Optimal power generation in microgrids using agent-based technology

Thair Mahmoud
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Optimal Power Generation in Microgrids using
Agent-Based Technology

by
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BSc(Control Systems Engineering); MSc(Control and Automation Engineering)

This thesis is presented in fulfilment of the requirements for the degree of
Doctor of Philosophy

SCHOOL OF ENGINEERING
FACULTY OF COMPUTING, HEALTH AND SCIENCE
EDITH COWAN UNIVERSITY
August 9, 2013
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Abstract

The existing power grids that form the basis of the respective electrical power infrastructures for various states and nations around the world, are expected to undergo a period of rapid change in the near future. The key element driving this change is the emergence of the Smartgrid. The Smartgrid paradigm represents a transition towards an intelligent, digitally enhanced, two-way power delivery grid. The aim of the Smartgrid is to promote and enhance the efficient management and operation of the power generation and delivery facilities, by incorporating advanced communications, information technology, automation, and control methodologies into the power grid proper. Smartgrid's are currently an active topic for research, where the research is strongly focused on developing new technologies such as: demand response, power generation management, pricing modelling and energy markets participation, power quality, and self-healing scenarios. In recent times, in both the United States of America and Europe, many new projects have begun which are specifically directed towards developing “Smartgrid” technologies. In Australia, the Federal Government has recently initiated funding plans to promote the commercialisation of renewable energy. In order to exploit these developments, Edith Cowan University (ECU); which is a High Voltage (HV) customer for the major utility network of Western Australia, and which owns its own transformers and Low Voltage (LV) network; is planning to integrate renewable energy suppliers within its LV network.

The aim of this research is to introduce a smart decision making system, which can manage the operation of disparate power generation sources installed on a LV network (microgrid); such as that owned by ECU on its campuses. The proposed energy management system is to gather data in real-time, and it must be capable of anticipating and optimising energy needs for each operational scenario that the microgrid might be expected to experience. The system must take into account risk levels, while systematically favouring low economic and environmental costs. A management system application, based on autonomous and distributed controllers, is investigated in a virtual environment. The virtual environment being a full-scale simulation of ECU’s microgrid; with solar panels, wind tur-
bines, storage devices, gas gen-sets, and utility supply. Hence the simulation studies were conducted on the basis of realistic demand trends and weather conditions data.

The major factors for reducing the cost of generation in the case study, were identified as being: 1) demand forecasting; 2) generation scheduling; 3) markets participation; and 4) autonomous strategies configuration, which is required to cope with the unpredictable operation scenarios in LV networks. Due to the high uncertainty inherent within the operational scenarios; an Artificial Intelligence (AI) deployment for managing the distributed sub-systems was identified as being an ideal mechanism for achieving the above mentioned objectives. Consequently it is proposed that Multi-Agent System (MAS) technology be deployed, to enable the system to respond dynamically to the unpredictable operational conditions by updating the method of analysis. The proposed system is to behave in a strategic manner when dealing with the expected operational scenarios, by aiming to achieve the lowest possible cost of power generation for the microgrid. The simulated system is based on realistic operational scenarios, which have been scaled to suit the size and type of load in the case study. The distributed intelligent modules have proven to be successful in achieving the potential benefits of the dynamic operational conditions, by minimising the cost of power generation.

The distributed intelligent modules, which form the basis of the proposed management systems, have been designed to perform the following functions:

1. Provide accurate demand forecasts through the utilisation of an AI-based adaptive demand forecasting model. The novel demand-forecast modelling technique, which was introduced to model demand in the case study, has been utilised to supply reasonably accurate demand forecasts to other stages of processing in the management system. The forecasts are generated from this model, by monitoring and controlling the forecasting error to ensure consistent and satisfactory forecasts.

2. Make optimum decisions concerning the operation of the power generators by considering the economic and the environmental costs. In order to deal with the complexity of the operational conditions, a smart and adaptive generation scheduling method was implemented for the case study. The method was primarily applied to control the charging/discharging process of the Storage Devices (SDs) among the other generators. The proposed method aims at controlling the resources, and extracting the benefit of having an hourly based variable generation cost.

3. Integrate the microgrid into the electricity market, in order to enable the microgrid to offer its spinning and non-spinning power generation reserve as Ancillary Services (AS)
to the grid. To this end, studying the operational mechanisms of the Australian market was essential prior to building the proposed market participation rules which form an integral part of the proposed management system. As a result we used the market data, by approaching the market operators to create a semi-realistic competitive market environment for our simulations. Consequently, a smart and adaptive pricing mechanism, that adapts the AS prices to the amount of electricity on offer, and the level of demand in the market has been presented.

The motivation for introducing the proposed management system, is to achieve a transition plan for current microgrids, so that they can have a commercial connection to the future Smartgrid. The results obtained in this work show that there is a significant economic and environmental advantage to be gained from utilising intelligence when managing electricity generation within a power grid. As a consequence, selecting the appropriate management strategy is fundamental to the success of the proposed management system.

In conclusion, modelling of the proposed strategies using MAS technology has proven to be a successful approach, and one that is able to reflect the human attitude; in making critical decisions and in reducing the cost of generation.
DECLARATION

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Chapter 1

INTRODUCTION

Building a *Smartgrid* is a challenge which involves upgrading the current grid with the necessary infrastructure in order to facilitate the new trends concerning electricity generation, transmission and distribution. These new trends are leading towards more reliable, secure, economic, and environmentally friendly electricity generation. The *Smartgrid* is expected to be comprised of a network of grids (microgrids), all of which are decentralised, and which work independently to enhance the overall operation of the main grid. Looking at the distribution side of the grid (Low Voltage), it is expected to have more penetration from Distributed Generators (DGs). These estimates are based on the price increment forecasts for oil and gas, and the price decrement forecasts for renewable energy sources. Distributed generation involves the interconnection of small-scale, on-site generators, e.g. diesel/gas, storage devices, and renewable energy resources. In this study, DGs will be limited to solar panels, wind turbines, storage devices, and local gas generators. It is anticipated that the smart utilisation of these resources within the utility grid, would lead to a big economic and environmental benefits for both the electricity provider and the consumers. Accordingly, new market schemes will emerge along with the new trends of demand and supply in the grid. So, providing the ideas and the strategies, for dealing with the complexity of managing resources in these networks, is the targeted research topic of this work. In this chapter, Section 1.1 points out the research significance of this work, and justifies the reasons behind approaching this research problem. Section 1.2 briefly details the statement of the research problem targeted in this work, and also illustrates the solutions required by this work to achieve optimum results. Section 1.3 introduces the research questions raised by this thesis. Sections 1.4 and 1.5 highlight the main objectives and the contributions aimed by this thesis respectively. Section 1.6 lists the publication resulted of conducting this research, and finally Section 1.7 outlines the thesis structure.
1.1 Motivation

The motivation for this research was the obvious need to upgrade the current grids for more economic and environmentally friendly electricity generation. Initially we considered the levels of upgrade that were required, along with their relative importance from both economic and environmental perspectives. We found that the first challenge in the upgrade process relates to the ability of the current grid to accommodate the higher number of DGs. Financial, political, and geographical considerations must also be taken into account when upgrading, which make this process even harder. When considering the technical challenges, variable efficiency is expected depending on the installation procedure for these resources. Ultimately, all of the efficiency and cost losses are expected to be compensated for, and considered in the project planning. Having multiple sources of dispatch to compensate for these losses would result in a power quality issue. Depending on the type of the project and the complexity of managing the installed resources, variable generation cost and uncertainty of demand profile are expected, and hence a complex management problem arises whilst operating the system. As a result, a modern infrastructure is required to accommodate this complexity, and a greater level of project expenditure is anticipated in order to control the operation and to maintain its efficiency.

Choosing the appropriate management strategy necessitates a deep understanding of the system’s operational conditions, and requires the ability to apply the decisions to the system. When building a management strategy which can cope with the uncertainty in the demand and the generation cost in a power system, it is essential to categorise the operational conditions based on their cost and safety factors; thus identifying the reasons for, and solutions to, the problem. The problem can be solved using either classical or intelligent management methods, depending on its level of complexity. The operational scenarios for microgrids differ based on their load profile and the location where they are installed. In the case of medium sized enterprise microgrids, the problem becomes bigger depending on their operational scenario, specifically when they are connected or disconnected, as there is a chance to have two-way power flow. This leads to a challenging process called the “Generation Scheduling Problem”. The generation scheduling problem can be defined as the challenge of accommodating the uncertainty and complexity of having multiple sources of dispatch to provide a secure and reliable supply for a specific power system. A brief introduction to this problem is provided in this thesis, along with some supporting references.

Identifying the demand range in power systems is essential in making strategic decisions
about the reliability and sustainability of these systems. By studying a demand profile of a typical microgrid that is usually supplied from DGs, a certain amount of lost energy is identified when it is compared with the amount of supplied energy. This is needed to secure the supply at all demand levels, because it is impractical to generate energy to match the exact amount of variable demand only. Concurrently, this information is needed when building energy management systems. Furthermore, demand forecasting is essential in performing energy management system applications [5]. This can be achieved by applying modern (computerised) infrastructure and implementing intelligent strategies on the network. Figure 1.1 shows the full capacity and the desired generated supply, which can be obtained by developing an effective Energy Management System (EMS). Problems arise when a microgrid is supplied from a range of different types of generators in line with the utility supply, each with variable generation availability and cost. Problems arise when a microgrid is supplied from a range of different types of generators in line with the utility supply, each having variable generation availability and variable cost. In the literature, this problem with the uncertainties of parameters or constraints, have been discussed, and a range of planning techniques has been presented [6, 7, 5]. This problem has also been targeted by different optimisation techniques in [8, 9, 10, 7].
Ultimately, intelligence is essential in most critical issues in the microgrid’s operation, such as forecasting, demand response, self-healing, generation scheduling and markets participation. Dealing with these issues has been widely addressed by researchers in this field. Fuzzy Logic, Artificial Neural Network, Linear Programming, Particle Swarm Optimisation, and Genetic Algorithms have been applied extensively to solve these problems due to their reputation for solving problems in many research areas. In the literature, Multi-Agent System (MAS) technology has also been widely applied to solve microgrid management problems.

Although Artificial Intelligence (AI) based methods are found to be successful in solving microgrid management problems, they still lack accuracy due to their very high demand for computation resources. Consequently, using the right management structure with the right AI-based method to solve microgrid management problems can reduce the required computation resources and increase the efficiency. By considering the uncertainty of generation of renewable energy sources and storage devices, a logical sequence of operations for reducing the required computation resources is needed in tackling this uncertainty. Thus,
the right sequence of operation and the smart utilisation of resources can also increase the operational efficiency of the managed system. Storage devices and electric vehicles are very important factors in improving power systems’ operational efficiency. So, operating these resources, in a smart manner among other resources, would impose a substantial environmental and economic cost reduction.

While cooperation between the centralised (Smartgrid) and the decentralised (microgrids) is expected, it is also expected that the challenge of participation under the competitive market environment be encountered. Since development of standards and regulations for a Smartgrid connection is an active research topic, contributing to the research with novel ideas about connecting microgrids would have a positive impact on the literature. In fact this work was inspired by the need for reliable management strategies that connect microgrids with the Smartgrid; and as a result the proposed strategy carries a novel strategic plan for performing reliable generation decision making on a simulated microgrid.

1.2 Problem statement

A recent visit by an ECU Smartgrid research group to Western Power, the public power supplier for the state of Western Australia was very productive. The visit resulted in a successful discussion of the roadmap and challenges for obtaining power from multiple sources of dispatch system, as well as the intention to connect them to the grid in the near future. Two major issues relating to running multiple sources of dispatch for a microgrid in parallel with utility supply were identified, which are power quality and resources scheduling. It is assumed that power quality is maintained at a satisfactory level, while managing variable quality supply is a problem which can be solved in future extensions of this work. On the scheduling side, the proposed management strategy is expected to deal with three kinds of microgrid connection scenarios: 1) Islanding mode; 2) Connection mode when the microgrid is buying/selling energy from/to the main grid; and 3) Emergency mode when the microgrid generation encounters an operational fault. These scenarios are always dependent on the dynamic generation cost and the intermittent generation from the participant resources. Dynamic utility price, solar irradiation, wind speed, and consumer demand are the targeted variables to be managed to minimise the microgrid generation cost in this research. As forecasting demand was found to be essential to provide the knowledge required about the needed generation in managing resources, finding the most accurate modelling method that suits the type of the demand profile (residential, commercial or industrial) is another considerable challenge. Accordingly, a comprehensive study concerning modelling
the demand, and choosing the most effective parameters that affect the demand profile, is needed in building the proposed management strategies. A more challenging state of operation arises when local DGs propose to dispatch their reserve to the grid, by bidding in a competitive market environment. This state of operation needs to be considered in conjunction with a bidding strategy that works, depending on the microgrid’s reserve status. Hence these engineering problems can be solved by implementing a multi-processing unit management system that comprises distributed sub-systems, each with its independent computational resources, to maintain low-cost generation for the microgrid in the shorter and the longer terms. A communication and synchronisation problems will then arise out of incorporating decentralised processing units that are controlled by a central unit. The main reason behind building distributed processing system is to enable mobility and independence in making decisions, thus forming a multi-level of priority for the decision making. This structure enables the system to run under different operating modes, and also allows the system to accommodate additional generators/loads when required. Finally, the concept of building the system required in this work will be based on the concept of implementing a Distributed Control System (DCS).

1.3 Research questions

The following research questions will be answered in this work:

- How to introduce a demand forecasting model for a microgrid?
- How to nominate the most effective parameters in modelling the demand for a microgrid?
- How to enhance the robustness and the stability of the demand forecasting model?
- How to make the forecasting adaptive to sudden and unexpected changes in the microgrid operation?
- What are the constraints and the problems involved in installing renewable energy sources on the current traditional microgrids?
- How to sequence the operation of sources based on the operational conditions, which makes the generation cost lower in the longer terms of microgrid operation?
- How to perform a beneficial charging/discharging process for the storage devices that run in parallel with other sources that deliver variable cost and intermittent
generation?

- How to offer the microgrid’s generation reserve to the markets at competitive prices?
- How to model the strategic thinking in placing reserve prices under a competitive market environment?
- How to integrate all of the above intelligent modules into one framework that works towards achieving low-cost generation?
- How AI-based MAS technology is utilised in implementing power system generation management systems, and what are the limitations of the proposed power management system for the microgrid?

1.4 Aims of this thesis

The thesis aims to provide AI-based solutions for energy management systems that target low-cost generation for microgrids. More specifically, the thesis introduces new techniques to solve the identified problems for managing multiple sources of dispatch within medium-sized enterprise microgrids. The main aims of this thesis can be explained as follows:

- Identifying the impact of integrating demand forecasting into management strategies that aim to reduce the generation cost for microgrids, and also applying an adaptive forecasting model to adapt the forecasts to sudden unexpected demand changes in microgrids.

- Studying the possibilities of installing renewable energy sources on a medium-sized enterprise microgrid, and also highlighting the challenges of implementing the proposed solutions. The study and analysis address the role of geographical location, weather conditions, utility price rises and expected demand growth in a targeted case study. In addition, estimates about the economic and environmental benefits based on a set of conservative engineering assumptions will be reported. Accordingly, the cost of upgrading the infrastructure in microgrids will be justified.

- Implementing an optimisation technique that utilises the information provided every 30 minutes about the instantaneous cost of generation of utility, storage devices and gas generation, coupled with the availability of installed solar panels and wind turbines generation. This technique targets the smart utilisation of storage devices
among other resources, to reduce the generation cost in the longer term for the managed microgrid.

- Reflecting the human attitude in achieving competitive power trading with the utility. Setting sale prices for the energy in a competitive market environment is implemented by utilising AI in four stages: 1) generating initial sale prices; 2) forecasting the weather conditions and price changes around the microgrid; 3) estimating the operational conditions of the microgrid based on the delivered forecasts; and 4) adapting the sale prices to these conditions, which make the prices adaptive and attractive to sellers in the market.

- Applying management strategies that include all of the above goals to achieve low economic and environmental generation costs for the simulated microgrid. The proposed strategies will be evaluated in a simulated environment based on a set of engineering hypotheses. The thesis will also cover the steps of the development that encompass the logical sequence of running the intelligent modules to help make optimum decisions.

- Investigating the success of utilising Multi-Agent System (MAS) technology in the microgrid resources management system. At this level, the thesis will cover the stages of building a MAS for the proposed system. This will include the details of embedding the proposed intelligent modules in software agents, to perform the required optimum operation for the microgrid resources.

Ultimately, the thesis will provide to the research community, novel ideas about: 1) demand forecasting; 2) optimising the cost of generation; 3) embedding the human sense of trading within a competitive market environment; and 4) modelling strategic plans for running the microgrid resources under different scenarios of operation.

1.5 Thesis contributions

The contributions of this thesis come from developing new methods for solving the most critical issues in the field of smart microgrid management systems. The novelty of the work is found in:

- Detailing a novel demand forecasting strategy, that is comprised of an adaptive structure to accommodate the unexpected demand profile on the managed microgrid, based on a 30-minute sampling interval. The modelling stages are covered in detail,
including nominating the most effective modelling parameters, dividing the demand patterns into 12-month-based patterns, working on increasing the robustness of the model, and considering the real-time demand changes in the forecasting.

- Introducing a novel optimisation technique, that tackles the uncertainties of intermittent generation of the installed renewable energy sources, in line with the variable generation cost of the participant gas gen-sets, utility and the storage devices. The proposed optimisation technique aims at achieving the lowest economic and environmental generation cost from the participant DGs in line with utility supply. The novelty of this work is also introduced by implementing a novel storage device charging/discharging control method, which reacts based on the daily generation cost pattern, making the storage devices important players in reducing the microgrid generation cost.

- Proposing novel Ancillary Services (AS) pricing rules, that help in selling microgrid electrical power reserve to the utility in a competitive market environment. The thesis will detail the pricing rules, along with their adaptation mechanism that makes them adaptive based on the operational conditions in microgrids, such as the availability of generation and the attitude of the markets. Estimation these parameters will result from forecasting models that are embedded into the pricing rules.

- Implementing a strategic management system that operates all of the above-listed modules in a reliable manner, in order to optimise the operation of the microgrid under different types of operational conditions. The implementation includes modelling the behaviours of the proposed management system using MAS technology. Thereafter, a set of decision priority levels is embedded into the system to enable running reconfigurable optimisation structure for all the operating modes. The optimisation structure can be reconfigured by identifying the microgrid operational conditions, and/or by reading the operational status of the intelligent modules.

1.6 Publications from this research


1.7 Thesis outline

The organisation of this thesis is as follows:
• **Chapter 1** has introduced power generation trends, including microgrid roles and operation mechanisms based on their structures, types and connection modes, along with the challenges of operation and performance control. This chapter has also introduced the economic and environmental impact of the decentralised power generation units on the main utility grid. Several management strategies to utilise multi-type decentralised generation units have been proposed in this context. Concurrently, a brief explanation of the strategies needed to perform microgrid operation has been provided in this chapter.

