Model-Based Optimisation Approaches for System Energy Performance Improvement and Evaluation

PhD Thesis

Jiangfeng Zhang

Supervisor: Dr Hong Yue

Co-supervisor: Professor Kwok L Lo

Department of Electronic and Electrical Engineering

University of Strathclyde, Glasgow

September 2018

Signed: *Jiangfeng Zhang*

Date: 10/09/2018

Abstract

The aim of this PhD study is to provide model-based optimisation approaches for system energy performance improvement and evaluation, and such approaches can solve many energy performance related problems, for example, they are able to optimise conveyor belt system energy performance, avoid ramp rate violation problem in the periodic implementation of dynamic economic dispatch solutions, reduce the number of voltage sensors in photovoltaic (PV) fault diagnosis, improve PV maximum power generation through rearranging PV modules, and also measure and verify energy savings. For this purpose, three objectives are set in this study: i) To summarise existing model-based optimisation approaches for energy system modelling; ii) To apply obtained modelling methodologies in energy performance optimisation; and iii) To apply obtained modelling methodologies in energy performance evaluation. In order to achieve these objectives, the relevant theoretical preparations on model-based optimisation approaches for energy modelling are developed and then applied in these practical energy problems. This thesis presents my contributions on modelling methodologies for energy performance optimisation, applications of these modelling methods in industrial energy systems, power generation dispatch, PV array fault diagnosis, and PV array power generation maximisation through rearrangement. Mathematical models are derived for energy system performance evaluation, optimal control models are introduced to minimise measurement and verification cost, and physical modelling and data regression modelling methodologies are also applied in practical measurement and verification projects on air conditioner intelligent switch control and heat pump water heaters. Weakness of these obtained results are analysed, and future work is presented too.

Acknoweledgement

First and foremost my gratitude goes to my supervisor Dr Hong Yue for her valuable help, support, review and feedback during my study. Without her support, this PhD work would never be completed. I am very grateful to my second supervisor Prof KL Lo for his guidance, help and encouragement. His insight in power systems benefits me much in my current research. I would like to thank my former collaborators Dr Y Hu, Prof X Xia, Dr A Elaiw, Dr X Ye, and Mr A Middelberg for their valuable help.

Many thanks to former colleagues at the University of Strathclyde for their kind support and help. I am also extremely grateful to examiners Prof Olimpo Anaya-Lara, Prof Kenneth Grattan, Prof Jihong Wang, and Prof Lie Xu for their valuable comments and efforts which greatly improve the quality of this work.

Finally, my sincere gratitude goes to my father Mingyi who passed away in August 2018, my mother Bingye, my wife Rose and kids Shenrun, Odette and Christina for their love and support.

Table of Contents

Model-Based Optimisation Approaches for System Energy Performance Improvement and Evaluation
–A Critical Appraisal

Jiangfeng Zhang
Department of Electronic and Electrical Engineering,
University of Strathclyde

Abstract This is a critical appraisal for my PhD project *Model-Based Optimisation Approaches for System Energy Performance Improvement and Evaluation*. The aim of this PhD study is to provide model-based optimisation approaches for system energy performance improvement and evaluation, and such approaches can solve many energy performance related problems, for example, they are able to optimise conveyor belt system energy performance, avoid ramp rate violation problem in the periodic implementation of dynamic economic dispatch solutions, reduce the number of voltage sensors in photovoltaic (PV) fault diagnosis, improve PV maximum power generation through rearranging PV modules, and also measure and verify energy savings. For this purpose, three objectives are set in this study: i) To summarise existing model-based optimisation approaches for energy system modelling; ii) To apply obtained modelling methodologies in energy performance optimisation; and iii) To apply obtained modelling methodologies in energy performance evaluation. In order to achieve these objectives, the relevant theoretical preparations on model-based optimisation approaches for energy modelling are developed and then applied in these practical energy problems. This critical appraisal briefly reviews my contributions on modelling methodologies for energy performance optimisation, applications of these modelling methods in industrial energy systems, power generation dispatch, PV array fault diagnosis, and PV array power generation maximisation through rearrangement. Mathematical models are derived for energy performance evaluation, optimal control models are introduced to minimise measurement and verification cost, and physical modelling and data regression modelling methodologies are also applied in practical measurement and verification projects on air conditioner intelligent switch control and heat pump water heaters. Weakness of these obtained results are analysed, and future work is presented too.

Keywords: Energy Systems, Optimisation, Measurement and Verification, Model Predictive Control

1 Overview

I would like to apply for the Doctorate Degree by Publication under the project title *Model-Based Optimisation Approaches for System Energy Performance Improvement and Evaluation*.

The completion of this thesis is supported by my key contributions in the following 10 publications (8 journal papers, 1 book chapter and 1 confidential industrial guideline, [K1]-[K10]), which are further supported by my contributions in 11 supporting publications (7 journal papers [S1]-[S7] and 4 book chapters [S8-S11]). My contributions in the 10 key publications are major, and the supporting publications are those work where I contribute mostly on mathematical modelling. Recently updated Google scholar citations are also provided (accessed on 10/09/2018).

This PhD work focuses on model-based optimisation modelling approaches for energy performance and evaluation. Key contents include theoretical contributions on model-based energy optimisation modelling methodologies ([K1, K2]), the application of modelling methodologies in the conveyor belt system at a colliery ([K3]), electric power dispatch ([K4]), photovoltaic (PV) system fault diagnosis and maximum power improvement ([K5, K6, K7]), and practical applications of system modelling methodologies in real world measurement and verification projects ([K8, K9, K10]). Supporting publications [S1]-[S11] are also provided to support the above-mentioned key contributions.

List of Key Publications

[K1] X Xia and J Zhang, Operation efficiency optimisation modelling and application of model predictive control, IEEE/CAA Journal of Automatica Sinica, 2015, 2(2), pp.166-172. Google Scholar Citations: 11

[K2] J Zhang and X Xia, A model predictive control approach to the periodic implementation of the solutions of the optimal dynamic resource allocation problem, Automatica, vol.47, 2011, pp. 358-362. Google Scholar Citations: 55

[K3] A Middelberg, J Zhang and X Xia, An optimal control model for load shifting-with application in the energy management of a colliery, Applied Energy, vol. 86, 2009, pp. 1266-1273. Google Scholar Citations: 128

[K4] X Xia, J Zhang and A Elaiw, An application of model predictive control to the dynamic economic dispatch of power generation, Control Engineering Practice, vol. 19, no. 6, 2011, pp. 638-648. Google Scholar Citations:: 97

[K5] Y Hu, J Zhang, W Cao, J Wu, G Tian, S Finney and J Kirtley, Online two-section PV array fault diagnosis with optimized voltage sensor locations, IEEE Transactions on Industrial Electronics, vol. 62, 2015, pp. 7237 - 7246. Google Scholar Citations: 31

[K6] Y Hu, J Zhang, J Wu, W Cao, G Tian and J Kirtley, Efficiency improvement of non-uniformly-aged PV arrays, IEEE Transactions on Power Electronics, vol. 32, Feb 2017, pp. 1124-1137. Google Scholar Citations: 8

[K7] Y Hu, J Zhang, P Li, D Yu and L Jiang, Non-uniform aged modules reconfiguration for large scale PV array, IEEE Transactions on Device and Materials Reliability, vol. 17, 2017, pp. 560-569. Google Scholar Citations: 2

[K8] X Xia and J Zhang, Mathematical description for the measurement and verification of energy efficiency improvement, Applied Energy, vol. 111, 2013, pp. 247-256. Google Scholar Citations: 62

[K9] J Zhang and X Xia, Air Conditioner Intelligent Switch Control in Commercial Buildings, Chapter 1, Energy Efficiency Measurement & Verification Practices–Demystifying M&V through South African Case Studies (X Xia and J Zhang eds.), Media in Africa, Pretoria, October 2012.

[K10] J Zhang, Measurement and Verification Guideline Residential Heat Pump Rebate Programme, ESKOM Report PM/M&V/UP-10/11-054, 2012 (Confidential).

List of Supporting Publications

[S1] H Tazvinga, X Xia and J Zhang, Minimum cost solution of photovoltaic-diesel-battery hybrid power systems for remote consumers, Solar Energy, 96 (2013) 292-299. Google Scholar Citations: 106

[S2] N Wang, J Zhang and X Xia, Energy consumption of air conditioners at different temperature set points, Energy and Buildings, vol.65, 2013, pp. 412-418. Google Scholar Citations: 36

[S3] D Setlhaolo, X Xia and J Zhang, Optimal scheduling of household appliances for demand response, Electric Power Systems Research, vol. 116, 2014, pp 24-28. Google Scholar Citations: 125

[S4] EM Malatji, J Zhang, and X Xia, A multiple objective optimisation model for building energy efficiency investment decision, Energy and Buildings, vol.61, 2013, pp. 81-87. Google Scholar Citations: 91

[S5] H Zhang, J Zhang and X Xia, Optimal sizing and operation of pumping systems to achieve energy efficiency and load shifting, Electric Power Systems Research, vol. 86, 2012, pp. 41- 50. Google Scholar Citations: 61

[S6] X Ye, X Xia and J Zhang, Optimal sampling plan for clean development mechanism energy efficiency lighting projects, Applied Energy, vol. 112, 2013, 1006-1015. Google Scholar Citations: 30

[S7] X Ye, X Xia and J Zhang, Optimal sampling plan for clean development mechanism lighting projects with lamp population decay, Applied Energy, vol.136, 2014, pp. 1184-1192. Google Scholar Citations: 21

[S8] U Ekpenyong, X Xia and J Zhang, Building Energy Efficiency Projects, Chapter 3, Energy Efficiency Measurement & Verification Practices–Demystifying M&V through South African Case Studies (X Xia and J Zhang eds.), Media in Africa, Pretoria, October 2012.

[S9] X Ye, X Xia and J Zhang, Residential Heat Pump Rebate Programme, Chapter 14, Energy Efficiency Measurement & Verification Practices–Demystifying M&V through South African Case Studies (X Xia and J Zhang eds.), Media in Africa, Pretoria, October 2012.

[S10] Z Olinga, X Xia and J Zhang, Air Conditioning System Replacement at Industrial Facilities, Chapter 17, Energy Efficiency Measurement & Verification Practices–Demystifying M&V through South African Case Studies (X Xia and J Zhang eds.), Media in Africa, Pretoria, October 2012.

[S11] N Wang, X Xia and J Zhang, Energy Efficiency Improvement and Load Reduction of Refrigeration Systems at Supermarket Stores, Chapter 18, Energy Efficiency Measurement & Verification Practices–Demystifying M&V through South African Case Studies (X Xia and J Zhang eds.), Media in Africa, Pretoria, October 2012.

The remaining sections are highlighted below. In Section 2, an introduction is provided to discuss the relevant background and objectives of this study. In Section 3, contributions on model-based system modelling methodologies to optimise energy performance are reviewed. Section 4 discusses contributions on the application of the modelling methodologies developed in Section 3 to industrial energy systems and electric power dispatch. Section 5 is on the application of the modelling methodologies in PV systems. Section 6 provides the application of modelling methodologies in energy performance evaluation. Conclusions are made in Section 7.

2 Introduction

This section provides a brief introduction to the background, aims, objectives, and targeted problems of this PhD study.

2.1 Background

Energy system modelling provides important methods to generate a range of insight and analysis on the supply and demand of energy [1]. There are many existing model-based optimisation modelling methodologies in literature which are successfully applied to solve many energy performance problems. For example, linear programming approach is applied in the development of a powerful energy and environmental policy analysis software MARKAL to facilitate long term economic analysis of different energy related systems at country level [2, 3]. This MARKAL tool is also applied to analyse the minimum discounted cost configurations for the Australian liquid-fuel production over the period 1980-2020 [4]. A multi-objective linear dynamic programming model is formulated in [5] to analyse the renewable energy policy for biogas synthesis in a state of India. Linear regression model is developed in [6] to estimate the end-use energy demand of a rural household at Nepal. Linear programming is also applied to set time-of-day tariff for a power distribution utility in [7]. Linear integer programming models are applied in [8] to minimise the electricity cost of an industrial plant by scheduling the load to satisfy process, storage and production constraints. Mixed-integer nonlinear programming models are applied in [9] to optimally schedule building energy systems for the operational cost saving purpose. Fuzzy logic is introduced in [10, 11] and [12] to solve the load shifting problem of electric water heating and the energy management of a domestic photovoltaic panel, respectively. An artificial neural network regression model is used in [13] for a petrochemical plant. Integer programming is applied in [14] and [15] for mid-term management of a thermal and electricity supply system of an industrial consumer and the peak-load management of a steel plant, respectively. General applications of multi-level stochastic programming approaches in electricity market are summarised in a monograph [16]. A multi-follower bi-level stochastic programming model is derived in [17] to solve the 24-hour power and energy management problem for a microgrid equipped with a combined heat and power system.

