University of Strathclyde

Department of Electronic and Electrical Engineering

Self-Organising Multi-Agent Control for Distribution Networks with Distributed Energy Resources

Badr Al Faiya

Submitted in fulfilment of the requirements for the degree of

Doctor of Philosophy at the University of Strathclyde

Feb 2023

Abstract

Recent years have seen an increase in the connection of dispersed distributed energy resources (DERs) and advanced control and operational components to the distribution network. These DERs can come in various forms, including distributed generation (DG), electric vehicles (EV), energy storage, etc. The conditions of these DERs can be varying and unpredictably intermittent. The integration of these distributed components adds more complexity and uncertainty to the operation of future power networks, such as voltage, frequency, and active/reactive power control. The stochastic and distributed nature of DGs and the difficulty in predicting EV charging patterns presents problems to the control and management of the distribution network. This adds more challenges to the planning and operation of such systems. Traditional methods for dealing with network problems such as voltage and power control could therefore be inadequate. In addition, conventional optimisation techniques will be difficult to apply successfully and will be accompanied with a large computational load.

There is therefore a need for new control techniques that break the problem into smaller subsets and one that uses a multi-agent system (MAS) to implement distributed solutions. These groups of agents would coordinate amongst themselves, to regulate local resources and voltage levels in a distributed and adaptive manner considering varying conditions of the network.

This thesis investigates the use of self-organising systems, presenting suitable approaches and identifying the challenges of implementing such techniques. It presents the development of fully functioning self-organising multi-agent control algorithms that can perform as effectively as full optimization techniques. It also demonstrates these new control algorithms on models of large and complex networks with DERs. Simulation results validate the autonomy of the system to control the voltage independently using only local DERs and proves the robustness and adaptability of the system by maintaining stable voltage control in response to network conditions over time.

Acknowledgements

I wish to thank my PhD supervisor, Professor Stephen McArthur, for always being there when I needed his support, reviewing my progress constantly, and guiding me through my PhD studies. This thesis would not have been possible without his knowledge and support. I would also like to thank my second supervisor, Dr Ivana Kockar, for her great guidance, knowledge, discussions, and support throughout this period. Most of all, I wish to thank my wife and family for their support throughout my PhD.

I would also like to thank Prof. Francisco de León from New York University (NYU) for his help and collaboration especially in the epsilon decomposition and the real network model. I would also like to thank Dr Bruce Stephen for the support on IEEE European LV Test network model, and Gary Howorth for the discussions on intelligent systems. This thesis leverages the open-source multi-agent system software library Presage2 developed by researchers from Imperial College, London, and with the support of Prof. Jeremy Pitt and Dr Sam Macbeth, whom we thank for their discussions and support.

Dedication

In gratitude to my higher education, I dedicate this thesis to my God, Allah, to my mother, Halima Alhadi, to my father and mentor, Mohammed Asiri, who passed away before seeing me completing this thesis, and to my wife, Hanan Asiri, for all her love and support.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

Abbreviations	Definition
AC	Alternating current
ACL	Agent communication language
ADMM	Alternating Direction Method of Multipliers
ADN	Active distribution network
AGR	Agent / group / role
AI	Artificial intelligence
AMS	Agent management service
ANM	Active network management
BDI	Beliefs-desires-intentions
COHDA	Combinatorial Optimization Heuristic for Distributed Agents
DAI	Distributed artificial intelligence
DC	Direct current
DDS	Data distribution service
DER	Distributed energy resources
DF	Directory facilitator
DG	Distributed generation
DMU	Decision-making unit
DORPC	Decentralized optimal reactive power control
DSM	Demand side management
DYCE	Dynamic Coalition in Electricity Markets
EIS	Energy information system
EMS	Energy management systems
ESS	Energy storage system
ETP	European technology platform
EV	Electric vehicle
FIPA	Foundation for Intelligent Physical Agents

μGIM	Microgrid intelligent management
HES	Home electronic system
HMAS	Holonic multi-agent system
HV	High voltage
ICT	Information and communication technology
IEC	International electro-technical commission
IEEE	Institute of Electrical and Electronics Engineers
IIoT	Industrial internet of things
IoT	Internet of Things
ISO	Independent system operator
JADE	Java Agent development
KQML	Knowledge Query and Manipulation Language
LCSG	Living city smart grid
LFC	Load frequency control
LP	Linear programming
LV	Low voltage
M2M	Machine-to-machine
MADRL	Multi-agent deep reinforcement learning
MARL	Multi-agent reinforcement learning
MAS	Multi-agent systems
MENSA	Micro self-organised management
MG	Microgrid
MV	Medium voltage
NIST	National Institute of Standards and Technology
NYU	New York University
OLTC	On-load tap changer
P2P	Peer to Peer
PADE	Python Agent development
PES	Power & Energy Society
PFC	Power factor control
PV	Photovoltaic
SGAE	Smart grid algorithm engineering

SOM	Self-organised map
TE	Transactive energy
UAV	Unmanned aerial vehicles
UPF	Unity power factor
VAR	Volt-amps reactive
VPP	Virtual power plant

Chapter 1

Introduction

This thesis examines the use of autonomous and dynamic control mechanisms for distributed energy resources (DER) in distribution networks. These techniques coordinate production/consumption of energy resources in large networks, primarily as a means to control the voltage in a distributed and unpredictable environment. Connected resources are considered in a multi-agent control setting situated in time-varying electrical power networks. The system is designed to enable distributed and self-organising control of agents residing in DERs (e.g., distributed generation and electric vehicles) to maintain robust and adaptive control mechanisms. The technique develops lower-level autonomous mechanisms (agents) for coordination amongst multiple DERs within control areas and enables each control area to regulate its local resources and voltage levels simultaneously and independently. The following sections introduce the background and motivation for the research into distributed and self-organising control mechanisms for future power networks, the problem statement, research questions, scientific contributions, and thesis outline.

1.1 Background and Motivation

The transition to a low carbon electricity system is dependent upon the roll-out of smart grid concepts and requires the real-time control of distributed energy resources (DER) within large distribution networks. Conventional methods for controlling distribution networks use top-down strategies designed for distribution systems supplied mainly from large assets located on the transmission network and can result in the curtailment of those resources. However, introducing advanced components such as DERs into modern networks presents new challenges to the operation of future smart grids such as voltage and frequency control, and active/reactive power management and control. Improving these control strategies and methodologies to incorporate an ever-growing level of DERs is therefore an essential element in the development of any future smart grid.

In the past decade, power networks have seen a surge in DERs capacity, with a substantial proportion of that being composed of distributed generation (DG). In the coming years, the increased penetration of electric vehicles (EVs) will put further pressure on distribution networks. Introducing these advanced technologies is adding more complexity, uncertainty, and challenges to the control, management, and operation of future networks. It is anticipated that the decentralization of control and management of grid components will increase in distribution networks due to the large-scale integration of DGs, EVs and storage. For instance, with the predicted rise in penetration of the DGs and renewables as shown in Figure 1.1, distributed control and management of these distributed resources will be made possible by the information and communication technology (ICT) infrastructure under the smart grid model.

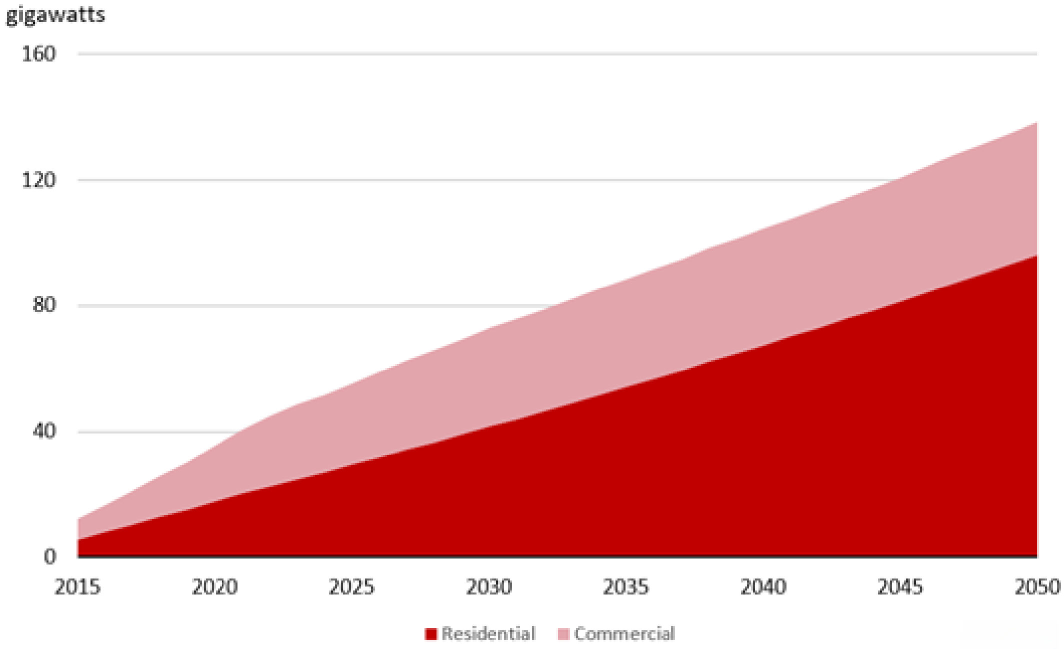


Figure 1.1: Installed PV rooftop capacity (GW) by 2050 [1].

There is a growing understanding of the adverse effects of fossil fuel usage on environmental sustainability and CO2 levels. Oil consumption associated with light-duty cars, motorcycles, and sports utility vehicles accounted for around 62% of the transportation sector over the previous decade [2]. Governments have pledged to restructure the transportation industry, transitioning from gasoline vehicles to an integrated system powered by electricity [3]. As a consequence, for example, EV sales has increased significantly across Europe, accounting for 18.7 percent of overall EV registrations in 2021, up from 10.5 percent in 2020 [4]. Although the increased penetration of EVs introduces new challenges to the power system in general [5], and to the control of demand and voltage in distribution networks in particular, the control of EV charging will be made possible with the automation of the operation of the future networks using smart grid principles [6]. Recently, a technical report “Future Energy Scenarios (FES) 2021”, by National Grid, UK [6], states that "Smart charging, where EV owners release some control on the best time to charge to third parties or automation based on price signals, will be an effective tool to support the local and national electricity networks." This is illustrated in Figure 1.2; the green line "Leading the Way" shows that over 80% of consumers could be engaged in EV smart charging by 2050.

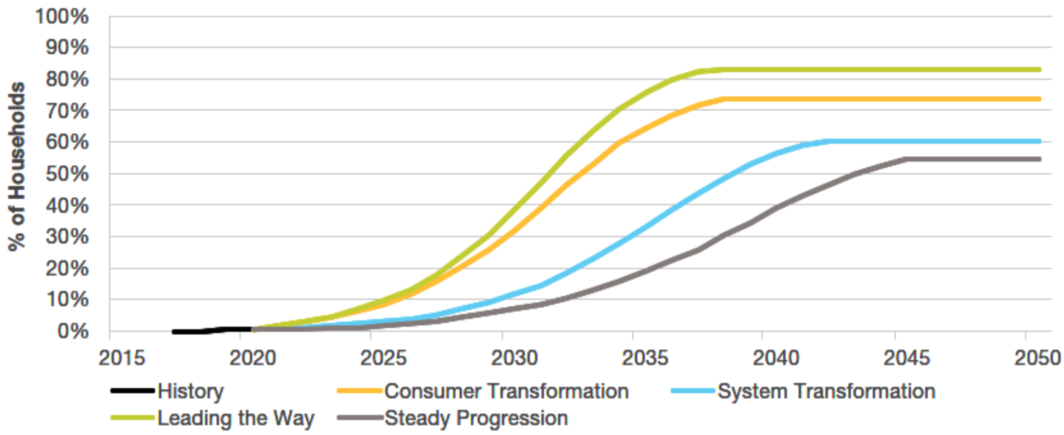


Figure 1.2: Over 80% of customer engagement in EV smart charging by 2050 [6].

As discussed, the rapid changes in the smart grid featured by the unprecedented growing penetration of DER and the introduction of prosumers increase the future network complexity. DERs are inherently intermittent and can cause voltage issues and bi-directional power flow through distribution lines. The growing number of controllable devices (e.g., DG, EVs, etc.) and the corresponding control variables, as well as the increasing volume of data and information in future smart distribution networks, are leading to unprecedented complexity in the required control paradigm [7-9]. Additionally, time-varying network conditions and the availability of DERs over time cannot be easily predicted during design, and thus, flexible techniques that can deal with such evolving control requirements are necessary.

In the vision of smart grids, all network components, such as loads, generation units, measurement devices, substations, and the network itself, are interconnected by an automation system and use a communication system to monitor, control and optimize it by means of intelligent and advanced methods [10, 11]. This is made possible due to advancements in information and communication technologies (ICT) and power electronics, enabling effective and real-time services and distributed controls [7, 12]. Thus, recently, the IEEE 1547 Standard encourages timely coordination and control of DER reactive and active power for dynamic voltage support [13]. As a result, novel techniques for voltage and power regulation have been presented in the literature, including distributed control and management methods to maintain reliable operations [7] such as using agent-based methods (a review of agent-based literature is presented in section 4.4).

Over the past decade, agent-based techniques have been increasingly used in a number of disciplines and applications such as physics, control systems, systems engineering, software engineering, and many others [14, 15]. Agent-based techniques use groups of autonomous decision-making entities called agents. Each agent individually assesses its situation/environment, interacts with other agents, and makes decisions on the basis of a set of rules. Multi-Agent System (MAS) is a subset of agent-based methodologies that focuses on engineering applications and the detailed communication and interaction between agents. MAS has already demonstrated its capabilities for building flexible and reliable industrial application domains, including aerospace, robotics, computer networks, and air traffic control [16]. For example, in control theory, the application of cooperative control and MAS has seen interest by developers for many real-world applications such as coordination of formation and organisation of mobile robots and unmanned aerial vehicles (UAV) [14].

The future smart grid infrastructure is anticipated to support a more sophisticated cyber-physical interaction and monitoring, thus enabling distributed intelligence characteristics and techniques. To handle the complexity of dealing with distributed components (agents) in smart grid infrastructure, it will be critical to investigate distributed artificial intelligence (DAI) architectures and programming methodologies. As the agent, which may be regarded as a piece of hardware/software with some characteristics, is the fundamental component of a DAI, a system problem can be solved by the agents' interactions to improve its performance [17]. MAS provides the ideal methodology for implementing those agents capable of representing communications and self-organisation within the smart grid setting.

Multi-agent control is one of the most recent control paradigms for smart grids as a technique to enable distributed control [14, 18]. DERs equipped with sensing, communication, and computation capabilities can be represented as autonomous agents to act and deliver flexible and quick control of their active and reactive output [7]. MAS is expected to play an important role in developing smart grids in a number of different areas especially in control, management, monitoring, protection, market, and planning [19]. To handle these problems for future power systems, existing literature (also discussed in section 4.4) provides an insight into the use of distributed intelligence and control techniques [7]. Although these techniques can solve network problems, additional intelligence and autonomous adaptivity to deal effectively with disturbances over large networks could be achieved by adding self-organising agents. However, limited work exists to provide an insight into applications of self-organising MAS for power networks.

1.2 Problem Statement

Historically, unidirectional power flows and associated static drop of voltage along the power line negated the need for dynamic or sophisticated voltage control in low-voltage distribution networks. Conventional voltage control devices, namely step voltage regulators in feeders, on-load tap-changers in HV/MV substations transformers, and capacitor banks/shunts are also deployed in voltage control. However, these methods do not react fast enough during emergency conditions while inverter-based DERs connected to the distribution network can provide a faster response [20]. Transformers in LV networks typically do not have tap-changing abilities and therefore were incorporated into the system design so that the voltage was adequate at the end of the line. The voltage control challenges are introduced to this conventional static setup with the increased penetration of resources on distribution networks. In this instance, power injection control of grid-connected DERs (e.g. batteries, EVs, demand side response (DSR), DG units) could be more dynamically controlled for distributed voltage regulation [21].

One method to maintain the voltage within an acceptable range is to involve the DERs in network control by means of dynamic adaptation of the reactive and active power based on variations of the voltage in the network. These distributed systems need to be controlled in a distributed manner to avoid voltage fluctuation in the network. Based on this, the controllers can be represented by intelligent agents, providing control and coordination of DER production/consumption. Additionally, to enable automatic adaptation when the network conditions change, agents should be capable of detecting and reacting to unpredictable changes in the network. These dynamic changes in power distribution networks are expected to develop because of the stochastic nature of distributed resources that need to be considered when controlling the network. Also, this can be due to unanticipated network conditions, such as loss of communication with distributed controllers that are participating in the control. In both scenarios, it is usually inappropriate to implement manual coordination and reconfiguration of the distributed controllers' parameters. Hence, agents that realize automatic organisation can be a suitable tool in this situation.

Recently, MAS has been used to implement distributed voltage control schemes based on DERs [7]; (presented in Chapter 4). Although these techniques are able to deal with network challenges, they are not able to provide distributed and autonomous control with dynamic operation considering the unpredictable conditions of DERs and the highly dynamic behaviour of the emerging smart grids. One way to deal with large networks is dynamically partitioning them into smaller control groups1. However, in the prior art, when dealing with sub-systems (groups) of DERs, it is assumed that each sub-system is static and also typically needs to coordinate with other groups to solve each control problem. This assumption was widely used in the literature when partitioning the network. Unfortunately, when resources in a sub-system are not sufficient to maintain its stable control, and when the condition of the network is changing, current static methodologies may not perform well. This suggests that a more dynamic and self-organising strategy may provide a better approach. There is

[1] This helps to reduce the size of the optimization/control problem and reduces its complexity.

limited literature about exploring how to make sub-systems dynamical by self-organisation based on the condition of its resources whilst maintaining stable power system operation. Additionally, there has been limited investigation into how to control appropriate resources within each group independently and simultaneously during normal operations and during disturbances.

The advantage of a properly designed control of a distribution network with DER is that it allows control, management, and disconnection and connection of network components, as well as maintaining automatic and stable coordination under varying conditions. As presented, control solutions for large and complex networks would create autonomous groups of network components that could then be used to control and regulate networks in a distributed manner. When a distribution network incorporates groups of heterogeneous DERs whose output might fluctuate widely, the aggregated power output of relevant resources in each region can be dispatched by coordinating the power output level within the given area. In general, the required control method should be capable of controlling and managing many DERs using local information. Hence, developing automatic and dynamic groups based on DERs can improve the control mechanism, especially under unexpected and time-varying changes and conditions.

As discussed above and in Chapter 2, the voltage in the power networks depends on the network's structure and topology, and the flows of active and reactive power. Developing a robust network is a key step in controlling future distribution networks. Solutions should take into account the intermittent and unpredictable nature of DER, the dynamical behaviour of electrical power grids, as well as constraints such as line and voltage. Although MAS techniques can control power grids, current solutions are mostly focused on small-scale networks. On larger networks, MAS could handle the smart grid's dynamic behaviour by dynamically partitioning the network into sub-networks under varying conditions and controlling appropriate resources. However, there is a lack of a comprehensive method that simultaneously deals with control, technical constraints, and time-varying changes in large-scale distribution networks. Self-organisation of these autonomous agents would be an effective solution required for future networks.

Previous research on self-organising techniques for power networks has mainly targeted energy markets rather than technical parameters and constraints (presented in section 3.3). Despite increased awareness and continuous research and development in smart grid control, there are still several key research questions that need to be addressed. Vrba et al. [22] stated as an open research question that "Advanced control functions: The ability to provide self-corrective reconfiguration and restoration in the grid. Also handling the fluctuating behaviour of DER devices as well as the upcoming integration of electric vehicles and grid-scale storage devices is still an open point for further research. An integrated solution addressing advanced automation and control functions is missing. Such an approach should be based on the MAS…". In the previous studies, the problems of how to control the voltage using appropriate DERs in large networks in a distributed manner and how to make the control of DERs autonomous and exhibit dynamic behaviours have not been investigated.

This thesis presents self-organising multiagent control mechanisms implemented by cooperative agents in large distribution networks. The technique considers system uncertainty caused by events, such as outages and loss of communication, to maintain stable control of the network. It is distinctive that the presented distributed control can cope with the unpredictable time-varying conditions of the distribution network. This control technique also subdivides large networks into groups and coordinates the DERs within each group to provide distributed voltage control, while each group can control local resources and regulate its voltage simultaneously and independently. To test various control architectures, the work in this thesis uses the Presage2 multiagent platform [23] to implement the framework in large-scale distribution networks.

1.3 Key Research Question

As discussed above, the primary objective of this work is to design a distributed control architecture for large distribution networks. This thesis will seek to answer the following key research questions:

- How can we design an autonomous and robust control system for large-scale distribution networks with DER, and allow the system to deal with uncertainties such as outages, communication failure, etc.?
- How can we deploy this mechanism using self-organisation principles with agents resident in distribution network components?

1.4 Research Contributions

Future distribution networks can contain hundreds of distributed and renewable resources whose conditions may be varying and can be unpredictably intermittent. As discussed above, control and management of these resources should allow them to form multiple partitions of DERs such that their outputs can be distributively dispatched. This thesis aims to design and implement a distributed and robust control architecture for large distribution networks and test various concepts to identify its applicability and usefulness. We consider partitioning the network into subnetworks regulated through a distributed control architecture to realize some common objective (e.g., maintain voltage levels), and consider the time-varying conditions of DER and communication network to enable coordination and self-organisation of the network and its components. The research presented in this thesis tackles the challenges faced by smart distribution networks in maintaining reliable operation of the network while dealing with variable and unanticipated power outputs of geographically dispersed DERs.

This thesis presents novel frameworks for distributed and adaptive control schemes based on a self-organising MAS for large complex networks, enabling autonomous and robust distribution networks. The main contributions of this work are as follows.

- Implementation of a MAS architecture to enable partitioning of a network in which a large distribution network autonomously self-subdivides into smaller subnetworks of sub-MASs, thereby distributing control tasks among agents.

- Implementing distributed and cooperative voltage control that can facilitate the exploitation of the inherent flexibility of DERs in network operations. Each control area controls its voltage autonomously and independently by locating the closest local DER that has highest influence on the desired nodal voltage. The use of the "closest" local resources further simplifies and reduces the size of the optimization problem and the interaction requirements, and the communication bandwidth of minimum.

- Introducing mechanisms for the agents to allow the system to self-organise in response to various conditions such as uncertainty and the availability of energy resources over time. The self-organisation is enabled through a mechanism that adapts network subdivisions to reflect varying network conditions. The desired control mechanism is resilient to network anomalies and uses local interactions to adjust the structure of the MAS without stopping the system.

- Presenting a partitioning technique based on the community detection algorithm to group network components and nodes, and to dynamically identify and control the neighbouring nodes to each resource (or group of resources) within each group.

- Implementing the presented control schemes for distributed generation (DG) and for electric vehicles (EV) under various production and charging conditions and network changes.

- The verification and validation of the algorithms on a model of a real heavily-meshed distribution network, and in the large-scale IEEE European test system [24], and comparison with other schemes demonstrating its autonomy and robustness under time-varying network conditions.

- An investigation of the challenges related to the application of MAS and self-organisation for large and complex networks in smart grids.

1.5 Thesis Structure

The work in this thesis is organised in the following manner:

- **Chapter 2** summarises background and presents analysis of recent and most relevant work in the literature on the control and management of electricity networks.
- **Chapter 3** introduces the concept of self-organisation. It also defines the mechanism of self-organisation and its advantages, and presents an investigation of relevant literature on its application for electricity networks.
- **Chapter 4** presents the multiagent systems (MAS) concept, describing the advantages and the problem and challenges of implementing such systems, and presents a critical analysis of relevant literature on distributed intelligence and control for power networks.
- **Chapter 5** introduces the development and design of proposed self-organising MAS frameworks for the control of DERs. Two approaches are discussed. The first uses the epsilon decomposition method to group networks and uses agents to control DGs for self-organising distributed voltage regulation. The second method introduces the proposed community detection partitioning technique, and the control, management, and self-organisation of electric vehicles based on MAS frameworks. The chapter also details the implementation of the proposed solutions.
- **Chapter 6** presents the simulation results and discussions for the various use cases for both the control and management of DG and EV designs discussed in Chapter 5.
- **Chapter 7** presents the conclusions of this thesis, including an overview of the work performed in meeting the aims and objectives

of this research. Finally, recommendations for future work are provided.

1.6 Associated Publications

- **B. Al Faiya**, D. Athanasiadis, M. Chen, S. McArthur, I. Kockar, H. Lu, and F. de León "A Self-Organizing Multi-Agent System for Distributed Voltage Regulation, " *IEEE Transactions on Smart Grid*, vol. 12, no. 5, pp. 4102-4112, Sept. 2021.

- **B. Al Faiya**, S. McArthur, and I. Kockar, "Partitioning and Self-organization of Distributed Generation in Large Distribution Networks," in *2021 IEEE Power & Energy Society General Meeting (PESGM)*, 2021: IEEE, pp. 1-5.

- M. Chen, D. Athanasiadis, **B. Al Faiya**, S. McArthur, I. Kockar, H. Lu, and F. d. Leon, "Design of a multi-agent system for distributed voltage regulation," in *2017 19th International Conference on Intelligent System Application to Power Systems (ISAP)*, 17-20 Sept. 2017, pp. 1-6.

- **B. Al Faiya**, S. McArthur, and I. Kockar, "Distributed and Robust Voltage Control through Partitioning and Self-Organization of Electric Vehicles in Smart Distribution Networks," *IEEE* (writing).

Chapter 2

Future Electricity Networks and Control Techniques

Future electricity networks are evolving both in terms of the network topology and the technical characteristics (e.g., control devices) in which consumers and generators will participate. In this chapter, the control techniques and state-of-the-art in distributed and decentralised control methods that offer solutions to the challenges faced by the evolving structures of future power networks and smart grids are outlined and examined. It also discusses difficulties in addressing network issues and potential solutions. Various control methods in power networks have been researched, and relevant examples are shown.

2.1 Introduction

As the integration of distributed energy resources (DERs) increases in future distribution networks, their presence introduces new challenges as system power flows become more stochastic. This increases the complexity of the system and can lead to voltage quality issues. These DERs include distributed generation (DG), electric vehicles (EV), demand response technologies, as well as interactive and flexible resources such as smart thermostats, heat-pumps and space heaters [25]. This thesis focuses on the impacts of and control solutions for DGs and EVs, which can also be extended to control various network components.

Although, many challenges are introduced when DGs are integrated into distribution networks, voltage regulation and control is key requirement for the operation of distribution networks [7]. The voltage regulation on a distribution network is customarily implemented by regulating devices, such as on-load tap changer (OLTC) substation transformers, capacitor banks (CB), and voltage regulators (VR) in the feeders. For a distribution network with multiple DGs, however, the settings of these traditional regulating devices are not the same as for a network without DGs [20, 26]. Additionally, these regulating devices do not react fast enough during emergency conditions [20].

As discussed in Chapter 1, the connection of EVs into the future distribution networks is projected to increase in the near future, but one of the main challenges of these distribution networks, with EVs, is voltage control [6]. The connection of many EVs onto a network, coupled with the fact that these loads are stochastic and mobile, presents serious issues for distribution network operators (DNO) especially at the end of radial network power lines [27]. In addition, until recently load profiles have been relatively stable and easy for

DNOs to predict for planning and control purposes. These DGs and EVs present new challenges to the operation of future smart grids such as voltage and active/reactive power management and control, so more research is needed to implement distributed control strategies using DGs and EVs in MV and LV distribution networks. This applies to both normal network operation and during disturbances.

This chapter reviews a number of techniques where DERs have been used to control distribution power networks and provides various examples from the literature. In the sections that follow, a brief description and summary of the methods for controlling DERs is presented, and is followed by a number of examples of academic research in the field. The effect of DERs on distribution network control is investigated, and the techniques developed in these systems are discussed.

2.2 Future Electricity Networks: Advantages and Challenges

In power networks, local elements, including loads, distributed generation, and the network itself, have varying degrees of coupling and influence to each other. In addition, the increasing number of controllable devices, such as DG and EVs, the corresponding control variables, and the increasing volume of exchanged information and data in future smart distribution networks are leading to unprecedented complexity in the required control paradigm [7, 9, 28, 29]. These challenges can be solved using distributed and decentralized control methods based on local information while still maintaining system-level coordination.

The enormous amount of data and information needed to achieve a desired level of overall system performance using DERs to control the network is another difficulty with this approach, resulting in large computational loads. Therefore, it is important to research the benefits of cooperative and distributed control techniques and understand how these might be beneficial for large and complex networks. Thus, control problems for such networks can be tackled by simplifying the structures of large and complex distribution networks considering local DERs to enable distributed control while dealing with the network time-varying conditions. Additionally, artificial intelligence and control can play an important role in dealing with future power networks by implementing intelligent systems able to maintain the complexity of the network operation. Thus, smart grids can be more intelligent with local, autonomous and adaptive control in the future to accommodate the increased penetration of DERs.

In the following sections, the related prior art is investigated, and various techniques are analysed and conclusions are drawn to control and integrate DER in distribution network. These methods are used to solve technical problems within distribution networks, such as voltage control, grid losses, and power quality.

2.3 Distributed Coordination and Control for Active Distribution Networks

This section provides an overview of relevant distributed/decentralized control applications in power networks. In distributed energy systems, coordinated control actions are applied by local controllers, and the system components can be expanded to include DERs that can be controlled locally. Moreover, as a result, each local controller/agent's computational needs are decreased. In power networks, controlling the voltage is influenced by the topology and structure of the network as well as the flows of reactive and active energy. Therefore, coordination amongst DERs is required to employ DERs for voltage control [30-33]. Various smart grid components, such as smaller energy generators, storage devices, and renewable energy sources, as shown in Figure 2.1, can be connected along with these component's measurements to manage and maintain the performance of these devices [9, 32, 34]. As discussed, this thesis focuses on the distributed control and management of DGs and EVs in large distribution network, which can also be extended to control various network components. A review of control and technologies in relevant literature is presented and discussed.

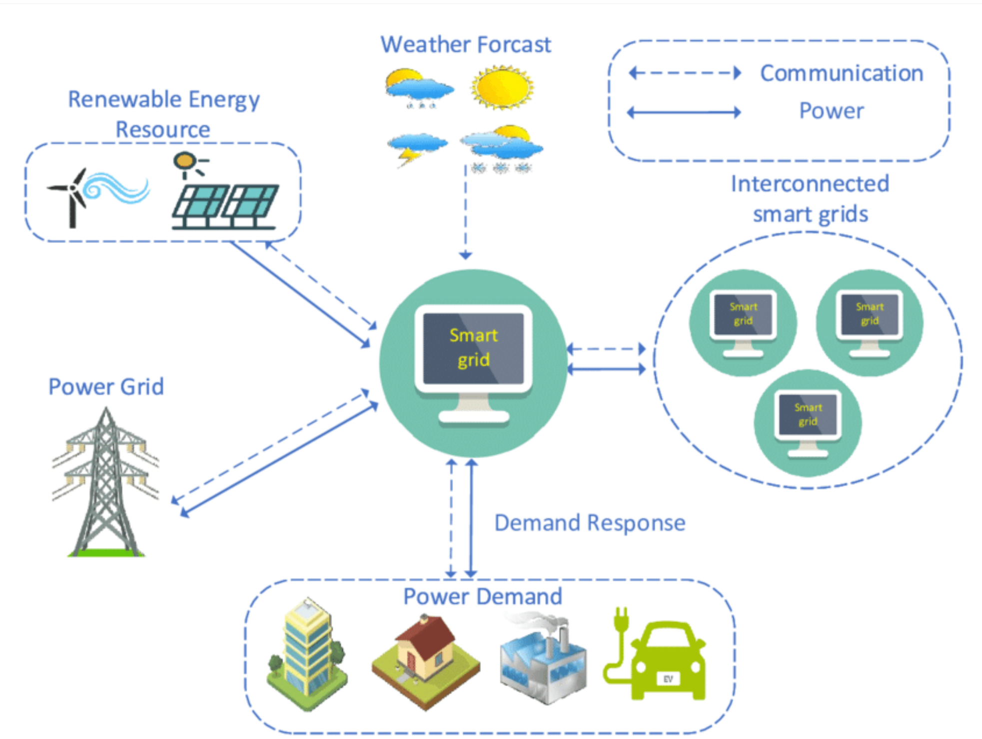


Figure 2.1: Structure and components of smart grids [34].

2.3.1 Distributed Generation

Distribution networks were originally designed to be used with one-way flows, providing power to fixed loads. Recent years have seen a surge in the connection of many smaller but dispersed DG units and innovative, cutting-edge components to the power distribution network. These DGs can come in a variety of forms, including photovoltaic (PV) systems, wind turbines, fuel cells, and diesel generators. The integration of these components adds more complexity and uncertainty to the management and control of modern power systems, such as voltage, frequency, and active/reactive power control [9, 11, 33]. Furthermore, one of the main causes of recent blackouts and voltage drops around the world is a lack of reactive power [35]. Using distributed algorithms through data exchange between various devices is one of these networks' essential requirements [14, 36]. Investigating the benefits of computational approaches and distributed control is therefore necessary. Various research schemes have investigated local control and measurement for distributed resources, and examples from relevant literature are presented next.

Recently, researchers studied distributed control techniques to control DGs in power networks. The authors in [37] presented a “range-consensus-based distributed control” approach to address cooperative voltage control of DGs for island microgrids. The technique builds input-to-voltage control models and unifies the control states for many DGs using a collaborative design approach. A reference range rather than a consensus state is used to regulate the voltages of all DGs. Additionally, the range-consensus-based method can prevent the average consensus control’s tendency to cause overvoltage at the head and tail nodes. This allows the system to expand the control scheme of different DGs in a practical system.

An optimal voltage regulation technique is proposed in [26] using the decomposition of the sensitivity matrix to group the network into sub-networks in which DGs and their influence on voltage is obtained. The presented voltage regulation is applicable for both power factor control (PFC) and unity power factor (UPF) mode. The authors carried out planning studies in advance to test anticipated worst-case scenarios. At the planning stage, anticipated issues are analysed when the system is usually designed and built to cope with the possible worst-case scenarios. However, power networks worldwide are transforming into more stochastic and complex networks that allow integration of DGs and distributed decision-making and sensing components. Therefore, this method can benefit from local distributed and coordinated control schemes. That is those schemes that consider the conditions of involved DGs, and can be implemented using agents. This would allow DGs to coordinate their control actions and allow them to perform control actions based on system conditions.

In [38], a distributed control technique for mitigating overvoltage events by controlling the active and reactive power outputs of inverters in feeders was proposed that requires coordination between feeders. Remote measurements are not required for this method, but the feeder node is required to provide a control signal to all PV units, as shown in Figure 2.2. Each feeder is assumed to have sufficient power, which doesn’t account for time-varying conditions of DGs. However, a more decentralised approach can be achieved by PVs operating independently or in conjunction with other PV units depending on the conditions of other units. These PV units can benefit from local agents that can coordinate and negotiate the injection of power from the units as required.

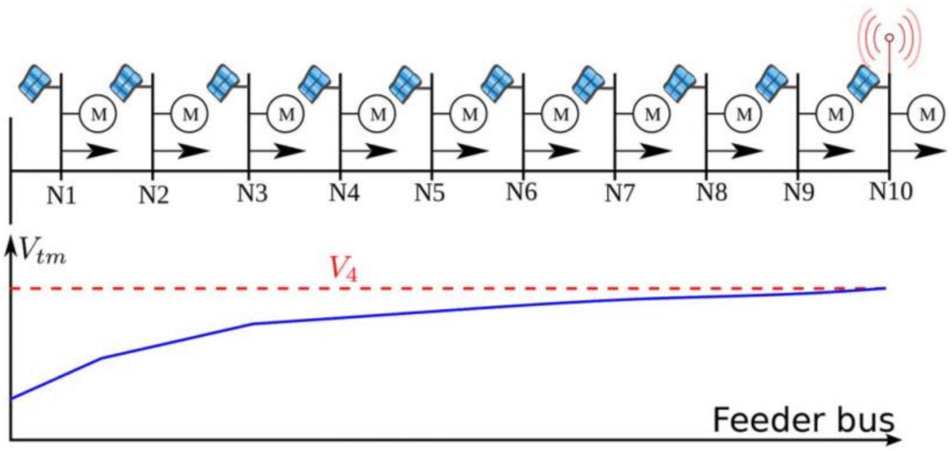


Figure 2.2: Feeder emergency signal is provided to all PVs [38].

An optimal distributed control mechanism for coordinating multiple DGs is presented in [39] using a two-level integrated control technique. The first stage implements a control system based on the droop control. Using an improved PID controller, a secondary frequency control technique is used to reduce the small signal error and eliminate voltage deviation. The results show that insufficient secondary loop adjustment results in poor and unsatisfactory outcomes and fails to reach the required power quality. Nonetheless, the proposed strategy enables the microgrid to operate properly in the presence of disturbances. This strategy implements power sharing, manages the system in the face of large changes, eliminates large fluctuations, and provides references for voltage and frequency.

The study in [40] proposed a distributed cooperation voltage regulation method for complex distribution networks. This technique aims to reduce both the number of agents and change in power necessary to regulate voltage. In addition, the presented solution performs online optimization, which reduces the response time by physically implementing the decision variable's value as a controller set-point at each iteration. This approach uses voltage sensitivity to only activate agents with the greatest potential for voltage regulation. This results in a system with a much faster response time. It directly applies the calculated injections in each iteration rather than waiting for convergence before implementation making it outperform similar methods such as ADMM.

In [41], a modularity index method is used to detect communities for a network using reactive power balance degree for managing high penetration of photovoltaic (PV) to prevent overvoltages. The optimal active/reactive power within and between communities, as well as voltage values, are calculated in a central controller by calculating network power flows. The method used predetermined planned scenarios, and the evaluation of communities for (near) real-time voltage regulation considering network conditions and changes was not investigated.