• **Chapter 2** presents the evolution, the technical background of power systems and the generation problems, along with their prospective solutions. A comprehensive review of the methods of management strategies applied to control power systems, including microgrid control and optimisation techniques, is provided in this chapter. In addition, a review of the artificial intelligence methods used in controlling and managing the distributed generators in microgrids is presented. The review also includes modelling the demand in power systems, managing multiple sources of dispatch for microgrids, and performing energy trade with the utility based on different utility and trading rules.

• **Chapter 3** introduces a novel modelling method that targets the demand forecasting in the managed microgrid, and also investigates the utilisation of forecasting in other roles within the proposed management system. The chapter also reviews the current trends for modelling the demand, and provides a summary of the other works in the field. The details of the design of the proposed model are presented, along with the details of the AI techniques used in the modelling. The modelling process is proposed to cover 12 months of operational demand types throughout the year. The results and verification of the modelling technique, which are used in other intelligent modules of this work, are also presented in this chapter.

• **Chapter 4** illustrates the second intelligent module of the management system, which is responsible for making optimised and low-cost generation decisions. The chapter starts by detailing the problem and reviewing other people’s works in this context. In addition, it details the proposed optimisation technique that targets achieving low economic and environmental generation costs by exploring the range of opportunities for changing the variable generation factors for the participant generators. The chapter also introduces a new method for utilising the storage devices
among the participant generators, which imposes a lower generation cost in the longer term for the targeted case study. As part of that, all the simulation data, which have been used, have been generated based on several engineering assumptions that make the data semi-realistic for testing the proposed optimisation technique and the overall management system. Highlights of the proposed optimisation structure, the design outlines and the AI utilised are also covered in this chapter.

- **Chapter 5** proposes a new bidding strategy and pricing rules for the case study’s AS. In this chapter the steps for extracting the pricing rules for selling AS to the utility are detailed. Furthermore, the modes of adapting these rules to the microgrid operational conditions, the market supply and the demand levels are detailed.

- **Chapter 6** covers the proposed management structure that connects all the proposed intelligent modules to build a management system. The chapter addresses the logical sequence of running the intelligent modules and exchanging information among them. It also shows the impact of the proposed management strategies in reducing the economic and environmental costs through utilising the forecasting models, the optimisation techniques, and the bidding strategies. It also addresses the impact of MAS technology in supporting the reconfigurable management strategies.

- Finally, **Chapter 7** summarises the contribution of this thesis in providing a microgrid, multiple sources of dispatch management solutions that aim to minimise the generation cost in autonomous type microgrids. Furthermore, several research directions are recommended in this chapter as future extensions of this work.
Chapter 2

Background and Literature Review

This chapter introduces the problem of managing multiple sources of dispatch in a typical microgrid, and also lists a historical background about the trends of power system technologies involved to solve this problem. It was essential to investigate the current technology trends that have been utilised by researchers and engineers to solve microgrids management and control problems. Building the knowledge about these technologies has been aligned in this work with our experience in artificial intelligence implementation, system modelling and software development to conduct a valuable investigation that answers some of the highly regarded research questions in this area. In this chapter, the literature has been critically revised and the missing parts of knowledge have been identified in order to introduce our research proposal. Ultimately, this chapter has utilised the facts and evidences introduced by other researchers to develop new advanced management strategies for microgrids that can cope with the current research problems. In this chapter, we firstly list a historical background about power systems and their problems in Section 2.1. Section 2.2 details the Australian Government initiatives for reducing emission and installing renewable energy sources that have been considered in the planning part of this work. Section 2.3 introduces the generation scheduling and the resources utilisation problems. Section 2.4 explains the role of demand forecasting in managing the resources for power systems. Sections 2.5 details the methods of performing optimal operation for microgrid resources, and also highlights the role of integrating the microgrid with electricity markets under various market policies. Section 2.8 covers the role of Multi-Agent System (MAS) technologies in managing microgrids resources while detailing the modelling and simulation tools used by research communities. Finally Section 2.9 summarises the literature and identifies the limitations of the current research methodologies in answering the research questions in this field.
2.1 Background

The definition of an electric power system basically represents a system that comprises generating, transmitting and distributing the electricity power via various types of generators, transmission lines and distribution networks through various types of connection layouts. The first design in the electricity industry was proposed by Edison in 1881, and it has been changed with several modifications. Most of the implementations were made for the first time using the limited technology available in the 19th century until the second half of the 20th century, when the design of generation and transmission has faced rapid challenges due the increased plants of power systems [11]. In the last 50 years, power networks have witnessed an enormous amount of development to cope with the modern challenges such as security threats, high demand profile, reliability and power quality issues. The increased network complexity that resulted from the diversity of load and generator types has forced the power industry to plan for grid management advancement. Since then, industry has come up with strategies to use the communication and information technology to increase the network reliability. In the 1960s, the industry started to use the computer to implement monitoring and control for the power systems [12]. In the last 25 years, the developed countries have modernised their electrical power systems with the use of communication, control and automation to become a complex multi-level voltage grid. Concerns over catastrophic climate change, increased industrialisation, CO$_2$ emissions and fuel price rises were the reasons behind creating incentives for reliable, safe and environment-friendly energy sources. To help achieve a clean and secure electric power industry, the current power grid has been modernised to accept a range of renewable energy sources [13]. These are expected to become more competitive with conventional generators, as they were involved to help integrating the renewable energy resources within the power grid. The key point in automating the network is dependent upon incorporating advanced management strategies and reliable sensors and actuators. Since the 1980s, the automatic meter reading has been used to monitor the loads, and in 1990s Advance Metering Infrastructure (AMI) has been evolved. Smart meters have been used later to achieve real time monitoring with continuous communications. Synchronisation and wide area networks monitoring have been revolutionised in the early 1990s. Demand response and demand side management are the developed control strategies for the power grid by the use of smart metering.

Recent technological advances in the power generation and information technologies areas are helping to change the modern electricity supply system in order to comply with higher energy efficiency and sustainability standards. The term “Smartgrid” started to
be in use in 2005 [14], and is currently known as the use of smart meters, communications, computational abilities and control in the form of enhancing the overall functionality of two-way electric power delivery system. Smartgrid is an emerging trend of intelligence in the power grid to optimise the network resources operation. In order for this intelligence to be effective, it is necessary to retrieve enough information about the grid operation together with other context data such as environmental variables. It is also essential to intelligently modify the behaviour of the network elements accordingly. Currently, many design challenges of Smartgrids are resulting from the advanced integration of digital technology with power grid and its information flows. Economic generation and electric market participation are the other concerns that are currently under considerations in Smartgrid development.

As part of the international trend towards restructuring electricity grids, many developed countries are establishing new investment support policies, and also developing legislation for commercialising “Green Energy”. As new clean-energy markets have been emerging around the world, opportunities exist for economic development, jobs creation and energy diversification benefits [15]. Thus, there is a need to develop efficient clean-energy regulations, so that socio-economic benefits are maximised [16]. Regulators are initiating new programs for energy efficiency, renewable energy capacity generation and reliability improvements [17]. Liberalising power markets will also become more important because of the advantages of pooling large generation stations, sharing spinning reserves and using the most efficient energy resources [18]. Therefore, managing the grid resources with this much complexity has become a strategic matter, which has also been subject to the governmental regulations and policies. Identifying the regulations and the possible governmental support are essential in implementing new technologies on the grid. Thus, we firstly explore the Australian Government regulations before conducting this research to justify the impact of our research outcomes.

2.2 Australian Government schemes for emissions reduction and promotion of renewable energy sources uptake

The Australian Government has taken on a responsibility to reduce the carbon pollution in all its states and territories. Its main target is reducing Australian’s carbon footprint by nearly one third to one half. They have also started to develop new policies and rules which are needed to help Australian businesses and households reduce their carbon pollu-
tion [19]. Given that Australia has a very large ecological footprint, which is dominated by carbon dioxide emissions from fossil fuels, it is appropriate that Australia be very active in responding to climate change. This indicates major research and initiative project funding for energy balance and emissions reduction, for example the Low Emission Technology Demonstration Fund (LETDF) to support the Australian firms to commercialise low emissions technologies [20]. Carbon Pollution Reduction Scheme (CPRS) would introduce a price on carbon pollution and ensure that all businesses take this into account when developing their business plan. Concurrently, the Australian Government is developing, commercialising, and investing in clean energy technologies [19]. The Australian Government has initiated major funding support plans to promote commercialisation of renewable energy [21]. Australia is considered one of the most favourable nations for investment in energy resource development because of low political and regulatory risks [22]. Foreign investment is welcomed by the Australian Government and no mandatory local equity or local content requirements are imposed on energy resources development [23]. The Office of the Renewable Energy Regulator (ORER) in Australia administers the Renewable Energy (Electricity) Act 2000 (the Act), the Renewable Energy (Electricity) Charge Act 2000, the Renewable Energy (Electricity) (Small-scale Technology Shortfall Charge) Act 2010 and the Renewable Energy (Electricity) Regulations 2001 (the regulations) to increase renewable electricity generation from Australia’s renewable energy sources by encouraging the generation of an additional 45,000 GWh of renewable energy per year by 2020 [24]. The Australian Government has established the Renewable Energy Target (RET) scheme to ensure that 20 per cent of Australia’s electricity supply will come from renewable sources by 2020. The plan is to make the amount of energy coming from sources like solar, wind, wave and geothermal sources be around the same as all of Australia’s current household electricity use [25]. These will be crucial for Australia’s efforts to reduce its carbon pollution emissions. These technologies will also be important to the rest of the world as they also need to reduce their carbon pollution. Australia’s RET goal will be met from renewable sources such as wind, solar and geothermal power by 2020. The aim of the initiative is to create more jobs in clean industries by giving investors the confidence to back low emissions technologies. In line with these initiatives, there is a need to promote research and development in this area. Hence the mentioned schemes and initiatives are considered in the planning for integrating renewable energy sources in the case study. Consequently, this will also be considered in the simulation were the data are elaborated from the case study based on the operational conditions and the governmental initiatives for installing
renewable energy sources.

2.3 Microgrid resources operation management problem

A microgrid is a low voltage, decentralised power system that comprises various types of distributed generators (DGs), storage devices, and controllable loads. It can also be defined as a cluster of loads and micro sources working as a single controllable system that provides power to its local area [26]. The microgrid might incorporate distributed generators of different sizes and types such as gas and/or diesel generators, wind turbines, solar panels, fuel cells and storage devices. Depending on the location and the connection requirement of the microgrid, it may also have a switchable connection that connects or disconnects the microgrid from the utility grid depending on the operational conditions. In islanding mode, a microgrid is fully supplied by its local resources, whereas in case of connecting mode, it is supplied by both the local resources and the utility grid. Ultimately, this would result in a complex optimisation problem called “generation scheduling”.

Basically, this problem is defined as the challenge of matching the amount of generation with the demand in a power system. This might also include matching the demand with the most cost effective generation from both the economic and environmental perspectives, which makes it a significant research topic. Generally, generation scheduling might be encountered with utility grids, in addition to the microgrids. In this case, adequate management strategies are the key solutions for the performing efficient operation and control of the microgrid [27]. In addition, robust control and management strategies are needed to schedule these resources safely and sustainably [28].

By looking at the utilities, planning their generation has been introduced by [9], where the generation planning and scheduling of the Iranian power plants has been investigated using a new fuzzy hierarchical approach. A short-term scheduling of Fujian Electric hydropower, to maximise economic dispatch benefits was introduced in [10]. Adaptive Neural Fuzzy Inference System (ANFIS) has been considered to estimate the next day generation based on the last 10 days generation information in [29]. In contrast with utilities, generation problem in microgrids is relatively more challenging. The major challenge initially arises when the microgrid is supplied from various types of generators, each with different generation cost, while having unknown amount demand. For this problem, an optimal generation scheduling of a microgrid in the islanded mode has been presented in [7]. This problem, with uncertainties in parameters or constraints, has been solved by various types of optimisation techniques such as fuzzy optimisation-based method, which has been pre-
sented in [8]. Performing optimum microgrid power dispatch by controlling the amount of reserve to reduce the amount of fuel consumption in the microgrid connection modes has been addressed in [30], with a detailed formulation of the constraint for stable islanded operation in accordance with two power-sharing principles: i) fixed droop and ii) adjustable droop. The formulated generation scheduling problem as a mixed integer non-linear problem has been computed by the generalised Benders decomposition technique to perform economic dispatch in [6]. As the multiple sources of dispatch in the microgrid may operate under three different reactive power control strategies, including PV, PQ and voltage droop schemes, reactive power scheduling has been proposed by a new stochastic programming approach that considers the uncertainty of wind farms [31]. A multi-objective function has been proposed in [32] to maximise the reactive power reserve and voltage security margin by mixed linear programming. The main objective of this approach was to manage the resources operation under grid connecting mode by considering the purchase/sale power from/to the grid and the limitations of the distributed generators capacity. The outcome of the above mentioned works states that scheduling the generation in a microgrid that comprises multiple sources of dispatch is a challenging process, yet it is also of significance to reducing the microgrid’s economic and environmental costs. Furthermore, to extract the benefit of obtaining an electricity generation from multiple resources, analysing the demand profile is found essential to help identify the gap between the generation capacity and the expected demand. The intelligence of a microgrid has been enhanced by applying distributed control agents to tackle the challenges of operation that includes forecasting demand in managing the microgrid resources in [33]. Eventually, this will help identify the amount of spinning and non-spinning reserve, which can be a solution for cutting the generation cost in microgrids [34].

2.4 Demand forecasting in energy management systems

The substantial role of considering the demand forecasting in solving electrical systems operational planning problems has been introduced in [35, 5, 36]. The demand forecasting has been utilised to prepare the generation planning and storage devices utilisation for the next day of operation in a university campus load type in [37]. Estimating demand values has been utilised to control wind power in order to take action according to a foreseen amount of power deficit or excess in the system in [38]. Forecasting the demand has also been found essential in the management applications of microgrids such as demand side management and load and generation scheduling. Dynamic Demand Response and
generation management has been proposed for a microgrid of a residential community in [39] to consider the stochastic elements such as stochastic load and wind power, to cut the generation cost for the community. Demand response management in line with price, load and renewable energy generation forecasting have been utilised in [40] to involve community with the grid to reduce the generation cost on both the loads and the grid sides on the concept of a Smartgrid. Offline demand side management that considers the uncertainty of user’s behaviour and weather forecasts in scheduling the energy consumption has been proposed in [41], which has also considered the intermittence of renewable sources generation in line with the storage devices capacity.

Among the most effective adaptive modelling methods, neuro fuzzy has been widely applied due its high modelling efficiency and low modelling complexity. Neuro fuzzy modelling comprises two main stages: 1) developing the fuzzy membership functions that represent the model by clustering the historical operating data, 2) training the developed fuzzy membership functions with the Artificial Neural Network (ANN) to normalise the model output with the data attitude. Therefore in this chapter, we firstly cover the concept of fuzzy modelling, and then follow it with the neuro fuzzy adaptation as follows:

2.4.1 Fuzzy modelling

Fuzzy logic is a widely utilised modelling method, as it has attracted attention throughout the academic and industrial research sectors because of its applicability and flexibility in mimicking and embedding human decision making in a logical way. Despite its complexity and high number of rules that can influence performance, fuzzy modelling is still one of the most efficient modelling techniques. It shares some modelling concepts with other techniques, which is nesting mathematical expressions derived from a set of supplied data. Moreover it is considered to be an effective technique for establishing a Fuzzy Inference System (FIS) from a given nonlinear input-output data set. In fuzzy modelling, the data is partitioned in the input space, and an optimum fuzzy rule table and membership functions are developed. The data partitioning is performed using a data clustering method, which partitions the input-output set of data into a set of clusters. Depending on the type of clustering method, different types and numbers of clusters can be identified.

Various data clustering methods have been characterised in the literature, including; the nearest neighborhood clustering [42], Gustafson-Kessel clustering [43], Gath-Geva clustering [44], Fuzzy C-means Clustering (FCC) [45], the mountain clustering [46][47], and Fuzzy Subtractive Clustering (FSC) [48]. Among the above mentioned clustering meth-
ods, FSC was nominated to cluster the historical load profile data for this work. FSC was selected based on its reasonable computation resource requirements in comparison to other methods that achieve the same clustering performance. The main problem with the clustering comes from the difficulty of choosing the right range of parameters, which in turn influences the rules that are produced. Inaccurate parameter settings undermine the final forecasting accuracy of the system. Appropriate fuzzy modelling parameter settings arise from having a good understanding of the physical system and the challenges likely to be encountered when modelling that physical system. As an example, when the number of clusters is increased, the forecasting output will have strong alignment with the modelled data. However, when the number of clusters equals the number of data elements, the performance and operation of the clusters so developed will closely resemble the characteristics of the training data, having lost the resemblance to the systems operational characteristics. Consequently, the clusters will tend to resemble only a part of the overall operational data. In this circumstance the modelling results in a high forecasting error. In contrast, when the number of clusters is reasonable, the forecasting will cover the training data regions, as well as any other types of operational data insofar as they are located within the range of the training data. Accordingly, the forecasting will result in a much narrower and more acceptable range of error. Thus, suitable parameter choices are the key to successful fuzzy modelling, based on an optimised number of rules and a suitable level of accuracy achieved in the forecasting. Suitable modelling parameters can be identified by an analysis of the modelled system’s operational history. While having experience with fuzzy modelling can be helpful, satisfactory output tuning can be achieved by trial and error in most of the modelling cases.

The major limitations of the typical fuzzy modelling approaches are: 1) the limited forecasting scope within the supplied operational history data range, and 2) the system ignores any external or unexpected changes. From the literature, it is clear that essential knowledge points for enhancing the forecasting output could be added by fuzzy logic-based systems, especially with highly non-linear systems. Support vector regression has proved to be useful when dealing with non-linear forecasting problems in recent years, and it has been utilised to nest supporting knowledge for forecasting [49]. It is anticipated that the introduction of self-tuning systems will improve the forecasting accuracy and add the missing knowledge to the proposed models. In the development of the demand forecasting model, the adaptation of the self-tuning fuzzy-ANFIS as a feature of the (predefined knowledge) forecasting model is proposed to enhance the overall forecasting accuracy.
failure forecasting approach, which integrates a fuzzy logic-based adaptive inference system with the learning ability of a neural network to generate knowledge in the form of a fuzzy rule base, has been developed in [50], where it has been proved that utilising this structure yields reducing the forecasting error.

When comparing fuzzy modelling with Artificial Neural Networks (ANN), we conclude that in order to select the right modelling method, it is crucial to consider the type and the size of the system, the amount of historical operational data that is available, and also the computation resources that will be required. An examination of the character and the size of the modelled case study revealed that fuzzy modelling is a suitable mechanism for the modelling process. More details about the case study and the data analysis are provided in the case study section in Chapter 4. Full details about the fuzzy modelling process, including the clustering method that was utilised, are also provided in subsection 2.4.2.