The above-mentioned energy system modelling methodologies play an extremely important role to optimise energy performance, and they have been applied in many scenarios to achieve various targets. However, there are still many potential places to further explore these modelling approaches in energy systems. For example, there are many energy system optimisation problems from industrial plants, power generation plants, commercial and residential buildings which have not been studied.

In order to explore further the applications of these model-based energy system modelling methodologies, this PhD project is particularly interested in applying these methodologies to the energy performance optimisation and evaluation of some systems which are discussed in the following subsection.

2.2 Aims and objectives of the work

The aim of this PhD study is to provide model-based optimisation approaches for energy performance improvement and evaluation. As mentioned in the previous subsection, such model-based optimisation approaches can solve many energy related performance and evaluation problems. A particular interest of this study is to develop new modelling methods and then apply these modelling approaches to optimise conveyor belt system energy performance, avoid ramp rate violation problem in the periodic implementation of dynamic economic dispatch solutions, reduce the number of voltage sensors in photovoltaic (PV) fault diagnosis, improve PV maximum power generation through rearranging PV modules, and also measure and verify energy savings.

Therefore, the following three objectives are identified in this study.
i) To summarise existing model-based optimisation approaches for energy system modelling;
ii) To apply obtained modelling methodologies in energy performance optimisation; and
iii) To apply obtained modelling methodologies in energy performance evaluation.

The first objective will include the study of existing model-based optimisation approaches, and then summarise them into concisely stated methodologies which are easily applicable to solve the targeted energy performance optimisation and evaluation problems. New modelling methodologies will also be developed during the study of existing methodologies. The obtained modelling methods will involve different approaches from linear programming, nonlinear programming, optimal control and model predictive control.

The second objective will include the application of the above obtained modelling methodologies to the energy performance optimisation of many practical scenarios, such as the energy cost minimisation of conveyor belt systems at a colliery, dynamic economic dispatch of electric power generation, PV system fault diagnosis, and aged PV system maximum power generation. Optimisation objective functions can be built following the direct needs of investigated systems, while optimisation constraints are more difficult to be formulated since physical processes and system dynamics need to be sufficiently understood in order to apply the obtained modelling methods.

The third objective will need the development of tailor-made modelling methodologies for the performance evaluation of energy systems, although the general modelling methods developed for energy performance optimisation will still be applicable to performance evaluation. After obtaining the tailor-made modelling methods for evaluation purpose, then these evaluation methods will be applied to practical energy systems, such as air conditioner intelligent switch and residential heat pump water heater.

2.3 Targeted problems to be studied

Targeted problems to be studied will include the optimisation of conveyor belt system at a colliery, the ramp rate violation problem in the periodic implementation of dynamic economic power dispatch solutions, a low cost PV fault diagnosis method based on voltage sensors, maximum power generation optimisation for aged PV arrays through PV module rearrangement, and the savings quantification for practical energy measurement and verification projects–motivations to study these objects will be explained in later sections. For this purpose, the relevant theoretical preparations on model-based system modelling methodologies are developed and then applied to these practical energy-related problems.

This is to say, this PhD project studies both theoretical modelling methodologies and their practical applications. On the theoretical part, energy system operation modelling problem is formulated as an optimisation problem subject to constraints formulated in terms of logic correlations, mass balance, energy balance, process and service correlations, and variable boundaries in [K1]; a model predictive control (MPC) method for a large class of energy optimisation problems is developed in [K2], where the corresponding convergence and robustness of the MPC algorithm are proved. On the practical application part, the developed model predictive control methods are applied to dynamic economic dispatch in [K4] to avoid ramp rate violations during periodic implementations of the power dispatch solutions. The modelling methodologies in [K1] and [K2] are also applied in supporting documents where I contributed on the key modelling part during the supervision of postgraduate student projects. For instance, these methodologies are applied to minimise the operational cost of a photovoltaic-diesel-battery hybrid system at a rural residential home in [S1], to estimate the energy savings from the temperature set point adjustment for air conditioners in [S2], to schedule home appliances for demand response in [S3], to determine the optimal building energy efficiency investment plan in [S4], to optimally size and schedule water pumping systems in [S5], and to minimise energy cost at a water purification plant by MPC approaches in [18]. The developed methods have also been applied by other researchers, for instance, the MPC approaches are applied in [19] to determine the energy dispatch strategy for a hybrid residential energy system, and in [20] to minimise the operational cost of conveyor belts.

The modelling methodologies developed in [K1] are applied in [K3] to minimise the energy consumption and energy cost of conveyor belt systems at a colliery, where the cumulative active energy costs are reduced by up to 49% during 5 weekdays in a high-demand season. This conveyor belt system energy optimisation study was further continued by other researchers in [21] and [22] to improve the relevant energy efficiency. The energy optimisation methods in [K1] are also applied to solve other types of energy problems, for example, it is applied in [S1] to minimise the operational cost of a photovoltaic-diesel-battery hybrid system at a rural residential home, and the logic and service correlation models in [K1] are also applied in [S3] to schedule residential loads. The modelling ideas are further applied in [K5, K6, K7] to identify faulty or poorly performed modules in PV arrays, and then optimally rearrange the PV modules to increase the maximum power output of the PV array. The energy optimisation modelling ideas developed in [K1] are also tailor-made in the performance evaluation of energy systems in [K8], where energy savings measurement and verification (M&V) process is mathematically modelled, and the M&V plan is characterised by an optimal control model to minimise M&V cost. This M&V plan optimal control modelling method has been applied in [S6] and [S7] to save metering cost for large scale lighting retrofit M&V projects. The M&V modelling methods, such as physical and data regression models, are practically implemented in an air conditioner intelligent switch control project in [K9], and also applied in designing the M&V guideline for heat pump rollout programme in [K10] which is further practically implemented by 6 M&V teams contracted by ESKOM in South Africa. The guideline [K10] was also implemented by my own group, and the relevant results are published in [S9].

Besides the above mentioned applications of the energy optimisation modelling methods in [K1], I also apply these methods in identifying the energy savings for air conditioners from set point adjustment [S2], building energy efficiency investment optimal decision-making [S4], and water pumping system efficiency improvement [S5]. I apply further the modelling ideas and methodologies from [K1] and [K8] to the practical M&V for building energy baseline identification [S8], savings from installing efficient air conditioning systems for industrial plants [S10], and the savings identification from the food refrigeration system energy efficiency improvement at supermarkets [S11].

Further detailed critical appraisal on my above publications are given in the following sections.

3 New Modelling Methodologies to Improve Energy Performance

My contribution on new modelling methodologies to improve energy performance includes publications [K1] and [K2], where [K1] is about building general models for energy system operational process, and [K2] is on the application of the MPC approach in load management. The main purpose of this section is to summarise existing modelling procedures and methodologies to help the performance optimisation and evaluation for practical energy systems.

3.1 Modelling methodologies for energy performance

On the energy performance optimisation modelling part, [K1] summarises the modelling target as an optimal control problem which is also discretised as an optimisation problem, then it classifies the corresponding model constraints in terms of mass balance, energy balance, boundary constraints, process and service correlations, etc., and in particular, it proposes a new type of constraints–logic correlation constraints. Logic correlations refer to logic relationships between energy system control variables, for example, the residential home energy system control system must ensure that the tumble drier can only be switched on after the washing machine has completed its job. Details of such a logic correlation modelling is given below (see [K1]).

Assume that an electrical energy system consists of N components, each of them can be independently controlled as on or off. Whenever the i-th component is switched on, its power consumption will be its rated power P_i kW for $i = 1, 2, \cdots, N_1$, and be any value between 0 and its rated power P_i kW for $i = N_1 + 1, N_1 + 2, \cdots, N$, where $N_1 \leq N$. The first N_1 components have only simple on/off status and include examples such as electric water heaters, electric kettles, and incandescent lights, while the last $N - N_1$ components have variant powers and examples can be motors controlled by variable speed drives. Let $u_i(t)$ represent the on/off status variable and is defined as follows:

$$u_i(t) \begin{cases} = 1, \text{if the } i\text{-th component is on and } 1 \leq i \leq N_1 \\ = 0, \text{if the } i\text{-th component is off and } 1 \leq i \leq N_1 \\ \in [0, 1], \text{ if } N_1 + 1 \leq i \leq N \end{cases}$$

For simplicity, I write the logic correlation models in [K1] only for the following example scenarios at two different time instants t_a and t_b.

(i) If $u_i(t_a)$ is in the switched on status, then $u_j(t_b)$ must be in the off status. To find out a mathematical equivalent expression for this constraint, the following sign function is introduced. Let $sgn(x)$ be 1 if $x > 0$; 0 if $x = 0$; and -1 if $x < 0$. Noting the fact that $u_i(t_a)$ and $u_j(t_b)$ are nonnegative, then it follows that this constraint is equivalent to:

$$(sgn(u_i(t_a)) + 1)(sgn(u_j(t_b)) + 2) \neq 6. \tag{1}$$

A prominent benefit to use sign function to obtain the above constraint is that this type of constraint covers the case when i or j is greater than N_1, that is, it allows the components to have constant power or variable power. An example for this type of requirement can be that a piece of equipment is powered either by the grid, or by a distributed generation system, but cannot be powered by the two at the same time. Then the connection status of the main grid to the equipment at time t corresponds to $u_1(t)$, while the connecting status of the distributed generation system at time t corresponds to $u_2(t)$. The following constraints are derived:

$$(sgn(u_1(t)) + 1)(sgn(u_2(t)) + 2) \neq 6, \text{for all } t.$$

(ii) If $u_i(t_a)$ is in the switched on status, then $u_j(t_b)$ must be in the on status. This constraint is equivalent to the following inequality.

$$(sgn(u_i(t_a)) + 1)(sgn(u_j(t_b)) + 2) \neq 4. \tag{2}$$

An example for this case is that at a residential home, when people switched on the TV at the lounge in the evening, they must have switched on the light in the lounge first. That is, when the status of the TV at time t_a is on, then the status of the light must already be on at t_a.

(iii) If $u_i(t_a)$ is in the switched off status, then $u_j(t_b)$ must be in the on status. This constraint is equivalent to:

$$(sgn(u_i(t_a)) + 1)(sgn(u_j(t_b)) + 2) \neq 2. \tag{3}$$

(iv) If $u_i(t_a)$ is in the switched off status, then $u_j(t_b)$ must be in the off status. This constraint is equivalent to:

$$(sgn(u_i(t_a)) + 1)(sgn(u_j(t_b)) + 2) \neq 3. \tag{4}$$

In practice, the logic correlations can be presented in other ways than the above example scenarios, and we need to write the corresponding mathematical models according to exact requirements in the practical scenarios. Even in exactly the same scenarios as above, the above obtained mathematical models are not unique and we can use many different approaches to obtain different models representing the same logic correlations. These points have not been fully explored in [K1] and are thus discussed here. Indeed, the above mathematical models are put into inequalities of the form $A \neq B$, which often need to be converted into equivalent forms like $(A - B)^2 > 0$.

Weakness in the above logic correlation models mainly lies in the presence of nonlinearity, that is, multiplications and the sign functions appear in these inequalities. Further research needs to be done to improve the above models, and in some special situations, other researchers introduce additional variables to avoid the presence of nonlinear constraints, for instance an additional variable is introduced in [23] to remove the absolute value of a variable. However, these logic correlations are often related to switching functions, and the obtained energy optimisation problems are thus integer or mixed integer programming problems. Any simplified representation to remove nonlinearity and obtain integer or mixed integer linear programming problem will only help researchers to use directly some optimisation software tools, e.g., GAMS, but would not help to reduce computational complexity generally as linear integer programming problems are still NP hard.

Nevertheless, the above obtained integer or mixed integer nonlinear programming problems can still be solved by existing software tools like the GA function in Matlab.

Besides the above logic correlation constraints, there is also the process and service correlation constraints which are difficult to be summarised by a general formula to cover all situations. This kind of process and service correlations cover many special requirements for specific process and services, for instance, a piece of equipment must be switched on for a minimum duration of certain time period. As an example, I applied this kind of constraints in deriving the following appliance continuous operation requirement for residential demand response in [S3]:

$$\sum_{t=d_i}^{e_i-(N_i-1)} u_{i,t}^{opt} \cdot u_{i,t+1}^{opt} \cdot u_{i,t+2}^{opt} \cdots u_{i,t+N_i-1}^{opt} \geq 1, \tag{5}$$

where $u_{i,t}^{opt}$ represents the optimal switching on/off status of appliance i at time t, and the above constraint means that appliance i must be switched on at least once during the considered time periods, and whenever this appliance is switched on, it must be kept switching on for at least a continuous period of N_i sampling time intervals.

Besides deriving the above (5), I applied further the modelling methodologies to derive all the other objective functions and constraints in [S3]. I also applied these modelling methodologies to derive the quadratic optimisation model for the PV-diesel-battery hybrid energy system in [S1], the air conditioner energy consumption model in [S2], the building energy efficiency investment model in [S4], the pump efficiency model in [S5], and the crusher energy consumption model in [24].