The study in [42] shows that changes on the network structure and the availability of the system controllable devices is considered as one of the main factors that affects the voltage control using DERs in distribution networks. The technique presents an improved decentralised voltage control scheme based on [43] that considers changes in the system configuration. The system configuration is identified using an impedance identification capability of the DERs inverters in order to improve the system. The study also shows that the voltage control objectives cannot be achieved without an adaptive control technique and proper communication between system components.

A distributed event-triggered cooperative control scheme is introduced in [44] and [45]. The test system is shown in Figure 2.3, where the solid lines denote the electric and dashed communication lines. To achieve power-sharing and voltage management in isolated microgrids powered by inverters, an initial starting supply and demand balance is required. To overcome the limitations of these techniques, the method in [46] introduced a distributed control algorithm for microgrids that does not require initialisation in order to implement active power-sharing and frequency regulation with event-triggered communication.

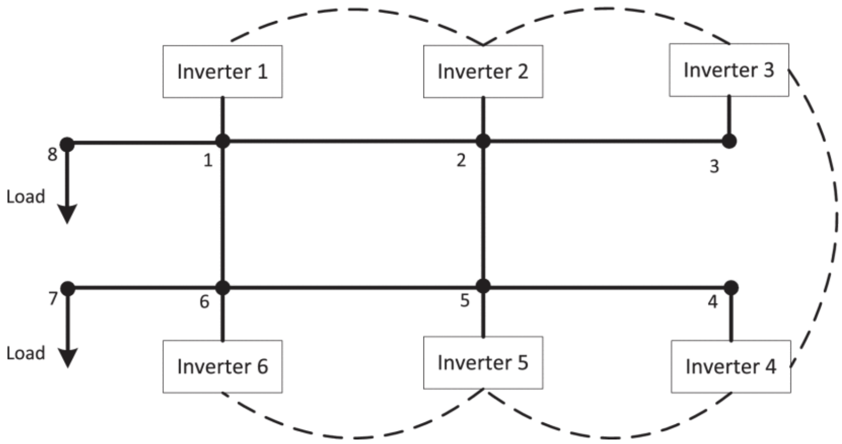


Figure 2.3: Inverter-based test system with communication between inverters [44].

To enable decentralised Volt/VAR management, a coordinated reactive power regulation with adaptive zoning is proposed in [47]. Zones are created within a radial distribution network using voltage regulators on-load tap changers. To reduce complexity and communication requirements, generators in this approach are split into zones. However, additional research is required into how to define dynamic zones for larger and complex networks.

Additional publications have integrated distributed control schemes for DGs by various techniques. The authors in [48] proposed an “adaptive backstepping sliding mode control” strategy for improved dynamic regulation performance. It uses only local measurements and provides better dynamic regulation performance. In [49], a decentralized reactive power control mechanism for DGs is proposed based on optimal set-point design and an off-line coordination to control the voltage in radial feeders. Communication is only required when network events cause network structural changes. In [20], an MAS-based voltage support scheme was presented using DGs in a distribution feeder. An agent-based control model was presented in [50] in which the output power of the DGs is adjusted to reach the balance between the supply and demand while providing stability of the voltage and frequency. The technique presented in [51] integrates the sensitivity methods for a coordinated decentralized control scheme for DGs along a radial feeder with reduced sensing and data exchange requirements. More investigations and reviews of distributed and decentralised control strategies for DGs on electric power systems and microgrids are presented in [33, 52-54]. The reviews provide various methods of integrating DGs and discuss future challenges in future power networks. They also present that although these various studies have considered distributed control techniques, expanding these methods to large systems could result in large computational loads and therefore improved and intelligent techniques are needed to deal with complexity and uncertainty of large networks.

All the above distributed techniques can tackle network challenges; however, none of them is able to provide distributed and autonomous voltage regulation with dynamic grouping of DGs by considering the unanticipated conditions of DGs and the highly dynamic behaviour of the emerging smart grids. As presented in the literature, there is need for dynamic and distributed coordination of distributed resources in power networks to control the voltage and ensure system stability. As the thesis will present, an appropriate approach that can autonomously and dynamically control DGs (see Chapter 5 and Chapter 6) in large and complex networks could overcome these challenges.

2.3.2 Electric Vehicles

The deployment of EVs in power networks may raise serious voltage control challenges [55]. In addition to the challenges posed by the mobility and probabilistic nature of EV charging demand, as already discussed, voltage reliability and stability can introduce additional challenges due to the lack of voltage compensation devices [56]. More control over supply and demand characteristics, including controlled charging, real-time pricing, and as well as peak shaving is made possible by EV integration into power networks [57]. Because of their greater flexibility benefits, EVs have been used for a variety of ancillary services, including demand-side response and voltage regulation [56, 58]. Using EVs for distributed voltage regulation services and controlling both active and reactive power for active distribution networks (ADNs) is therefore a promising field for future research. It is necessary to provide a distributed control system that is intelligent and autonomous for coordinating EVs in a highly complex environment with a variety of uncertainties and dynamics. Distributed control of EVs in these circumstances, however, presents a challenging problem involving complicated decision-making with significant dynamics and uncertainty.

According to studies, around 50% of EV penetration causes 50% of distribution transformers to be overloaded [59] and 25% greater energy losses in the feeders [60]. If EV penetration level reaches about 40%, uncoordinated EV charging requires upgrading most distribution transformers [61]. Coordinated charging methods can be developed to reduce the detrimental effects of EVs on network operations and equipment [53, 58]. To enable the effective integration of EVs into the existing networks, various techniques and control strategies have been undertaken on EVs. Among these control strategies, various techniques are investigated and presented next.

Researchers and developers have investigated the control and integration of EVs in distribution networks to address network issues. In [62], a parallel consensus technique is used to establish a local power dispatch strategy and identifies the best active and reactive power allocation for charging electric vehicles. The approach uses fair pricing schemes that take into account each vehicle's amount of involvement in the resistive distribution network. The maximum profit for each EV user from the regulation provision is ensured during the ideal planning stage, and the requirement for transportation can be met. An adaptive voltage sensitivity coefficient is created during the regulation stage to determine how much power is needed to regulate the voltage in a distributed manner.

The authors in [63] present a charge strategy that establishes the EV charge rate by using the local nodal voltage and a voltage sensitivity to load change at the point of charging. The aim is to maintain the network within acceptable operating limits while delivering the maximum amount of energy to each individual EVs. The results show that local control scheme allows more EV charging when compared with uncontrolled EV charging. Additionally, an EV charge control technique that minimises the negative impacts of EV charging is proposed in [64] based on voltage and sensitivity. Both the local nodal voltage and the sensitivity of voltage to load are used as inputs to the controller to ensure equal contribution from EVs linked to various nodes. The suggested EV charge controller's output is the charging rate, while the technique takes into account the voltage and sensitivity as input signals.

The study in [65] presented a multiagent reinforcement learning algorithm to solve the EVs' coordinated active and reactive power control problem. It uses both demand-side response and voltage regulations. The goal is to formulate an EV charging and discharging scheduling problem from the user's perspective. The method is tested on a modified IEEE 15-bus network. The system learns uncertain grid prices and demands without building hypothetical probability distributions.

A hierarchical distributed control strategy for reactive power support is proposed in [66] to control power flow and improve distribution system performance. The technique created models for the distribution of power and EV charging that make use of the grid-supporting ability of EVs' reactive power injection. As shown in Figure 2.4, the operation is split into two levels: the operator level solves optimal power flows to assess the technical limitations to provide to the aggregators, and the aggregator level schedules the fleet of EVs according to best practices. The grid control centre receives the best EV charging profiles from each node after first solving models at the EV aggregation level. The grid control centre then addresses the distribution OPF with the goal of minimising the deviation of EV charging scheduling through load shifting and load curtailment.

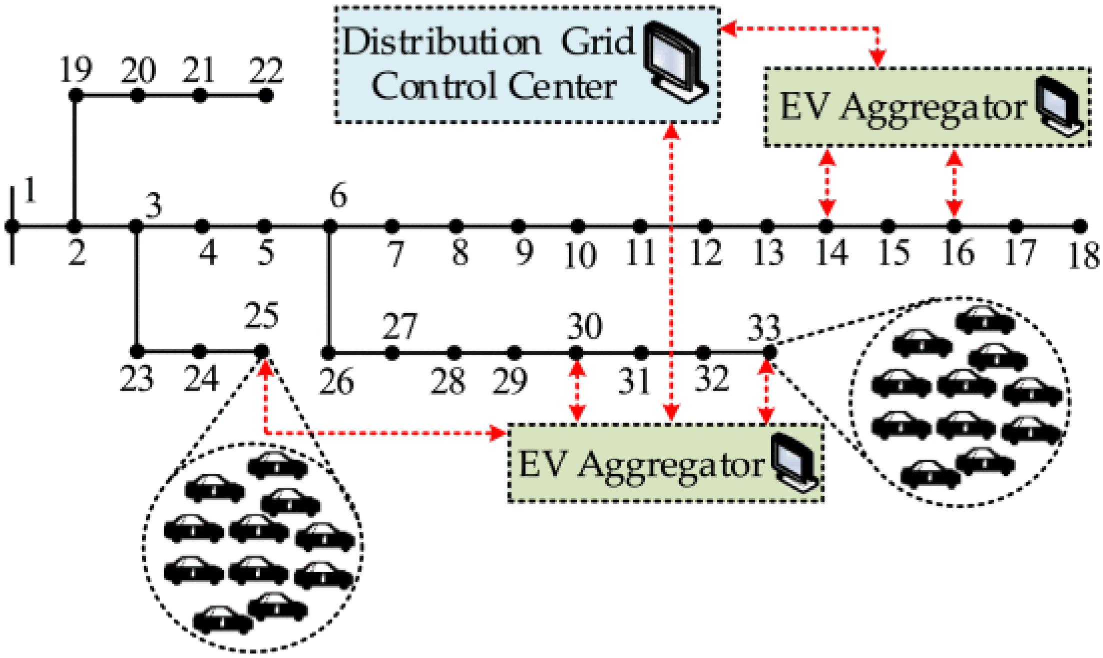


Figure 2.4: Operator level and aggregators level [66].

To meet supply-demand balance and improve the reliability of power grids with EV changing stations, researchers propose an EV charging station architecture with an energy storage system (ESS) [67, 68]. The EV demand is accommodated from the grid power, while the storage units are charged from the grid power during off-peak hours. During high demand, the energy storage units discharge to meet grid and EV demand. The storage unit can serve several EVs to maintain the grid reliability. Also, these techniques can be improved to minimise operation cost of charging station and energy storage.

Further research and studies reveal that among a wide range of DERs, EVs are one of the crucial components of future active distribution networks and can be employed as flexible loads or storage to engage in various auxiliary functions for the electrical network. The effect of EV load profiles on the distribution network under stochastic charging behaviour is evaluated in [69] demonstrating the need for careful coordination and planning of EV charging to prevent voltage drops. By creating a real-time charging plan for plug-in EVs and an optimal dispatch strategy for EVs, [70] and [71] both aim to smooth out wind generation fluctuations. Reference [72] describes a method for reducing PV power quality fluctuations that uses the distribution network to charge EVs. In [73], the load profile of the distribution network is flattened by the use of several V2G-capable EVs. Finding the best EV charging station is a problem that is addressed in [74] with a smart charging method. The authors in [55] review and discuss smart grid technologies and communication networks that are applicable to EV technologies while also empowering distributed generation systems. They also address some limitations and challenges before offering suggestions and guidelines to address the current problems.

The above-mentioned investigation shows that EVs can be controlled to solve power network challenges such as voltage drops and over-voltages in a particular area, or overloading of the distribution transformer. Distributed control of EVs in these conditions for large networks, however, is a difficult problem with significant dynamics and uncertainties that requires improved methods. In addition, solving such problems can be computationally complex. To avoid such a situation, EVs in distribution networks can be divided into groups to allow controllable charging rates, which can also be used to maintain the acceptable voltage levels. Controlled charging of EVs offers a solution to allow the charging of large numbers of EV, whilst at the same time, allows the use of the existing grid. In contrast, in an uncontrolled charging mechanism, EVs are scheduled to charge at their maximum charging rate and therefore limit the number of EVs allowed to charge simultaneously. Electric vehicles, owing to their mobility and flexibility features (e.g., charge rate, charge, discharge), could offer several supportive services including voltage regulation, which is presented and discussed later in this thesis.

2.4 Partitioning for Large Distribution Networks

As presented in the previous sections, future smart distribution networks will require a control paradigm that is unprecedentedly complex due to the growing number of controllable devices, such as EV and DG and, the control variables, and the growing volume of exchanged data and information. For large distribution networks, managing all node voltages also presents new challenges. The requirement for coordination control of all nodes in these larger networks causes a significant computing load, which restricts the advantages of coordinated control to small dispersed systems.

The clustering of large power networks into smaller partitions allows the control problem to be split into manageable sub-problems. There is significant prior art in this area. In [75], [76], the K-means algorithm based on electrical distance is used to divide power networks into partitions. The community detection algorithm-based method is used to find optimal partitioning using reactive power balance degree [41], and coupling strength based on the impedance matrix [77]. An optimal voltage regulation approach is presented in [26] based on the application of the epsilon-decomposition method to the sensitivity matrix. In [78], a distributed optimization technique for solving the optimal power flow (OPF) problem uses a spectral-clustering algorithm. An overview of two of these techniques that can be used for large power networks and the benefits of each technique to solve the complexity of such networks is discussed next.

2.4.1 Epsilon Decomposition Method

Epsilon (ε) decomposition is an algorithm that breaks up a matrix into diagonal submatrices [79]. The concept is based on the premise that in a given Jacobian matrix A and a threshold ε, all the entries that are less than ε are set to zero as follows.

$$A = A' + \varepsilon \cdot B \tag{2.1}$$

$$0 < \varepsilon < 1 \tag{2.2}$$

where A' is the block diagonal decomposed submatrix, and $\varepsilon \cdot B$ contains elements less than ε.

The "new" matrix A', which is a block diagonal decomposed matrix, contains all the variables that are strongly coupled in the same block and describes the topology of each subnetwork, while the weak couplings are discarded. The number of discarded weak couplings depends on the ε decomposition value, e.g., for the higher values of ε there are fewer couplings that need to be considered, which provides smaller groups in terms of the number of variables.

The epsilon decomposition method could be used to partition networks into smaller sub-networks so that agents could be used to control these subsystems. Choosing an appropriate value for epsilon is key in this context as it determines the optimal split of the network for control. Therefore, dynamic self-partitioning using agents can be achieved by updating the epsilon value to adapt to network conditions, as presented in section 5.2.

To demonstrate the decomposition algorithm, a small network with a 4 ×4 sensitivity matrix is used [26]. The epsilon value ε = 0.5 is used as an example of the decomposition. Figure 2.5 shows the matrix and diagram of the network before and after the decomposition where the elements that are smaller than or equal to 0.5 are set to 0. The new matrix shows the decomposition of the network diagram into two groups with no couplings between the two groups; nodes 1 and 3 are coupled and nodes 2 and 4 are coupled.

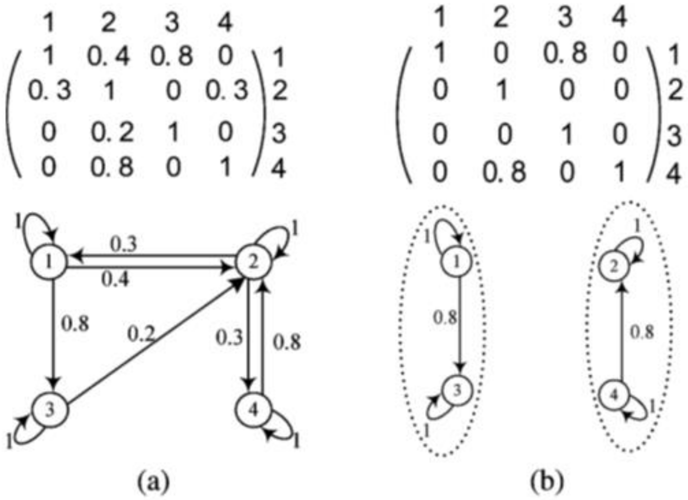


Figure 2.5: (a) Matrix and diagram of the network before epsilon decomposition. (b) Matrix and diagram of the network after epsilon decomposition [26].

2.4.2 Community Detection Algorithm

Newman's fast algorithm based on a modularity index is one of the most popular and widely used community detection algorithms for large complex networks [80], [81]. The modularity index is a function that gives an indication of the quality of the network's partitioning into communities, expressed as

$$M = \frac{1}{2n}\sum_{i,j}\left(A_{ij} - k_i k_j/2n\right)\delta_{ij} \tag{2.3}$$

where n is the number of edges; A_{ij} is the edge weight between *i* and *j*; k_i (k_j) is the degree of node *i* (*j*); and δ_{ij} equals 1 if nodes *i* and *j* are in the same community, otherwise equals 0.

The edge weight between nodes *i* and *j* is represented in this thesis by the sensitivity factors between nodes presented in Chapter 5. The value M is calculated after each step of joining two communities. The larger the value of the modularity index, the stronger the partition structure. The maximum value of *M* gives the best partition of the network.

Unlike most partitioning algorithms that require a predetermined threshold or number of groups, the community detection method can obtain the optimal number of communities without predetermining the number of communities or a threshold value. Additionally, all nodes are grouped in communities (i.e., each node belongs to a community cluster) and there is no overlap among the sub-communities. Thus, this technique can be implemented for large power networks using agents to allow splitting the system into manageable sub-problems and control each partition autonomously and independently, as presented in section 5.3.

2.5 Summary

The growing penetration of DERs into distribution networks has increased the complexity of their operation. The distributed and stochastic nature of DGs and the difficulty in predicting EV charging patterns presents problems to DNOs.

This makes planning and operating such systems more challenging. Traditional approaches for dealing with problems such as voltage violations could be inadequate. Distributed intelligence and control applications in power systems could provide approaches that can be used to solve these problems. There is currently a lack of publications in creating methods for overcoming implementation difficulties in the integration and control of distributed systems and components. Reducing computational load and interaction requirements between devices is important in this regard. Therefore, methods that reduce the complexity of large problems and deal with the system uncertainties is an important aim of this work.

When dividing the network into several zones to solve the system problems at a smaller scale in each zone, this approach creates new challenges. First, distributed control requires each partition to control its voltage locally and independently. Second, the local controls need to adapt to changing network conditions within each partition. In order to enable global solutions, smart grids require applications that can adapt in response to internal interactions of distributed components and dynamic settings. Therefore, to maintain and control network issues, adaptive grouping of DERs can be a potential research field. Thus, the solutions based on self-organising algorithms are becoming more attractive.

With distributed controllers, it is possible to extend the system components to integrate DERs that can be controlled locally. However, coordination of these distributed systems is required to prevent voltage violations and maintain stability. In complex power systems, it is critical to provide intelligent and powerful tools, such as distributed artificial intelligence (DAI), to deliver adaptive and quick control of their power output. For this reason, the controllers can be implemented by local entities (agents) to negotiate and co-ordinate actions. DERs equipped with sensing, communication, and computation capabilities can be represented as autonomous agents to act and control injection/consumption of power.

Although limited literature exists to provide an insight into the dynamic capabilities of power based intelligent control mechanisms (presented in the next chapters), MAS is a useful distributed intelligence technique. In the context of modern power systems control, it is able to adapt to newly emerging issues in a variety of different settings. The distributed and stochastic nature of the future power network components makes self-organising MAS suitable and effective mechanisms. Solutions should take into account the intermittent and unpredictable nature of DER, the dynamical behaviour of electrical power networks, as well as constraints such as voltage and line constraints. Thus, these systems need to coordinate to achieve optimal operation and to prevent voltage disturbances by enabling the system to self-organise in response to various network conditions. This technique can facilitate the exploitation of the inherent flexibility of DERs in network operations. Developing self-organising power networks is a key step in controlling future distribution networks, presented in the next chapters, which is the main contributions of this thesis.

The next chapters investigate how to design a distributed intelligence and control for future power networks to advance future intelligent distribution networks. They will also investigate how new intelligent control strategies can contribute to meet the power quality and other performance requirements in the future distribution networks. With the help of state-of-the-art solutions, current problems and challenges can be solved. In particular, there is a focus on moving to novel self-organising MAS control implementations. The goal is to integrate the control algorithms and add further novel control and intelligent decision-making contributions. Through this, this thesis develops control approaches that can be integrated within smart grids. Simulations will be conducted to investigate and implement distributed control using DER for power networks during various operating conditions. This will also demonstrate potentials and limitations of current network tools and develop solutions to overcome these challenges and limitations. The goal is to develop distributed artificial intelligence and control methods for self-organising energy systems for large-scale power networks, focusing on voltage control, active/reactive power control, and the integration of DGs and EVs, enabling robust and adaptive power networks.

Chapter 3

Self-Organisation Techniques and Applications

This chapter discusses the main concepts of self-organisation and the desired deliverables from applying such a technique. The chapter also presents various methods and applications of self-organisation within various domains with the aim to explore the different challenges and techniques around implementing self-organising systems used for this thesis (sections 3.1 & 3.2). Following this, examples from literature are introduced whereby self-organising methods have been implemented for power network applications (section 3.3). Finally, conclusions (section 3.4) on the use of self-organising architectures and control methodologies are presented supporting the work proposed in this thesis.

3.1 Introduction

The concept of self-organisation is grounded in both evolutionary theory and computing. In such techniques, the system can adjust itself when the outcome of dynamic interaction among lower-level components causes an unexpected higher-level system behaviour, which is difficult to explain just from the lower-level behaviours [82]. The use of self-organising systems has been researched in many domains, including biology, chemistry, economics, and organisational theory. From the perspective of a distributed power system, the ability of DERs or other system components to self-organise to solve problems and issues on the network would be a great addition to the solution space for controlling power assets. This thesis proposes that self-organisation should be used to deal with the complexity of controlling and adapting DER elements such as DGs and EVs in power systems. To achieve self-organisation for controlling various resources of large network and managing its complexity, the thesis uses MAS approaches (Chapter 4) with network decomposition algorithms (section 2.4).

For large and complex power networks, the system's different events cannot all be known during the design phase of the system development. As a result, designers require new techniques for designing intelligent and dynamic systems, such as allowing the system to adjust itself and components (agents) to reorganise their behaviour in response to unforeseen events; allowing the system to self-organise in order to achieve an organisation that allows efficient (optimised) control. This increased complexity of the real-world applications can be addressed from a higher abstraction level using self-organisation which may be applied to manage uncertainty [83]. The concept and theory of self-organisation has frequently been explored by researchers and developers as part of the broader field of complexity science [17]. Therefore, over the last two decades, artificial system research has been focused on implementing self-organisation mechanisms, especially for applications of complex systems [84-87]. Hence, self-organising mechanism can be a suitable technique to deal with the complexity of future power networks discussed in Chapter 2. Examples of questions in this context are typically how to enable many system components to efficiently self-organise.

The application of self-organisation in Smart Grids[2] is an attractive domain for several reasons. The distributed and stochastic nature of the future power network components, as discussed in the previous chapter, makes self-organisation suitable and effective mechanisms for modern power networks. Additionally, greater accessibility of advanced technology has motivated the power industry to invest more in grid development, thus creating advancements in the Smart Grid domain that uses information and communication technology (ICT). In future power networks, as the number of distributed components that are stochastic in nature increases, the system can benefit from allowing interacting between these entities and forming smaller groups to help simplify the management and control of such complex systems. It is noted that these entities can be represented as separate agents which interact and act within their own environment, which is more discussed in Chapter 4. Therefore, when dealing with large and complex networks, as presented in Chapter 2, dividing the system into sub-systems simplifies and enables the control and management of network components such as resources and loads. Usually, in the literature of power networks (as presented in 2.4), it is reasonable to assume the scenario when the groups are deterministic with sufficient services or resources. Thus, most research activities on the application of dividing power networks problem

[2] This would typically be implemented using a MAS platform presented in Chapter 4.

to small problems were conducted under static connection links between network components. Nevertheless, when considering unpredictable behaviours of DER such as in smart grids, it is necessary to study the stochastic conditions where links between distributed components evolve and to enable system self-organisation according to the conditions and distributions of the network components.

3.2 Self-Organising Techniques

3.2.1 The Concept and Advantages of Self-Organisation

Self-organisation can be defined as "the spontaneous creation of a globally coherent (i.e., entropy lowering) pattern out of local interactions" [84]. The term 'self-organising systems' is commonly used in distributed computing to refer to systems that are capable of reorganising their distributed architecture to cope with changes and meet global system goals [88]. Therefore, self-organisation is a popular method to handle scalability, uncertainty, dynamics, and complexity of systems [89]. Robustness and self-organisation properties result from the system's ability to detect any new state, failure, or malfunction, and take proper actions (e.g., changing roles or connections). This requires system components (or agents) to have sensing, reasoning, and acting capabilities, and have their own local rules that drive their behaviour toward some optimal outcome [90].

In networks (such as power, social, transportation, communication), it is important to clarify the meaning of frequently used terms in the self-organising domain. These include adaptive, autonomous, and cognitive networks [91].

- **Adaptive networks**: The system changes its configuration to cope with the change in the system. They do not have to be scalable, agile or exhibit any form of intelligence. Adaptive networks can be based on simple or complex feedback control loops.

- **Autonomous networks**: These are adaptive networks with no human intervention. They are not necessarily scalable or stable. In general, all self-organised methods are autonomous and adaptive. On the other hand, autonomous or adaptive networks are not necessarily self-organised.

- **Cognitive networks**: They are autonomous networks that are capable of adapting and learning parameters of the system based on interaction with the environment. Elements in the network are able to plan, observe and execute actions independently.

Self-organised networks, on the other hand, are not only adaptable and autonomous but can also decide when and how to initiate particular activities based on ongoing interaction with a changing environment [91]. As a result, self-organisation is a property that can be observed in any network, including cognitive networks. Successful self-organising networks will employ a combination of the above features, allowing the system to be robust and endure disturbances without losing its goal or function. They may also enhance their performance by learning from feedback and previous status and actions.

According to Ferber [92], representing a system organisation with agents consisting of roles that can form groups of agents (statically or dynamically) has many advantages for complex systems. The organisational structure describes how agents in a system should collaborate in order to enable the completion of successful coordination [93]. This may be used to provide a framework for organising and controlling agent interactions, as well as to tune the agents' level of autonomy. As a result, the design of a MAS “organisation” is a crucial part of improved system performance, especially when complexity increases. The organisation of agents may consist of a number of partitions, and agents in each partition may interact with the aim to coordinate. *Groups* and *interest groups* are essential concepts in organisational dynamics [84]. A group allows its members to work together to achieve a shared purpose. The overall task of the agent community is broken into a series of subtasks that are assigned to group members or agents. In the context of interest groups, organisations whose members have common interests may work together to attain their own objectives. Such structure/designs might be static, conceived by the system designer, or they can be dynamic. The implementation of dynamic "self-organisation" techniques and the advantages of such techniques to control complex systems and achieve a dynamic and autonomous structure is presented in the following sections.

3.2.2 Self-Organising Systems Using Agents

As presented in the previous chapter, there is a need for intelligent control and management for future complex power networks. Such systems can be handled with mechanisms that can self-organise to adapt and maintain control objectives. To implement self-organisation for power networks, methods to enable the system components to interact and enable dynamic and adaptive operation are required. Particularly, system robustness and the ability to adapt are two essential properties for self-organising designs. This section presents properties and mechanisms for self-organising approaches applied to solve large systems.

The self-organising mechanism can be achieved by interactions between entities represented by agents participating in system monitoring and decision making. Due to potential changes in the environment, the system needs to self-organise and self-reorganise in order to improve internal processes, deliver better services or manage resources. Such adaptation includes restructuring the components of organisational architecture (processes, strategy, structure, and individual agents) in response to specific conditions in the environment of an organisation. Systems with the capability to dynamically reorganise (regardless of whether the reorganisation is self-imposed or forced) should be resilient enough to survive in a dynamic and constantly changing environment. Furthermore, the system must stay in a “stable” operation throughout this transition and cannot be offline until the re-organisation process is complete. An organisation of system components or entities (e.g. agents) [86] can be formed by:

- The agent’s functionality.
- By lines of connections between agents.
- The agent authority relationships.

Changes in any of these aspects will affect agent dynamics and their organisation. An important element in this organisational behaviour is the agent rules within the individual autonomous agents that are capable to interact (communicate, coordinate, negotiate) with each other with the aim to cooperate. The local agents maintain their autonomous decision making process, but may request advice from higher-level agents to perform global dynamics [86]. To achieve a self-organising mechanism, the system may use one or more of the following methods [86]:

- **Change the internal agent behaviour**: This can be achieved by modifying thresholds on performance metrics, changing the roles of agents, or interaction protocols.

- **Change structure**: Such as introducing changes to the connections in the network structure by modifying the number of individuals within the population, or by restructuring the connections between agents.

- **Influencing the environment**: The agents change a physical structure of a system that agents are controlling. For instance, the electrical network topology could restructure and reconfigure in response to a fault condition, assuming that agents are able to change the environmental structure.

Dynamic rearrangement can take various forms; for example, agents might modify their behaviours, roles, connections, or the whole system structure can be dynamically changed [93]. The work in [93] presents a system with organisational structures can be designed according to the following general principles:

- Introduce a means of decomposing the system into groups (partitions), either statically or dynamically, with each group constituting a context of interaction for agents. As a result, a group is an organisational unit that defines how members can interact.

- Agents should be autonomous but can be guided by norms or constraints. Full autonomy is difficult to achieve in a computational setting, and typically engineering applications require safety constraints.

Based on the mechanisms presented above, in this thesis the self-organisation design will focus on the adaption of network structure and through a mixture of the adaption of the lines of communication between agents including agent authority relationships. Using a combination of presented self-organising methods, the system organises based on its components and resources. In the context of this work, a complex and large system can be a composite of sub-systems, each of which has agents interacting with each other and the optimisation can be dynamically distributed and maintained by each group independently. This mechanism allows reducing the complexity of the network by enabling agents to interact with each other and define data flows, resource assigning, relationships, and interaction strategies. The challenge of such a mechanism lies in maintaining self-organisation, making the system distinctive in that it is robust and can react to disturbances by dynamically maintaining the distribution and allocation of these dispersed control problems, which is the aim of this thesis. This introduced robustness enables the system to continue operating in the face of disturbances and any type of change.

3.3 Self-Organisation: A Review of Literature

3.3.1 Overview

Since the 1980s, the notion of self-organisation has emerged from a range of fields, primarily control theory, thermodynamics and cybernetics [84]. For instance, the effort by Ilya Prigogine [94], who received a Nobel Prize for his research on self-organising "dissipative structures" for complex systems, and the work by Hermann Haken [95], who named his self-organising method as "synergetics". In general, in this context, nonlinear systems such as systems observed in thermodynamics [94] have several equilibrium states. This number tends to increase (bifurcate) as an increasing energy input forces the system away from its equilibrium. The feedback relationships between the system components cause the dynamics of a system to generally be nonlinear. Positive feedback causes rapid development that ends when components have been involved in the new structure, resulting in a stable, negative feedback state. The self-organising system can respond to disturbances to adapt to a changing environment and to maintain appropriate states based on direct environment or subsystem conditions.

The application of self-organisation, especially in large-scale systems that contains distributed entities, is a matter of an ever-growing research area [83, 93]. For example, there has been increased interest in artificial intelligence research, especially that incorporating self-organisation methods, such as applications in software engineering and complex systems to solve their uncertainties and dynamic requirements [84-87]. Some researchers attempt to explore self-organisation to deal with the complexity of physical systems such as multi-robot systems, networks, intelligent transportation systems, and planning and control of manufacturing resources [36, 83, 87, 89, 96, 97]. The authors in [83, 98, 99] provide a thorough and broad introduction to self-organisation, as well as a discussion of applications. For example, in the European AgentLink project [100], a relevant effort was made to analyse the state of the art, structure the research effort, and set a roadmap in the self-organisation domain.

The implementation of smart grid technologies, such as intelligent computation technologies, ICT, and smart sensors, in future networks will improve the operation and capabilities of the network, including control and management, optimisation, system restoration, energy sharing and trading, and integration of renewable and storage systems [101-103]. However, the smart grid architecture is rapidly evolving due to its highly distributed, complex, and unpredictable nature [14, 101] which requires these systems to adjust and adapt (self-organise) their mechanisms over time. In this context, components can be represented as agents, able to take actions or interact to adapt to system requirements. Overall, there have been limited efforts to apply self-organising techniques to power networks. Using self-organisation can be an effective distributed artificial intelligence technique to deal with new emerging challenges in different contexts, especially in the smart grid domain [17, 104-107]. The properties of self-organising MAS, such as flexibility, adaptability, cooperation, and extendibility, make it suitable for smart grid applications. This work aims to explore and analyse techniques that can be used to design and implement self-organising mechanisms for the control and management of distributed resources in the smart grid domain. In the following, a review of the literature is presented and investigated.

3.3.2 Applications of Self-Organisation for Power Networks

Generally, the research trend of self-organising properties in smart grids is focusing on energy markets, e.g., price bidding, with limited research on applications of self-organising systems for controlling power networks. The work in [108] outlines the challenges in the operation of power systems and presents example solutions for decentralized power flow control systems using functional self-organising approaches. It concludes that the application of self-organising systems offers promising solutions for voltage control and stability. This section summarises the main application areas of self-organising mechanisms in power systems and provides some relevant examples.

In [109], the authors outline that distributed control techniques, such as self-organisation, are very promising mechanisms to provide solutions for both technical (reliability, accessibility, flexibility) and economic requirements for smart grids that integrate DERs and demand side management (DSM). They propose a Smart Grid Algorithm Engineering (SGAE) framework to develop large-scale smart grids, with extended implementation of self-organising properties as a core control concept to offer resilience, autonomy, and adaptivity required for distributed algorithms.

A consensus-like diffusion information sharing concept for a self-organising microgrid is developed in [110] to achieve power sharing of DGs in microgrids. The DGs are represented by agents that can communicate iteratively to estimate the required global information. In this scenario, all microgrid DGs are controlled to operate with the same active or reactive power output ratios. The method enables DG agents to adapt to changing topologies as a result of connecting or disconnecting DGs in the network. Although the iterations and synchronised updates can take time to converge, the results suggest that the presented algorithm outperforms consensus techniques in terms of convergence speed. The authors in [111] presented a distributed secondary control method for inverters during unbalanced microgrid reconfiguration. The inverters in distribution feeders are grouped by smart switches and are managed dynamically for self-organised microgrid reconfiguration. The control strategy ensures proportional power-sharing among connected DGs and minimises the voltage unbalance.

A self-organising communication architecture was proposed in [112] to mitigate cyber-threats applied to control schemes in smart grids. To support trusted communication requirements within the microgrid, a distributed and scalable *key management* and authentication scheme is proposed in [113] to establish secure machine-to-machine (M2M) messaging and trust relationships for microgrids. The proposed method, namely Micro sElf-orgaNiSed mAnagement (MENSA), combines the concepts of public key infrastructure and web-of-trust to realise the full potential of microgrids in terms of performance efficiency and scalability. The mechanism allows nodes to leave and join frequently while maintaining the operation of the network.

The Holonic architecture[3], which is evolving and self-organising in structure, has been used to solve emerging challenges in power systems. The paper [114] recommended DORPC (decentralized optimal reactive power control) using a model based on a Holonic architecture. Holons can manage the internal organisation members and interact with other Holons. The approach is applied to control reactive power from the transmission lines level to LV transformers. The Energy Management System Holon (EMS-Holon) is considered the upper part of a hierarchy containing several information layers and manages the feeders from the distribution substations. Another Holonic Multi-Agent System (HMAS) with a decentralised secondary control strategy is presented in [115] and implemented for hierarchical control in Microgrids. The design of HMAS aims to introduce holarchy microgrids management and control to facilitate decentralized decision making, as shown in Figure 3.1. The study also suggests that some learning capabilities for agents can also be introduced through cooperation between agents in a dynamic environment using this model.

[3] The term Holon is defined as "A Holon is an identifiable part of one or more systems and is, at the same time, a system formed by subordinate parts that integrates it as a whole" (source: www.igi-global.com /dictionary/holon).

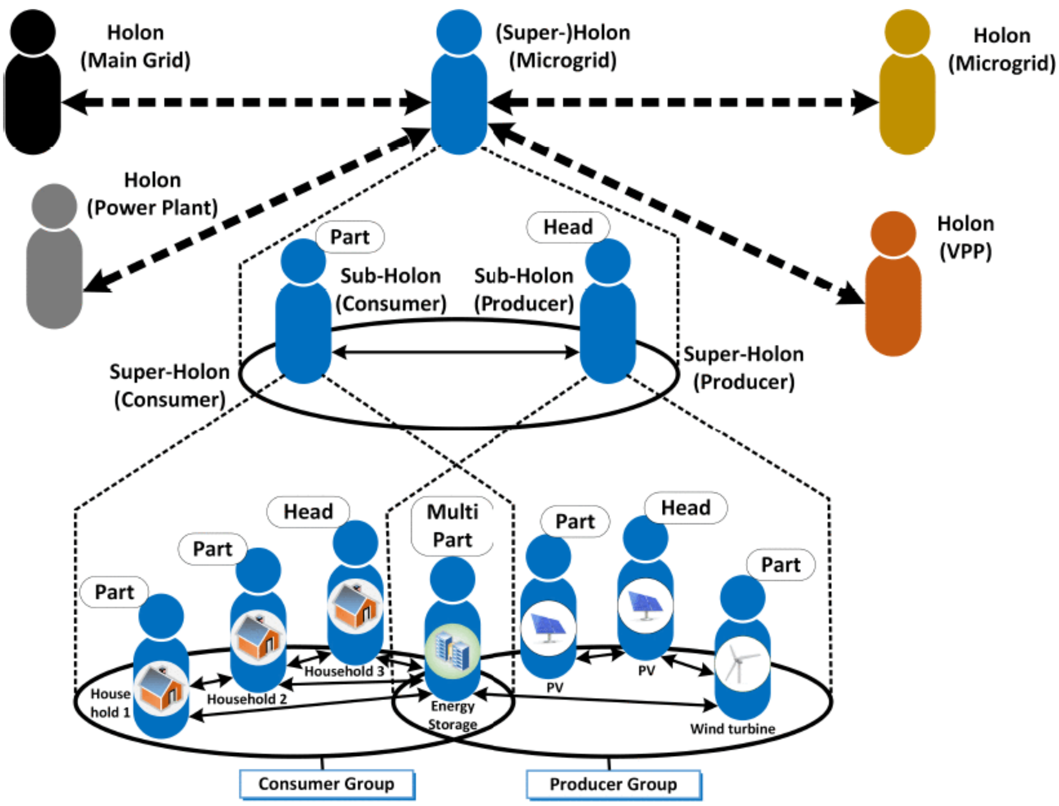


Figure 3.1: Simplified holonic MAS implementation in a microgrid model [115].