2.4.2 Fuzzy subtractive clustering method

The Fuzzy Subtractive Clustering Method (FSCM) [48] has been utilised to cluster the historical operational data in the modelling process for this work. The data supplied was tested under the condition that it has the highest density among the tested individuals. Every individual datum was considered to be a candidate for the cluster centering. The individual density was evaluated as follows:

\[ P_i = \sum_{j=1}^{n} e^{-\alpha \|x_i - x_j\|^2} \]  

(2.1)

where

\[ \alpha = \frac{4}{r_a^2} \]  

(2.2)

and \( r_a \) is a positive constant that represents the radius of the data neighbourhood. In 2.1, \( P_i \) is the density of each examined point, \( x_i \) is the point that is examined at the time of measuring the density \( p_i \) of the same point, and \( x_j \) refers to the other data within the neighbourhood. After finding the density for each data point, the highest density point will be selected to be the first cluster centre. The data density for a specific cluster centre candidate is evaluated from the number of nearer individuals that contribute to the cluster.
centre. The highest density identified becomes the first cluster centre. The cluster size is decided when the FSCM parameters have been set to cover a range of data individuals in the cluster’s neighborhood. The radius $r_a$, which is also referred to as the Range of Influence (ROI), defines the range of the neighborhood for the cluster’s extraction. Each of the clusters developed in this way becomes the base of a fuzzy rule that describes the system’s attitude; the number of these clusters being equal to the number of fuzzy rules in the modelled network. When the first cluster centre is found, the next highest density is evaluated. Let the new investigated cluster centre be $x_i$, and $P_i$ be its density measure. When every individual datum is $x_{c1}$, the next cluster centre is identified as follows:

$$P_i = P_i - P_{c1} e^{-\beta \|x_i - x_{c1}\|^2}$$

(2.3)

where $P_{c1}$, is the next density point to be examined, $c_1$ is the next data point to be examined, and

$$\beta = \frac{4}{r_b^3}$$

(2.4)

$$r_b = 1.5r_a$$

(2.5)

where $r_b$ is a constant, which influences the density measure and the value of which is established from the previous experience of data clustering, and from trial and error. Usually, $r_b$ is larger than $r_a$ to avoid closely placed clusters. In this research work, the value of $r_b$ was set to $1.5r_a$ reflecting the values employed in the literature [48], and the value of $r_a$ was determined from our previous experience with data clustering. In the cases we investigated, different values were applied, depending on the nature of the problem. It was observed that the number of membership functions is a direct outcome of the value of ROI, thus the ROI value controls the complexity of the developed network. Table 2.1 illustrates the full details concerning $r_a$ settings for the cases that we investigated.

The next stage is to repeat the above estimation process to identify other cluster centres. The process of identifying clusters is repeated until the value of the newly identified density is equal to or less than 0.15 of the highest identified density. More information about FSCM parameter details is found in [48].

The data clusters that have been identified can then be easily utilised as fuzzy rule
centres in the zero-order Sugeno fuzzy models. When an individual datum is located within the cluster range, a membership function between that particular datum and its cluster centre is derived. Data affiliation to the cluster centres is derived as follows:

$$\mu_i = e^{-\left(\frac{\|x_i - x_c\|^2}{(ra/2)^2}\right)}$$

(2.6)

where $x_i$ is the cluster centre and $x_c$ is the input set of data.

At the end of the clustering process, a fuzzy reasoning system will be developed and trained with the input/output data set. The Adaptive Neuro Fuzzy Inference System (ANFIS) is used as a structure for the training phase of the development of the targeted fuzzy models in this work. In the final phase, the model is verified using the Mean Absolute Error (MAE) to evaluate the final modelling performance for the specific data set. The complete modelling process is illustrated in Figure 2.1.

### 2.4.3 Adaptive Neuro Fuzzy Inference System (ANFIS)

ANFIS was selected to be our modelling method in this work; largely because of its advanced learning mechanism and its minimal training time. In contrast with other learning systems such as the Artificial Neural Network (ANN), ANFIS has a hybrid learning mechanism which provides significantly faster convergence. The ANFIS structure was firstly proposed by [51], where other models of ANFIS were proposed by [52] and [53]. Figure 2.2 illustrates the ANFIS structure with its learning mechanism,

where $f$ is the output of the net, $x$ and $y$ are the inputs to this net. The weights of layer 3 are represented by $(\vec{w}_1, \vec{w}_2)$, and the weights of layer 4 are represented by $(\vec{w}_1 f_1, \vec{w}_2 f_2)$, where the used rules of Sugeno fuzzy in this model are expressed in the following form:

- If $x$ is $A_1$ and $y$ is $B_1$ THEN $f_1 = p_1 x + q_1 y + r_1$
- If $x$ is $A_2$ and $y$ is $B_2$ THEN $f_2 = p_2 x + q_2 y + r_2$

Where $(p_1, q_1, r_1)$ are the parameters that have been determined, and are referred to as the consequent parameters. More details about ANFIS parameters can be found in [51]. In conventional neuro-fuzzy networks, the Back-Propagation algorithm is used to adjust the network parameters, while in ANFIS the adjusting mechanism is performed by the Hybrid Learning Algorithm (HLA). The HLA is a composite of two identification methods: the least-squares method, to identify consequent parameters for the forward pass in layer 4, and the Back-Propagation method for the backward pass, to identify the premise parameters
by the gradient descent in layer 2. This combination achieves faster convergence than that of the original Back-Propagation method. Table 2.1 illustrates the hybrid learning passes with their identified parameters.

This combination has been utilised for modelling in various types of applications under different modelling mechanisms. ANFIS has been utilised as part of a hybrid modelling mechanism to cope with the uncertainty of process operational conditions in [54, 55, 56], and also in a modelling method that incorporates one step ahead concept into ANFIS, which has been built to a fusion ANFIS model to enhance the forecasting for electric-

Table 2.1: Hybrid learning passes directions [1]

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Forward pass</th>
<th>Back pass</th>
</tr>
</thead>
<tbody>
<tr>
<td>Premise Parameters</td>
<td>Fixed</td>
<td>Gradient Descent</td>
</tr>
<tr>
<td>Consequent Parameters</td>
<td>Least Square Estimator</td>
<td>Fixed</td>
</tr>
<tr>
<td>Signals</td>
<td>Node Outputs</td>
<td>Error Signals</td>
</tr>
</tbody>
</table>
Figure 2.2: ANFIS structure

It has been proved that ANFIS was successful in being part of hybrid modelling mechanisms, which allows having time-varying characteristics-based adaptive forecasting. ANFIS modelling structure has also been utilised as a base for developing adaptive models. Adaptive models have been introduced to cover long and short term demand forecasting in power systems. In [58], adaptive fuzzy rule-based systems, in a top-down modelling framework, for a long term forecasting of daily time series in the Neural forecasting competition has been presented. [59] has proposed self-adaptive technique that addresses the shortcomings of the adaptive evolutionary techniques for time series forecasting in non-static environments.

In the next stage of the modelling procedure, we will discuss how to stabilise the newly developed models, and how to improve their forecasting accuracy through the addition of the Self Tuning Fuzzy System. To increase the accuracy of the forecasting and cope with the unexpected behaviours, adaptive forecasting mechanism was necessary in building the microgrids energy management systems. An automatic parameter tuning based on the monitored attitude of the model has been proposed in [60] to perform an adaptive forecasting for next day electricity price and load in a microgrid. A new self-adaptive technique that addresses shortcomings identified during recent studies investigating adaptive evolutionary techniques for time series forecasting has been presented in [59]. An adaptive model based on wavelet transform and adaptive learning time series models has been proposed in [61] to forecast the daily energy consumption and generation price. By analysing the above mentioned works, it has been proved that there is a need to include
the demand in building energy management systems, and an intelligent method for forecasting is needed in this work. Investigating ANFIS role in performing demand forecasting has resulted in attractive outcomes that nominate ANFIS for modelling the demand and integrating the model in the proposed management system. Due to the complexity of the modelled demand profiles, an adaptive mechanism has also been proved to be essential for more accurate forecasting as part of the proposed interactive management system.

2.5 Microgrids operation performance optimisation

Managing the microgrid operation is the main part of this work and the core of analysis required to achieve low cost generation in the microgrid. Hence this stage of analysis and processing is subject to forecasting the demand and obtaining the generation instantaneous cost and availability of the distributed generators. In literature, this problem has been targeted by researchers and engineers introducing new technologies and methods for managing the microgrid resources under various types of operation scenarios. The power dispatch in an islanded microgrid with solar panels and wind turbines has been managed in [62] by modelling the generation cost and correlating the cost function to the investment cost, lifetime and the fluctuant energy of wind and solar resources. An optimal energy management system that aims at providing sustainable low environmental cost generation through controlling the generators based on utilising the demand forecasts and the amount of renewable energy sources generation and the storage devices data has been proposed in [63], which has also covered the charging/discharging process for the distributed storage devices in the microgrid. Where charging/discharging the storage devices is a challenging process in providing low cost generation for microgrids, a set of control strategies have been tested to define the charging or discharging rates of the batteries in [64]. Microgrids operation management design and testing using Fuzzy Logic Energy Management System (FLEMS) has been proposed in [65, 66] to manage the electricity, transport and water needs in an autonomous polygeneration microgrid. Ant colony optimisation method has been proposed to manage the generation in a typical microgrid by considering the complex constraints such as generation availability and cost by finding Pareto optimal dispatch solutions in [34].

Reducing the generation cost in microgrids, in most of the cases, is the art of reducing the generators fuel consumption by matching the amount of generation with the demand. Therefore, controlling the fuel consumption in a typical microgrid based on an optimised operation of the reciprocating gas engines, a combined heat and power plant, a
photovoltaic array and a wind generator in a typical microgrid has been proposed in [67]. Fuel consumption reduction has also been introduced via planning strategies based energy management system that incorporates the optimum placing and utilisation for distributed generators in [68]. Apart from that, Genetic Algorithms based optimisation model with cost and reliability cost functions that works based on a nested strategy and a limited information objective functions has been proposed in [69], to provide low cost generation decisions based on Pareto optimal trade-off curves between cost and reliability. A niching evolutionary algorithm (NEA)-based optimisation procedure has been proposed to minimise the generation cost in a medium level voltage microgrid that encompasses distributed renewable energy sources and storage devices in [70]. Basically this problem is defined as an optimisation problem that requires a quick solution in order to match the generation with the dynamic cost factors variation. On this purpose, Linear Programming (LP) was identified as an ideal method for representing the problem and generating initial results for further computation stages within our management system. To provide a linear programming-based solution for a complex problem, four main components have to be considered:

1. The decision variables, which represent the amount of resources to be determined.
2. The developed rules, which represent the backbone of the decision strategies.
3. The type of objective functions (single or multi), which define the size and direction of the solution (achieving maximum or minimum).
4. The constraints and the bonds, which control the solution limits and thus reduce the time and computation resources needed to find a solution.

Generally, linear programming is defined as follows:

Let $X = \{x_1, x_2, \ldots, x_n\}$ be the set of decision variables and $C = \{c_1, c_2, \ldots, c_n\}$ denote the cost of one unit of decision variables, respectively. The value of $c_ix_i$ denotes the cost of using resource $i$. The general form of an LP model is described as:

- **The objective function:**

  Minimise or Maximise: $F = \sum_{i=1}^{n} c_ix_i$  

- **Subject to constraints:**
  
  - Equalities:
\begin{align}
    a_{11}x_1 + a_{12}x_2 + \cdots + a_{1n}x_n &= b_1 \\
    a_{21}x_1 + a_{22}x_2 + \cdots + a_{2n}x_n &= b_2 \\
    \vdots & \quad \vdots \\
    a_{m1}x_1 + a_{m2}x_2 + \cdots + a_{mn}x_n &= b_m
\end{align} \tag{2.8}

- Inequalities:

\begin{align}
    a'_{11}x_1 + a'_{12}x_2 + \cdots + a'_{1n}x_n & \leq (\geq) b'_1 \\
    a'_{21}x_1 + a'_{22}x_2 + \cdots + a'_{2n}x_n & \leq (\geq) b'_2 \\
    \vdots & \quad \vdots \\
    a'_{k1}x_1 + a'_{k2}x_2 + \cdots + a'_{kn}x_n & \leq (\geq) b'_k
\end{align} \tag{2.9}

- Bounds:

\begin{align}
    x_i \geq LB (\text{Lower Bound}), \quad j = 1, \ldots, n \tag{2.10}
\end{align}

\begin{align}
    x_i \leq UB (\text{Upper Bound}), \quad j = 1, \ldots, n \tag{2.11}
\end{align}

A linear programming method, Particle Swarm Optimisation (PSO), has been proposed for producing the final optimum results due to its convergence speed, robustness and simplicity of implementation [71]. PSO is a well known optimisation method that has been increasingly utilised in solving optimisation problems. In power systems, PSO has been applied to provide solutions for the operation optimisation problems [72, 73, 74]. It has also been proposed to achieve optimal dispatch for loads and generators in a typical microgrid in [75]. PSO, which has been inspired by the flocking social behaviour of birds, explores the best location in the swarm (solutions matrix) by updating its place and velocity. By utilising the defined LP problem representation by PSO, each solution candidate of the rules called “particle”, represents a member of the solutions set i.e., a swarm of candidates. Finding optimum solution is performed by substituting the candidate’s best positions in the cost function [76]. A guided update mechanism is applied to the best achieved solution in the swarm to investigate the possibilities of finding a better solution around the best solution. The update mechanism is illustrated in Figure 2.3.

The velocity equations that represent the update for the selected values are illustrated as
follow:

\[
V_{i,j}^{k+1} = wV_{i,j}^k + (P_{\text{best},i,j}^k - X_{i,j}^k)C_1\cdot\text{rand}_1 + (G_{\text{best},i,j}^k - X_{i,j}^k)C_2\cdot\text{rand}_2 \quad (2.12)
\]

\[
X_{i,j}^{k+1} = X_{i,j}^k + V_{i,j}^{k+1} \quad (2.13)
\]

where \(V_{i,j}^{k+1}\) is the updated velocity for the input variable \(j\) at iteration \(i\). \(w\) is the inertia weight, \(\text{rand}_1\) and \(\text{rand}_2\) are random generated numbers between 0 and 1, and \(C_1\) and \(C_2\) are the learning factors. The update process is repeated based on the predefined number of iterations \(i\), or based on a predefined targeted cost value.

### 2.6 Multi-agent based microgrid management systems

The need for using the computational methods in performing high level control and management for the microgrids with the Smartgrid has been detailed in [77] as the need for multiple levels of distributed intelligence was clarified, along with the potentials and promises of the computational intelligence to realise an intelligent Smartgrid. This clarifies the role of distributed intelligent systems in achieving high level performance in the next generation of power systems that includes the smart distributed power system that is called the Smartgrid. Ultimately, Multi-Agent System (MAS) technology has proved its efficiency in achieving satisfactory performance in complex power systems, especially in the control and management side.
2.6.1 Multi-Agent System (MAS) technology

The term Agent in computer science refers to a software component that behaves in a human manner to perform tasks autonomously. What make the agent unique from other software components are mainly: 1) its ability to perform tasks independently, or being a part of environment that performs tasks based on a sequenced operation mechanism and data exchange with other local or external agents. 2) its ability to sense and react to changes in the environment based on a predefined timing setting and a developed rule base. 3) its ability to learn and establish a new rule base to cope with its environmental changes.

Depending on the type and the reason why the agent is developed, different operation mechanisms can be implemented to perform the tasks. Therefore, predefined settings for the type and the size of the inter-connectivity messages based on a local predefined vocabulary (Ontologies) can be implemented to serve and report coding and decoding among the developed agents. Predefined settings for the behaviours to model a specific attitude can also be implemented within the agent. Eventually, agent’s architecture varies depending on the task that it is built for. However, the agent’s most common architecture details are the sensing and reacting parts, in addition to the processing part. Figure 2.4 illustrates the basic agent inter-connection structure with external information source.

Building a bigger software that incorporates common or additional objectives with other agents yields building a software network called: Multi-Agent System (MAS), which can perform more complicated tasks. Performing a centralised and decentralised decision making among distributed systems, in line with distributed sensors and actuators needs a standardised communication protocol to allow compatibility and ease of application. Eventually, MAS has been widely integrated with various types of applications such as robotics
and manufacturing, electronic trade and negotiation, health care systems, information management, traffic management and telecommunication systems.

Depending on the MAS implementation tool, various design and communication standards applied in agents development were found in literature. Since this work was implemented using JAVA Agent DEvelopment Framework (JADE), the next subsection will detail this tool along with its standards compliance details.

2.6.2 JAVA Agent DEvelopment Framework (JADE)

Java Agent DEvelopment Framework (JADE) is a software-based framework, which is developed using Java programming language [2]. JADE is an easy way to develop MAS using a middle ware that complies with the Foundation for Intelligent Physical Agents (FIPA) [78] design specifications with a set of graphical user interface tools. FIPA is an IEEE standards organisation community that promotes developing agent-based technology standards. JADE allows the agents to work on different computers at the same time, which will allow decentralised monitoring and easy control implementation. Figure 2.5 illustrates the structure of distributed agents and platforms installation on different separate machines using JADE.

Figure 2.5: Distributed agents and platforms installation using JADE [2]
As it is shown in Figure 2.5, each main agents platform container comes with Agent Management System agent (AMS), to monitor the platform, and a Directory Facilitator (DF) agent to create the Yellow Pages services to allow services registration for the participant agents. Including these two agents in the agents platform is a FIPA-agent management standard, which is needed in this work to implement the distributed energy management agents.

Apart from that, the following functionalities are enabled in JADE framework to allow developers embed their proposed agent-based strategies: 1) It allows running same platform’s agents on different remote machine by creating Agent IDentifier (AID) to address the agents, transparently monitor them and communicate with them. 2) Its agents framework operation and design complies FIPA standards. 3) It has the ability to create White Pages and Yellow Pages services within the platform to help addressing agents’ services and status. 4) It has the ability to create and manage the life-cycle for its agents based on the tasks that agents are developed for. 5) It supports agents mobility to allow agents migration between the process and the machines when needed. 6) It supports subscription mechanism, which allows external applications to subscribe in the platform and be addressed and classified by local agents. 7) It has the ability to develop content languages and Ontologies, as this will increase the security applied to the data transferred between the agents and the environment. 8) It permits the web applications integration with the agents to allow remote monitoring and control. 9) It supports Graphical User Interfacing (GUI) to ease agents monitoring and debugging. 10) Finally, it allows for Kernel extension to facilitate extending framework functionalities. These functionalities were found viable tools for implementing management systems using MAS technology and JADE.

The architecture of context aware FIPA [78] compliant MAS for the lightweight devices called SAGE-Lite has been presented in [79] to illustrate the lightweight devices and their communications methods in implementing a framework for applications like business or e-commerce using MAS. The proposed architecture has been enriched with many ideas, which will help in future research and development of the framework. Consequently in the management side of the microgrids, an agent-based intelligent energy management system has been proposed to facilitate power trading among microgrids and allow customers to participate in demand response. The proposed intelligence comprises demand response, diversity in electricity consumption patterns of the customers and availability of power from distributed generators as the vital means in managing power in the system. A smart power restoration mechanism was developed using multi agent technology in [80] that offers
the prototype of a monitoring platform that exploits the agent approach for computation capability improvement. An interesting concept where microgrids and other production or consumption units form a virtual power plant control has been presented in [81]. MAS technology role has been evaluated through implementing electronics markets on a real test sites using JADE in [82, 83]. JADE has been utilised in developing intelligent management frameworks for managing microgrid resources over different types of management strategies. An intelligent management framework has been implemented using JADE in [84] to allow active participation for the microgrid distributed storage devices in the demand side management, and eventually in the market. The power trading among microgrids has been implemented through an agent-based intelligent energy management system, developed using JADE in [85], to allow customers to participate in demand response that can cope with all type of demand patterns in line with the intermittence of renewable energy source generation.