It is important to note that the intention of [K1] is to provide a summary of existing model-based system modelling methodologies to facilitate energy system management, and there are scenarios that we need to develop other specific modelling methods to cater for special needs. With the help of the modelling methods in [K1], we are able to solve many energy problems, as to be demonstrated in later part of this critical appraisal. Therefore, the first objective of this study on summarising existing optimisation modelling approaches is partially achieved.

3.2 Model predictive control for load management

Besides the above energy modelling methodologies developed in [K1], I noted also the importance to apply MPC approaches to improve energy performance control, and proved the corresponding convergence and robustness of MPC algorithms to solve a large class of load management problem in [K2].

In many industrial energy systems, the load profile at working days within a week typically does not change much. In other words, the daily load profile is roughly periodic with a period of 24 hours, for example, the pumping system load profile at water pump stations, the overall load profile at a food packaging plant, etc., have very stable repetitive patterns. For these kind of energy systems, it is possible to implement optimal solutions obtained over a 24 hour moving horizon by the MPC approach. This kind of MPC approach will have the benefit of closed loop controllers, therefore, it is able to feed back real time system changes to the controller, which makes the control solutions able to adapt to real time changes and robust against disturbances and noises. However, all such benefits of MPC will require convergence of the implemented solutions in MPC iteration loops. Therefore, it is the main intention of [K2] to prove the relevant convergence and robustness of the MPC algorithm for energy performance improvement, where it is also called a class of dynamic resource allocation problem in [K2].

Since the mathematics, and in particular the mathematical notations and definitions, in [K2] is quite complicated, these mathematical details are omitted here and the discussions in this subsection focus mainly on its key ideas. The MPC algorithm discussed in [K2] for energy systems is similar to all other types of nonlinear MPC algorithms: it needs to solve an optimisation problem at each iteration step. This optimisation problem is assumed to be a convex optimisation problem, which is possible in many load management problems. This implies that the problem under consideration can be nonlinear, provided it is convex. Usually for a nonlinear MPC algorithm, it is challenging to prove its convergence and robustness. To resolve this difficulty, [K2] applies the convergence and robustness results from convex optimisation, that is, the iteration steps in MPC are proved to correspond to a feasible solution algorithm in convex optimisation, and then traditional theory from convex optimisation is applied to prove convergence and robustness. To be more specific, an extended convex optimisation problem is defined, which is called the perfection of optimal dynamic resource allocation problem. Then it is found that each optimisation problem solved in the MPC iteration steps correspond to a special optimisation problem obtained by restricting the extended convex optimisation problem to certain region (i.e., through substituting part of its optimisation variables by known constants). Then a one-to-one correspondence is found between the MPC iteration loops of Algorithm $1'$ in [K2] and the gradient based iteration loops for convex optimisation. By a theorem from convex optimisation (Theorem 3.4.3 of [25]), Theorem 1 in [K2] shows the convergence of Algorithm 2 to the global optimisation solution of the convex optimisation problem, from which Theorem 2 shows that the MPC Algorithm $1'$ converges to the global solution of the extended convex optimisation problem (i.e. the perfection of optimal dynamic resource allocation problem). Following the same approach, the bound of system disturbance is provided in Corollary 1, under which the MPC Algorithm $1'$ solution is robust (i.e. the solutions will lie within expected error bounds).

The key contributions in [K2] lie in that it will secure the convergence and robustness performance to apply MPC approaches in many energy system performance optimisation problems. Although [K2] requires certain periodic conditions of system dynamics (e.g. the load), the corresponding robustness results actually relax this requirement, therefore, convergence and robustness of MPC are guaranteed for those practical energy problems if the load changes slightly over different periods. A water pumping system example is also provided in [K2] to illustrate the application of MPC in practical energy systems. A more involved example from dynamic economic dispatch will be discussed later (see also [K4]).

The weakness of [K2] lies in the following two aspects: the first is that the energy system under consideration must be a convex optimisation problem in the corresponding MPC algorithm, and the second is that the robustness bound will restrict the applicability of the MPC algorithm in terms of convergence and robustness. In practice, many MPC algorithms are applied to solve energy problems without considering convergence and robustness performances, and these energy problems may not satisfy the relevant convex or robustness boundary conditions. One possible way to resolve the convex requirement in proving the convergence of an MPC algorithm might be to check the possibility of relaxing the nonconvex optimisation problem in MPC iterations into a convex problem. It is noted that this kind of convex relaxation techniques has been successfully developed for optimal power flow in [26] and [27] in 2014, and it is also applied in distribution radial networks in [28] in 2015. It is therefore worthy investigating convexification of energy performance improvement problems so as to prove the corresponding convergence and robustness for the MPC algorithm. The second issue on robustness bound comes from the fact that this bound will relax the requirement of periodic condition, e.g., the periodic property of the load, therefore, we expect such a bound to be as big as possible so as to accommodate large variations of non-periodic loads. Potential ways to resolve this second issue could be using approaches other than convex optimisation, for example, Lipschitz optimisation might be a potential solution. I will try this in future studies. Nevertheless, the new MPC approach developed in [K2] enriches the modelling methodologies for energy performance optimisation, and the first objective on summarising existing model-based optimisation approaches is achieved.

3.3 Section conclusions

In this section, existing energy performance modelling methodologies are summarised in [K1] as an optimisation problem along with constraints from logic correlations, mass balance, energy balance, process and service correlations, and variable boundaries. Then the MPC approach to a large class of load management problems is presented together with the proof of the convergence and robustness of the MPC algorithm. Practical applications of these modelling methodologies will be shown in later sections. Therefore, the first objective of this PhD thesis on summarising existing model-based optimisation approaches has been successfully achieved, and the obtained logic correlations and the proofs of convergence and robustness for MPC algorithm provide also helpful guidance in the application of existing modelling methodologies.

4 Application of Modelling Methodologies in Industrial Energy Systems and Electric Power Dispatch

The modelling methodologies published in [K1] and [K2] are indeed developed gradually and are summarised from some of my previous research projects. After the publication of [K1] and [K2], the methodologies therein are further applied by myself and also other researchers in energy system performance optimisation. In this section, the relevant applications are studied in the conveyor belt system load management of a colliery ([K3]) and the electric power dispatch of generators ([K4]). The reason to choose the conveyor belt system at a colliery as a case study is that mining industry is one of the main contributors to the South African economy (The candidate was working in South Africa while these papers were wrote), and also mining system is typically very complicated, this case study will provide a very good example to show how we start from a complicated real world energy problem, prioritise key objectives to be studied, and eventually build an energy optimisation model to reduce energy cost. The reason to choose dynamic economic power dispatch as a case study is that this is a classical problem in electric power systems and has attracted the attention of many researchers for dozens of years. In practice, there is still the need to investigate this in the South African context since the main South African electricity generation company ESKOM periodically implements dynamic economic dispatch solutions and encounters the ramp rate violation problem which they actually left to the Automatic Generation Control to manage at machine's level. Therefore, this electric power dispatch problem will provide a very good example to illustrate the MPC approach developed in [K2].

4.1 Application of modelling methodologies in conveyor belt load management

As an example, let us consider the paper [K3] where I applied the modelling methodologies in [K1] to the conveyor belt system load management problem for a colliery.

In [K3], the primary target is to reduce energy cost at a South African colliery, where similar studies prior [K3] on conveyor belt system load management was still lacking. For this purpose, I developed an optimal control model (this part was firstly published in my conference paper [29] and formally appeared in journal version in [K3], then it is also included in [K1]) for general load management problem:

$$\begin{aligned} &\min J = \int_{t_0}^{t_f} \sum_{i=1}^{n} P_i(t)u_i(t)p(t)\mathrm{d}t, \\ &g(u(t), t) \leq 0, \end{aligned} \tag{6}$$

where J represents the total electricity cost of a general energy system consisting of n modules, $P_i(t)$ is the power consumption of the i-th module at time t, $[t_0, t_f]$ is the control period, $u(t) = (u_1(t), u_2(t), \cdots, u_n(t))$ is the switching status function, $p(t)$ is the electricity price, and $g(u(t), t)$ is a vector function representing the relevant nonlinear constraints. The above problem (6) is an optimal control problem. The general methods for solving the optimal control problems (6) are usually based on Pontryagin's Maximum Principle or its variations, see, for example, references in [30], [31], [32] and [33]. These methods often depend on some smooth conditions and the solutions of some differential equations which restrict their applications in practical problems.

Therefore, it is reasonable to discretise the optimal control problem to obtain an ordinary optimisation problem, where the optimal solution is not a time-varying function but a fixed point. Before applying the discretisation process, two implementation details are worthy to note. The first is that the time interval of the optimal control problem should be divided as many as possible so that the resulted ordinary optimisation problem is a close approximation of the optimal control problem, the second is that when the number of divided sub-intervals increases, the number of variables in the optimisation problem increases, and the computational complexity increases accordingly. Therefore, this kind of discretisation idea is applicable only if the total number of obtained variables is not too big so that computer algorithms can solve it quickly.

Now (6) can be discritised as follows. Divide the time interval $[t_0, t_f]$ into N sub-intervals so that each subinterval has the length $T_s := \frac{t_f - t_0}{N}$. Then the optimal control problem (6) can be approximated by

$$\begin{array}{rcl} \min \ J & = & \sum_{i=1}^{n} \sum_{j=1}^{N} P_i^j u_i^j p^j T_s, \\ s.t. & & g(u^1, u^2, \cdots, u^N) \leq 0, \end{array} \tag{7}$$

where $P_i^j = P_i((j-1)T_s), u_i^j = u_i((j-1)T_s), p^j = p((j-1)T_s)$, and $u^j = (u_1^j, \cdots, u_n^j)^T$. This is an ordinary optimisation problem with nN number of variables $\{u_i^j : 1 \leq i \leq n, 1 \leq j \leq N\}$. (Note: A typo in [K3] about the arguments of g is corrected.) Therefore, various solution algorithms from linear and nonlinear programming can be employed to solve this simplified problem.

The above modelling methods are applied in the energy management of a South African colliery. This colliery has a very complicated energy system. The whole plant has two identical Dense Media Separation (DMS) plant modules which are responsible for processing the ore materials from an open cast mine. The ore material from the mine is delivered to the colliery by train, and is dumped in rail bins before being transported to either the run-of-mine stockpile or directly to the DMS feed bin by the upstream group of conveyor belt system (called Group D in [K3], see also the system process flow chart in [K3]). After passing through the DMS plant modules, the processed material follows one of four paths according to the size and quality of the material:

- Discarded material is transported to the Discard Silo, m_{DS}, via the $N10$ and $N11$ conveyor belts;
- Export quality coal is transported to the Product Stockpile, m_{PRS}, via the $P10$ conveyor belt;
- Coal classified as *inland product* is transported to the *inland stockpile*, m_{INS}, via the $P15$ and $P16$ conveyor belts; and
- Product material that falls within the *PEAS* category sizes is transported to the *PEAS silo*, m_{PEAS}, via the $P14$ conveyor belt.

From the *product silo*, the export quality coal is either stacked on the *product stockpile* or transported, via the $Q10$ overland conveyor belt, to the *Rapid Loading Terminal* (RLT) silo. The *RLT silo* is used as a central base for loading the trains that transport export quality coal to the Y terminal. The trains are named RBCT trains, and the mass of the coal in an RBCT train at time t is denoted by $m_{RBCT}(t)$.

Solving the load management problem for this colliery at plant wide level is challenging due to the complicated process flows indicated above. For this purpose, I consider to prioritise certain subsystems to simplify the study–this is indeed a popular technique in the scoping study of energy audit. I first focus on the conveyor belt energy consumptions, as these are the major electric power consumption equipment at the plant. A general energy audit is done to analyse historical energy consumptions of each system components by using one years' power consumption data at this colliery. It is quite interesting to find that the downstream Q-group conveyor belt system makes the largest percentage (26%) contribution to the overall power consumption of all the conveyor belts at the colliery. The Q-group conveyor belts are also most suitable for load shifting energy management because this system can be isolated to be controlled independently from the rest of the colliery.

Then the above discretised optimal control model is applied to the Q-group conveyor belts to obtain the objective function and constraints. It is worth mentioning that the constraints are mainly obtained through the mass balance modelling method mentioned in [K1]. For example, one constraint obtained from the mass balance requirement is the following one, where the meanings of notations can be found in [K3].

$$m_{RLT}(t_{t0}) + T_s \sum_{t_i=t_{t0}}^{(t_{t1}-T_s)} r_{Q10\_MAX} \cdot u_{Q10}(t_i) - T_s \sum_{t_i=t_{t0}}^{(t_{t1}-T_s)} r_{Q13\_MAX} \cdot u_{Q13}(t_i) \geq m_{RLT\_THR},$$

By solving the above obtained optimisation problem, the obtained solution can reduce the cumulative active energy costs by up to 49% during five week days in a high-demand season. The percentage of total amount of energy used during peak time is also reduced from 25% to 8%. This case study shows the potential of using optimal control as a starting point for developing controllers to facilitate both load shifting and process optimisation. Furthermore, the ease with which approximated optimal solutions can be obtained by discretising these problems as ordinary optimisation problems is convenient for some other practical problems such as the load shifting in pumping processes and irrigation on farms etc.