The work in [116] investigates the notion of holonic virtual power plants (VPP) to overcome the reactive power scheduling problem in VPP. The author of this paper suggested the use of holons in combination with distributed scheduling techniques to provide bids to the market. The holons are set up in a self-organising manner using agents. The concept is connected to virtual tree topologies. A holon can be made up of one or more agents, as well as other holons. Each holon is represented as a single agent. As a result, the terms "agent" and "holon" can be used interchangeably in this context, and at the same time, a holon can also be part of many holons. In the above presented holonic methods, the DERs at the distribution level are usually managed from upstream transmission lines (from Holons at a higher level). Therefore, low voltage transformers are selected as lowest level Holon that are controlled by highest level holons, but are not used as "local controllers" for the DERs.

A methodology for managing the order of charging EVs is proposed in [117] with the aim of reducing the impact on the grid by organising the charging patterns. A mechanism is introduced through the interactions on the smart grid architecture's lowest layer, where the demands of the connected EVs determine control priorities. Generally, the self-organised charging of EV in this work is arguably a decentralised scheduling technique because no network configuration or control is made to the network – only the sequence of charging EVs. The paper [118] presents energy unit planning and aggregation software based on the principles of controlled self-organisation to apply scheduling for DERs. This software is built based on the COHDA (Combinatorial Optimization Heuristic for Distributed Agents) [119] and is used for the scheduling of DER using agents. The resulting software is capable of collectively scheduling of hundreds of DER units while fulfilling system requirements. The authors argue that "as the application domain of energy systems is driven by high reliability and safety requirements, self-organisation as an underlying principle for a heuristic approach might not be sufficient." To overcome these issues, the authors suggest that centralizing some parts of the COHDA enables the system to identify and manage unwanted behaviour in the self-organised systems combining the benefits of scalability and stability.

The authors in [120] proposed a self-organising flexible demand in smart grids by introducing the use of Social Capital[4], where consumers can cooperate

---

[4] Social Capital represents the value associated within the relationships of people who live and work together. It represents benefits that the individuals gain from the whole through membership in social networks.

to have required electricity for a pre-determined certain period of time. The approach was demonstrated with the use of the Presage2 simulation framework [121] by creating a simulation of the electricity exchange market and analysing the self-organisation of flexible demand. The simulation results demonstrate that allowing customers to commute within their assigned timeslots greatly improves the results. The same authors in a related work [122] adapted energy demand day-ahead allocation in a microgrid, where joint decisions are made by a set of DERs for the energy demand allocation problem. To this extent, they use self-organisation to set the rules determined by the agents to allow heterogeneous DERs scheduling to enjoy fair outcomes.

Various approaches in the literature are proposed based on pre-planned organisation. For example, the work in [123] proposed an agent-based decentralized energy management method. The objective is to locally balance supply and demand of electricity within each control group. Pre-planned dynamic grouping is implemented using the consumers and producers profile for one and eight hour profiles. The results show that more dynamic grouping produces overall less supply and demand mismatches. However, the algorithm does not take real-time actions to minimize the net imbalance. This always results in at least one unbalanced group, and, therefore, the net imbalance for the whole system still exists even with the grouping algorithm.

The theory of distributed consensus is proposed in [124] for self-organising properties to allow fuzzy agents (sensors) to synchronise to general functions of the local variables for monitoring voltage quality. Based on these synchronised values, the system decides when reactive power flow injection in the network is useful and can support the voltage in the grid. However, the approach needs information to be exchanged iteratively by the agents located at each bus to reach a consensus, which causes a heavy communication burden even with tested small 30-bus network. Also, generators are assumed to be connected solely to their bus, which does not demonstrate DG units usually coupled with a load at one bus. Even if a solution is found to consider connecting DG with a load, this will increase the information exchanged between agents. Some limitations of this research could be overcome by grouping the network agents/sensors.

In the context of consensus-based methods, researchers have also attempted to explore self-organisation properties using decentralized consensus-based protocols for economic dispatch problems using agents [125, 126], and the monitoring and synchronization of voltage set points to improve the voltage profile [124, 127]. Although consensus approaches have promising properties, they require iterative global updates to reach consensus and synchronized results [128], and are mostly applied in small-scale or radial networks.

A first formal model for a self-organised solution for the electricity market has been presented in [129] using MAS. Termed DYCE (Dynamic Coalition in Electricity Markets), it allows unit supervising agents to dynamically form coalitions (groups) for the supply and demand of power products in electricity markets while taking topology-related aspects into account. In a MAS structure, the market can be simulated by representing buyers and sellers as agents. One such model, the competitive MAS can use self-organising agents that negotiate with other agents to either supply or buy goods or services. Moreover, energy market problems have been widely investigated such as blockchain model for self-organising integration of energy trading [130], self-organising economic dispatch approach based on hierarchical particle swarm optimization [131], and price and performance management for microgrids [132].

Reference [133] investigates the design of cooperative agents to implement a self-organised power dispatch in islanded microgrid. The droop-based primary controller shares the (active and reactive) power mismatch of the microgrid between the controllable DGs. The reference values of the microgrid voltage and frequency are determined by the virtual leader. DGs are connected with their neighbour DGs based on graph theory to update their output. However, the digraph is required at each time step. The limitation is that it requires global information to be exchanged among all coordinating DGs for the next update. Even though this feature yields distributed architecture, it was tested for a small-scale radial network. Larger networks could lead to complex digraph and information to be exchanged.

Through the abovementioned methods, previous research has focused on system formation and the applied approaches mainly target energy markets rather than technical parameters and constraints. Also, the approaches did not make full use of self-organising techniques. More research is needed to implement self-organising capable models[5] for controlling power networks in a technical capacity. According to a recent article on cyber-enabled microgrids [134], there are still many important but complex research problems that require the examination of robust architectures such as self-organisation. The authors suggest that because of common issues of DER such as a shortage of power and bandwidth or physical damage, further study on self-organisation in heterogeneous networks is required.

[5] Especially methods based on MAS introduced in Chapter 4.

3.4 Summary

This chapter has introduced the concepts of self-organisation (definition, techniques, and development) and their potential use in the power domain. The chapter started with an overview of the need to design and implement intelligent control and management for complex and large systems. These systems can benefit from some degree of intelligence with autonomous entities that can interact with each other. It also presented the idea that self-organisation of distributed components and resources can be implemented using agents with sensing, communicating and computing capabilities can act autonomously to provide fast and flexible control to handle the operational needs for the future smart grid. As discussed in this chapter, self-organising systems of autonomous agents can intelligently enable distributed control and facilitate the exploitation of the inherent flexibility of DERs in network operations. These techniques exhibit adaptive (dynamic) and robust organisation behaviour to permit the realization of the desired objective while intelligently and autonomously adapting to the conditions of the immediate environment.

In terms of self-organisation, various research areas have been well studied such as biological systems (e.g., ant colonies), networks (e.g., wireless communications, sensor networks), and artificial systems (e.g., robotics). In recent literature, self-organisation techniques have gained more interest in systems and software engineering to explore it as a fundamental method for the organisation of a system. However, there is limited research documented in the literature on the applications of self-organisation methods for power networks. These techniques support the design and functional implementation of autonomous and dynamic control of clusters in power networks especially those considering time-varying network conditions. Previous literature indicates that voltage control is a promising field for the application of self-organising systems and could be applied for distributed voltage control with self-organising capabilities. The potential applications of self-organising mechanisms for controlling DER in power networks have yet to be further explored. The next chapter discusses the MAS architecture and its use for implementing self-organising methodologies.

Chapter 4

Multi-Agent Systems

Multi-Agent Systems (MAS) provide distributed and artificial intelligence techniques that can be used to implement self-organisation in the power network domain, which will be used in this work for the development and deployment of presented methods. Prior art (presented in the previous chapters) indicates that self-organisation with agents provides capabilities to group local components in order to enable the control of large-scale power networks based on local signals and are able to adapt to unanticipated events. The following sections introduce the concept of MAS and the development techniques, followed by an investigation of examples of MAS applications for distributed control and management of power networks. The MAS techniques will be used in conjunction with self-organisational methods to create a design for controlling distribution networks discussed later in Chapter 5.

4.1 Introduction

A MAS is an organisation of multiple agents that communicate with each other in a common environment to achieve its objectives. The agent organisation approach imposes norms or rules so that agents are able to coordinate their local behaviours and interactions with other agents. As presented in the above section, the aim of this work is to design a self-organising system and use MAS to implement such a technique to deal with the increased complexity of smart grids. When designing self-organising MAS, developers need to consider three important factors that influence the dynamics and structure of system architecture.

- The first key factor is the relation between agents, i.e., the interaction mechanism that allows agents to achieve coordination in performing their tasks and to reach the global pre-assigned objective for MAS.
- The second is the formation or organisation of agents in MAS that identifies the interconnections and implemented structures between agents in the MAS, i.e., how the agents are related to one another to form a MAS.
- The third factor is maintaining the cooperation of MAS structure in response to time-varying conditions and changes that affect the control of the system which requires a dynamic and adaptive system, i.e., self-organising mechanism.

In this thesis, the MAS is used to develop and implement systems that are able to self-organise and control the power networks based on the three key factors discussed above. In the following, an overview of the background, development, implementation and tools of agent-based techniques is presented and analysed.

The definition of agents has many forms from different disciplines. The definition we adopt here is wildly acceptable by industry and researchers as "an agent is a software (or hardware) entity that is situated in some environment and is able to autonomously react to changes in that environment" [104, 105]. The agent has the ability to observe and perform actions in its environment. The environment is basically everything that is external to the agent, which may be uncertain and dynamic. The environment may be [135]:

- computing environment: agents are monitoring conditions and taking actions on software components, such as daemon security agents.
- physical environment: the environment can be observed through electrical and mechanical sensors, such as in power networks.

An intelligent agent is a distinct autonomous entity with its own behaviours and has the ability to interact, adapt, and adjust those behaviours. The key concept of this sophisticated entity is that it has reactive, proactive, and social properties [97, 104]:

- **Reactivity:** agents can perceive and respond promptly to the environment changes by initiating decisions to complete tasks or take control actions based on what has been designed.
- **Pro-activeness:** agents can change their behaviour dynamically in order to complete their tasks. It is also characterised by the agent's capacity to take the initiative. For instance, if one agent loses communication with another agent whose services it requires to achieve its objectives, it will communicate with another agent who offers the same or similar services.

- **Sociability**: agents have the ability to communicate and negotiate cooperatively with other agents using an agent communication language (ACL) in order to regulate their activities and achieve their goals.

Agents receive information from other agents and their environment, and they have internal rules that determine their behaviour and define how they respond. These rules might represent simple functions of the inputs received or could be complex involving various internal components and state parameters. The rules can be either fixed or agents may adapt those rules to improve their performance. Additionally, agents may adapt to various external conditions, implementing a closed-loop feedback method to act on their environment. Thus, the agents within a MAS can interact, i.e., coordinate or negotiate, organise, and exchange information with other agents to attain a better solution through collaboration.

In general, the internal structure of an agent can vary depending on its use, where agents are placed in an environment and get feedback using their sensors and act using their actuators [136]. The internal structure of agents, as presented in Figure 4.1, consists of sensors (inputs), actuators (outputs), a communication unit, and a decision-making unit (DMU) [137].

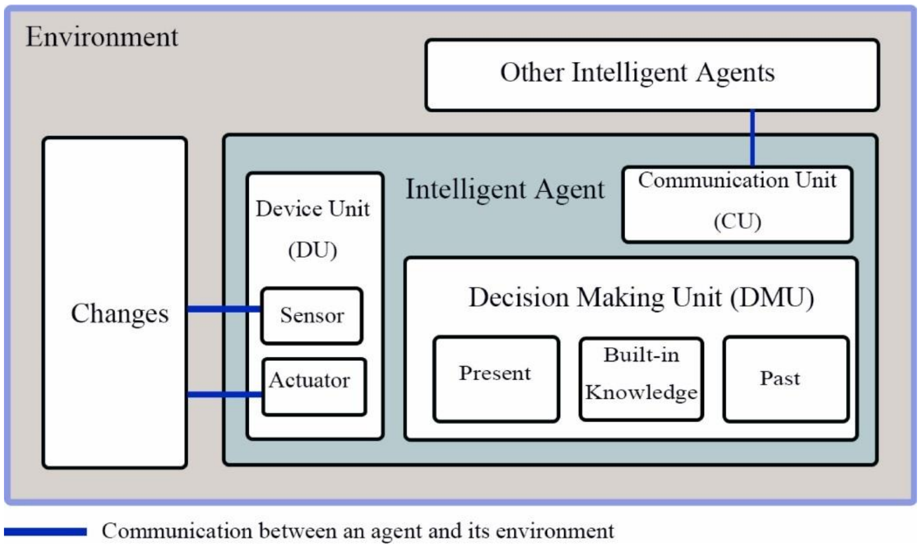


Figure 4.1: The internal structure of the intelligent agent [137].

MAS provides users with the ability to represent agents that can interact using communication languages. A MAS is an interdisciplinary technique that attracts research interests from different fields such as software engineering [138], computer science [97, 139], control engineering [140, 141], manufacturing [142], smart cities [143], power systems [104, 135], and systems engineering [15]. As shown in

Figure 4.2 and Table 4.1, the work in [36] summarises some of the advancements of intelligent control for MAS applications in different disciplines such as robotics, smart transportation, complex networks (such as smart grids), and many others.

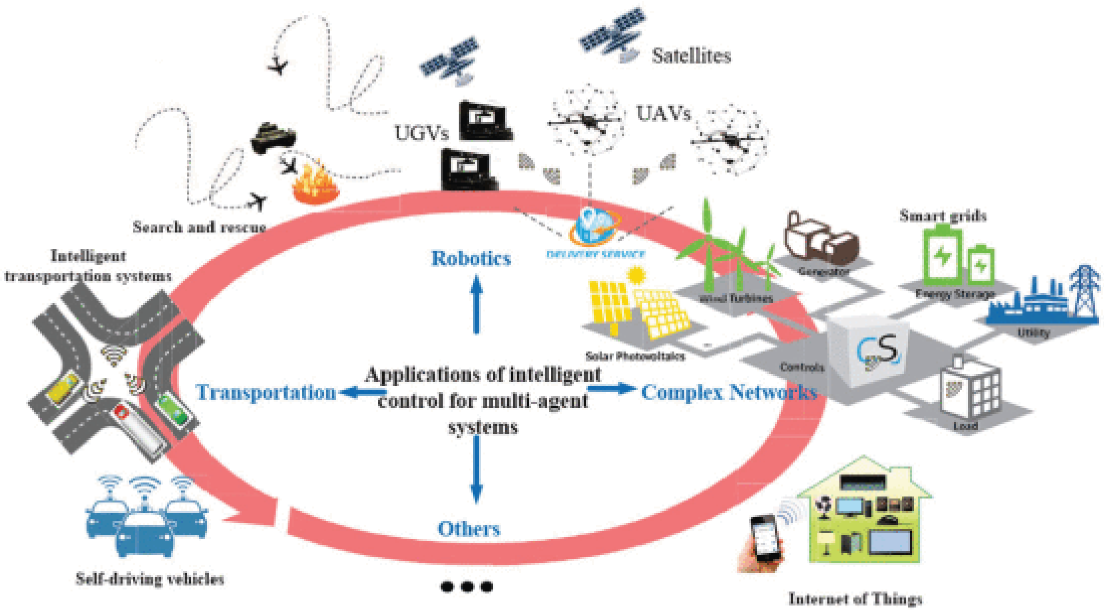


Figure 4.2: Applications of MAS in various domains for intelligent control [36].

Table 4.1: Applications of MAS for intelligent control

Applications	Feature-specific MAS
Robotics	UAVs
	UGVs
	AUVs
Complex networks	Smart grid systems
	Internet of Things
Transportation	Traffic light systems
	Smart driving systems

In power systems, for example, agents use the sensed value (such as voltage and power levels) to observe the system for decision making. The agents can communicate observed values with other agents, or take control actions to control the system, such as controlling the voltage, improving load flow, or closing or opening circuit breakers. These agents are characterised by a degree of autonomy; that is, they have the ability to initiate actions based on their own internal built-in knowledge and take appropriate action when needed. These actions can be in response to interaction with other agents or changes in its environment to solve a problem or maintain a stable state. The following sections present the MAS architecture and how agents interact and self-organise to build MASs.

4.2 Development of Multi-agent Systems

According to Wooldridge [144], MAS gives a method for designing distributed systems by arranging the system to decrease and handle its complexity. From a control perspective, MAS is a group of independent systems forming a loosely coupled network with agents cooperating to accomplish tasks that are not easily solved or computed by each individual agent. The agents involved in a MAS may have distinct objectives, but the fundamental benefit comes from collaborating with other agents. The MAS methodology therefore makes it well suited to solve complex and distributed applications [135, 145, 146].

One of the challenges that researchers and developers face in smart grids is how to deal with large-scale, distributed, heterogeneous, and dynamic systems such as smart distribution networks with DERs. MAS systems, which are made up of many distributed intelligent agents, can provide flexibility and scalability to manage complex systems. This allows power systems to be more responsive to the needs of a future evolving power grid [146]. In this thesis, the MAS is used to implement self-organising and autonomous power networks that are able to control and adapt to network conditions over time.

The primary purpose of MAS is to distribute tasks among agents in an efficient manner. The ability of agents to coordinate their individual actions and behaviours and cooperate with other agents has a significant impact on the global behaviour of a MAS system. Cooperation[6] of agents is one of the main characteristics that distinguish MAS from comparable fields such as distributed computing. The general process for coordinated and cooperative task-solving is provided in [86, 148] and summarised below:

- *group formation phase*: uses communication to request and obtain assistance from other agents that can help solve the problem collectively.
- *identifying need phase*: agent(s) identify that their abilities and resources are insufficient to achieve their goals independently.
- *group action phase*: agents carry out actions to reach their common goal.

This process is implemented in this thesis to achieve coordinated and cooperative control among agents. In complex power systems, it is critical to provide quick and powerful computation tools, such as distributed artificial intelligence (DAI). MAS can provide an effective tool for dealing with the complexity of modern power networks. MAS in power systems allows distributed heterogeneous information flows to be handled locally, as well as used globally, to coordinate distributed actions and knowledge sharing. This method has the potential to reduce information processing time and hence network bandwidth.

[6] Although there are many definitions of Coordination process, in a biological sense, it is defined as “the process where groups of organisms work or act together for common or mutual benefits. It is commonly defined as any adaptation that has evolved, at least in part, to increase the reproductive success of the actor’s social partners” [147] A. Gardner, A. S. Griffin, and S. A. West, "Theory of cooperation," *eLS*, pp. 1-8, 2016..

In most literature, the proposed MAS architectures have two layers: a power system (grid model) and a multi-agent layer [149], as shown in

Figure 4.3. Agents' independent activities and parallel processes enable MAS to respond to dynamic changes in the environment, thereby enhancing the power system's dependability, responsiveness, and fault tolerance [146].

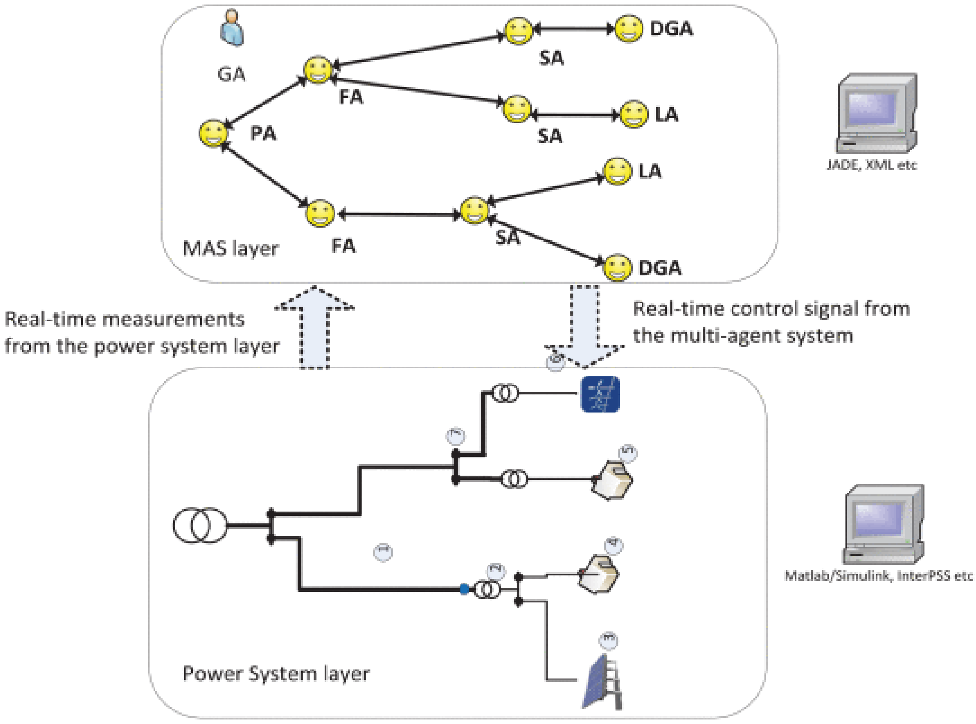


Figure 4.3: Overview of MAS layers for a power system [149].

4.2.1 Communication Between Agents

Communication networks are essential for enabling coordinated operation and management of services and resources in smart distribution networks [150-152]. Recently, the revised IEEE 1547-2018 and IEEE 1547-2020 standard supports the interconnection of DER, as presented in Appendix C which also presents other relevant standards. In MAS, agents require a two-way data flow to communicate using some common language format. Data interoperability among devices is a key requirement in the development of a future smart grid system. Thus, several standards and specifications have been proposed by IEEE (Institute of Electrical and Electronics Engineers) working groups and IEC (International Electro-Technical Commission), such as Foundation for Intelligent Physical Agents (FIPA) [153] and IEC 61850 [154]. Agent Communication Languages (ACL) are used to interact and exchange information between agents in the MAS environment. Standardization of ACL provides communication tools that have specific meanings and protocols between agents. ACL also provides a unique message format and ontology for all agents to communicate and interpret received messages. Although literature reflects many developments in the domain of ACL, the most popular languages are FIPA-ACL [153] and Knowledge Query and Manipulation Language (KQML) [155]. The authors in [105] provide a review and comparison of communication languages, standards and technologies used in MAS power systems.

4.2.2 FIPA-Agent Communication Language

Most of the MAS literature uses the FIPA as a communication framework standard. FIPA-ACL is used in this thesis to develop and implement the communication language between agents for the following reasons:

- It provides a widely used and comprehensive ACL framework (message protocol) for agents.
- A language is used that allows interoperability between different agents and other systems.

A FIPA-ACL message comprises three components shown in the example below in Figure 4.4. In summary, as shown in the figure, the key elements are:

- *inform* is the communicative act. What is the message about – its type.
- :*sender*, :*receiver*, :*content*, etc., represent the message parameters. A complete list of reserved message parameters permitted by FIPA-ACL is given in Table 4.2.
- *agent a*, *agent b*, etc., provide the content of a message.

*(**inform*** ← communicative act

Message parameters

:sender *agent a*
:receiver*agent b*
:content *(InfoEnv(info) Windows)*
:in-reply-to *info-about-env*
:reply-with *info-about-env*
:language *Java*

Content of the message

Figure 4.4: Example of FIPA-ACL messaging [156].

Table 4.2: Message parameters by FIPA-ACL, source [156]

Parameter	Description
:sender	Represents the name of the agent sending the message
:receiver	Represents name(s) of the recipient(s) of the message.
:content	The content of the message is expressed in this section
:in-reply-to	Represents that this message is a reply referring to an earlier action
:language	Language of representing the content of the message.
:reply-with	Reply desired with an expression or a conversation thread identifying the original message.
:ontology	Ontology gives meaning to the symbols in the contents
:reply-by	Represents the deadline by which reply must be received
:protocol	Protocol being used by communicating agents.
:conversation id	Represents the identification for ongoing sequence of communicative acts.

To communicate with one another, agents must use the same language, terminology, and procedures. FIPA-ACL enables agents to interact with one another, ensuring data interoperability. The agents in communication must have the same ontology[7] provided by FIPA-ACL that enables the formal specification of types, attributes, and connections between entities.

The structure and components used in the FIPA standards are shown in Figure 4.5, where two agents are communicating using ACL. The Agent Management Service (AMS) directory contains list of agents, the Agent Communication Channel (ACC) manages the communication channel, and the Directory Facilitator (DF) contains the services provided by the agents.

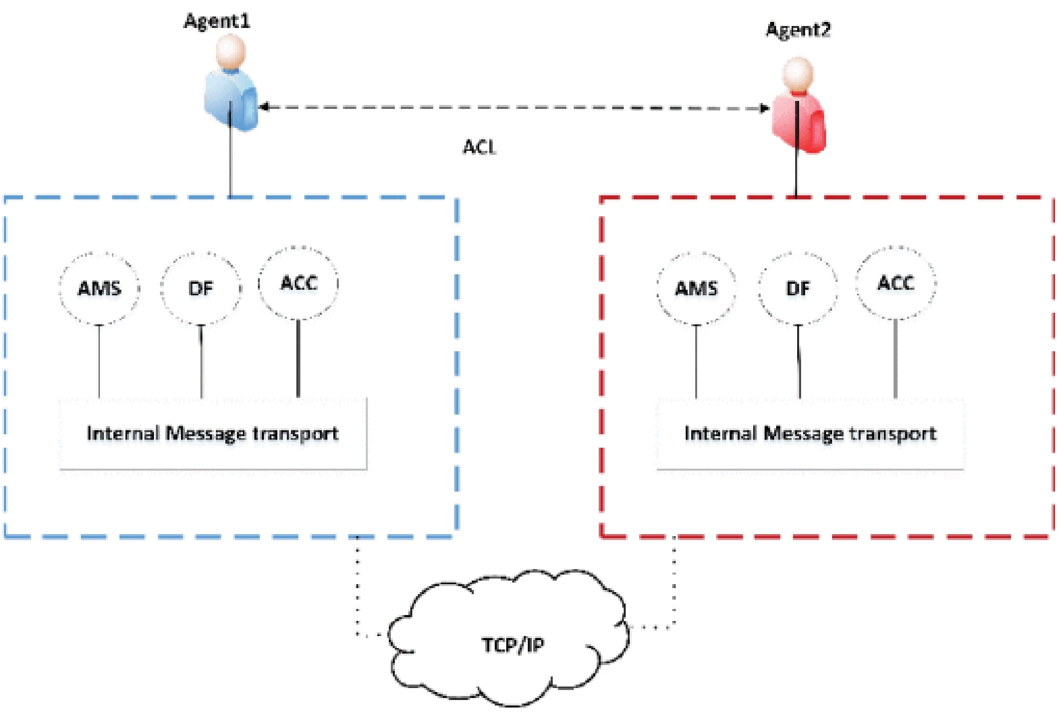


Figure 4.5: Architecture of FIPA agent platform [101].

[7] According to Oxford Dictionary of English, ontology is "a set of concepts and categories in a subject area or domain that shows their properties and the relations between them".

4.2.3 ICT Advancements for MAS Communication

A major component of MAS architecture is the ability of agents to communicate. ICT infrastructure and methodologies will be essential to providing those agents with the necessary ability in real-time to carry out their tasks. Advancements in communication/computation technologies, e.g., 5G network, internet of Things (IoT), edge computing, and the Industrial-IoT (IIoT), will present new possibilities and challenges to smart grid distributed control and communication [157]. Furthermore, these frameworks aim to encourage interoperability and enable information transfers between devices. For example, because of their common philosophy of distributed and coordinated decision making, the merger of IoT communication frameworks and MAS control systems might bring great benefits to power system control and operation methodologies. Agents in this case could benefit from the use of IoT communication frameworks. The paper [157] reviews the potential applications of 5G network-based IoT for demand response in smart grids.

A practical, real-world project for the use of IoT for MAS in active distribution networks (ADNs) is demonstrated in [158] at the Living City Smart Grid (LCSG), located in Vaughan, Canada. This is achieved by assigning an agent for each DER in order to communicate and manage a Volt/VAR control scheme. As shown in Figure 4.6, agents coordinate through an open communication framework, Data Distribution Service (DDS), to request help from each other. This project demonstrates interoperability of the communication used by the agents by making use of open communication frameworks and standards (e.g., IEC 61850, SunSpec).

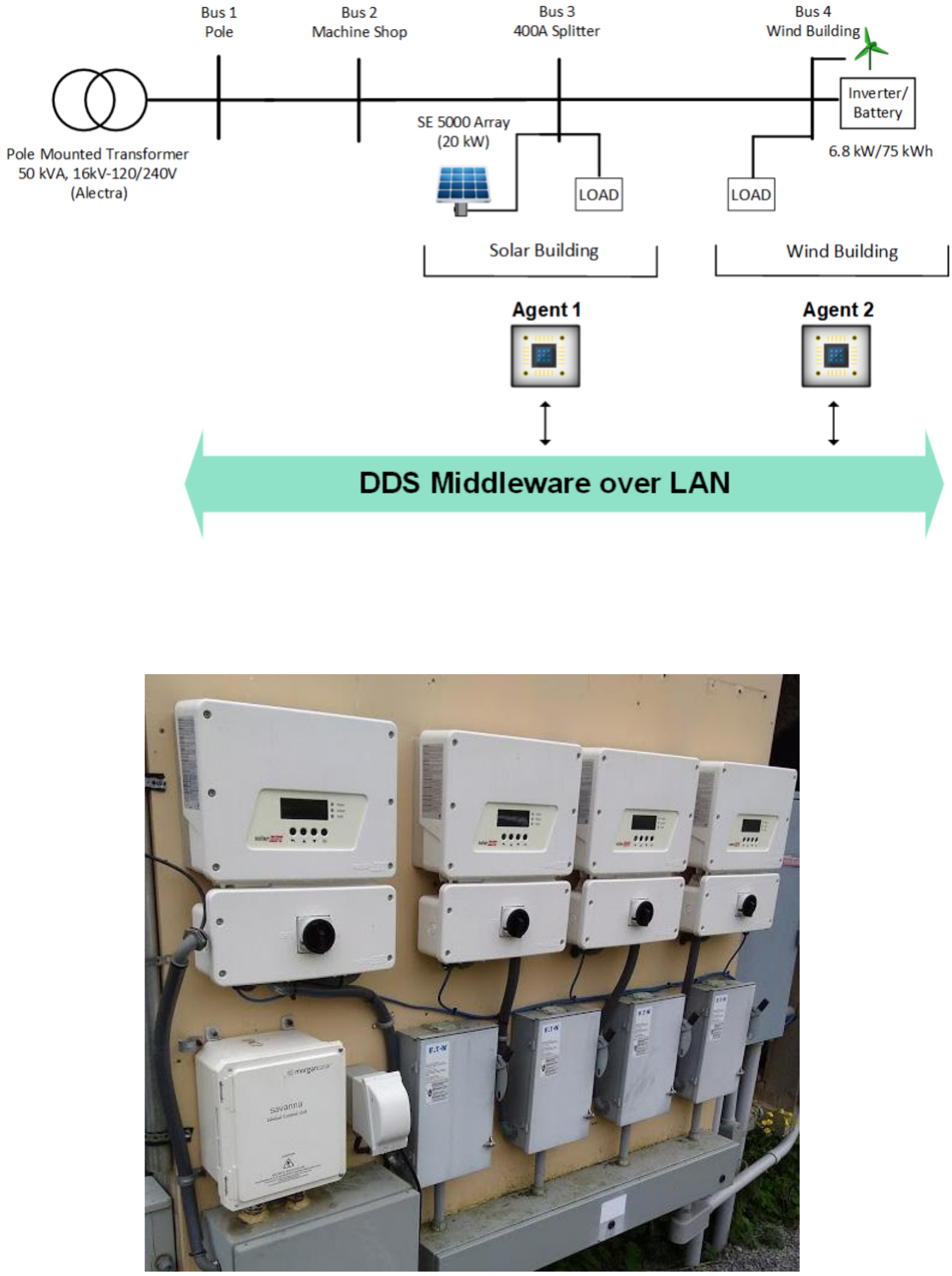


Figure 4.6: Implementing MAS within the LCSG practical project using IoT [158].

4.3 MAS Platforms and Development Toolkits

The previous section introduced MAS applications and their communication protocols. In this section, tools for implementation and simulations of such systems using software platforms are introduced and reviewed.

MAS platforms are development tools that facilitate the design and development of:

- Agents,
- Individual agent behaviour,
- Development of interactions and communication protocols,
- A representation of the environment, e.g., the power network.

In the field of power networks, it is essential to use an agent toolkit to develop and test the MAS methodology prior to physical deployment. Various development platforms and toolkits, known as middleware, have been used by researchers and developers for the design and implementation of MAS, such as Jason [159], JADE [160], ZEUS [161], JANUS [162], PADE [163], Presage2 [23], MaDKit [164], and many others. Table 4.3 compares various toolkits for MAS development, presenting an overview of the platforms used in the power networks available in the literature. They range from their developers, compatibility, application domains and other special features [101, 165-167]. A summary of these platforms and features is discussed next which provides a higher overview of criteria when choosing the preferred tool for different applications.

Table 4.3: Comparison of platforms for MAS development

Platform	Developer/ Organisation	Application Type	Open Source	Programming languages	Popularity in smart grid domain
Jason	Universities of Rio Grande do Sul & Santa Catarina, Brazil	Distributed applications based on the Beliefs-Desires-Intentions (BDI) architecture	Y	Java, AgentSpeak	Medium
Repast	University of Chicago, USA	General purpose agent based simulations with scheduling	Y	Java, C/C++	Low
Presage2	Imperial College London, UK	Multi-agent systems with organisation based simulation	Y	Java	Low
JADE	Telecom Italia (TILAB), Italy	Distributed applications composed of autonomous entities	Y	Java	High
PADE	Federal University of Ceara, Brazil	Distributed computer environments and restoration problems	Y	Python	Medium
Netlogo	Northwestern University, USA	Agent based toolkit for simulating natural and social phenomena	N	NetLogo	Low
Zeus	British Telecom (BT) ISRL, UK	General purpose agent based simulations	Y	Java	Medium

Jason is a platform for the development of MAS implemented in Java as an extended version of AgentSpeak[8] [159]. Jason is the fully-fledged translator for an upgraded version of AgentSpeak, which includes speech-act based inter-agent communication. Jason includes capabilities such as annotations on plan

[8] Agents designed using AgentSpeak are also known as reactive planning systems.

labels, completely adjustable selection mechanisms, trust functions, and overall agent architecture.

Repast 3 is a software framework for creating agent-based simulations [168]. It offers a library of codes for "creating, running, displaying, and collecting data from an agent-based simulation" [168]. Repast 3 also includes several pre-packaged utilities for visualization and is commonly used for complex dynamic scheduling applications.

Presage2 was developed by Imperial College London, UK, that provides a prototyping platform that enables systems simulation [169]. The platform is able to simulate computationally intensive agent algorithms with a large number of agents, as well as simulate the networked and physical environment, including unexpected external events, reasoning about interaction and relationships between agents. This toolkit enables structured experimentation and the animation of simulation results. Figure 4.7 shows the general architecture of the Presage2 simulator.

NetLogo is a modelling environment and agent-based programming language for simulating complex systems [170]. It is written in Java but uses its own simulation language. It is beneficial for simulating systems that change over time. It may be used to simulate related phenomena by both experienced programmers and teachers and students in the academic sector without programming experience. It has focused on the social science domain.

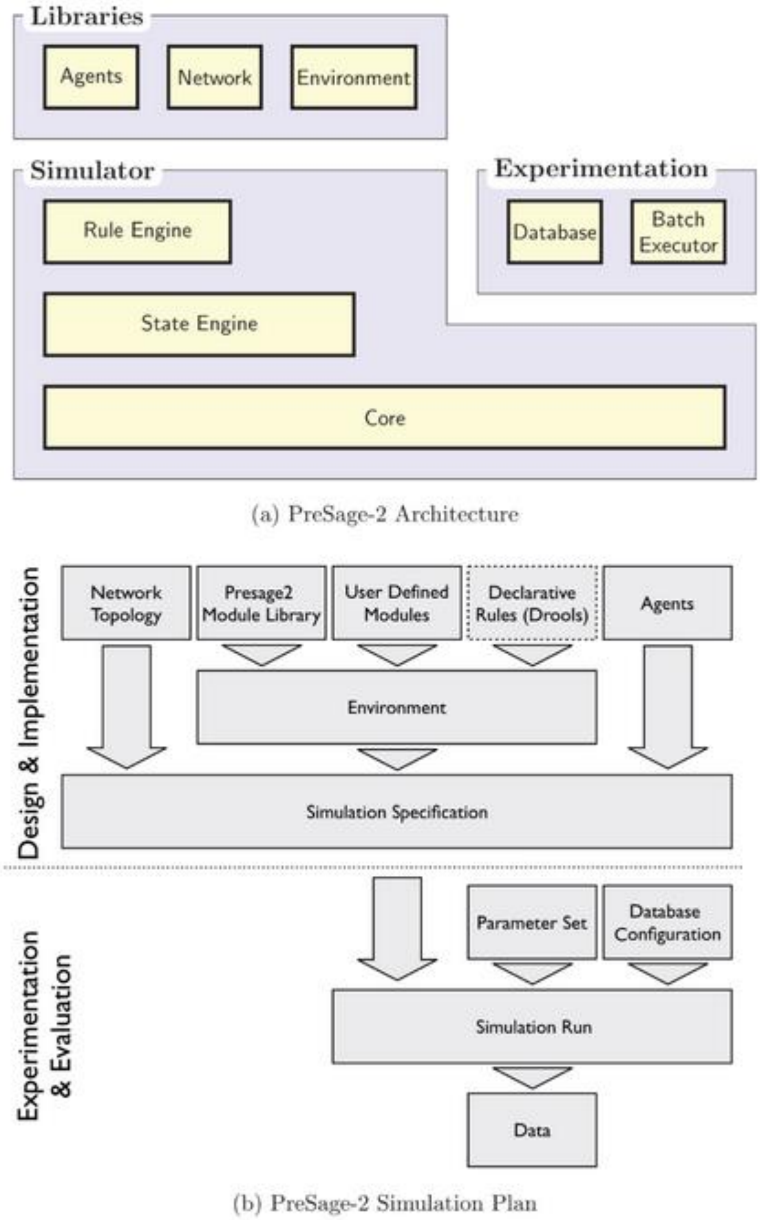


Figure 4.7: Architecture of Presage2 MAS simulator [23].