To enable microgrids to operate in parallel to the grid, as an autonomous power system, a robust control for the local voltage and frequency, and network protection are needed to facilitate demand side management and resynchronization. Various types of microgrids around the world (North America, Europe and Asia) with their test systems and control options have been summarised in a table comparing and contrasting the technologies utilised in performing smart microgrids in [86]. MAS have been developed and implemented to control power on microgrid by [87], which has been proposed to be compatible with IEEE standard on FIPA IP-based network. This work has been implemented using simulation, where the results showed that MAS was successful in achieving seamless transition from the grid connection to islanding mode when an upstream outage is detected, and it also showed the possibilities of the MAS in managing microgrids. JADE framework has been implemented on control systems to achieve decentralized control objectives. It has been implemented on microgrids control to achieve multi-tasking on substation automation and controls. The developed agents control strategies were implemented using JADE and DlgSILENT. A decentralized control-based scheme has been introduced to handle the large number of renewable components by implementing distributed control system using JADE as the platform for agent communications, as well as developing customisable agents for specific microgrid requirements such as ancillary services, power trading and negotiation and network security [88]. A reinforcement learning method to minimise the generation cost and also maintaining power balance in microgrids under connecting mode has been presented by [89] to build an objective function that targets achieving optimal cost and
control for microgrids. Hence this method has been proposed to include dynamic hierarchical reinforcement learning to establish optimal policy based on the microgrids operational scenarios, where the simulation results have been presented using JADE.

JADE-based agent development characteristics also allow for markets modelling, which has also been an active research topic in literature. Virtual markets have been simulated using MAS based architecture to enable customers to participate in demand response and trading power with the grid using intelligent agents and JADE in [90]. MAS have been proposed as distributed intelligent systems in [91] to schedule the operation of the distributed resources to the local demand in the microgrid in line with the demand that incurred from selling power to the grid. A priority index has been proposed for customers participating in the market based on frequency and size of load in the demand response. In order to validate the proposed method, a case study with two interconnected microgrids is simulated. Based on extensive simulation results of the system developed using JADE, it has been found that multi-agent based demand response is successful in reducing the system peak in addition to cost benefit for the customers with high priority index [85]. By identifying the role of JADE in modelling the markets attitude, we found it attractive to investigate integrating the microgrid market participation after identifying the critical research points for this issue.

2.7 Microgrids market participation and pricing mechanisms

Apart from optimising the operation of the microgrid through controlling the distributed generators around the microgrid, there is another possibility to reduce the microgrid generation cost, which is the optimal utilisation for the reserve through market participation under different policies. Integrating the microgrid with electricity market is a timely research topic in the power engineering. The role of integrating microgrids with the electricity market based on the sustainability index has been investigated in a large scale studies to include the North West European market in [92]. In [93], the inclusion of flexible CHP production in balancing the electricity in smart energy system as part of the Smartgrid in the Danish electricity market has been illustrated. In addition, the effect of the microgrid market participation has been tested with a smaller scale, as it has been described in [94] by implementing a central controllers that runs based on an optimal power flow under different market pricing policies. The structure of the microgrid and the characteristics of MAS have been outlined in [95]. A novel approach called multi agent reinforcement learning has been introduced in [96] to increase the intelligence and the efficiency of the
Furthermore, microgrids market participation has been addressed in literature with various types of methods for active and reactive power. Microgrids reactive power market participation has been introduced by [97] by bidding to the VAR market that operates based on an optimal price sensitive power flow that controls the day ahead operation of the distributed generators. In active power, the generation reserve in a typical microgrid has been utilised through an optimal price sensitive dispatch and offered to the market by [75]. Microgrid market participation may involve optimising the resources operation before generating a beneficial bids to the market, though involving optimisation techniques has been essential. The microgrid market participation with a hybrid market model has been compared with the pool electricity market by optimizing the production of local DGs and power exchanges with the main distribution grid in [98]. A multi-period optimisation model for connecting a microgrid comprising a multiple sources of dispatch with market under different operational scenarios has been presented in [99]. PSO has been proposed to optimise the operation of the microgrid based on the capital and operating costs, and interconnect the microgrid with the market as an independent generation company which sells electricity to the main grid under dynamic selling price and different market policies in [100]. Markets participation has also been subject to load control and demand response in advance management strategies. Fully connected Neuron networks combined with optimal operation for the microgrid have been implemented as an Energy Management System that comprises adaptive tuning using Genetic Algorithms and Fuzzy Clustering to perform Demand Side Management and Active Management Schemes on High Voltage (HV) network in [101]. A special case for the development of Dynamic Stochastic Optimal Power Flow technology has been shown in this work to be needed in Smartgrid design. MAS was developed in context of intelligent distributed autonomous power systems using Matlab and Zeus agent development toolkit [102]. Infotility’s GridAgents™ software [103] has been used for large-scale integration of distributed energy and renewable energy resources. The developed agents software was proposed to achieve microgrid management, intelligent load control and smart charging applications. Finally MAS-based two level management architecture has been proposed to solve the microgrid optimal power flow problems in [104] to perform active market participation for the distributed generators under different operational scenarios. It has been indicated in this Section how importance of each of the listed technologies are imposing significance to managing the resources in microgrid, and eventually helping microgrids to be part of the Smartgrid under common operational
policies and communication protocols.

2.8 Microgrids and Smartgrid

Integrating the microgrids with the Smartgrid is the challenge of incorporating advanced management and control strategies in the microgrid to allow safe and reliable connection that can cope with the requirement and operation standards of the Smartgrid. More specifically, connecting the microgrids to the Smartgrid targets three major goals: market participation, improving the power quality and increasing customer role in the grid power generation and stability. The capabilities of MAS technology for connecting microgrids to Smartgrid have been presented in [105], while this topic has been largely discussed by researchers to develop new implementation methods and simulation tools.

By investigating the role of managing microgrids in connecting microgrids with Smartgrid, it has been found that asset management techniques have been used to develop an automation system for medium voltage network in [106] to show the application of a new automation concept that results in network reliability and enables the temporisation of asset replacement programs for Smartgrid. Microgrid management systems development using agent based technologies and application to the effective management of generation and storage devices has been described in [14]. Active Distribution networks with full integration of Demand and Distributed energy RESourceS (ADDRESS), the European project that aims to deliver a comprehensive commercial framework for the active demand development for the Smartgrid has been presented in [107] to investigate the development of the participation of domestic and small commercial consumers in the Smartgrid energy markets. ADDRESS represented a unique and timely opportunity to coordinate and combine the expertise and resources of partners from all Europe. A new type of smart demand side technology to allow the customer to have a more dynamic role in improving the grid voltage control, as this technology can be provided by thermostatically controlled loads as well as other types of loads, has been introduced by [108]. This technology has been applied on distribution systems with large composition of induction motors. Ultimately its modelling technique, discussion and simulation results proved the effectiveness of the demand as voltage controlled reserve technology for short-term voltage control under Smartgrid connection.

Furthermore, a framework for Smartgrid operation that comprises control objectives to incorporate the participation of the distributed generators and flexible AC transmissions technologies to the Smartgrid has been applied to achieve voltage and stability control.
for microgrids in [109]. In this framework, the control strategies have been developed in such a way, that the voltage controller is operated by a global coordinated strategy, and stability control is applied by a decentralized controller. Intelligent control strategies have been applied to enhance stability in all modes of operation of the microgrid by [110], to show that the stability in different modes (Parallel, Transient, and Autonomous modes) has been improved. Agent technology has also been utilised in this role, where a control structure has been proposed using agent-based technology to be implemented and tested on a pilot microgrid of Kythnos Island, Greece. The developed autonomous agents have been used to control the power grid while being connected to Smartgrid based on several conversations and scenarios among agents [111]. Agent-based control framework has been proposed to control the distributed energy resources microgrids [112, 113, 114] by considering Smartgrid connection, while a control scheme has been implemented with MAS for the operation of the microgrids in [115].

As stated earlier in this section, the Smartgrid research community has investigated the challenges of achieving active participation of the distributed generation with energy markets. In this field particularly, increasing energy efficiency, under Smartgrid connection, by introducing a market mechanism that facilitates the efficient matching of energy demand and supply through a double auction mechanism for the allocation and pricing of energy resources has been presented in [116]. Another research has investigated the use of automatic bids generation for allocating resources for demand in their various applications in microgrids for efficient Smartgrid connection in [117], where an automatic bidding generating strategies were presented to use reinforcement learning techniques in generating bids. Bidding language for communicating consumer has been provided using MAS technology as a simulation tool for performing specific control and management applications for microgrids Smartgrid connection. PowerMatcher, a Smartgrid market-based control concept for supply and demand matching in electricity networks has been applied on the microgrid to achieve supply and demand matching with high share of distributed generations in [118]. A number of results from two field tests performed with the PowerMatcher concept has been discussed in [119].

The identified technologies in the this section clarify the possibilities and the limitations of simulating a proposed management strategy that operates microgrids resources under Smartgird connection. This section has also stated the level of research conducted on performing smart management systems for microgrids under Smartgrid connection, which that by its turn helps identifying the critical research questions in this field.
2.9 Closing remarks

This chapter outlined the most up to date methods and technologies utilised to perform smart management strategies to optimise microgrids operation. By studying the operational scenarios and the characteristics of the microgrids connection with the utility grid, further details about the operation challenges were identified, and therefore, the literature exploration converged towards investigating the technical challenges relating the smart utilisation of microgrids' resources to reduce their economic and environmental costs. To operate the microgrid in parallel with the Smartgrid, other implementation challenges have been highlighted, thus new automation technologies have also been identified to cope with these challenges. Identifying the role of demand forecasting in performing resources management has been stated with the needs of involving advance methods for more accurate forecasting in conjunction with the high uncertainties of users' behaviour and weather conditions. Utilising the demand value in line with other microgrid operational details will help analysing the operation, and then finding a suitable solution based on a predefined rule base. The literature has highlighted this problem and also identified the role of various types of optimisation techniques in solving this problem. However, this part has included different implementation methods depending on the complexity of the operational scenarios, like having markets participation, which would encompass more cost effective parameters that need to be considered in the management decisions. To combine these management decision stages in a comprehensive management framework, MAS technology has been found a successful candidate for implementing energy management systems. MAS technology has also been targeted in this research to test the possibility of implementing a specific management strategy that relies on the local demand profile and the dynamic generation costs. From the literature it has also been noticed, that the researchers have investigated the impact of using MAS technology on the microgrids management and control as well. The highlighted challenges in performing reliable management on microgrids resources were as follow: 1) the operation reliability, since microgrid can be connected or disconnected to or from the utility grid depending on the operational scenarios, its power supply should always be reliable, 2) the need for obtaining instantaneous information about the demand profile in the microgrid, as this will help following the demand patterns instantaneously, which will eventually match the generation capacity with the demand profile, 3) the need for scheduling resources to reduce their operating maintenance and generation costs, especially when their cost is dynamic and dependent on other local and/or external cost factors, 4) the possibilities of involving the microgrid with the market depending on
the offer and the demand in the market itself, 5) finally, it has been found that there is a need for developing comprehensive commercial framework which has the ability to achieve economic and market participant energy production based on running multi-stage analysis and decision making system. Ultimately, artificial intelligence algorithms are needed to be applied for better framework operation, which can be implemented as distributed intelligent systems for optimising the microgrid operation. In conclusion, this thesis is targeting all of the listed challenges by introducing a system developed to make optimum generation decisions for the microgrid’s resources.
Chapter 3

Load Forecasting Model

Estimating the amount of electrical demand is the key to minimising generation cost in power systems. In this work, utilising the demand forecasts is essential in our planning to maximise the utilisation of the generated power, and also to maximise the benefit of having variable generation cost in line with the intermittent generation from renewable energy sources. It is therefore important to introduce a novel demand forecasting technique, that can cope with the challenges encountered with the dynamic operational conditions of microgrids, prior to introducing other intelligent modules in the proposed EMS. Ultimately, this chapter details the development of an adaptive demand forecasting model. This model aims to generate adaptive demand forecasting, that reflects the real-time demand values in the forecasts. The proposed demand forecasting model was implemented to provide a 30-minutes in-advance forecast of the electricity demand on the Joondalup campus of Edith Cowan University (ECU). The proposed modelling mechanism aims to utilise the historical operational data to build a base model for forecasting, and then adjusts the base model forecast in response to measured changes in the load profile. These measurements are taken on the real-time load. The model requires three stages of computation in order to perform the forecasting, which are as follows: 1) forecasting demand, 2) controlling the forecasting accuracy, and 3) adapting the results to the real-time demand values. In the forecasting stage, the Adaptive Neural Fuzzy Inference System (ANFIS) was used to build the model by utilising the historical operational data. Concurrently, a fuzzy system for tuning was used to control the model’s output. For the forecasting output adaptation, an additional fuzzy system was used to consider the instantaneous load profile in the forecasting. Successfully implementing the third fuzzy system for the adaptation stage was challenging because of the unexpected user behaviour on the campus. As a consequence, an Artificial Neural Network (ANN) based optimisation technique was proposed to tune the adaptation parameters; based on the identified real-time load profile at time of fore-
casting. In this chapter the modelling strategy is discussed, and we organise it as follows. Sections 6.1 and 5.2 give a historical background about modelling trends with respect to the work of other researchers in modelling the load profiles of power systems. Section 3.3 introduces the problems encountered with forecasting the demand in microgrids, and also highlights the objectives aimed by the proposed modelling method. Section 3.4 lists the research assumptions considered in the modelling procedure. Section 3.5 covers the proposed modelling procedure, including some verification tests for the methods which were utilised. Section 3.6 provides a discussion of the results, and in Section 3.7 we evaluate the findings and the outcomes of this work, and nominate extended works within this research field.

3.1 Background

Modern power generation management systems may include the Smartgrid applications to perform more complicated tasks such as power trading, demand response, and resources scheduling. In all of the above mentioned applications, forecasting the load profile, in both short and long terms of operation, is essential. Providing accurate forecasts of the load profile is a critical research target for mathematicians and engineers in this area.

In modern automation, adaptability has become crucial factor when implementing smart applications. The addition of adaptability enables the smart applications to more closely resemble the human sense of adaptive thinking. Including an adaptive demand forecasting within a power generation management system would result in an interactive application that resembles the human behaviour in making critical decisions. Investigating the implication of including an adaptive demand forecasting model within the power generation management system is of significance to the research community due to the necessity to obtain accurate forecasts prior to making decisions concerning managing power systems.

Artificial Neural Networks (ANN) are typically utilised when implementing adaptive systems; however, self tuning and adaptive algorithms are not restricted to ANN, as they can also be implemented through a range of optimisation techniques, as well as Fuzzy Logic (FL). The latter has been proved to be one of the most efficient modelling techniques due to its ability to reflect the human sense in making decisions on a particular problem. The specific implementation of the tuning mechanism is governed by the nature of the problem to be solved, and/or the system which is to undertake the processing. The tuner and main systems may share the same input parameters, or they may receive two different
types of inputs from external sources, depending on the nature of the operation. Self-tuning systems have practically unlimited applications, and to date they have been widely utilised in various academic and industrial applications. Eventually, Self Tuning Fuzzy System (STFS) is hypothesised to achieve a satisfactory modelling performance when it is attached to a forecasting model.

In essence a STFS is an on-line adaptive output fuzzy system, where the output is changed depending on the type of input and predefined knowledge rules. In general terms, a fuzzy system is called tunable when any of its parameters (input/output scaling factors, membership functions shape and type, or rules) are changeable on an instantaneous basis. A tunable fuzzy system is a combination of a general and a tuner Fuzzy Inference System (FIS), where the tuner FIS tunes the general (main) FIS parameters. Although at times both systems have the same input parameters, they still perform independent roles. The reason STFS is used in modelling is to enable short term forecasting to be conducted, which improves the overall system flexibility by adding the safe forecasting estimation knowledge to the forecasting; either by adding extra knowledge to the forecasting, or by adapting the forecasting to the external effects.

The case study that we have modelled has highly non-linear characteristics, so developing a model for high precision forecasting is a major challenge. Hence it becomes necessary to focus on the model’s forecasting accuracy in order to consider its weak points. By considering the electricity demand in the targeted case study, modelling knowledge could be added regardless of whether or not that knowledge is initially available within the supplied operation data.

Through the use of the STFS, so if the gaps in the knowledge can be added back to the operational history data. For such systems, a design with external input parameters for tuning the main fuzzy model output, based on a knowledge base, could be implemented. In this chapter, the real-time demand change measure was utilised in order to investigate the FIS’ ability to adapt the forecasting output to the actual demand change. The main fuzzy system’s input parameters were also used to tune the forecasting, based on a knowledge base system. Similarly, the tuning part may use alternative mechanisms, e.g. rules, membership functions, or output scale tuning. The Weights Adjusting Method (WAM), is the mechanism for adjusting the output of the main system, enabling the system to adapt to changing circumstances. WAM adjusts the weights of the output of the main system with its tuner, according to the level of forecasting needed. By giving consideration to the tuner’s fuzzy rule base, a suitable WAM can be derived. For simplicity, an output
scale adaptation was applied. Figure 3.1 illustrates the general structure of the STFS. The full design details of the particular STFS being employed are explained in subsection 3.5.2, where the results of the implementation will be discussed from the perspective of improving both forecasting and adaptation performance.

More specifically, STFS will be implemented in two computation stages within these models: 1) in improving ANFIS forecasting accuracy by applying the FeedForward Tuning System (FFTFS). 2) in adapting the demand forecast values to the external operational condition changes through the FeedBack Tuning Fuzzy System (FBTFS).

The final model structure will be built and verified with simulation results in this chapter. In addition, it will also be implemented as part of the proposed management system in Chapter 6, to work with other intelligent modules to solve the more complicated problems concerning minimising the power generation cost for the microgrid.

3.2 Related works

At the time of application, ANFIS was successfully employed to perform short term demand forecasting for wide range of applications in a variety of fields, such as: 1) finance- where it was used to create a forecasting model for the domestic debt based on 10 years of monthly values of currency, total money supply, consumer price index and interest rate in [120]; 2) tourism- where the ANFIS model was used to forecast the tourist arrivals coming to Taiwan in [121]; 3) control engineering- where ANFIS modelling was introduced in order
to reduce a large number of FL controller rules in [122], in [123] where ANFIS model was utilised as classifier for control decision making, and in [124], an ANFIS based space vector modulation technique was utilised to control the voltage source inverter; 4) Natural Gas consumption- an ANFIS stochastic frontier analysis approach for long-term natural gas (NG) consumption forecasting and analysis of the behavior of NG consumption was proposed in [125].