The main weakness of [K3] lies in that we focus only on Q-group conveyor belts, while the mining industry has more and more interest in plant-wide energy management solutions, in particular the application of renewable energy in mining systems. There are also many other aspects which can help to improve the study of the conveyor belt system in [K3]. For example, other researchers from our same group have continued this conveyor belt system study, conveyor belt power consumption is analysed, and the conveyor belt load control under variable speed drive and time-of-use electricity tariff are studied in [21] and [22]. For further studies, I intend to develop a software tool on plant-wide load management for mineral processing energy systems so as to integrate my previous mining system component studies. For the moment, I have supervised group members to complete the studies on the load shifting of the rock winder systems at a deep gold mine [34], deep mine jaw crushing energy efficiency [24], energy minimisation of the cyclone circuits of a colliery beneficiary plant through pumping storage [35], and medium density control in coal washing cyclone circuits [36]. A plant-wide load management system incorporating solar or wind energy sources will be a very attractive topic in countries where mining industry makes a significant contribution to the economy, for instance, Australia and South Africa.

To summarise, energy performance optimisation modelling methods, such as mass balance modelling, optimal control, and nonlinear programming, are successfully applied in [K3] for the energy optimisation of the conveyor belt system at a colliery, thus the second objective on the application of performance optimisation modelling methodologies is partially achieved.

4.2 Application of MPC in dynamic economic dispatch of electric power

Now consider the application of the previously mentioned MPC algorithm in [K2]. An illustrative example is provided in [K4], where dynamic economic dispatch (DED) for electric power generation dispatch is studied under this MPC approach. Motivation of this DED study lies in the fact that existing studies on DED focus mainly on the power dispatch over a 24-hour period and there are no discussions on how this solution is to be implemented. In practice, a simply repeated implementation of this 24-hour solution may still have the ramp rate violation problem, although ramp rate violation is avoided within the 24 hour period. This is because that such an violation might happen at switch stages, i.e., between the power generated at the 24-th hour and the 25-th hour (i.e. the 1-st hour if the 24-hour solution is repeatedly implemented). Such a ramp rate violation has been show by examples in Figs. 2 and 3 in [K4], where the solutions are taken from standard examples on a 10 generation unit system over a 24 hour period. In South Africa, the main electricity supplier ESKOM also encounters the ramp rate violation problem which is left to the Automatic Generation Control to take care at the machine level. Therefore, the main target of [K4] is to solve this ramp rate violation problem by using the MPC approach developed in [K2]. Furthermore, the MPC approach needs to solve less number of optimisation variables than the original DED problem, thus computational complexity is reduced. Another interesting fact discovered in [K4] is that there are two different types of models for the dynamic economic power dispatch problem which were believed to be the same but actually not. Indeed, the dynamic dispatch problem of power generation is first considered in the early 1970's in an optimal control system framework [38]. Since then there are actually two formulations to solve optimal power dispatch problem with ramp rate constraints: the optimal control dynamic dispatch (OCDD) [38, 39] formulation based on control system models, and the DED [40, 41] formulation based on global optimisation. Both are useful for the dispatch problem over a fixed time horizon, and they were treated as equivalent formulations in literature. Indeed, the two are different as shown by the example in Fig. 1 of [K4]. Both formulations suffer from the same technical deficiency of ramp rate violation during the periodic implementation of the optimal solutions. In the proposed MPC approach for DED, the MPC algorithm from [K2] is applied to achieve the corresponding convergence and robustness of the MPC solutions. That is, the following Extended DED (EDED) problem (i.e. the perfection of the corresponding DED problem) is introduced so that the MPC solutions will converge to the solution determined by this EDED problem.

Problem: Extended DED Given n, N, DR_i, UR_i, $P_i^{\min}$, $P_i^{\max}$, $1 \leq i \leq n$, and D^k, $1 \leq k \leq N$, solve the following minimisation problem:

$$\begin{array}{ll} \min & C(P_i^k : 1 \leq i \leq n, 1 \leq k \leq N) \\ & = \sum_{k=1}^{N} \sum_{i=1}^{n} [C_i(P_i^k) + R_i(P_i^k)] \\ \text{subject to} & (P_i^k : 1 \leq i \leq n, 1 \leq k \leq N) \in \Omega_{EDED}, \end{array} \tag{8}$$

where n is the number of generators, T is the time duration of each sampling time interval, N is the total number of sampling time intervals under consideration, P_i^k is the power generation of the i-th generator at the k-th time interval, DR_i and UR_i are the ramp down and ramp up rates respectively, $P_i^{\min}$ is the minimum power of the i-th generator, $P_i^{\max}$ is the maximum power of the i-th generator, D^k is the demand at time k, $C_i(P_i^k)$ is the generation cost, $R_i(P_i^k)$ is the ramping cost, and the feasible domain Ω_{EDED} is defined to be the set of $(P_i^k : 1 \le i \le n, 1 \le k \le N)$ satisfying

$$\begin{array}{l}\sum_{i=1}^{n} P_i^k = D^k, \\ -DR_i \cdot T \le P_i^{j+1} - P_i^j \le UR_i \cdot T, \\ -DR_i \cdot T \le P_i^1 - P_i^N \le UR_i \cdot T, \\ P_i^{\min} \le P_i^k \le P_i^{\max}, \\ (1 \le i \le n, 1 \le j \le N-1, 1 \le k \le N).\end{array}$$

Compared to traditional DED constraints on ramp rate, the above EDED has one additional constraint $-DR_i \cdot T \le P_i^1 - P_i^N \le UR_i \cdot T$ which requires the power difference between the first time interval and the last time interval will not exceed the ramp rates. This constraint will avoid the ramp rate violation in case this EDED solution would be implemented periodically. However, with the MPC approach, this additional constraint is not needed, and in each MPC iteration loop, a revised OCDD problem with a reduced number of variables is solved, and the solutions from the MPC iterations are proved to converge to the solution of the above EDED.

From the robustness result from [K2], the following kind of disturbance Tw_i^{m+1} during solution implementation is considered:

$$\bar{P}_i^{m+2} = \bar{P}_i^{m+1} + T\bar{u}_i^{m+1}|_m + Tw_i^{m+1}. \tag{9}$$

where w_i^{m+1} is a disturbance vector satisfying $||w_i^{m+1}|| < e$, e is a positive constant, $\bar{P}_i^{m+1}$ is the power of the i-th generator at the $(m+1)$-th interation step, and T is the constant sampling time interval. It is concluded from [K2] that the corresponding MPC is robust under the above disturbance. In a remark of [K4], it is also noted that the above disturbance is quite general and can cover disturbance from forecasted demand, which allows the robustness results to be applied to more practical DED problems.

Case studies to verify the convergence and robustness of the MPC algorithm are undertaken using standard examples of a 6 unit system from [42] and a 10 unit system from [43]. It is important to note that the MPC approach to DED in [K4] does not contradict with any existing DED or OCDD methods. These existing DED and OCDD methods provide various optimisation solution methods to find the optimal dispatch over a fixed time horizon; while the MPC method in [K4] provides a periodic implementation framework and does not specify any particular optimisation method to solve the dispatch problem over a fixed time period. Furthermore, the MPC approach is in fact a very general philosophy: calculating an optimisation problem over a fixed period, implementing the solution only at the beginning part of this fixed period, recalculating the optimisation problem over a new time horizon, and repeating these steps. Following this idea, it is possible to incorporate these existing solution methods for DED and OCDD into this MPC framework.

Weakness of [K4] lies mainly on the following aspects. Firstly, the DED model considered in [K4] includes only basic constraints such as load balance and ramp rates, while more involved constraints such as line flow thermal limit, range of voltage, etc., are ignored. Including these security constraints will need to solve the nonlinear AC power flow problem, which will make the computation much more demanding. Intelligent computing techniques, for example, granular computing in [44], or the convex relaxation approach for power flow with line constraints in [26, 27], can be applied to improve the results in [K4]. Secondly, the case studies in [K4] are provided for smaller scale systems (e.g., 6 units or 10 units), a real power generation system together with complicated transmission system will be needed to verify the proposed MPC approach. Thirdly, recent development of distributed renewable generation and demand response in smart grid has not been considered in [K4], and the corresponding problem formulation can be improved by considering these new applications.

In summary, the MPC approach for the DED problem provides a closed-loop power dispatch solution which can optimise the solution according to system dynamic changes, avoid ramp rate violations, and also reduce the computational complexity. Thus the power dispatch problem targeted in the second objective of this thesis is solved.

4.3 Section conclusions

In this section, the modelling methodologies developed in [K1] are applied in a practical energy system-the conveyor belt system at a colliery, and the obtained solution has been shown to reduce the cumulative active energy costs by up to 49% during five week days in a high-demand season (see [K3]). The MPC method developed in [K2] is applied in the DED problem to avoid ramp rate violations during the periodic implementation of the power dispatch solutions (see [K4]). These case studies demonstrate that the modelling methods developed in [K1] and [K2] are applicable to real world scenarios. Thus the second objective of this thesis on the application of modelling methodologies in energy performance optimisation has been partially achieved. In the next section, more applications in PV systems will be studied to fully achieve the second objective.

5 Application of Modelling Methodologies in PV System Performance Improvement

In this section, model-based energy system modelling methodologies are applied to PV systems to reduce the cost of fault diagnosis and improve maximum power output. These results are published in [K5], [K6] and [K7]. The reason to study PV systems is because that the previous section studies only the application of modelling methodologies in traditional energy systems, e.g. conveyor belt systems and thermal plant power generation dispatch, while more and more renewable energy systems are now connected to the power grid, and there is a need to study the applications of possible modelling methodologies in renewable energy systems. Since solar PV system is one of the major renewable energy resources, it is selected to show how model-based energy system modelling methodologies are applied to solar PV research.

5.1 Modelling in PV fault diagnosis

In [K5], a new two-section PV array fault diagnosis method is proposed by optimising voltage sensor locations, where the terminology 'fault' covers both permanent fault (e.g. open circuit, short circuit and device aging) and temporary fault (such as dust, leaves, bird droppings and shadows). The mathematical modelling methods applied here is mainly to represent those physical properties of PV systems by mathematical functions, and then analyse the corresponding power generation capacity and process correlations. Fault diagnosis is very important in the maintenance of PV plant. Existing popular fault diagnosis technologies include thermal cameras ([45, 46, 47]), earth capacitance measurements (ECMs) [48], and time-domain reflectometry (TDR) [49]. In the thermal camera method, a gradual change in the thermal image of a PV module (e.g., due to device aging) poses a technical challenge [50], and high system costs also limit the wide application of thermal cameras. The ECM can locate the disconnection of PV strings, whereas the TDR technology can predict the degradation of a PV array. However, both the ECM and the TDR can only operate offline [48, 49]. In practice, online diagnosis methods are highly desired, which can take measurements while the tested device is in operation. To improve this, other online fault detection and reconfiguration methods are developed in [51, 52, 53, 54, 55]. However, its success depends on three conditions as follows: 1) a large number of relays are used; 2) the health state of all PV modules should be monitored; and 3) the high computing resource of the controller is required to calculate complex optimal arrangements. These increase the system cost and the control complexity. Therefore, [K5] proposes a low-cost and online fault diagnosis method with optimised voltage sensor locations that can effectively locate faulty PV strings and faulty modules.

In [K5], a $p \times s$ PV array consists of p strings connected in parallel, with each string consists of s PV modules connected in series. Voltage sensors are installed to monitor voltage differences across different places of the PV array. Following the current-voltage properties of the PV array and the corresponding power calculation models, a general sensor placement procedure is developed as follows, where voltage sensors are put between two nodes, and a node refers to the interface between two adjacent PV modules.

- All the nodes should be covered by voltage sensors.
- A sensor can only connect to one node in a string.
- Voltage sensor nodes cover different isoelectric points from different strings.
- If p or s is an even number, then each node is connected to and only to one sensor. If both p and s are odd, then there is one and only one node to be connected to two different sensors, whereas each of the remaining nodes is connected to one sensor.

With the measurement of the voltage sensors, a two-section fault diagnosis method is then proposed. That is, the fault diagnosis is conducted at both the low voltage section and high voltage section on the I-V curve of the PV array, and the following three steps will be conducted.

i) Locating a healthy PV string, i.e. a string with all modules healthy;
ii) Locating faulty PV modules in the low voltage diagnosis section; and
iii) Locating faulty PV modules in the high voltage diagnosis section.

In each diagnosis step, detailed criterion is proposed to assist the identification of healthy strings or faulty modules. For a 3×3 PV array, tables are given to list voltage characteristics of all the possible combinations of fault modules. Both simulation and experiment are done for the 3×3 PV array to verify the proposed methodology. These results show that the proposed diagnosis methodology work efficiently for the 3×3 PV array.

Compared with existing methods in literature, [K5] has made the following improvements. First, string current sensors are removed, and the number of voltage sensors is also reduced by optimising the location of voltage sensors. Second, an online two-section fault diagnosis method is developed to locate faulty PV modules. Finally, the state-of-health information can also be used for the Maximum Power Point Tracking (MPPT) and the PV array dynamic reconfiguration.