The JADE (Java Agent DEvelopment) Framework [160] contains extensive reference material that enables the building of agents in a fairly straightforward manner for people with a modest degree of programming knowledge [160]. JADE has widespread adoption in the scholarly community and even in industry. The platform seeks to facilitate the development of interoperable MAS and deliver FIPA-compliant applications. JADE platform comprises a Runtime Environment, class libraries, and a set of graphical tools for this purpose. Figure 4.8 presents the structure of JADE software.

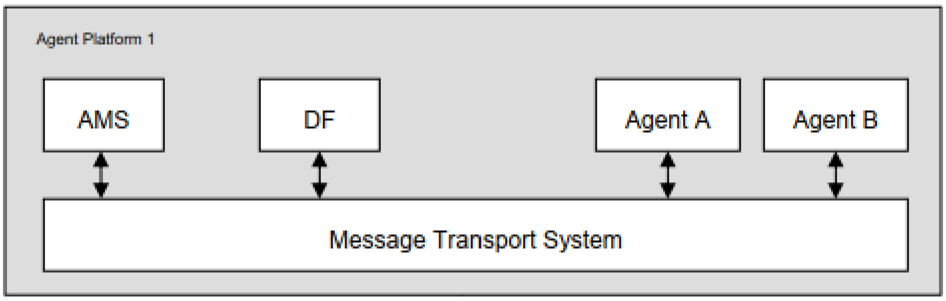


Figure 4.8: Software architecture of JADE [160].

MADKit is a multi-agent platform that was inspired by the need for a more flexible platform that could adapt to various agent types and application domains [164]. It enables the development of MAS based on the relational model AGR (Agent / Group / Role). In this model, agents are organised into groups and assigned roles, as shown in Figure 4.9.

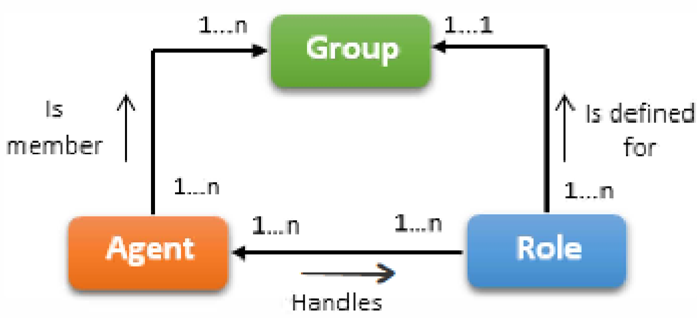


Figure 4.9: AGR (Agent / Group / Role) model in MADKit [164].

The PADE (Python Agent Development) framework [163] is a platform for developing, executing, and managing multi-agent systems in distributed computing environments. It was developed by the Smart Grid Group, Federal University of Ceará, Brazil. The framework employs FIPA-ACL standard messages, using the FIPA communication protocol. In PADE, like in other applications, the AMS provides control and supervisory responsibilities and keeps a database with the identities of the agents.

Zeus is a multi-agent platform developed by the British Telecom intelligent system research laboratory [161]. Zeus enables the rapid development of collaborative agent applications. This programme automatically creates Java code based on the agents that are defined visually. The platform ZEUS is founded on the following concepts: Agents, Their Goals, Their Tasks, and The Facts. It includes theoretical and practical tools and employs real-world programming approaches. However, it only supports one agent model, limiting the spectrum of feasible MAS designs.

Literature reviews and studies of the features of MAS-based platforms can be found in [165-167], which also provide evaluations of which platforms are suitable for particular tasks. Choosing an appropriate MAS platform for simulation can be difficult for developers. In an ideal world agent, platforms should be open-source, easy to use, scalable, and extendable. Presage2 achieves all these goals and is also capable of engineering self-organising mechanisms that can meet the objectives of electrical network control and management applications. In this thesis, we use Presage2 platform as a tool to test and demonstrate the proposed self-organising control architecture, primarily as it meets the needs of the project. The following sections present a review of MAS techniques and applications for power systems.

4.4 MAS Applications for Future Power Networks: A Review of Literature

This section summarises the main application areas of MAS mechanisms and provides relevant examples. It reviews different frameworks for power systems and explores the advantages and challenges of MAS in power domain.

4.4.1 Multi-agent Control Techniques

The increasing complexity of future power system networks requires local control and management techniques to solve local control tasks and increase the flexibility of the network. From a power distribution network point of view, the goal of the MAS is to build local decision-making agents that use local information and interact with each other to solve network problems. A comprehensive review of MAS for power engineering applications is presented by McArthur et al. [104, 105], covering the technologies, standards and tools for building MAS concepts, approaches and technical challenges within the field of MAS that are appropriate to power engineering, which has helped to advance MAS applications for power engineering. To apply MAS to the control category of power systems, different frameworks have been discussed in the literature.

Using MAS architecture, two control schemes are developed in [171] to provide real and reactive power support. The model is based on a hierarchical structure, which follows a pattern of command chain from the top-level (transmission) to the bottom level (distribution network and loads). This method introduced an algorithm for reactive load control optimization in order to improve the voltage profile on the distribution grid. The authors suggested that further research is needed to apply the control method to larger transmission and distribution power networks to explore its effectiveness for large networks. In [172], a system of intelligent agents is presented to investigate integration between the distribution and transmission networks and control the line overloads by controlling loads. However, these methods were applied to a small scale of transmission and radial distribution networks.

A distributed voltage control scheme based on a MAS is presented in [173] by adjusting on-load tap-changing transformers for distribution systems. Similarly, in [174], an agent-based technique has been employed to control voltage regulators and shunt capacitors to determine optimal settings for the system. This method implemented an event-triggered approach to reduce the communication burden of the network. The authors suggested that additional devices could be included in the control problem as a future work, such as DGs and energy storage, to investigate distributed voltage control with integrated resources.

The increased penetration of DERs and their stochastic behaviour has introduced additional complexities into power dispatch. In the last decade, these challenges, such as distributed control and integration of resources, have been addressed by researchers. MAS has been used in controlling distribution networks with DERs using power balance, voltage control, and cost minimization and maximization of the DG power output [175]. Energy storage (ES), EVs and distributed generation provide solutions to many power network problems, while at the same time adding new operational and technical challenges. In [176], a MAS framework is proposed to integrate various forms of DERs in a residential house into a control system. These resources are represented by agents, while the MAS architecture links DERs to a central coordination controller. The control system is implemented for a grid-connected DC home with integrated DG and ES technologies and enables controlling of the home and supporting the grid. However, controlling a large number of DERs can add more complexity to the system due to the increasing size of the control problem and the communication burden.

Researchers have also used agent-based control schemes to integrate and control DGs in distribution networks. A agent-based model was presented in [50] in which the output power of DGs in a microgrid is adjusted to reach the balance between the supply and demand. The results show that fluctuations of the voltage and frequency meet the standard requirements. To study how to balance customer demand and energy from DG, Ren et al. [177] build a MAS by introducing five types of autonomous agents: substation agent, the bus agent, the feeder agent, the load agent, and the generation agent. The distributed network is effectively balanced by satisfying the objectives through the communication and cooperation between these agents. A multi-agent-based dispatching scheme of DGs for voltage support on distribution feeders is presented in [20]. This paper presents MAS as an auxiliary service that supports voltage regulation on distribution feeders. Agents are implemented on the local controllers on the voltage regulator and DGs that can act as supervisory controllers to the local controller. A coordination strategy is proposed in [178] using MAS to coordinate the reactive power of the photovoltaic (PV) inverters with the voltage regulators. The scheme is able to minimize the voltage deviations and reduce the excessive tap operations on the tap operations of voltage regulators by controlling the reactive power of the PVs.

Another application of agent-based based techniques is the employment of distributed management and control for EVs in power networks. A framework for distributed peer-to-peer MAS model is presented in [179] for power sharing management in the microgrid and to maintain the supply-demand balance. The presented algorithm is applied to EVs based on graph theory to allow agents to communicate directly. The results demonstrated that coordination and exchange of information enhanced the performance of the system. A multi-agent reinforcement learning control algorithm is proposed in [180] for the management of EV charging. This decentralised algorithm uses "congestion signals" from network deployed sensors. Each charging point uses a deep reinforcement learning algorithm to learn network congestion parameters. Changes in the distribution network topology, such as transformer tap changes and feeder reconfiguration, can be accommodated by the control approach presented in the paper. However, the congestion signal is only issued downstream of the voltage problems and does not provide details on the operational strategy between EVs and aggregators. Also, the condition of the charging points is not considered. This can be solved by implementing coordination between EVs to enable the system to collaborate charging of EVs and maintaining the voltage within operational limits. Additionally, for such a large network, the control problem can be simplified by dividing the network into control areas.

Agent-based reinforcement learning techniques have also been used in power systems to allow agents to learn and adjust their control policy. Zhou, et al. [181] adopted a cooperative multi-agent reinforcement learning (MARL) algorithm to realize real-time energy management and ensure reliable electricity supply. In [182], a reinforcement learning MAS-based is adopted to design an intelligent controller for the load frequency control (LFC) in smart grids. This mechanism considers changes in communication topology and time delays to examine and improve the performance of the system.

Recently, a multi-agent deep reinforcement learning (MADRL) technique is also used in [183] to coordinate between PVs and battery storage systems. The framework enables centralized training, decentralized execution for voltage regulation. The proposed technique divides the system into voltage control areas where each area is represented by an agent. The authors in [184] also formulated a cooperative MADRL algorithm, named PowerNet, in which each agent learns a control policy. Experiment results demonstrate improved control system performance in voltage control convergence speed. The decentralized learning techniques make it suitable for large-scale power systems, however, the control scheme needs to be tested with a large-scale model from a real-world system for a more practical demonstration. The work [185] implemented deep reinforcement learning to optimize PV inverter reactive power output setpoints considering communication delays. The training performance is enhanced in the proposed algorithm and agents are trained to maintain variations of regional bus voltage and minimise power losses.

A MAS method is proposed in [186] for the emergency control of long-term voltage instability in a multi-area power system. The concept is to get the best solution using the information about voltage angles requested by agents. Another MAS architecture is proposed in [187] to perform distributed decision making by dispatching DER for network voltage control. The agents estimate the effect of their local actions on their node voltage and choose the optimal solution with regard to the cost function. The work in [188] presents an agent-based self-healing algorithm to reconfigure the grid at the distribution level in the event of a fault. The distributed MAS-based algorithm enables the system to correct the system with a focus on the problematic areas only.

Other related applications of MAS for smart grids were conducted in a number of disciplines including condition monitoring and diagnostics, and protection [189]. An extended review of MAS applications for power networks is presented in Appendix D. Practical applications of multi-agent control in the power industry control and some of the key implementations are investigated in [190-192] which cover the design and methodologies.

Although network challenges can be addressed by the above techniques, none of them can provide dynamic and autonomous voltage regulation considering the unanticipated conditions of DERs and the highly dynamic behaviour of the emerging smart grids. Additionally, the previous research mainly focused on implementing MAS for small-scale systems and with assumptions to simplify some constraints.

4.4.2 Applications of MAS for Microgrids

The microgrid (MG) is a group of interconnected DER and flexible loads within an area that is represented as a single controllable entity [193]. Although this thesis focuses on a larger network area, the microgrid applications shown here provide useful examples of potential use cases as the concept of MGs supports the increased penetration of DERs at low voltage (LV) distribution networks9. Due to the increased complexity of the microgrid operation, MAS has arisen as a novel technology in this sector. The use of MAS-based control has introduced a new paradigm in the development of a decentralised microgrid

[9] Usually defined as networks below 1000 V a.c.

structure. The MAS framework is applied to control, test, or manage functionalities of MGs [102].

Figure 4.10 shows the architecture of an MG demonstrating an energy management systems (EMS) that handles interactions with different agents [193, 194]. In recent literature, the MAS has been widely used in microgrid applications ranging from design and modelling to control.

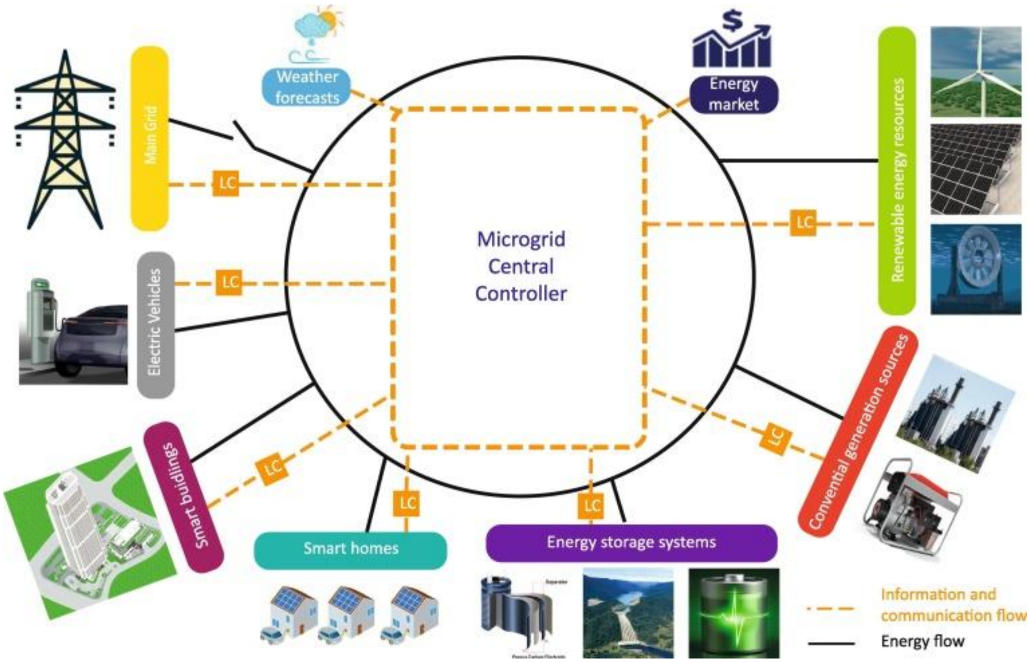


Figure 4.10: A simple microgrid architecture [193, 194].

A cooperative multi-agent for power sharing technique is proposed for microgrids in reference [195]. The MAS scheme is designed with a communication link to allow power to be shared proportionally using battery storage units. An island-based microgrid is implemented in [196] using MAS based on peer-to-peer distributed control architecture for networked microgrids. The multi-layer control algorithms achieved several tasks which can be run simultaneously by agents with communication capabilities. The proposed three control layers (primary, secondary and tertiary) are operated by the agents of each MG. Another agent-based distributed energy management architecture is proposed by [197] to provide control for each of the energy sources and loads in a microgrid system, and to coordinate between different types of agents.

Selected recent summary and comparison of MAS architectures for microgrid management and control are presented in [198-200], and summarised in Table 4.4. These papers present that from simulations, MAS can scale and can be implemented for microgrids with many interconnected resources, buses, loads, breakers, and other network components. However, hardware and practical implementation of conceptual microgrid architectures can be challenging and is yet to be widely tested where MAS offers an effective tool to design, test and implement such systems. With increasing trends in computational power, researchers are able to model increasingly complex interconnected microgrids. Finally, in [9, 190, 200], the advantages of MAS for microgrid are presented in comparison to closed-loop feedback controllers, simple optimizers, and learning mechanisms.

Table 4.4: Types of MAS architectures for control and management of microgrids

Architecture	Agent type	Role
Centralized	Cognitive	Complex energy computations
	Reactive	Quick response
Distributed	Local	Local information discovery
Two-level hierarchical	High-level	Infrastructure management, scheduling
	Low-level	Asset management
Three-level hierarchical	High-level	Critical decisions, data management
	Mid-level	Grid-connected/islanded mode switching
	Low-level	Sensors and resources management

4.5 Summary

In summary, this chapter started with an overview of the need to design and implement MAS to handle distributed systems. These systems can benefit from some degree of intelligence with autonomous entities that can interact with each other in order to build and deploy self-organising mechanisms. The MAS architecture (definition, techniques, and simulations) has also been reviewed and analysed. MAS is a suitable framework for implementing self-organisation strategies in the power domain. Methods and techniques for developing MAS were introduced, which will be used in Chapter 5. There are a number of MAS platforms that could be used in MAS simulation and are summarised in Table 4.3. For the needs of this thesis, Presage2 has been chosen as the platform in which to carry out the work discussed in this thesis.

Over the last two decades, there has been increased interest in distributed artificial intelligence research such as MAS methods to solve the problem of controlling and managing power systems. This chapter summarises these various applications from the literature. It shows that MAS provides the system with flexibility and extensibility to design and implement distributed control and management architectures. The following chapters build upon the work presented in this chapter and the previous chapters and present the development and implementation of self-organising techniques to manage and control large and complex power networks.

Chapter 5

The Development of Self-Organising MAS for Distribution Networks with DER

This chapter presents the design of novel self-organising multiagent control techniques able to autonomously and distributively control and manage DERs in large networks while dealing with time-varying conditions. They build on the work presented in the previous chapters using a multiagent-based control technique and uses partitioning of the network to handle network complexity.

5.1 Introduction

The concept of using self-organisation introduced in Chapter 3 shows that self-organising systems exhibit flexible organisation behaviour to enable the realization of a desired objective while adapting to the conditions of the immediate environment. This provides means to develop adaptive behaviour able to control DERs in complex networks. The main objective of this work is to develop self-organising MAS techniques to intelligently enable distributed and robust control with autonomous agents, which can explore the flexibility of DERs in network operations. This chapter presents a prototype self-organising MAS control system for distributed control and management of DERs and voltage in large networks through local interactions of agents in a cooperative way. The proposed techniques address the challenge of enabling distributed control and the self-organisation of multiple sub-systems while dealing with uncertainties in the network.

The key to this approach is to divide large networks into smaller, more controllable groups, as presented in Chapter 2 which introduced the idea of partitioning networks to reduce complexity. To deploy the desired scheme and control the network in a distributed and flexible manner, multi-agent systems (Chapter 4) provide a means for implementing in the real world a self-organising system design using agents. The development of this self-organising MAS system has used the key methods discussed in Chapters 3 and 4.

In the following sections, the design and development of the proposed self-organising techniques are presented. Different network setups and different techniques are used to implement dynamic and adaptive networks. Section 5.2 discusses the design of a system using DGs with epsilon decomposition. Following this, section 5.3 considers a system of EVs and implementation of community detection algorithms. The two designs and techniques were chosen to show the effectiveness of the self-organising approach for complex power networks.

5.2 Self-Organisation for Complex Distribution Networks with DGs

To address the challenges discussed in Chapter 2, this section presents a control scheme for distributed voltage regulation using appropriate DGs. This work implements a self-organising mechanism using a MAS architecture within a large distribution network by distributing multiple instances of the agent objects. To achieve this, the epsilon decomposition methodology, developed by New York University (section 2.4), is used for voltage control on distribution networks. This work extends the New York University (NYU) concepts by implementing intelligent agents with adaptive group dynamics (based on the conditions of the network) in a MAS environment developed in this section. The rest of this section discusses the roles of the various agents in the design, the implementation in MAS, and the application of the self-organisation of DG for distribution networks.

5.2.1 Epsilon-Decomposition Technique

As presented in section 2.4.1, an optimal voltage regulation approach was presented in [26] based on the application of the epsilon decomposition method to the sensitivity matrix to group the DG into matrices based on their influence on the voltage. The authors in [26] carried out planning studies in advance to test anticipated worst-case scenarios to be used in the future. However, this decomposition and voltage regulation method can be realized by means of a distributed control scheme, such as using MAS. The desired decomposition method is implemented in a MAS architecture and this method is extended by introducing a dynamic self-partitioning technique to resolve voltage issues considering the changing conditions of the network.

To achieve this, the system is developed using a MAS that enables a large distribution network to autonomously self-subdivides itself into smaller subnetworks, thereby reducing the size of the problem while enabling voltage control in a distributed and cooperative manner. Each subnetwork regulates its voltage autonomously and independently using appropriate DGs in the same subnetwork. The control method is also extended by introducing a self-organising technique to resolve unpredictable changes in the system. Self-organisation is enabled through a mechanism that adapts network subdivisions to reflect varying network conditions. It uses the self-organisation methods of adapting network structure, lines of communication and authority relationships discussed in Chapter 3. The design of the MAS system follows the key steps outlined in Chapter 4. The desired control mechanism is resilient to network anomalies and uses local interactions to adjust the structure of the MAS without stopping the system.

5.2.2 Design of the of the Multi-Agent Control Architecture

To deploy this proposed approach, the system contains four types of agents: epsilon decomposition (ED) agent, violation detection (VD) agent, linear programming solver (LPS) agent, and distributed generation (DG) agent. Each agent uses its knowledge and behaviour to autonomously manage its own activities and coordinate with only the appropriate agents while maintaining stable state of the system as described below. The epsilon decomposition algorithm is implemented using a MAS architecture, thereby allowing the agents in a large network to group into small subnetworks with the communication links between agents being autonomously determined.

1) Epsilon Decomposition (ED) Agent:

The ED agent applies epsilon decomposition to the sensitivity matrix and activates LPS and VD agents, informing them about the other agents in the same subnetwork so that each agent links only with other agents within the same subnetwork.

The network sensitivity matrix A can be expressed as

$$A = \begin{pmatrix} A_{\vartheta P} & A_{\vartheta Q} \\ A_{VP} & A_{VQ} \end{pmatrix} \tag{5.1}$$

where $A_{\theta_p Q}$ and $A_{\theta_s Q}$ are the sensitivity submatrices of the reactive power adjustments and the transformer voltage angles on the primary and secondary sides, respectively; and $A_{\theta_p p}$ and $A_{\theta_s P}$ are the sensitivity submatrices of the active power adjustments and the transformer voltage angles on the primary and secondary sides, respectively.

As an example of decomposition, let us consider the sensitivity submatrix A_{VQ} in (5.1), which can be expressed as

$$A_{VQ} = A'_{VQ} + \varepsilon \cdot B \tag{5.2}$$

where A'_{VQ} is the decomposed submatrix, which retains the strong couplings represented by elements greater than ε, and $\varepsilon \cdot B$ contains weak couplings. The resulting submatrix defines the topology of the subnetworks and the influence range of each DG. After decomposition, it is possible that not all DGs in a subnetwork will have strong couplings with all nodes in this subnetwork. Thus, the "range of influence" of a DG is defined as the nodes within its subnetwork for which the voltages can be affected by the output of the DG. This influence range can be contracted or expanded by adjusting the threshold value.

The ED agent selects and updates the ε value based on its knowledge or when triggered by other agents or changes in the network. For example, this can be triggered by an LPS agent to request involving more DGs in the control when a DG has tripped, or when this DG is back online to restore the previous operation before the trip event. Moreover, this can be initiated by the network changes when a new DG unit is installed. This resets and updates the subnetworks and the ranges of influence of the DG in accordance with (5.1) and (5.2). The agents regroup and self-organise to adapt to the new network conditions without a complete re-engineering of the overall MAS framework. This process can occur at any time without stopping or restarting the MAS platform and its agents.

2) Violation Detection (VD) Agent:

The VD agents monitor the status of busses and have knowledge of the voltage violation constraints, as specified by the voltage upper and lower normal operating limits (between 0.95 pu and 1.05 pu in this thesis). When a VD agent observes a voltage violation at its bus, it requests the LPS agent in the same subnetwork to resolve the network voltage issue.

3) Linear Programming Solver (LPS) Agent:

Each LPS agent acts as a control agent for its subnetwork. When an LPS agent receives a violation message from a VD agent in its subnetwork, it calculates the optimal adjustments to the generation of the involved DGs using a linear programming (LP) algorithm that is integrated within each LPS agent. Thus, the

LPS agent has knowledge of: a) the DG agents in the same subnetwork and the surplus capacity of each DG; b) the sensitivity submatrix of the subnetwork that is used to determine how each DG affects the voltages of the nodes within its range of influence; c) the sensitivity coefficients, obtained from (5.1), that define how a DG influences the voltage magnitudes and phase angles of the primary and secondary sides of the network transformers; and d) the acceptable voltage limits (in this thesis, 0.95–1.05 pu). The third constraint ensures that the network protectors used to avoid reverse active power flows through the network from the secondary side to the primary side are not tripped, as shown in (5.5) and (5.7). This approach can be applied to networks with DGs operating in the unity power factor (UPF) mode by increasing or decreasing the active power output and to networks with DGs operating in the power factor control (PFC) mode by injecting or absorbing reactive power.

It follows that when all DGs are operating in the PFC mode, the LPS agent can control the voltage optimally by minimally decreasing or increasing the reactive power outputs of the local DGs involved. For the LP problem in the PFC mode, the objective function is

$$\text{Max:}\, Min\{x_i\} \;\; \text{(to control overvoltage)} \tag{5.3}$$

$$\text{Min:}\;\; Max\{x_i\} \; \text{(to control undervoltage)} \tag{5.4}$$

subject to the following constraints:

$$\begin{cases} V_l \ \le \ V_0 + A_{VQ} \cdot x \le V_u \\ x \ \le \ Q_{Sur} \\ 0 \le \theta_{p0} + A_{\theta_p Q} \cdot x - (\theta_{s0} + \theta_{shift} + A_{\theta_s Q} \cdot x) \end{cases} . \tag{5.5}$$

When operating in the UPF mode, DGs can generate only active power. The LPS agent calculates the optimal generation adjustments for the involved DG to control the voltage with the following objective function:

$$\text{Max:}\, Min\{x_i\} \tag{5.6}$$

s.t.

$$\begin{cases} V_l \le V_0 + A_{VP} \cdot x \le V_u \\ x \ \le \ P_{Sur} \\ 0 \le \theta_{p0} + A_{\theta_p P} \cdot x - (\theta_{s0} + \theta_{shift} + A_{\theta_s P} \cdot x) \end{cases} . \tag{5.7}$$

To solve this LP problem in the same way as the standard LP problem, a slack variable *y* can be added to bring it into the same form as the standard LP problem. Let us consider overvoltage control in the PFC mode as an example:

$$\text{Max:}\, y \ \ \text{(to control overvoltage)} \tag{5.8}$$

s.t.

$$\begin{cases} V_l \le V_0 + A_{VQ} \cdot x \le V_u \\ x \le Q_{Sur} \\ 0 \le \theta_{p0} + A_{\theta_p Q} \cdot x - \left(\theta_{s0} + \theta_{shift} + A_{\theta_s Q} \cdot x\right) \\ x_i \ge y \ (i = 1 \sim n, n \text{ DG agents are involved}) \end{cases} . \quad (5.9)$$

In the above equations, x_i is the power generation adjustment of the *i*-th DG agent; *x* is the vector of all x_i; V_u and V_l are the upper and lower voltage limits (in this thesis, 1.05-0.95pu), respectively; Q_{Sur} and P_{Sur} are the surplus capacities of the DG; θ_{p0} and θ_{s0} are the initial values of the network transformer voltage angles on the primary side and secondary side, respectively.

Once an LPS agent receives a violation message from a VD agent, it first determines which of the DGs of its subnetwork are the "closest" to this violation, and then, considering only these involved DGs, it seeks a solution by employing the LP algorithm. The closest DGs to a node are defined as the neighbouring DGs that can influence the node's voltage by adjusting their outputs, as determined by the range of influence of the DGs and as expressed in (5.2). Thus, when the LPS agent solves the LP problem in its subnetwork, only the closest DG agents to the violating node participate in voltage control, which further reduces the size of the optimization problem and the interaction requirements. The voltage control also becomes more "local" within each subnetwork, i.e., the VD agents coordinate with their local LPS agent to optimize only the local closest DG agents in the subnetwork.

After determining how to resolve the voltage violation problem, the LPS agent communicates the control adjustments to the involved DG agents to request an increase or decrease in the DG outputs and to restore the voltage of the subnetwork to within the normal operating limits. However, if the subnetwork is unable to resolve the voltage issue (e.g., a DG is not available or has lost communication), it will request the ED agent to update the ε value to involve more DG agents in the problem. As a result, the control agents reconfigure and self-organise in the new identified subnetworks to regulate the voltage.

4) Distributed Generation (DG) Agent:

Each DG agent represents its DG that is connected to the distribution network and performs control actions to adjust its output. DG agents receive generation adjustment signals from the LPS agent in the same subnetwork to maintain appropriate voltage levels.

The DG agent has knowledge of its constraints (such as generation capacity) and the decomposed sensitivity A' matrix in order to dynamically update its range of influence. It also shares its constraints and availability with other agents. For instance, if a DG is not available (e.g., disconnected from the network), the DG agent informs the LPS agent so that the LPS agent can find solutions using other DGs through the self-organising mechanism. When the DG is back online, it informs the LPS agent sharing its availability and constraints.

It is also noted that the DG agent shares its constraints, such as its available surplus capacity, with the LPS agent in order for the LPS agent to consider when solving the LP problem. This is used by the LPS agent to maintain the operation of the involved DGs and the voltage regulation process, and to enable the system to adapt based on conditions and constraints of involved DGs and network events as summarised next.

5.2.3 Implementation of Self-Organising MAS for Distributed Voltage Regulation

The ED agent decomposes the sensitivity matrix with the initial ε value as shown in (5.2). The number of subnetworks depends on the ε value, which is selected and updated autonomously in accordance with the purpose of decomposition, i.e., the desire to achieve smaller subnetworks for distributed control. The ε value is initialized with the value that yields the largest number of groups.

The LPS and VD agents receive the required knowledge of the decomposed network, including which agents are in the same subnetwork, so that the agents only need to communicate with other agents in the same subnetwork. After decomposition, the agents within each subnetwork coordinate to realize and maintain distributed voltage regulation. If a subnetwork cannot regulate the voltage using the involved DGs (e.g., a DG has tripped or does not have enough surplus capacity), the agents will coordinate and self-organise to involve more DG agents in the control problem.

The process and steps of implementing the algorithm are summarised below.

Step 1): The ED agent initiates the system via (5.2) and activates the LPS and VD agents according to the subnetworks identified.

Step 2): Each VD agent starts monitoring its bus for voltage violations; if such a violation occurs, it sends a violation message to the LPS agent of its subnetwork.

Step 3): The LPS agent checks the violation messages received from its subnetwork and identifies generation adjustments for the involved

DG agents, as expressed in (5.3)-(5.5) for the PFC mode or in (5.6) and (5.7) for the UPF mode.

Step 4): The LPS agent then sends the control actions to the DG agents to adjust their output.

Step 5): After the voltage is normalized in the subnetwork, the agents return to Step 2 to continue monitoring and controlling the system.

Step 6): If the subnetwork cannot regulate the voltage (e.g., an involved DG has tripped), the LPS agent will request the ED agent to determine a new ε value for decomposition and involve more DG agents in the control problem. Subsequently, the agents will self-organise to regulate the voltage.

Step 7): When the network returns to normal operation (e.g., the DG is back online), the agents reorganise and return to Step 2 to continue monitoring and controlling the system.

In addition to the above steps, the system is able to adapt to network changes, such as expansion of the network or the removal of DGs through its self-organising mechanism. The system will dynamically update the decomposition of the network, and the agents will organise into new subnetworks.

Simulations performed on a highly-meshed secondary distribution network are used to verify the effectiveness of the proposed approach. The simulation results of various case studies under different network conditions are presented and discussed in Chapter 6.

5.3 Partitioning and Self-organisation for Controlled Charging of EVs in Large Distribution Networks

The method presented in this section focuses on the controlled charging of EVs in large distribution networks to address the challenges of the control and management of EVs presented in Chapter 2. The proposed partitioning and self-organising technique for the control of EV is presented with applications for large distribution networks. The network in this case is divided into areas that can control and manage EVs using a community detection algorithm. The control scheme dynamically coordinates EVs within each group with the objective of providing distributed control and management of EV and voltage. The proposed control method can cope with the conditions of the distribution network, the local resources, and communication network. This mechanism enables distributed and adaptive control that uses local interactions to adapt its structure without stopping or restarting the system.

The remainder of this section presents the algorithm for partitioning the network, the design of the multiagent control, and the implementation of the distributed and self-organised control of EVs.

5.3.1 EV-Based Partitioning: A Community Detection-Based Algorithm

The community detection technique, presented in section 0, is used to partition the large networks into sub-systems in order to solve the control and management of EVs in distribution networks. EVs are controlled locally and adaptively within each community, which results in a coordinated and self-organised control system that considers the charging of EVs. This results in a system that is able to withstand the time-varying changes in network conditions.

In this study, a large power network is divided into smaller communities using a modularity index-based algorithm. The function for the modularity index M, where Max *M* gives the best partition of the network, is given as

$$M = \frac{1}{2n}\sum_{i,j}\left(A_{ij} - k_i k_j/2n\right)\delta_{ij} \tag{5.10}$$

where: n is the number of nodes; A_{ij} is the edge weight between nodes *i* and *j;* δ_{ij} is 1 if nodes *i* and *j* are in the same community, otherwise δ_{ij}= 0; k_i (k_j) is the degree of node *i* (*j*).

The case study assumes that EVs are attached to charging points at homes on the network represented as flexible load nodes. The sensitivity matrix of the distribution network (5.11) is used to represent the edge weight information about the degree of coupling between nodes, represented as

$$\Lambda = \begin{pmatrix} \Lambda_{\vartheta P} & \Lambda_{\vartheta Q} \\ \Lambda_{VP} & \Lambda_{VQ} \end{pmatrix} \tag{5.11}$$

To evaluate the strength of a community structure based on EVs, the sensitivity matrix is used to find the coupling strength between all nodes. As an example of the partitioning, let us consider the sensitivity submatrix Λ_{VP} in (5.11). To find the EV that has the highest influence on a particular node, the algorithm uses the elements of an EV adjacency matrix D_{VP} that describes the edges that have the highest weight connecting a node *i* with the nearest EV *j*, which can be expressed as

$$D_{VP}^{ij} = \begin{cases} 1, \Lambda_{VP}^{ij} = \max\{\Lambda_{VP}^{i1}, \dots, \Lambda_{VP}^{iN}\}, \\ 0, \text{otherise}, \end{cases} \tag{5.12}$$

where D_{VP}^{ij} represents the element of the EV adjacency matrix between node i and EV j, N is the number of EVs in the network, and Λ_{VP}^{ij} is the element of the sensitivity matrix. Thus, the matrix A_{ij} of the modularity index in (5.10) is implemented using the sensitivity matrix and EV adjacency matrix as

$$A_{VP}^{ij} = \Lambda_{VP}^{ij} + D_{VP}^{ij} \cdot \tag{5.13}$$

This modular measure of community quality considers the network topology and the degree of coupling between the EV and nodes, enabling each partition to control the voltage independently using its local EVs. The purpose of the partitioning is to reduce the number of variables and constraints within each small community to create a small optimization problem with minimal interaction requirements. The community structure with high modularity has stronger intra-community connections between its nodes. The process and steps to implement the partitioning algorithm are as follows:

Step 1: Begin with each node in the adjacency matrix (i.e., D_{VP}) as a separate community.

Step 2: For each step, iteratively merge communities in pairs and calculate community quality *M* using (5.10) and (5.13), choosing at each step the community pair that results in the highest *M* in (5.10) until all communities are merged.

Step 3: Finally, the partitioning that results in a local peak in the *M* value indicates satisfactory partitioning.

The partitioning algorithm is first implemented to divide all the EVs and nodes in the distribution network into communities. After determining the communities, each community dynamically controls the local EVs in its community and maintains voltage levels of all intra-community nodes within certain limits, as discussed below.

5.3.1.1 Control and Management of EVs within Each Community

The objective of this implementation is to control EVs with the aim to maintain the voltage within operational limits. After determining the communities as described above for a large network, some communities may still contain a large number of EVs that can have varying influence and couplings with intra-community nodes. Rather than using all EV's in large communities to control the voltage, the algorithm finds which the EVs in a community that are most influential to a node, defined as "neighbouring EVs". Subsets of these neighbouring EVs are defined using the community EVs matrix D_{com} in (5.10) as follows.

$$A_{com}^{ij} = D_{com}^{ij} \tag{5.14}$$

where

$$D_{com}^{ij} = \begin{cases} 1, \Lambda_{com}^{ij} = \max\{\Lambda_{com}^{i1}, \dots, \Lambda_{com}^{iN}\}, \\ 0, \text{otherise.} \end{cases} \tag{5.15}$$

This enables each community to regulate the voltage of a node by calculating the optimal adjustments of the charge rate of only the neighbouring EVs to the voltage violation. It is noted that each subset contains one or more EVs depending on the size and topology of the community. Based on the community sensitivity submatrix, e.g., Λ_{VPcom} , adjustments to the EVs charging rate $x_P = P_r - P_0$ to control the voltage at a particular node from an initial voltage V_0 to a reference voltage V_r can be calculated as

$$V_r = V_0 + \Lambda_{VPcom} \cdot x_P \tag{5.16}$$

where P_0 and P_r are the charge rate of EV before and after control, respectively.