ANFIS has already achieved a successful track record in modelling the forecast for electricity demand. Under various modelling structures, ANFIS was included when modelling the electricity demand for a number of power utilities. A two-dimensional wavelet based state dependent parameter modelling approach, was proposed to produce a compact mathematical model for this complex nonlinear dynamic system; for short-term forecast of daily demand in the state of Victoria, Australia in [126]. A new hybrid ANFIS model was proposed for short-term load forecasting for two Brazilian power companies in [127], while in Taiwan, ANFIS was applied to forecast regional loads in Taiwan and to demonstrate the forecasting performance of the same model in [128]. For smaller load sizes, a number of studies evaluating the forecasting of energy consumption within buildings were conducted, in order to select the best control strategies to manage the excessive energy consumptions. A model of short term forecasting based on variables such as; maximum and minimum temperature, climate change, and the previous days consumed load; for forecasting the power load consumption was developed using ANFIS in [129]. ANFIS was also applied to forecast the demand change in the cold regions in [130]. A short term forecasting model was developed using the neuro fuzzy system Locally Linear Model Tree (LoLiMoT) learning algorithm in [131]. Next-day load demand forecasting in electrical power generation was developed using ANFIS; improving the power system as an application of artificial neural networks and FL-based hourly load demand forecasting, with linear polynomial and exponential equations in [132]. The demand forecasting using time series modelling and ANFIS estimator was developed in [133], where an ANFIS model based on the data field was proposed to solve the drawbacks of the general fuzzy neural network, and to optimise the FL rules in [134].

The ANFIS-based models were found to present opportunities for managing power demand, as a response to electricity market participation. ANFIS was proved to be suitable for undertaking demand forecasting based on its sensitivity to real-time external parameters, such as fluctuations in the market price of electricity [135], and real-time pricing which was integrated in the short-term energy demand forecasting modelling in [136].
Real-time electricity pricing and bidding were used in modelling demand in [137] and [138] respectively.

Although ANFIS has already been established as a successful modelling technique, it was previously used with only a simple modification to deal with highly non-linear load profiles. ANFIS modelling accuracy, however, depends on many factors including the ANFIS structure parameters selection. An approach based on the combination of Particle Swarm Optimisation (PSO) and adaptive-network based FIS was proposed to forecast the electricity prices in a competitive market in [139]. Importantly, the results obtained show significant improvement in both price and load forecasting. The other important factor that affects ANFIS modelling accuracy is the data clustering parameters. When evaluating existing clustering techniques and clustering methods, it was found that a technique utilising multivariate inputs for electrical load forecasting on hybrid neuro-fuzzy and fuzzy C-means forecaster has previously been proposed. It used a neuro-fuzzy approach, with additional fuzzy c-Means clustering before the inputs enter the networks [140]. A clustering-based, genetic fuzzy expert system for power demand forecasting has also been presented, which has a novel load forecasting approach that integrates genetic fuzzy systems and data clustering for extracting a load forecaster expert system [141]. A clustering algorithm based neuro-fuzzy method for estimating wind speed profile, based on knowledge of wind speed at different heights, was applied in [142]. Among the proposed modelling methods, the ANFIS based Fuzzy Subtractive Clustering Method (FSCM) was deemed relevant to this project due to its applicability and ease of utilisation for the purpose of research. Ultimately, the experience in clustering the system’s operational data would result in a more efficient ANFIS model.

3.3 Research objectives and challenges

Obtaining accurate demand profile forecasts for a typical power system is the challenge of understanding the consumer’s behaviour throughout the year. Hence identifying the type of the demand profile (residential, commercial or industrial) facilitates evaluating the demand diversity factor, which is needed in making reliable estimates about the demand forecasts. However, this cannot be used in autonomous management systems unless it is added to a mathematical model that has been developed in accordance with the historical trends of that particular demand. The other major challenges, encountered with modelling a demand profile for a power system, are:

1. Selecting the modelling technique and embedding the knowledge required in order
to cope with unpredictable operational scenarios.

2. Reflecting the system operator experience about the system’s operational scenarios.

3. Dealing with the unpredictable load profile that may result in a higher forecasting error, which might affect the management system performance.

4. Monitoring the forecasting error rate and controlling it by adapting the forecasts to the actual demand values.

3.4 Research assumptions

This model was initially intended to be part of our proposed generation management system, in line with other intelligent modules. Thus the model gives considerations to the amount of uncertainty presents at each part of the system, including the forecasting component. Based on the expected uncertainty of the load profile in the case study, the following assumptions underpinned the research methodology:

1. The proposed demand forecasting model is targeting a university type load profile.

2. The model is proposed to deal with 12 different demand pattern changes throughout the year. Ultimately, 12 models are required to forecast the demand throughout the year for the targeted case study.

3. All university function- or event-type load changes resulting from on campus activities are ignored in the modelling process. Therefore, it is assumed that the system may operate with full load capacity when such kinds of activities take place.

4. During faults and emergencies, the forecasting model is immediately suspended and the system operates in emergency mode. The load profile forecast is ignored when supplying power for the case study where the system has faulted.

3.5 Modelling methodology

This section covers the methodology for modelling the electricity demand profile, and is based on a series of 30-minute intervals in the case study. The proposed model was developed in two distinct modelling stages, encompassing three computation modules, each of which performs an essential role in contributing to the overall modelling. In the first modelling stage, the demand is forecast and then corrections are made based on the added knowledge gained through FFTFS. Two FIS are integrated together in the first
modelling stage: 1) the main FIS which is developed from modelling the input-output data using FSCM and ANFIS, and 2) the second FIS that represents FeedForward Tuning Fuzzy System (FFTFS). The FFTFS is either developed by using the correlation between the power demand and the temperature throughout the day into future decision making, or developed by using knowledge about the real-time demand.

In the second modelling stage, the demand forecast is adapted to the real-time changes relating to the case study. At this stage of computation, two systems are utilised; a two-input-one-output FIS FeedBack Tuning Fuzzy System (FBTFS), in conjunction with an ANN-based optimisation technique, to tune the FIS parameters in the second stage of computation.

Figure 3.2 describes the full details for the proposed modelling mechanism of a one-month, randomly selected January model. The whole year model is illustrated in Figure 3.3.

To improve the forecasting accuracy and reduce the model complexity, the annual power demand of ECU’s Joondalup campus was split into twelve monthly models, represented by twelve discrete demand pattern models. Each model represents a one month demand model, which can be activated depending upon the type of the input set. Figure 3.3 illustrates the annual power demand forecasting structure for ECU’s Joondalup campus.

Splitting the annual demand model into twelve sub-models expands the system’s forecasting ability by being able to draw from twelve different load change patterns. In addition, the twelve sub-models reduces the computation resource requirement, since only
Figure 3.3: The electric power annual demand forecasting structure for ECU’s Joondalup campus

One month’s model is active at a time. Thus the modelling process uses twelve separate modelling methodologies depending on the load change analysis for the individual months. A switching control is applied to automate the running of the one month model, based on the type of input parameters, and extended for the forecasting throughout the year in this composite model. Each one month model consists of the main modelling structure, including the forecasting and the FeedForward and FeedBack adaptations. The following subsections detail the model’s structure for each month:

3.5.1 ANFIS model

In this subsection, we discuss the use of FIS in the modelling process, and also provide specific details about the stages of ANFIS modelling of the power demand in the targeted case study. In this investigation, data clustering methods are nominated to perform fuzzy modelling. More specifically, FSCM and ANFIS are used to model the demand in the
Table 3.1: ROI values and complexity of the 12-month electricity energy demand models

<table>
<thead>
<tr>
<th>Months</th>
<th>Membership Functions ranges</th>
<th>ROI</th>
<th>Rules</th>
<th>Membership Fctn.</th>
</tr>
</thead>
<tbody>
<tr>
<td>January</td>
<td></td>
<td>0.35</td>
<td>28</td>
<td>112</td>
</tr>
<tr>
<td>February</td>
<td></td>
<td>0.4</td>
<td>23</td>
<td>92</td>
</tr>
<tr>
<td>March</td>
<td></td>
<td>0.5</td>
<td>14</td>
<td>56</td>
</tr>
<tr>
<td>April</td>
<td></td>
<td>0.33</td>
<td>40</td>
<td>160</td>
</tr>
<tr>
<td>May</td>
<td></td>
<td>0.44</td>
<td>17</td>
<td>68</td>
</tr>
<tr>
<td>June</td>
<td></td>
<td>0.4</td>
<td>25</td>
<td>100</td>
</tr>
<tr>
<td>July</td>
<td></td>
<td>0.45</td>
<td>20</td>
<td>80</td>
</tr>
<tr>
<td>August</td>
<td></td>
<td>0.48</td>
<td>19</td>
<td>76</td>
</tr>
<tr>
<td>September</td>
<td></td>
<td>0.43</td>
<td>18</td>
<td>72</td>
</tr>
<tr>
<td>October</td>
<td></td>
<td>0.5</td>
<td>11</td>
<td>44</td>
</tr>
<tr>
<td>November</td>
<td></td>
<td>0.5</td>
<td>16</td>
<td>64</td>
</tr>
<tr>
<td>December</td>
<td></td>
<td>0.41</td>
<td>20</td>
<td>80</td>
</tr>
</tbody>
</table>

Case study, based on the detailed methods of modelling from Section 6.1. Generally, the optimum selection of the modelling parameters is the key factor in achieving the highest performance from the developed models. Based on experience gained in modelling and parameters selection, different clustering parameters for each month were selected, depending on the amount of non-linearity of the data-set. By clustering: ambient temperature, hour, day, and load change data; random FSCM parameters values (e.g. Range Of Influence (ROI), Squash, Accept Ratio, and Reject Ratio) are applied. These selected values may increase the complexity of the models that are developed. Table 3.1 illustrates the selected modelling parameters, along with the complexity achieved for each of the 12-month power demand models.

After clustering is complete, the membership functions previously developed are then trained. Following this step, a simple test is carried out to verify the forecasting accuracy of the models that have been developed. In this work, each month’s model is developed by using the microgrid’s historical operation data for that particular month in three subsequent years (A, B, and C). The three years of data are then divided into three different sets. The first set is used to extract the clusters, which is taken as 90% of the A and B years historical data. The second set of data, which is used to train the fuzzy systems which have been developed, used the whole set of A and B data. Finally, the third set of data, which is used to verify the success of the developed model, was taken as the year C operation data. Fig. 3.4 shows the data utilisation in developing the demand models in this work.

After the rules which relate the input-output data have been developed, the clusters are then utilised in neuro-fuzzy networks to develop a zero-order Sugeno fuzzy inference
system, which can then perform a 30-minute ahead short-term forecast. In conventional fuzzy systems, a trial and error approach is applied to tune the membership functions of the input-output universe of discourse of the fuzzy system. When ANN is used to tune the membership functions, an automated selection process is performed based on the performance index. The membership functions are trained to resemble the training data characteristics. In neuro-fuzzy networks, the structure is changed in accordance with the operational scenarios. Neuro-fuzzy networks, however, utilise the neural network’s ability to learn to achieve the best tuning process, with better performance and less time [143]. Since fuzzy systems have the property of universal approximation [51, 144], it is expected that the equivalent neuro-fuzzy networks representation will have the same property.

Finally, when a verification result is within an acceptable error bound, the modelling procedure is complete. Figure 3.5 illustrates the input membership functions that were developed for the four inputs, zero-order, Sugeno fuzzy system of January’s operation for ECU’s Joondalup campus power system.

From Figure 3.5, and from the Sugeno-fuzzy system for January demand forecasting, the rules that were developed are explained as follows:

If (Temperature is Temperature in Cluster $n$) and (Hour is Hour in Cluster $n$) and (Day is Day in Cluster $n$) and (Day-type is Day-type in Cluster $n$), then (Demand is Demand in Cluster $n$)

where $0 < n \leq$ number of developed rules.

Finally, for the other eleven months of the year, it was found that each of the models had a different range of inputs, based on the pattern of operation and weather change across the four seasons throughout the year, in the city of Joondalup. Although other effective modelling parameters have been nominated for the proposed models, experimental investigations were applied to use three, four, and five-input modelling parameters to
Figure 3.5: The membership functions for the four inputs zero-order Sugeno fuzzy system of January's power demand forecasting
Figure 3.6: Forecasting results comparison for demand in ECU from the 17th to the 21st of January, year C

achieve demand forecasting performance. Ultimately, the four-input modelling parameters approach was chosen, which proved to be an optimal selection.

At this stage, modelling approach robustness was tested with the nominated input parameters. The results obtained demonstrated the dependence of the forecasting accuracy on both the number of inputs and on the the type of inputs. Figure 3.6 illustrates the different forecasting accuracy for the three, four, and five-input systems.

Table 3.2 presents modelling complexity for all investigated cases. Modelling complexity is shown in terms of extracted number of membership functions (MMFcn) and the value of (ROI). The complexity of the models was raised to double or triple in most cases, indicating that the input does not have a big influence on the load changes at ECU. As a result, adding the fifth input to the models will not have a significant influence on forecasting improvement, or may even have a negative affect. Figure 3.6 shows the forecast results for the three, four, and five-input systems for the period from the 17th to the 21st of January, year C.
Table 3.2: Three, four, and five-input systems forecasting accuracy

<table>
<thead>
<tr>
<th>Month</th>
<th>Three inputs</th>
<th>Four inputs</th>
<th>Five inputs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MMFns ROI</td>
<td>MMFns ROI</td>
<td>MMFns ROI</td>
</tr>
<tr>
<td>January</td>
<td>63 0.35</td>
<td>76 0.43</td>
<td>150 0.5</td>
</tr>
<tr>
<td>February</td>
<td>69 0.38</td>
<td>72 0.4</td>
<td>150 0.5</td>
</tr>
<tr>
<td>March</td>
<td>33 0.45</td>
<td>56 0.5</td>
<td>145 0.5</td>
</tr>
<tr>
<td>April</td>
<td>78 0.33</td>
<td>160 0.33</td>
<td>140 0.5</td>
</tr>
<tr>
<td>May</td>
<td>39 0.44</td>
<td>68 0.44</td>
<td>145 0.5</td>
</tr>
<tr>
<td>June</td>
<td>45 0.48</td>
<td>100 0.4</td>
<td>320 0.4</td>
</tr>
<tr>
<td>July</td>
<td>36 0.5</td>
<td>80 0.45</td>
<td>145 0.5</td>
</tr>
<tr>
<td>August</td>
<td>36 0.5</td>
<td>76 0.48</td>
<td>145 0.5</td>
</tr>
<tr>
<td>September</td>
<td>54 0.45</td>
<td>76 0.43</td>
<td>120 0.55</td>
</tr>
<tr>
<td>October</td>
<td>24 0.5</td>
<td>44 0.5</td>
<td>125 0.5</td>
</tr>
<tr>
<td>November</td>
<td>33 0.48</td>
<td>64 0.5</td>
<td>135 0.5</td>
</tr>
<tr>
<td>December</td>
<td>45 0.41</td>
<td>60 0.41</td>
<td>182 0.45</td>
</tr>
</tbody>
</table>

Studying system operational conditions e.g., the operation time, the number of people, and the amount of consumed power during the day or night, may help develop supportive variables to improve the forecasting accuracy, as long as the significance of the input is assessed prior to its use in the model development. Figure 3.7 presents the surfaces of the developed fuzzy systems for the three, four, and five input variables.

3.5.2 FeedForward Tuning Fuzzy System (FFTFS)

In this subsection, we investigate improving the forecast results, based on knowledge of the power demand conditions, which could have been imperfectly represented in the given set of historical operational data. The system is required to enhance the performance of the forecasting model, by using the knowledge of the system performance, safe operational estimations, and the actual decisions that are required. In this work, FFTFS is proposed to improve the forecasting accuracy. Two of the model’s inputs are selected to develop the fuzzy rule-based system, so that there is a smooth transition between the specified operational cases in the decision making. In this work, we typically investigate use of a one rule based system for application to all of the 12-month models. Table 3.3 illustrates the proposed rule based system in this investigation.

To cope with changes to the operational patterns throughout the year, different ranges of membership functions universe of discourse are proposed for each month’s model. Triangular type membership functions have been proposed in developing FFTFS. The rule base
Figure 3.7: Fuzzy surface for the developed fuzzy models of the three, four, and five-input system

Table 3.3: Self tuning fuzzy rule-based system

<table>
<thead>
<tr>
<th>Hour</th>
<th>Temperature</th>
<th>V. Cold</th>
<th>Cold</th>
<th>L. warm</th>
<th>Room temp.</th>
<th>Warm</th>
<th>Hot</th>
<th>V. hot</th>
</tr>
</thead>
<tbody>
<tr>
<td>Midnight</td>
<td>S. low</td>
<td>Normal</td>
<td>Normal</td>
<td>S. High</td>
<td>High</td>
<td>V. High</td>
<td>V. High</td>
<td></td>
</tr>
<tr>
<td>Dawn</td>
<td>Normal</td>
<td>S. High</td>
<td>High</td>
<td>V. High</td>
<td>V. High</td>
<td>Vv. High</td>
<td>Vv. High</td>
<td></td>
</tr>
<tr>
<td>Morning</td>
<td>Low</td>
<td>S. Low</td>
<td>Normal</td>
<td>Normal</td>
<td>S. High</td>
<td>High</td>
<td>V. High</td>
<td></td>
</tr>
<tr>
<td>Afternoon</td>
<td>V. Low</td>
<td>V. Low</td>
<td>Low</td>
<td>Low</td>
<td>S. Low</td>
<td>Normal</td>
<td>Normal</td>
<td></td>
</tr>
<tr>
<td>Sunset</td>
<td>V. Low</td>
<td>Low</td>
<td>S. Low</td>
<td>Normal</td>
<td>S. High</td>
<td>High</td>
<td>V. High</td>
<td></td>
</tr>
<tr>
<td>Evening</td>
<td>Low</td>
<td>S. Low</td>
<td>S. Low</td>
<td>Normal</td>
<td>S. High</td>
<td>High</td>
<td>V. High</td>
<td></td>
</tr>
<tr>
<td>Night</td>
<td>S. Low</td>
<td>Normal</td>
<td>S. High</td>
<td>High</td>
<td>V. High</td>
<td>V. High</td>
<td>Vv. High</td>
<td></td>
</tr>
</tbody>
</table>
system consists of seven membership functions; in both universe of discourse of the Hour, and the Temperature: Vv (very very ) High, V (very) High, High, Normal, Low, V (very) Low and Vv (very very) Low. The output of the rule base system consists of nine membership functions, which are the same as the input’s membership functions, except that there are two extra membership functions added (S (small) High and S (small) Low), in order to increase precision of the output. All twelve monthly models have the same membership functions shape, however, they also have different input/output ranges. Figure 3.8 shows the proposed membership functions design for FFTFS in the January forecasting model.

Table 3.4 illustrates the membership function design for all 12-month FFTFS.