Weakness of [K5] is mainly that the methodology will become more and more complicated for large scale PV arrays. The voltage characteristics are given for a 3×3 PV array only in [K5], for large size PV arrays, obtaining similar voltage characteristic tables will be difficult, and indeed unnecessary since it will contain too many items to be verified. Therefore, a computer based algorithm needs to be developed to automatically calculate the corresponding voltage characteristics and identify the location of faulty modules. With the fault monitoring results from [K5], the PV modules can be rearranged to improve the maximum power output as to be introduced in the next subsection.

To conclude, mathematical modelling approaches are applied in [K5] to minimise the number of voltage sensors for the PV fault diagnosis problem, thus the target on PV diagnosis of the second objective in this PhD project is achieved.

5.2 Modelling methodologies to improve the maximum power of nonuniformly aged PV arrays through module rearrangement

Different PV modules of a PV array may have different aging conditions, and thus their power output performance will be different. Assume that these different aging conditions are monitored, e.g. by the method in [K5] or any others, then model-based optimisation approaches are applied in [K6] and [K7] to characterise this kind of nonuniformly aged PV arrays, and the maximum power of the overall PV array is maximised by rearranging the PV modules. A mathematical expression calculating the maximum power under all possible PV module rearrangement is presented in a proposition of [K6]. Note that although the PV modules are allowed to have different power output performance in [K6], it is assumed that all PV cells within any same PV module will have the same aging condition, and thus perform the same in terms of power generation. In [K7], this assumption is relaxed and each PV module is divided into 3 sub-modules, and the 3 sub-modules within a same PV module are allowed to have different aging conditions, and thus different power generation capacities. For the relaxed situation in [K7], a mathematical expression calculating the maximum power under rearrangement cannot be derived, however, a nonlinear constrained integer programming problem is formulated to search the optimal rearrangement plan for particularly large scale PV arrays. Therefore, the optimisation model obtained in [K7] provides a convincing illustration of applying the optimisation modelling approaches in [K1] and [K3].

For aged PV systems, usually there are two solutions to improve the PV power output efficiency. The first one is to use global maximum power point tracking (GMPPT) strategy to pursue high energy conversion efficiency. Although GMPPT can improve the PV array output efficiency under fault conditions compared to traditional MPPT, there are still power generation capacities not being fully developed. In order to fully explore PV array generation capacity under fault or aging conditions, the second solution is proposed, which employs on-site PV array reconfiguration to improve PV array efficiency. There are some existing studies on on-site PV array reconfiguration, for example, reference [56] proposed a classical optimisation algorithm for a reconfigurable total cross-tied (RTCT) array, and a branch and bound algorithm is applied for a 6×4 PV array which still needs much computational efforts. Tabular search method was developed in [57] and tested for a small scale PV array (24 PV modules), it is almost impossible to use this method for large PV arrays due to its computational complexity. For a 3×2 PV array, [58] reduced the searching space by fixing the number of modules per row, while paper [59] developed an exhaustive searching algorithm in a 3×2 PV array. In order to speed up the configuration selection process, paper [60] developed a sorting algorithm based on the best-worst paradigm and applied this method to a 3×3 array. Reference [61] proposes a genetic algorithm to solve the rearrangement problem, however it does not provide a mathematically explicit formulation and thus restricts the application of other optimisation algorithms. To summarise, existing approaches for PV reconfiguration are either limited to small size PV systems, or algorithm specific and does not allow applications of other optimisation algorithms. Furthermore, none of the existing studies can provide any simple mathematical expression to calculate the maximum power under reconfiguration for the case where the PV cells inside a same PV module have the same aging conditions.

The above mentioned problems are solved in [K6] and [K7]. In [K6], first principle modelling technique is applied to derive the relations of maximum power output, current and voltage at each PV module and string. Then the following proposition is proved to calculate the maximum power for a $p \times s$ PV array (i.e. p strings, and each string has s PV modules).

Proposition Assume that all the PV cells within any same PV module have the same aging conditions, and the maximum short circuit currents of the ps PV modules are arranged from big to small as follows.

$$\beta_1 \geq \beta_2 \geq \cdots \geq \beta_{ps}.$$

Then the maximum power output of this PV array under module rearrangement is:

$$\max\{P_1^{\max}, P_2^{\max}, \cdots, P_s^{\max}\}, \tag{10}$$

where $P_1^{\max}, P_2^{\max}, \cdots, P_s^{\max}$ are determined by the following:

$$\begin{aligned}
P_1^{\max} &= (\beta_1 + \beta_2 + \beta_3 + \cdots + \beta_{p-1} + \beta_p)V_{\text{module}}, \\
P_2^{\max} &= 2(\beta_2 + \beta_4 + \beta_6 + \cdots + \beta_{2(p-1)} + \beta_{2p})V_{\text{module}}, \\
&\vdots \\
P_{s-1}^{\max} &= (s-1)(\beta_{(s-1)} + \beta_{2(s-1)} + \beta_{3(s-1)} + \cdots + \beta_{(p-1)(s-1)} + \beta_{p(s-1)})V_{\text{module}}, \\
P_s^{\max} &= s(\beta_s + \beta_{2s} + \beta_{3s} + \cdots + \beta_{(p-1)s} + \beta_{ps})V_{\text{module}},
\end{aligned}$$

and V_{module} is the maximum power point voltage supplied by a single PV module.

Following the above Proposition, a PV module rearrangement algorithm is developed in [K6] to achieve the maximum power calculated in (10). Simulation for a 5×10 PV array shows that the maximum power can be improved by 14.28%. Experiment on a 3×3 PV array illustrates further that the maximum power output can be improved by 13.5%.

In [K7], the uniform aging assumption within each PV module is relaxed in the way that each module is modelled by a series connection of 3 sub-modules, and these sub-modules can have different aging conditions. Although these 3 sub-modules inside a same PV module can have different aging conditions, they still physically locate in the same module and cannot be decomposed during the PV reconfiguration. That is, the reconfiguration can only rearrange each PV module, but cannot rearrange each sub-modules. This would imply that conclusions from the above Proposition in [K6] cannot be applied anymore, and we need to find a new method to calculate the maximum power output under the rearrangement of PV modules. For this purpose, the following optimisation model is formulated to calculate the maximum power.

Denote the original locations of the ps modules in the $p \times s$ PV array by the integer vector $(1, 2, 3, \cdots, ps)$, where the first s components $(1, 2, \cdots, s)$ in this vector represents the locations of the s modules in the first string, the second s components $(s+1, s+2, \cdots, 2s)$ represents the locations of the modules in the second string, and similarly, the last s components $((p-1)s+1, (p-1)s+2, \cdots, ps)$ represents the locations of the modules in the p-th string. By this convention, any rearrangement of the original PV array will correspond to a permutation of the vector $(1, 2, 3, \cdots, ps)$. Thus we can define the optimisation variable $x = (x_1, x_2, \cdots, x_{ps})$ to be a ps dimensional integer vector which is a permutation of $(1, 2, 3, \cdots, ps)$, and the first s components of x will correspond to the new locations of the s modules of the first string after a rearrangement, the second s components of x will correspond to the new locations of the s modules of the second string, and the last s components of x correspond to the new locations of the s modules of the p-th string after the rearrangement. Then the maximum power under re-arrangement is calculated by the following nonlinear integer programming problem.

$$
\begin{array}{rl}
\max & P_{\max}(x) \\
\text{subject to:} & x_i \in \{1, 2, \cdots, ps\}, i = 1, 2, \cdots, ps \\
& \Pi_{1 \le i < j \le ps} \ (x_i - x_j)^2 \ge 1,
\end{array}
$$

where $P_{\max}(x)$ is calculated by

$$P_{\max}(x) = \max\{P_{\text{m}}^1, P_{\text{m}}^2, \cdots, P_{\text{m}}^{3s}\},$$

and P_{m}^j is the maximum power genreated by the PV array when there are only j sub-modules generating electricity in each PV string, $j = 1, \cdots, 3s$. Assume that the maximum short circuit currents of all the $3s$ sub-modules in the i-th PV string are arranged from big to small as

$$\delta_1^i \ge \delta_2^i \ge \delta_3^i \ge \cdots \ge_{3s-1}^i \ge \delta_{3s}^i,$$

then the maximum power P_{m}^j mentioned above is calculated by:

$$P_{\text{m}}^j = j(\delta_1^j + \delta_j^2 + \cdots + \delta_j^{p-1} + \delta_j^p) V_{\text{module}}/3.$$

After obtaining the above mathematical representations of the rearrangement optimisation problem, any possible optimisation algorithm can be applied. For convenience, Matlab built-in genetic algorithm function is applied in the simulations. For randomly generated aging conditions, the above rearrangement optimisation can improve 6.33%-8.96% maximum power for a 20×10 PV array under 20 random tests. For a much larger 125×20 PV array, simulations have been studied for 15 randomly generated aging conditions. It has been observed that the power improvement through re-arrangement is from 7.58% to 10.93%, and the corresponding average computing time for these tests is 3.925 seconds by using the Matlab GA function on a computer with Intel (R) Core (TM) i7-3540M CPU 3.00GHz, 8G RAM. Note that the above nonlinear integer programming problem is NP hard, and the number of potential rearrangement choices, which equals $\binom{2500}{20}\binom{2480}{20}\cdots\binom{40}{20}\binom{20}{20}/(125!)$, is extremely large (calculating this number will cause memory overflow for Matlab), therefore, the computing time of 3.925 seconds is quite satisfactory.

To summarise, the reconfiguration methods in [K6] provide an explicit mathematical expression to calculate the maximum power under rearrangement for PV arrays ignoring the different aging conditions of PV cells within any same PV module, while the optimisation model in [K7] can calculate the maximum power under arrangement for PV arrays with differently aged submodules. Experiments and simulations show the effectiveness of these reconfiguration methods.

Weakness of the reconfiguration results in [K6] lies in that different aging performance of PV cells within a same PV module is ignored. This has been improved in [K7] where it is assumed that each PV module is a series connection of 3 sub-modules, and these sub-modules are allowed to have different aging conditions. Even though, this is still a strong assumption compared to real scenarios. A real world PV module may have many aging situations, and different cells within the same module may display different characteristics, thus a simple series connection of 3 sub-modules would not be able to fully characterise real world aging conditions. More complicated connection structures of more sub-modules can be considered to improve the accuracy of the PV model, and detection of such aging conditions might need more advanced fault monitoring systems. The optimisation model in [K7] can be further revised to cater for the need of more complicated models of PV modules.

Note that the PV power maximisation in [K6] and [K7] is obtained through model-based optimisation approaches, therefore, the target on PV maximum power generation of the second objective in this PhD study is achieved.

5.3 Section conclusions

In this section, model-based optimisation approaches are applied to investigate PV fault diagnosis problem and the rearrangement problem for aged PV systems. A cost saving two-section online fault diagnosis process is proposed to optimally determine the locations of voltage sensors and identify locations of faulty modules. Then for those PV arrays, where PV cells within any same PV module are assumed to have the same aging conditions, an explicit mathematical expression is derived to calculate the maximum power under all possible PV module rearrangements. For PV arrays where each PV module is further divided into 3 sub-modules and different sub-modules may have different aging conditions, a nonlinear integer programming problem is formulated to determine the optimal PV module rearrangement. Simulations and experiments are carried out to verify the effectiveness of these obtained results. Since aging phenomenon happens gradually, the developed rearrangement technique can be implemented offline during scheduled maintenances (e.g., once a few years or even longer). It can be combined together with other online maximum power point tracking and reconfiguration techniques for real time shadowing to improve the overall power generation efficiency. The results in this section shows that the optimisation models in [K1] and [K3] can be applied in PV systems to maximise power generation, and the mathematical models for PV power output and minimum number of voltage sensors can be applied to achieve a low cost PV fault diagnosis method. Note that the previous Section 4 has discussed the applications of modelling methodologies to optimise industrial energy systems and power dispatch, and this section presented the relevant applications in PV systems, therefore, the second objective of this PhD project on the applications of modelling methodologies in energy performance optimisation has been fully achieved.

