
No. of dominance solutions	≤ 100	≥ 1000
CPU time	≈1.38 hrs	≈1.38 hrs

According to the results above, the comprehensive model implementation is more beneficial than simple model, hence the comprehensive model will be adopted for river basin management strategy.

4.2 River Basin Management Strategy

The optimum solutions were analysed for all alternatives, and solutions close to the median values were selected for each alternative. Figure 8 and 9 illustrates the Pareto-front for scenario-1 and 2 in Case1 and 2, respectively. The impact of the comprehensive model using OP-IWRM approach is emerged on the delivered water to the farms after the Derbendikhan dam. The range of objective function (f_{Del-SW}) is reduced about 85%, from 82-102.68 in Case1, to 10.87 - 12.85 in Case2 ($f_{Del-SW-GW}$). Other objectives were effected slightly toward higher or lower values. All physical model penalties are zero (f_{phy-M}), except in scenario-2 Case 2. For zero values, the total violation model (f_{MD}) will equal to the sum of environmental model constraints over the total time period, while for non-zero value, f_{MD} will represents both physical and environmental model violation. However, the overall f_{MD} values for all alternatives ranged between 3.0 to 8.38.

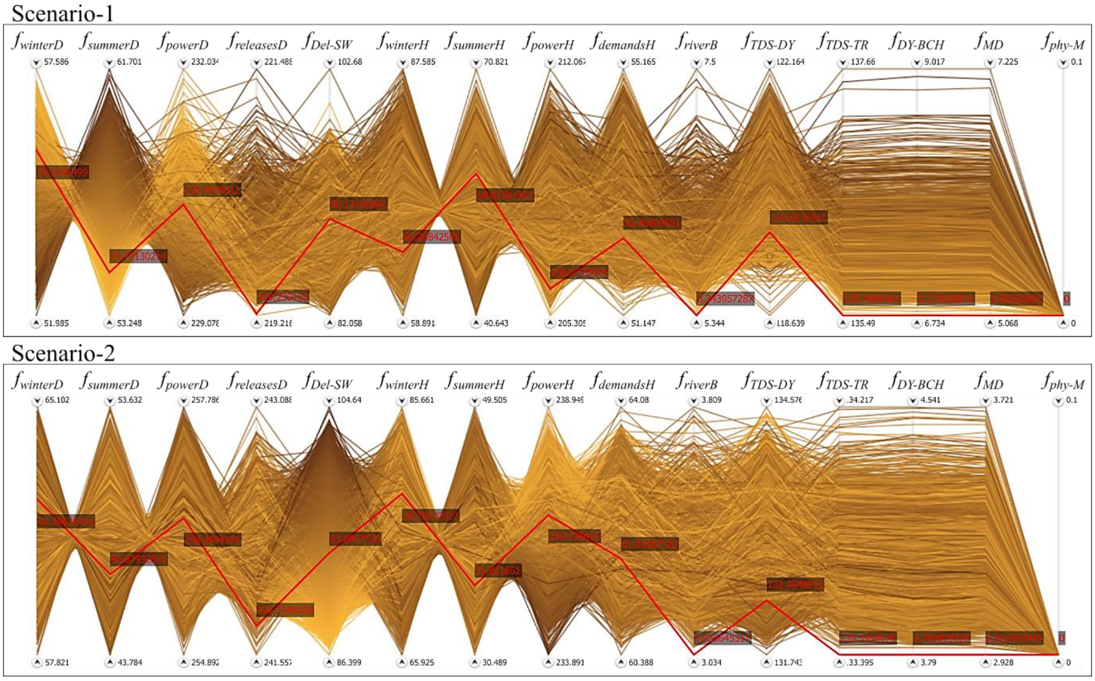

Figure 8. Pareto-front optimum solutions of Diyala river basin optimization model for case 1 using scenario1 and 2 for inflows. Letters *D* and *H* refer to Derbendikhan and Himren n dams, respectively. Solution with minimum model violation is marked in red colour.

Some of the optimum solutions in Figure 7 scenario-2 are located in the border region of feasible space by having non-zero values of f_{phy-M} function. The reduction in the reservoir inflows proposed in scenario- 2, and include more objectives and constraints to the model for Case 2 alternative, boost the problem complexity. However, the ε-DSEA succeed to overcome this challenge and produce optimum solutions for the problem. However, solutions violations are very small and can be neglected in compare with river basin water budget. Hence, these optimum solutions can also be adopted for river basin management strategy.

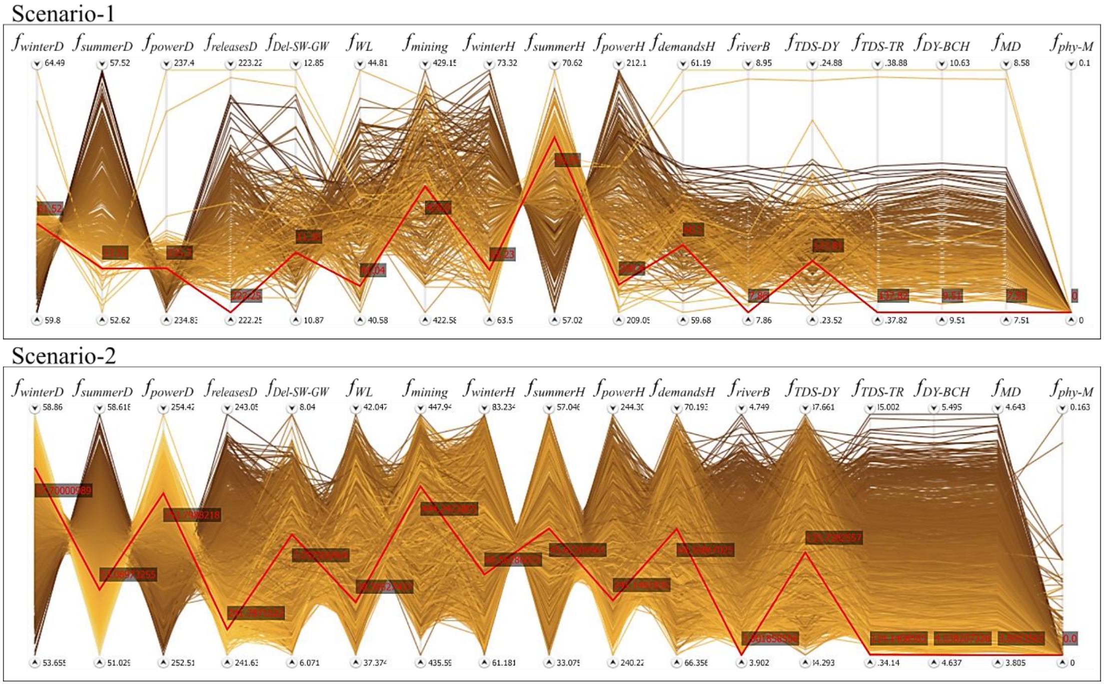

Figure 9. Pareto-front optimum solutions of Diyala river basin optimization model for case 2 using scenario1 and 2 for inflows. Letter *D* and *H* refer to Derbendikhan and Himren dams, respectively. Solution with minimum model violation is marked in red colour.

Notably Figures 8 and 9 show objectives conflicts for the entire system, except for f_{TDS-TR} and f_{DY-BCH}, but in fact there are slight conflicts for many solutions. The Diyala river bed changes are directly affected by the river discharge, and the concentration of TDS in the Tigris river is affected by both discharges and quality of Diyala river. Hence the relation between the two function is indirect, with lower level of conflicts than other objectives functions.

Generally the water resources models provide information rather than the decisions itself (Loucks, 2012). Hence, the selection of a solution from the Pareto-front should be set by the decision makers. Here, solutions have minimum model violation (f_{MD}) were selected for the river basin management strategy, since they have the lowest impacts on river basin environments (red lines in Figures 8 and 9). Summary of the selected solutions for all alternatives are presented in Table 7. Details are available in the *supplementary data*, *Table A8*. The table shows the average, median and the gross sum of Diyala river basin system.

Table 7. Showing the average, median, and gross sum of selected optimum solutions with minimum model violations for the entire Diyala river basin system. The design required water demands are in italic grey shade, while the deficit in bold grey shade.

	Scenario-1						**Scenario-2**					
	Case 1			Case 2			Case 1			Case 2		
	Av.[a]	Med.[a]	Gross[b]	Av.	Med.	Gross	Av.	Med.	Gross	Av.	Med.	Gross
Upper dam system (Debendikhan dam)												
Area	59.75	52.04	-	57.20	47.87	-	54.61	43.71	-	58.90	52.37	-
Head	467.62	469.41	-	466.51	467.12	-	464.88	464.50	-	466.86	469.58	-
Power	68.60	45.23	27.16	68.06	44.80	26.95	54.32	41.00	21.51	55.45	42.07	21.96
Storage	1.421	1.338	562.66	1.368	1.242	541.53	1.308	1.141	517.99	1.397	1.345	553.23
Releases	259.72	164.74	102.85	260.07	173.28	102.99	212.64	148.58	84.20	211.95	156.29	83.93
Middle part (intermediate region)												
FQ-DES	*47.22*	*52.28*	*18.70*	*47.22*	*52.28*	*18.70*	*47.22*	*52.28*	*18.70*	*47.22*	*52.28*	*18.70*
Q-SUR	27.82	24.26	11.02	26.36	21.80	10.44	23.28	20.00	9.22	26.32	20.97	10.42
Q-GW	-	-	-	17.68	7.76	7.00	-	-	-	18.29	4.80	7.24
N-wells	-	-	-	757.67	332.50	-	-	-	-	783.54	205.50	-
TWD	27.82	24.26	11.02	44.05	45.64	17.44	23.28	20.00	9.22	44.61	45.73	17.67
Deficit	**19.40**	**28.02**	**7.68**	**3.17**	**6.64**	**1.26**	**23.94**	**32.28**	**9.48**	**2.61**	**6.55**	**1.03**
ST-GW	-	-	-	8.780	8.867	-	-	-	-	8.564	8.487	-
Middle dam system (Himren dam)												
Inflows	217.88	134.89	86.28	219.69	141.17	87.00	175.34	118.15	69.43	171.61	125.18	67.96
Area	185.98	184.14	-	192.83	199.58	-	160.64	150.34	-	175.95	171.45	-
Head	99.10	99.22	-	99.34	99.89	-	97.96	97.71	-	98.71	98.66	-
Power	15.74	11.47	6.23	15.70	11.19	6.22	11.80	10.54	4.67	11.58	10.04	4.59
Storage	1.195	1.154	473.36	1.256	1.280	497.36	0.987	0.888	390.86	1.107	1.053	438.54
Releases	183.30	138.14	72.59	183.85	133.10	72.81	145.95	131.66	57.80	139.21	121.10	55.13
Lower part (downstream Himren dam)												
Q-river	70.66	42.14	27.98	77.02	41.01	30.50	51.25	39.16	20.29	50.25	37.64	19.90
FQ-DES	*191.00*	*200.13*	*75.60*	*191.00*	*200.13*	*75.60*	*191.00*	*200.13*	*75.60*	*191.00*	*200.13*	*75.60*
Q-SUR	112.64	96.38	44.60	106.83	86.17	42.31	94.70	90.18	37.50	88.96	80.28	35.23
Deficit	**78.36**	**103.75**	**31.00**	**84.17**	**113.96**	**33.29**	**96.30**	**109.95**	**38.10**	**102.04**	**119.85**	**40.37**
TDS-B	1.670	1.770	-	1.680	1.801	-	1.808	1.907	-	1.821	1.976	-
TDS-A	2.569	2.737	-	2.573	2.780	-	2.774	2.901	-	2.800	2.979	-
TDS-T	0.574	0.575	-	0.573	0.575	-	0.574	0.575	-	0.573	0.575	-
|Bed-C|	0.30	0.22	-	0.33	0.24	-	0.22	0.16	-	0.22	0.16	-

[a] Discharges values are in (m^3/month $\times 10^6$), storages are in (m^3/month $\times 10^9$), power in (MW), areas are in (km^2), water head in (m.a.s.l), TDS concentrations in (g/l), bed river changes in (m); [b] Gross sum over the entire periods (33 years), discharges are in ($m^3 \times 10^9$), storages in ($m^3 \times 10^9$), power in (GW); FQ-DES: Design water delivery; Q-SUR: surface water discharges to the farms; N-wells: No. of wells; Q-GW: groundwater discharge; ST-GW: groundwater storage; TWD: Total water delivery to the farms; Q-river: river discharge; TDS-B: TDS concentration before WWTP; TDS-A: TDS concentration after WWTP; TDS-T: TDS concentration in Tigris river; |Bed-C|: absolute river bed changes.

4.3 Impact of OP-IWRM Implementation

The optimum integrated water resources management implementation has a generally positive impact on the whole river basin system, and particularly on the middle part of the basin. Figure 10 illustrates the gross differences between Case 2 and Case 1 (Δ_{C2-C1}) for river basin features for both scenarios, based on Table 7. The positive impact is evident in scenario-1 for the middle and lower part of the basin. In scenario-2, the impact on reservoir storages are obvious coupled with the intermediate basin region. The proposed model succeeds to maintain reservoir storages in water crisis condition. Hence, combining groundwater management with surface water management leads to sustainable water resources management for the river basin. The deficits are reduced about 84% and 89% for the average and gross values, and about 76% and 79% for the median value, in both scenarios, respectively (Table 7). The optimum conjunctive use significantly improved farms' water delivery, which increase the economic benefits and society food security in this region. Policy for future investment opportunities may consider in energy and food sectors. However, the regional uncertainty management produced gross deficit in delivered surface water about 50% in all alternatives, which represents the barriers maintaining system stability. If extra water is consumed in this part, the system may lose management optimality is some sectors, such as hydropower generation. Hence, the government should consider future policy for controlling and managing the deep uncertainty in water consumption in this region. Moreover, the impacts of upstream river system on downstream farms' water delivery are observed with deficits around 45% to 50% in both adopted alternatives. Therefore, other alternatives may be considered in the policy like drip system, crops types changing, reducing summer crops patterns. Although the potential regional groundwater having a high salinity concentration and not suitable for agriculture process (SGI et al., 2014), further study may also consider for using advance treatment technologies or mixing with freshwater (Kulkarni, 2011). As a result, the OP-IWRM implementation produces more sustainable water resources management strategy for the river basin system by improving the entire system environments and sectors.

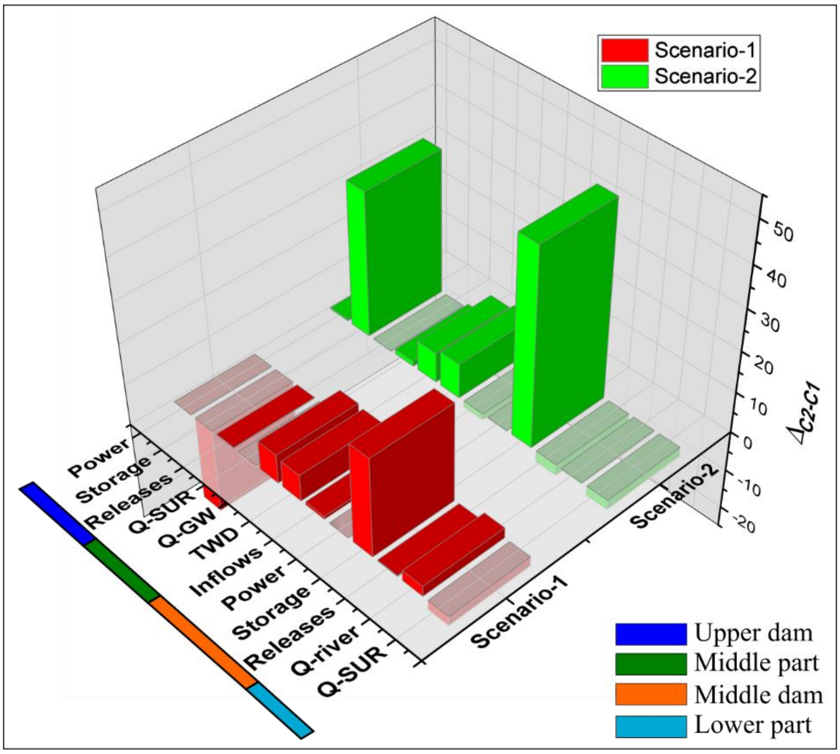

Figure 10. Cases gross differences for river basin system features based on Table 7 for both scenarios.

4.4 Impact of Upstream River Basin Future Development

The out of border future development impact on the Diyala river basin water resources were represented by scenario-2. Table 7 (Gross column) shows that the total Derbendikhan dam releases will reduced and its power production about 19×10^9 m^3

and 5.0 GW (about 18% for each), respectively. For the Himren dam, the inflows will be reduced about 18×10^9 m^3 (about 20%), and its releases about 17.0×10^9 m^3 (about 23%), while the power generation will be reduced about 1.4 GW (about 23%), in compare with scenario-1 for both dams. Moreover, Diyala river discharges in the lower part of the river basin were extremely effected by the reduction in the water resources. The total water volumes reduced about 10.0×10^9 m^3 (about 66%) in compare with scenario-1. The total water delivery also affected in this part by a deficit about 7.0×10^9 m^3 (about 16%), in compare with scenario-1. Figure 11 illustrates the impact of river water resources on the system. The scenarios gross differences (Δ_{S2-S1}) shows overall reductions in all sectors in both cases, even with IWRM implementation, water scarcity is still exist in the river basin. Hence, the government needs to consider a policy to set an international agreement with Iran to avoid future expected deterioration in river basin water resources, since there is no such agreement till now (Abdulrahman, 2017).