The twelve monthly models have different FFTFS designs. Use of each of the twelve designs results in different forecasting improvement outcomes. By considering the forecasting results from January operational data, variable amount of forecasting error is encountered throughout the month, however conservatively, the weakest forecasting region throughout January, which presents that highest amount of forecasting error, is shown in the results. Figure 3.9 shows the demand forecasting for the 17th to the 21st of January, year C, using ANFIS and FFTFS. The amount of forecasting improvement is calculated by evaluating the Root Mean Square Error (RMSE), Integral Square Error (ISE), and Mean Absolute Percentage Error (MAPE). From the results, it is found that FFTFS has an enhanced
Table 3.4: Membership function ranges design for the 12-month FFTFS

<table>
<thead>
<tr>
<th>Months</th>
<th>Temperature</th>
<th>Hour</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>January</td>
<td>[-10, 30]</td>
<td>[0, 24]</td>
<td>[-75, 75]</td>
</tr>
<tr>
<td>February</td>
<td>[-10, 35]</td>
<td>[0, 24]</td>
<td>[-75, 75]</td>
</tr>
<tr>
<td>March</td>
<td>[-10, 20]</td>
<td>[0, 24]</td>
<td>[-50, 50]</td>
</tr>
<tr>
<td>April</td>
<td>[15, 35]</td>
<td>[0, 24]</td>
<td>[-30, 30]</td>
</tr>
<tr>
<td>May</td>
<td>[0, 20]</td>
<td>[0, 24]</td>
<td>[-40, 40]</td>
</tr>
<tr>
<td>June</td>
<td>[0, 25]</td>
<td>[0, 24]</td>
<td>[-50, 50]</td>
</tr>
<tr>
<td>July</td>
<td>[-20, 20]</td>
<td>[0, 24]</td>
<td>[-50, 50]</td>
</tr>
<tr>
<td>August</td>
<td>[5, 20]</td>
<td>[0, 24]</td>
<td>[-30, 30]</td>
</tr>
<tr>
<td>October</td>
<td>[30, 70]</td>
<td>[0, 18]</td>
<td>[-200, 200]</td>
</tr>
<tr>
<td>November</td>
<td>[10, 50]</td>
<td>[-4, 18]</td>
<td>[-100, 100]</td>
</tr>
<tr>
<td>December</td>
<td>[-10, 20]</td>
<td>[-4, 18]</td>
<td>[-100, 100]</td>
</tr>
</tbody>
</table>

Table 3.5: Statistical results for each month with the improvement rate made by FFTFS-ANFIS model

<table>
<thead>
<tr>
<th>Month</th>
<th>ANFIS</th>
<th>FFSTFS-ANFIS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Rules</td>
<td>RMSE</td>
</tr>
<tr>
<td>January</td>
<td>28</td>
<td>0.0058</td>
</tr>
<tr>
<td>February</td>
<td>23</td>
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</tr>
<tr>
<td>March</td>
<td>14</td>
<td>0.0049</td>
</tr>
<tr>
<td>April</td>
<td>40</td>
<td>0.005</td>
</tr>
<tr>
<td>May</td>
<td>17</td>
<td>0.0059</td>
</tr>
<tr>
<td>June</td>
<td>25</td>
<td>0.0072</td>
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<tr>
<td>July</td>
<td>20</td>
<td>0.0072</td>
</tr>
<tr>
<td>August</td>
<td>19</td>
<td>0.0063</td>
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<td>September</td>
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<td>October</td>
<td>11</td>
<td>0.0058</td>
</tr>
<tr>
<td>November</td>
<td>16</td>
<td>0.006</td>
</tr>
<tr>
<td>December</td>
<td>20</td>
<td>0.0055</td>
</tr>
</tbody>
</table>

forecasting accuracy. Table 3.5 lists the statistical results evaluated for each month, and the improvement achieved by FFTFS.

It is shown from the applied statistical analysis, that the proposed design can successfully maintain the forecasting accuracy for year C, where its design was based on year A and year B data. The results obtained showed that the model has the ability to improve the forecasting accuracy and maintain it within a desired range. However, table 3.5 also shows that the range of improvement varies depending on the demand pattern in each month, where for certain months, FFTFS causes a deterioration of the forecasting accuracy as a result of some statistical measures. The deterioration of the monitored accuracy
Figure 3.9: Self tuning and ANFIS Demand forecasting in the ECU microgrid for the 17th to the 21st of January, year C

in these months is still acceptable, providing that the model is showing a positive attitude throughout the 12 months of the year. It is expected that any changes to future demand will cause a deterioration in the model. Even so, the overall performance after applying FFTFS to increase the model’s robustness is encouraging, and providing that this deterioration is always found to be within an acceptable error range, the overall results are significant and worthwhile in terms of improvement. Ultimately, FFTFS was added to the forecasting model to increase its robustness in parallel with the feedback adaptation tuning system.

3.5.3 FeedBack Tuning Fuzzy System (FBTFS)

The utilisation of actual demand as a feedback to the model will introduce a real-time adaptive demand forecasting capability. In order to introduce an external parameter so that we can improve the forecasting, the forecasting model is treated as a process, while the real time demand value is treated as the desired set-point. The difference between the forecast and the actual demand values is fed back to the model via a controller, in order to improve the subsequent forecasting accuracy, so that the system’s range of operation could
be established. In order to gain further insights into the design considerations, the system was simulated with a classical Proportional Integral (PI) system. After introducing PI to control the accuracy error, we monitored the performance of the model. In this work, the proposed PI controllers are manually tuned based on the error performance. At this stage, a decision was made to replace the classical PI with an intelligent system (fuzzy logic), largely because of its ability to achieve better transient response. The proposed intelligent system uses the measured error in order to: 1) adapt the subsequent forecasting output to the actual demand changes; and 2) control its accuracy. In this part of the model, the proposed two-inputs-one-output PI-fuzzy system was applied to redo the PI system's job. For the sake of simplicity, we proposed that a one rule based system for the 12-monthly demand models be deployed. The proposed intelligent system in this modelling strategy is the FeedBack Tuning Fuzzy System (FBTFS). In this component, the proposed rule base system was developed utilising knowledge about the power demand changes in the case study. Accordingly, the fuzzy systems have a set of other design parameters to cope with the 12-monthly demand patterns. Table 3.6 illustrates the rule base system for the proposed two-inputs-one-output FBTFS.

Table 3.6: Rule base table for the two-input-one-output FBTFS

<table>
<thead>
<tr>
<th>ΔError Error</th>
<th>Vv High</th>
<th>V High</th>
<th>High</th>
<th>Normal</th>
<th>Low</th>
<th>V Low</th>
<th>Vv Low</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vv High</td>
<td>V Low</td>
<td>V Low</td>
<td>Normal</td>
<td>S High</td>
<td>High</td>
<td>V High</td>
<td>V High</td>
</tr>
<tr>
<td>V High</td>
<td>V Low</td>
<td>S High</td>
<td>High</td>
<td>V High</td>
<td>V High</td>
<td>Vv High</td>
<td>Vv High</td>
</tr>
<tr>
<td>High</td>
<td>LOW</td>
<td>S LOW</td>
<td>Normal</td>
<td>Normal</td>
<td>S High</td>
<td>High</td>
<td>V High</td>
</tr>
<tr>
<td>Normal</td>
<td>Vv Low</td>
<td>V Low</td>
<td>LOW</td>
<td>LOW</td>
<td>S LOW</td>
<td>Normal</td>
<td>Normal</td>
</tr>
<tr>
<td>LOW</td>
<td>V Low</td>
<td>LOW</td>
<td>S LOW</td>
<td>Normal</td>
<td>S High</td>
<td>High</td>
<td>V High</td>
</tr>
<tr>
<td>V Low</td>
<td>LOW</td>
<td>S Low</td>
<td>S Low</td>
<td>Normal</td>
<td>S High</td>
<td>High</td>
<td>V High</td>
</tr>
<tr>
<td>Vv Low</td>
<td>S LOW</td>
<td>Normal</td>
<td>S High</td>
<td>High</td>
<td>V High</td>
<td>V High</td>
<td>Vv High</td>
</tr>
</tbody>
</table>

The rule base system consists of seven membership functions; in both universe of discourse of the error, and change of error (ΔError): Vv (very very) High, V (very) High, High, Normal, Low, V (very) Low and Vv (very very) Low. The range of the universe of discourse is set by analysing the error, and the change of error behaviour. Therefore the error and the change of error operation for the proposed model is set between -1650 and 1650 kW, in order to cover the maximum expected difference between the forecast and the actual demands, in the +ve and the -ve sides range. The output of the rule base system consists of nine membership functions, which are the same as the input’s membership.
functions, except that there are two extra membership functions added (S (small) High and S (small) Low), in order to increase precision of the output. These have a range of action between -600 and 600 kW. The same design parameters are applied for year C, as it is impractical to monitor and tune the gains manually based on the real time demand changes. In the design of the membership functions, triangular type membership functions were applied. Figure 3.10 shows the proposed membership function design for the FBTFS that we have developed.

For the proposed FBTFS, a manual gain selection was derived from the experience with the system’s operation, while trial and error tuning was also applied at the final stages of the design. Table 3.7 illustrates the gain values for the PI-FBTFS.

In proposing that the FBTFS will adapt the forecasting to the actual demand changes, the aim is to produce a model that can cope with the unmonitored demand changes, at the stage that it becomes impractical to tune the gains manually. The proposed FBTFS has the ability to cope with the monitored demand change, based on the manual defined settings. However the FBTFS, requires an optimised parameter selection in order to cope with the wide range of demand changes. The major obstacle that arises when performing
Table 3.7: Year B Model feedback fuzzy tuning system gains selection

<table>
<thead>
<tr>
<th>Month</th>
<th>$K_P$</th>
<th>$K_I$</th>
</tr>
</thead>
<tbody>
<tr>
<td>January</td>
<td>0.01</td>
<td>0.1</td>
</tr>
<tr>
<td>February</td>
<td>0.01</td>
<td>0.05</td>
</tr>
<tr>
<td>March</td>
<td>0.01</td>
<td>0.05</td>
</tr>
<tr>
<td>April</td>
<td>0.01</td>
<td>0.06</td>
</tr>
<tr>
<td>May</td>
<td>0.01</td>
<td>0.06</td>
</tr>
<tr>
<td>June</td>
<td>0.01</td>
<td>0.2</td>
</tr>
<tr>
<td>July</td>
<td>0.1</td>
<td>0.15</td>
</tr>
<tr>
<td>August</td>
<td>0.1</td>
<td>0.15</td>
</tr>
<tr>
<td>September</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>October</td>
<td>0.1</td>
<td>0.15</td>
</tr>
<tr>
<td>November</td>
<td>0.05</td>
<td>0.1</td>
</tr>
<tr>
<td>December</td>
<td>0.01</td>
<td>0.005</td>
</tr>
</tbody>
</table>

The optimisation, similarly to other optimisation techniques, is the parameter searching time. The proposed FBTFS was designed to adjust itself to the demand changes automatically in a one iteration optimised gain selection mechanism. This mechanism will make the searching time the lowest as compared with other optimisation techniques. An ANN optimisation technique was used to tune the fuzzy input parameters. The design for the ANN to take into consideration the 12-month demand patterns, thus 12 ANNs have been developed so that a high level of accuracy can be maintained throughout the year. In this modelling strategy, each ANN was trained to tune the fuzzy parameters, depending on the input pattern. Consequently an ANN model was implemented to perform the proposed online optimised FBTFS gains selection. Although ANFIS was successful in performing the modelling; when consideration was given to its training time and modelling performance; in this instance the optimisation technique was developed with back-propagation ANN. Back-propagation ANN was chosen because of the potential for ANN to achieve better performance with Multi Input Multi Output (MIMO) systems. In the proposed model it was found that fuzzy input parameters are the most effective parameters for controlling the forecasting accuracy. To implement an adaptive (tuneable gains) fuzzy system, three main issues must be considered simultaneously: 1) dynamic characteristics of a plant; 2) self-selection of the performance index; and 3) self-tuning of the controller parameters. In this work, FBTFS gain tuning was targeted. The proposed ANN was designed to optimise the gains selection by learning from the experience of selecting the relevant gain values for every expected demand pattern. For this auto-tuned FBTFS, a membership function design was firstly proposed having the same membership functions’ number of that in the manually tuned FBFTS, accept that a normalised universe of discourse is proposed, for
both the inputs and the output of this system as shown in Figure 3.11.

In order to collect the data that trains the ANN to perform an optimised gain selection, a range of historical operational data was generated. A software was developed to automate the process of generating and collecting the relevant data for the training purposes. The process of collecting the data was developed by setting a history of suitable gain selection for each specific range of operation. The suitable gain setting is arrived at by searching a range of gains with a specified precision, for that particular range of operation. The best selected gain values are determined by achieving the lowest statistical results for the forecasting error, within the investigated operation period. The search range converged around the manually tuned parameters, following which, the gains can then be set for the manually tuned FBTFS. This process reduces the searching time and resembles the behaviour of human-operator tuning. The limits and the precision of the search are established by setting the gains manually in the first instance, then by monitoring the attitude of the model. A data set of the most accurate results are then saved, along with their selected gain values for use in the next stage for the ANN training. In this phase of the work, demand is divided into a day-by-day demand change, where 29, 30 or 31 data sets are carried
out for each monthly model, depending on the month in question. The structure of the proposed ANN for the 12-monthly demand patterns consists of five-inputs (Temperature, Hour, Date, Date-type and month number) and two-outputs ($K_p$ and $K_i$), which represent the gains of the proposed PI-like fuzzy system. Tables 3.8 and 3.9 show the best nominated gain values for the FBTFS in everyday tuning throughout the year. These tables are used to build the optimisation ANN for tuning ($K_p$ and $K_i$) of the proposed FBTFS. The results in these tables are also used to identify the operational limits of $K_p$ and $K_i$. In addition, they are the key solutions for converging the optimisation decisions applied by the ANN.

From Tables 3.8 and 3.9, it can be seen that some of the selected gains have been chosen around the manually predefined gains values for the proposed models, while the rest have been selected as a result of having a large disparity in values. The variety present in the selection proves that the automated search process was successful in performing the scan over a wide range of operation by employing high resolution searching. Tables 3.8 and 3.9 also shows that $K_i$ affects the accuracy of the forecasting more than $K_p$, as it shows a wider range of change within the same month as compared with $K_p$. The set of historical operational data is used to develop the ANN for the proposed model. The selection of the ANN parameters is based on modelling experience and the type of system being modelled. The proposed ANN also includes one hidden layer network, with a bi-polar log-sigmoid activation function in the hidden layer, and a bi-polar linear type activation function in the output layer. Tables 3.8 and 3.9 illustrate the set of the best selected gains in the training data, out of the everyday data. For all of the proposed ANN, the training parameters including the used learning rate, number of nodes, and the resulted Mean Square Error (MSE) are illustrated in Table 5.3.

### 3.6 Results

The completed model was verified by employing realistic demand change data from ECU. The year C demand change data is utilised to perform the model testing and verify the robustness of the modelling strategy. The simulation started with the classical PI system to establish an understanding of the forecasting error behaviour, which resulted in various ranges of demand accuracy. The accuracy of the forecasts was evaluated by the statistical methods: RMSE, ISE, and MAPE. By looking at the results in Table 3.11, various demand improvement rates can be identified, depending on the non-linearity of the demand in each month, and depending upon the precision of the model. Starting with the classical PI
Table 3.8: The selected gains in the training data set of everyday data from January to June

<table>
<thead>
<tr>
<th>Day</th>
<th>Jan</th>
<th>Feb</th>
<th>Mar</th>
<th>Apr</th>
<th>May</th>
<th>Jan</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$K_P$</td>
<td>$K_i$</td>
<td>$K_P$</td>
<td>$K_i$</td>
<td>$K_P$</td>
<td>$K_i$</td>
</tr>
<tr>
<td>1</td>
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<td>0.075</td>
<td>0.01</td>
<td>0.02</td>
<td>0.05</td>
<td>0.011</td>
</tr>
<tr>
<td>2</td>
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<td>0.125</td>
<td>0.01</td>
<td>1</td>
<td>0.05</td>
<td>0.011</td>
</tr>
<tr>
<td>3</td>
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<td>0.02</td>
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<td>0.011</td>
</tr>
<tr>
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<td>0.01</td>
<td>0.02</td>
<td>0.05</td>
<td>0.011</td>
</tr>
<tr>
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<td>0.03</td>
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<td>0.011</td>
</tr>
<tr>
<td>8</td>
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<td>0.02</td>
<td>0.05</td>
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</tr>
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<td>-</td>
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</tbody>
</table>
Table 3.9: The selected gains in the training data set of everyday data from July to December

<table>
<thead>
<tr>
<th>Day</th>
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<th>Aug</th>
<th>Sep</th>
<th>Oct</th>
<th>Nov</th>
<th>Dec</th>
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<td>$K_P$</td>
<td>$K_i$</td>
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</tr>
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<td>0.1</td>
<td>0.15</td>
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</tr>
<tr>
<td>3</td>
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<td>0.01</td>
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<td>0.11</td>
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<td>0.51</td>
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<td>0.15</td>
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</tr>
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<td>0.51</td>
</tr>
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<td>0.1</td>
<td>0.15</td>
<td>0.01</td>
<td>0.51</td>
</tr>
<tr>
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<td>0.2</td>
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<td>0.1</td>
<td>0.15</td>
<td>0.01</td>
<td>0.51</td>
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<td>0.15</td>
<td>0.01</td>
<td>0.06</td>
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<td>0.15</td>
<td>0.01</td>
<td>0.06</td>
</tr>
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<td>0.15</td>
<td>0.01</td>
<td>0.51</td>
</tr>
<tr>
<td>31</td>
<td>0.2</td>
<td>0.07</td>
<td>0.1</td>
<td>0.11</td>
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</tr>
</tbody>
</table>
Table 3.10: Neural networks design parameters for the gain adaptation of the 12-month forecasting FBTFS

<table>
<thead>
<tr>
<th>Month</th>
<th>Nodes</th>
<th>Learning Rate</th>
<th>epochs</th>
<th>MSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>January</td>
<td>25</td>
<td>0.05</td>
<td>7</td>
<td>0.0022287</td>
</tr>
<tr>
<td>February</td>
<td>10</td>
<td>0.05</td>
<td>135</td>
<td>0.00935</td>
</tr>
<tr>
<td>March</td>
<td>10</td>
<td>0.05</td>
<td>2</td>
<td>0.0000481</td>
</tr>
<tr>
<td>April</td>
<td>15</td>
<td>0.05</td>
<td>2</td>
<td>0.00602</td>
</tr>
<tr>
<td>May</td>
<td>10</td>
<td>0.05</td>
<td>2</td>
<td>0.0011696</td>
</tr>
<tr>
<td>June</td>
<td>20</td>
<td>0.05</td>
<td>3</td>
<td>0.0083366</td>
</tr>
<tr>
<td>July</td>
<td>20</td>
<td>0.05</td>
<td>2</td>
<td>0.0027826</td>
</tr>
<tr>
<td>August</td>
<td>7</td>
<td>0.05</td>
<td>2</td>
<td>0.0002594</td>
</tr>
<tr>
<td>September</td>
<td>20</td>
<td>0.05</td>
<td>1</td>
<td>0.008631</td>
</tr>
<tr>
<td>October</td>
<td>11</td>
<td>0.05</td>
<td>4</td>
<td>0.007355</td>
</tr>
<tr>
<td>November</td>
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<td>0.08</td>
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<td>0.005618</td>
</tr>
<tr>
<td>December</td>
<td>15</td>
<td>0.05</td>
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<td>0.0002097</td>
</tr>
</tbody>
</table>

system, a wide range of statistical results were identified, as differences arise from the number of days (29, 30 or 31) in the month, in addition to the different demand patterns that are encountered throughout the year. From the control theory point of view, a slow response was observed when the tested interval time was less than the required transient time, in order to completely eliminate the error of the forecast demand. That was why the system recorded this value of the steady state error for the simulated periods. This problem was partially resolved by adding the intelligent FBTFS, as it was proposed that the applied rule based system, with its control action, was able to achieve a faster response than it could achieve with the classical PI system.