6 Application of Modelling Methodologies in Energy Performance Evaluation

In this section, modelling methodologies will be applied in the performance evaluation of energy systems, which is also called measurement and verification (M&V). The target of M&V is to evaluate if an energy project has achieved its savings target, and the models built in this section are targeted to calculate such savings, therefore, M&V itself does not provide energy or energy cost savings, and it only provides reasonably calculated savings information to the relevant stakeholders. This section will briefly introduce publications [K8], [K9] and [K10]. In [K8], the M&V process is first modelled mathematically, and then the M&V plan is formulated as an optimal control model to save M&V cost. It is noted that this M&V cost saving is for the M&V process only, and is not directly related to the energy cost savings of the energy project being measured and verified. The optimal control approach for M&V plan obtained in [K8], which is indeed an application of the optimal control models in [K1] and [k3], is further applied in [S6] and [S7] to minimise the metering cost for United Nation's Clean Development Mechanism lighting projects, where I formulated the optimisation models. I apply also these mathematical modelling methods, such as the physical models and data regression models in [K8], to more than 100 practical M&V projects. For instance, I completed the M&V for the energy savings from the installation of air conditioner intelligent switch control units in 123 office buildings of ESKOM, the results are submitted in a series of reports to ESKOM, and a brief project summary is published as a book chapter (see [K9]) in a book I co-edited [62]. I also developed the M&V guideline in [K10] for the quantification of energy savings from the installation of 65,586 heat pump water heaters throughout South Africa, where the classification and regression analysis methods are applied to calculate the energy savings, and an Excel Application is also developed and distributed to 6 ESKOM contracted universities for practical implementation. As an example, this guideline and the corresponding Excel Application were applied to the M&V of the ESKOM Northern Distribution Region, where I supervised a team member to deliver the corresponding metering, modelling, data analysis and reporting, and the results are also published as a chapter of the above mentioned book (see [S9]). Other practical implementations of the M&V modelling methods are provided in the supporting documents, such as the M&V for building energy performance ([S8]), industrial plant air conditioning systems ([S10]) and supermarket food refrigeration energy efficiency ([S11]).

6.1 Mathematical modelling for M&V process

Note that the modelling methodologies in [K1] and [K2] are developed to characterise general energy system performance, and they may not be very efficient in measuring and verifying the performance of energy systems, therefore, tailor-made M&V modelling methodologies are developed in [K8] and are reviewed in this subsection.

Motivations for the study in [K8] are given as follows. Since there are many energy efficiency projects initiated to achieve various energy saving targets for the purpose of energy security and emission reduction, the performance of these energy projects needs to be measured and verified, and in many countries such an M&V activity is guided by the International Performance Measurement and Verification Protocol (IPMVP) [63]. There are also some other energy saving M&V guidelines which are essentially similar to IPMVP, and these guidelines include, but are not limited to, the M&V Guideline for the Federal Energy Management Programme [64]; the M&V Guideline of the American Society of Heating, Refrigeration and Air Conditioning Engineers (ASHRAE) [65]; and the South African M&V guideline for Demand Side Management Projects [66]. Researchers have put more attention in applying these M&V guidelines in practical energy projects. For instance, [67] discusses the M&V method for a motor sequencing control of a conveyor belt system, [68] gives a general method for calculating plant-wide industrial energy savings, [69] and [70] propose a bottom-up approach to energy saving calculations, [71], [72], [73], [74] and [75] study the uncertainties in M&V, [76] considers the Louisiana home energy rebate offer programme, [77] proposes general guidelines for energy modelling in M&V, and [78] provides the M&V strategies for energy savings certificates.

In M&V, the most challenging part is to find out a proper M&V plan so as to quantify the relevant power and energy savings accurately at the least cost. The competitive targets of accurate savings quantification and minimum M&V cost need to be properly balanced. In many existing practical M&V projects, the savings accuracy is often not discussed due to its complicated nature and the lack of proper mathematical models. Therefore, [K8] presents a mathematical description of the M&V process to solve this problem. Note that the mathematical models in [K8], [K9] and [K10] are designed according to ESKOM M&V Guideline [66] on power and energy savings calculation, where its concept of 'power' is not instantaneous power, but indeed 'energy' as it is calculated by taking average values of real power consumption per half hour ([79] allows integrating for 30 min, 15 min, 5 min or 1 min for different storage durations, and in practice most of projects use 30 min integration period to save longer period of data), although it is required to measure and verify the load profile (power vs time curve, see Appendix F Example of an M&V Plan, Page F12, in the Fifth Version, Revision 3, of ESKOM M&V Guideline [66], note also late versions of ESKOM M&V Guidelines do not have appendices for samples of M&V plan or any other M&V reports due to commercial reasons). Starting from energy system modelling, [K8] introduces mathematical models for baseline function, exogenous factor function, M&V baseline, and the target of M&V problem. Physical models, data models, and stochastic models are provided in [K8] to model the M&V problems and calculate energy savings. With the help of these concepts and also the concept of optimal control, the following optimal M&V plan problem is formulated to minimise the modelling approximation errors in identifying pre-implementation baseline and the post-implementation performance, and also the M&V cost.

$$
\begin{cases}
\quad \min \ \int_{t_0}^{t_1} |f(x_B(t), p_B(t)) - G(x_\alpha(t), p_B(t))| \mathrm{d}t, & \\
\quad \min \ \int_{t_2}^{t_f} |g(x_A(t), p_A(t)) - H(x_\alpha(t), p_A(t))| \mathrm{d}t, & \\
\quad \min \ C_\alpha(x_\alpha, t_f) & \\
s.t. \ |f(x_B(t), p_B(t)) - G(x_\alpha(t), p_B(t))| < \epsilon, & t \in [t_0, t_1], \\
\quad |g(x_A(t), p_A(t)) - H(x_\alpha(t), p_A(t))| < \epsilon, & t \in [t_2, t_f], \\
\quad \Xi(x_\alpha(t), p_B(t)) = 0, & t \in [t_0, t_1], \\
\quad \Omega(x_\alpha(t), p_A(t)) = 0, & t \in [t_2, t_f], \\
\quad C_\alpha(t_f) := C_\alpha(x_\alpha, t_f) < U, &
\end{cases} \tag{11}
$$

where t is time, $[t_0, t_1]$ is the baseline time period, $[t_2, t_f]$ is the post-implementation period, p_A and p_B are parameters, x_A and x_B are state variables, $x_\alpha = (x_{i_1}, x_{i_2}, \cdots, x_{i_k})$ represents state variables to be measured, f is the baseline power consumption function, g is the post-implementation power consumption function, G and H are optimal control functions to be identified so as to approximate f and g respectively, C_α is the M&V cost function, Ξ and Ω define the constraints that x_α satisfies, U is the upper bound for available M&V budget, and ϵ is an acceptable error bound. The first minimisation objective in (11) is to minimise the approximation errors of G to the baseline function f over the pre-implementation period $[t_0, t_1]$, the second objective is to minimise the approximation errors of H to the actual performance function g over the post-implementation period $[t_2, t_f]$, and the last objective is to minimise the M&V cost.

This optimal control model is successfully applied to the M&V of a large scale lighting retrofit project in [S6] and [S7], where I formulated the optimisation models to minimise the metering cost while satisfying the 90% confidence and 10% precision requirement of the United Nation's Clean Development Mechanism projects. The difference between [S6] and [S7] is that [S6] does not consider the life decay of lighting bulbs, while [S7] considers this.

The weakness of [K8] mainly lies in the lack of a practical M&V example, and it would be much improved if any similar example like those in [S6] or [S7] would be included. Other aspects to improve [K8] is to reduce some mathematical descriptions and add more examples, particularly any practical example using stochastic modelling approaches to identify the optimal M&V plan.

In summary, tailor-made M&V evaluation models are built in [K8] to efficiently evaluate the performance of energy savings projects. The third objective on the application of modelling methodologies in performance evaluation is therefore partially achieved.

6.2 Modelling in practical M&V projects

In this subsection, several practical M&V projects I conducted are reviewed to illustrate the application of M&V modelling methodologies, in particular the physical modelling and data regression modelling methods in [K8]. This includes mainly the M&V projects on the air conditioner intelligent switch control in commercial buildings [K9], and the mass rollout of heat pump water heaters [K10].

In [K9], 1,743 intelligent switch air conditioner control units on split air condition units are installed in 2011 for 123 office buildings of ESKOM northern region. The targeted power saving is 0.5 MW during the period 07:00 am to 17:00 pm each day, and the expected energy saving is 1.8 GWh per annum. In order to quantify these claimed savings, I first conducted an energy audit for these buildings. It is found that these buildings have a wide range of floor sizes and power consumption levels. The floor area ranges from 60 m^2 to 15,800 m^2, and the average power consumption of air conditioners in each building ranges from 2.1 kW to 566 kW in summer and from 2.3 kW to 663 kW in winter. These buildings also perform different functions, some are general offices, some are for technical support, and some are for client consulting services. To control the M&V cost within the available budget, the metering design plan should minimise the metering cost while at the same time maintain necessary accuracy. For this project, it will cost too much if all the air conditioners in each building are placed with power meters. It is therefore necessary to classify these buildings in terms of size, function and power consumption levels into a few groups, and then take samples at metering points from each group. Following this idea, the 123 buildings are classified into 4 groups in terms of both the floor area size and the number of air conditioner units, then each group is further divided into 3 subgroups in terms of functionalities: general office, technical support, and client consulting. 2 to 5 meters are installed at each of these 12 subgroups, and the exact number of meters depends on the population size of a particular subgroup.

After collecting metering data from pre-implementation and post-implementation of the intelligent switches, linear regression is applied to analyse impact of outdoor dry bulb temperature, working day/weekends, hours of day, and heating/cooling load to the corresponding energy savings. From the assessment the averaged power saving is 0.6013 MW, 0.4876 MW, and 0.3386 MW during the period 07:00 am to 17:00 pm in weekday, Saturday, and Sunday, respectively. The overall average power saving is 0.5475 MW, and the estimated annual energy saving is 1.998 GWh. Therefore, the targeted power saving of 0.5 MW has been achieved successfully at the reporting period.

In [K10], an M&V guideline is provided for the savings quantification of the rollout of 65,586 heat pump water heaters during November 2010 to March 2013 in South Africa. These heat pumps will replace existing electric water heater geysers for mainly residential customers, lodges, and B&B (Bed and Breakfast). There are two categories of heat pumps, Category 1 is the low priced 100 to 300 litres domestic heat pumps, while Category 2 is the high priced 300 to 500 litres domestic heat pumps. Input electric power to the first category is between 0.8 kW to 1 kW, while the corresponding same volume electric water heater (i.e. without heat pump) is usually between 3 kW to 4 kW. The input electric power of the second category is around 1.7 kW as contrast to the input electric power from 4 kW to 6 kW of electric water heater with the same volume.

It is noted that ESKOM has conducted extensive research on water heater load profile through its Residential Load Management (RLM) project [80], and this RLM classifies water heater load in terms of costal area and inland area, therefore, this heat pump project classifies the heat pump load into four groups: inland category 1 heat pump, costal category 1 heat pump, inland category 2 heat pump, and costal category 2 heat pump. The baseline load will be identified through the corresponding RLM project and be built in an Excel Application toolkit. Meters are installed at selected sample heat pumps from each group to collect the performance of heat pumps and minimise metering cost. Coefficients of performance (COP) of heat pumps will be used to calculate the equivalent thermal energy, and also the energy savings.

After providing the above technical details in [K10], I also lead the development of the above-mentioned Excel Application to implement the corresponding heat pump M&V. The guideline [K10] and the corresponding Excel tool are implemented by 6 ESKOM contracted universities, and as part of these contracted university M&V teams, I implemented them for the performance of 382 installed heat pumps in ESKOM Norther Distribution Region (see [S9]). The initial target for these heat pumps is the power reduction of 157.68 kW, while the average actual power reduction at weekday evening peak is 67.6 kW. The targeted monthly energy consumption saving is 39.15 MWh, while the verified energy consumption saving is 39.61 MWh for these 382 heat pumps.

Weakness in [K9] and [K10] is that many technical details are included in the corresponding technical reports and Excel Application toolkit, such as details of baseline data, regression analysis, etc., and it is copyright protected by ESKOM due to commercial reasons. Each M&V project needs to deliver a series of report, starting from scoping report, then baseline report, M&V plan report, performance assessment report, and multiple performance tracking reports at different time periods. [K10] provides only an overview of the heap pump project, and these detailed reports are unable to be released to the public because of commercial reasons.

In addition to the above heat pump project, I also implemented the M&V modelling methodologies, e.g. regression modelling to calculate savings in terms of sampled metering data, temperature, etc., for other projects, such as the building project in [S8], air conditioner project in [S10] and food refrigeration in [S11]. The main purpose of [S8] is to obtain building energy consumption baseline for further energy efficiency improvement. The baseline is obtained for more than 100 ESKOM Northern Region office buildings following questionnaires, energy bills, metered data, and the regression analysis of temperature, floor size, etc. The purpose of [S10] is to measure and verify the expected target of a 2.5 kW reduction in power use and a 1.70 MWh annual reduction in energy use by replacing existing air conditioners with more energy efficient ones in the office building of an industrial plant. Temperature data are applied to calculate its impact to energy savings. In [S11], food refrigeration system energy efficiency at a supermarket company are considered. This is a pilot project at 8 stores of the company, and it is later on rolled out to all other hundreds of branch stores of the company. The project includes installations of electronic expansion valves, variable speed drives, anti-sweat heater controller, automatic night blinds, and ventilation controls. Temperature information has been used to analyse its impact to power and energy savings. The averaged power saving actually achieved is 0.4417 MW, 0.4385 MW, and 0.4288 MW in weekday, Saturday, and Sunday, respectively. The targeted power saving of 0.383 MW has been achieved successfully during the reporting period.