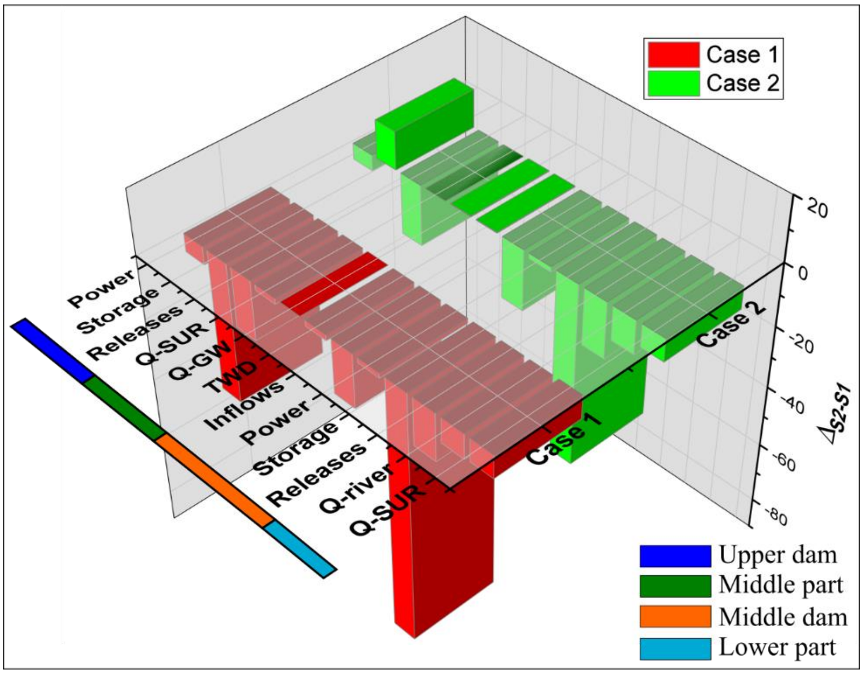

Figure 11. Scenarios gross differences for river basin system features based on Table 7 for both cases.

5. CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

In this research a comprehensive optimum integrated water resources management (OP-IWRM) approach is proposed for river basin management strategy. This novel approach combines all common environmental, social, and economic objectives, coupled with all available water resources, to generate optimum trade-off solutions for the decision makers. The approach is evaluated by comparative assessment with simple model using many alternatives. A challenging case study using the transboundary Diyala river basin in Iraq was adopted for the comparative analysis. Future climate change and upstream development plan impacts alternatives are formulated and considered. The system has two large multipurpose dams, named Derbendikhan and Himren, which located in the upper and middle part of the basin, respectively. Also it has a potential groundwater storage in the middle part of the basin. The ε-DSEA optimization algorithm (Al-Jawad and Tanyimboh, 2018) was utilized to combine up to 17 objective functions with 1584 decision variables for the next three decades.

The comprehensive approach provides decision variables for sustainable management for the entire river basin resources for the considered alternatives including power generation, storages, and river discharges. Execution time (computer) is not a limitation for the model, and was not greatly affected by complexity. Accordingly, the implementation of a comprehensive approach is evident in water resources management strategy. Consistency, combining groundwater exploitation with the OP-IWRM approach succeed to suggest that improvements water delivery fulfilment might be increased from 50% to more than 85% in the middle part of the river basin with minor impact on groundwater storage. Furthermore, the OP-IWRM succeed to address water exploitation uncertainty in the middle part of the river basin and presents water consumption barriers for the decision makers to be considered for future management policy.

This approach demonstrates the significant impact of transboundary water development plans on the river basin system. The gross Derbendikhan dam releases and power generation are reduced from about 102.8 to 84.0×10^9 m^3 and from about 27.0 to 21.8 GW, respectively. For Himren dam system, the inflows, releases and power generating are also depleted from about 86.5 to 68.0×10^9 m^3, 73.0 to 56.0×10^9 m^3, and 6.2 to 4.6 GW, respectively. While the river discharge in the lower part of the river basin was extremely affected from 30.0 to 20.0×10^9 m^3, hence the correlated water delivery was drop from about 43.0 to 36.0×10^9 m^3. The deficit in delivered water in this part is about more than 50% for all adopted alternatives.

The value of this OP-IWRM approach is evident, it produced optimum sustainable management strategies using; the common Social, Environmental, and Economic objectives; and the existing surface and groundwater resources for a river basin system under different scenarios. It is possible to add more objectives for additional sectors like; governmental legislation; human resources development; economic revenues. Hence, the proposed methodology reactivates the implementation of the IWRM principles.

5.2 Case Study Specific Recommendations

The middle basin exploitation has significant impact on the water resources of the lower basin, hence a policy should be considered to reduce water requirements to mitigate the impact on the lower part of the basin. Also, similar policy may be considered for the lower basin farming practice.

- Replace the traditional irrigation method with new recent techniques, if applicable, to reduce allocated and infiltrated water losses.
- Replace high water demands summer crops with lower water demands to reduce water demands in hot season.
- Reduce crop pattern summer plan to reduce water demands in hot season.
- Rehabilitate water conveyance infrastructure to reduce water losses over water delivery process.

New government policy may include restriction in water exploitation in the middle part of the basin for farms and remove any unauthorized outlets on the river and Himren reservoir lake. The lower basin water demands could be improved by using the existing saline groundwater after specific treatment or mixing with fresh surface water. Regarding development plans in Iran, the government should consider a policy to set water sharing agreements to mitigate water monopolizing from Iran, which may cause severe drought of Diyala river basin water resources inside Iraq. The current research results could be adopted in the negotiation process for this agreement.

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REFERENCES

Abbas, N., Wasimi, S.A., Al-Ansari, N., 2016. Impacts of Climate Change on Water Resources in Diyala River Basin, Iraq. J. Civ. Eng. Archit. 10, 1059–1074.

Abdulrahman, S.A., 2017. Failure to securitise environmental problems in Iraq: the case of the Alwand and Sirwan Rivers. Int. J. Environ. Stud. 74, 540–557. https://doi.org/10.1080/00207233.2017.1330493

Ahmadianfar, I., Adib, A., Taghian, M., Faculty, E., Resources, N., 2015. a Multi-Objective Evolutionary Algorithm Using Decomposition (Moea/D) and Its Application in Multipurpose Multi-Reservoir Operations. Int. J. Optim. Civ. Eng. 5, 167–187.

Al-Ansari, N., Ali, A.A., Knutsson, S., 2014. Present Conditions and Future Challenges of Water Resources Problems in Iraq. J. Water Resour. Prot. 6, 1066–1098. https://doi.org/10.4236/jwarp.2014.612102

Al-Ansari, N.A., 2013. Management of Water Resources in Iraq: Perspectives and Prognoses. Engineering 05, 667–684. https://doi.org/10.4236/eng.2013.58080

Al-Faraj, F.A.M., Scholz, M., 2014. Assessment of temporal hydrologic anomalies coupled with drought impact for a transboundary river flow regime: The Diyala watershed case study. J. Hydrol. 517, 64–73. https://doi.org/10.1016/j.jhydrol.2014.05.021

Al-Jawad, J.Y., Al-Jawad, S.B., Tanyimboh, T.T., Kalin, R.M., 2018a. Comprehensive Evolutionary Algorithms Performance Assessment Using a Multi-Objectives Water Resources Management Problem. Water Resour. Manag.

In review.

Al-Jawad, J.Y., Alsaffar, H.M., Bertram, D., Kalin, R.M., 2018b. Optimum Socio-Environmental Flows Approach for Reservoir Operation Strategy Using Many-Objectives Evolutionary Optimization Algorithm. Sci. Total Environ. In review.

Al-Jawad, J.Y., Tanyimboh, T.T., 2018. Epsilon-Dominance-Driven Self-Adaptive Evolutionary Algorithm For Many-Objective Optimization. Swarm Evol. Comput. In review.

Al-Tamimi, O.S., 2007. Water resources evaluation in Diyala River basin – Middle part. PhD Thesis (in Arabic). College of Science,University of Baghdad, Iraq.

Ali, A.A., 2016. Three Dimensional Hydro-Morphological Modeling of Tigris River. PhD. Thesis, Luleå University of Technology, Sweden.

Ali, A.A., Al-Ansari, N.A., Knutsson, S., 2012. Morphology of tigris river within baghdad city. Hydrol. Earth Syst. Sci. 16, 3783–3790. https://doi.org/10.5194/hess-16-3783-2012

Alsaffar, H.M., 2017. Personal communication. , 15 July.

Amirkhani, M., Bozorg-Haddad, O., Fallah-Mehdipour, E., Loáiciga, H.A., 2016. Multiobjective Reservoir Operation for Water Quality Optimization. J. Irrig. Drain. Eng. 142. https://doi.org/10.1061/(ASCE)IR.1943-4774

Back, T., Fogel, D.B., Michalewicz, Z. (Eds.), 2000. Handbook of Evolutionary Computation. IOP Publishing Ltd., Bristol, UK, UK.

Biswas, A.K., 2008. Integrated water resources management: Is it working? Int. J.

Water Resour. Dev. 24, 5–22. https://doi.org/10.1080/07900620701871718

Cardwell, H.E., Cole, R.A., Cartwright, L.A., Martin, L.A., 2006. Integrated Water Resources Management: Definitions and Conceptual Musings. J. Contemp. Water Res. Educ. 8–18. https://doi.org/10.1111/j.1936-704X.2006.mp135001002.x

Carriaga, C.C., Mays, L.W., 1995. Optimization Modeling For Sedimentation In Alluvial Rivers. J. WATER Resour. Plan. Manag. 121, 251–259.

CEB, (Consulting Engineering Bureau), 2011. Tigris and Euphrates Sampling. Unpublished report, University of Baghdad, Baghdad, Iraq.

Chang, L.C., Chang, F.J., 2009. Multi-objective evolutionary algorithm for operating parallel reservoir system. J. Hydrol. 377, 12–20. https://doi.org/10.1016/j.jhydrol.2009.07.061

Chen, D., Chen, Q., Leon, A.S., Li, R., 2016. A Genetic Algorithm Parallel Strategy for Optimizing the Operation of Reservoir with Multiple Eco-environmental Objectives. Water Resour. Manag. 30, 2127–2142. https://doi.org/10.1007/s11269-016-1274-1

Coelho, A.C., Labadie, J.W., Fontane, D.G., 2012. Multicriteria Decision Support System for Regionalization of Integrated Water Resources Management. Water Resour. Manag. 26, 1325–1346. https://doi.org/10.1007/s11269-011-9961-4

Coello, C.A.C., Lamont, G.L., van Veldhuizen, D.A., 2007. Evolutionary Algorithms for Solving Multi-Objective Problems, 2nd ed, Genetic and Evolutionary

Computation. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-0-387-36797-2

Dai, L., Zhang, P., Wang, Y., Jiang, D., Dai, H., Mao, J., Wang, M., 2017. Multi-objective optimization of cascade reservoirs using NSGA-II: A case study of the Three Gorges-Gezhouba cascade reservoirs in the middle Yangtze River, China. Hum. Ecol. Risk Assess. 23, 814–835. https://doi.org/10.1080/10807039.2017.1285692

Deb, K., Pratap, A., Agarwal, S., Meyarivan, T., 2002. A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Trans. Evol. Comput. 6, 182–197. https://doi.org/10.1109/4235.996017

Dittmann, R., Froehlich, F., Pohl, R., Ostrowski, M., 2009. Optimum multi-objective reservoir operation with emphasis on flood control and ecology. Nat. Hazards Earth Syst. Sci. 9, 1973–1980. https://doi.org/10.5194/nhess-9-1973-2009

Evan, R., Soppe, R., Saleh, R., Abbas, A., 2012. Report B1.4: Water and salt trends and balances for the Mesopotamian plain. Technical report No.6, ICARDA (International Center for Agricultural Research in the Dry Areas), Lebanon.

GEOSURV, (State Company of Geological Survey and Mining), 1993. Geological maps of Iraq. Series of geological maps of Iraq, Ministry of Industry and Minerals, Baghdad, Iraq.

Giacomoni, M.H., Kanta, L., Zechman, E.M., 2013. Complex Adaptive Systems Apporach to Simulate the Sustainability of Water Resources and Urbanization. J. Water Resour. Plan. Manag. 139, 554–564.

https://doi.org/10.1061/(ASCE)WR.1943-5452

Giordano, M., Shah, T., 2014. From IWRM back to integrated water resources management. Int. J. Water Resour. Dev. 30, 364–376. https://doi.org/10.1080/07900627.2013.851521

Giuliani, M., Castelletti, A., Pianosi, F., Mason, E., Reed, P.M., 2016. Curses, Tradeoffs, and Scalable Management: Advancing Evolutionary Multiobjective Direct Policy Search to Improve Water Reservoir Operations. J. Water Resour. Plan. Manag. 142, 04015050. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000570

Giuliani, M., Galelli, S., Soncini-Sessa, R., 2014a. A dimensionality reduction approach for many-objective Markov Decision Processes: Application to a water reservoir operation problem. Environ. Model. Softw. 57, 101–114. https://doi.org/10.1016/j.envsoft.2014.02.011

Giuliani, M., Herman, J.D., Castelletti, A., Reed, P., 2014b. Many-objective reservoir policy identification and refinement to reduce policy inertia and myopia in water management. Water Resour. Res. 50, 3355–3377. https://doi.org/10.1002/2013WR014700

Grigg, N.S., 2016. Integrated Water Resource Management: An Interdisciplinary Approach. Palgrave Macmillan, London. https://doi.org/10.1057/978-1-137-57615-6

GWP, 2000. Integrated Water Resources Management. Global Water Partnership, Technical Advisory Committee (TAC) Background paper No.4, Stockholm, Sweden. https://doi.org/10.2166/wst.2010.262

Hadka, D., Reed, P., 2013. Borg: An Auto-Adaptive Many-Objective Evolutionary Computing Framework. Evol. Comput. 21, 1–30. https://doi.org/10.1162/EVCO_a_00075

Hadka, D., Reed, P., 2012. Diagnostic Assessment of Search Controls and Failure Modes in Many-Objective Evolutionary Optimization. Evol. Comput. 20, 423–452. https://doi.org/10.1162/EVCO_a_00053

Hadka, D., Reed, P.M., Simpson, T.W., 2012. Diagnostic assessment of the borg MOEA for many-objective product family design problems, in: 2012 IEEE Congress on Evolutionary Computation, CEC 2012. pp. 10–15. https://doi.org/10.1109/CEC.2012.6256466

Haimes, Y.Y., Hall, W.A., 1977. Sensitivity, responsivity, stability and irreversibility as multiple objectives in civil systems. Adv. Water Resour. 1, 71–81. https://doi.org/10.1016/0309-1708(77)90025-2

Hakimi-Asiabar, M., Ghodsypour, S.H., Kerachian, R., 2010. Deriving operating policies for multi-objective reservoir systems: Application of Self-Learning Genetic Algorithm. Appl. Soft Comput. J. 10, 1151–1163. https://doi.org/10.1016/j.asoc.2009.08.016

Hering, J.G., Ingold, K.M., 2012. Water Resources Management: What Should Be Integrated? Science (80-.). 336, 1234–1235. https://doi.org/10.1126/science.1218230

Horne, A., Kaur, S., Szemis, J., Costa, A., Webb, J.A., Nathan, R., Stewardson, M., Lowe, L., Boland, N., 2017. Using optimization to develop a "designer" environmental flow regime. Environ. Model. Softw. 88, 188–199. https://doi.org/10.1016/j.envsoft.2016.11.020

Horne, A., Szemis, J.M., Kaur, S., Webb, J.A., Stewardson, M.J., Costa, A., Boland, N., 2016. Optimization tools for environmental water decisions: A review of strengths, weaknesses, and opportunities to improve adoption. Environ. Model. Softw. 84, 326–338. https://doi.org/10.1016/j.envsoft.2016.06.028

IPCC, 2007. Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, M.L. Parry, O.F. Canziani, J.P. Palutikof, P.J. van der Linden and C. Hanson, Eds., Cambridge University Press, Cambridge, UK, 976pp.

Issa, I., Al-Ansari, N., 2014. Expected Future of Water Resources within Tigris-Euphrates Rivers Basin, Iraq. J. Water Resour. Prot. 421–432. https://doi.org/10.4236/jwarp.2014.65042

Jassim, S.Z., Goff, J.C., 2006. Geology of Iraq, First. ed. , Dolin, Prague and Moravian Museum, Brno, Czech Republic.

Jazmin, Z.S., Reed, P.M., Quinn, J.D., Giuliani, M., Castelletti, A., 2017. Balancing exploration, uncertainty and computational demands in many objective reservoir optimization. Adv. Water Resour. 109, 196–210. https://doi.org/10.1016/j.advwatres.2017.09.014

Kasprzyk, J.R., Nataraj, S., Reed, P.M., Lempert, R.J., 2013. Many objective robust decision making for complex environmental systems undergoing change. Environ. Model. Softw. 42, 55–71. https://doi.org/10.1016/j.envsoft.2012.12.007

Kim, T., Heo, J.-H., Bae, D.-H., Kim, J.-H., 2008. Single-reservoir operating rules for a year using multiobjective genetic algorithm. J. Hydroinformatics 10, 163. https://doi.org/10.2166/hydro.2008.019

Klinger, J., Goldscheider, N., Hötzl, H., 2015. Integrated Water Resources Management in the Lower Jordan Rift Valley. Final Report Phase II, KIT Scientific Reports ; 7698, Karlsruhe, Germany.

Kubba, F.A., Joodi, A.S., Al-Sudani, H.A.H., 2014. Two Dimensional Mathematical Model of Contamination Distribution in the Lower Reach. Int. J. Eng. Sci. Res. Technol. 3, 213–225.

Kulkarni, S., 2011. Innovative Technologies for Water Saving in Irrigated Agriculture. Int. J. Water Resour. Arid Environ. 1, 226–231.

Lelieveld, J., Proestos, Y., Hadjinicolaou, P., Tanarhte, M., Tyrlis, E., Zittis, G., 2016. Strongly increasing heat extremes in the Middle East and North Africa (MENA) in the 21st century. Clim. Change 137, 245–260. https://doi.org/10.1007/s10584-016-1665-6

Li, F.F., Qiu, J., 2015. Multi-objective reservoir optimization balancing energy generation and firm power. Energies 8, 6962–6976. https://doi.org/10.3390/en8076962

Loucks, D.P., 2012. Water Resource Management Modeling in 2050. Towar. a Sustain. Water Futur. 341–349.

Maier, H.R., Kapelan, Z., Kasprzyk, J., Kollat, J., Matott, L.S., Cunha, M.C., Dandy, G.C., Gibbs, M.S., Keedwell, E., Marchi, A., Ostfeld, A., Savic, D., Solomatine, D.P., Vrugt, J.A., Zecchin, A.C., Minsker, B.S., Barbour, E.J., Kuczera, G., Pasha, F., Castelletti, A., Giuliani, M., Reed, P.M., 2014. Evolutionary algorithms and other metaheuristics in water resources: Current status, research challenges and future directions. Environ. Model. Softw. 62, 271–299. https://doi.org/10.1016/j.envsoft.2014.09.013

Malekmohammadi, B., Zahraie, B., Kerachian, R., 2011. Ranking solutions of multi-objective reservoir operation optimization models using multi-criteria decision analysis. Expert Syst. Appl. 38, 7851–7863. https://doi.org/10.1016/j.eswa.2010.12.119

Mohtar, R.H., Lawford, R., 2016. Present and future of the water-energy-food nexus and the role of the community of practice. J. Environ. Stud. Sci. 6, 192–199. https://doi.org/10.1007/s13412-016-0378-5

Molina, J.L., Bromley, J., García-Aróstegui, J.L., Sullivan, C., Benavente, J., 2010. Integrated water resources management of overexploited hydrogeological systems using Object-Oriented Bayesian Networks. Environ. Model. Softw. 25, 383–397. https://doi.org/10.1016/j.envsoft.2009.10.007

Nicklow, J., Reed, P., Savic, D., Dessalegne, T., Harrell, L., Chan-Hilton, A., Karamouz, M., Minsker, B., Ostfeld, A., Singh, A., Zechman, E., 2010. State of the art for genetic algorithms and beyond in water resources planning and management. J. Water Resour. Plann. Manag. 136, 412–432.