In the case of the intelligent system, manual and automatically tuned two-inputs-one-output FBTFS were tested. When the automatic tuning is considered, the target becomes achieving an optimum forecasting accuracy with the lowest evaluated statistical error. A safety margin is added to the forecast output to ensure that the forecast is always above the actual demand. Thus safety can be guaranteed after nominating the required number of generators for every 30 minutes interval. The result is presented in Table 3.11 in terms of the type of the used feedback system in each month models.

From Table 3.11, it was shown that the proposed FBTFS, in its manual and automatic tuning, was superior to the classical PI system in improving the forecasting accuracy. It is also shown that the FBTFS had a faster tracking response than that of the classical PI system. This proves that the knowledge embedded in the FBTFS rule base system could achieve better transient response for the forecasting error control system. Therefore, for
Table 3.11: The statistical analysis results in each month with improvement rate made by the auto tuned FBTFS over the manually tuned and PI system

<table>
<thead>
<tr>
<th>Month</th>
<th>Classical PI</th>
<th>Manual Tuning</th>
<th>Automatic Tuning</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RMSE</td>
<td>ISE</td>
<td>MAPE</td>
</tr>
<tr>
<td>January</td>
<td>0.0024</td>
<td>24160</td>
<td>29%</td>
</tr>
<tr>
<td>February</td>
<td>0.0025</td>
<td>23590</td>
<td>25.1%</td>
</tr>
<tr>
<td>March</td>
<td>0.0024</td>
<td>25130</td>
<td>27%</td>
</tr>
<tr>
<td>April</td>
<td>0.0024</td>
<td>24150</td>
<td>29%</td>
</tr>
<tr>
<td>May</td>
<td>0.0024</td>
<td>24640</td>
<td>31.5%</td>
</tr>
<tr>
<td>June</td>
<td>0.0024</td>
<td>24590</td>
<td>32.9%</td>
</tr>
<tr>
<td>July</td>
<td>0.0024</td>
<td>24720</td>
<td>33%</td>
</tr>
<tr>
<td>August</td>
<td>0.0024</td>
<td>24820</td>
<td>32.8%</td>
</tr>
<tr>
<td>September</td>
<td>0.0024</td>
<td>23940</td>
<td>31%</td>
</tr>
<tr>
<td>October</td>
<td>0.0025</td>
<td>23980</td>
<td>31%</td>
</tr>
<tr>
<td>November</td>
<td>0.0025</td>
<td>23010</td>
<td>31%</td>
</tr>
<tr>
<td>December</td>
<td>0.0024</td>
<td>24690</td>
<td>32.7%</td>
</tr>
</tbody>
</table>

the same simulated periods, better demand forecasting accuracy had been achieved. A different range of improvement was recorded when simulating the proposed model with the FBTFS throughout the year; mainly because of the difference in the demand change patterns throughout the year. It is observed that the results are generally better, except in December and February. Realistically, an imperfect result is still expected, largely because of the unmonitored behaviour of the controller, along with the unexpected type of demand pattern. The results can be enhanced by tuning the model’s parameters based on the forecasting error rate. This task can be formulated as an optimisation problem that aims to find optimum modelling values based on the amount of error measured at time of forecasting. Yet the proposed model is also expected to encounter this limitation with other months when a completely different demand change is encountered. From simulating the model with year C data and comparing Figure 3.12 with Table 3.8, a clear understanding about the robustness of the proposed ANN in this role was established. This reveals that $K_i$ is reacting more than $K_P$, as the demand changes, which shows that the developed ANN was successfully reflecting the smart search mechanism for the optimised gain selection. Ultimately, the proposed optimisation technique was well modelled, thus the forecasting model was achieving the required level of accuracy. Figure 3.12 shows $K_P$ and $K_i$ behaviour for the same simulation period that was presented in Figure 5.5. As it is clearly shown in this Figure, $K_P$ was not active in changing the demand forecasting accuracy in the working days from Monday till Friday; whereas in the weekend, it had a large role in changing the demand forecasting output. Importantly these results reflect the attitude of the ANN, which has been taught how to select the best gain for each
demand pattern; consequently $K_P$ was found with higher values in the weekends. As it is observed that the forecast error rate was generally higher on weekends than on working days, changing $K_P$ was more beneficial in achieving lower error rate. However, the results show that $K_i$ had more effect on the demand changes throughout the week. The results of the analysis will give pertinent information for building a more accurate demand forecasting model in future extensions to this work. Table 3.11 shows that the accuracy was improved over the classical PI system by adding intelligence, especially by implementing the ANN based, auto tuned, two-input-one-output fuzzy systems. The results also show that the use of optimisation techniques to perform automatic gain selection, achieved better forecasting with an average improvement rate of 5.6% compared with the manually tuned systems. To show the results of the proposed forecasting model, Figure 5.5 illustrates the forecasting output for the period from the 17th until the 23rd of January, year C.

![Figure 3.12: $K_P$ and $K_i$ behaviour in feedback-tuning fuzzy system ANN](image)

Figure 3.12: $K_P$ and $K_i$ behaviour in feedback-tuning fuzzy system ANN
Figure 3.13: The proposed model forecasting output for the period from the 17th till the 23’rd of January, year C

It also shows the added safety margin value over the actual load, in order to prepare the forecasting for the generation scheduling application. In Figure 5.5, the results were also shown in terms of the load profile for the normal working days and the weekend.

In the results shown in Figure 5.5, it is observed that there is an array that indicates the number of the assigned generators, evaluated as a result of bundling the evaluated demand into 500 kW lots. The nominated number of generation units was either increased or decreased in each 500 kW demand increment or decrement as shown in Figure 5.5. It is shown that the number of nominated generation units was evaluated by adding the safety generation margin to the demand. Table 3.12 reflects more details about the actual, forecast and supplied electric energy to the case study, along with the generation schedule based on the amount of demand. In this Table, (1) indicates active generation and (0) indicates inactive generation.

Based on the demand (of multiples of 500 kW), a lost generation (reserve) amount equal to the difference between the actual demand and the generated energy from the nominated
Table 3.12: Number of generators relating the predicted demand

<table>
<thead>
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<th>Hour</th>
<th>Generators</th>
<th>Demand kW</th>
<th></th>
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<th></th>
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<td></td>
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<td>G3</td>
<td>G4</td>
<td>G5</td>
<td>G6</td>
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</tr>
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<td>0</td>
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</tr>
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</tr>
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<td>1</td>
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<td>1</td>
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</tr>
</tbody>
</table>

generation units was expected. A future extension to this work may be in researching the reduction in the amount of lost generation through further optimisation. Figure 5.5 also shows that the assigned generator duty is rotated over the installed generators to achieve longer waiting and operation times, which leads to a longer life time cycles for the installed generation units. In the case study where the safety margin is added to the demand value, it was anticipated that the lowest possible switching time from OFF to ON or from ON to OFF for any generation units be not less than 3 hours; which is indicated in the demand change between hour 100 and 150 in Figure 5.5. A clearer view about the relationship between the demand forecasts and the generation scheduling with multiple sources of dispatch is provided in Chapter 4.

3.7 Closing remarks

In this chapter, we presented an adaptive demand forecasting model where the actual real-time load changes were included in the short term forecasting. Firstly, an investigation was conducted into the design of a model of the load profile in a university type power system. In addition, model stability was tested and improved by adding a self tuning fuzzy system. However, the main aim was to develop a model which included the real-time load changes in the forecast output. These changes were incorporated within the forecast
through the actions of an intelligent system performing adaptive demand forecasting. The model employs an optimised parameter selection to suit the demand characteristics. The results demonstrated that the optimised parameters selection for tuning the adaptation parameters has been implemented successfully. Moreover, the results also proved that this auto-tuned adaptation system was superior to the manually tuned systems in providing an accurate forecast. Ultimately, in this chapter, we have successfully introduced a novel demand forecasting model that adapts itself to the real-time load variation and reduces the subsequent forecasting error accordingly. After scaling the forecasting values with the necessary safety factors, the potential for utilising the adaptive forecasting in the generation scheduling problem was investigated. Finally, the model output is then sent to the other intelligent modules, responsible for scheduling and managing the installed resources in the case study. For future extensions to this work, scope exists for an investigation into tuning the adaptation fuzzy membership functions in order to further improve the accuracy of the system.
Chapter 4

Power Generation Management and Storage Devices Control System

This chapter details the second intelligent module in our management system. Since Storage Devices (SDs) can contribute most to improving power generation performance when they include other sources of dispatch such as renewable energy sources and micro-turbines, the potential for utilising SDs more efficiently is critically important. In this chapter, we will look at the possibilities of achieving the lowest economic and environmental costs for the targeted case study. The major challenges that we expected to be confronted with in order to achieve these goals were: 1) tackling the uncertainty of demand, 2) generation cost, 3) availability of renewable energy sources, and 4) (charging/discharging) time, and price for the installed SDs. Therefore, the goal of this research was an optimisation technique, that encompassed a strategy to achieve the lowest generation cost from multiple sources, and was also able to perform smart utilisation for the SDs with these sources. The first task was to estimate the best charging price for the SDs, in order to achieve a profitable charging and to maximise the opportunity to participate during the SDs’ lifetime; as this would result in a greater efficiency for the installed SDs. A Fuzzy Logic (FL) based adaptive charging price was set for charging the SDs, which was based on monitoring the microgrid’s local generation price at the time of charging, and the amount of the daily SDs participation in the microgrid dispatch. Thereafter, when the SDs status was evaluated, another stage of calculation was conducted in 30-minute intervals, in order to evaluate the optimum amount of dispatch from each participant source. A multi-objective Particle Swarm Optimisation (PSO) method was applied to achieve the targeted low generation costs. This chapter will detail the design and testing of the proposed technique as follows: Sections 6.1 and 5.2 consider the historical background and relate other researchers’ work to the proposed method. Section 5.3 details the targeted problems and the main solution.
objectives of the proposed method. Section 4.4 discusses the research assumptions that underpin the design considerations in order for the research results to have significant and reasonable justifications. For the planning side of this study, Sections 4.6 and 4.5 cover the installation of renewable energy sources for the case study. Section 4.7 details the proposed optimisation technique in this work Sections 6.6 and 6.7 discuss the results and provide recommendations for future research.

4.1 Background

Just as the deregulation of electricity power markets has empowered the business of power generation in the recent years, the prospective Smartgrid will move residential and small business electricity power consumers/producers beyond the role of passive price accepters in the near future. Therefore, dealing with the complex management of a network of networks will be one of the most active research fields in power engineering. When considering our case study, the provision of management solutions for the power flow of the decentralised resources will facilitate future connections with the Smartgrid. Although sufficient intelligence in the current traditional grid exists, performance can still be improved by introducing more sophisticated infrastructure. Therefore, starting to upgrade the decentralised power systems is a major participation in building the Smartgrid. The current level of intelligence can support a high level of performance, including demand response and smart utilisation for the installed resources. However, running a beneficial microgrid requires initial management strategies to control the resources within the grid. Due to the high non-linearity in system operation models, there are diverse options for improving the performance of the electricity supply for such power systems. The problem arises due to the uncertainty of demand, generation cost, availability of renewable energy sources and (charging/discharging) time and price for the participant SDs, if there is any. This problem is considered to be a power engineering optimisation problem, especially when the power flow encompasses intermittent generation in line with highly non-linear demand. Eventually, efficient utilisation of SDs within microgrids among multiple sources of dispatch has a substantial impact on reducing the economic and the environmental generation costs. The dynamic charging price for the SDs was identified to be the key to achieve a profitable charging, and also to maximise the opportunity of participation during the SDs lifetime. By considering both the economic and environmental generation costs in the decisions made to optimise the performance of SDs, a multi-objective optimisation method is required for this role. Therefore, studying the operational conditions of the case
study is crucial before selecting the right method and nominating the operational factors that can reduce the generation cost. In this work, a general review about the targeted case study will be covered in Section 4.5, to highlight the effective generation cost factors, and also to identify the constraints that need to be considered in the calculation required to make the optimum generation decisions.

4.2 Related works

The operational management of microgrids and large power grids was compared, and it was found that from both the economic and environmental perspective, microgrids could successfully reduce generation costs and CO2 emissions [145]. Computational intelligence methods such as Mesh Adaptive Direct Search (MADS), FL, PSO, and Ant Colony Optimiser (ACO) have been introduced to deal with this problem by minimising the generation cost by considering the environmental issues in [146, 147, 148, 149]. A mixed integer nonlinear cost function was proposed to minimise the operation cost in [150], while the potential financial return for utilising electrical vehicles as a grid resource was addressed in [151].

Successful microgrid management strategies can include other factors that result in a better operational performance, such as smart utilisation of the resources and loads within the managed microgrid. Optimal operation strategies have been formulated for smart microgrids in [152], to accommodate the integration of renewable energy sources and maximise the profit for microgrid systems in Taiwan. On this basis, SDs have been nominated as a solution to maximise the profit and increase the microgrid operation efficiency. SDs have been proved to play a key role in improving microgrids’ DER performance, and also in providing more reliable ancillary services to the power grid in [153, 154]. Moreover SDs have been utilised to stabilise the operation of microgrid by tackling the fluctuation and intermittence resulted from unstable micro-sources and nonlinear loads in [155].

In smart buildings, SDs have been applied to reduce energy cost in [156]. This proves that SDs can tackle the variable generation price problem and can benefit microgrids that include autonomous generators, renewable sources and controllable loads.

The concept of demand response or smart load shedding can enhance the overall management performance in microgrids. Dealing with the behaviours of numerous consumers in an intelligent fashion can result in a low cost generation for such microgrids. This was proved by using a mixed integer linear program to include on-site electricity power generation facilities for an organisation with numerous employees in [157].
Since SDs can work as either loads or sources, depending on the situation, managing them yields a complex optimisation problem. Microgrid operation uncertainty problem, as a result of incorporating multiple type of DER including SDs, has been presented in [158]. As discussed earlier in this chapter, while the complexity is elevated by the uncertainty associated with their assigned dispatch, charging time and price, and life time; their smart utilisation yields rapid performance improvement. Power quality issues are still the major problems associated with incorporating SDs in the grid, so a decentralised electricity SDs may solve power quality problems in microgrids [159, 160]. Microgrid power quality problem has been illustrated in [161], where a novel approach has been proposed to compensate for the voltage harmonics in a grid-connected microgrid. This problem has been resolved using a proper control for the distributed generators interface converters to provide a high voltage quality at the point of coupling. Electric vehicles have also been utilised in balancing the microgrids’ voltage and frequency. The control and management strategies for unbalanced microgrid voltage that incorporates electrical vehicles have been identified in [64]. The role of integrating SDs in building a reliable microgrid power dispatch has also been discussed in the literature, as they can dictate the economic benefits for the current grid, if they are upgraded with the needed infrastructure for Smartgrid integration [162]. SDs (electric vehicles) have had major impact on reducing the capital costs of microgrids [163]. SDs have also been utilised to manage the power flow in microgrids in [164]. Ultimately, the key issue for performing smart utilisation for the SDs is their charging/discharging time and cost. A smart charging method with a load control management module has been presented in [165].

A literature analysis has revealed that efforts to enhance the performance of the microgrid’s operation through the use of numerous employees, is a key topic in the power engineering research field. Therefore, the study proposes a power generation management system that seeks an optimum generation cost for the microgrid. Since the major challenge will be the SDs charging/discharging time and price uncertainties, their utilisation (charging/discharging) control was targeted at this stage. The proposed control method will consider demand and price changes, in order to achieve the optimum utilisation for the SDs and the lowest possible generation cost for the same microgrid. This method will be implemented and tested in this chapter as an independent system, works autonomously to provide optimum decisions concerning the power generation in a microgrid. This method will also be implemented as a decentralised module, controlled by a central processing unit, to deal with more complicated operational scenarios in making optimum decisions.
concerning the power generation of a microgrid. This implementation is not covered in this chapter, and it will be detailed in Chapter 6.

4.3 Research objectives and challenges

Performing low cost generation for a microgrid that encompasses multiple sources of generation, including intermittent renewable sources (wind and solar), SDs (batteries and electrical vehicles), distributed gen-sets (gas or diesel), and utility grid; is a complex optimisation problem. Therefore, to cope with the uncertainty of the demand and supply from different power sources, a comprehensive study was needed prior to nominating this optimisation method. The study was mainly conducted due to the necessity to identify the challenges encountered with operating the distributed generators in the microgrid. Ultimately, the challenges identified are:

1. The intermittent nature of renewable generation sources.
2. The variable demand.
3. The dynamic utility price change.
4. The uncertain charging price and time SDs.
5. The difficulty of finding simultaneous solutions for achieving low economic and environmental generation costs.

The following sections will broadly identify the solutions for these challenges, along with the design details for the proposed optimisation technique.

4.4 Research assumptions

The following assumptions were made prior to testing our power generation management method:

1. Data are read from source files which have been pre-prepared to behave like real-time systems.
2. The effective price change sampling time that is needed to set the SDs charging price, is seven operational days.
3. SDs' lifetime is not considered in the calculations of generation cost.
4. The electricity power generated from the microgrid resources is with reasonable power quality.

5. Both microgrids’ local generation cost and external utility cost are proposed to be competitive with each other; varied in response to the operational conditions.

4.5 Case study

In this work we have targeted the power grid of Edith Cowan University (ECU), Joondalup Campus in Western Australia as a case study for simulating the proposed optimisation method. The case study is a High Voltage (HV) customer for the major power utility supplier in Western Australia. In Western Australia, HV network connection is obliged for customers consuming more than 2 MVA. This kind of connections forces customers to install their transformers on the network, but it also allows customers to freely configure their Low Voltage (LV) network. The nature of connection of our case study allows the system operator to freely select the design of the power network, including installing distributed generators. On this basis, we study the possibilities of including solar panels, wind turbines, storage devices, distributed gas gen-sets, and utility connection for supplying the case study with the required power, as illustrated in Figure 4.1. From monitoring the operational conditions around the Joondalup’s campus power grid, a range of possible generation scenarios were estimated. Accordingly, in order to obtain more precise results about the generation scenarios so that simulation data for testing could be accurately compiled, some planning studies were made for installing renewable energy sources on the existing grid. Consequently, semi-realistic operational data for the generation scenarios will be available to test the proposed optimisation technique for the case study. Although some of the required simulation data were collected directly from the system’s archive, the rest were generated based on several engineering assumptions underpinning the planning results. The simulation data were compiled using realistic historic operational conditions pertaining to the case study, such as the weather conditions, generation cost, and the internal demand.