Therefore, the M&V modelling methodologies are successfully applied in many practical energy evaluation projects, which achieves the performance evaluation objective of this PhD study.

6.3 Section conclusions

In this section, modelling methodologies are applied in M&V. Key contributions include the derivation of the optimal control model to minimise M&V cost in [K8], the practical implementation of physical modelling and data regression modelling methods in air conditioner intelligent switches for office buildings in [K9] and the mass rollout of domestic heat pumps in [K10]. The optimal control model in [K8] is further applied to large scale lighting projects in [S6] and [S7], and the heat pump M&V guideline in [K10] is also implemented in [S9]. More practical applications on M&V modelling methods are also reported, such as building baselines in [S8], air conditioner replacement in [S10], and food refrigeration systems in [S11]. Therefore, the third objective of this PhD study on the applications of modelling methodologies in energy performance evaluation has been successfully achieved.

7 Conclusions

This PhD work discusses applications of model-based optimisation approaches for energy performance optimisation and evaluation. The main contributions consist of the following three parts, which are summarised in key publications [K1]-[K10].

i) Theoretical contribution on energy performance modelling:

- Optimal control model and its equivalent discritisation as an optimisation problem are applied to energy performance improvement problems ([K1, K3, [29]]);
- The above obtained optimal control or optimisation problem is subject to constraints obtained from logic correlations, mass balance, energy balance, process and service correlations, and boundary constraints ([K1]);
- The above logic correlation is a new concept and has important applications in describing logic constraints such as two events cannot happen at the same time or one event must happen after another, more practical applications are illustrated in [S3]; and
- Model predictive control is proposed for a class of load management problems, and the convergence and robustness are proved in [K2] and further validated by dynamic economic dispatch examples in [K4].

ii) Application of the obtained modelling methodologies in energy performance optimisation:

- Mass balance, process and service correlations amongst other modelling methods are applied to solve the conveyor belt load management problem at a colliery for operational cost minimisation ([K3]), where the cumulative active energy costs are reduced by up to 49% during 5 weekdays in a high-demand season;
- Model predictive control approach is applied to dynamic economic dispatch problem to solve the ramp rate violation problem during the periodic implementation of the power dispatch solutions ([K4]);
- Process and service correlations, logic correlations and other energy modelling methods are applied in many other energy problems, such as those in [S1]-[S5];
- A two-section PV fault online diagnosis process is proposed to minimise the number of voltage sensors ([K5]);

- Mathematical models are built for the maximum power output of aged PV arrays, and a mathematical expression is derived to calculate the maximum power under PV module rearrangement when PV cells inside any same PV module are assumed to have the same aging conditions ([K6]); and

- An optimisation model is presented to calculate the optimal module reconfiguration and the corresponding maximum power output of aged PV arrays where each PV module may have three differently aged submodules ([K7]).

iii) Applications of the obtained modelling methodologies in energy performance evaluation:

- Mathematical models are developed for energy performance measurement and verification, and in particular, an optimal control model is presented to minimise measurement and verification cost ([K8]); this optimal control model is applied in large scale efficient lighting projects in [S6] and [S7] for metering cost minimisation in the United Nations' Clean Development Mechanism projects;

- Physical models and data regression models from [K8] are applied in practical energy measurement and verification projects for the installation of 1,743 air conditioner intelligent switch control units in 123 office buildings ([K9]) and the rollout of 65,586 heat pumps in South Africa ([K10, S9]); and

- Similar modelling methods are also applied in building energy baseline, air conditioner replacement, and food refrigeration systems in supporting documents of [S8, S10, S11].

From the above listed contributions, the expected objectives on summarising existing model-based optimisation approaches for energy system modelling, and applying the obtained modelling methodologies to energy performance optimisation and evaluation are achieved.

I have had some further work to improve and extend the above obtained results. For example, the colliery conveyor belt load management results in [K3] are extended to other parts of mining plants by the modelling methods in [K1, K2, K3], and rock winder systems are studied in [34], crushing process is studied in [24], medium density control for coal washing dense medium cyclone circuits is studied in [36]. The DED problems investigated in [K4] is studied by intelligent computing approach in [81], and it is also combined with modern smart grid technologies and other energy sources in [82, 83]. The modelling methodologies used in [K8, K9, K10] are applied to deliver more than 100 practical measurement and verification projects during 2009-2013.

As mentioned in the reviews of the weakness of each publications in [K1]-[K10], there are a lot of other further work to be done to improve and expand this PhD study. For example, the modelling methodologies developed in [K1] can be much improved by providing linearised constraints to simplify representations and computations, and there are some possible approaches to strengthen results from [K2]-[K8], such as the convexification approach to extend the applicability of the MPC approach in [K2], plant-wide energy optimisation to improve the limited scope of [K3], inclusion of demand response and distributed renewable generation in the study of DED in [K4], voltage characteristics for large scale PV array diagnosis (see [K5]), development of a better optimisation model to cater for the different aging conditions of each cells within a PV module during PV array rearrangement (see [K6, K7]), and further applications of the optimal control models in [K8] for M&V cost minimisation. Besides working on these problems, I am also working on the application of stochastic programming approaches in energy performance optimisation and evaluation.

References

[1] S Pfenninger, A Hawkes and J Keirstead, Energy systems modelling for twenty-first century energy challengs, Renewable and Sustainable Energy Reviews, vol. 33, 2014, pp. 74-86.

[2] MARKAL, International Energy Agency, https://iea-etsap.org/index.php/etsap-tools/model-generators/markal

[3] LG Fishbone and H Abilock, MARKAL, a linear-programming model for energy systems analysis: Technical description of the bnl version. International journal of Energy research, vol. 5, 1981, pp.353-375.

[4] AR De Musgrove, A linear programming analysis of liquid-furl production and use options for Australia, Energy, vol. 9, 1984, pp. 281-302.

[5] TK Das, Multiobjective linear programming approach to renewable energy policy analysis, Energy Management, vol. 11, 1987, pp. 55-121.

[6] K Rijal, NK Bansal and PD Grover, Rural household energy demand modeling: A case study of Nepal, Energy Economics, vol. 12, 1990, pp. 279-88.

[7] KL Lo, JR McDonald and TQ Le, Time of day electricity pricing incorporating elasticity for load management purpose, International Journal of electrical Power and Energy Systems, vol. 13, No. 4, 1991, pp. 230-239.

[8] S. Ashok and R. Banerjee, An optimisation mode for industrial load management, IEEE Trans Power Systems, vol. 16, 2001, 879-884.

[9] Y Lu, S Wang, Y Sun and C Yan, Optimal scheduling of buildings with energy generation and thermal energy storage under dynamic electricity pricing using mixed-integer nonlinear programming, Applied Energy, vol. 147, pp. 49-58, 2015.

[10] MH Nehrir, BJ LaMeres and V. Gerez, A customer-interactive electric water heater demand-side management strategy using fuzzy logic, IEEE Power Engineering Society 1999 Winter Meeting, vol. 1; 31 January-4 February 1999. p. 433-436.

[11] C Haissaig, Adaptive fuzzy temperature control for hydronic heating systems, in: Proceedings of the 1999 IEEE International Conference on Control Applications, Hawaii, USA, August 22-27, 1999, pp. 582-588.

[12] M Chaabene, MB Ammar and A Elhajjaji, Fuzzy approach for optimal energymanagement of a domestic photovoltaic panel, Applied Energy, vol. 84, 2007, pp. 992-1001.

[13] TY Wu, SS Shieh, SS Jang and CC Liu, Optimal energy management integration for a petrochemical plant under considerations of uncertain power supplies, IEEE Trans. Power Syst., vol. 20, 2005, pp. 1431-1439.

[14] S Ashok, Peak-load management in steel plants, Applied Energy, vol. 83, 2006, pp. 413-424.

[15] S Ashok and R Banerjee, Load-management applications for the industrial sector, Applied Energy, vol. 66, 2000, pp. 105-111.

[16] AJ Conejo, M Carrion and JM Morales, Decision Making under Uncertainty in Electricity Markets, Springer, New York, 2010.

[17] M Alipour, K Zare and H Seyedi, A multi-follower bilevel stochastic programming approach for energy management of combined heat and power micro-grids, Energy, vol. 149, pp. 135-146, 2018.

[18] AJ van Staden, J Zhang and X Xia, A model predictive control strategy for load shifting in a water pumping scheme with maximum demand charges, Applied Energy, vol. 88, 2011, pp. 4785-4794.

[19] H Tazvinga, B Zhu, and X Xia, Energy dispatch strategy for a photovoltaic-wind-diesel-battery hybrid power system, Solar Energy, vol. 108, 2014, pp. 412-420.

[20] J Luo, W Huang, and S Zhang, Energy cost optimal operation of belt conveyors using model predictive control methodology, Journal of Cleaner Production, vol. 105, 2015, pp. 196-205.

[21] S Zhang and X Xia, Optimal control of operation efficiency of belt conveyor systems, Applied Energy, vol. 86, pp. 1929-1937, 2010.

[22] S Zhang and X Xia, Modelling and energy efficiency optimization of belt conveyors, Applied Energy, vol. 88, pp. 3061-3071, 2011.

[23] H Yuan, F Li, Y Wei and J Zhu, Novel linearized power flow and linearized OPF models for active distribution networks with application in distribution LMP, IEEE Transactions on Smart Grid, vol. 9, pp. 438-448, 2018.

[24] B P Numbi, J Zhang and X Xia, Optimal energy management for a jaw crushing process in deep mines, Energy, vol. 68, pp. 337-348, 2014.

[25] MS Bazaraa, H. D. Sherali and C. M. Shetty, Nonlinear programming theory and algorithms, New York: John Wiley & Sons, 1993.

[26] SH Low, Convex relaxation of optimal power flow, I: Formulations and relaxations, IEEE Transactions on Control of Network Systems, vol. 1, 2014, pp. 15-27.

[27] SH Low, Convex relaxation of optimal power flow, II: Exactness, IEEE Transactions on Control of Network Systems, vol. 1, 2014, pp. 177-189.

[28] L Gan, N Li, U Topcu and SH Low, Exact convex relaxation of optimal power flow in radial networks, IEEE Transactions on Automatic Control, vol. 60, 2015, pp. 72-87.

[29] J Zhang and X Xia, Best switching time of hot water cylinder-switched optimal control approach, IEEE AFRICON 2007. Windhoek, Namibia; 26-28 September, 2007.

[30] DE Kirk, Optimal Control Theory: An Introduction, Prentice-Hall, Englewood Cliffs, N.J., 1970.

[31] LD Berkovitz, Optimal Control Theory, The American Mathematical Monthly, Vol. 83, No. 4, 1976, pp. 225-239.

[32] RF Hartl, SP Sethi, and RG Vickson, A survey of the maximum principles for optimal control problems with state constraints, SIAM Review, vol.37, no.2, 1995, pp. 181-218.

[33] LS Pontryagin, et al. The Mathematical Theory of Optimal Processes, Wiley, New York, 1962.

[34] W Badenhorst, J Zhang and X Xia, Optimal hoist scheduling of a deep level mine twin rock winder system for demand side management, Electric Power Systems Research, vol. 81, pp. 1088-1095, 2011.

[35] L Zhang, X Xia and J Zhang, Improving energy efficiency of cyclone circuits in coal beneficiation plants by pump-storage systems, Applied Energy, vol. 119, pp. 306-313, 2014.

[36] L Zhang, X Xia and J Zhang, Medium density control for coal washing dense medium cyclone circuits, IEEE Transactions on Control Systems Technology, vol. 23, pp. 1117-1222, 2015.

[37] D Attaviriyanupap, H Kita, E Tanaka and J Hasegawa, A hybrid EP and SQP for dynamic economic dispatch with nonsmooth incremental fuel cost function, IEEE Trans. Power Systems, vol. 17, pp. 411-416, 2002.

[38] TE Bechert and HG Kwatny, On the optimal dynamic dispatch of real power, IEEE Trans. Power Apparatus Syst., vol. PAS-91,1972, pp. 889-898.

[39] DL Travers and RJ Kaye, Dynamic dispatch by constructive dynamic programming, IEEE Trans. Power Syst., vol. 13, 1998, pp. 72-78.

[40] WG Wood, Spinning reserve constraints static and dynamic economic dispatch, IEEE Trans. Power Apparatus Syst., vol. PAS-101, 1982, pp. 331-338.

[41] XS Han and HB Gooi, Effective economic dispatch model and algorithm, Electr. Power Energy Syst., vol. 29, 2007, pp. 113-120.

[42] ZL Gaing, Constrained dynamic economic dispatch solution using particle swarm optimization, In: Proc. IEEE Power Engineering Society General Meeting, 2004, pp. 153-158.

[43] D Attaviriyanupap, H Kita, E Tanaka and J Hasegawa, A hybrid EP and SQP for dynamic economic dispatch with nonsmooth incremental fuel cost function, IEEE Trans. Power Systems, vol. 17, 2002, pp. 411-416.