Nicklow, J.W., Mays, L.W., 2001. Optimal control of reservoir releases to minimize sedimentation in rivers and reservoirs. J. Am. Water Resour. Assoc. 37, 197–211. https://doi.org/DOI 10.1111/j.1752-1688.2001.tb05486.x

Nikolic, V. V., Simonovic, S.P., 2015. Multi-method Modeling Framework for Support of Integrated Water Resources Management. Environ. Process. 2, 461–483.

Poff, N.L., Brown, C.M., Grantham, T.E., Matthews, J.H., Palmer, M.A., Spence, C.M., Wilby, R.L., Haasnoot, M., Mendoza, G.F., Dominique, K.C., Baeza, A., 2016. Sustainable water management under future uncertainty with eco-engineering decision scaling. Nat. Clim. Chang. 6, 25–34. https://doi.org/10.1038/nclimate2765

Qi, Y., Bao, L., Ma, X., Miao, Q., Li, X., 2016. Self-adaptive multi-objective evolutionary algorithm based on decomposition for large-scale problems: A case study on reservoir flood control operation. Inf. Sci. (Ny). 367–368, 529–549. https://doi.org/10.1016/j.ins.2016.06.005

Reddy, M.J., Kumar, D.N., 2009. Performance evaluation of elitist-mutated multi-objective particle swarm optimization for integrated water resources management. J. Hydroinformatics 11, 79–88. https://doi.org/10.2166/hydro.2009.042

Regulwar, D.G., 2009. Multi Objective Multireservoir Optimization in Fuzzy

Environment for River Sub Basin Development and Management. J. Water Resour. Prot. 01, 271–280. https://doi.org/10.4236/jwarp.2009.14033

Safavi, H.R., Golmohammadi, M.H., Sandoval-Solis, S., 2016. Scenario analysis for integrated water resources planning and management under uncertainty in the Zayandehrud river basin. J. Hydrol. 539, 625–639. https://doi.org/10.1016/j.jhydrol.2016.05.073

Salazar, J.Z., Reed, P.M., Herman, J.D., Giuliani, M., Castelletti, A., 2016. A diagnostic assessment of evolutionary algorithms for multi-objective surface water reservoir control. Adv. Water Resour. 92, 172–185. https://doi.org/10.1016/j.advwatres.2016.04.006

Saleh, S.A.H., 2013. A Study of Himreen Reservoir Water Quality Using in Situ Measurement and Remote Sensing Techniques. J. Environ. Earth Sci. 3, 96–105.

Schardong, A., Ph, D., Simonovic, S.P., Asce, F., Vasan, A., 2013. Multiobjective Evolutionary Approach to Optimal Reservoir Operation. J. Comput. Civ. Eng. 27, 139–147. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000213.

SGI, (Studio Galli Ingegneria S.p.A.), MED, (INGEGNERIA S.r.l.), EL CONCORDE, (Construction LLC), 2014. The Strategic Study for Water and Land Resources in Iraq. Technical Study (unpublished), Accomplished for the General Directorate for Water Resources Management, Ministry of water resources, Baghdad, Iraq.

Soyuzgiprovodkhoz, 1982. General Scheme of Water Resources and Land Development in Iraq. Technical Study (unpublished), Ministry of Water

Resources, Iraq.

Wang, K.W., Chang, L.C., Chang, F.J., 2011. Multi-tier interactive genetic algorithms for the optimization of long-term reservoir operation. Adv. Water Resour. 34, 1343–1351. https://doi.org/10.1016/j.advwatres.2011.07.004

WCC, (Water Control Center), 2006. Technical Data for Dams, Reservoirs and Main Control Structures with Mean Monthly Flow Rates and Water Quality for Main Water Resources (1976-Sep 2005). General Directorate of Water Resources Management, Ministry of Water Resources, Baghdad, Iraq.

Weng, S.Q., Huang, G.H., Li, Y.P., 2010. An integrated scenario-based multi-criteria decision support system for water resources management and planning - A case study in the Haihe River Basin. Expert Syst. Appl. 37, 8242–8254. https://doi.org/10.1016/j.eswa.2010.05.061

Woodruff, M.J., Simpson, T.W., Reed, P.M., 2015. Multi-Objective Evolutionary Algorithms' Performance in a Support Role, in: ASME 2015 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference. p. 12.

Yang, C.T., 1996. Sediment transport: theory and practice. McGraw-Hill Inc, USA.

Yeh, W.W., 1985. Reservoir Management and Operations Models: A State-of-the-Art Review. Water Resour. Res. 21, 1797–1818.

8.3 Supplementary Data

1. OBJECTIVES FUNCTIONS DETAILS

1.1. Derbendikhan Dam

Reservoir water balance equation and other objectives functions are presented in Table A1. Parameters definitions are illustrated in Table A2.

Table A1. Formulae used for Derbendikhan dam operation management

Functions		***No.***
$S_{t+1}^{D} = S_t^D + I_t^D - R_t^D - E_t^D + P_t^D - SE_t^D + GR_t^D$	$\forall t = 1, \ldots T$	*(A1)*
$min\, f_{winterD} = \sum_{t=1}^{Tw} \left(\frac{S_{max}^D - S_t^D}{S_{max}^D} \right)^2 + C_P$	$\forall t = 1, \ldots T_w$	*(A2)*
$min\, f_{summerD} = \sum_{t=1}^{Ts} \left(\frac{S_t^D - S_{minp}^D}{S_{max}^D} \right)^2 + C_P$	$\forall t = 1, \ldots T_s$	*(A3)*
$min\, f_{powerD} = \sum_{t=1}^{T} \left(\frac{Pw_{max}^D - Pw_t^D}{Pw_{max}^D} \right)^2 + C_P$	$\forall t = 1, \ldots T$	*(A4)*
$min\, f_{releasesD} = \sum_{t=1}^{T} \left(\frac{R_t^D - R_{max}^D}{R_{max}^D} \right)^2 + C_P$	$\forall t = 1, \ldots T$	*(A5)*
$C_P = \sum_{i=1}^{PN} C_i^e$	$\forall i = 1, \ldots PN$	*(A6)*
$Pw_t^D = \eta_e^D . \gamma_w . Q_t^{tuD} . H_t^{nD}$	$\forall t = 1, \ldots T$	*(A7)*

Table A2. Formulae parameter definitions used in Table A1

Symbol	***Definition***	***Symbol***	***Definition***
S_t^D , S_{t+1}^D	Reservoir water storage at time *t* and *t*+1	Pw_{max}^D	Maximum hydropower generation
S_{max}^D	Maximum reservoir storage	C_P	Total penalty factor
S_{minp}^D	Minimum water storage for hydropower generation	C_i^e	Penalty factor for the i^{th} penalty function
I_t^D	Reservoir inflows at time *t*	e	Any positive integer
R_t^D	Reservoir releases at time *t*	PN	Number of penalty functions
R_{max}^D	Maximum reservoir releases	η_e^D	Hydropower plant efficiency
E_t^D	Reservoir Evaporation rate at time *t*	γ_w	Water specific weight
P_t^D	Direct rainfall on reservoir lake at time *t*	Q_t^{tuD}	Turbine discharge at time *t*
SE_t^D	Reservoir seepage losses at time *t*	H_t^{nD}	Reservoir water net head at time *t*
GR_t^D	Reservoir recharges from groundwater at time *t*	T, T_w, T_s	Total, winter, and summer time
Pw_t^D	Hydropower generation at time *t*		

1.2. Between Two Dams (Middle Part)

The management formulae in the middle mart of the river basin after Derbendikhan dam are presented in Table A3, while its definitions are shown in Table A4

Table A3. Middle part region objectives functions and water balance equations

Functions		***No.***
$min\ f_{Del-SW} = \sum_{t=1}^{T}\left(\frac{PD_t - Del_t^M}{PD_{max}}\right)^2 + C_P$	$\forall t = 1, \dots T$	*(A8)*
$min\ f_{Del-SW-GW} = \sum_{t=1}^{T}\left(\frac{PD_t - (Del_t^M + G_t^M)}{PD_{max}}\right)^2 + C_P$	$\forall t = 1, \dots T$	*(A9)*
$min\ f_{WL} = \sum_{t=1}^{T}\left(\frac{DP_t}{maxSM}\right)^2 + C_P$	$\forall t = 1, \dots T$	*(A10)*
$min\ f_{mining} = \sum_{t=1}^{T}\left(\frac{S_{st}}{S_{aq,t}}\right)^2 + C_P$	$\forall t = 1, \dots T$	*(A11)*
$G_t^M = \sum_{j=1}^{N_t} Q_{w,j}$	$\forall t = 1, \dots T$ $\forall j = 1, \dots N_t$	*(A12)*
$SM_{t+1} = SM_t + P_t + IR_t - ET_t - RO_t - DP_t$	$\forall t = 1, \dots T$	*(A13)*
$DP_t = SM_{t+1} - maxSM\ at\ SM_{t+1} > maxSM$	$\forall t = 1, \dots T$	*(A14)*
$S_{aq,t+1} = S_{aq,t} + TR_t - G_t$	$\forall t = 1, \dots T$	*(A15)*

Table A4. Formulae parameter definitions used in Table A3

Symbol	***Definition***	***Symbol***	***Definition***
PD_t	Projects water demands at time *t*	N_t	number of operated wells at time *t*
PD_{max}	Maximum projects water demands	SM_t, SM_{t+1}	Soil moisture content at time t and *t+1*
Del_t^M	Water delivery discharge at time *t*	$maxSM$	Maximum soil moisture content
G_t^M	Groundwater pumping discharge at time *t*	P_t	Rainfall rate at time *t*
DP_t	Water deep percolation at time *t*	IR_t	Irrigation water rate at time *t*
S_{st}	Groundwater storage at time *t*	ET_t	Evapotranspiration rate at time *t*
$S_{aq,t}$	aquifer storage at time *t*	RO_t	Runoff rate at time *t*
$Q_{w,j}$	pumping discharge for the j^{th} well	TR_t	Aquifer recharge at time *t*

1.3. Himren Dam:

The operation objectives and equations for Himren dam are presented in Table A5. Parameters definitions are illustrated in Table A6.

Table A5. Formulae used for Himren dam operation management (Al-Jawad et al., 2018b)

Functions		***No.***
$I_t^H = R_t^D + ROF_t^M + QST_t^M - DU_t^M - Del_t^M$	$\forall t = 1, \dots T$	*(A16)*
$S_{t+1}^H = S_t^H + I_t^H - R_t^H - E_t^H + P_t^H - SE_t^H + GR_t^H$	$\forall t = 1, \dots T$	*(A17)*
$min\, f_{demandsH} = \sum_{t=1}^{T} \left(\frac{R_t^H - DD_t^H}{DD_{max}^H} \right)^2 + C_P$	$\forall t = 1, \dots T$	*(A18)*
$min\, f_{winterH} = \sum_{t=1}^{Tw} \left(\frac{S_{max}^H - S_t^H}{S_{max}^H} \right)^2 + C_P$	$\forall t = 1, \dots T_w$	*(A19)*
$min\, f_{summerH} = \sum_{t=1}^{Ts} \left(\frac{S_t^H - S_{minp}^H}{S_{max}^H} \right)^2 + C_P$	$\forall t = 1, \dots T_s$	*(A20)*
$min\, f_{powerH} = \sum_{t=1}^{T} \left(\frac{Pw_{max}^H - Pw_t^H}{Pw_{max}^H} \right)^2 + C_P$	$\forall t = 1, \dots T$	*(A21)*
$min\, f_{riverB} = \sum_{t=1}^{T} \left(\frac{Q_t^r - Q_{t+1}^r}{Q_{max}^r} \right)^2 + C_P$	$\forall t = 1, \dots T$	*(A22)*
$min\, f_{TDS-DY} = \sum_{t=1}^{T} \left(\frac{TDS_t^{r2}}{TDS_t^{PS}} \right)^2 + C_P$	$\forall t = 1, \dots T$	*(A23)*
$min\, f_{DY-BCH} = \sum_{i=1}^{NS} \left(\frac{BL_{i,t=0} - BL_{i,t=T}}{\Delta BL_{max}} \right)^2 + C_P$	$\forall t = 1, \dots T$	*(A24)*
$min\, f_{TDS-TR} = \sum_{t=1}^{T} \left(\frac{TDS_t^R}{TDS_{max}} \right)^2 + C_P$	$\forall t = 1, \dots T$	*(A25)*
$TDS_t^{r2} = \frac{TDS_t^{r1} \times Q_t^{r1} + TDS_t^{PS} \times Q_t^{PS}}{Q_t^{r1} + Q_t^{PS}}$	$\forall t = 1, \dots T$	*(A26)*
$Pw_t^H = \eta_e^H . \gamma_w . Q_t^{tuH} . H_t^{nH}$	$\forall t = 1, \dots T$	*(A27)*

$$TDS_t^R = \frac{TDS_t^{r2} \times Q_t^{r2} + TDS_t^{r3} \times Q_t^{r3}}{Q_t^{r2} + Q_t^{r3}} \qquad \forall t = 1, \dots T \qquad (A28)$$

$$BL_{i,t+1} = BL_{i,t} - \frac{\Delta T_t}{0.5\gamma_m W_i} \frac{\left(BD_{i-1,t} - BD_{i+1,t}\right)}{\left(L_{u,t} + L_{d,t}\right)} \qquad \forall t = 1, \dots T \quad \forall i = 1, \dots NS \qquad (A29)$$

$$BD_{i,t} = \frac{7000\, HG_{i,t}^{3/2}}{\sqrt{d_s}} .\left(q_{i,t}^r - q_{i,t}^c\right) \qquad \forall t = 1, \dots T \quad \forall i = 1, \dots NS \qquad (A30)$$

$$q_{i,t}^c = \frac{1.944 \times 10^{-5}. d_s}{HG_{i,t}^{4/3}} \qquad \forall t = 1, \dots T \quad \forall i = 1, \dots NS \qquad (A31)$$

$$HG_{i,t} = \frac{n^2 (Q_t^r)^2}{A_{i,t}^2 HR_{i,t}^{4/3}} \qquad \forall t = 1, \dots T \quad \forall i = 1, \dots NS \qquad (A32)$$

[1] *Carriaga and Mays (1995), Nicklow and Mays (2001)*
[2] *Schoklisch formula (1934) (Yang 1996 in Ali 2016)*

Table A6. Parameter definitions for Himren dam system approach

Symbol	***Definition***	***Symbol***	***Definition***
I_t^H	Reservoir inflows at time *t*	TDS_t^{r3}	Total dissolved solids for Tigris river before the confluence at time t
DU_t^M	Domestic use water requirement at time *t*	TDS_t^{PS}	Total dissolved solids for WWTP at time t
ROF_t^M	Runoff rate at time *t*	TDS_t^R	Total dissolved solids for Tigris river after the confluence at time *t*
QST_t^M	Seasonal stream discharge at time *t*	TDS_{max}	Maximum total dissolved solids for Tigris river
R_t^H	Reservoir releases at time *t*	$BL_{i,t=0}$	Initial bed river level
E_t^H	Reservoir Evaporation rate at time *t*	$BL_{i,t=T}$	Final Bed river level
P_t^H	Direct rainfall on reservoir lake at time *t*	ΔBL_{max}	Maximum allowable river bed changes
SE_t^H	Reservoir seepage losses at time *t*	$BL_{i,t}$, $BL_{i,t+1}$	Bed river level at section i at time *t* and *t*+1, respectively
GR_t^H	Reservoir recharges from groundwater at time *t*	$BD_{i,t}$, $BD_{i+1,t}$, $BD_{i-1,t}$	Bed river sediment discharge at time *t* for section *i*, *i*+1 and *i*-1, respectively

DD_t^H	Downstream water demands at time *t*	ΔT_t	Time interval
DD_{max}^H	Maximum downstream water demands	γ_m	Density of water-solid mixture
S_t^H	Reservoir water storage at time *t*	W_i	River bed width at section *i*
S_{max}^H	Maximum reservoir water storage	$L_{u,t}$, $L_{d,t}$	Length of river section between the current section and the upstream and downstream sections, respectively
S_{minp}^H	Minimum water storage for hydropower generation	$q_{i,t}^r$	River discharge per unit width
Pw_t^H	Power generation at time *t*	$q_{i,t}^c$	Critical discharge per unit width
Pw_{max}^H	Maximum hydropower generation	$HG_{i,t}$	River hydraulic gradient at section *i* and time *t*
Q_t^r, Q_{t+1}^r	Diyala river discharge at time *t* and *t*+1, respectively	d_s	Diameter size of bed river
Q_{max}^r	Maximum Diyala river discharge	n	Manning coefficient
Q_t^{r1}, Q_t^{r2}	Diyala river discharge before and after the WWTP at time *t*, respectively	$A_{i,t}$	Wet cross-section area of the river at section *i* and time *t*
Q_t^{r3}	Tigris river discharge at time *t*	$HR_{i,t}$	Wet hydraulic radius for the river at section *i* and time *t*
Q_t^{PS}	Wastewater treatment plant discharge at time *t*	*T*, *Tw*, *Ts*	Total, winter and summer time
TDS_t^{r1}	Total dissolved solids for Diyala river before the WWTP at time *t*	*NS*	Number of river cross sections
TDS_t^{r2}	Total dissolved solids for Diyala river after the WWTP at time *t*		

Additionally, two objectives functions for Derbendikhan and Himren dams were adopted to minimize the physical (C_{D-H-Ph}) violations, which can be expressed as follows, respectively:

$$min\, f_{phy-M} = C_{D-H-Ph} \tag{A33}$$

While the final objective function was to minimize the total system violation (C_p):

$$min\, f_{MD} = C_p \tag{A34}$$

Additional parameters used in the optimization model are presented in Table A7 below.