5.3.2 Development of the Self-Organising Multiagent System

As presented above, the proposed community detection-based partitioning technique considers the location of EVs and degree of coupling between EVs and nodes in large distribution networks. The deployment of the control and management of EVs is realized by means of a distributed control mechanism based on a MAS architecture with a dynamic structure within each community to resolve voltage issues using only neighbouring EVs, thereby reducing the size of the control problem and the interaction requirements within each community. This control scheme enables each community to self-organise based on local EVs conditions and network changes. In addition, the self-organisation enables decentralization, as only local interactions are allowed. The MAS is implemented using three types of agents: community agent (CA), bus agent (BA), and electric vehicle agent (EVA). After determining the communities of the network, each community is assigned one CA that acts as its control agent. Interactions and coordination between these various agent types are discussed below.

1) Community Agent (CA):

The CA finds solutions for the community voltage control problem using the EVs that are closer to the voltage violation. First, the CA defines the subsets of nodes and neighbouring EVs by using (5.10) and (5.15) to describe how the community nodes are affected by the community EVs. In addition, the CA updates the elements of the community EVs matrix D_{com}^{ij} based on its knowledge or when triggered by other agents or changes in the network. This updates the community EV matrix in accordance with (5.15). The agents self-organise in new subsets to adapt to the network and EV conditions without interrupting the control mechanism or stopping its agents.

When the CA receives a message from the other agents in the same community, it determines the optimal adjustments to the charging speed of the neighbouring EVs. The CA solves the control problems using a linear programming method. Therefore, the CA has knowledge of: a) the voltage sensitivity submatrix to define how the charging of each EV influences the voltages of the nodes; b) the maximum charge rate of each EV in the same community; and c) the voltage upper and lower normal operating levels, which is between 0.95 pu and 1.05 pu.

The CA determines the adjustments of charging rate of the neighbouring (subset) EV agents (EVA) using the community sensitivity submatrix, e.g., Λ_{VPcom} , to control the charge rate of EVs using the following objective function:

$$\text{Max: } y \tag{5.17}$$

s.t.

$$\begin{cases} V_l \leq V_0 + \Lambda_{VPcom} \cdot x \leq V_u \\ 0 \leq x \leq P_{max} \\ x_i \geq y \; (i = 1 \; to \; n, n \text{ EVA in the same subset}) \end{cases} \cdot \tag{5.18}$$

where V_l and V_u are voltage lower and upper limits, respectively; *y* is the slack variable for solving the LP problem, P_{max} is the maximum charge rate of EV; *x* is the vector of all x_i; x_i is the charging adjustment of the *i*-th EVA.

When the CA solves the linear programming problem in its community, only the EVs in the same subset participate in voltage control. After determining how to control the charging rate of the EVs, the CA communicates the control adjustments to the subset's EVAs to request an increase or decrease in the EVs charging rate and to restore the community's voltage to be within the acceptable operating limits. However, if the EV is unable to resolve the voltage issue, the CA updates the D_{com}^{ij} elements based on the available community EVs. Similarly, if an EV is not connected to participate in the control, the corresponding EVA informs the CA to update D_{com}^{ij} based on the other available EVAs. As a result, the community agents reconfigure and self-organise in subsets to continue the control and management of EVs and to regulate the voltage.

2) EV Agent (EVA):

Each EVA represents an EV that is connected to the distribution network and executes control actions to adjust the charge rate. In order to maintain acceptable voltage limits, the EV receives adjustment signals from its CA. The EVA communicates its availability status and EV limits with other agents and is aware of its own constraints, such as the maximum charging rate. For instance, the EVA will inform the CA if an EV is unavailable so that the community can use its self-organising mechanism to maintain stable control.

3) Bus Agent (BA):

The BAs monitor the condition of the buses in the network for the voltage operating constraints (0.95 pu - 1.05 pu). When a BA detects a voltage violation on its bus, it communicates this event with its CA to solve the community voltage problem.

5.3.3 Controlled Charging of EVs Through Self-Organisation

After partitioning the network into communities, the agents in each community coordinate and self-organise to realise distributed control, as follows.

Step 1): Each CA initialises its community EV submatrix Λ_{com} and finds how EVs influence nodes by employing (5.10) and (5.15).

Step 2): Each EVA communicates the condition and changes of status of its corresponding EV, while each BA begins monitoring its bus and communicate any violation events to the CA.

Step 3): The CA coordinates control messages received from other agents in the community and determines the charge rate using (5.17) - (5.18) for the related EVAs, and sends the control actions to the EVAs to optimize the charging of their EVs and maintain the voltage levels in its community within normal limits.

Step 4): If an EV has changed its status or not able to participate in the control problem (e.g., an EV is not online or has reached its minimum charge rate), the corresponding EVA informs its community so that the CA can update the community EV adjacency submatrix in (5.15) based on the available EVs.

<u>Step 5)</u>: Then, the agents in the community regroup and self-organise in the newly identified subsets and return to Step 2 above.

To validate the robustness and autonomy of the algorithm under time-varying EV conditions, its effectiveness is tested on a large distribution network with EVs (simulations are presented in Chapter 6).

5.4 Deployment of Self-Organising Multiagent System for Power Networks

The MAS architecture was deployed using the Simulation of Agent Societies 2 (Presage2) framework [169], which offers agent communication capabilities and improved autonomy. As presented in the previous chapter, Presage2 provides the flexibility to design self-organising MASs able to meet the requirements of electrical network control and management applications.

The message format in Presage2 is as follows:

message (performative, sender, destination, time, content)

- The message *performative* identifies the purpose of the message, for instance "*inform*", "*confirm*", and "*query-if*" as described in the FIPA-ACL standard [153].
- The message *sender* and the message *destination* denote the agents that are sending and receiving the message, respectively.
- The message *time* is the time at which the message was sent,
- The message *content* carries information that is sent between the agents.

A message example is as follows:

message (inform, VD^{362}, LPS^{24}, 21:06:56, V<0.912>)

The MAS architecture and self-organising mechanism are implemented using Presage2 in large-scale test systems presented in Chapter 6. An example of selected knowledge and behaviour of an LPS agent within Presage2 and its interactions with other agents is illustrated in Figure 5.1. An example of Java code for implementing the LPS agent and simulation environment in Presage2 is presented in Appendix A.

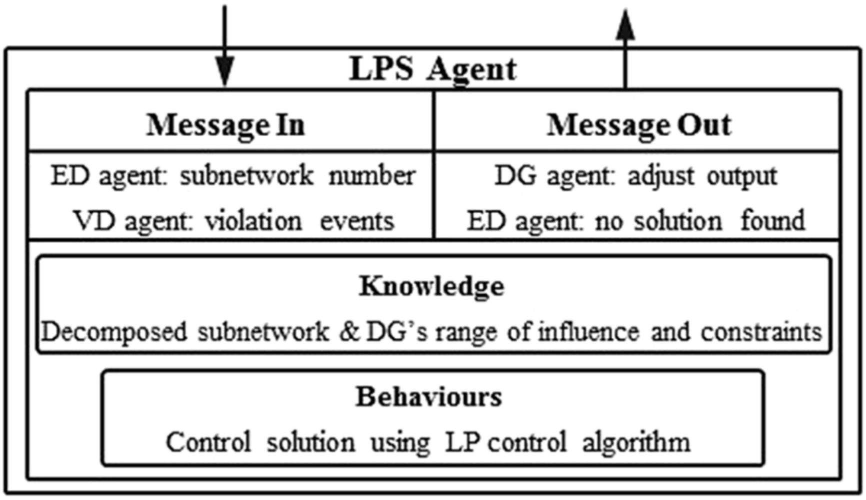


Figure 5.1: LPS agent architecture in Presage2.

5.5 Summary

This chapter presented self-organising distributed control approaches that can be applied in large networks to control DER considering the unpredictable and stochastic nature of DER. The distributed control techniques are implemented using MAS frameworks, in which the agents autonomously group themselves into subnetworks to control the local resources and voltage through local interactions of agents in a cooperative way. Greater distributed control and intelligence will allow challenges of controlling DERs to be handled effectively.

In the first approach (Section 5.2), the network sub-divides itself using an epsilon decomposition approach and agents communicate between them to coordinate the voltage control using DGs. Additionally, the system can realize the adjustment of DG active power outputs in UPF mode or reactive power outputs in PFC mode. The system can also adapt to time-varying network conditions to maintain stable control by dynamically updating the grouping of the network without re-engineering the complete system.

In the second application (section 5.3), a distribution network with EVs is partitioned using the proposed community detection technique. The system is implemented using a MAS framework to control and manage the EVs with the aim to control the voltage using only EVs neighbouring the voltage violation through local interactions of agents in a cooperative way. Each community cluster can also adapt to time-varying EV conditions to maintain stable control.

The proposed MAS architecture is implemented using the Presage2 framework which allows deployment of the proposed self-organising MASs and test the system under time-varying conditions.

In summary, these techniques facilitate reliable distributed control techniques for large, complex power networks using only local resources. As a result, the network is able self-organise into small control areas. The closest resources are found in each control area, and their outputs are optimised. The size of the control problem and interaction requirements are further reduced and simplified by using these methodologies. Self-reorganisation enables dynamic partitioning of the network and maintains a stable operation in response to time-varying network changes and requirements.

Dynamic agent simulations of the control techniques using the proposed DER architectures (DG and EV), discussed above, are shown in Chapter 6. The effectiveness of the proposed approaches are validated through simulations based on models of complex and large networks, and the performance of the techniques are compared to various methods.

Chapter 6

Simulation Results

Chapter 5 introduced the design of self-organising MAS techniques for large and complex distribution networks to control DERs, with a focus on control and management of DGs and EVs. This Chapter presents the results and discussions from the simulations on the self-organising control of DER implementations. Section 6.1 focusses on the control of DGs and uses local resources to regulate voltage violations, whereas section 6.2 implements partitioning of large distribution networks to enable adaptive and distributed control and management of EV and voltage.

6.1 Results and Discussion: Self-organisation of Heavily Meshed Distribution Networks with DGs

This section presents the simulation results of the proposed distributed control algorithm for DGs under various conditions performed in a model of a real heavily-meshed secondary network. The results are compared to other control schemes to validate the control system performance and validate the autonomy and adaptability of the system. An example of the simulation of the agents in Presage2 for related results is shown in Appendix B.

6.1.1 The Test System: A Model of a Real Heavily-Meshed Distribution Network

The test system is a model of a real heavily-meshed secondary network containing 2083 nodes, 224 network transformers (13.8 kV to 480 V or 216 V), and 311 PQ loads. As shown in Figure 6.1, the primary feeders are at 13.8 kV and contain 1043 nodes, while the secondary network contains the remaining 1040 nodes at 216 V or 480 V. In this network, the 311 DGs are installed at the load buses in the secondary network. The largest network in the secondary network has all of its transformers connected on the secondary side, which creates a heavily-meshed network of 284 loads. The decomposition of the network is demonstrated in Figure 6.1.

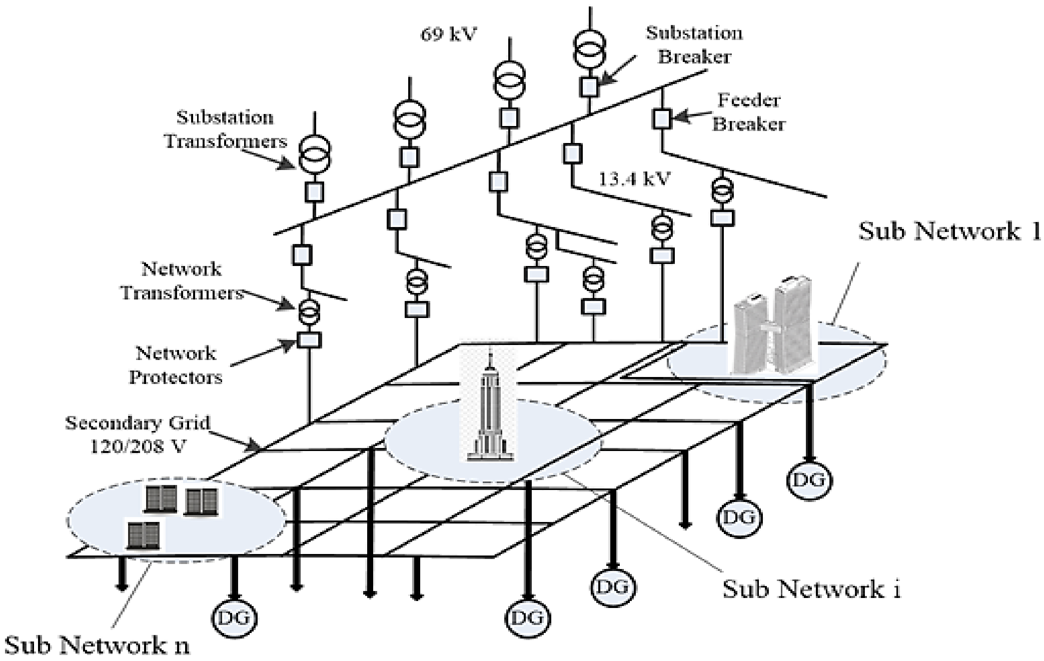


Figure 6.1: Test system demonstrating subnetworks after decomposition.

Table 6.1 shows how the value of ε influences the number of control subnetworks. For example, a smaller value of 0.004 results in fewer groups than a larger value of 0.016, while a larger ε value provides more small-size subnetworks, which results in a smaller control problem. However, a large ε value may also yield suboptimal control strategies as a result of neglecting links with some significance. The MAS architecture is deployed in the model system, and the agents self-organise into subnetworks defined by the communication links between agents.

Table 6.1: Results of epsilon decomposition with various ε values for DGs operating in PFC and UPF modes

ε	DG with PFC mode	DG with UFC mode
	No. of DG subnetworks	No. of DG subnetworks
0.004	19	20
0.006	24	35
0.008	34	47
0.010	57	65
0.012	82	75
0.014	80	72

In this simulation of DGs, the network autonomously organises itself into small sub-networks through the epsilon decomposition of the sensitivity matrix, and agents group themselves into these subnetworks with the communication links being autonomously determined. Each sub-network controls its voltage by locating the closest local distributed generation and optimizing their outputs. This further simplifies and reduces the size of the optimization problem and the interaction requirements. This approach also facilitates adaptive grouping of the network by self-reorganising to maintain a stable state in response to time-varying network requirements and changes. In summary, this technique enables distributed and robust voltage regulation method using DGs for large and complex distribution networks as presented next.

It is noted that when the network is going under high penetration of distributed renewable resources, intermittent renewables may increase the voltage violations events in the networks. However, to reduce the pressure on the overall network and maintain the performance of the control method, it is assumed that DGs have a mechanism (such as using energy storage [201]) to help reduce variations of generation. This can also offer dispatchable resources available to use by the proposed distributed voltage regulation scheme.

In the following sections, the effectiveness of the presented approach is validated through simulations on the model of the real heavily-meshed secondary distribution network and the simulation results of various case studies and network conditions are presented and discussed.

6.1.2 Case Study 1: Distributed Voltage Regulation

The algorithm is simulated in the network to demonstrate effective distributed voltage regulations with $\varepsilon = 0.012$ in PFC and UPF modes. For PFC mode, the agents in the secondary network are decomposed into 82 isolated subnetworks, with one LPS agent activated in each subnetwork. As demonstrated in the agent interaction chart in Figure 6.2, the ED agent informs the VD and LPS agents about their subnetworks. To create a voltage violation, DG unit 71, in subnetwork 5, from the secondary network is disconnected. This causes a voltage violation to appear in the distribution network. The violation is detected by VD agent 1327, in subnetwork 5, with a voltage value of 0.9488 pu. This VD agent sends a message with the location and value of the voltage to the corresponding subnetwork's control agent, LPS agent 5, as illustrated in Figure 6.2.

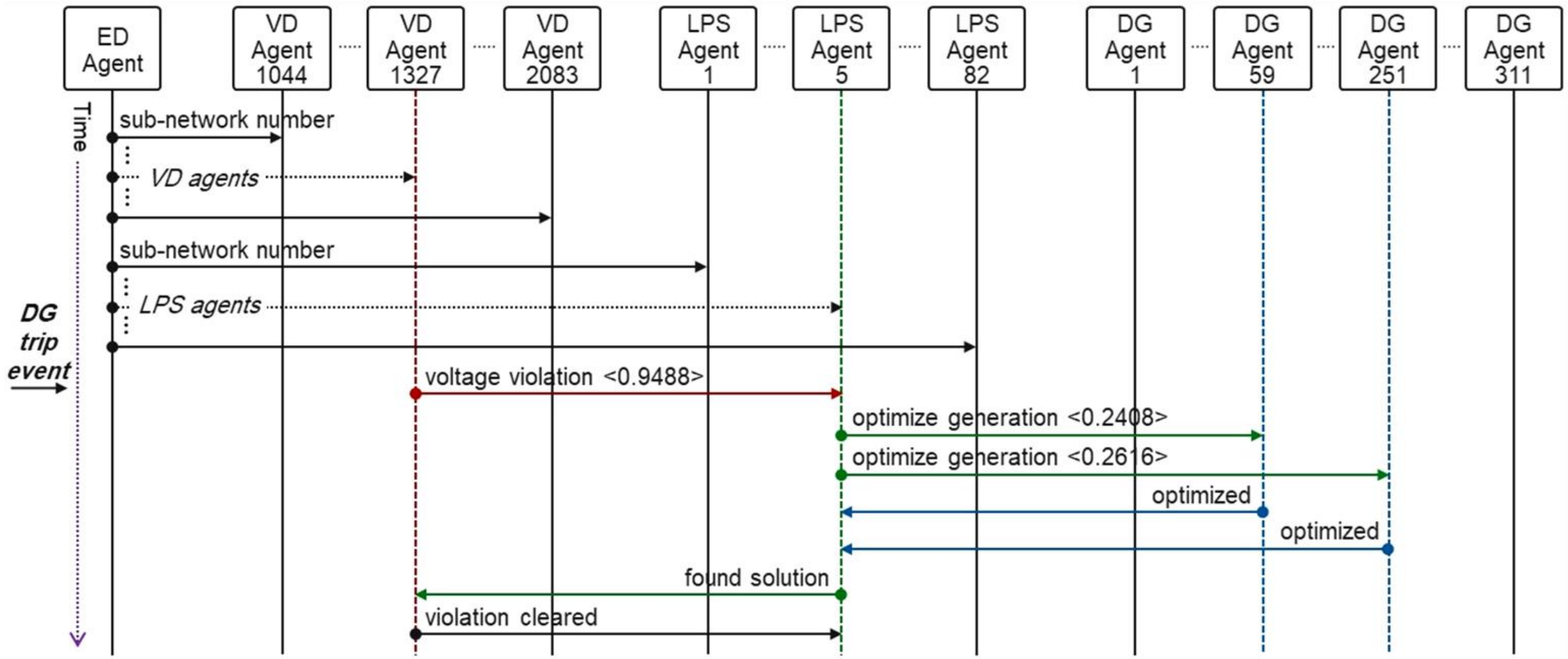


Figure 6.2: Communication among agents for distributed voltage regulation (Case Study 1).

For this case study, subnetwork 5 is the largest DG group, containing 81 DGs and around 250 nodes of the total 311 DGs and 1040 nodes in the secondary network. Although the size of this subnetwork is much smaller than the original secondary network, solving the LP problem may still have 81 variables and around 500 constraints if all the DGs of this subnetwork are involved in the voltage regulation function. However, for such a large subnetwork, it is possible that not all DGs have a strong coupling with all nodes in the subnetwork. Thus, after decomposition, only the corresponding closest DG or DGs whose range of influence covers the node voltage are involved in the voltage regulation process. Therefore, LPS agent 5 first determines the DG agents in its subnetwork that can influence the node voltage, which are DG agent 59 and DG agent 251 in this case, as shown in Figure 6.2. As a result, out of the 81 DG agents in this subnetwork, only two DGs are involved in the control problem. This further reduces the size of the LP control problem from 81 variables and nearly 500 constraints, to only 2 variables and 42 constraints, as shown in Table 6.2. It also simultaneously reduces the interactions required between only the involved agents. As shown in Figure 6.2, when LPS agent 5 finds the solution, it sends messages to DG agents 59 and 251, instructing them to inject reactive powers of 0.241 pu and 0.262 pu, respectively.

To test the algorithm in UPF control mode, the same voltage drop as above is analysed. Table 6.2 compares the results of voltage regulation under the different control modes for the same ε value. It also shows that in the UPF mode, fewer DGs and nodes are involved in solving the control problem, with lower system power losses.

This case study demonstrates effective distributed voltage regulation based on the proposed MAS architecture for a particular area with sufficient local DG.

This architecture may also have further applications for static partitioning when considering proper DG allocation planning in distribution networks [26], [202], which can be used as a reference to expand the network.

Table 6.2: Results of control with ε =0.012 in PFC and UPF modes for the same violation event (case study 1)

Control Mode	PFC	UPF
No. of DG agents in the subnetwork	81	25
No. of DG agents involved in the control	2	1
No. of involved nodes in the control	21	8
P_{loss} after control (pu)	0.2507	0.2330
Q_{loss} after control (pu)	0.8332	0.8061

6.1.3 Performance Comparison

To verify the overall performance of the proposed framework, the results of the proposed algorithm are compared with the following: no DG control, using a self-organising method without partitioning, the local voltage control only without coordination where each DG acts on its local bus voltage only [203, 204], and when partitioning the network using the community detection method in [41] using all DGs in a partition. It is worth noting that when implementing the presented method without partitioning, it uses the voltage sensitivity coefficients associated with the whole network; therefore, it can be used as a centralized equivalent control case benchmark since its LP problem accounts for all the links between nodes and DGs in the secondary network.

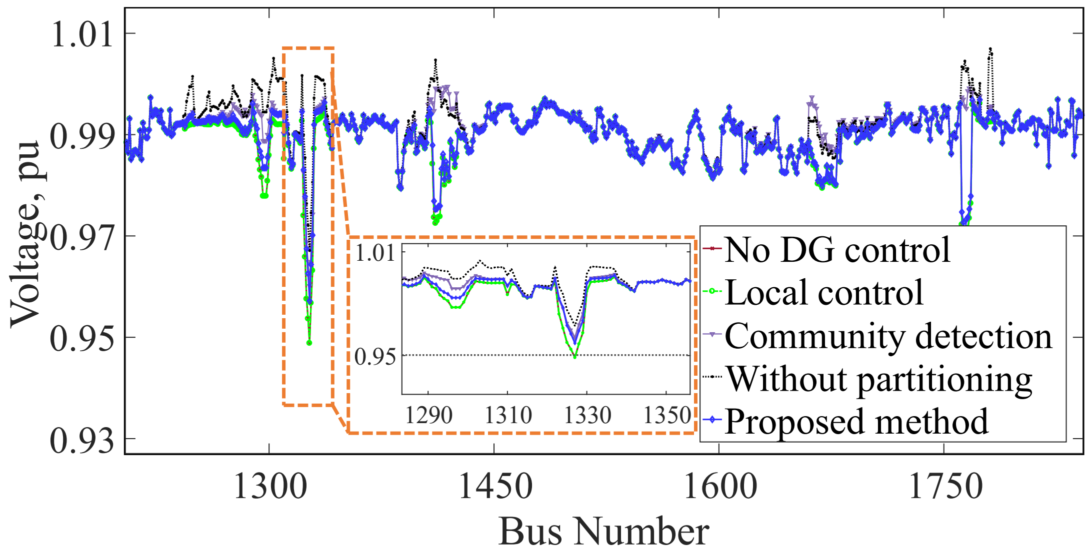


Figure 6.3: Voltage profiles of the secondary network under different scenarios.

Case study 1 above is used to compare the performance of the presented distributed voltage regulation to the methods presented above. Figure 6.3 illustrates the voltage profiles of the nodes after the control actions for all compared methodologies. The horizontal dotted line in the inset in Figure 6.3 represents the lower voltage limit (0.95 pu), which is exceeded at bus 1327.

Figure 6.3 shows that the best solution could be achieved by the global optimization method without partitioning the network (black dotted line), which regulates the voltage by solving the control problem considering all links between DGs and nodes in the network. The figure also shows that the proposed method (blue line) is as effective as the method without partitioning, while having less influence on other nodes when compared to no partition and to the community detection algorithm. When the community approach (purple line) is applied, the affected partition uses all DGs in its partition when solving the control problem and regulating the voltage, while the proposed methodology seeks to use the closest DGs only, as summarised in Table 6.3. This table indicates that when compared to no partition and the community method, fewer DGs are involved in the control of the voltage, and the size of the control problem is reduced significantly. When the uncoordinated local control method (green dotted line) is applied, the voltage at bus 1327 is below the 0.95 pu limit. This is because it does not have a coordination mechanism to regulate the voltage when the corresponding local DG 71 at bus 1327 has tripped.

Table 6.3: Comparison of the control parameters and results

Technique	Proposed Method	Without Partitioning	Local Control [203]	Community Detection [41]
No. of involved DGs	2	12	1	9
No. of involved nodes	21	138	1	123
P_{loss} after control (pu)	0.2507	0.2667	0.2512	0.2594
Q_{loss} after control (pu)	0.8332	0.8395	0.8360	0.83735

The final solution of the proposed method may not lead to the same result obtained by the overall optimization of the entire secondary network without partitioning, but, as shown in Figure 6.3, they are comparable. However, the aim of the proposed technique is to provide a voltage regulation platform that uses distributed approach with sufficiently accurate results, while dealing with the increasing complexity of such large networks with DGs and a need to obtain fast solutions. Table 6.3 also reports the power losses in the secondary network after control. This can be seen as another criterion showing that the proposed method maintains power losses comparable to solving for the whole network, and also may result in reduced power losses such as in this case study.

6.1.4 Case Study 2: Voltage Violations in Multiple Subnetworks

Simulations were performed to test the performance of the system when multiple voltage violation events occur in different subnetworks at the same time. This is simulated by simultaneously tripping multiple DGs in different subnetworks, causing voltages to exceed the acceptable operating limits in each affected subnetwork. In this case, in addition to the disconnection of DG 71, as in the first case study, a second DG disconnection (DG 119 in subnetwork 45) occurs at the same time. As a result, as shown in Figure 6.4 and Figure 6.5, in addition to a voltage drop appearing in subnetwork 5 and being detected by VD agent 1327 (similar to Case Study 1), violation events are detected by VD agents 1635 and 1636 (in subnetwork 45), which communicate these violations to LPS agent 45.

The agent communication diagram in Figure 6.4 shows the agents involved in this control problem. To study the control algorithm, it is assumed that there is no communication delay, such that each LPS agent receives the violation messages at the same time; i.e., each of LPS agent 5 and LPS agent 45 receives violation messages simultaneously from the VD agents in its subnetworks. Each LPS agent identifies solutions for its own subnetwork to optimize the involved DG outputs and to control the voltage in its area. Therefore, the voltage control problem is divided into 2 LP problems that are solved independently by each corresponding LPS agent. The information of these two LPS agents to solve their LP problems is summarised in Table 6.4.

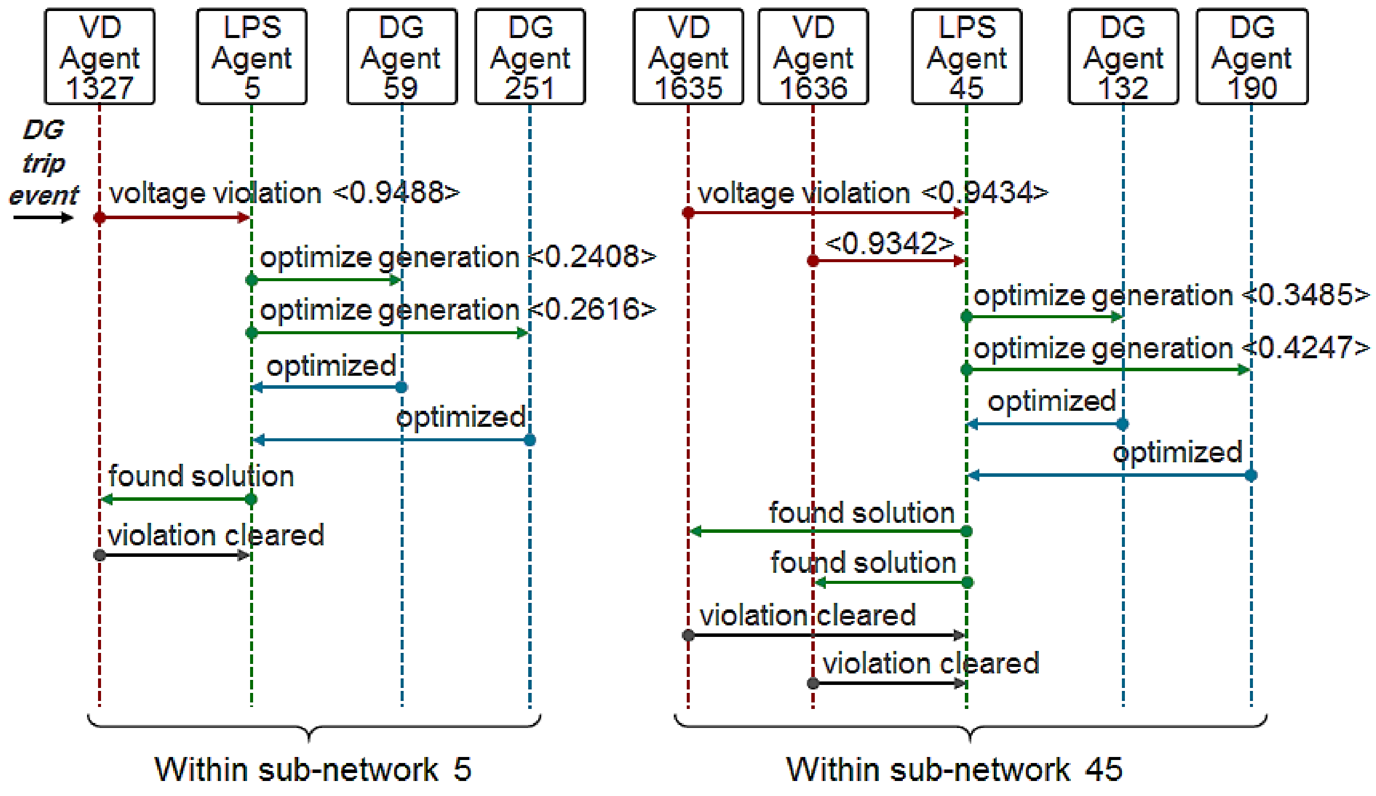


Figure 6.4: Coordination among agents to simultaneously and independently control the voltage within each subnetwork (Case Study 2).

Table 6.4: Data used by 2 LPS agents to solve their individual LP problems for voltage control (Case Study 2)

Area	Subnetwork 5	Subnetwork 45
LPS agent ID	5	45
No. of DG agents in the subnetwork	81	3
No. of DG agents involved in the control	2	2
No. of nodes involved in the control	21	4

The voltage profiles of the secondary network after control for various methods are presented in Figure 6.5. The voltage at the affected buses 1635 and 1636 in subnetwork 45 before and after control is shown in Figure 6.6. The performance is compared with the method without partitioning and when using basic local control. As expected, the results show that the voltage regulation of the proposed distributed method is almost equivalent to the method without partitioning. As shown in Figure 6.5, the voltage limits in the proposed method are maintained in each subnetwork with very little influence on other areas. This is because the proposed distributed voltage regulation enables each subnetwork to regulate the voltage independently and to use the closest DGs to a node.

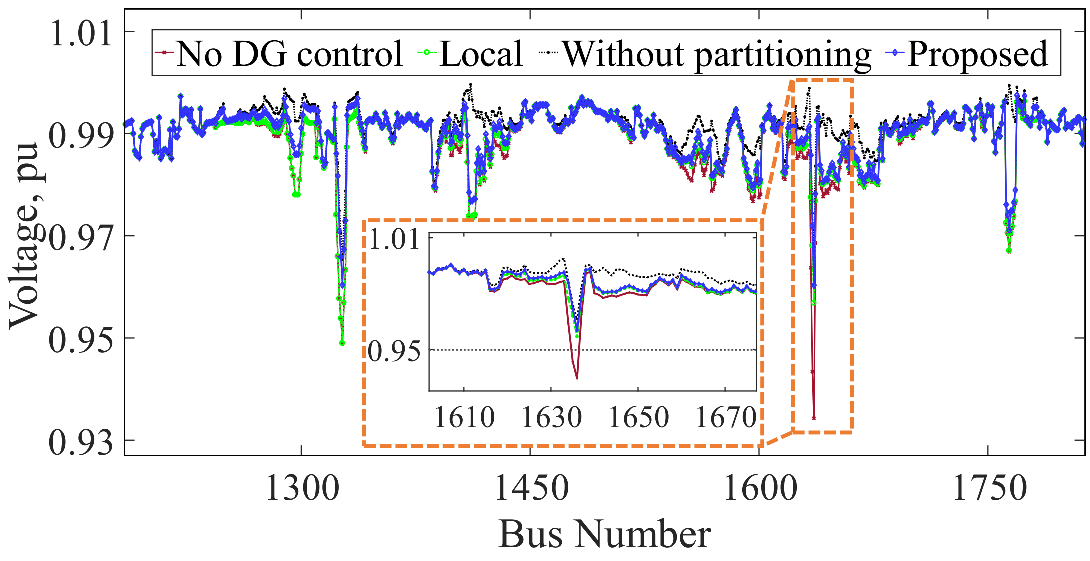
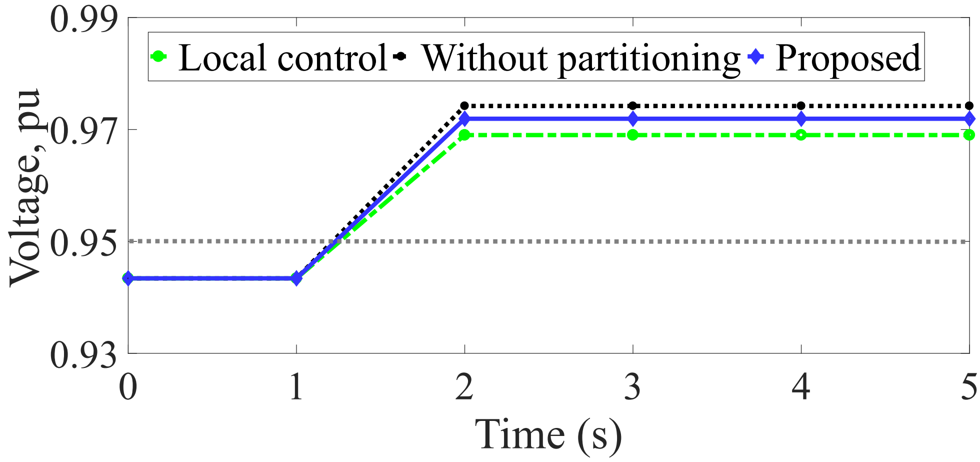
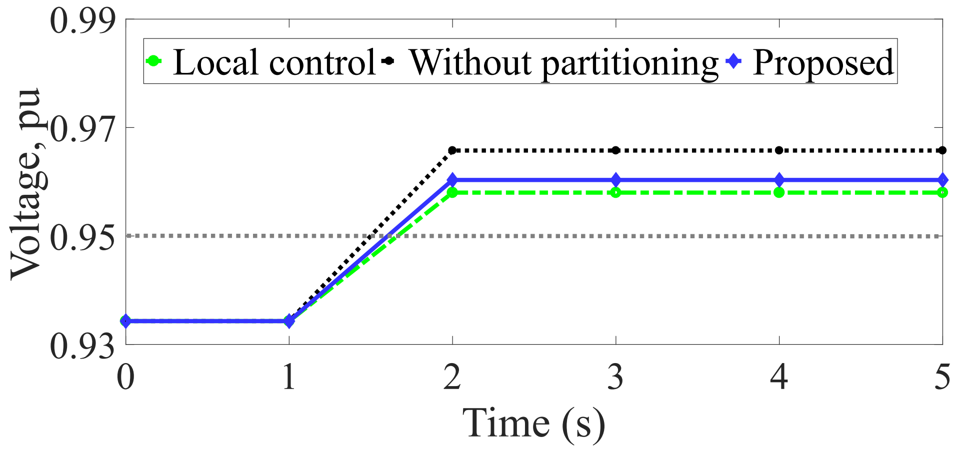


Figure 6.5: Voltage profiles of busses showing violations and regulation in multiple subnetworks at the same time (Case Study 2).

As summarised in Table 6.5, in comparison to the situation where the network is not partitioned, the proposed method enables solving the control problem with less DG involved and with reduced size of the control problem. This not only leads to results comparable to solving for the whole network, but also allows dividing and simplifying the problem into smaller independent sub-problems. In this case study, the basic local control without coordination was not able to regulate the voltage in subnetwork 5, but was able to regulate the voltage in subnetwork 45.



(a)



(b)

Figure 6.6: Voltage of nodes in subnetwork 45. (a) Bus 1635 . (b) Bus 1636.

Table 6.5: Comparison of the control parameters for Case Study 2

Technique	Proposed Method	Local Control	Without Partitioning
No. of involved DGs	4	3	15
No. of involved nodes	25	3	271
P_{loss} after control (pu)	0.3263	0.3255	0.3402
Q_{loss} after control (pu)	0.9076	0.9105	0.9161

6.1.5 Case Study 3: The Self-Organising Mechanism

The self-organising property of the system is implemented by autonomously adjusting the decomposition of the subnetworks to adapt to anomalies. For $\varepsilon = 0.012$, with the DGs operating in the UPF mode, 75 subnetworks are generated. A disconnection of DG 192 in subnetwork 51 is considered in this test. As illustrated in the communication diagram in Figure 6.7, VD agent 1694 (in subnetwork 51) reports a voltage violation event to LPS agent 51, which identifies two DG agents in its network, namely, DG agents 192 and 247, that can influence the voltage of the violating bus. However, because DG agent 192 was disconnected from the network, the subnetwork attempts to control the voltage with the one available DG agent (247).