[44] X Li, L Fang, Z Lu, J Zhang and H Zhao, A line flow granular computing approach for economic dispatch with line constraints, IEEE Transactions on Power Systems, vol.32, 2017, pp. 4832-4842.

[45] C Buerhopa et al., Reliability of IR-imaging of PV-plants under operating conditions, Sol. Energy Mater. Sol. Cells, vol. 107, 2012, pp. 154-164.

[46] A Krenzinger and AC Andrade, Accurate outdoor glass thermographic thermometry applied to solar energy devices, Solar Energy, vol. 81, 2007, pp. 1025-1034.

[47] Y Hu, W Cao, J Wu, B Ji, and D Holliday, Thermography-based virtual MPPT scheme for improving PV energy efficiency at partial shading conditions, IEEE Transactions on Power Electronics, vol. 29, 2014, pp. 5667-5672.

[48] T Takashima, J Yamaguchi, K Otani, T Oozeki, and K Kato, Experimental studies of fault location in PV module strings, Sol. Energy Mater. Sol. Cells, vol. 93, 2009, pp. 1079-1082.

[49] RA Kumar, MS Suresh, and J Nagaraju, Measurement of AC parameters of gallium arsenide (GaAs/Ge) solar cell by impedance spectroscopy, IEEE Trans. Electron Devices, vol. 48, 2001, pp. 2177-2179.

[50] Z Zou, Y Hu, B Gao, WL Woo, and X Zhao, Study of the gradual change phenomenon in the infrared image when monitoring photovoltaic array, J. Appl. Phys., vol. 115, no. 4, 2014, pp. 1-11.

[51] X Lin, Y Wang, D Zhu, N Chang, and M Pedram, Online fault detection and tolerance for photovoltaic energy harvesting systems, in Proc. IEEE/ACM ICCAD, San Jose, CA, USA, 2012, pp. 1-6.

[52] D Nguyen and B Lehman, An adaptive solar photovoltaic array using model-based reconfiguration algorithm, IEEE Trans. Ind. Electron., vol. 55, 2008, pp. 2644-2654.

[53] JP Storey, PR Wilson, and D Bagnall, Improved optimization strategy for irradiance equalization in dynamic photovoltaic arrays, IEEE Trans. Power Electron., vol. 28, 2013, pp. 2946-2956.

[54] G Velasco-Quesada, F Guinjoan-Gispert, R Pique-Lopez, M Roman-Lumbreras, and A Conesa-Roca, Electrical PV array reconfiguration strategy for energy extraction improvement in grid-connected PV systems, IEEE Trans. Ind. Electron., vol. 56, 2009, pp. 4319-4331.

[55] Y Wang, X Lin, Y Kim, N Chang, and M Pedram, Architecture and control algorithms for combating partial shading in photovoltaic systems, IEEE Trans. Comput.-Aided Design Integr. Circuits Syst., vol. 33, 2014, pp. 917-929.

[56] MZS El-Dein, M Kazerani, and MMA Salama, Optimal photovoltaic array reconfiguration to reduce partial shading losses, IEEE Trans. Sustain. Energy, vol. 4, 2013, pp. 145-153.

[57] E Faldella, GC Cardinali, and PU Calzolari, Architectural and design issues on optimal management of photovoltaic pumping systems, IEEE Trans. Ind. Electron., vol. 38, 1991, pp. 385-392.

[58] G Velasco-Quesada, F Guinjoan-Gispert, R Pique-Lopez, M Roman-Lumbreras, and A Conesa-Roca, Electrical PV array reconfiguration strategy for energy extraction improvement in grid-connected PV systems, IEEE Trans. Ind. Electron., vol. 56, 2009, pp. 4319-4331.

[59] JD Bastidas-Rodriguez, CA Ramos-Paja, and AJ Saavedra-Montes, Reconfiguration analysis of photovoltaic arrays based on parameters estimation, Simul. Model. Pract. Theory, vol. 35, 2013, pp. 50-68.

[60] M Alahmad, MA Chaaban, SK Lau, J Shi, and J Neal, An adaptive utility interactive photovoltaic system based on a flexible switch matrix to optimize performance in real-time, Solar Energy, vol. 86, 2012, pp. 951-963.

[61] PL Carotenuto, AD Cioppa, A Marcelli, and G Spagnuolo, An evolutionary approach to the dynamical reconfiguration of photovoltaic fields, Neurocomputing, vol. 170, 2015, pp. 393-405.

[62] X Xia and J Zhang eds., Energy Efficiency Measurement & Verification Practices–Demystifying M&V through South African Case Studies, Media in Africa, Pretoria, October 2012.

[63] Efficiency Valuation Organization, International Performance Measurement and Verification Protocol, Volume 1, EVO 10000-1.2007, http://www.evo-world.org

[64] Department of Energy (USA), M&V Guidelines: Measurement and Verification for Federal Energy Projects, Version 2.2, 2002. Available at: http://www.eren.doe.gov/femp

[65] American Society of Heating, Refrigeration and Air Conditioning Engineers, Measurement of Energy and Demand Savings, Guideline 14-2002, Atlanta: ASHRAE, 2002.

[66] ESKOM, The Measurement and Verification Guideline for Demand-Side Management Projects. Version 5. 2006.

[67] AZ Dalgleish and LJ Grobler, Measurement and verification of a motor sequencing controller on a conveyor belt, Energy, vol. 28, 2003, pp. 913-927.

[68] JK Kissock and C Eger, Measuring industrial energy savings, Applied Energy, vol. 85, 2008, pp. 347-361.

[69] J Reichl and A Kollmann, The baseline in bottom-up energy efficiency and saving calculations-A concept for its formalisation and a discussion of relevant options, Applied Energy, vol. 88, 2011, pp. 422-431.

[70] S Moser, K Leutgob, J Reichl and A Kollmann, Making the rules of bottom-up energy savings comparable, Thermal Science, vol. 16, 2012, pp. 687-702.

[71] TA Reddy, JK Kissock and DK Ruch, Uncertainty in baseline regression modeling and in determination of retrofit Savings, ASME Journal of Solar Energy Engineering, vol. 120, 1998, pp. 185-192.

[72] TA Reddy, JS Haberl and JS Elleson, Engineering uncertainty analysis in the evaluation of energy and cost savings of cooling system alternatives based on field-monitored data, ASHRAE Transactions, vol. 105, 1999, pp. 1047-1057.

[73] T A Reddy, DE Claridge, Uncertainty of “measured” energy savings from statistical baseline models, HVAC&R Research, vol. 6, 2000, pp. 3-20.

[74] Y Heo and V Zavala, Gaussian process modeling for measurement and verification of building energy savings, Energy and Buildings, vol. 53, 2012, pp. 7-18.

[75] Y Heo, R Choudhary and G A Augenbroe, Calibration of building energy models for retrofit analysis under uncertainty, Energy and Buildings, vol. 47, 2012, pp. 550-560.

[76] MJ Kaiser and AG Pulsipher, Preliminary assessment of the Louisiana home energy rebate offer program using IPMVP guidelines, Applied Energy, vol. 87, 2010, pp. 691-702.

[77] L Morrison, R Azerbegi and A Walker, Energy modeling for measurement and verification, In: The Third National Conference of IBPSA-USA, Berkeley, July 30-August 1, 2008.

[78] S Meyers and S Kromer, Measurement and verification strategies for energy savings certificates, meeting the challenges of an uncertain world, Energy Efficiency, vol. 1, 2008, pp. 313-321.

[79] ESKOM-Corporate Technical Audit Department, Specification for three phase energy metering for use with measuremnet and verification (M&V) projects, PM/M&V/STD001, Rev 1.0, Nov 2005 (Confidential).

[80] ESKOM, RLM Research, deliverd and compiled by the North-West University M&V Team, July 2008 (internal and confidential report).

[81] X Li, L Fang, Z Lu, J Zhang and H Zhao, A line flow granular computing approach for economic dispatch with line constraints, IEEE Transactions on Power Systems, vol.32, 2017, pp. 4832-4842.

[82] Z Lu, H Xiao, J Zhang, X Li and H Zhao, Robust DED based on bad scenario set considering wind, EV, and battery switching station, IET Generation, Transmission and Distribution, vol. 11, 2017, pp. 354-362.

[83] L He, Z Lu, J Zhang, L Geng, H Zhao and X Li, Low-carbon economic dispatch for electricity and natural gas systems considering carbon capture systems and power-to-gas, Applied Energy, vol. 224, 2018, pp. 357-370.

List of Key Publications

[K1] X Xia and J Zhang, Operation efficiency optimisation modelling and application of model predictive control, IEEE/CAA Journal of Automatica Sinica, 2015, 2(2), pp.166-172.

[K2] J Zhang and X Xia, A model predictive control approach to the periodic implementation of the solutions of the optimal dynamic resource allocation problem, Automatica, vol.47, 2011, pp. 358-362.

[K3] A Middelberg, J Zhang and X Xia, An optimal control model for load shifting-with application in the energy management of a colliery, Applied Energy, vol. 86, 2009, pp. 1266-1273.

[K4] X Xia, J Zhang and A Elaiw, An application of model predictive control to the dynamic economic dispatch of power generation, Control Engineering Practice, vol. 19, no. 6, 2011, pp. 638-648.

[K5] Y Hu, J Zhang, W Cao, J Wu, G Tian, S Finney and J Kirtley, Online two-section PV array fault diagnosis with optimized voltage sensor locations, IEEE Transactions on Industrial Electronics, vol. 62, 2015, pp. 7237 - 7246.

[K6] Y Hu, J Zhang, J Wu, W Cao, G Tian and J Kirtley, Efficiency improvement of non-uniformly-aged PV arrays, IEEE Transactions on Power Electronics, vol. 32, Feb 2017, pp. 1124-1137.

[K7] Y Hu, J Zhang, P Li, D Yu and L Jiang, Non-uniform aged modules reconfiguration for large scale PV array, IEEE Transactions on Device and Materials Reliability, vol. 17, 2017, pp. 560-569.

[K8] X Xia and J Zhang, Mathematical description for the measurement and verification of energy efficiency improvement, Applied Energy, vol. 111, 2013, pp. 247-256.

[K9] J Zhang and X Xia, Air Conditioner Intelligent Switch Control in Commercial Buildings, Chapter 1, Energy Efficiency Measurement & Verification Practices--Demystifying M&V through South African Case Studies (X Xia and J Zhang eds.), Media in Africa, Pretoria, October 2012.

[K10] J Zhang, Measurement and Verification Guideline Residential Heat Pump Rebate Programme, ESKOM Report PM/M&V/UP-10/11-054, 2012 (Confidential).

List of Supporting Publications

[S1] H Tazvinga, X Xia and J Zhang, Minimum cost solution of photovoltaic-diesel-battery hybrid power systems for remote consumers, Solar Energy, 96 (2013) 292-299.

[S2] N Wang, J Zhang and X Xia, Energy consumption of air conditioners at different temperature set points, Energy and Buildings, vol.65, 2013, pp. 412-418.

[S3] Setlhaolo, X Xia and J Zhang, Optimal scheduling of household appliances for demand response, Electric Power Systems Research, vol. 116, 2014, pp 24-28.

[S4] EM Malatji, J Zhang, and X Xia, A multiple objective optimisation model for building energy efficiency investment decision, Energy and Buildings, vol.61, 2013, pp. 81-87.

[S5] H Zhang, J Zhang and X Xia, Optimal sizing and operation of pumping systems to achieve energy efficiency and load shifting, Electric Power Systems Research, vol. 86, 2012, pp. 41- 50.

[S6] X Ye, X Xia and J Zhang, Optimal sampling plan for clean development mechanism energy efficiency lighting projects, Applied Energy, vol. 112, 2013, 1006-1015.

[S7] X Ye, X Xia and J Zhang, Optimal sampling plan for clean development mechanism lighting projects with lamp population decay, Applied Energy, vol.136, 2014, pp. 1184-1192.

[S8] U Ekpenyong, X Xia and J Zhang, Building Energy Efficiency Projects, Chapter 3, Energy Efficiency Measurement & Verification Practices--Demystifying M&V through South

African Case Studies (X Xia and J Zhang eds.), Media in Africa, Pretoria, October 2012.

[S9] X Ye, X Xia and J Zhang, Residential Heat Pump Rebate Programme, Chapter 14, Energy Efficiency Measurement & Verification Practices--Demystifying M&V through South African Case Studies (X Xia and J Zhang eds.), Media in Africa, Pretoria, October 2012.

[S10] Z Olinga, X Xia and J Zhang, Air Conditioning System Replacement at Industrial Facilities, Chapter 17, Energy Efficiency Measurement & Verification Practices--Demystifying M&V through South African Case Studies (X Xia and J Zhang eds.), Media in Africa, Pretoria, October 2012.

[S11] N Wang, X Xia and J Zhang, Energy Efficiency Improvement and Load Reduction of Refrigeration Systems at Supermarket Stores, Chapter 18, Energy Efficiency Measurement & Verification Practices--Demystifying M&V through South African Case Studies (X Xia and J Zhang eds.), Media in Africa, Pretoria, October 2012.