Table A7. Optimization model parameters for the Diyala River basin system (SGI et al., 2014)

Parameter	*Value*	*Unit*	*Parameter*	*Value*	*Unit*
η_e^D	78	%	Q_t^{PS}	15[1]	m^3/s
η_e^H	88	%	W_i *(mean)*	80.0	m
γ_w	≈1000	KN/m^3	d_s	20.0 - 0.177	mm
γ_m	1486[2]	kg/m^3	*NS*	41	-
TDS_t^{r1} *at* Q_{min}^r	2220[1]	mg/l	T_W	October – March	Month
TDS_t^{PS}	5000[1]	mg/l	T_S	April - September	Month
TDS^U	500[3]	mg/l	ΔT_t	1	Month

[1] Kubba et al. (2014), [2] Nicklow and Mays (2001), [3] Saleh (2013)

2. AREA-STORAGE AND HEAD-STORAGE RELATIONSHIPS OF RESERVOIRS

Polynomial equations (Equation A35 and A36) for the area-storage and head-storage relation were constructed depending on the design data available in the NCWRM. For Himren dam, the evaporation losses from the reservoir surface area at time *t* (Ar_t^H) in meter square, which can be expressed as follows, where the storage (S_t^H) in million cubic meters (MCM):

$$Ar_t^H = 2.3 \times 10^7 + 156915.48 \times S_t^H - 16.369 \times (S_t^H)^2 + 0.0012 \times (S_t^H)^3 \tag{A35}$$

Equation A36 is used to calculate the water head in the reservoir for hydropower generation, where (H_t^H) is Himren water level in meters (m) and (S_t^H) is reservoir storage in MCM:

$$H_t^H = 86.51 + 0.031 \times S_t^H - 4.37{\times}10^{-5} \times (S_t^H)^2 + 4.33{\times}10^{-8} \times (S_t^H)^3 - 2.55{\times}10^{-11} \times (S_t^H)^4 + 8.63{\times}10^{-15} \times (S_t^H)^5 - 1.54{\times}10^{-18} \times (S_t^H)^6 + 1.13{\times}10^{-22} \times (S_t^H)^7 \qquad \text{(A36)}$$

where

$S_t^H \in [S_{min}^H, S_{max}^H]$ for Equations A35 and A36

Consistency, Derbendikhan dam formulae are as follows:

$$Ar_t^D = 5.26 \times 10^6 + 34458.8 \times S_t^D - 9.065 \times (S_t^D)^2 + 0.00903 \times (S_t^D)^3 - 1.47061 \times 10^{-6} \times (S_t^D)^4 \qquad \text{(A37)}$$

$$H_t^D = \frac{492.91869}{\left(1 + e^{(-0.00102 \times (S_t^D + 1597.48638)}\right)} \qquad \text{(A38)}$$

where

$S_t^D \in [S_{min}^D, S_{max}^D]$ for Equations A37 and A38

2. OPTIMUM RIVER BASIN MANAGEMENT RESULTS

Detail summary of the adopted river basin optimum management solutions for all alternatives are presented in Table A8.

Table A8. Summary of optimum solutions for the Diyala river basin system for the adopted alternatives. The scenarios refer to the river basin inflows alternatives, while case 1 and case 2 refers to the surface water and surface-groundwater models, respectively.

		Scenario-1										Scenario-2									
		Case 1					Case 2					Case 1					Case 2				
		Min.	Max.	Av.	Med.	Std.	Min.	Max.	Av.	Med.	Std.	Min.	Max.	Av.	Med.	Std.	Min.	Max.	Av.	Med.	Std.
Area	Upper Dam	16.92	121.34	59.75	52.04	29.22	15.72	123.18	57.20	47.87	29.09	17.04	118.58	54.61	43.71	28.63	16.92	121.94	58.90	52.37	30.18
Head		434.07	485.81	467.62	469.41	13.77	432.01	486.01	466.51	467.12	13.54	434.27	485.51	464.88	464.50	14.40	434.06	485.88	466.86	469.58	14.13
Power		20.93	249.00	68.60	45.23	52.30	22.36	249.00	68.06	44.80	54.10	21.52	247.44	54.32	41.00	42.40	21.72	249.00	55.45	42.07	40.98
Storage		361.12	2544.07	1420.85	1337.63	605.98	322.74	2571.65	1367.51	1241.77	600.10	365.01	2502.67	1308.05	1141.41	607.36	361.02	2553.12	1397.06	1345.18	625.61
Releases		130.31	877.40	259.72	164.74	185.63	129.63	878.60	260.07	173.28	189.80	129.68	821.41	212.64	148.58	148.36	129.67	872.90	211.95	156.29	139.61
FQ-DES	Middle part	1.21	74.27	47.22	52.28	25.34	1.21	74.27	47.22	52.28	25.34	1.21	74.27	47.22	52.28	25.34	1.21	74.27	47.22	52.28	25.34
Q-SUR		0.00	74.27	27.82	24.26	19.27	0.00	74.17	26.36	21.80	21.53	0.26	73.56	23.28	20.00	17.92	0.00	74.23	26.32	20.97	23.53
Q-GW		-	-	-	-	-	0.02	71.75	17.68	7.76	20.72	-	-	-	-	-	0.02	74.27	18.29	4.80	22.79
N-wells		-	-	-	-	-	1.00	3074.00	757.67	332.50	887.91	-	-	-	-	-	1.00	3182.00	783.54	205.50	976.48
TWD		0.00	74.27	27.82	24.26	19.27	0.03	74.27	44.05	45.64	26.11	0.26	73.56	23.28	20.00	17.92	0.02	74.27	44.61	45.73	26.10
ST-GW		-	-	-	-	-	7695.25	9332.04	8779.67	8867.25	367.03	-	-	-	-	-	7673.74	9254.06	8563.98	8486.75	412.46
Inflows	Middle dam	38.85	872.48	217.88	134.89	182.68	37.27	873.49	219.69	141.17	192.42	37.63	763.47	175.34	118.15	149.03	30.28	886.28	171.61	125.18	144.94
Area		40.64	319.69	185.98	184.14	64.08	39.17	315.87	192.83	199.58	69.53	38.93	287.07	160.64	150.34	55.65	50.17	302.07	175.95	171.45	54.84
Head		89.48	105.24	99.10	99.22	3.02	89.26	105.02	99.34	99.89	3.39	89.23	103.55	97.96	97.71	2.70	90.75	104.27	98.71	98.66	2.55
Power		7.60	48.17	15.74	11.47	9.74	7.51	47.96	15.70	11.19	9.91	7.50	33.60	11.80	10.54	4.07	7.51	47.73	11.58	10.04	4.74
Storage		113.76	2377.74	1195.35	1154.14	520.65	104.17	2339.48	1255.96	1280.23	564.95	102.59	2058.08	987.03	888.49	440.76	176.35	2203.06	1107.42	1052.71	439.87
Releases		98.80	508.13	183.30	138.14	101.17	98.86	509.39	183.85	133.10	109.35	99.75	441.43	145.95	131.66	45.37	98.57	507.12	139.21	121.10	51.44
Q-river	Lower part	30.86	464.75	70.66	42.14	69.30	30.86	478.41	77.02	41.01	83.13	30.91	304.63	51.25	39.16	34.25	30.85	250.49	50.25	37.64	34.20
FQ-DES		30.46	313.34	191.00	200.13	87.45	30.46	313.34	191.00	200.13	87.45	30.86	464.75	70.66	42.14	69.30	30.46	313.34	191.00	200.13	87.45
Q-SUR		30.46	313.34	112.64	96.38	63.28	30.46	313.34	106.83	86.17	61.32	30.46	268.43	94.70	90.18	39.45	30.46	297.82	88.96	80.28	40.43
TDS-B		595.93	2220.00	1670.13	1769.70	518.35	593.19	2220.00	1679.59	1805.49	546.03	646.35	2220.00	1807.81	1906.81	458.21	695.51	2220.00	1821.41	1975.78	460.27
TDS-A		733.63	3585.25	2569.44	2736.61	801.79	727.16	3590.29	2572.61	2780.42	851.02	850.66	3588.24	2773.77	2900.55	691.18	961.20	3589.53	2799.88	2979.19	699.39
TDS-T		530.88	613.67	573.54	574.77	19.94	530.83	613.39	573.30	575.42	20.07	531.24	613.45	573.65	574.76	19.81	527.96	613.33	573.36	574.63	19.79
|Bed-C|		0.00	1.09	0.30	0.22	0.28	0.00	1.20	0.33	0.24	0.31	0.00	0.79	0.22	0.16	0.20	0.00	0.77	0.22	0.16	0.20

Upper dam = Derbendikhan dam; Middle part = between two dams; Middle dam = Himren dam; Lower part = downstream river after the Himren dam; FQ-DES: Design water delivery (m^3/month $\times 10^6$); Q-SUR: surface water discharges to the farms (m^3/month $\times 10^6$); N-wells: No. of wells; Q-GW: groundwater discharge (m^3/month$\times 10^6$); ST-GW: groundwater storage (m^3/month $\times 10^6$); TWD: Total water delivery to the farms (m^3/month $\times 10^6$); Q-river: river discharge (m^3/month $\times 10^6$); TDS-B: TDS concentration before WWTP(mg/l); TDS-A: TDS concentration after WWTP(mg/l); TDS-T: TDS concentration in Tigris river (mg/l); |Bed-C|: absolute river bed changes (m). The reservoir releases, storage and inflows are in m^3/month $\times 10^6$ units. The reservoir surface areas are in km^2. The hydropower generation are in Mw. The reservoir water head is in m.a.s.l.

8.4 Further Discussion

The results also demonstrate a minor impact on river morphology achieved in all considered alternatives. The absolute riverbed changes (average and median) did not exceed 0.5 m, while the maximums were less than or equal 1.2 m in all cases. River morphology is directly proportion to river velocity, which was related to reservoir releases in a managed river basin. Since future water scarcity is mapped due to upstream development projects, reservoir releases are reduced to maintain other multidisciplinary sectors demands, which mitigate sediment degradation and/or aggregation process in the river. Here, due to lack in river morphology detail database for the river lower part zone (e.g. recent river cross sections survey, bed grain size distribution analysis, etc.), a simple sediment-load transport mathematical model was adopted, since only grain size and river bed width are required. However, this formula shows promising results at Tigris River (Ali et al., 2012), as it has consistent geological formation (flood plain deposits; Gravel, sand, silt, and clay) (GEOSURV, 1993). The key point is to observe the effectiveness of river morphology management model as an objective on reservoir management model, and its degree of conflicts with other major objectives like hydropower generation, agriculture projects' demands, flood risk and river quality management.

The pollutant source, represented by Al-Rustumiya wastewater treatment plant, has severe impact on Diyala River water quality. The average and median values of river TDS concentration exceeded 2500 mg/l for all alternatives. Since the mixed pollutant concentration depends on the quantity and quality of the mixed sources, the government should consider future policy to enhance the plant's remediation performance to mitigate its impact on river environment. Although the average and median water quality in Tigris River did not exceed the preferable value (600 mg/l of TDS) in all cases, quality deterioration may occur in downstream region in case of water scarcity in Tigris River, accordingly Himren releases should be reduced.

According to the final findings, it can be concluded that the proposed approach can be used to diagnose the sustainability of the embedded objectives and resources of the regional-scale system under consideration, which fulfils the research's aim.

8.5 Conclusions

In this chapter, a comprehensive approach was proposed, which combines common social-environmental-economic objectives and available water resources at a river basin level. The approach is implemented for the entire Diyala River basin using ε-DSEA optimization algorithm to improve its environment its potential economic revenues in different sectors. Two scenarios were implemented to assess the impacts of future climate changes and upstream development projects in Iran on the River basin environment. The comprehensive approach provides decision variables for sustainable management for the entire river basin resources for considerations including power generation, storages, and river discharges. Execution time (by the computer) is not a limitation for the model, and it was not greatly affected by complexity. Accordingly, the implementation of a comprehensive approach is evident in water resources management strategy. Combining groundwater exploitation with the OP-IWRM approach succeeds to suggest that improvements water delivery fulfilment might be increased from 50% to more than 85% in the middle part of the river basin with minor impact on groundwater storage. Furthermore, the OP-IWRM succeed to address water exploitation uncertainty in the middle part of the river basin and presents water consumption barriers for the decision makers consider for future management policy.

This approach demonstrates the significant impact of transboundary water development plans on the river basin system. The gross Derbendikhan dam releases and power generation are reduced from about 102.8 to 84.0×10^9 m^3 and from about 27.0 to 21.8 GW, respectively. For Himren dam system, the inflows, releases and power generating are also depleted from about 86.5 to 68.0×10^9 m^3, 73.0 to 56.0×10^9 m^3, and 6.2 to 4.6 GW, respectively. While the river discharge in the lower part of the river basin was reduced from 30.0 to 20.0×10^9 m^3, hence the correlated water delivery declined from about 43.0 to 36.0×10^9 m^3. The deficit in delivered water in this part is about more than 50% for all adopted alternatives.

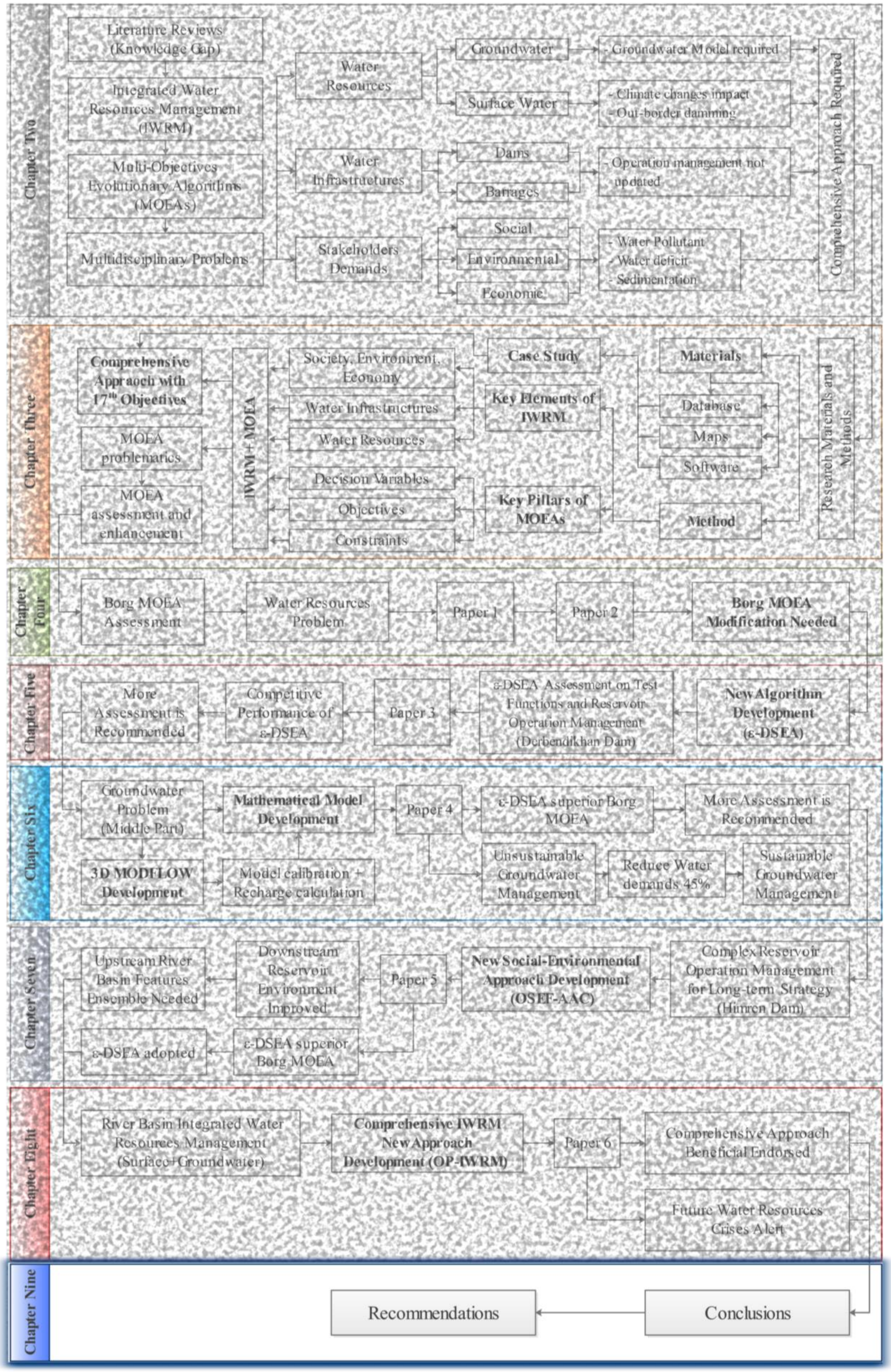
The value of this OP-IWRM approach is evident; it produced optimum sustainable management strategies using the common Social, Environmental, and Economic objectives; and the existing surface and groundwater resources for a river basin system under different scenarios. It is possible to add more objectives for additional sectors like: governmental legislation, human resources development, economic revenues. Hence, the proposed methodology reactivates the implementation of the IWRM principles.

8.6 Recommendations

Exploitation of the middle basin has significant impact on the water resources of the lower basin, hence a policy should be considered to reduce water requirements to mitigate the impact on the lower part of the basin. Also, similar policy may be considered for the lower basin farming practice.

- Replace the traditional irrigation method with new recent techniques such as drip irrigation system, if applicable, to reduce allocated and infiltrated water losses.
- Replace summer crops with higher water demands with those with lower water demands to reduce water demands in hot season.
- Reduce crop pattern's summer plan to reduce water demands in the hot season.
- Rehabilitate water conveyance infrastructure to reduce water losses over water delivery process.

New government policy should include restrictions in water exploitation in the middle part of the basin for farms and remove any unauthorized outlets on the river and Himren reservoir lake. The lower basin's water demands could be improved by using the existing saline groundwater after specific treatment or mixing with fresh surface water. Regarding development plans in upstream river basin, the government should consider a policy to set water sharing agreements to mitigate water monopolizing, which may cause severe drought within Diyala river basin and water resources inside Iraq. The current research results could be adopted in the negotiation process for this agreement.