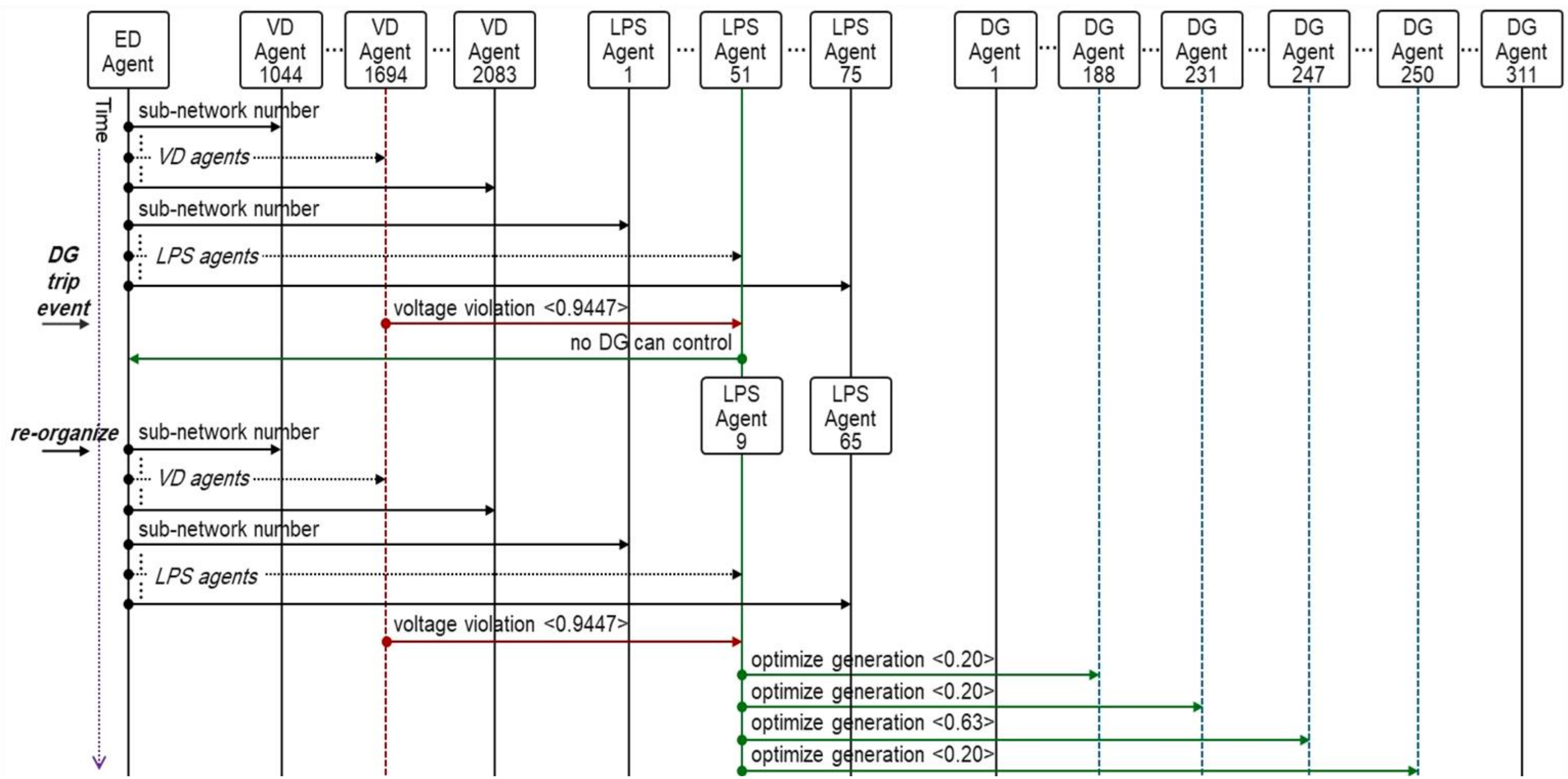


Figure 6.7: Coordination and self-organisation of agents for distributed voltage regulation (Case Study 3).

In this scenario, the subnetwork is not able to restore the voltage using the available DG resources of its subnetwork and informs the ED agent to select a smaller ε value to expand the ranges of influence of the DGs and to involve more DG agents in the voltage control problem. When selecting ε=0.01, the network is reset, and the agents regroup and reorganise based on the new decomposition. As shown in Figure 6.7, VD agent 1694 is now in subnetwork 9, in which four DGs can influence the bus voltage. Thus, the corresponding control agent, LPS agent 9, finds a solution and sends the optimal adjustment messages to the DG agents to take control actions. Due to the limited space available for the interaction diagram, Figure 6.7 shows only the agents that are involved in this control problem. Table 6.6 also summarises the proposed distributed control results for scenarios with different ε values for the same violation event.

Table 6.6: Results of the violation event with the self-organising mechanism (Case Study 3)

Control Mode	UPF	
ε value	0.012	0.010
No. of DG agents can influence the node	1	4
Sufficient DG resources	No	Yes

As presented in Figure 6.8, after the self-organising mechanism and the outputs are optimized, the voltage is controlled and returned to an acceptable level. The performance of various methods is also included in Figure 6.8 and Table 6.7. Figure 6.8 shows that the proposed mechanism can perform as effectively as the system without partitioning. Although the basic local control does not require any communication, it does not have a coordination mechanism to adapt and regulate the voltage when the involved local DG has tripped. Table 6.7 summarises the results of the methods under study. They are consistent with the conclusions of case studies 1 and 2.

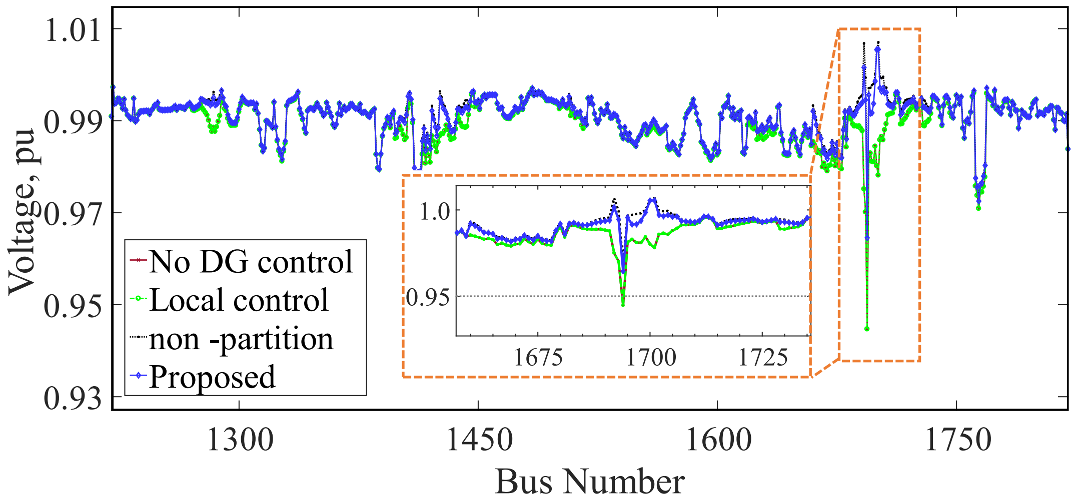


Figure 6.8: The voltage profiles after regulation through self-organisation.

Table 6.7: Comparison of the control parameters for Case Study 3

Technique	Proposed Method	Local Control	Without Partitioning
No. of involved DGs	4	0	7
No. of involved nodes	25	1	146
P_{loss} after control (pu)	0.2640	0.2840	0.2722
Q_{loss} after control (pu)	0.8427	0.8658	0.8495

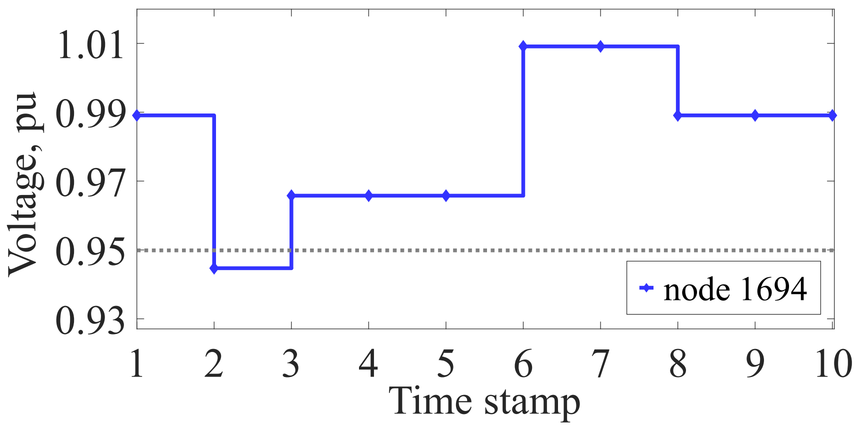


Figure 6.9: The voltage levels at bus 1694 realized through self-organisation.

The system is not only capable of maintaining a stable state, e.g., by expanding the network when DG resources are not available, but can also self-divide into a more distributed state of small groups once the network returns to normal operation (e.g. when a DG is back online in this cases study). As illustrated in Figure 6.9, in this case study, DG 192 trips at time T2 causing undervoltage at bus 1694. The agents self-organise at time T3 to regulate the voltage successfully. When DG agent 192 returns back online at T6, it informs the LPS agent in order to return to the previous operation before the DG trip. The LPS agent first resets the four DGs agent (used to regulate the voltage due to the trip of DG 192) at T8 to return to normal operation. The LPS agent then informs the ED agent to restore the initial ε value before the DG trip event. The system self-reorganises, and the ε value is reset to its value before the DG tripped. This mechanism also allows the system to self-organise in response to various conditions such as uncertainty and the availability of energy resources over time (e.g., DG does not have sufficient power or has lost communication).

6.2 Results and Discussion: Self-organised Control and Management of EVs in Large Distribution Networks

The proposed community detection partitioning technique and distributed control algorithm has been used for a large distribution system to validate the distributed and adaptive control of EVs. The system is tested under various events and conditions and comparative results are presented to validate the performance of the proposed algorithm. An example of agent simulation code using this approach in Presage2 is shown in Appendix B.

6.2.1 Deployment for a Large Distribution Network

The system under study is based on the IEEE European LV Test system [24] and consists of 906 LV nodes. Researchers willing to investigate the LV networks in Europe can use this test network, which was provided by the IEEE PES Test Feeder Working Group, as a reliable benchmark. As shown in Figure 6.10, it is assumed that 55 EVs are connected to the network. In this network, the substation transformer steps down the voltage from 11 kV to 416 V. More details of the network parameters can be found in [24]. The technique is tested on the test network to demonstrate effective partitioning and distributed control of EV as presented below.

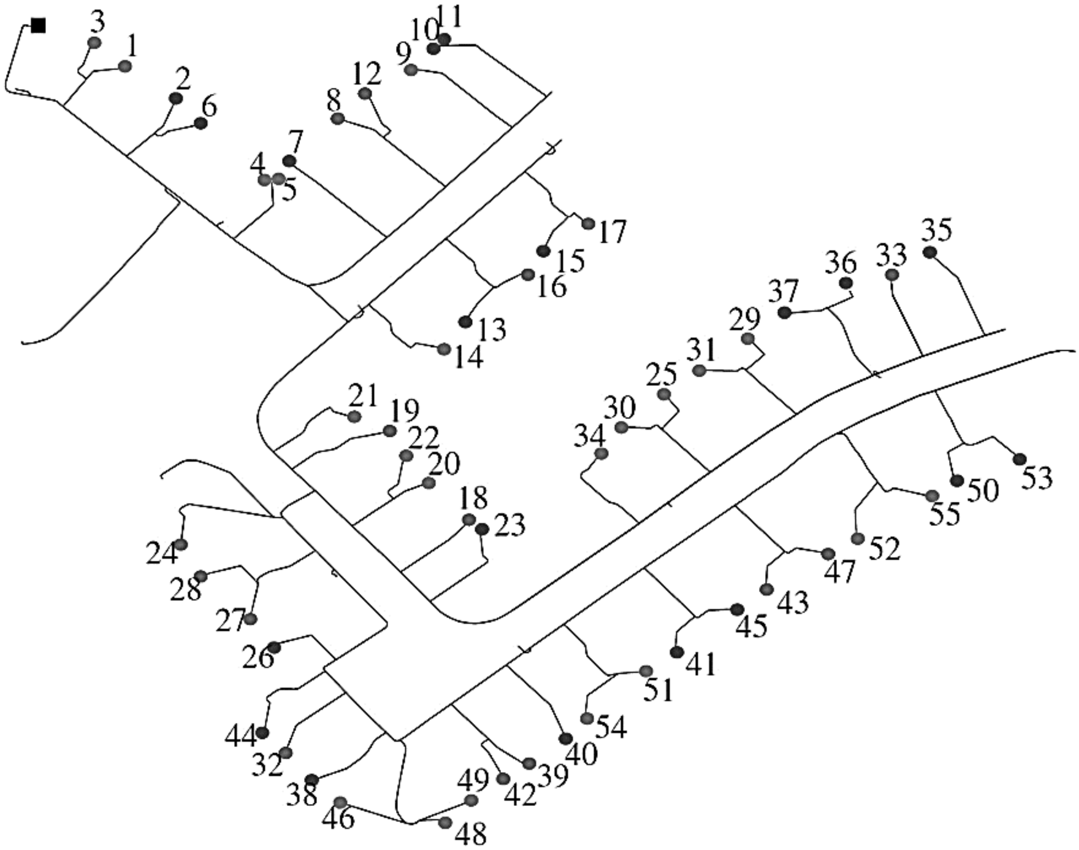


Figure 6.10: The topology of the IEEE European LV test network with EVs connected to load nodes.

6.2.2 Formation of Communities

The community detection method for the partitioning of the network under study is applied using the sensitivity matrix in (5.11). The sensitivity matrix for this network is an 1810x1810 matrix. Based on the application of the method presented in Section 5.3.1, information on the allocation of EVs, nodes, and loads can be obtained. As shown in Table 6.8 and Figure 6.11, after implementing the method, the network is divided into 11 communities. Table 6.8 and Figure 6.11 also show that communities have varying number of EVs and nodes with a maximum of 191 nodes and a minimum of 12 nodes per community. There is also a maximum of 12 EVs and a minimum of one EV per community. It is noted that, in this technique, all nodes in the network are covered by the communities, thus all nodes and loads in the network are in the influence range of the EVs. Thus, the agents in the network are grouped into 11 communities, with one Community Agent (CA) assigned in each community. The CA informs the Bus Agents (BA) and EV Agents (EVA) in the same community so that each agent is linked with agents in the same community.

It is apparent that the partitioning determines how far the control algorithm is distributed. This reduces the size of the control problem and the network communication requirements, which results from breaking the network up into smaller groups. Additionally, this reduces voltage measurements taken over a large area to those taken locally.

Table 6.8: Results of the application of the community detection algorithm

Community No.	1	2	3	4	5	6	7	8	9	10	11
No. of Nodes	163	115	112	36	54	141	12	191	27	39	16
No. of EVs	12	5	6	1	2	9	1	12	3	2	2

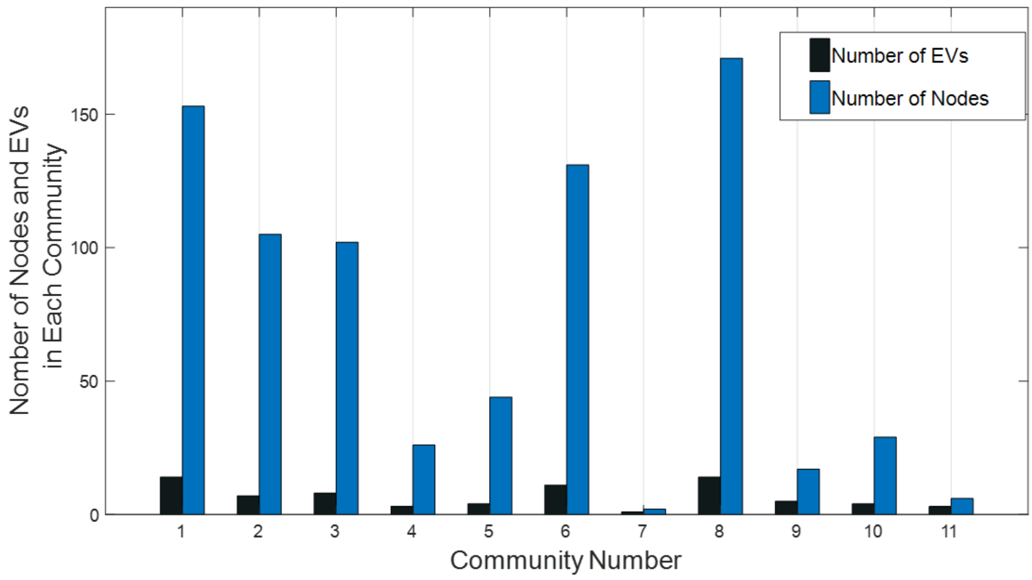


Figure 6.11: The information of EVs and nodes in each community.

6.2.3 Control Areas of Electric Vehicles

For such a large network, the voltage could exceed safe operating limits in large communities, such as community number 6, which contains 141 nodes and 9 EVs. Although the size of this community is much smaller than the original distribution network (906 nodes and 55 EVs), the solution for the control problem could still have 9 variables and nearly 280 constraints if all the EVs of this community are participating in the voltage control process. However, it is very likely that not all EVs will have a strong coupling with every node in this type of large community. Thus, in order to identify the EVs with a strong impact over a node or group of nodes and reduce the size of the control problem, it is important to identify the neighbouring EVs to those nodes where voltage violations occur.

In the proposed technique, as presented in section 5.3, the subset of EVs and nodes are those EVs that have the highest influence on the neighbouring nodes. Taking community 6 as an example, the method is implemented to this community submatrix using the (5.14) and (5.15), resulting in 4 subsets that define how EVs affect nodes voltages in this community. Figure 6.12 shows community number 6 containing 4 subsets, and shows that the number of EVs and nodes that are in the same subset varies from 1 to 4 EVs and from 15 to 71 nodes. Only the corresponding EVs in the same subset will perform the voltage control function when a voltage violation occurs in a node or nodes. As a result, the EVs that have more influence on nodes are defined and the control problem is decreased from 9 variables and over 280 constraints to just a few variables and a small number of constraints. It is obvious that for a community with a small number of EVs and nodes, the control subset would usually consist of all of the EVs and nodes in this community.

After determining the community subsets, the community agents solve the local control problems using local signals and measurements. For example, in community number 6, the CA 6 first finds the subsets and then informs BA and EVA agents in its community so that each agent is connected to neighbouring agents in the same subset. This identifies the communication links between agents, thus reducing the size of the optimisation problem and the interaction requirements, and maintaining minimal use of the communication bandwidth. The system is also able to maintain dynamic subsets considering the changing conditions of EVs over time as presented next.

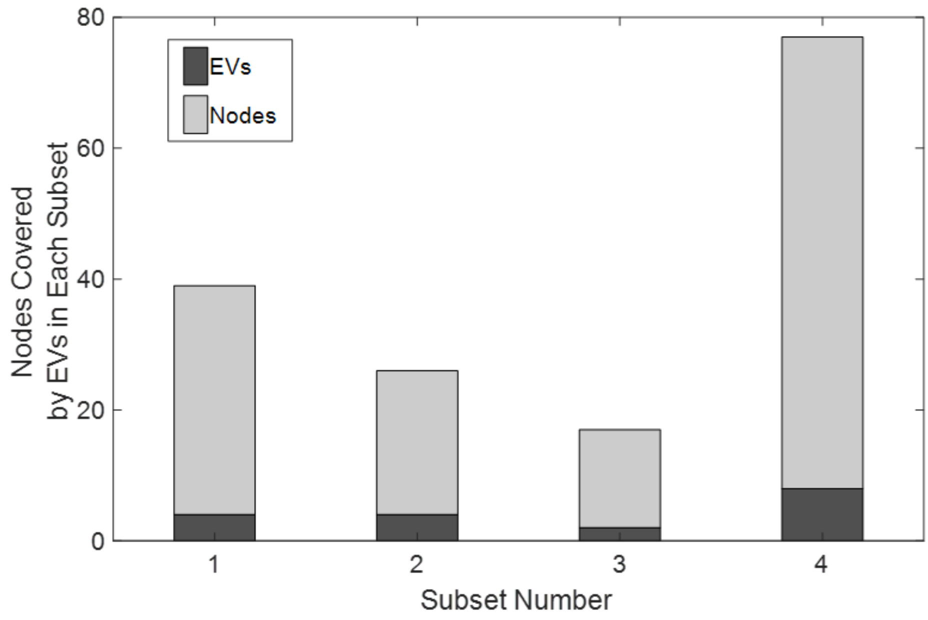


Figure 6.12: Number of nodes covered by EVs in each subset of community 6.

6.2.4 Self-Organisation of Electric Vehicles

As the conditions of EVs change over time, the agents in a community need to adapt and self-organise in their subsets to maintain adequate organisation over their control areas. Taking community number 8 as an example as shown in Table 6.9 (a), the community determines subsets of nodes and EVs within the community for which the EVs have more influence on those nodes. The EVA and BA agents in this community first organise in these subsets for local monitoring and control of the local nodes and resources.

To demonstrate self-organisation in this community, a disconnection of EV 43 in subset number 5 is simulated. As a result, the agents in this network self-organise to find the best partitioning. To achieve this, the corresponding EVA 43 first informs its CA 8 about this event so that the CA can find the updated D_{com}

Table 6.9: Self-organisation of EVA and subsets in community number 8

(a) Subsets with EVA 43

Subset No.	List of EVA agents		
1	32	38	44
2	40	42	
3	51	54	
4	41	45	
5	43	47	

(b) EVA 47 joins subset 4

Subset No.	List of EVA agents		
1	32	38	44
2	40	42	
3	51	54	
4	41	45	47

(c) EVA 39 joins subset 2

Subset No.	List of EVA agents		
1	32	38	44
2	40	42	39
3	51	54	
4	41	45	47

sub-matrix in (5.15). As shown in Table 6.9-(a) and Table 6.9-(b), the CA now identifies four subsets for the community. Following this, the subsets are formed, resulting in EVA 47 to join subset number 4. Additionally, the connection of EV 39 is assumed, which results in EVA 39 to join subset 2, as presented in Table 6.9-(c).

This can take place based on time-varying conditions of the EVs and network without stopping the system. After the self-organisation of agents, the agents continue solving local control problems using local signals and measurements. The following section shows the implementation of the charge rate control of EVs to maintain the network voltage levels within acceptable limits.

6.2.5 Controlled Charging of EVs

To test the system, simulations are conducted in order to evaluate the performance of the control system when controlling the EVs with the aim to resolve voltage violation events. This is demonstrated by connecting EVs in community number 6, causing voltages to exceed the safe operating limits before applying the proposed EV control (shown in Figure 6.14). These community violation events are detected by bus agents BA 493 and BA 502 (in subset 2), which communicate violations to the corresponding CA agent 6. The agent communication diagram in Figure 6.13 shows the agents that are involved in this control problem. The CA agent identifies solutions using EV agents 25 and 30 and sends the charging control adjustment to the corresponding EVAs 25 and 30 to regulate the voltage in its area as shown in Figure 6.14. Therefore, out of the 9 EVAs in this community, only two EVAs are involved in the control problem. This simplifies the solution and reduces the number of control parameters from 9 EVs to 2 EVs and from 141 nodes to 35 nodes that are in this same subset, while simultaneously reducing the interactions required between only the involved agents.

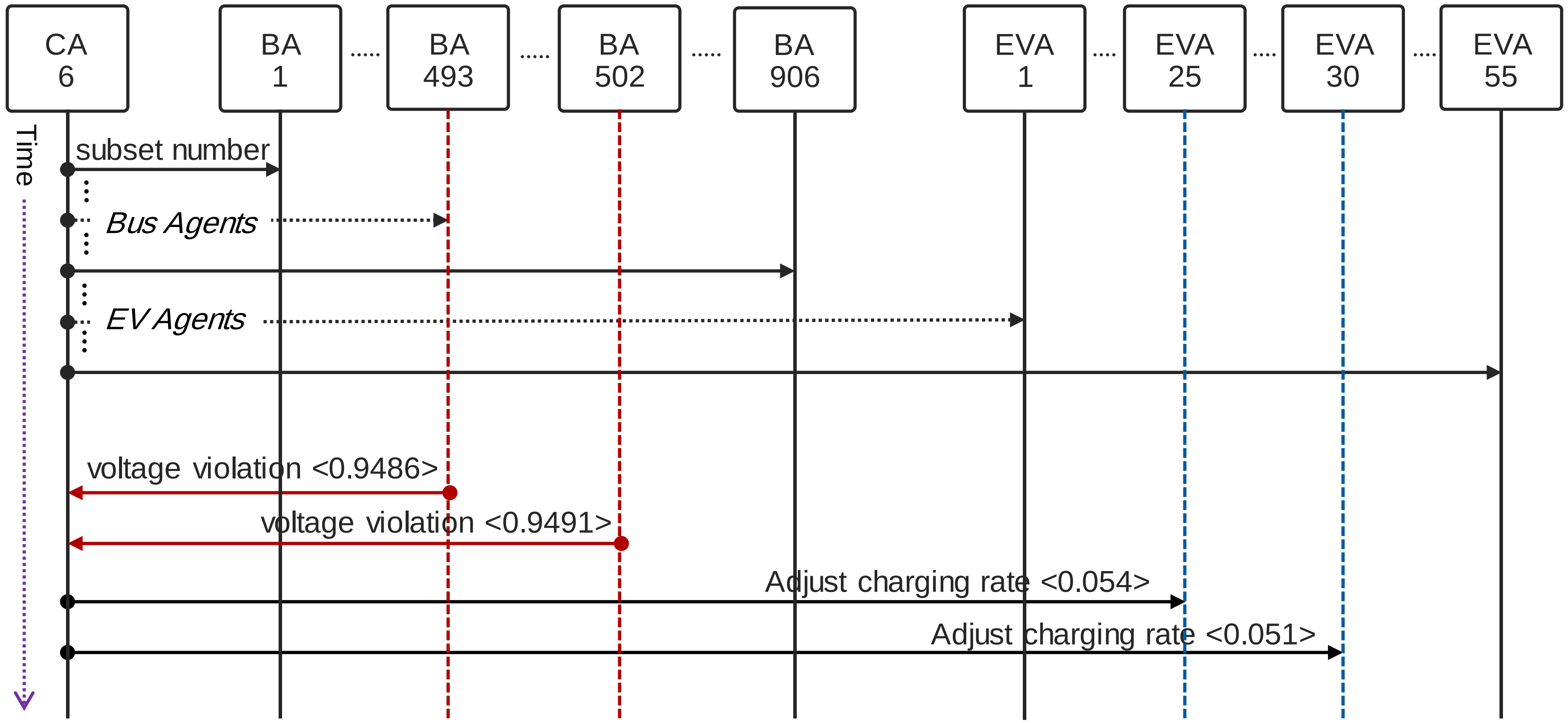


Figure 6.13: Interaction of gents to coordinate controlling the voltage within communiy 6.

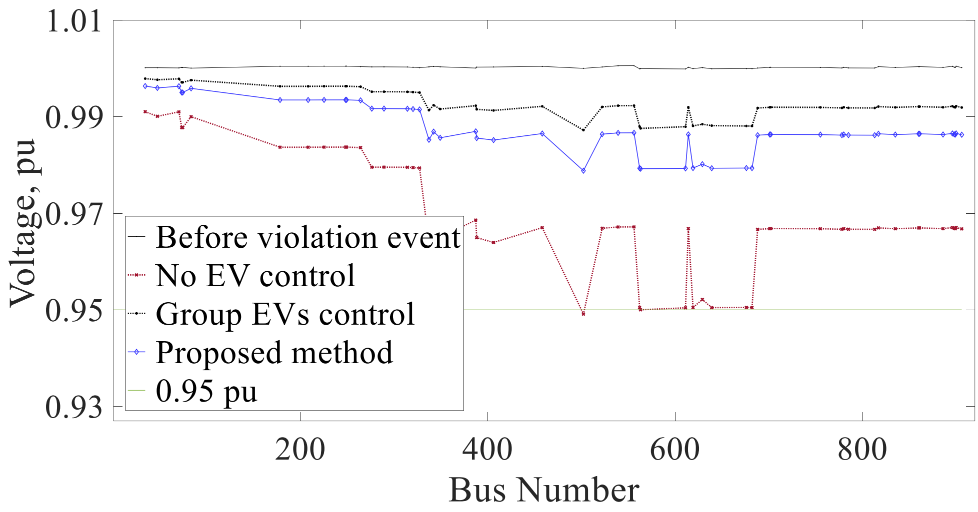


Figure 6.14: Voltage profiles of busses after controlling the charge rate of EVs.

Table 6.10: Results of control parameters for controlled changing of EVs

Technique	Proposed Method	All Community EVs
No. of controlled EVs	2	9
No. of control nodes	34	141

The distribution network voltage profiles after control are presented in Figure 6.14. The performance of the system is compared with the method when controlling all EVs in the community and without EV control. It is noted that when using all community nodes and EVs, the CA accounts for all community EVs and nodes to find the solution. As shown in Figure 6.14, the voltage limits in the presented approach are maintained within acceptable limits. As expected, the results demonstrate that the voltage regulation of the presented distributed control method can perform as effectively as the system when considering all

EVs in the community. This is due to the proposed distributed voltage regulation's ability to control EVs with the greatest influence on the nodes voltage. Table 6.10 shows that in comparison with the condition when using all community EVs, the proposed method allows for the control problem to be solved by controlling only neighbouring EVs to the nodes and reducing the size of the control problem. This not only enables simplifying and subdividing the control problem into smaller sub-problems, but also leads to results comparable to controlling all EVs in the community.

6.3 Summary

This study presented distributed and intelligent control techniques with improved self-organisation capabilities to solve large and complex network problems. The effectiveness of the proposed approaches are validated through simulations based on complex network models, and the results are presented and discussed.

To control DGs and regulate voltage violations in distribution networks, the presented technique is tested on a model of a real heavily-meshed secondary network, and the performance is compared to various techniques. Simulation results prove the autonomy of subnetworks to control the voltage independently using only the involved DGs. The system was also tested to validate the adaptability and robustness of the system by maintaining stable voltage control in response to network anomalies over time.

The simulations of the community detection partitioning of a large distribution network considering local EVs is also presented to enable distributed control and management of EV and voltage. The control and management of EVs is tested, and the results validate the effectiveness of the presented technique based on a large distribution network. In particular it shows that the algorithm can control voltage and the EVs in a distributed manner using only the neighbouring EV while dealing with network time-varying conditions. This also validates that using subsets can reduce the size of the control problem and the interactions required within small control areas to maintain network voltage levels.

Although the work presented herein has focussed on two distinct techniques of controlling DERs using self-organising MAS techniques, i.e., DGs and EVs, it may be possible that a hybrid approach utilising various DERs within networks could provide additional benefits. In summary, the presented methods offer novel MAS-based distributed control approaches with improved self-organisation capabilities for complex distribution networks, potentially giving rise to an adaptive and robust control approach suitable for wider adoption in smart grids.

Chapter 7

Conclusions and Future Work

In this chapter the conclusions and main contributions of this thesis are summarised, and potential directions of future work and research are explored. The main aim of this thesis is to present novel intelligent and distributed control algorithms to deal with the increasing complexity and uncertainty of future power networks, and to implement these control solutions for potential real-world applications.

7.1 Conclusions

This thesis developed distributed control methods for self-organising autonomous energy systems and large-scale power networks, focusing on voltage and power control, and the integration of DGs and EVs, enabling adaptive and robust power networks. The proposed control strategies enable the development of self-organising MAS frameworks to equip the system with autonomy and adaptivity. To solve the control problems for large power systems, partitioning of power networks into smaller clusters was implemented using agents that are able to communicate and coordinate control actions. The techniques used are distinctive as the proposed control methods can tolerate the changes in the distribution network, and with minimum communication bandwidth requirements.

A literature review of the applications of control techniques in power networks is included. Techniques for managing distributed energy resources (DER) are described and summarised, and examples of research in the area are provided. The impact of new DER on distribution network control is examined, as well as the techniques developed to address these control issues. Researchers mostly use these strategies for microgrids and small-scale distribution networks with a limited number of DERs. Thus, the research in this thesis tackled the requirement to control and manage large numbers of DERs with greater coordination.

The distinctive characteristics of well-designed network control is the ability of the system to respond to changing conditions and to tolerate the disconnection and connection of network components. Additionally, dividing distribution networks into small groups, or control areas, offers a way to split the control problem into manageable subproblems. When the network contains

DERs with outputs that vary in wide ranges, the control of the DERs in each group can be achieved by coordinating the power levels of each DER internally within each subproblem group. In general, the required control system should be capable of managing a large number of DERs and only needs local data from neighbouring units. This enables the formation of DER groups and the effective dispatch and control of power in distribution networks. This thesis has proven that such systems can benefit from using multi-agent system (MAS) techniques to implement distributed solutions. Moreover, to enable the system to cope with the unpredictable time-varying conditions of the distribution network, self-organisation of these autonomous agents would be an effective solution essential for future networks. Consequently, creating self-organising networks based on DERs can enhance the control mechanism, particularly under unforeseen and time-varying and conditions and changes.

Self-organising MAS techniques have attracted interest in addressing the uncertainties and dynamic requirements in distributed and complex systems. In addition to its well-known benefit of adaptability, self-organisation also has key features such as dynamic and decentralized properties. The distributed nature of the future power networks and their components makes self-organising MAS an effective control technique for such networks. Previous research on self-organising approaches for power networks has focused on energy markets rather than technical parameters and constraints such as voltage and frequency regulations and system balance. Also, where agent-based approaches were used, they did not make full use of MAS techniques. More research is needed to implement MAS with self-organising capabilities for controlling and handling the increased complexity of power networks in terms of physical and electrical phenomena. Voltage stability, which is more of a local characteristic, and local power control of DERs are promising application areas for self-organising MAS mechanisms.

To control large power networks with distributed generation (DG), a self-organising distributed control approach is implemented using a MAS framework, in which the agents autonomously group themselves into subnetworks to control the voltage through local interactions of agents in a cooperative way. Additionally, the system can realize the adjustment of DG active power outputs in UPF mode or reactive power outputs in PFC mode. The system can also adapt to time-varying network conditions to maintain stable control by dynamically updating the grouping of the network without re-engineering the complete system. The effectiveness of the proposed approach is validated through simulations based on a complex network model of a real heavily-meshed secondary network, and the performance is compared to various techniques. Simulation results prove the autonomy of subnetworks to control the voltage independently using only the involved DGs. The system was also tested to validate the adaptability and robustness of the system by maintaining stable voltage control in response to network anomalies over time.

To address the challenges of controlling the charging of electric vehicles (EV) in distribution networks, this thesis presents a community detection-based partitioning technique that considers the degree of coupling between EVs and nodes in large distribution networks. It uses the control of EVs, allowing them to be grouped and controlled in a distributed manner by using local signals and measurements. The voltage control problem is realized by means of a distributed control mechanism based on a MAS architecture and is extended by implementing a dynamic structure within each community to resolve voltage issues using only neighbouring EVs, thereby reducing the size of the problem and the interaction requirements within each community. This control scheme enables each community to self-organise to reflect varying EV conditions and maintain stable control. The system implements controlled charging of EVs, maintaining the use of the existing distribution networks. Simulations demonstrate that the partitioning of the large distribution network is effective, and the robustness of each community to self-organise and maintain stable control to regulate the voltage independently using only its local EVs.

While this thesis introduces novel techniques towards addressing distributed control of large distribution network, this research solves the voltage issues to keep the network operating within acceptable limits. However, other constraints such as thermal play an important role in network control and constraints. Moreover, other limitations of this study include finding dynamic sensitivity matrix using local measurements and agents in order to improve the self-organisation mechanism. These limitations are planned to be addressed in the future work.

In summary, this thesis presented novel MAS-based distributed voltage control schemes with improved self-organisation capabilities for the control and management of complex distribution networks suitable for wider adoption in smart grids. The desired control mechanism is resilient to network anomalies and uses local interactions to adjust its structure without stopping the system. This research has presented the following contributions to knowledge.

- An investigation of the challenges associated with using MAS and self-organisation for large, complex networks in smart grids.
- Presented and implemented a MAS framework that splits the power network control problem into smaller sub-problems, to allow for distributed control tasks among the local entities.

- Integrated an intelligent control agent in each subnetwork to coordinate and control its local voltage autonomously and independently using only its local resources.
- Enabled each local group to locate the closest local DER that has highest influence on the desired node, to control the voltage in large distribution networks in a distributed and cooperative manner. This further simplifies the optimization problem and reduces the interaction requirements, and the communication bandwidth to a minimum.
- Presented a community detection-based partitioning algorithm to partition large power networks and dynamically identify and control the voltage of neighbouring nodes to each resource.
- Enabled self-organisation of these networks in response to various network conditions such as uncertainty of energy resources, outages, communication failure, etc., to maintain stable control.
- Implemented these partitioning and intelligent self-organising control and management techniques to control the network by optimising the generation of DGs and the charging of connected EVs while maintaining local network conditions and constraints within acceptable limits.
- Validated the effectiveness of the proposed approaches through simulations on complex network models with DERs, demonstrating the ability of the sub-systems to autonomously and independently control local DERs and to adapt to unpredictable network conditions over time.

7.2 Future Work

Research presented in this thesis can be expanded in a number of ways, including:

- Explore the integration and coordination between DGs and EVs in one network to maximise the charging rate of connected EVs, supported by optimising the outputs of neighbouring DGs in the same network. For instance, if a voltage violation happens, the groups of EVs and DGs participate in the voltage regulation by curtailing EV charging during high demand or increasing the generation of DGs.

- The extension of the presented method to explore and solve more voltage control challenges, such as voltage collapse analysis, posed by the increasing penetration of distributed and renewable generation sources in smart grids, as well to manage other constraints such as thermal limits of the network.

- Investigate the advantages of dispatching reactive power from EVs to the distribution grid as well as to the EV owners. This could maintain the operation and management of grid constraints such as undervoltages during the EV charging caused by the active power consumption.