Chapter Two
Literature Reviews (Knowledge Gap)
Integrated Water Resources Management (IWRM)
Multi-Objectives Evolutionary Algorithms (MOEAs)
Multidisciplinary Problems
Water Resources
Water Infrastructures
Stakeholders Demands
Groundwater
Surface Water
Dams
Barrages
Social
Environmental
Economic
- Groundwater Model required
- Climate changes impact
- Out-border damming
- Operation management not updated
- Water Pollutant
- Water deficit
- Sedimentation
Comprehensive Approach Required
Chapter Three
Comprehensive Approach with 17th Objectives
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MOEA assessment and enhancement
IWRM + MOEA
Society, Environment, Economy
Water Infrastructures
Water Resources
Decision Variables
Objectives
Constraints
Case Study
Key Elements of IWRM
Key Pillars of MOEAs
Materials
Database
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Method
Research Materials and Methods
Chapter Four
Borg MOEA Assessment
Water Resources Problem
Paper 1
Paper 2
Borg MOEA Modification Needed
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More Assessment is Recommended
Competitive Performance of ε-DSEA
Paper 3
ε-DSEA Assessment on Test Functions and Reservoir Operation Management (Derbendikhan Dam)
New Algorithm Development (ε-DSEA)
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Groundwater Problem (Middle Part)
Mathematical Model Development
Paper 4
ε-DSEA superior Borg MOEA
More Assessment is Recommended
3D MODFLOW Development
Model calibration + Recharge calculation
Unsustainable Groundwater Management
Reduce Water demands 45%
Sustainable Groundwater Management
Chapter Seven
Upstream River Basin Features Ensemble Needed
Downstream Reservoir Environment Improved
Paper 5
New Social-Environmental Approach Development (OSEF-AAC)
Complex Reservoir Operation Management for Long-term Strategy (Himren Dam)
ε-DSEA adopted
ε-DSEA superior Borg MOEA
Chapter Eight
River Basin Integrated Water Resources Management (Surface+Groundwater)
Comprehensive IWRM New Approach Development (OP-IWRM)
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Comprehensive Approach Beneficial Endorsed
Future Water Resources Crises Alert
Chapter Nine
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Conclusions

CHAPTER NINE

CONCLUSIONS AND RECOMMENDATIONS

9.1 Restatement of Research Aim and Objectives

The aim of the research was to develop a holistic, or comprehensive water resources management approach for a river system. Optimization techniques and IWRM principles are employed to generate long-term flow regime strategy under sustainable development framework. Hence, the approach integrates all the common sectors (e.g., society, environment, and economy) with the available water resources (e.g., surface water, groundwater and reused water) over water control systems (e.g., dams, barrages, pipes, and pumps). The following steps were achieved to address the research's aim in a concise form:

- a review of optimization techniques and their potential drawbacks;
- performance assessment is achieved for the nominated algorithm under different problem environments, including Derbendikhan dam;
- a new methodology of optimization algorithm is developed to tackle previous algorithms' drawbacks;
- Diyala River basin is selected as a real-world case study, having multidisciplinary problems to develop and evaluate the approach;
- groundwater flow and management models are developed for the middle region in the basin to evaluate sustainable use of aquifer storage;

- optimum flow-regime management strategy for Himren dam system is achieved to consider social and environmental objectives, under different inflows scenarios; and
- finally, developed the comprehensive approach of Diyala River basin using IWRM principles coupled with optimization algorithm to improve river basin environment and economic revenues under different scenarios.

9.2 Conclusions and Recommendations

1- From Chapter four, it was concluded that one of the Borg MOEA key element techniques show misleading behaviour, based on algorithm’s assessment using real-word reservoir operation problem, compare with GA. Thus, further assessment and insight investigation are recommended to enhance and /or develop an advance MOEA’s methodology to address any potential drawbacks.

2- From Chapter five, previous recommendation from Chapter four refer to enhancement and development is needed for MOEAs. Thus, it was concluded that the methodology proposed in new algorithm (ε-DSEA) is highly competitive. Good results were achieved, based on the computational efficiency and quality of the solutions found, based on intensive assessed in comparison with the state-of-the-art Borg MOEA using a set of commonly implemented benchmark test function, and a real-word reservoir management problem. It is recommended to involve other more complex real-world problems that may be computationally expensive for future works.

3- From Chapter six, based on previous recommendation from Chapter five, it was concluded that, the ε-DSEA provided more robust results when compared to the Borg MOEA for almost all caese. The ε-DSEA approaches' main advantage over the Borg MOEA is reliability, it repeatedly produced optimum solutions over computational budget replication. This was based on solving groundwater management problem. Although both algorithms results demonstrate unsustainability in groundwater resource management for both irrigation systems, the computational results illustrate results from the ε-DSEA were more robust. The storage depletion was 25% for ten years' water exploitation, which increase to about 60% for twenty-five years. The aquifer storage was completely exhausted after forty years in both alternatives due to low aquifer recharge, which caused by low rainfall and high evapotranspiration rates (semi-arid zone). The probability of sustainable groundwater resource management was modelled for the next half-century by reducing water delivery demands. The results show possible sustainable storage budget using open furrows system can be achieved for the next twenty-five years, and thirty-three years for drip system with 45% demand's yield for both. Hence, decision makers (the Iraqi government) should consider future policy to reduce water demands by either changing crops types, or reducing farms areas. Also, the use of drip system for water allocation should be considered in the policy since it has less impacts on groundwater yields. However, crop yield and productivity should consider over the alternatives. Conjunctive use with surface water and water harvesting may consider also to mitigate groundwater depletion and maintain its sustainability.

4- From Chapter seven, as recommended in Chapter six, it was concluded that The algorithms computational analysis results show the ε-DSEA outperformed the Borg MOEA in almost all cases, hence the ε-DSEA results were adopted. Moreover, the AAC approach succeed to overcome the complexity of the problem, boosting algorithm convergence toward possible optimum solutions and avoiding algorithm stagnation in local optima. This was based on solving reservoir management problem, as a case study. The results show improvement in reservoir system environments in all sectors considered. The adopted model for the current case study considers only the common management objectives based on the available database. However, other issues like water influent and affluent of reservoir lake, ecosystem and navigation objectives, etc. could be implemented for future works. Finally, the OSEF-AAC approach can be adopted to solve river basin management problems to generate optimum socio-environmental flows regime. These provide decision makers a trade-off for developing a robust management strategy towards achieving better economic revenues for the water-energy-food nexus of a river basin.

In order to improve the lower Diyala river basin environment, the following recommended policy changes should be considered for different sectors:

- *Environmental Sectors:* Monitoring and mitigation strategies must be developed to solve the high pollutant concentrations from Al-Rustumiya wastewater treatment plan outflows, which increases pollutant levels in Diyala and Tigris Rivers waters and the remediation costs of downstream water supply projects. Moreover, detail hydrological studies and field surveys are needed to explore and control sediment transport in the river.

- *Social Sector:* Adopt developed irrigation techniques (e.g. sprinkles, drips) to reduce losses due to crop water allocations, evaporation and infiltration. Also, change summer crop types or reduce crop patterns to reduce water exploitation in the summer for this part of the river basin. Further, rehabilitate water conveyance infrastructure (e.g. main channels, outlets, gates, etc.) and restrict water exploitation in the middle part of the river basin (upstream region of Himren dam) to mitigate water delivery losses and to improve water resource sustainability for the lower part of the basin. Other actions are to remove any unauthorized water exploitation pumps and develop a comprehensive seepage model from the Himren reservoir to improve accuracy of the actual water budget.

  In additional to above, a policy for adopting advanced daily monitoring system for data collections and flood alarm system should be consider to improve water resources management and forecasts in the basin.

  However, the middle part of the basin has significant effect on the considered reservoir system, which includes a multipurpose dam and potential groundwater storage. These could be integrated with the river basin model management by using integrated water resources management principles to improve understanding of the system. Finally, an International agreement with neighbour's country should be sought for the Diyala River and its tributaries to maintain the long-term sustainability of river water resources.

5- From Chapter eight, as previous recommendations referred, it is concluded that the comprehensive approach provides decision variables for sustainable management for the entire river basin resources for the considered alternatives including power generation, storages, and river discharges. Combining groundwater exploitation with the OP-IWRM approach succeeds to suggest that improvements water delivery fulfilment might increase from 50% to more than 85% in the middle part of the river basin with minor impact on groundwater storage. Furthermore, the OP-IWRM succeed to address water exploitation uncertainty in the middle part of the river basin and presents water consumption barriers for the decision makers to be considered for future management policy. The approach demonstrates the significant impact of transboundary water development plans on the river basin system. The gross Derbendikhan dam releases and power generation were reduced from about 102.8 to 84.0×10^9 m^3 and from about 27.0 to 21.8 GW, respectively. For Himren dam system, the inflows, releases and power generating are also depleted from about 86.5 to 68.0×10^9 m^3, 73.0 to 56.0×10^9 m^3, and 6.2 to 4.6 GW, respectively. While the river discharge in the lower part of the river basin was extremely affected from 30.0 to 20.0×10^9 m^3, hence the correlated water delivery was drop from about 43.0 to 36.0×10^9 m^3. The deficit in delivered water in this part is about more than 50% for all adopted alternatives.

The value of this OP-IWRM approach is evident, it produced optimum sustainable management strategies using; the common Social, Environmental, and Economic objectives; and the existing surface and groundwater resources for a river basin system under different scenarios. It is possible to add more objectives for additional sectors like; governmental legislation; human resources development; economic revenues. Hence, the proposed methodology reactivates the implementation of the IWRM principles.

However, the middle basin exploitation has significant impact on the water resources of the lower basin, hence it is recommended that a policy should be considered (as previously stated) to reduce water requirements to mitigate the impact on the lower part of the basin. Also, similar policy may be considered for the lower basin farming practice. In addition, increase stakeholders' knowledge (the farmers) of implementing and using recent irrigation techniques, such as sprinkler and drip system, is also recommended to optimize agriculture revenues.

Although the operational water level restriction of the Right Bank sliding hazard of Derbendikhan dam did not include in the model (as an objective or as a constraint), the mean and median head maintained above 455 m.a.s.l over all cases, however it is recommended to consider this issue for future research.

Sedimentation in Derbendikhan and Hirmen dams' reservoirs should also investigate and monitor in detail, since it has negative impact on reservoir storage capacity. Hence, it is recommended to consider these issues for future operation strategies.

New government policy may include restriction in water exploitation in the middle part of the basin for farms and remove any unauthorized outlets on the river and Himren reservoir lake. The lower basin water demands could be improved by using the existing saline groundwater after specific treatment or mixing with fresh surface water. Regarding development plans in out-boarder upstream region, the government should consider a policy to set water sharing agreements to restrict water monopolizing, which may cause severe drought of Diyala river basin water resources inside Iraq. The current research results could be adopted in the negotiation process for this agreement.

APPENDIX - 1

REFERENCES

REFERENCES

Abbas, N., Wasimi, S.A., Al-Ansari, N., 2016. Impacts of Climate Change on Water Resources in Diyala River Basin, Iraq. J. Civ. Eng. Archit. 10, 1059–1074.

Abdulrahman, S.A., 2017. Failure to securitise environmental problems in Iraq: the case of the Alwand and Sirwan Rivers. Int. J. Environ. Stud. 74, 540–557. https://doi.org/10.1080/00207233.2017.1330493

Abraham, A., Jain, L., Robert, G. (Eds), 2005. Evolutionary Multiobjective Optimization, Evolutionary Multiobjective Optimization. https://doi.org/10.1007/1-84628-137-7

Acreman, M., Arthington, A.H., Colloff, M.J., Couch, C., Crossman, N.D., Dyer, F., Overton, I., Pollino, C.A., Stewardson, M.J., Young, W., 2014. Environmental flows for natural, hybrid, and novel riverine ecosystems in a changing world. Front. Ecol. Environ. 12, 466–473. https://doi.org/10.1890/130134

Adamo, N., Al-ansari, N., Sissakian, V.K., Knutsson, S., 2018. Climate Change : Consequences on Iraq ' s Environment. J. Earth Sci. Geotech. Eng. 8, 43–58.

Aenab, A.M., Singh, S.K., 2014. Critical Assessment of River Water Quality and Wastewater Treatment Plant (WWTP). IOSR J. Environ. Sci. Toxicol. Food Technol. 8, 44–48.

Ahmad, A., El-Shafie, A., Razali, S.F.M., Mohamad, Z.S., 2014. Reservoir Optimization in Water Resources: a Review. Water Resour. Manag. 28, 3391–3405. https://doi.org/10.1007/s11269-014-0700-5

Ahmad, A.M., Abdul Razak, M.I., Dawood, K.S., 2005. Hydrogeological study of upper Diyala River Basin. Technical Report (in Arabic). The General Directorate for Water Resources Management, Ministry of Water Resources, Government of Iraq.

Ahmadianfar, I., Adib, A., Taghian, M., Faculty, E., Resources, N., 2015. a Multi-Objective Evolutionary Algorithm Using Decomposition (Moea/D) and Its Application in Multipurpose Multi-Reservoir Operations. Int. J. Optim. Civ. Eng.

5, 167–187.

Ahmed, A.M., Abdul Razzak, M.I., Daud, K.S., 2005. Hydrogiological Study of the Upper Reach of Diyala River. Report in Arabic (unpublished), Ministry of Water Resources, Baghdad, Iraq.

Al-Ansari, N., Ali, A.A., Knutsson, S., 2014. Present Conditions and Future Challenges of Water Resources Problems in Iraq. J. Water Resour. Prot. 6, 1066–1098. https://doi.org/10.4236/jwarp.2014.612102

Al-Ansari, N.A., 2013. Management of Water Resources in Iraq: Perspectives and Prognoses. Engineering 05, 667–684. https://doi.org/10.4236/eng.2013.58080

Al-Ansari, N.A., Al-Jabbari, M.H., Madhat, A., 1983. Sediment Discharge in Hemrin Dam Reservoir, in: Proceeding of the Second International Symposium On River Sedimentation. China.

Al-Delewy, A.H., 1995. Optimization of the Operation of a Complex Waters Resources System with Application to the Diyala River system. PhD Thesis. Building and Construction Engineering Department,University of Technology, Baghdad, Iraq.

Al-Faraj, F.A.M., Scholz, M., 2015. Impact of upstream anthropogenic river regulation on downstream water availability in transboundary river watersheds. Int. J. Water Resour. Dev. 31, 28–49. https://doi.org/10.1080/07900627.2014.924395

Al-Faraj, F.A.M., Scholz, M., 2014. Assessment of temporal hydrologic anomalies coupled with drought impact for a transboundary river flow regime: The Diyala watershed case study. J. Hydrol. 517, 64–73. https://doi.org/10.1016/j.jhydrol.2014.05.021

Al-Jawad, J.Y., Al-Jawad, S.B., Tanyimboh, T.T., Kalin, R.M., 2018a. Comprehensive Evolutionary Algorithms Performance Assessment Using a Multi-Objectives Water Resources Management Problem. Water Resour. Manag. In review.

Al-Jawad, J.Y., Alsaffar, H.M., Bertram, D., Kalin, R.M., 2018b. Optimum Socio-

Environmental Flows Approach for Reservoir Operation Strategy Using Many-Objectives Evolutionary Optimization Algorithm. Sci. Total Environ. In review.

Al-Jawad, J.Y., Tanyimboh, T.T., 2018. Epsilon-Dominance-Driven Self-Adaptive Evolutionary Algorithm For Many-Objective Optimization. Swarm Evol. Comput. In review.

Al-Jawad, J.Y., Tanyimboh, T.T., 2017. Reservoir operation using a robust evolutionary optimization algorithm. J. Environ. Manage. 197, 275–286. https://doi.org/10.1016/j.jenvman.2017.03.081

Al-Jibory, T., 1991. Geomorphology and Hydrology of Diyala River Basin. PhD Thesis, Department of Earth Sciences, University of Baghdad, Iraq.

Al-khaldy, M.A.T., Al-askari, A.J.H., 2015. Analysis of Physical characteristics of Fluvial Deposits in the Diyala Middle Basin (in Arabic). J. Res. Diyala Humanit. 1–24.

Al-Sunawai, G., 1985. Hydrochemistry of Diyala River. Msc Thesis (in Arabic), Department of earth Sciences, Baghdad University, Iraq.

Al-Tamimi, O.S., 2007. Water resources evaluation in Diyala River basin – Middle part. PhD Thesis (in Arabic). College of Science,University of Baghdad, Iraq.

Aleti, A., 2012. An Adaptive Approach to Controlling Parameters of Evolutionary Algorithms. PhD. Thesis, Swinburne University of Technology, Australia.

Ali, A.A., 2016. Three Dimensional Hydro-Morphological Modeling of Tigris River. PhD. Thesis, Luleå University of Technology, Sweden.

Ali, A.A., Al-Ansari, N.A., Knutsson, S., 2012. Morphology of tigris river within baghdad city. Hydrol. Earth Syst. Sci. 16, 3783–3790. https://doi.org/10.5194/hess-16-3783-2012

Allen, C., Metternicht, G., Wiedmann, T., 2016. National pathways to the Sustainable Development Goals (SDGs): A comparative review of scenario modelling tools. Environ. Sci. Policy 66, 199–207. https://doi.org/10.1016/j.envsci.2016.09.008

Allen, R.G., Pereira, L.S., Raes, D., Smith, M., 1998. Crop evapotranspiration - Guidelines for computing crop water requirements. FAO Irrigation and drainage paper 56.

Alsaffar, H.M., 2017a. Personal communication. , 9 October.

Alsaffar, H.M., 2017b. Personal communication. , 15 July.

Amirkhani, M., Bozorg-Haddad, O., Fallah-Mehdipour, E., Loáiciga, H.A., 2016. Multiobjective Reservoir Operation for Water Quality Optimization. J. Irrig. Drain. Eng. 142. https://doi.org/10.1061/(ASCE)IR.1943-4774

Anthony Cox, L., 2008. What's wrong with risk matrices? Risk Anal. 28, 497–512. https://doi.org/10.1111/j.1539-6924.2008.01030.x

Assad, M.N., 1978. Sediements and Sediment Discharge in the River Diyala. Master Thesis (Unpublished), Baghdad University, Baghdad, Iraq.

AWRA, (American Water Resources Association), 2011. Integrated Water Resources Management in the US [WWW Document]. URL https://www.awra.org/policy/policy-statements-IWRM.html (accessed 7.30.18).

Azizipour, M., Ghalenoei, V., Afshar, M.H., Solis, S.S., 2016. Optimal Operation of Hydropower Reservoir Systems Using Weed Optimization Algorithm. Water Resour. Manag. 30, 3995–4009. https://doi.org/10.1007/s11269-016-1407-6

Back, T., Fogel, D.B., Michalewicz, Z. (Eds.), 2000. Handbook of Evolutionary Computation. IOP Publishing Ltd., Bristol, UK, UK.

Barbour, E.J., Holz, L., Kuczera, G., Pollino, C.A., Jakeman, A.J., Loucks, D.P., 2016. Optimisation as a process for understanding and managing river ecosystems. Environ. Model. Softw. 83, 167–178. https://doi.org/10.1016/j.envsoft.2016.04.029

Barlow, E., Tanyimboh, T.T., 2014. Multiobjective Memetic Algorithm Applied to the Optimisation of Water Distribution Systems. Water Resour. Manag. 28, 2229–2242. https://doi.org/10.1007/s11269-014-0608-0

Bechikh, S., Elarbi, M., Ben Said, L., 2017. Many-objective Optimization Using Evolutionary Algorithms: A Survey, in: Bechikh, S., Datta, R., Gupta, A. (Eds.), Recent Advances in Evolutionary Multi-Objective Optimization. Springer International Publishing, Cham, pp. 105–137. https://doi.org/10.1007/978-3-319-42978-6_4

Biswas, A.K., 2008. Integrated water resources management: Is it working? Int. J. Water Resour. Dev. 24, 5–22. https://doi.org/10.1080/07900620701871718

Cancelliere, A., Giuliano, G., Nicolosi, V., Rossi, G., 2003. Optimal short-term operation of a multipurpose reservoir system under limited water supply. Water Resour. Syst. Risk Manag. Dev. 200–207.

Cardwell, H.E., Cole, R.A., Cartwright, L.A., Martin, L.A., 2006. Integrated Water Resources Management: Definitions and Conceptual Musings. J. Contemp. Water Res. Educ. 8–18. https://doi.org/10.1111/j.1936-704X.2006.mp135001002.x

Carriaga, C.C., Mays, L.W., 1995. Optimization Modeling For Sedimentation In Alluvial Rivers. J. WATER Resour. Plan. Manag. 121, 251–259.

CEB, (Consulting Engineering Bureau), 2011. Tigris and Euphrates Sampling. Unpublished report, University of Baghdad, Baghdad, Iraq.

Chang, L.C., Chang, F.J., 2009. Multi-objective evolutionary algorithm for operating parallel reservoir system. J. Hydrol. 377, 12–20. https://doi.org/10.1016/j.jhydrol.2009.07.061

Chang, L.C., Chang, F.J., Wang, K.W., Dai, S.Y., 2010. Constrained genetic algorithms for optimizing multi-use reservoir operation. J. Hydrol. 390, 66–74. https://doi.org/10.1016/j.jhydrol.2010.06.031

Chen, D., Chen, Q., Leon, A.S., Li, R., 2016. A Genetic Algorithm Parallel Strategy for Optimizing the Operation of Reservoir with Multiple Eco-environmental Objectives. Water Resour. Manag. 30, 2127–2142. https://doi.org/10.1007/s11269-016-1274-1

Chenari, K., Ghaderi, M., Reza, M., 2014. Improved adaptive genetic algorithm and its application in short-term optimal operation of water resources system. Agric. Environ. Mana gement 3, 209–217.

Chiong, R., Weise, T., Michalewicz, Z., 2012. Variants of Evolutionary Algorithms for Real-World Applications. Springer-Verlag Berlin Heidelberg.

Choong, S.-M., El-Shafie, A., 2015. State-of-the-Art for Modelling Reservoir Inflows and Management Optimization. Water Resour. Manag. 29, 1267–1282. https://doi.org/10.1007/s11269-014-0872-z

Coelho, A.C., Labadie, J.W., Fontane, D.G., 2012. Multicriteria Decision Support System for Regionalization of Integrated Water Resources Management. Water Resour. Manag. 26, 1325–1346. https://doi.org/10.1007/s11269-011-9961-4

Coello, C.A.C., Lamont, G.L., van Veldhuizen, D.A., 2007. Evolutionary Algorithms for Solving Multi-Objective Problems, 2nd ed, Genetic and Evolutionary Computation. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-0-387-36797-2

Coello Coello, C.A., 2002. Theoretical and numerical constraint-handling techniques used with evolutionary algorithms: a survey of the state of the art. Comput. Methods Appl. Mech. Eng. 191, 1245–1287. https://doi.org/http://dx.doi.org/10.1016/S0045-7825(01)00323-1

Coello Coello, C.A., Lamont, G.B., Veldhuizen, D. a Van, 2007. Evolutionary Algorithms for Solving Multi-Objective Problems Second Edition, Design. https://doi.org/10.1007/978-0-387-36797-2

Curry, D.M., Dagli, C.H., 2014. Computational complexity measures for many-objective optimization problems. Procedia Comput. Sci. 36, 185–191. https://doi.org/10.1016/j.procs.2014.09.077

Dai, L., Zhang, P., Wang, Y., Jiang, D., Dai, H., Mao, J., Wang, M., 2017. Multi-objective optimization of cascade reservoirs using NSGA-II: A case study of the Three Gorges-Gezhouba cascade reservoirs in the middle Yangtze River, China. Hum. Ecol. Risk Assess. 23, 814–835.

https://doi.org/10.1080/10807039.2017.1285692

De Jong, K., 2007. Parameter Setting in EAs: a 30 Year Perspective, in: Lobo, F.G., Lima, C.F., Michalewicz, Z. (Eds.), Parameter Setting in Evolutionary Algorithms. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 1–18. https://doi.org/10.1007/978-3-540-69432-8_1

Deb, K., 2001. Multi-Objective Optimization using Evolutionary Algorithms, 1st ed, Wiley-Interscience Series in Systems and Optimization. John Wiley & Sons, Chichester.

Deb, K., 2001. Multi-Objective Optimixation using Evolutionary Algorithm, 1st editio. ed. John Wiley & Sons Ltd.

Deb, K., Agrawal, R.B., 1994. Simulated Binary Crossover for Continuous Search Space, Complex Systems. https://doi.org/10.1.1.26.8485Cached

Deb, K., Agrawal, S., 1999. A Niched-Penalty Approach for Constraint Handling in Genetic Algorithms, in: ProcInternational Conference on Artificial Neural Network and Genetic Algorithms. pp. 235–243. https://doi.org/10.1007/978-3-7091-6384-9_40

Deb, K., Beyer, H.G., 2001. Self-adaptive genetic algorithms with simulated binary crossover. Evol. Comput. 9, 197–221. https://doi.org/10.1162/106365601750190406

Deb, K., Datta, R., 2013. A bi-objective constrained optimization algorithm using a hybrid evolutionary and penalty function approach. Eng. Optim. 45, 503–527. https://doi.org/10.1080/0305215X.2012.685074

Deb, K., Jain, H., 2013. An Evolutionary Many-Objective Optimization Algorithm Using Reference-point Based Non-dominated Sorting Approach, Part I: Solving Problems with Box Constraints. Ieeexplore.Ieee.Org 18, 1–1. https://doi.org/10.1109/TEVC.2013.2281534

Deb, K., Joshi, D., Anand, A., 2002a. Real-coded evolutionary algorithms with parent-centric recombination. Proc. 2002 Congr. Evol. Comput. CEC 2002 1, 61–66.

https://doi.org/10.1109/CEC.2002.1006210

Deb, K., Manikanth, M., Shikhar, M., 2003. A Fast Multi-objective Evolutionary Algorithm for Finding Well-Spread Pareto-Optimal Solutions. KanGAL Technical Report No.2003002, IIT, Kanpur, India.

Deb, K., Pratap, A., Agarwal, S., Meyarivan, T., 2002b. A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Trans. Evol. Comput. 6, 182–197. https://doi.org/10.1109/4235.996017

Deb, K., Thiele, L., Laumanns, M., Zitzler, E., Abraham, A., Jain, L., Goldberg, R., 2001. Scalable test problems for evolutionary multiobjective optimization, Computer Engineering and Networks Laboratory (TIK). https://doi.org/10.1007/1-84628-137-7

Deb, K., Tiwari, S., 2005. Multi-objective optimization of a leg mechanism using genetic algorithms. Eng. Optim. 37, 325–350. https://doi.org/10.1080/03052150500066695

Dittmann, R., Froehlich, F., Pohl, R., Ostrowski, M., 2009. Optimum multi-objective reservoir operation with emphasis on flood control and ecology. Nat. Hazards Earth Syst. Sci. 9, 1973–1980. https://doi.org/10.5194/nhess-9-1973-2009

Dorigo, M., Stützle, T., 2004. Ant Colony Optimization. Bradford Company, Scituate, MA, USA.

Dridi, L., Parizeau, M., Mailhot, A., Villeneuve, J.P., 2008. Using evolutionary optimization techniques for scheduling water pipe renewal considering a short planning horizon. Comput. Civ. Infrastruct. Eng. 23, 625–635. https://doi.org/10.1111/j.1467-8667.2008.00564.x

Eberhart, R., Kennedy, J., 1995. A new optimizer using particle swarm theory. MHS'95. Proc. Sixth Int. Symp. Micro Mach. Hum. Sci. 39–43. https://doi.org/10.1109/MHS.1995.494215

Eiben, A.E., Michalewicz, Z., Schoenauer, M., Smith, J.E., 1999. Parameter control in evolutionary algorithms. Stud. Comput. Intell. 54, 19–46.

https://doi.org/10.1007/978-3-540-69432-8_2

Eiben, A.E., Smit, S.K., 2011. Parameter tuning for configuring and analyzing evolutionary algorithms. Swarm Evol. Comput. 1, 19–31. https://doi.org/10.1016/j.swevo.2011.02.001

Eskandar, H., Sadollah, A., Bahreininejad, A., Hamdi, M., 2012. Water cycle algorithm – A novel metaheuristic optimization method for solving constrained engineering optimization problems. Comput. Struct. 110–111, 151–166. https://doi.org/http://dx.doi.org/10.1016/j.compstruc.2012.07.010

Evan, R., Soppe, R., Saleh, R., Abbas, A., 2012. Report B1.4: Water and salt trends and balances for the Mesopotamian plain. Technical report No.6, ICARDA (International Center for Agricultural Research in the Dry Areas), Lebanon.

Ezz-Aldeen, M., Hassan, R., Ali, A., Al-Ansari, N., Knutsson, S., 2018. Watershed Sediment and Its Effect on Storage Capacity: Case Study of Dokan Dam Reservoir. Water 10, 858. https://doi.org/10.3390/w10070858

FAO, (Food and Agriculture organization of the United Nations), 2004. Hydrogeology of Northern Iraq.

Farmani, R., Wright, J.A., 2003. Self-adaptive fitness formulation for constrained optimization. IEEE Trans. Evol. Comput. 7, 445–455. https://doi.org/10.1109/TEVC.2003.817236

Feng, B.C., Liu, L., Member, A., 1999. Using Genetic Algorithms to Solve Construction Time-Cost Trade-off Problems. Comput. Civ. Eng. 10, 184–189.

Fogel, L.J., Owens, A.J., Walsh, M.J., 1966. Artificial intelligence through simulated evolution. Wiley, New York.

Formiga, K.T.M., Chaudhry, F.H., Cheung, P.B., Reis, L.F.R., 2003. Optimal Design of Water Distribution System by Multiobjective Evolutionary Methods, in: Fonseca, C.M., Fleming, P.J., Zitzler, E., Thiele, L., Deb, K. (Eds.), Evolutionary Multi-Criterion Optimization: Second International Conference, EMO 2003, Faro, Portugal, April 8--11, 2003. Proceedings. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 677–691. https://doi.org/10.1007/3-540-36970-8_48

Geetha, T., Kumaran, K.M., 2013. An Observational Analysis of Genetic Operators. Int. J. Comput. Appl. 63, 24–34.

GEOSURV, (State Company of Geological Survey and Mining), 1993. Geological maps of Iraq. Series of geological maps of Iraq, Ministry of Industry and Minerals, Baghdad, Iraq.

Giacomoni, M.H., Kanta, L., Zechman, E.M., 2013. Complex Adaptive Systems Apporach to Simulate the Sustainability of Water Resources and Urbanization. J. Water Resour. Plan. Manag. 139, 554–564. https://doi.org/10.1061/(ASCE)WR.1943-5452

Giger, M., Keller, D., Ermanni, P., 2007. AORCEA – An adaptive operator rate controlled evolutionary algorithm. Comput. Struct. 85, 1547–1561. https://doi.org/http://dx.doi.org/10.1016/j.compstruc.2006.12.002

Giordano, M., Shah, T., 2014. From IWRM back to integrated water resources management. Int. J. Water Resour. Dev. 30, 364–376. https://doi.org/10.1080/07900627.2013.851521

Giuliani, M., Castelletti, A., Pianosi, F., Mason, E., Reed, P.M., 2016. Curses, Tradeoffs, and Scalable Management: Advancing Evolutionary Multiobjective Direct Policy Search to Improve Water Reservoir Operations. J. Water Resour. Plan. Manag. 142, 04015050. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000570

Giuliani, M., Galelli, S., Soncini-Sessa, R., 2014a. A dimensionality reduction approach for many-objective Markov Decision Processes: Application to a water reservoir operation problem. Environ. Model. Softw. 57, 101–114. https://doi.org/10.1016/j.envsoft.2014.02.011

Giuliani, M., Herman, J.D., Castelletti, A., Reed, P., 2014b. Many-objective reservoir policy identification and refinement to reduce policy inertia and myopia in water management. Water Resour. Res. 50, 3355–3377. https://doi.org/10.1002/2013WR014700

Goldberg, D.E., 1989a. Genetic Algorithms in Search, Optimization and Machine Learning, 1st ed. Addison-Wesley Longman Publishing Co., Inc., Boston, MA, USA.

Goldberg, D.E., 1989b. Sizing Populations for Serial and Parallel Genetic Algorithms, in: Proceedings of the 3rd International Conference on Genetic Algorithms. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, pp. 70–79.

GRID-Geneva, 2000. Tigris and Euphrates Sub-Basin map [WWW Document]. UNEP Glob. regonal Report. URL http://www.grid.unep.ch/products/4_Maps/tigris_sub_basinb.gif (accessed 6.26.18).

Grigg, N.S., 2016. Integrated Water Resource Management: An Interdisciplinary Approach. Palgrave Macmillan, London. https://doi.org/10.1057/978-1-137-57615-6

GWP, 2000. Integrated Water Resources Management. Global Water Partnership, Technical Advisory Committee (TAC) Background paper No.4, Stockholm, Sweden. https://doi.org/10.2166/wst.2010.262

Hadka, D., Reed, P., 2013. Borg: An Auto-Adaptive Many-Objective Evolutionary Computing Framework. Evol. Comput. 21, 1–30. https://doi.org/10.1162/EVCO_a_00075

Hadka, D., Reed, P., 2012. Diagnostic Assessment of Search Controls and Failure Modes in Many-Objective Evolutionary Optimization. Evol. Comput. 20, 423–452. https://doi.org/10.1162/EVCO_a_00053

Hadka, D., Reed, P.M., Simpson, T.W., 2012. Diagnostic assessment of the borg MOEA for many-objective product family design problems, in: 2012 IEEE Congress on Evolutionary Computation, CEC 2012. pp. 10–15. https://doi.org/10.1109/CEC.2012.6256466

Haimes, Y.Y., Hall, W.A., 1977. Sensitivity, responsivity, stability and irreversibility as multiple objectives in civil systems. Adv. Water Resour. 1, 71–81. https://doi.org/10.1016/0309-1708(77)90025-2

Hakimi-Asiabar, M., Ghodsypour, S.H., Kerachian, R., 2010. Deriving operating policies for multi-objective reservoir systems: Application of Self-Learning Genetic Algorithm. Appl. Soft Comput. J. 10, 1151–1163. https://doi.org/10.1016/j.asoc.2009.08.016

Hameed, A.S., 1986. Operation rules for Durbandi – Khan and Hemrin resvoir. M.Sc. Thesis, Irrigation and Drainage Department, College of engineering, University of Baghdad, Iraq.

Hanne, T., 1999. On the convergence of multiobjective evolutionary algorithms. Eur. J. Oper. Res. 117, 553–564. https://doi.org/10.1016/S0377-2217(98)00262-8

Harbaugh, A., McDonald, M., 1996. User’s documentation for MODFLOW-96, an update to the U.S. Geological Survey modular finite-difference groundwater flow model. Open file report 96–485,U.S. Geological Survey.

Harbaugh, A.W., 2005. MODFLOW-2005, The U.S. Geological Survey Modular Ground-Water Model—the Ground-Water Flow Process. U.S. Geological Survey Techniques and Methods 6-A16.

Harza, Binnie, 1963. Hydrological Survey of Iraq: Main Report. Main Report, Iraq.

He, Z., Yen, G.G., Zhang, J., 2014. Fuzzy-based pareto optimality for many-objective evolutionary algorithms. IEEE Trans. Evol. Comput. 18, 269–285. https://doi.org/10.1109/TEVC.2013.2258025

Hering, J.G., Ingold, K.M., 2012. Water Resources Management: What Should Be Integrated? Science (80-.). 336, 1234–1235. https://doi.org/10.1126/science.1218230

Hesser, J., Männer, R., 1991. Towards an optimal mutation probability for genetic algorithms, in: Schwefel, H.-P., Männer, R. (Eds.), Parallel Problem Solving from Nature: 1st Workshop, PPSN I Dortmund, FRG, October 1-3, 1990 Proceedings. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 23–32. https://doi.org/10.1007/BFb0029727

Holland, J.H., 1975. Adaptation in Natural and Artificial Systems. The University of

Michigan Press, Ann Arbor, Michigan, USA.

Holland, J.H., 1975. Adaptation in natural and artificial systems : an introductory analysis with applications to biology, control, and artificial intelligence. University of Michigan Press, Ann Arbor.

Horne, A., Kaur, S., Szemis, J., Costa, A., Webb, J.A., Nathan, R., Stewardson, M., Lowe, L., Boland, N., 2017. Using optimization to develop a "designer" environmental flow regime. Environ. Model. Softw. 88, 188–199. https://doi.org/10.1016/j.envsoft.2016.11.020

Horne, A., Szemis, J.M., Kaur, S., Webb, J.A., Stewardson, M.J., Costa, A., Boland, N., 2016. Optimization tools for environmental water decisions: A review of strengths, weaknesses, and opportunities to improve adoption. Environ. Model. Softw. 84, 326–338. https://doi.org/10.1016/j.envsoft.2016.06.028

Hosseini-Moghari, S.-M., Morovati, R., Moghadas, M., Araghinejad, S., 2015. Optimum Operation of Reservoir Using Two Evolutionary Algorithms: Imperialist Competitive Algorithm (ICA) and Cuckoo Optimization Algorithm (COA). Water Resour. Manag. 29, 3749–3769. https://doi.org/10.1007/s11269-015-1027-6

Hurford, A.P., Huskova, I., Harou, J.J., 2014. Using many-objective trade-off analysis to help dams promote economic development, protect the poor and enhance ecological health. Environ. Sci. Policy 38, 72–86. https://doi.org/10.1016/j.envsci.2013.10.003

IPCC, 2007. Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, M.L. Parry, O.F. Canziani, J.P. Palutikof, P.J. van der Linden and C. Hanson, Eds., Cambridge University Press, Cambridge, UK, 976pp.