- Examine how charging strategies could also be used to motivate EVs owners to move from a congested area to another less congested area, or shift charging to a later or earlier period with less demand. These strategies could also be used to avoid the addition of new EVs in an area where there are voltage drop/congestion issues and improve the changing of EVs.

- Explore the coordination of the DERs with demand response applications to facilitate increased penetration of DERs on constrained networks.

- Hardware in the Loop Testing. An agent-based distributed and self-organised mechanism described within this thesis is currently planned to be tested in a physical setting at the University of Strathclyde's Microgrid Laboratory. Physical implementation will help to develop and further validate the proposed MAS framework, by addressing application issues, such as deploying the system with "real" system devices, exploring various network conditions, and demonstrating real-time measurement and control.

- Finally, as network model and reconfiguration can influence the sensitivity factors used for network partitioning, it is proposed techniques such as real time distribution network measurements, could be used to implement the estimation techniques of the sensitivity factors, used by agents to autonomously adapt to network changes. For example, the changes in the network topology can be found by calculating time-varying voltage-to-power sensitivities. For instance, phasor measurement units (PMU) have been used recently to calculate/estimate entries of the Jacobian matrix [205] based on local and neighbouring measurements for distribution networks. Therefore, the work in this thesis could be improved by employing agents with the capability to calculate time-varying sensitivity factors in near real-time through interactions with neighbouring agents using local measurements. This allows an agent to calculate information about coupling with neighbouring DERs reactive/active power control, and agents can autonomously join a neighbouring group. When combined with appropriate techniques, such as k-nearest neighbours (KNN) methods, this control and estimation mechanism could be extended and implemented for all nodes and network components.

Appendices

Appendix A

Java Code from Presage2

A.1 Java code example of simulation environment in Presage2

```
package myAgent;

import java.util.HashSet;

public class MySimulation extends InjectedSimulation{
    public MySimulation(Set<AbstractModule> modules){
        super(modules);
    }
    @Parameter(name = "size")
    public int size;

    @Parameter(name = "agents")
    public int agents;

    @Override
    protected Set<AbstractModule> getModules(){
        Set<AbstractModule> modules = new HashSet<AbstractModule>();

        modules.add(Area.Bind.area2D(size, size));

        modules.add(new AbstractEnvironmentModule()
            .addActionHandler(MoveHandler.class)
            .addParticipantEnvironmentService(ParticipantLocationService.class));
        modules.add(NetworkModule.noNetworkModule());

        return modules;
    }

    @Override
    protected void addToScenario(Scenario s){
        for (int i = 0; i < agents; i++){
            int initialX = Random.randomInt(size);
            int initialY = Random.randomInt(size);
            Location startLoc = new Location(initialX, initialY);
            s.addParticipant(new MyAgent(Random.randomUUID(), "agent"+i, startLoc));
        }
    }
```

A.2 Example of LPS Agent Java code in Presage2

```java
@Override
public void execute() {

    // find out who's in my communication range
    Set<NetworkAddress> bconn = this.network.getConnectedNodes();
    logger.info("Connected to " + bconn.size() + " agents.");

    // send them messages
    for (NetworkAddress na: bconn) {
        UnicastMessage<?> sendMsg = new UnicastMessage<Object>(Performative.INFORM,
                this.network.getAddress(), na, time);
        this.network.sendMessage(sendMsg);
    }
    // check incoming messages (also from ManetAgent)
    List<Message<?>> vBelow = this.network.getMessages(); // to send/load array.

    int xTT=(Integer) ((Message<?>) vBelow).getData();
    // if message contains Voltage Violation form NVD, then run LP
    if (xTT == 0){
        System.out.println("no violation recieved");
    }
    else{
        for (NetworkAddress na: bconn){
            xTT= xTT+1;
            this.network.sendMessage(new UnicastMessage<Integer>(Performative.INFORM,
                    network.getAddress(), na, time, xTT));
```

Appendix B

Simulation Environment and Results in Presage2

B.1 LPS Agent sends new adjustments to involved DG agents

```
3083 [pool-1-thread-3] INFO  LPSAgentB8  - LPS revieved message form its NVD contains voltage violation n
3083 [pool-1-thread-3] INFO  LPSAgentB8  - start forming DG index here
3083 [pool-1-thread-3] INFO  LPSAgentB8  - DERInvInt[0] value is : 1238
3083 [pool-1-thread-3] INFO  LPSAgentB8  - DERInvInt[1] value is : 1382
3083 [pool-1-thread-3] INFO  LPSAgentB8  - DERInvInt[2] value is : 1364
3083 [pool-1-thread-3] INFO  LPSAgentB8  - start forming LP solution
3083 [pool-1-thread-3] INFO  LPSAgentB8  - DERChange[0] value is : 0.26652
3083 [pool-1-thread-3] INFO  LPSAgentB8  - DERChange[1] value is : 0.26652
3083 [pool-1-thread-3] INFO  LPSAgentB8  - DERChange[2] value is : 0.2579
3083 [pool-1-thread-3] INFO  LPSAgentB8  - New adjustment sent to DG Agent DGAgentB1238 is 0.26652
3083 [pool-1-thread-3] INFO  LPSAgentB8  - New adjustment sent to DG Agent DGAgentB1382 is 0.26652
3083 [pool-1-thread-3] INFO  LPSAgentB8  - New adjustment sent to DG Agent DGAgentB1364 is 0.2579
3083 [pool-1-thread-3] INFO  LPSAgentB77  - Connected to 934 nodes
3083 [pool-1-thread-3] INFO  LPSAgentB77  - LPS agnet Received number of message: 510
3083 [pool-1-thread-3] INFO  LPSAgentB77  - LPS.BM.: I recieved a message. Message included: D
3083 [pool-1-thread-3] INFO  LPSAgentB77  - This agent is deactivated
3083 [pool-1-thread-3] INFO  NVDAgentB263  - NVDAgentB263 : Connected to 934 nodes
```

……

```
6709 [pool-1-thread-4] INFO  DGAgentA221  - DGAgent received number of messages: 4
6709 [pool-1-thread-4] INFO  DGAgentA221  - DGAgent at node 1382 recieved optimized adjustment: 0.26652
```

B.2 Agents detect the violation events and report to control agent

```
5132 [pool-1-thread-3] INFO  DGAgentA57  - DGAgent connected to 934 nodes.
5132 [pool-1-thread-3] INFO  DGAgentA57  - DGAgent received number of messages: 1
5132 [pool-1-thread-3] INFO  DGAgentA247  - DGAgent connected to 934 nodes.
5132 [pool-1-thread-3] INFO  DGAgentA247  - DGAgent received number of messages: 1
5132 [pool-1-thread-3] INFO  LPSAgentA3  - Connected to 934 nodes
5132 [pool-1-thread-3] INFO  LPSAgentA3  - LPSAgnet received number of messages: 1
5132 [pool-1-thread-3] INFO  NVDAgentA33  - NVDAgentB33 : Connected to 934 nodes
5132 [pool-1-thread-3] INFO  NVDAgentA33  - NVDAgentB33 : Connected to 934 nodes
5132 [pool-1-thread-3] INFO  NVDAgentA33  - Ran Violation Detector in  NVDAgentB33
5132 [pool-1-thread-3] INFO  NVDAgentA33  - NVD: time step ended at 3
5132 [pool-1-thread-3] INFO  LPSAgentA249  - Connected to 934 nodes
5132 [pool-1-thread-3] INFO  LPSAgentA249  - LPSAgnet received number of messages: 1
5132 [pool-1-thread-3] INFO  LPSAgentA129  - Connected to 934 nodes
5132 [pool-1-thread-3] INFO  LPSAgentA129  - LPSAgnet received number of messages: 1
5132 [pool-1-thread-3] INFO  NVDAgentA8  - NVDAgentB8 : Connected to 934 nodes
5132 [pool-1-thread-3] INFO  NVDAgentA8  - NVDAgentB8 : Connected to 934 nodes
no messages for NVDAgent8
5132 [pool-1-thread-3] INFO  NVDAgentA8  - Ran Violation Detector in  NVDAgentB8
5132 [pool-1-thread-3] INFO  NVDAgentA8  - voltage violation detected in subnetwork 8(side note: MySNno8)
5132 [pool-1-thread-3] INFO  NVDAgentA8  - Message sent to LPS Agent No. 8
5132 [pool-1-thread-3] INFO  NVDAgentA8  - NVD: time step ended at 3
5132 [pool-1-thread-3] INFO  NVDAgentA258  - NVDAgentB258 : Connected to 934 nodes
5132 [pool-1-thread-3] INFO  NVDAgentA258  - NVDAgentB258 : Connected to 934 nodes
5132 [pool-1-thread-3] INFO  NVDAgentA258  - Ran Violation Detector in  NVDAgentB258
5132 [pool-1-thread-3] INFO  NVDAgentA258  - NVD: time step ended at 3
5132 [pool-1-thread-3] INFO  DGAgentA105  - DGAgent connected to 934 nodes.
5132 [pool-1-thread-3] INFO  DGAgentA105  - DGAgent received number of messages: 1
5132 [pool-1-thread-3] INFO  NVDAgentA15  - NVDAgentB15 : Connected to 934 nodes
5132 [pool-1-thread-3] INFO  NVDAgentA15  - NVDAgentB15 : Connected to 934 nodes
5132 [pool-1-thread-3] INFO  NVDAgentA15  - Ran Violation Detector in  NVDAgentB15
```

Appendix C

Smart Grid Implementation and Standards

C.1 Distributed Intelligence and Control for Smart Grid

Smart grids combine control systems, advanced technologies, and communication systems into the present power infrastructure. The smart grid, in general, is described as an intelligent electrical transmission and distribution system that leverages bidirectional communication, control centres, and energy resources to increase the system's efficiency by optimising power supply and demand. As shown in Figure C.1, this advanced electrical system integrates DERs, smart sensors, automation, and information and communication technologies [206]. Therefore, the energy system and the related market processes that support these functionalities must evolve into an intelligent infrastructure, or a “smart grid”.

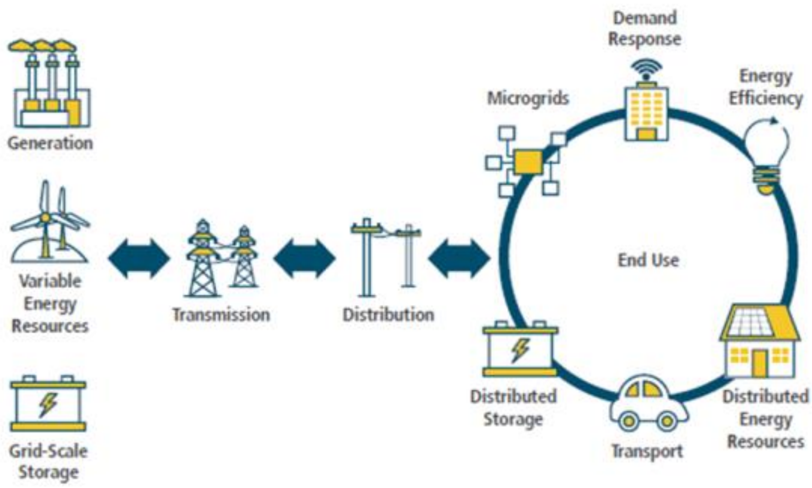


Figure C.1: Emerging future power networks infrastructure.

Smart grid controls will play an important role in providing the necessary architecture for monitoring and controlling power flows and managing the increasing penetration of distributed components. Control strategies must be able to cope with the conflicting goals of many different types of stakeholders (aggregators, generators, end-users, regulators, etc.) in the context of commercial, social, and technical constraints. In ageing infrastructure, this smart grid must be able to deal with rising intermittency in power generation as well as rapidly growing electrical consumption and any constraints in existing power lines. Furthermore, it must be sturdy enough to support a large number of micro-generators in distribution networks. In order to achieve this, the infrastructure must be able to [189]:

1. Enable small users (prosumers) to interact with the electricity system – usually via the distribution network.
2. Design and implement new control strategies to incorporate interacting DER units, DR and storage.

The smart grid potentially consists of many controllable devices and should perform efficiently on a large-scale and be fault-tolerant [18, 207]. Generally, the smart grid has the following characteristics:

- Smart grid components are often distributed and associated with communications (information exchange) between entities.
- It should be flexible, dynamic and adaptable in such a way that the changes on the system should not affect or stop the operations of the whole system.
- It should be scalable.

- It is usually composed of microgrids or control areas where tasks can be performed locally and may request help from other areas. In this context, smart grids may use AI and embrace self-* systems and machine learning.

- Smart grids leverage ICT.

- Smart grid technologies should be platform-independent and language-free, assuming that components communicate with the same or standardized protocols.

The self-organising MAS concept fits well with the objectives and characteristics of the smart grid presented above and can be used to help meet many of the aims of a smart grid.

C.2 Impact of Standards

The smart grid domain created by organisations such as IEEE (Institute of Electrical and Electronics Engineers), IEC (International Electro-Technical Commission), NIST (National Institute of Standards and Technology), and ETP (European Technology Platform) have been widely adopted in practical implementation [14]. For example, with their increased deployment of DERs, various organisations have looked to further develop the interconnection standards associated with DERs (e.g., IEEE 1547-2018) [208]. Hence, DER related standards are being developed to include advanced, standardized and autonomous functionalities, which is intended to make cooperative control possible [209]. Table C.1. summarises some of the main communication standards associated with the implementation of smart grids [209].

Table C.1. Summary of main communication standards for the control and operation of smart grids

Standard No.	Description
IEC 61850	Communication networks and systems for power utility automation
IEC 61970	Energy management system application program interface including the common information model
IEC 61968	System interfaces for distribution management
IEEE 1547	IEEE Standard for Interconnection and Interoperability of Distributed Energy Resources with Associated Electric Power Systems Interfaces
IEC 61131	Programmable controllers
IEC 62351	Standard for the data transfer security
IEC 61499	Distributed control and automation
ISO/IEC 14543	Home Electronic System (HES) architecture
IEC 61334	Distribution automation using distribution line carrier systems

The IEEE 1547 Std. [208] presents the technical requirements to integrate DERs into the smart grid. Additionally, the following amendments to the IEEE 1547 standards have been recently updated, which supports further integration of DERs and storage:

- IEEE 1547-2018: offers standards for interconnection and interoperability of DERs in power systems.
- Recently released IEEE 1547.1-2020: provides guidance for DER manufacturers, especially for testing. It provides grid support functionality for DERs connecting to the grid, including energy storage.

The essential and continuous interactions between agents in MAS require reliable and standardised communication [209]. ICT will therefore form an important part of the backbone of the smart grid system. Communication among agents follows certain protocols defined in what is known as an Agent Communication Language (ACL). The most commonly used ACL languages are

FIPA and KQML (as presented in section 4.2.1). The industrial communication protocol IEC 61850 deals with interoperability issues of the smart grid. However, the use of the IEC 61850 protocol for communication between agents in a MAS architecture still requires more investigation [137].

Appendix D

Extended Review of MAS Applications for Power Networks

D.1 Applications of MAS for Energy Market

In modern power systems, some operations are complex to be implemented using conventional methods that do not offer the extensibility and flexibility necessary in evolving systems. Topics associated with the use of MAS in energy markets have received a growing interest in power networks and progressed rapidly in the past few years with various techniques and applications. When MAS is used with local energy markets as a method to decentralise grid players, it can be used in energy market modelling and transmission expansion planning. For example, agents can establish dynamic clusters of producers and suppliers to match supply with demand over time by forecasting and communicating with other clusters. Within the context of cluster formation, producers and consumers might negotiate cluster membership based on perceived synergy in their features (such as size and generation type). In literature, agent-based techniques have been used extensively to implement flexible and decentralised energy markets.

An agent-based transactive energy (TE) management framework was proposed in [210] for transactions among microgrids to reduce the system cost of energy. The TE enables the operation and coordination between smart devices using value as the sole media, which can retain the autonomy and privacy of participants. The proposed technique improved the system's flexibility, scalability, transparency, and autonomy. The price oscillation is reduced which can protect and help small customers to increase their profit. Similarly, using MAS negotiation, the transactive energy trading method was adopted in [211] for real-time energy trading to address the complexity of aggregation in microgrids. The flexibilities and constraints of demand and generation of microgrids is considered in the transactive market interactions.

To integrate the electricity price response of DER into the coordination process, a bi-level agent-based coordinated operation strategy is presented in [212] for active distribution networks (AND). This method aims to maximize the profit of each agent and minimize the power imbalance in ADNs. Considering DER constraints, energy resources are able to generate power with power shortage in case of the price is higher than a certain value. A real-time MAS-based framework is presented [213] for the market operation in microgrids. A model of competitive game theory (reverse auction) is integrated into the model to plan the DER commitment on an hour ahead basis. The system is implemented realistically on a smart grid test system at Florida International University and demonstrated that it could be applied into the existing electricity grid.

Peer-to-peer (P2P) trading is an emerging concept that promotes the interaction of prosumers (with small scale DER) to trade energy. The consumers can be thought of as agents conducting negotiations on energy transfer. Autonomous DER participation in energy markets using MAS architectures is therefore naturally suited to this type of market. In [214], a framework of decentralised market for energy trading is presented for distribution networks. The market participants, P2P agents and Nodal agents are established and an Alternating Direction Method of Multipliers (ADMM) based algorithms are used to execute the market mechanism. The local optimization and coordination of agents ensure the market clearing mechanism's “fairness”. The presented framework ensures market equilibrium and satisfaction of grid constraints without violating market participants' privacy concerns.

To encourage local trade, an agent-based model is presented [215] to prioritise the exchange of energy resources over shorter distances. The use of MAS in the local energy market can assist in balancing local demand and supply and controlling congestion in transmission/distribution networks. The paper also considers resource placement and the optimal use of the current infrastructure.

D.2 MAS for Demand Side Management

Demand side management (DSM) has potential benefits to improve the operation and financial performance of smart grids and support grid integration of distributed and renewable energy resources [216, 217]. The introduction of artificial intelligence and machine learning in industrial energy management systems (EMS) can optimise users’ needs and preferences, resulting in reduced energy consumption and costs. The concept of DSM has been implemented as an enabler for smart grid operation and, recently, different agent-based techniques have been proposed to address DSM.

The coordination between demand centres in a decentralized manner within a cluster of buildings is proposed by [218] using a hierarchical transactive energy-based MAS framework. Using agents with scalable generation and demand allows for coordination and decentralized decision making. Moreover, energy management demand agents (EDMAs) are introduced at the building level to manage the operation of different appliances within the building and to take part in the day-ahead market at the cluster of buildings level. This method allows minimising the peak demand and avoiding the dispatch from expensive generation units.

The authors in [219] present a prosumer-based virtual power plant (VPP) architecture to enable optimal management of energy resources of the prosumers to engage in the DSM program. The methods apply a two-stage optimization technique for real-time and day-ahead pricing of VPP. Three main intelligent and automated systems are introduced, namely: the Energy Information System (EIS) as the information system of the VPP, the Energy Management System (EMS) for the optimal operational planning of the VPP, and the DER Automated Controller (DER-AC) as the real-time control of all of the virtual DERs. This agent-based framework implements intelligent operation and decisions of network infrastructure to solve uncertainties.

A DSM method for smart grids based on MAS is proposed in [220] for resources optimization using six layers to implement the DSM functionalities. The method is based on the concept of Micro-grid Intelligent Management (μ GIM) and introduced prosumer agents, DER agents, and microgrid agents. The system allows small and medium-sized end consumers to participate and balances supply and demand by minimising the electricity bought from the grid.

Additionally, agent-based energy management techniques have been studied and modelled from different points of view. For example, In [221], a multiagent-based hybrid control is proposed to manage the demand response (DR) composed of shifting and adjusting loads as part of the DSM program. The work in [222] presented a multi-agent-based optimal demand side management structure by introducing home agents (HAs) and retails agent (RA) in the distribution power network. The aim is to optimize residential DR by predicting electrical loads and enabling optimal load control for HAs. An investigation of the state-of-the-art applications and trends of MAS for energy systems integration is presented in [223].

Bibliography

[1] EIA, "Modeling Distributed Generation in the Buildings Sectors," 2020.

[2] B. P. (bp), "Statistical Review of World Energy 2021," United Kingdom, 2021.

[3] C. Cunanan, M.-K. Tran, Y. Lee, S. Kwok, V. Leung, and M. Fowler, "A Review of Heavy-Duty Vehicle Powertrain Technologies: Diesel Engine Vehicles, Battery Electric Vehicles, and Hydrogen Fuel Cell Electric Vehicles," *Clean Technologies,* vol. 3, no. 2, pp. 474-489, 2021.

[4] I. Wagner. "Share of passenger car sales in the European Union in 3rd quarter 2021, by fuel type." Statista. https://www.statista.com/statistics/1128792/passenger-car-registrations-in-europe-by-fuel-type/ (accessed 2023).

[5] B. Islam and T. Ali, *Plug-in Electric Vehicle Grid Integration*. Artech, 2017, pp. 1-289.

[6] N. Grid, "Future Energy Scenarios (FES) 2021," July 2021.

[7] K. E. Antoniadou-Plytaria, I. N. Kouveliotis-Lysikatos, P. S. Georgilakis, and N. D. Hatziargyriou, "Distributed and Decentralized Voltage Control of Smart Distribution Networks: Models, Methods, and Future Research," *IEEE Transactions on Smart Grid,* vol. 8, no. 6, pp. 2999-3008, 2017.

[8] D. E. Olivares, A. Mehrizi-Sani, A. H. Etemadi, C. A. Canizares, R. Iravani, M. Kazerani, A. H. Hajimiragha, O. Gomis-Bellmunt, M. Saeedifard, R. Palma-Behnke, G. A. Jimenez-Estevez, and N. D. Hatziargyriou, "Trends in Microgrid

Control," *IEEE Transactions on Smart Grid,* vol. 5, no. 4, pp. 1905-1919, 2014.

[9] C.-C. Liu, S. McArthur, and S.-J. Lee, *Smart grid handbook, 3 volume set*. John Wiley & Sons, 2016.

[10] O. P. Mahela, M. Khosravy, N. Gupta, B. Khan, H. H. Alhelou, R. Mahla, N. Patel, and P. Siano, "Comprehensive overview of multi-agent systems for controlling smart grids," *CSEE Journal of Power and Energy Systems,* pp. 1-16, 2020.

[11] H. Farhangi, "The path of the smart grid," *IEEE Power and Energy Magazine,* vol. 8, no. 1, pp. 18-28, 2010.

[12] M. You, X. Zhang, G. Zheng, J. Jiang, and H. Sun, "A Versatile Software Defined Smart Grid Testbed: Artificial Intelligence Enhanced Real-Time Co-Evaluation of ICT Systems and Power Systems," *IEEE Access,* vol. 8, pp. 88651-88663, 2020.

[13] "IEEE Standard for Interconnection and Interoperability of Distributed Energy Resources with Associated Electric Power Systems Interfaces," *IEEE Std 1547-2018 (Revision of IEEE Std 1547-2003),* pp. 1-138, 2018.

[14] O. P. Mahela, M. Khosravy, N. Gupta, B. Khan, H. H. Alhelou, R. Mahla, N. Patel, and P. Siano, "Comprehensive overview of multi-agent systems for controlling smart grids," *CSEE Journal of Power and Energy Systems,* 2022.

[15] M. Herrera, M. Pérez-Hernández, A. Kumar Parlikad, and J. Izquierdo, "Multi-agent systems and complex networks: Review and applications in systems engineering," *Processes,* vol. 8, no. 3, p. 312, 2020.

[16] P. Leitão, V. Mařík, and P. Vrba, "Past, Present, and Future of Industrial Agent Applications," *IEEE Transactions on Industrial Informatics,* vol. 9, no. 4, pp. 2360-2372, 2013.

[17] T. Strasser, F. Andren, J. Kathan, C. Cecati, C. Buccella, P. Siano, P. Leitao, G.

Zhabelova, V. Vyatkin, P. Vrba, and V. Marik, "A Review of Architectures and Concepts for Intelligence in Future Electric Energy Systems," *IEEE Transactions on Industrial Electronics,* vol. 62, no. 4, pp. 2424-2438, 2015.

[18] G. H. Merabet, M. Essaaidi, H. Talei, M. R. Abid, N. Khalil, M. Madkour, and D. Benhaddou, "Applications of Multi-Agent Systems in Smart Grids: A survey," in *2014 International Conference on Multimedia Computing and Systems (ICMCS)*, 14-16 April 2014 2014, pp. 1088-1094.

[19] M. H. Moradi, S. Razini, and S. Mahdi Hosseinian, "State of art of multiagent systems in power engineering: A review," *Renewable and Sustainable Energy Reviews,* vol. 58, pp. 814-824, 2016/05/01/ 2016.

[20] M. E. Baran and I. M. El-Markabi, "A Multiagent-Based Dispatching Scheme for Distributed Generators for Voltage Support on Distribution Feeders," *IEEE Transactions on Power Systems,* vol. 22, no. 1, pp. 52-59, 2007.

[21] S. M. Mohiuddin and J. Qi, "Optimal Distributed Control of AC Microgrids with Coordinated Voltage Regulation and Reactive Power Sharing," *IEEE Transactions on Smart Grid,* pp. 1-1, 2022.

[22] P. Vrba, V. Mařík, P. Siano, P. Leitão, G. Zhabelova, V. Vyatkin, and T. Strasser, "A Review of Agent and Service-Oriented Concepts Applied to Intelligent Energy Systems," *IEEE Transactions on Industrial Informatics,* vol. 10, no. 3, pp. 1890-1903, 2014.

[23] J. Pitt, *Self-Organising Multi-Agent Systems: Algorithmic Foundations of Cyber-Anarcho-Socialism*. World Scientific, 2021.

[24] "IEEE PES 906-Bus European Low Voltage Test Feeder." IEEE. https://cmte.ieee.org/pes-testfeeders/resources/. (accessed 2023).

[25] J. Ressler. "Defining DERs: Does it matter that we all seem to have slightly

different definitions?" Clean Power Research. https://www.cleanpower.com/2018/defining-ders-does-it-matter-definitions-vary/ (accessed January, 2023).

[26] L. Yu, D. Czarkowski, and F. d. Leon, "Optimal Distributed Voltage Regulation for Secondary Networks With DGs," *IEEE Transactions on Smart Grid,* vol. 3, no. 2, pp. 959-967, 2012.

[27] M. H. Hemmatpour, M. H. Rezaeian Koochi, P. Dehghanian, and P. Dehghanian, "Voltage and energy control in distribution systems in the presence of flexible loads considering coordinated charging of electric vehicles," *Energy,* vol. 239, p. 121880, 2022/01/15/ 2022.

[28] A. Keane, L. F. Ochoa, C. L. T. Borges, G. W. Ault, A. D. Alarcon-Rodriguez, R. A. F. Currie, F. Pilo, C. Dent, and G. P. Harrison, "State-of-the-Art Techniques and Challenges Ahead for Distributed Generation Planning and Optimization," *IEEE Transactions on Power Systems,* vol. 28, no. 2, pp. 1493-1502, 2013.

[29] S. Ahmad, M. Shafiullah, C. B. Ahmed, and M. Alowaifeer, "A Review of Microgrid Energy Management and Control Strategies," *IEEE Access,* vol. 11, pp. 21729-21757, 2023.

[30] L. F. Grisales-Noreña, B. J. Restrepo-Cuestas, B. Cortés-Caicedo, J. Montano, A. A. Rosales-Muñoz, and M. Rivera, "Optimal Location and Sizing of Distributed Generators and Energy Storage Systems in Microgrids: A Review," *Energies,* vol. 16, no. 1, p. 106, 2023.

[31] H. Sun, Q. Guo, J. Qi, V. Ajjarapu, R. Bravo, J. Chow, Z. Li, R. Moghe, E. Nasr-Azadani, U. Tamrakar, G. N. Taranto, R. Tonkoski, G. Valverde, Q. Wu, and G. Yang, "Review of Challenges and Research Opportunities for Voltage Control in Smart Grids," *IEEE Transactions on Power Systems,* vol. 34, no. 4, pp. 2790-2801, 2019.

[32] E. M. Davidson, S. D. J. Mcarthur, M. J. Dolan, and J. R. Mcdonald, "Exploiting intelligent systems techniques within an autonomous regional active network management system," in *2009 IEEE Power & Energy Society General Meeting*, 2009-07-01 2009: IEEE.

[33] R. Ufa, Y. Malkova, V. Rudnik, M. Andreev, and V. Borisov, "A review on distributed generation impacts on electric power system," *International Journal of Hydrogen Energy,* vol. 47, no. 47, pp. 20347-20361, 2022.

[34] Y. Shi, H. D. Tuan, A. V. Savkin, C.-T. Lin, J. G. Zhu, and H. V. Poor, "Distributed model predictive control for joint coordination of demand response and optimal power flow with renewables in smart grid," *Applied Energy,* vol. 290, p. 116701, 2021/05/15/ 2021.

[35] A. Atputharajah and T. K. Saha, "Power system blackouts-literature review," in *2009 International Conference on Industrial and Information Systems (ICIIS)*, 2009: IEEE, pp. 460-465.

[36] P. Shi and B. Yan, "A Survey on Intelligent Control for Multiagent Systems," *IEEE Transactions on Systems, Man, and Cybernetics: Systems,* vol. 51, no. 1, pp. 161-175, 2021.

[37] C. Zhang, X. Dou, L. Wang, Y. Dong, and Y. Ji, "Distributed Cooperative Voltage Control for Grid-Following and Grid-Forming Distributed Generators in Islanded Microgrids," *IEEE Transactions on Power Systems,* vol. 38, no. 1, pp. 589-602, 2023.

[38] F. Olivier, P. Aristidou, D. Ernst, and T. Van Cutsem, "Active Management of Low-Voltage Networks for Mitigating Overvoltages Due to Photovoltaic Units," *IEEE Transactions on Smart Grid,* vol. 7, no. 2, pp. 926-936, 2016.

[39] E. Akbari, N. Shafaghatian, F. Zishan, O. D. Montoya, and D. A. Giral-Ramírez,

"Optimized Two-Level Control of Islanded Microgrids to Reduce Fluctuations," *IEEE Access,* vol. 10, pp. 95824-95838, 2022.

[40] A. Fu, M. Cvetković, and P. Palensky, "Distributed Cooperation for Voltage Regulation in Future Distribution Networks," *IEEE Transactions on Smart Grid,* vol. 13, no. 6, pp. 4483-4493, 2022.

[41] B. Zhao, Z. Xu, C. Xu, C. Wang, and F. Lin, "Network Partition-Based Zonal Voltage Control for Distribution Networks With Distributed PV Systems," *IEEE Transactions on Smart Grid,* vol. 9, no. 5, pp. 4087-4098, 2018.

[42] A. Nouri, A. Soroudi, and A. Keane, "Resilient decentralised control of inverter-interfaced distributed energy sources in low-voltage distribution grids," *IET Smart Grid,* vol. 3, no. 2, pp. 153-161, 2020.

[43] A. O'Connell and A. Keane, "Volt–var curves for photovoltaic inverters in distribution systems," *IET Generation, Transmission & Distribution,* vol. 11, no. 3, pp. 730-739, 2017.

[44] S. Weng, D. Yue, C. Dou, J. Shi, and C. Huang, "Distributed Event-Triggered Cooperative Control for Frequency and Voltage Stability and Power Sharing in Isolated Inverter-Based Microgrid," *IEEE Transactions on Cybernetics,* vol. 49, no. 4, pp. 1427-1439, 2019.

[45] M. Chen, X. Xiao, and J. M. Guerrero, "Secondary Restoration Control of Islanded Microgrids With a Decentralized Event-Triggered Strategy," *IEEE Transactions on Industrial Informatics,* vol. 14, no. 9, pp. 3870-3880, 2018.

[46] L. Ding, Q. L. Han, and X. M. Zhang, "Distributed Secondary Control for Active Power Sharing and Frequency Regulation in Islanded Microgrids Using an Event-Triggered Communication Mechanism," *IEEE Transactions on Industrial Informatics,* vol. 15, no. 7, pp. 3910-3922, 2019.

[47] J. Barr and R. Majumder, "Integration of Distributed Generation in the Volt/VAR Management System for Active Distribution Networks," *IEEE Transactions on Smart Grid,* vol. 6, no. 2, pp. 576-586, 2015-03-01 2015.

[48] J. Wu and Y. Lu, "Adaptive Backstepping Sliding Mode Control for Boost Converter With Constant Power Load," *IEEE Access,* vol. 7, pp. 50797-50807, 2019.

[49] A. R. D. Fazio, G. Fusco, and M. Russo, "Decentralized Control of Distributed Generation for Voltage Profile Optimization in Smart Feeders," *IEEE Transactions on Smart Grid,* vol. 4, no. 3, pp. 1586-1596, 2013.

[50] Q. Li, F. Chen, M. Chen, J. M. Guerrero, and D. Abbott, "Agent-Based Decentralized Control Method for Islanded Microgrids," *IEEE Transactions on Smart Grid,* pp. 1-1, 2015.

[51] A. Samadi, R. Eriksson, L. Söder, B. G. Rawn, and J. C. Boemer, "Coordinated Active Power-Dependent Voltage Regulation in Distribution Grids With PV Systems," *IEEE Transactions on Power Delivery,* vol. 29, no. 3, pp. 1454-1464, 2014.

[52] D. K. Molzahn, F. Dörfler, H. Sandberg, S. H. Low, S. Chakrabarti, R. Baldick, and J. Lavaei, "A Survey of Distributed Optimization and Control Algorithms for Electric Power Systems," *IEEE Transactions on Smart Grid,* vol. 8, no. 6, pp. 2941-2962, 2017.

[53] A. Muhtadi, D. Pandit, N. Nguyen, and J. Mitra, "Distributed Energy Resources Based Microgrid: Review of Architecture, Control, and Reliability," *IEEE Transactions on Industry Applications,* vol. 57, no. 3, pp. 2223-2235, 2021.

[54] Z. Abdmouleh, A. Gastli, L. Ben-Brahim, M. Haouari, and N. A. Al-Emadi, "Review of optimization techniques applied for the integration of distributed

generation from renewable energy sources," *Renewable Energy,* vol. 113, pp. 266-280, 2017/12/01/ 2017.

[55] M. K. Hasan, A. A. Habib, S. Islam, M. Balfaqih, K. M. Alfawaz, and D. Singh, "Smart Grid Communication Networks for Electric Vehicles Empowering Distributed Energy Generation: Constraints, Challenges, and Recommendations," *Energies,* vol. 16, no. 3, p. 1140, 2023.

[56] M. H. K. Tushar, A. W. Zeineddine, and C. Assi, "Demand-Side Management by Regulating Charging and Discharging of the EV, ESS, and Utilizing Renewable Energy," *IEEE Transactions on Industrial Informatics,* vol. 14, no. 1, pp. 117-126, 2018.

[57] J. A. Sanguesa, V. Torres-Sanz, P. Garrido, F. J. Martinez, and J. M. Marquez-Barja, "A Review on Electric Vehicles: Technologies and Challenges," *Smart Cities,* vol. 4, no. 1, pp. 372-404, 2021.

[58] S. Rahman, I. A. Khan, A. A. Khan, A. Mallik, and M. F. Nadeem, "Comprehensive review & impact analysis of integrating projected electric vehicle charging load to the existing low voltage distribution system," *Renewable and Sustainable Energy Reviews,* vol. 153, p. 111756, 2022/01/01/ 2022.

[59] S. Shafiee, M. Fotuhi-Firuzabad, and M. Rastegar, "Investigating the impacts of plug-in hybrid electric vehicles on power distribution systems," *IEEE transactions on smart grid,* vol. 4, no. 3, pp. 1351-1360, 2013.

[60] A. S. Masoum, A. Abu-Siada, and S. Islam, "Impact of uncoordinated and coordinated charging of plug-in electric vehicles on substation transformer in smart grid with charging stations," in *2011 IEEE PES Innovative Smart Grid Technologies*, 2011: IEEE, pp. 1-7.

[61] M. S. ElNozahy and M. M. Salama, "A comprehensive study of the impacts of PHEVs on residential distribution networks," *IEEE Transactions on Sustainable Energy,* vol. 5, no. 1, pp. 332-342, 2014.

[62] Q. Hu, S. Bu, and V. Terzija, "A Distributed P and Q Provision-Based Voltage Regulation Scheme by Incentivized EV Fleet Charging for Resistive Distribution Networks," *IEEE Transactions on Transportation Electrification,* vol. 7, no. 4, pp. 2376-2389, 2021.

[63] P. Richardson, D. Flynn, and A. Keane, "Local Versus Centralized Charging Strategies for Electric Vehicles in Low Voltage Distribution Systems," *IEEE Transactions on Smart Grid,* vol. 3, no. 2, pp. 1020-1028, 2012.

[64] S. Shafiq and A. T. Al-Awami, "An Autonomous Charge Controller for Electric Vehicles Using Online Sensitivity Estimation," *IEEE Transactions on Industry Applications,* vol. 56, no. 1, pp. 22-33, 2020.

[65] Y. Wang, D. Qiu, G. Strbac, and Z. Gao, "Coordinated Electric Vehicle Active and Reactive Power Control for Active Distribution Networks," *IEEE Transactions on Industrial Informatics,* vol. 19, no. 2, pp. 1611-1622, 2023.

[66] J. Wang, G. R. Bharati, S. Paudyal, O. Ceylan, B. P. Bhattarai, and K. S. Myers, "Coordinated Electric Vehicle Charging With Reactive Power Support to Distribution Grids," *IEEE Transactions on Industrial Informatics,* vol. 15, no. 1, pp. 54-63, 2019.

[67] I. S. Bayram, S. Galloway, and G. Burt, "A probabilistic capacity planning methodology for plug-in electric vehicle charging lots with on-site energy storage systems," *Journal of Energy Storage,* vol. 32, p. 101730, 2020/12/01/ 2020.

[68] M. R. Khalid, I. A. Khan, S. Hameed, M. S. J. Asghar, and J. S. Ro, "A

Comprehensive Review on Structural Topologies, Power Levels, Energy Storage Systems, and Standards for Electric Vehicle Charging Stations and Their Impacts on Grid," *IEEE Access,* vol. 9, pp. 128069-128094, 2021.