Ishibuchi, H., Akedo, N., Nojima, Y., 2015. Behavior of Multiobjective Evolutionary Algorithms on Many-Objective Knapsack Problems. IEEE Trans. Evol. Comput. 19, 264–283. https://doi.org/10.1109/TEVC.2014.2315442

Ishibuchi, H., Setoguchi, Y., Masuda, H., Nojima, Y., 2017. Performance of Decomposition-Based Many-Objective Algorithms Strongly Depends on Pareto Front Shapes. IEEE Trans. Evol. Comput. 21, 169–190. https://doi.org/10.1109/TEVC.2016.2587749

Issa, I., Al-Ansari, N., 2014. Expected Future of Water Resources within Tigris-Euphrates Rivers Basin, Iraq. J. Water Resour. Prot. 421–432. https://doi.org/10.4236/jwarp.2014.65042

Jalut, Q.H., Abbas, N.L., Mohammad, A.T., 2018. Management of groundwater resources in the Al-Mansourieh zone in the Diyala River Basin in Eastern Iraq. Groundw. Sustain. Dev. 6, 79–86. https://doi.org/10.1016/j.gsd.2017.11.004

Jassim, S.Z., Goff, J.C., 2006. Geology of Iraq, First. ed. , Dolin, Prague and Moravian Museum, Brno, Czech Republic.

Javadi, A., Hussain, M., Sherif, M., Farmani, R., 2015. Multi-objective Optimization of Different Management Scenarios to Control Seawater Intrusion in Coastal Aquifers. Water Resour. Manag. 29, 1843–1857. https://doi.org/10.1007/s11269-015-0914-1

Jazmin, Z.S., Reed, P.M., Quinn, J.D., Giuliani, M., Castelletti, A., 2017. Balancing exploration, uncertainty and computational demands in many objective reservoir optimization. Adv. Water Resour. 109, 196–210. https://doi.org/10.1016/j.advwatres.2017.09.014

Jothiprakash, V., Shanthi, G., 2006. Single Reservoir Operating Policies Using Genetic Algorithm. Water Resour. Manag. 20, 917–929. https://doi.org/10.1007/s11269-005-9014-y

Karafotias, G., Hoogendoorn, M., Eiben, A.E., 2015. Parameter Control in Evolutionary Algorithms: Trends and Challenges. IEEE Trans. Evol. Comput. 19, 167–187. https://doi.org/10.1109/TEVC.2014.2308294

Kasprzyk, J.R., Nataraj, S., Reed, P.M., Lempert, R.J., 2013. Many objective robust decision making for complex environmental systems undergoing change. Environ. Model. Softw. 42, 55–71. https://doi.org/10.1016/j.envsoft.2012.12.007

Kaveh, A., Shahrouzi, M., 2008. Dynamic selective pressure using hybrid evolutionary and ant system strategies for structural optimization. Int. J. Numer. Methods Eng. 73, 544–563. https://doi.org/10.1002/nme.2088

Khalil, S., Ridha, S., 1993. The effect of Hamrin reservoir on the adjacent groundwater body. Report (in Arabic), Al Furat Center for Studies and Design of Agricultural Projects, Baghdad, Iraq.

Kim, T., Heo, J.-H., 2006. Multireservoir system optimization in the Han River basin using multi-objective genetic algorithms. Hydrol. Process. 20, 2057–2075. https://doi.org/10.1007/BF02830091

Kim, T., Heo, J.-H., Bae, D.-H., Kim, J.-H., 2008. Single-reservoir operating rules for a year using multiobjective genetic algorithm. J. Hydroinformatics 10, 163. https://doi.org/10.2166/hydro.2008.019

Kita, H., Ono, I., Kobayashi, S., 2000. Multi-Parental Extension of the Unimodal Normal Distribution Crossover for Real-Coded Genetic Algorithms. Trans. Soc. Instrum. Control Eng. 36, 875–883. https://doi.org/10.9746/sicetr1965.36.875

Kita, H., Ono, I., Kobayashi, S., 1999. Multi-parental extension of the unimodal normal distribution crossover for real-coded genetic algorithms. Proc. 1999 Congr. Evol. Comput. 1581–1587. https://doi.org/10.1109/CEC.1999.782672

Klinger, J., Goldscheider, N., Hötzl, H., 2015. Integrated Water Resources Management in the Lower Jordan Rift Valley. Final Report Phase II, KIT Scientific Reports ; 7698, Karlsruhe, Germany.

Knowles, J., Corne, D., 2002. On metrics for comparing nondominated sets, in: Evolutionary Computation, 2002. CEC ’02. Proceedings of the 2002 Congress On. pp. 711–716. https://doi.org/10.1109/CEC.2002.1007013

Kollat, J.B., Reed, P.M., 2007. A computational scaling analysis of multiobjective evolutionary algorithms in long-term groundwater monitoring applications. Adv. Water Resour. 30, 408–419. https://doi.org/10.1016/j.advwatres.2006.05.009

Kollat, J.B., Reed, P.M., 2006. Comparing state-of-the-art evolutionary multi-objective algorithms for long-term groundwater monitoring design. Adv. Water Resour. 29, 792–807. https://doi.org/10.1016/j.advwatres.2005.07.010

Kong, X.M., Huang, G.H., Fan, Y.R., Li, Y.P., Zeng, X.T., Zhu, Y., 2017. Risk analysis for water resources management under dual uncertainties through factorial analysis and fuzzy random value-at-risk. Stoch. Environ. Res. Risk Assess. 31, 2265–2280. https://doi.org/10.1007/s00477-017-1382-3

Koza, J.R., 1992. Genetic Programming: On the Programming of Computers by Means of Natural Selection. MIT Press, Cambridge, MA, USA.

Kubba, F.A., Joodi, A.S., Al-Sudani, H.A.H., 2014. Two Dimensional Mathematical Model of Contamination Distribution in the Lower Reach. Int. J. Eng. Sci. Res. Technol. 3, 213–225.

Kukkonen, S., Lampinen, J., 2005. GDE3: the third evolution step of generalized differential evolution. 2005 IEEE Congr. Evol. Comput. 1, 443–450. https://doi.org/10.1109/CEC.2005.1554717

Kulkarni, S., 2011. Innovative Technologies for Water Saving in Irrigated Agriculture. Int. J. Water Resour. Arid Environ. 1, 226–231.

Laumanns, M., Thiele, L., Deb, K., Zitzler, E., 2002. Combining convergence and diversity in evolutionary multiobjective optimization. Evol. Comput. 10, 263–282. https://doi.org/10.1162/106365602760234108

Lelieveld, J., Proestos, Y., Hadjinicolaou, P., Tanarhte, M., Tyrlis, E., Zittis, G., 2016. Strongly increasing heat extremes in the Middle East and North Africa (MENA) in the 21st century. Clim. Change 137, 245–260. https://doi.org/10.1007/s10584-016-1665-6

Li, B., Li, J., Tang, K., Yao, X., 2015a. Many-Objective Evolutionary Algorithms: A Survey. ACM Comput. Surv. 48, 13:1–13:35. https://doi.org/10.1145/2792984

Li, B., Li, J., Tang, K., Yao, X., 2015b. Many-objective evolutionary algorithms: A survey. ACM Comput. Surv. 48, 35. https://doi.org/10.1145/2792984

Li, F.F., Qiu, J., 2015. Multi-objective reservoir optimization balancing energy generation and firm power. Energies 8, 6962–6976. https://doi.org/10.3390/en8076962

Li, K., Deb, K., Zhang, Q., Kwong, S., 2015. An Evolutionary Many-Objective Optimization Algorithm Based on Dominance and Decomposition. IEEE Trans. Evol. Comput. 19, 694–716. https://doi.org/10.1109/TEVC.2014.2373386

Lobo, F.G., Lima, C.F., Michalewicz, Z., 2007. Parameter Setting in Evolutionary Algorithms, 1st ed. Springer Publishing Company, Incorporated.

Lokman, B., Köksalan, M., 2013. Finding all nondominated points of multi-objective integer programs. J. Glob. Optim. 57, 347–365. https://doi.org/10.1007/s10898-012-9955-7

Loucks, D.P., 2012. Water Resource Management Modeling in 2050. Towar. a Sustain. Water Futur. 341–349.

Maier, H.R., Guillaume, J.H.A., van Delden, H., Riddell, G.A., Haasnoot, M., Kwakkel, J.H., 2016. An uncertain future, deep uncertainty, scenarios, robustness and adaptation: How do they fit together? Environ. Model. Softw. 81, 154–164. https://doi.org/10.1016/j.envsoft.2016.03.014

Maier, H.R., Kapelan, Z., Kasprzyk, J., Kollat, J., Matott, L.S., Cunha, M.C., Dandy, G.C., Gibbs, M.S., Keedwell, E., Marchi, A., Ostfeld, A., Savic, D., Solomatine, D.P., Vrugt, J.A., Zecchin, A.C., Minsker, B.S., Barbour, E.J., Kuczera, G., Pasha, F., Castelletti, A., Giuliani, M., Reed, P.M., 2014. Evolutionary algorithms and other metaheuristics in water resources: Current status, research challenges and future directions. Environ. Model. Softw. 62, 271–299. https://doi.org/10.1016/j.envsoft.2014.09.013

Malekmohammadi, B., Zahraie, B., Kerachian, R., 2011. Ranking solutions of multi-objective reservoir operation optimization models using multi-criteria decision analysis. Expert Syst. Appl. 38, 7851–7863. https://doi.org/10.1016/j.eswa.2010.12.119

Marchi, A., Dandy, G., Wilkins, A., Rohrlach, H., 2014. Methodology for Comparing Evolutionary Algorithms for Optimization of Water Distribution Systems. J.

Water Resour. Plan. Manag. 140, 22–31. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000321

Michalewicz, Z., Logan, T., Swaminathan, S., 1994. Evolutionary operators for continuous convex parameter spaces. Proc. 3rd Annu. Conf. Evol. Program. 84–97.

Miettinen, K., 1999. Nonlinear multiobjective optimization. Boston : Kluwer Academic Publishers.

Mirchi, A., Madani, K., Watkins, D., Ahmad, S., 2012. Synthesis of System Dynamics Tools for Holistic Conceptualization of Water Resources Problems. Water Resour. Manag. 26, 2421–2442. https://doi.org/10.1007/s11269-012-0024-2

Mohamad, H.A., 2010. The problem of water in the province of Diyala and rationalization of water consumption. Wassit Jounal Humanit. 46, 101–163.

Mohtar, R.H., Lawford, R., 2016. Present and future of the water-energy-food nexus and the role of the community of practice. J. Environ. Stud. Sci. 6, 192–199. https://doi.org/10.1007/s13412-016-0378-5

Molina, J.L., Bromley, J., García-Aróstegui, J.L., Sullivan, C., Benavente, J., 2010. Integrated water resources management of overexploited hydrogeological systems using Object-Oriented Bayesian Networks. Environ. Model. Softw. 25, 383–397. https://doi.org/10.1016/j.envsoft.2009.10.007

Muhsun, S.S., 2002. The Effect of the Under Constructions Reservoirs on the Optimum Operation of the Tigris River System. Ph.D. thesis, Building and Construction Engineering Department, University of Technology, Baghdad, Iraq.

Muste, M., Mocanu, M., 2016. Interjurisdictional collaboration in water resource management. 2016 20th IEEE Int. Conf. Autom. Qual. Testing, Robot. AQTR 2016 - Proc. https://doi.org/10.1109/AQTR.2016.7501393

Naji, T., 1989. Optimal Operation of Darbandi – Khan – and Hemreen Reservoirs with Environmental Consideration. M.Sc. Thesis, Irrigation and Drainage Department, College of engineering, University of Baghdad, Iraq.

Nicklow, J., Reed, P., Savic, D., Dessalegne, T., Harrell, L., Chan-Hilton, A., Karamouz, M., Minsker, B., Ostfeld, A., Singh, A., Zechman, E., 2010. State of the art for genetic algorithms and beyond in water resources planning and management. J. Water Resour. Plann. Manag. 136, 412–432.

Nicklow, J.W., Mays, L.W., 2001. Optimal control of reservoir releases to minimize sedimentation in rivers and reservoirs. J. Am. Water Resour. Assoc. 37, 197–211. https://doi.org/DOI 10.1111/j.1752-1688.2001.tb05486.x

Nikolic, V. V., Simonovic, S.P., 2015. Multi-method Modeling Framework for Support of Integrated Water Resources Management. Environ. Process. 2, 461–483.

Noori, M., Othman, F., Sharifi, M., M, H., 2013. A New Flocculant-Coagulant with Potential Use for Industrial Wastewater Treatment. 2nd Int. Conf. Environ. Energy Biotechnol. 51, 139–142. https://doi.org/10.7763/IPCBEE.

Oxley, R.L., Mays, L.W., 2016. Application of an Optimization Model for the Sustainable Water Resource Management of River Basins. Water Resour. Manag. 30, 4883–4898. https://doi.org/10.1007/s11269-016-1459-7

Parsons, (Engineering Company), 1957. Groundwater Resources of Iraq. Development Board, Ministry of Development, Government of Iraq, Baghdad.

Pianosi, F., Thi, X.Q., Soncini-Sessa, R., 2011. Artificial Neural Networks and Multi Objective Genetic Algorithms for water resources management: An application to the Hoabinh reservoir in Vietnam. IFAC Proc. Vol. 18, 10579–10584. https://doi.org/10.3182/20110828-6-IT-1002.02208

Poff, N.L., Brown, C.M., Grantham, T.E., Matthews, J.H., Palmer, M.A., Spence, C.M., Wilby, R.L., Haasnoot, M., Mendoza, G.F., Dominique, K.C., Baeza, A., 2016. Sustainable water management under future uncertainty with eco-engineering decision scaling. Nat. Clim. Chang. 6, 25–34. https://doi.org/10.1038/nclimate2765

Price, K., Storn, R.M., Lampinen, J.A., 2005. Differential Evolution: A Practical Approach to Global Optimization (Natural Computing Series). Springer-Verlag

New York, Inc., Secaucus, NJ, USA.

Qi, W., Michele, G., Dragan, S., Zoran, K., 2015. Two-Objective Design of Benchmark Problems of a Water Distribution System via MOEAs: Towards the Best-Known Approximation of the True Pareto Front. J. Water Resour. Plan. Manag. 141, 4014060. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000460

Qi, Y., Bao, L., Ma, X., Miao, Q., Li, X., 2016a. Self-adaptive multi-objective evolutionary algorithm based on decomposition for large-scale problems: A case study on reservoir flood control operation. Inf. Sci. (Ny). 367–368, 529–549. https://doi.org/10.1016/j.ins.2016.06.005

Qi, Y., Bao, L., Sun, Y., Luo, J., Miao, Q., 2016b. A Memetic Multi-objective Immune Algorithm for Reservoir Flood Control Operation. Water Resour. Manag. 30, 2957–2977. https://doi.org/10.1007/s11269-016-1317-7

Rani, D., Moreira, M.M., 2010. Simulation-optimization modeling: A survey and potential application in reservoir systems operation. Water Resour. Manag. 24, 1107–1138. https://doi.org/10.1007/s11269-009-9488-0

Rathnayake, U.S., Tanyimboh, T.T., 2015. Evolutionary Multi-Objective Optimal Control of Combined Sewer Overflows. Water Resour. Manag. 29, 2715–2731. https://doi.org/10.1007/s11269-015-0965-3

Reddy, M.J., Kumar, D.N., 2009. Performance evaluation of elitist-mutated multi-objective particle swarm optimization for integrated water resources management. J. Hydroinformatics 11, 79–88. https://doi.org/10.2166/hydro.2009.042

Reddy, M.J., Kumar, D.N., 2006. Optimal reservoir operation using multi-objective evolutionary algorithm. Water Resour. Manag. 20, 861–878. https://doi.org/10.1007/s11269-005-9011-1

Reed, P.M., Hadka, D., Herman, J.D., Kasprzyk, J.R., Kollat, J.B., 2013. Evolutionary multiobjective optimization in water resources: The past, present, and future. Adv. Water Resour. 51, 438–456. https://doi.org/10.1016/j.advwatres.2012.01.005

Régnier, J., Sareni, B., Roboam, X., 2005. System optimization by multiobjective genetic algorithms and analysis of the coupling between variables, constraints and objectives. COMPEL - Int. J. Comput. Math. Electr. Electron. Eng. 24, 805–820. https://doi.org/10.1108/03321640510598157

Regulwar, D.G., 2009. Multi Objective Multireservoir Optimization in Fuzzy Environment for River Sub Basin Development and Management. J. Water Resour. Prot. 01, 271–280. https://doi.org/10.4236/jwarp.2009.14033

Reynoso-Meza, G., Sanchis, J., Blasco, X., Martínez, M., 2011. An empirical study on parameter selection for multiobjective optimization algorithms using Differential Evolution, in: Differential Evolution (SDE), 2011 IEEE Symposium On. pp. 1–7. https://doi.org/10.1109/SDE.2011.5952055

Rossman, L.A., 2009. SWMM 5.0 User's Manual EPA/600/R-05/040. Water Supply and Water Resources Division, National Risk Management Research Laboratory, Cincinnati.

Roy, P.C., Islam, M.M., Murase, K., Yao, X., 2015. Evolutionary Path Control Strategy for Solving Many-Objective Optimization Problem. IEEE Trans. Cybern. 45, 702–715. https://doi.org/10.1109/TCYB.2014.2334632

Sadeghi-Tabas, S., Zahra Samadi, S., Akbarpour, A., Pourreza-Bilondi, M., 2017. Sustainable groundwater modeling using single- and multi-objective optimization algorithms. J. Hydroinformatics 19, 97–114.

Safavi, H.R., Golmohammadi, M.H., Sandoval-Solis, S., 2016. Scenario analysis for integrated water resources planning and management under uncertainty in the Zayandehrud river basin. J. Hydrol. 539, 625–639. https://doi.org/10.1016/j.jhydrol.2016.05.073

Salazar, J.Z., Reed, P.M., Herman, J.D., Giuliani, M., Castelletti, A., 2016. A diagnostic assessment of evolutionary algorithms for multi-objective surface water reservoir control. Adv. Water Resour. 92, 172–185. https://doi.org/10.1016/j.advwatres.2016.04.006

Saleh, S., Tanyimboh, T.T., 2016. Multi-Directional Maximum-Entropy Approach to the Evolutionary Design Optimization of Water Distribution Systems. Water Resour. Manag. 30, 1885–1901. https://doi.org/10.1007/s11269-016-1253-6

Saleh, S.A.H., 2013. A Study of Himreen Reservoir Water Quality Using in Situ Measurement and Remote Sensing Techniques. J. Environ. Earth Sci. 3, 96–105.

Saleh, S.H.A., Tanyimboh, T.T., 2014. Optimal Design of Water Distribution Systems Based on Entropy and Topology. Water Resour. Manag. 28, 3555–3575. https://doi.org/10.1007/s11269-014-0687-y

Saleh, S.H.A., Tanyimboh, T.T., 2013. Coupled Topology and Pipe Size Optimization of Water Distribution Systems. Water Resour. Manag. 27, 4795–4814. https://doi.org/10.1007/s11269-013-0439-4

Schaffer, J.D., 1985. Multiple objective optimization with vector evaluated genetic algorithms, in: The 1st International Conference on Genetic Algorithms. pp. 93–100.

Schardong, A., Ph, D., Simonovic, S.P., Asce, F., Vasan, A., 2013. Multiobjective Evolutionary Approach to Optimal Reservoir Operation. J. Comput. Civ. Eng. 27, 139–147. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000213.

Schwefel, H.-P., 1981. Numerical Optimization of Computer Models. John Wiley & Sons, Inc., New York, NY, USA.

Scola, L.A., Takahashi, R.H.C., Cerqueira, S.A.A.G., 2014. Multipurpose Water Reservoir Management: An Evolutionary Multiobjective Optimization Approach. Math. Probl. Eng. 2014, 14. https://doi.org/10.1155/2014/638259

Scopel, C., 2012. SWAT: Soil & Water Assessment Tool [WWW Document]. URL https://www.esri.com/arcgis-blog/products/product/water/swat-soil-water-assessment-tool/

Scott, K., Gelatt, C.D., Vecchi, M.P., 1983. Optimization by simulated annealing. Science (80-.). 220, 671–680. https://doi.org/10.1126/science.220.4598.671

Seada, H., Deb, K., 2015. U-NSGA-III: A Unified Evolutionary Optimization Procedure for Single, Multiple, and Many Objectives: Proof-of-Principle Results, in: Gaspar-Cunha, A., Henggeler Antunes, C., Coello, C.C. (Eds.), Evolutionary Multi-Criterion Optimization: 8th International Conference, EMO 2015, Guimar{ã}es, Portugal, March 29 --April 1, 2015. Proceedings, Part II. Springer International Publishing, Cham, pp. 34–49. https://doi.org/10.1007/978-3-319-15892-1_3

Seyoum, A.G., Tanyimboh, T.T., Siew, C., 2016. Practical Application of Penalty-Free Evolutionary Multi-Objective Optimisation of Water Distribution Systems. Water Util. J. 49–55.

SGI, (Studio Galli Ingegneria S.p.A.), MED, (INGEGNERIA S.r.l.), EL CONCORDE, (Construction LLC), 2014. The Strategic Study for Water and Land Resources in Iraq. Technical Study (unpublished), Accomplished for the General Directorate for Water Resources Management, Ministry of water resources, Baghdad, Iraq.

Sharawat, I., Dahiya, R.P., Dahiya, R., Kumari, S., 2014. System Dynamics Approach : A Novel Water Resource Management Tool. Int. J. Environ. Res. Dev. 4, 297–302.

Sharif, M., Wardlaw, R., 2000. Multireservoir Systems Optimization Using Genetic Algorithms: Case Study. J. Comput. Civ. Eng. 14, 255–263.

Sidiropoulos, P., Mylopoulos, N., Loukas, A., 2016. Reservoir-aquifer combined optimization for groundwater restoration : The case of Lake Karla watershed , Greece. Water Util. J. 17–26.

Sierra, M.R., Coello Coello, C.A., 2005. Improving PSO-Based Multi-objective Optimization Using Crowding, Mutation and ∈-Dominance, in: Coello Coello, C.A., Hernández Aguirre, A., Zitzler, E. (Eds.), Evolutionary Multi-Criterion Optimization: Third International Conference, EMO 2005, Guanajuato, Mexico, March 9-11, 2005. Proceedings. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 505–519. https://doi.org/10.1007/978-3-540-31880-4_35

Siew, C., Tanyimboh, T., 2010. Penalty-Free Multi-Objective Evolutionary Optimization of Water Distribution Systems. Water Distrib. Syst. Anal. 2010

41203, 764–770. https://doi.org/doi:10.1061/41203(425)71

Siew, C., Tanyimboh, T.T., 2012. Penalty-Free Feasibility Boundary Convergent Multi-Objective Evolutionary Algorithm for the Optimization of Water Distribution Systems. Water Resour. Manag. 26, 4485–4507. https://doi.org/10.1007/s11269-012-0158-2

Siew, C., Tanyimboh, T.T., Seyoum, A.G., 2016. Penalty-Free Multi-Objective Evolutionary Approach to Optimization of Anytown Water Distribution Network. Water Resour. Manag. 30, 3671–3688. https://doi.org/10.1007/s11269-016-1371-1

Siew, C., Tanyimboh, T.T., Seyoum, A.G., 2014. Assessment of Penalty-Free Multi-Objective Evolutionary Optimization Approach for the Design and Rehabilitation of Water Distribution Systems. Water Resour. Manag. 28, 373–389. https://doi.org/10.1007/s11269-013-0488-8

Silver, E.A., 2004. An overview of heuristic solution methods. J. Oper. Res. Soc. 55, 936–956. https://doi.org/10.1057/palgrave.jors.2601758

Simon, D., 2013. Evolutionary optimization algorithms: biologically-Inspired and population-based approaches to computer intelligence. Hoboken, New Jersey, John Wiley & Sons Inc. http://site.ebrary.com/id/10722521.

Smit, S.K., 2012. Parameter Tuning and Scientific Testing in Evolutionary Algorithms. Department of Computer Science, PhD Thesis, VU University Amesterdam, Amsterdam, Netherland.

SOGREAH, 1983. Upper Adhaim Dams Project. Appendix(I), Republic of Iraq, Ministry of Irrigation, State Organization for Dams.

Soyuzgiprovodkhoz, 1982. General Scheme of Water Resources and Land Development in Iraq. Technical Study (unpublished), Ministry of Water Resources, Iraq.

Sreekanth, J., Moore, C., Wolf, L., 2016. Pareto-based efficient stochastic simulation–optimization for robust and reliable groundwater management. J. Hydrol. 533, 180–190. https://doi.org/http://dx.doi.org/10.1016/j.jhydrol.2015.12.001

Srivastava, R.P., 2002. Time continuation in genetic algorithms. Technical report, Illinois Genetic Algorithm Laboratory. Storn,.

Stadler, W., 1979. A survey of multicriteria optimization or the vector maximum problem, part I: 1776-1960. J. Optim. Theory Appl. 29, 1–52. https://doi.org/10.1007/BF00932634

Stephens, C.R., Garcia Olmedo, I., Mora Vargas, J., Waelbroeck, H., 1998. Self-adaptation in evolving systems. Artif. Life 4, 183–201.

Sterman, J.D., 2000. Business dynamics, systems thinking and modeling for a complex world. McGraw-Hill, Boston.

Storn, R., Price, K., 1997a. Differential Evolution : A Simple and Efficient Heuristic for global Optimization over Continuous Spaces. J. Glob. Optim. 11, 341–359. https://doi.org/10.1023/A:1008202821328

Storn, R., Price, K., 1997b. Differential evolution–a simple and efficient heuristic for global optimization over continuous spaces. J. Glob. Optim. 341–359. https://doi.org/10.1023/A:1008202821328

Storn, R., Price, K., 1997c. Differential Evolution -- A Simple and Efficient Heuristic for global Optimization over Continuous Spaces. J. Glob. Optim. 11, 341–359. https://doi.org/10.1023/A:1008202821328

Tagawa, K., Imamura, A., 2013. Many-hard-objective optimization using differential evolution based on two-stage constraint-handling. Proceeding fifteenth Annu. Conf. Genet. Evol. Comput. Conf. - GECCO ’13 671. https://doi.org/10.1145/2463372.2463446

Tang, Y., Reed, P., Wagener, T., 2006. How effective and efficient are multiobjective evolutionary algorithms at hydrologic model calibration? Hydrol. Earth Syst. Sci. 10, 289–307. https://doi.org/10.5194/hess-10-289-2006

Tanyimboh, T.T., Seyoum, A.G., 2016. Multiobjective evolutionary optimization of water distribution systems: Exploiting diversity with infeasible solutions. J.

Environ. Manage. 183, Part, 133–141. https://doi.org/http://dx.doi.org/10.1016/j.jenvman.2016.08.048

Tayebiyan, A., Mohammed Ali, T.A., Ghazali, A.H., Malek, M.A., 2016. Optimization of Exclusive Release Policies for Hydropower Reservoir Operation by Using Genetic Algorithm. Water Resour. Manag. 30, 1203–1216. https://doi.org/10.1007/s11269-015-1221-6

Tayfur, G., 2017. Modern Optimization Methods in Water Resources Planning, Engineering and Management. Water Resour. Manag. 31, 3205–3233. https://doi.org/10.1007/s11269-017-1694-6

Tejada-Guibert, J.A., Setegn, S.G., Stoa, R.B., 2015. Sustainable Development and Integrated Water Resources Management, in: Sustainability of Integrated Water Resources Management. Springer International Publishing Switzerland.

Tigkas, D., Christelis, V., Tsakiris, G., 2016. Comparative Study of Evolutionary Algorithms for the Automatic Calibration of the Medbasin-D Conceptual Hydrological Model. Environ. Process. 3, 629–644. https://doi.org/10.1007/s40710-016-0147-1

Tilmant, a., Fortemps, P., Vanclooster, M., 2002. Effect of averaging operators in fuzzy optimization of reservoir operation. Water Resour. Manag. 16, 1–22. https://doi.org/10.1023/A:1015523901205

Tract, A.B., 1997. Multiobjective optimization design with pareto genetic algorithm. Struct. Eng. 123, 1252–1261.

Tsutsui, S., Yamamura, M., Higuchi, T., 1999. Multi-parent recombination with simplex crossover in real coded genetic algorithms, in: Proceedings of the 1st Annual Conference on Genetic and Evolutionary Computation-Volume 1. pp. 657–664.

Tsutsui, S., Yamamura, M., Higuchi, T., 1999. Multi-parent recombination with simplex crossover in real coded genetic algorithms. Proc. 1999 Genet. Evol. Comput. Conf. 657–664.

UN, (United Nations), 2018. Sustainable Development Goals [WWW Document]. URL http://www.un.org/sustainabledevelopment/news/communications-material/ (accessed 7.31.18).

UN, (United Nations), 2015. Transforming our world: The 2030 agenda for sustainable development, Sustainable development knowledge platform. sustainabledevelopment.un.org. https://doi.org/10.1007/s13398-014-0173-7.2

UN, (United Nations), 1987. Report of the World Commission on Environment and Development: Our Common Future. Published as Annex to General Assembly document A/42/427, Development and International Co-operation: Environment, New York.

Vafaee, F., Nelson, P.C., 2010. An explorative and exploitative mutation scheme. 2010 IEEE World Congr. Comput. Intell. WCCI 2010 - 2010 IEEE Congr. Evol. Comput. CEC 2010. https://doi.org/10.1109/CEC.2010.5586142

Van Veldhuizen, D. a, Lamont, G.B., 1998. Evolutionary Computation and Convergence to a Pareto Front. Late Break. Pap. Genet. Program. 1998 Conf. 221–228.

Vrugt, J. a, Robinson, B. a, 2007. Improved evolutionary optimization from genetically adaptive multimethod search. Proc. Natl. Acad. Sci. 104, 708–711. https://doi.org/10.1073/pnas.0610471104

Vrugt, J.A., Robinson, B.A., Hyman, J.M., 2009. Self-adaptive multimethod search for global optimization in real-parameter spaces. IEEE Trans. Evol. Comput. 13, 243–259. https://doi.org/10.1109/TEVC.2008.924428

Wang, H., Jiao, L., Yao, X., 2015. Two_Arch2: An Improved Two-Archive Algorithm for Many-Objective Optimization. IEEE Trans. Evol. Comput. 19, 524–541. https://doi.org/10.1109/TEVC.2014.2350987

Wang, K.W., Chang, L.C., Chang, F.J., 2011. Multi-tier interactive genetic algorithms for the optimization of long-term reservoir operation. Adv. Water Resour. 34, 1343–1351. https://doi.org/10.1016/j.advwatres.2011.07.004

WCC, (Water Control Center), 2006. Technical Data for Dams, Reservoirs and Main Control Structures with Mean Monthly Flow Rates and Water Quality for Main Water Resources (1976-Sep 2005). General Directorate of Water Resources Management, Ministry of Water Resources, Baghdad, Iraq.

Weng, S.Q., Huang, G.H., Li, Y.P., 2010. An integrated scenario-based multi-criteria decision support system for water resources management and planning - A case study in the Haihe River Basin. Expert Syst. Appl. 37, 8242–8254. https://doi.org/10.1016/j.eswa.2010.05.061

Woldesenbet, Y.G., Yen, G.G., Tessema, B.G., 2009. Constraint Handling in Multiobjective Evolutionary Optimization. IEEE Trans. Evol. Comput. 13, 514–525. https://doi.org/10.1109/TEVC.2008.2009032

Woodruff, M.J., Simpson, T.W., Reed, P.M., 2015. Multi-Objective Evolutionary Algorithms' Performance in a Support Role, in: ASME 2015 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference. p. 12.

World Bank, 2006. Dokan and Derbendikhan Dam Inspections Report. Consultant services by SMEC International Pty. Ltd., Australia.

Wu, Y.G., Zou, J., 2012. An Advanced Multi-Objective Genetic Algorithm Based on Borda Number, in: Progress in Industrial and Civil Engineering, Applied Mechanics and Materials. Trans Tech Publications, pp. 4909–4915. https://doi.org/10.4028/www.scientific.net/AMM.204-208.4909

Yang, C.T., 1996. Sediment transport: theory and practice. McGraw-Hill Inc, USA.

Yang, J., Soh, C.K., 1997. Structural Optimization by Genetic Algorithms with Tournament Selection. J. Comput. Civ. Eng. 11, 195–200. https://doi.org/10.1061/(ASCE)0887-3801(1997)11:3(195)

Yang, Y.S., Kalin, R.M., Zhang, Y., Lin, X., Zou, L., 2001. Multi-objective optimization for sustainable groundwater resource management in a semiarid catchment. Hydrol. Sci. J. 46, 55–72. https://doi.org/10.1080/02626660109492800

Yeh, W.W., 1985. Reservoir Management and Operations Models: A State- of- the-Art Review. Water Resour. Res. 21, 1797–1818.

Yuan, Y., Xu, H., Wang, B., Yao, X., 2016. A New Dominance Relation-Based Evolutionary Algorithm for Many-Objective Optimization. IEEE Trans. Evol. Comput. 20, 16–37. https://doi.org/10.1109/TEVC.2015.2420112

Zecchin, A.C., Simpson, A.R., Maier, H.R., Marchi, A., Nixon, J.B., 2012. Improved understanding of the searching behavior of ant colony optimization algorithms applied to the water distribution design problem. Water Resour. Res. 48. https://doi.org/10.1029/2011WR011652

Zhang, Q., Li, H., 2007. MOEA/D: A Multiobjective Evolutionary Algorithm Based on Decomposition. IEEE Trans. Evol. Comput. 11, 712–731. https://doi.org/10.1109/TEVC.2007.892759

Zhang, Q., Liu, W., Li, H., 2009. The performance of a new version of MOEA/D on CEC09 unconstrained MOP test instances, in: 2009 IEEE Congress on Evolutionary Computation. pp. 203–208. https://doi.org/10.1109/CEC.2009.4982949

Zhang, Q., Liu, W., Li, H., 2009. The Performance of a New Version of {MOEA/D} on {CEC09} Unconstrained {MOP} Test Instances.

Zhang, W., Liu, P., Wang, H., Chen, J., Lei, X., Feng, M., 2017. Reservoir adaptive operating rules based on both of historical streamflow and future projections. J. Hydrol. 553, 691–707. https://doi.org/10.1016/j.jhydrol.2017.08.031

Zhang, X., Tian, Y., Jin, Y., 2015. A Knee Point-Driven Evolutionary Algorithm for Many-Objective Optimization. IEEE Trans. Evol. Comput. 19, 761–776. https://doi.org/10.1109/TEVC.2014.2378512

Zheng, F., Simpson, A.R., Zecchin, A.C., Maier, H.R., Feifei, Zh., 2016. Comparison of the Searching Behavior of NSGA-II, SAMODE, and Borg MOEAs Applied to Water Distribution System Design Problems. J. Water Resour. Plan. Manag. 142. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000650

Zhou, A., Qu, B.-Y., Li, H., Zhao, S.-Z., Suganthan, P.N., Zhang, Q., 2011. Multiobjective evolutionary algorithms: A survey of the state of the art. Swarm Evol. Comput. 1, 32–49. https://doi.org/10.1016/j.swevo.2011.03.001

Zhu, C., Xu, L., Goodman, E.D., 2016. Generalization of Pareto-Optimality for Many-Objective Evolutionary Optimization. IEEE Trans. Evol. Comput. 20, 299–315. https://doi.org/10.1109/TEVC.2015.2457245

Zitzler, E., 1999. Evolutionary Algorithms for Multiobjective Optimization: Methods and Applications.

Zitzler, E., Laumanns, M., Thiele, L., 2002. SPEA2: Improving the Strength Pareto Evolutionary Algorithm for Multiobjective Optimization, in: Evolutionary Methods for Design, Optimisation, and Control. CIMNE, Barcelona, Spain, pp. 95–100.

Zitzler, E., Lothar, T., Kalyanmoy, D., 2000. Comparison of Multiobjective Evolutionary Algorithms: Empirical Results. Evol.\ Comput. 8, 173–195.

Zitzler, E., Simon, K., 2004. Indicator-Based Selection in Multiobjective Search. 8th Int. Conf. Parallel Probl. Solving from Nat. (PPSN VIII) 3242, 832–842. https://doi.org/10.1007/b100601

APPENDIX - 2

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