[69] Q. Hu, H. Li, and S. Bu, "The prediction of electric vehicles load profiles considering stochastic charging and discharging behavior and their impact assessment on a real UK distribution network," *Energy Procedia,* vol. 158, pp. 6458-6465, 2019.

[70] S. Xia, S. Q. Bu, X. Luo, K. W. Chan, and X. Lu, "An Autonomous Real-Time Charging Strategy for Plug-In Electric Vehicles to Regulate Frequency of Distribution System With Fluctuating Wind Generation," *IEEE Transactions on Sustainable Energy,* vol. 9, no. 2, pp. 511-524, 2018.

[71] W. Wang, L. Liu, J. Liu, and Z. Chen, "Energy management and optimization of vehicle-to-grid systems for wind power integration," *CSEE Journal of Power and Energy Systems,* vol. 7, no. 1, pp. 172-180, 2021.

[72] N. Brinkel, M. Gerritsma, T. AlSkaif, I. Lampropoulos, A. van Voorden, H. Fidder, and W. van Sark, "Impact of rapid PV fluctuations on power quality in the low-voltage grid and mitigation strategies using electric vehicles," *International Journal of Electrical Power & Energy Systems,* vol. 118, p. 105741, 2020.

[73] Z. Huang, B. Fang, and J. Deng, "Multi-objective optimization strategy for distribution network considering V2G-enabled electric vehicles in building integrated energy system," *Protection and Control of Modern Power Systems,* vol. 5, pp. 1-8, 2020.

[74] Z. Moghaddam, I. Ahmad, D. Habibi, and Q. V. Phung, "Smart charging strategy for electric vehicle charging stations," *IEEE Transactions on transportation electrification,* vol. 4, no. 1, pp. 76-88, 2017.

[75] E. Cotilla-Sanchez, P. D. H. Hines, C. Barrows, S. Blumsack, and M. Patel, "Multi-Attribute Partitioning of Power Networks Based on Electrical Distance," *IEEE Transactions on Power Systems,* vol. 28, no. 4, pp. 4979-4987, 2013.

[76] V. Alimisis and P. C. Taylor, "Zoning Evaluation for Improved Coordinated Automatic Voltage Control," *IEEE Transactions on Power Systems,* vol. 30, no. 5, pp. 2736-2746, 2015.

[77] X. Xu, F. Xue, S. Lu, H. Zhu, L. Jiang, and B. Han, "Structural and Hierarchical Partitioning of Virtual Microgrids in Power Distribution Network," *IEEE Systems Journal,* vol. 13, no. 1, pp. 823-832, 2019.

[78] J. Guo, G. Hug, and O. K. Tonguz, "Intelligent Partitioning in Distributed Optimization of Electric Power Systems," *IEEE Transactions on Smart Grid,* vol. 7, no. 3, pp. 1249-1258, 2016.

[79] N. Gacic, A. I. Zecevic, and D. D. Siljak, "Coherency recognition using epsilon decomposition," *IEEE Transactions on Power Systems,* vol. 13, no. 2, pp. 314-319, May 1998.

[80] D. Zhuang, J. M. Chang, and M. Li, "DynaMo: Dynamic Community Detection by Incrementally Maximizing Modularity," *IEEE Transactions on Knowledge and Data Engineering,* vol. 33, no. 5, pp. 1934-1945, 2021.

[81] V. D. Blondel, J.-L. Guillaume, R. Lambiotte, and E. Lefebvre, "Fast unfolding of communities in large networks," *Journal of statistical mechanics: theory and experiment,* vol. 2008, no. 10, p. P10008, 2008.

[82] C. Hooker, "Introduction to Philosophy of Complex Systems: A: Part A: Towards a framework for complex systems," in *Philosophy of Complex Systems*, vol. 10, C. Hooker Ed. Amsterdam: North-Holland, 2011, pp. 3-90.

[83] D. Ye, M. Zhang, and A. V. Vasilakos, "A Survey of Self-Organization

Mechanisms in Multiagent Systems," *IEEE Transactions on Systems, Man, and Cybernetics: Systems,* vol. 47, no. 3, pp. 441-461, 2017.

[84] M. A. O. Sotomayor, J. D. Pérez-Castrillo, and F. Castiglione, *Complex Social and Behavioral Systems: Game Theory and Agent-Based Models, A Volume in the Encyclopedia of Complexity and Systems Science*. Springer, 2020.

[85] F. Heylighen, "Self-organization in Communicating Groups: the emergence of coordination, shared references and collective intelligence," in *Complexity Perspectives on Language, Communication and Society*: Springer, 2013, pp. 117-149.

[86] G. Di Marzo Serugendo, M.-P. Gleizes, and A. Karageorgos, "Self-organising software: From natural to artificial adaptation," ed: Springer Publishing Company, Incorporated, 2011.

[87] J. C. Burguillo, Burguillo, and Ditzinger, *Self-organizing coalitions for managing complexity*. Springer, 2018.

[88] R. V. R. Filho, "Emergent software systems," 2018.

[89] H. V. D. Parunak and S. A. Brueckner, "Software engineering for self-organizing systems," *The Knowledge Engineering Review,* vol. 30, no. 4, pp. 419-434, 2015.

[90] G. D. M. Serugendo, J. S. Fitzgerald, A. Romanovsky, and N. Guelfi, "A Generic Framework for the Engineering of Self-Adaptive and Self-Organising Systems," in *Organic Computing - Controlled Self-organization*, 2008.

[91] O. G. Aliu, A. Imran, M. A. Imran, and B. Evans, "A Survey of Self Organisation in Future Cellular Networks," *IEEE Communications Surveys & Tutorials,* vol. 15, no. 1, pp. 336-361, 2013.

[92] J. Ferber, O. Gutknecht, and F. Michel, "From agents to organizations: an organizational view of multi-agent systems," in *International workshop on agent-oriented software engineering*, 2003: Springer, pp. 214-230.

[93] H. A. Abbas, S. I. Shaheen, and M. H. Amin, "Organization of Multi-Agent Systems: An Overview," *International Journal of Intelligent Information Systems,* vol. abs/1506.09032, 2015.

[94] G. Nicolis, I. Prigogine, and P. Carruthers, "Exploring Complexity: An Introduction," *Physics Today,* vol. 43, no. 10, pp. 96-97, 1990.

[95] H. Haken, *Information and self-organization: A macroscopic approach to complex systems*. Springer Science & Business Media, 2006.

[96] D. Zhang, G. Feng, Y. Shi, and D. Srinivasan, "Physical Safety and Cyber Security Analysis of Multi-Agent Systems: A Survey of Recent Advances," *IEEE/CAA Journal of Automatica Sinica,* vol. 8, no. 2, pp. 319-333, 2021.

[97] A. Dorri, S. S. Kanhere, and R. Jurdak, "Multi-agent systems: A survey," *Ieee Access,* vol. 6, pp. 28573-28593, 2018.

[98] V. Gorodetskii, "Self-organization and multiagent systems: I. Models of multiagent self-organization," *Journal of Computer and Systems Sciences International,* vol. 51, no. 2, pp. 256-281, 2012.

[99] V. Gorodetskii, "Self-organization and multiagent systems: II. Applications and the development technology," *Journal of Computer and Systems Sciences International,* vol. 51, no. 3, pp. 391-409, 2012.

[100] M. Luck, P. McBurney, and C. Preist, *Agent technology: enabling next generation computing (a roadmap for agent based computing)*. AgentLink, 2003.

[101] M. H. Shawon, S. M. Muyeen, A. Ghosh, S. M. Islam, and M. S. Baptista, "Multi-Agent Systems in ICT Enabled Smart Grid: A Status Update on Technology Framework and Applications," *IEEE Access,* vol. 7, pp. 97959-97973, 2019.

[102] V. N. Coelho, M. W. Cohen, I. M. Coelho, N. Liu, and F. G. Guimarães, "Multi-agent systems applied for energy systems integration: State-of-the-art applications and trends in microgrids," *Applied energy,* vol. 187, pp. 820-832, 2017.

[103] A. Sujil, J. Verma, and R. Kumar, "Multi agent system: concepts, platforms and applications in power systems," *Artificial Intelligence Review,* vol. 49, no. 2, pp. 153-182, 2018.

[104] S. D. J. Mcarthur, E. M. Davidson, V. M. Catterson, A. L. Dimeas, N. D. Hatziargyriou, F. Ponci, and T. Funabashi, "Multi-Agent Systems for Power Engineering Applications—Part I: Concepts, Approaches, and Technical Challenges," *IEEE Transactions on Power Systems,* vol. 22, no. 4, pp. 1743-1752, 2007-11-01 2007.

[105] S. D. McArthur, E. M. Davidson, V. M. Catterson, A. L. Dimeas, N. D. Hatziargyriou, F. Ponci, and T. Funabashi, "Multi-agent systems for power engineering applications—Part II: Technologies, standards, and tools for building multi-agent systems," *IEEE Transactions on Power Systems,* vol. 22, no. 4, pp. 1753-1759, 2007.

[106] M. Meliani, A. e. Barkany, I. e. Abbassi, A. M. Darcherif, and M. Mahmoudi, "Control system in the smart grid: State of the art and opportunities," in *2020 IEEE 13th International Colloquium of Logistics and Supply Chain Management (LOGISTIQUA)*, 2-4 Dec. 2020 2020, pp. 1-6.

[107] S. Boudoudouh and M. Maâroufi, "Multi agent system solution to microgrid

implementation," *Sustainable cities and society,* vol. 39, pp. 252-261, 2018.

[108] S. C. Müller, U. Häger, C. Rehtanz, and H. F. Wedde, "Application of self-organizing systems in power systems control," in *International Conference on Product Focused Software Process Improvement*, 2012: Springer, pp. 320-334.

[109] A. Nieße, M. Tröschel, and M. Sonnenschein, "Designing dependable and sustainable Smart Grids – How to apply Algorithm Engineering to distributed control in power systems," *Environmental Modelling & Software,* vol. 56, pp. 37-51, 2014/06/01/ 2014.

[110] J. Lai, X. Lu, and F. Wang, "Distributed Diffusion-Oriented Cooperation for Power Sharing in Self-Expanding Microgrids," in *2021 IEEE/IAS 57th Industrial and Commercial Power Systems Technical Conference (I&CPS)*, 27-30 April 2021 2021, pp. 1-9, doi: 10.1109/ICPS51807.2021.9416592.

[111] Y. Du, X. Lu, H. Tu, J. Wang, and S. Lukic, "Dynamic Microgrids With Self-Organized Grid-Forming Inverters in Unbalanced Distribution Feeders," *IEEE Journal of Emerging and Selected Topics in Power Electronics,* vol. 8, no. 2, pp. 1097-1107, 2020.

[112] C. Cameron, C. Patsios, P. C. Taylor, and Z. Pourmirza, "Using Self-Organizing Architectures to Mitigate the Impacts of Denial-of-Service Attacks on Voltage Control Schemes," *IEEE Transactions on Smart Grid,* vol. 10, no. 3, pp. 3010-3019, 2019.

[113] V. Bolgouras, C. Ntantogian, E. Panaousis, and C. Xenakis, "Distributed Key Management in Microgrids," *IEEE Transactions on Industrial Informatics,* vol. 16, no. 3, pp. 2125-2133, 2020.

[114] J. Ansari, A. Gholami, and A. Kazemi, "Multi-agent systems for reactive power control in smart grids," *International Journal of Electrical Power &*

Energy Systems, vol. 83, pp. 411-425, 2016/12/01/ 2016.

[115] Y. Nurdin and S. Muchallil, "Holonic Multi-Agent System for Microgrid Hierarchical Control," in *2019 IEEE International Conference on Cybernetics and Computational Intelligence (CyberneticsCom)*, 22-24 Aug. 2019 2019, pp. 66-71.

[116] M. Tröschel, *Aktive Einsatzplanung in holonischen virtuellen Kraftwerken*. 2010.

[117] U. Reiner, C. Elsinger, and T. Leibfried, "Distributed self organising Electric Vehicle charge controller system: Peak power demand and grid load reduction with adaptive EV charging stations," in *2012 IEEE International Electric Vehicle Conference*, 4-8 March 2012 2012, pp. 1-6, doi: 10.1109/IEVC.2012.6183277.

[118] A. Nieße and M. Tröschel, "Controlled self-organization in smart grids," in *2016 IEEE International Symposium on Systems Engineering (ISSE)*, 3-5 Oct. 2016 2016, pp. 1-6, doi: 10.1109/SysEng.2016.7753189.

[119] C. Hinrichs, S. Lehnhoff, and M. Sonnenschein, "COHDA: A combinatorial optimization heuristic for distributed agents," presented at the International Conference on Agents and Artificial Intelligence, 2013.

[120] P. E. Petruzzi, D. Busquets, and J. Pitt, "Self organising flexible demand for smart grid," in *2013 IEEE 7th International Conference on Self-Adaptation and Self-Organizing Systems Workshops*, 2013: IEEE, pp. 21-22.

[121] S. Macbeth, D. Busquets, and J. Pitt, "System modeling: Principled operationalization of social systems using Presage2," in *Modeling and simulation-based systems engineering handbook*: CRC Press, 2018, pp. 74-97.

[122] F. Torrent-Fontbona, B. López, D. Busquets, and J. Pitt, "Self-organising energy demand allocation through canons of distributive justice in a microgrid," *Engineering Applications of Artificial Intelligence,* vol. 52, pp. 108-

118, 2016.

[123] S. Čaušević, M. Warnier, and F. M. T. Brazier, "Dynamic, self-organized clusters as a means to supply and demand matching in large-scale energy systems," in *2017 IEEE 14th International Conference on Networking, Sensing and Control (ICNSC)*, 16-18 May 2017 2017, pp. 568-573, doi: 10.1109/ICNSC.2017.8000154.

[124] V. Loia, A. Vaccaro, and K. Vaisakh, "A self-organizing architecture based on cooperative fuzzy agents for smart grid voltage control," *IEEE Transactions on Industrial Informatics,* vol. 9, no. 3, pp. 1415-1422, 2013.

[125] V. Loia and A. Vaccaro, "Decentralized economic dispatch in smart grids by self-organizing dynamic agents," *IEEE Transactions on Systems, Man, and Cybernetics: Systems,* vol. 44, no. 4, pp. 397-408, 2013.

[126] G. Hug, S. Kar, and C. Wu, "Consensus+ innovations approach for distributed multiagent coordination in a microgrid," *IEEE Transactions on Smart Grid,* vol. 6, no. 4, pp. 1893-1903, 2015.

[127] A. Vaccaro, V. Loia, G. Formato, P. Wall, and V. Terzija, "A self-organizing architecture for decentralized smart microgrids synchronization, control, and monitoring," *IEEE transactions on Industrial Informatics,* vol. 11, no. 1, pp. 289-298, 2014.

[128] R. de Azevedo, M. H. Cintuglu, T. Ma, and O. A. Mohammed, "Multiagent-based optimal microgrid control using fully distributed diffusion strategy," *IEEE Transactions on Smart Grid,* vol. 8, no. 4, pp. 1997-2008, 2017.

[129] S. Beer, "A formal model for agent-based Coalition Formation in Electricity Markets," in *IEEE PES ISGT Europe 2013*, 6-9 Oct. 2013 2013, pp. 1-5.

[130] I. Ostheimer, M. Hercog, B. Bijelić, and D. Vranješ, "Efficient Integration

Model of MAS and Blockchain for emergence of Self-Organized Smart Grids," in *2021 International Conference on Electrical, Communication, and Computer Engineering (ICECCE)*, 12-13 June 2021 2021, pp. 1-6, doi: 10.1109/ICECCE52056.2021.9514137.

[131] K. T. Chaturvedi, M. Pandit, and L. Srivastava, "Self-Organizing Hierarchical Particle Swarm Optimization for Nonconvex Economic Dispatch," *IEEE Transactions on Power Systems,* vol. 23, no. 3, pp. 1079-1087, 2008.

[132] C. M. Colson and M. H. Nehrir, "Comprehensive Real-Time Microgrid Power Management and Control With Distributed Agents," *IEEE Transactions on Smart Grid,* vol. 4, no. 1, pp. 617-627, 2013.

[133] A. M. Shotorbani, S. G. Zadeh, B. Mohammadi-Ivatloo, and S. H. Hosseini, "A distributed non-Lipschitz control framework for self-organizing microgrids with uncooperative and renewable generations," *International Journal of Electrical Power and Energy Systems,* vol. 90, no. Complete, pp. 267-279, 2017.

[134] X. Lu and J. Lai, "Communication Constraints for Distributed Secondary Control of Heterogeneous Microgrids: A Survey," *IEEE Transactions on Industry Applications,* vol. 57, no. 6, pp. 5636-5648, 2021.

[135] M. S. Mahmoud, *Multiagent Systems: Introduction and Coordination Control*. CRC Press, 2020.

[136] S. Russell and N. Peter, *Artificial intelligence : a modern approach*. Boston: Pearson, 2020.

[137] A. A. Shobole and M. Wadi, "Multiagent systems application for the smart grid protection," *Renewable and Sustainable Energy Reviews,* vol. 149, p. 111352, 2021/10/01/ 2021.

[138] J. P. Müller and K. Fischer, "Application impact of multi-agent systems and

technologies: A survey," in *Agent-oriented software engineering*, 2014: Springer, pp. 27-53.

[139] P. Iñigo-Blasco, F. Diaz-del-Rio, M. C. Romero-Ternero, D. Cagigas-Muñiz, and S. Vicente-Diaz, "Robotics software frameworks for multi-agent robotic systems development," *Robotics and Autonomous Systems,* vol. 60, no. 6, pp. 803-821, 2012.

[140] G. Antonelli, "Interconnected dynamic systems: An overview on distributed control," *IEEE Control Systems Magazine,* vol. 33, no. 1, pp. 76-88, 2013.

[141] X. Ge, Q.-L. Han, D. Ding, X.-M. Zhang, and B. Ning, "A survey on recent advances in distributed sampled-data cooperative control of multi-agent systems," *Neurocomputing,* vol. 275, pp. 1684-1701, 2018.

[142] W. Shen, *Multi-agent systems for concurrent intelligent design and manufacturing*. CRC press, 2019.

[143] Z. Tong, F. Ye, M. Yan, H. Liu, and S. Basodi, "A survey on algorithms for intelligent computing and smart city applications," *Big Data Mining and Analytics,* vol. 4, no. 3, pp. 155-172, 2021.

[144] M. Wooldridge, *An introduction to multiagent systems*. John wiley & sons, 2009.

[145] E. M. Davidson, S. D. J. McArthur, J. R. McDonald, T. Cumming, and I. Watt, "Applying multi-agent system technology in practice: automated management and analysis of SCADA and digital fault recorder data," *IEEE Transactions on Power Systems,* vol. 21, no. 2, pp. 559-567, 2006.

[146] L. Raju and A. A. Morais, "Multi-Agent Systems Based Advanced Energy Management of Smart Micro-grid," *Multi Agent Systems: Strategies and Applications,* p. 111, 2020.

[147] A. Gardner, A. S. Griffin, and S. A. West, "Theory of cooperation," *eLS,* pp. 1-8, 2016.

[148] M. Hajduk, M. Sukop, and M. Haun, *Cognitive multi-agent systems*. Springer, 2019.

[149] M. Z. Degefa, A. Alahäivälä, O. Kilkki, M. Humayun, I. Seilonen, V. Vyatkin, and M. Lehtonen, "MAS-Based Modeling of Active Distribution Network: The Simulation of Emerging Behaviors," *IEEE Transactions on Smart Grid,* vol. 7, no. 6, pp. 2615-2623, 2016.

[150] F. H. Malik and M. Lehtonen, "A review: Agents in smart grids," *Electric Power Systems Research,* vol. 131, pp. 71-79, 2016.

[151] Q. Zhou, M. Shahidehpour, A. Paaso, S. Bahramirad, A. Alabdulwahab, and A. Abusorrah, "Distributed control and communication strategies in networked microgrids," *IEEE Communications Surveys & Tutorials,* vol. 22, no. 4, pp. 2586-2633, 2020.

[152] T. A. Zarma, A. A. Galadima, A. Modibbo, and S. U. Hussein, "Review of Multi-Agent Micro-Grid Systems," in *2020 IEEE PES/IAS PowerAfrica*, 2020: IEEE, pp. 1-5.

[153] Foundation for Intelligent Physical Agents (FIPA), 2001. [Online] Available: http://www.fipa.org/repository/standardspecs.html

[154] I. Standard, "IEC 61850: Communication networks and systems in substations," *Int. Electrotech. Commission, Geneva, Switzerland,* 2003.

[155] T. Finin, R. Fritzson, D. McKay, and R. McEntire, "KQML as an agent communication language," in *Proceedings of the third international conference on Information and knowledge management*, 1994, pp. 456-463.

[156] D. Juneja, A. Singh, R. Singh, and S. Mukherjee, "A Thorough Insight into Theoretical and Practical Developments in MultiAgent Systems," *Int. J. Ambient Comput. Intell.,* vol. 8, pp. 23-49, 2017.

[157] H. Hui, Y. Ding, Q. Shi, F. Li, Y. Song, and J. Yan, "5G network-based Internet of Things for demand response in smart grid: A survey on application potential," *Applied Energy,* vol. 257, p. 113972, 2020/01/01/ 2020.

[158] T. a. R. C. A. T. a. Y. University", "Managing Volt/VAR in Active Distribution Networks Using Distributed Generation Units and Peer to Peer Communication," March 2018 2018.

[159] R. H. Bordini, J. F. Hübner, and M. Wooldridge, *Programming multi-agent systems in AgentSpeak using Jason*. John Wiley & Sons, 2007.

[160] F. Bellifemine, G. Caire, T. Trucco, and G. Rimassa, "Jade programmer’s guide," *Jade version,* vol. 3, pp. 13-39, 2002.

[161] H. S. Nwana, D. T. Ndumu, L. C. Lee, and J. C. Collis, "Zeus: A toolkit for building distributed multiagent systems," *Applied Artificial Intelligence,* vol. 13, no. 1-2, pp. 129-185, 1999.

[162] S. Galland, S. Rodriguez, and N. Gaud, "Run-time environment for the SARL agent-programming language: the example of the Janus platform," *Future Generation Computer Systems,* vol. 107, pp. 1105-1115, 2020/06/01/ 2020.

[163] L. S. Melo, R. F. Sampaio, R. P. S. Leão, G. C. Barroso, and J. R. Bezerra, "Python-based multi-agent platform for application on power grids," *International Transactions on Electrical Energy Systems,* vol. 29, no. 6, p. e12012, 2019.

[164] O. Gutknecht and J. Ferber, "MadKit: a generic multi-agent platform," presented at the Proceedings of the fourth international conference on

Autonomous agents, Barcelona, Spain, 2000. [Online]. Available: https://doi.org/10.1145/336595.337048.

[165] K. Kravari and N. Bassiliades, "A survey of agent platforms," *Journal of Artificial Societies and Social Simulation,* vol. 18, no. 1, p. 11, 2015.

[166] F. Leon, M. Paprzycki, and M. Ganzha, "A review of agent platforms," *Multi-Paradigm Modelling for Cyber-Physical Systems (MPM4CPS), ICT COST Action IC1404,* pp. 1-15, 2015.

[167] R. C. Cardoso and A. Ferrando, "A Review of Agent-Based Programming for Multi-Agent Systems," *Computers,* vol. 10, no. 2, p. 16, 2021.

[168] M. J. North, N. T. Collier, and J. R. Vos, "Experiences creating three implementations of the repast agent modeling toolkit," *ACM Transactions on Modeling and Computer Simulation (TOMACS),* vol. 16, no. 1, pp. 1-25, 2006.

[169] S. Macbeth, D. Busquets, and J. Pitt, "System modeling: principled operationalisation of social systems using presage2," *Modeling &Simulation-based Systems Engineering Handbook,* 2015.

[170] U. Wilensky and W. Rand, *An introduction to agent-based modeling: modeling natural, social, and engineered complex systems with NetLogo*. MIT Press, 2015.

[171] A. A. Aquino-Lugo, R. Klump, and T. J. Overbye, "A Control Framework for the Smart Grid for Voltage Support Using Agent-Based Technologies," *IEEE Transactions on Smart Grid,* vol. 2, no. 1, pp. 173-180, 2011.

[172] A. A. Aquino-Lugo and T. Overbye, "Agent Technologies for Control Applications in the Power Grid," in *2010 43rd Hawaii International Conference on System Sciences*, 5-8 Jan. 2010 2010, pp. 1-10, doi: 10.1109/HICSS.2010.43.

[173] N. Yorino, Y. Zoka, M. Watanabe, and T. Kurushima, "An Optimal Autonomous Decentralized Control Method for Voltage Control Devices by Using a Multi-Agent System," *IEEE Transactions on Power Systems,* vol. 30, no. 5, pp. 2225-2233, 2015.

[174] X. Zhang, A. J. Flueck, and C. P. Nguyen, "Agent-based distributed volt/var control with distributed power flow solver in smart grid," *IEEE Transactions on Smart Grid,* vol. 7, no. 2, pp. 600-607, 2015.

[175] F. Brazier, H. L. Poutre, A. R. Abhyankar, K. Saxena, S. N. Singh, and K. K. Tomar, "A review of multi agent based decentralised energy management issues," in *2015 International Conference on Energy Economics and Environment (ICEEE)*, 27-28 March 2015 2015, pp. 1-5, doi: 10.1109/EnergyEconomics.2015.7235106.

[176] M. Starke, B. Xiao, P. K. Bhowmik, S. L. Campbell, M. Chinthavali, B. R. Dean, R. S. K. Moorthy, M. Smith, and A. Thapa, "Agent-Based Distributed Energy Resources for Supporting Intelligence at the Grid Edge," *IEEE Journal of Emerging and Selected Topics in Industrial Electronics,* vol. 3, no. 1, pp. 69-78, 2022.

[177] F. Ren, M. Zhang, and D. Sutanto, "A Multi-Agent Solution to Distribution System Management by Considering Distributed Generators," *IEEE Transactions on Power Systems,* vol. 28, no. 2, pp. 1442-1451, 2013.

[178] A. Bedawy, N. Yorino, K. Mahmoud, and M. Lehtonen, "An Effective Coordination Strategy for Voltage Regulation in Distribution System Containing High Intermittent Photovoltaic Penetrations," *IEEE Access,* vol. 9, pp. 117404-117414, 2021.

[179] M. S. Rahman and A. Oo, "Distributed multi-agent based coordinated power management and control strategy for microgrids with distributed energy

resources," *Energy conversion and management,* vol. 139, pp. 20-32, 2017.

[180] A. A. Zishan, M. M. Haji, and O. Ardakanian, "Adaptive Congestion Control for Electric Vehicle Charging in the Smart Grid," *IEEE Transactions on Smart Grid,* vol. 12, no. 3, pp. 2439-2449, 2021.

[181] P. Kofinas, A. I. Dounis, and G. A. Vouros, "Fuzzy Q-Learning for multi-agent decentralized energy management in microgrids," *Applied energy,* vol. 219, pp. 53-67, 2018.

[182] V. P. Singh, N. Kishor, and P. Samuel, "Distributed Multi-Agent System-Based Load Frequency Control for Multi-Area Power System in Smart Grid," *IEEE Transactions on Industrial Electronics,* vol. 64, no. 6, pp. 5151-5160, 2017.

[183] D. Cao, J. Zhao, W. Hu, F. Ding, Q. Huang, Z. Chen, and F. Blaabjerg, "Data-Driven Multi-Agent Deep Reinforcement Learning for Distribution System Decentralized Voltage Control With High Penetration of PVs," *IEEE Transactions on Smart Grid,* vol. 12, no. 5, pp. 4137-4150, 2021.

[184] D. Chen, K. Chen, Z. Li, T. Chu, R. Yao, F. Qiu, and K. Lin, "PowerNet: Multi-agent Deep Reinforcement Learning for Scalable Powergrid Control," *IEEE Transactions on Power Systems,* pp. 1-1, 2021.

[185] H. Liu, C. Zhang, Q. Chai, K. Meng, Q. Guo, and Z. Y. Dong, "Robust Regional Coordination of Inverter-Based Volt/Var Control via Multi-Agent Deep Reinforcement Learning," *IEEE Transactions on Smart Grid,* vol. 12, no. 6, pp. 5420-5433, 2021.

[186] S. R. Islam, K. M. Muttaqi, and D. Sutanto, "Multi-agent receding horizon control with neighbour-to-neighbour communication for prevention of voltage collapse in a multi-area power system," *IET Generation, Transmission & Distribution,* vol. 8, no. 9, pp. 1604-1615, 2014.

[187] M. E. Collins, R. W. Silversides, and T. C. Green, "Control and coordination of a distribution network via decentralised decision making," in *2013 IEEE Power & Energy Society General Meeting*, 21-25 July 2013 2013, pp. 1-5, doi: 10.1109/PESMG.2013.6672429.

[188] I. Campos and F. Saraiva, "A Reactive Multi-agent System for Self-healing in Smart Distribution Grids," in *2021 IEEE Congress on Evolutionary Computation (CEC)*, 28 June-1 July 2021 2021, pp. 209-216, doi: 10.1109/CEC45853.2021.9505004.

[189] G. Dileep, "A survey on smart grid technologies and applications," *Renewable Energy,* vol. 146, pp. 2589-2625, 2020/02/01/ 2020.

[190] Y. Han, K. Zhang, H. Li, E. A. A. Coelho, and J. M. Guerrero, "MAS-Based Distributed Coordinated Control and Optimization in Microgrid and Microgrid Clusters: A Comprehensive Overview," *IEEE Transactions on Power Electronics,* vol. 33, no. 8, pp. 6488-6508, 2018.

[191] V. M. Catterson, E. M. Davidson, and S. D. J. McArthur, "Practical applications of multi-agent systems in electric power systems," *European Transactions on Electrical Power,* vol. 22, no. 2, pp. 235-252, 2012.

[192] N. Hatziargyriou, *Microgrids: architectures and control*. John Wiley & Sons, 2014.

[193] A. Anvari-Moghaddam, H. Abdi, B. Mohammadi-Ivatloo, and N. Hatziargyriou, *Microgrids: Advances in Operation, Control, and Protection*. Springer International Publishing, 2021.

[194] M. F. Zia, E. Elbouchikhi, and M. Benbouzid, "Microgrids energy management systems: A critical review on methods, solutions, and prospects," *Applied Energy,* vol. 222, pp. 1033-1055, 2018/07/15/ 2018.

[195] M. S. Rahman, T. Orchi, S. Saha, and M. E. Haque, "Cooperative Multiagent Based Distributed Power Sharing Strategy in Low-Voltage Microgrids," *IEEE Transactions on Industry Applications,* vol. 56, no. 4, pp. 3285-3296, 2020.

[196] Y. Wang, T. L. Nguyen, Y. Xu, Q. T. Tran, and R. Caire, "Peer-to-Peer Control for Networked Microgrids: Multi-Layer and Multi-Agent Architecture Design," *IEEE Transactions on Smart Grid,* vol. 11, no. 6, pp. 4688-4699, 2020.

[197] M. R. Basir Khan, R. Jidin, and J. Pasupuleti, "Multi-agent based distributed control architecture for microgrid energy management and optimization," *Energy Conversion and Management,* vol. 112, pp. 288-307, 2016/03/15/ 2016.

[198] K. Tazi, F. M. Abbou, and F. Abdi, "Multi-agent system for microgrids: design, optimization and performance," *Artificial Intelligence Review,* vol. 53, no. 2, pp. 1233-1292, 2020.

[199] A. Kantamneni, L. E. Brown, G. Parker, and W. W. Weaver, "Survey of multi-agent systems for microgrid control," *Engineering applications of artificial intelligence,* vol. 45, pp. 192-203, 2015.

[200] V. Nikam and V. Kalkhambkar, "A review on control strategies for microgrids with distributed energy resources, energy storage systems, and electric vehicles," *International Transactions on Electrical Energy Systems,* vol. 31, no. 1, p. e12607, 2021.

[201] R. C. Dugan and M. McGranaghan, "Sim city," *IEEE Power and Energy Magazine,* vol. 9, no. 5, pp. 74-81, 2011.

[202] P.-C. Chen, R. Salcedo, Q. Zhu, F. De Leon, D. Czarkowski, Z.-P. Jiang, V. Spitsa, Z. Zabar, and R. E. Uosef, "Analysis of voltage profile problems due to the penetration of distributed generation in low-voltage secondary distribution networks," *IEEE Transactions on Power Delivery,* vol. 27, no. 4, pp. 2020-2028,

Oct. 2012.

[203] B. Seal, "Standard language protocols for photovoltaics and storage grid integration," *Electric Power Research Institute (EPRI), Tech. Rep,* 2010.

[204] K. Turitsyn, P. Sulc, S. Backhaus, and M. Chertkov, "Options for control of reactive power by distributed photovoltaic generators," *Proceedings of the IEEE,* vol. 99, no. 6, pp. 1063-1073, 2011.

[205] Y. C. Chen, J. Wang, A. D. Domínguez-García, and P. W. Sauer, "Measurement-Based Estimation of the Power Flow Jacobian Matrix," *IEEE Transactions on Smart Grid,* vol. 7, no. 5, pp. 2507-2515, 2016.

[206] R. J. Campbell, "The smart grid: Status and outlook," *Congressional Research Service,* pp. 7-5700, 2018.

[207] R. Roche, B. Blunier, A. Miraoui, V. Hilaire, and A. Koukam, "Multi-agent systems for grid energy management: A short review," in *IECON 2010 - 36th Annual Conference on IEEE Industrial Electronics Society*, 7-10 Nov. 2010 2010, pp. 3341-3346, doi: 10.1109/IECON.2010.5675295.

[208] "IEEE 1547-2018 Standard for Interconnection and Interoperability of Distributed Energy Resources with Associated Electric Power Systems Interfaces," *IEEE Std 1547-2018 (Revision of IEEE Std 1547-2003),* pp. 1-138, 2018.

[209] L. Tightiz and H. Yang, "A Comprehensive Review on IoT Protocols’ Features in Smart Grid Communication," *Energies,* vol. 13, no. 11, p. 2762, 2020.

[210] S. A. Janko and N. G. Johnson, "Scalable multi-agent microgrid negotiations for a transactive energy market," *Applied energy,* vol. 229, pp. 715-727, 2018.

[211] H. S. V. S. K. Nunna and D. Srinivasan, "Multiagent-based transactive energy

framework for distribution systems with smart microgrids," *IEEE Transactions on Industrial Informatics,* vol. 13, no. 5, pp. 2241-2250, 2017.

[212] S. Hu, Y. Xiang, J. Liu, C. Gu, X. Zhang, Y. Tian, Z. Liu, and J. Xiong, "Agent-Based Coordinated Operation Strategy for Active Distribution Network With Distributed Energy Resources," *IEEE Transactions on Industry Applications,* vol. 55, no. 4, pp. 3310-3320, 2019.

[213] M. H. Cintuglu, H. Martin, and O. A. Mohammed, "Real-Time Implementation of Multiagent-Based Game Theory Reverse Auction Model for Microgrid Market Operation," *IEEE Transactions on Smart Grid,* vol. 6, no. 2, pp. 1064-1072, 2015.

[214] L. P. M. I. Sampath, A. Paudel, H. D. Nguyen, E. Y. S. Foo, and H. B. Gooi, "Peer-to-Peer Energy Trading Enabled Optimal Decentralized Operation of Smart Distribution Grids," *IEEE Transactions on Smart Grid,* vol. 13, no. 1, pp. 654-666, 2022.

[215] X. Fang, Q. Zhao, J. Wang, Y. Han, and Y. Li, "Multi-agent Deep Reinforcement Learning for Distributed Energy Management and Strategy Optimization of Microgrid Market," *Sustainable Cities and Society,* vol. 74, p. 103163, 2021/11/01/ 2021.

[216] H. J. Jabir, J. Teh, D. Ishak, and H. Abunima, "Impacts of Demand-Side Management on Electrical Power Systems: A Review," *Energies,* vol. 11, no. 5, p. 1050, 2018.

[217] T. Nasir, S. S. H. Bukhari, S. Raza, H. M. Munir, M. Abrar, H. A. u. Muqeet, K. L. Bhatti, J.-S. Ro, and R. Masroor, "Recent Challenges and Methodologies in Smart Grid Demand Side Management: State-of-the-Art Literature Review," *Mathematical Problems in Engineering,* vol. 2021, p. 5821301, 2021/08/09 2021.

[218] R. Chandra, S. Banerjee, K. K. Radhakrishnan, and S. K. Panda, "Transactive Energy Market Framework for Decentralized Coordination of Demand Side Management Within a Cluster of Buildings," *IEEE Transactions on Industry Applications,* vol. 57, no. 4, pp. 3385-3395, 2021.

[219] M. Pasetti, S. Rinaldi, and D. Manerba, "A Virtual Power Plant Architecture for the Demand-Side Management of Smart Prosumers," *Applied Sciences,* vol. 8, no. 3, p. 432, 2018.

[220] L. Gomes, J. Spínola, Z. Vale, and J. M. Corchado, "Agent-based architecture for demand side management using real-time resources' priorities and a deterministic optimization algorithm," *Journal of Cleaner Production,* vol. 241, p. 118154, 2019/12/20/ 2019.

[221] C. Albea, C. Bordons, and M. A. Ridao, "Robust Hybrid Control for Demand Side Management in Islanded Microgrids," *IEEE Transactions on Smart Grid,* vol. 12, no. 6, pp. 4865-4875, 2021.

[222] Z. Wang and R. Paranjape, "Optimal Residential Demand Response for Multiple Heterogeneous Homes With Real-Time Price Prediction in a Multiagent Framework," *IEEE Transactions on Smart Grid,* vol. 8, no. 3, pp. 1173-1184, 2017.

[223] V. N. Coelho, M. Weiss Cohen, I. M. Coelho, N. Liu, and F. G. Guimarães, "Multi-agent systems applied for energy systems integration: State-of-the-art applications and trends in microgrids," *Applied Energy,* vol. 187, pp. 820-832, 2017/02/01/ 2017.