The first challenge in compiling the needed simulation data was in forecasting the internal electricity demand for the case study. In the simulation, the demand data will be received from the demand forecasting model agent every 30-minutes, based on predefined communication settings amongst the proposed agents. The other challenge in compiling the simulation data was in evaluating the relative amounts of distributed generator penetration.
for the case study. Based on the design considerations for installing distributed generation units, a comprehensive study was made of solar panel and wind turbine installations for the case study, as detailed in the next section.

4.6 Planning for installing solar panels and wind turbines

For this project, realistic operational scenarios were not available; therefore the research was aligned with the planning for installing distributed generators on the existing ECU’s microgrid. The major planning limitation was the availability of installation space. A sufficient share of renewable energy supply, requires a high number of generation units located within new or existing facilities; or at more remote installation sites. There is still an alternative solution for solving the installation space problem, which is to increase the utility grid share in such a way that is compatible with utilising all the available space in the project land, and then supplying the rest from the utility grid. The Smartgrid connection is another planning consideration. Since Smartgrid is a foundation for commercialising energy suppliers, it will be a key solution for solving the installation space problem. Smartgrid will allow the private sector to feed energy into the public grid. The power consumers will be able to get their powerback from the Smartgrid from different
substations in different locations covered by the Smartgrid connection. Selling and buying power to and from the grid from different locations will impose other expenses, which will be analysed from an economic perspective, and added to the project cost. Figure 4.2 shows the proposed planning strategy for adding renewable energy sources to an existing microgrid.

ECU’s microgrid at its Joondalup campus was selected as a case study for project development planning. The average climate from minimum to maximum values and safety limits are considered in the studies. The City of Joondalup is located in one of the world’s five Mediterranean climate zones.

The geographical information for this city is
- Country: Australia
- State: Western Australia
- City: Joondalup
- Latitude: 31.44° S
- Longitude: 115.45° E
- Elevation / Altitude: 25 m
- Average solar irradiation: 5.35 kWh/m²/day
- Average wind speed: 12.24 km/h

The above details are helpful for identifying the installation challenges and likely solutions when employing solar panels and wind turbines. For maximum output, solar-electric (photovoltaic; PV) modules or solar thermal collectors need to be located where they receive the most sunshine. Ideally, the installation site should not be shaded by hills, trees, buildings, or other obstructions at any time during the year; so identifying the best location can be a complex undertaking.

Based on the university’s power demand readings, the highest amount of demand per hour occurs on summer’s afternoons, reaching 3 MWh; while the lowest energy occurs on winter nights or holidays, falling to a low of 0.5 MWh. To meet the existing demand at ECU’s Joondalup campus, a specific number of solar panels and wind turbines are needed. As the highest demands are always during the day time, more emphasis should be placed on solar panels, rather than on wind turbines.
Figure 4.2: Project development planning flowchart
4.6.1 Solar panel installation

Based on the installation space available in the case study, we found that it is possible to utilise $5193.2\ m^2$ for installing solar panels. After an investigation on the cost and the amount of generation to identify the most feasible solar panels for this project, the “Sharp NUS5E3E 185 W mono” was selected. Each solar panel unit requires $(1318 \times 994 \times 46)\ mm^2$ of the available installation space. This results in an installation of 3964 solar panel units, which is estimated to deliver up to 735 kWh at its maximum generation capacity.

Generation outcomes were estimated based on the City of Joondalup climate data, and the generation efficiency of solar panels from a variety of manufacturers. For best generation outcomes, the installation angles of the solar panels must be adjusted according to the location of the project, and the angle of the sun during the winter and summer seasons. To optimise the installation of solar panels for the city of Joondalup, the angle of inclination should be adjusted to $23^\circ$, facing north, as depicted in Figure 4.3.

![Solar Panel Installation Diagram](image)

Figure 4.3: Summer, winter and optimal angles for solar panel installation
The average lost generation for solar panel was estimated to be about 10% of the overall annual generation capacity; arising from such installation challenges as sub-optimal angles of inclination and shading by trees and built-structures.

### 4.6.2 Wind turbine installation

The useful energy contribution (work) gained by capturing the available wind energy, is calculated by summing the amount of generated power over time, taking into account variation in wind and operational conditions. The relationship between the size of the wind turbine and the generation outcomes may vary, depending on the threshold point for wind speed and the amount of wind speed available annually. From the climate study results, it has been shown that wind speed drops to zero from midnight till sunrise on a regular basis. The average wind speed is 12.24 km/h, while the minimum and maximum (monthly average) wind speeds are 9.36 km/h and 15.84 km/h respectively. The minimum wind speed required to activate generation in the nominated unit is 9 km/h. For a secure power supply design, the utility supply will cover the missing hours of generation during situations when both the solar panels and wind turbines are ineffective. The wind speed readings were collected from the City of Perth station, which is located about 20 km south from the project location.

As a conservative estimate, the average monthly wind speed at 9 am for the City of Perth, since 1993 is illustrated in Figure 4.4.

From the climate study, the estimated average of missing wind generation hours varied between 20 hours in the winter season, and zero hours per day in the summer season. For wind turbines, the technical layout and design of the wind park installations are important. When installing several wind turbines concentrated in an array, the major challenge which arises is the spacing between turbines. Hence in this study, wind turbines noise has been ignored. The relationship between rotor distance and aerodynamic array efficiency is illustrated in Figure 4.5. A minimum clearance between the wind turbines must be guaranteed, otherwise power losses will be so high that the wind park will not operate economically.
Figure 4.4: Average monthly wind speed in the city of Perth [3]

Figure 4.5: Aerodynamic array efficiency as a function of rotor distance in the wind direction [4], where $D$ is the wind turbine rotor diameter, $dl$ is the space length between the two installed wind turbines in project land, and $dc$ is the space width between the two installed wind turbines in project land.
In this case, the “WinPower 48V DC/240V 2000Watt” product was selected after studying the suitability of many other products for this project. The selected unit carries a 4 m rotor diameter. Accordingly, 300 m$^2$ of installation space is required for each unit, which provides for the 83 wind turbines for this project. Therefore, it is expected to receive up to 250 kWh from the proposed wind turbines.

This influences the required space needed for this project at Joondalup, where space can be limiting. However, for the Smartgrid connection, an off-campus location is used and land cost becomes a factor. For this project, a satellite image for the project’s land is added to identify available allocated installation space for solar panels and wind turbines as shown in Figure 4.6.

![Figure 4.6: A satellite image for the case study shows the available allocated installation space for solar panels and wind turbines](image)

Other calculation assumptions for the missing generation hours due to clouds and low speed wind have to be considered under generation capacity for the installed renewable energy sources. The average calculated missing hours of generation are summarised in Table 4.1, based on the 10 years of weather data obtained from the Australian Bureau of
Table 4.1: The daily average of missing generation hours

<table>
<thead>
<tr>
<th>Energy Source</th>
<th>Day time (8:00-17:00)</th>
<th>Night time (17:00-8:00)</th>
<th>Total missing hours</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wind turbine</td>
<td>3 hours</td>
<td>7 hours</td>
<td>10 hours</td>
</tr>
<tr>
<td>Solar panel</td>
<td>2 hours</td>
<td>13 hours</td>
<td>15 hours</td>
</tr>
</tbody>
</table>

Table 4.2: Estimated generation capacity for the simulated resources

<table>
<thead>
<tr>
<th>Source</th>
<th>Capacity (kWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$G_P$</td>
<td>0-3500</td>
</tr>
<tr>
<td>$P_{hG}$</td>
<td>0-735</td>
</tr>
<tr>
<td>$W_G$</td>
<td>0-250</td>
</tr>
<tr>
<td>$S_G$</td>
<td>0-350</td>
</tr>
<tr>
<td>$U_G$</td>
<td>0-Demand</td>
</tr>
</tbody>
</table>

Meteorology [3].

4.6.3 Other resources installation

In case of gas gen-sets; other studies were applied in order to identify the design requirement for installing distributed gas generators on the campus property. The major concern regarding the installation of the distributed generators, comes from the demand limits. Depending on structure and the load distribution in the case study, it was more suitable to bundle the demand into 0.5 MW lots; thus a set of 0.5 MWh gas generators have been identified for this design. Therefore in order to cover this demand, the design requires the installation of local generation units that provide 3.5 MWh, based on the inclusion of an extra generation unit for safety and emergency requirements. Finally, in the proposed management software, seven gas gen-sets, each of 0.5 MWh of capacity, were incorporated to meet the maximum demand, including the added safety dispatch. For storage devices needs, it was estimated that 0.35 MWh would be needed to provide the total required generation capacity.

The final simulation data ranges are illustrated in Table 4.2.

Subsequently, gas generation costs were estimated based on gas price information for Western Australia in [166]. It was necessary to convert the units of gas supply into $Nm^3/hr$ to follow the gen-sets fuel consumption units standard:

$$1 Nm^3/hr = 0.031736 GJ$$

There is also an additional variable cost resulting from the operating and starting-up
and shutting-down costs for the installed units; in addition to the fixed annual maintenance and insurance costs, where the final gas generation cost is evaluated as follows:

\[ G_p = G + MoV + MoAn \]  \hspace{1cm} (4.2)

Based on a management decision, the gas generation was prioritised as the second major supplier after the utility, due to the sustainability of the utility supply. The future electricity utility prices in Western Australia can be predicted by multiplying the price by the dynamic energy price change pattern observed in Australia’s eastern states. The price change pattern data was provided by AEMO [167].

### 4.7 Power generation management and storage control

The proposed management method encompasses three stages of calculation: 1) microgrid internal operational conditions monitoring, 2) SDs operation control using FL system, and 3) overall optimum generation cost management decisions using PSO. Figure 4.7 illustrates the proposed SDs charging management strategy block diagram.

The three stages of calculation are illustrated as follows:

#### 4.7.1 Monitoring the microgrid’s internal operational conditions

In this work, a method for monitoring the microgrid’s internal operational conditions, is applied to build a rule base for charging the SDs. Based on evaluating the economic and environmental cost factors in the most recent seven days of operation, an adaptive rule base can be obtained to tackle the non-linearity of the operational conditions. The SDs charging price is set as the difference between the mean of the maximum daily prices, and the mean of the minimum daily prices for \( U_p \) or \( G_p \). These values are updated every 24 hours, to follow the most recent daily price change trends based on monitoring the most recent seven days of operation. Figure 4.8 shows a sample of seven days of price change, which helps to identify the minimum and maximum price values, thus finding \( G_{ChP} \) and \( U_{ChP} \), which will in turn set the discharging price for SDs.

For discharging; decisions are made by the PSO in the later stages of calculation which will be discussed in subsection 4.7.3. However, a decision will then be made, based on comparing the SDs dispatch cost with other dispatch parameter cost; e.g., gas, and utility dynamic generation price. To implement smart involvement for the SDs in dispatching the electricity power for the managed microgrid, a fuzzy system described in subsection
Figure 4.7: The proposed SDs charging management strategy block diagram
Figure 4.8: A sample of seven days generation price change for $G_P$

Table 4.3: Local generation price based on the demand, the availability of the sources and the dynamic generation price within the managed microgrid

<table>
<thead>
<tr>
<th>Price</th>
<th>$RE \geq Dmnd$</th>
<th>$RE &lt; Dmnd &lt; RE + S_G$</th>
<th>$Dmnd \geq RE + S_G$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$G_P &lt; U_P &lt; S_P$</td>
<td>0</td>
<td>$G_P \cdot (\frac{G_S G}{Dmnd})$</td>
<td>$G_P \cdot (\frac{Dmnd - (P_{G1} + W_G)}{Dmnd})$</td>
</tr>
<tr>
<td>$G_P &lt; S_P &lt; U_P$</td>
<td>0</td>
<td>$G_P \cdot (\frac{G_S G}{Dmnd})$</td>
<td>$G_P \cdot (\frac{Dmnd - (P_{G1} + W_G)}{Dmnd})$</td>
</tr>
<tr>
<td>$S_P &lt; G_P &lt; U_P$</td>
<td>0</td>
<td>$S_P \cdot (\frac{S_G}{Dmnd})$</td>
<td>$G_P \cdot (\frac{Dmnd - (P_{G1} + W_G)}{Dmnd})$</td>
</tr>
<tr>
<td>$U_P &lt; G_P &lt; S_P$</td>
<td>0</td>
<td>$U_P \cdot (\frac{U_G}{Dmnd})$</td>
<td>$U_P \cdot (\frac{Dmnd - (P_{G1} + W_G)}{Dmnd})$</td>
</tr>
<tr>
<td>$U_P &lt; S_P &lt; G_P$</td>
<td>0</td>
<td>$U_P \cdot (\frac{U_G}{Dmnd})$</td>
<td>$U_P \cdot (\frac{Dmnd - (P_{G1} + W_G)}{Dmnd})$</td>
</tr>
<tr>
<td>$S_P &lt; U_P &lt; G_P$</td>
<td>0</td>
<td>$S_P \cdot (\frac{Dmnd - (P_{G1} + W_G)}{Dmnd})$</td>
<td>$U_P \cdot (\frac{Dmnd - (P_{G1} + W_G)}{Dmnd})$</td>
</tr>
</tbody>
</table>

4.7.2 was developed with two inputs. The first input is the local generation price, which was initially evaluated by studying each and every operational scenario in the microgrid. Eventually, it was represented by the equations illustrated in Table 4.3. These equations were derived to reflect the amount of generators’ participation in supplying the power required to match the microgrid’s demand. The operational scenarios are identified by three factors: 1) the demand value, 2) the resources generation availability, 3) and the dynamic generation cost. By relating these factors to each other, a decision tree was established to represent the $LG_P$ at each scenario.
\[ RE = W_G + P h_G \] (4.3)

After intialisation, \( LG_P \) is evaluated by equation 4.6. The details about the proposed cost functions are utilised in this thesis are explained in sub-section 4.7.3.

The second input is the actual daily accumulated SDs participation in the microgrid dispatch. The local generation price should affect the operation status for the SDs in the microgrid electricity power dispatch. This favours creating an adaptive charging price; to follow the operational conditions, and to maximise the chance of participation in the microgrid’s electricity power dispatch. For the best amount of SDs participation within the microgrid, half of the total operational time should be the ideal target for the SDs, with the other half being ideal for charging. As per optimum operation, storage devices are anticipated to work continuously between charging and discharging, thus dividing the operational time 50%:50% between charging and discharging.

4.7.2 Adaptation fuzzy system

This section discusses the switching mechanism, which is integrated with the PSO in subsection 4.7.3 to control the behaviour of the storage devices. A signal indicator was developed that indicates the SDs status (charging, discharging or standby). The indicator compares the SDs instantaneous capacity with the full practical SDs capacity, and generates a signal whenever the capacity goes below 100%. This signal will be treated under other pricing conditions:

1) when the local generation price is below the adaptive pricing threshold, a charging signal will be activated.

2) when SDs charging price is less than the price of other generation sources, a discharging signal is activated to dispatch the power to the microgrid’s loads.

3) when SDs charging price is greater than the local generation price, or greater than other generation units generation price at the time of comparison, a standby signal is activated.

To normalise these values for the fuzzy system input, the actual accumulated amount of SDs participation value is multiplied by two, to establish an input membership functions’ universe of discourse with a range of one. This resulted from combining the charging and discharging times in the microgrid’s operational participation. The optimum accumulated amount of the SDs for the most recent seven days of operation is evaluated as follows:
The Amount of Participation = \( \frac{1}{h} \sum_{h=0}^{336} 2 \cdot \frac{S_G(h)}{S_{Gmax}} \)  

where \( h \) is the half hour operation interval in the seven days of operation.

It is proposed that the output of the fuzzy system carries the amount of the charging price change \( \Delta G_{ChP} \), which updates the charging price value as follows:

\[
G_{ChP}(t+1) = G_{ChP}(t) + \Delta G_{ChP}
\]

where \( t \) is a 30-minutes operational interval.

The proposed fuzzy system included triangular and trapezoidal membership functions. Figure 4.9 illustrates the proposed membership functions design, for the proposed charging price adaptation fuzzy system.

![Membership Functions](image)

Figure 4.9: The design of charging price generator fuzzy system membership functions

The relationship between the two fuzzy inputs and their output is detailed in Table 4.4, which illustrates the rules that adapt the SDs charging price in the managed microgrid.
4.7.3 Optimum generation cost performance

The Particle Swarm Optimisation (PSO) method is applied to solve the generation cost optimisation problem in the managed microgrid. It also covers the changes to the dynamic variables and the solution constraints in the economic and environmental generation costs within the PSO’s considerations. Accordingly, the proposed PSO will consider SDs as loads, sources or not counted, based on the generated signals from the charging price FL system at the time of processing. Hence the proposed PSO aims to find an optimum solution for minimising the economic and environmental costs by introducing a general multi-objective cost function, which is described as follows:

\[
F_{\text{min}}(\text{Cost}) = \sum_{c=1}^{n_{\text{SwarmSize}}} \sum_{\text{swarm}=1}^{n} \left( G_G + G_{\text{lostG}} \right) i \ast \left( \text{Discharging} + G_c + MoAG_c + MoVG_c \right) MoAi + S_G i \ast \left( S_c + MoVS_c \right) \ast \text{Charging} + U_G i \ast \left( U_c + MoAU_c + \text{Discharging} \right)
\]

(4.6)

where \( F_{\text{min}} \) is a multi-objective cost function, \( c \) is the cost function to be tested, \( n \) is the number of the tested cost functions, and \( \text{swarm} \) is the PSO swarm size. In all applied cost functions, there are variable and fixed cost factors for each source of dispatch. For utility, \( MoAU \) represents the cost of the annual utility feeder utilisation percentage reserved to supply the power for the microgrid (\$/kWh). In the environmental cost considerations, it was assumed that \( MoAU = 0 \). In Gas gen-set generation, \( MoAG \) represents the fixed annual insurance, inspection and operating cost (\$/kWh). In economic cost considerations (\( MoVG \)) represents the variable maintenance and starting and shutting down costs (\$/kWh), while in environmental cost considerations, it represents the gas emission cost (Kg/MWh).

Furthermore, the environmental and economic cost functions are subject to the following constraints:

a) SDs charging/discharging values are evaluated as follows:

<table>
<thead>
<tr>
<th>LGp</th>
<th>Amount of Participation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low</td>
</tr>
<tr>
<td>Low</td>
<td>Low</td>
</tr>
<tr>
<td>Medium</td>
<td>Low</td>
</tr>
<tr>
<td>High</td>
<td>Medium</td>
</tr>
</tbody>
</table>
\[ SD_{n,t+1} = \begin{cases} \ SD_{n,t} + A_n \cdot P_{n,t} \cdot \Delta T & \text{if SDs are charging} \\ \ SD_{n,t} - A_n \cdot P_{n,t} \cdot \Delta T & \text{if SDs are discharging} \\ S_{n,t} & \text{if SDs are idle} \end{cases} \quad (4.7) \]

\[
A_n = \begin{cases} \frac{1}{\eta_C} \\ 0 \\ \eta_D \end{cases} \quad (4.8)
\]

where \( S_{g_{n,t}} \) is the power stored in the \( n \)th storage unit at time \( t \). \( A_n \) is the \( n \)th storage units charging/discharging efficiency. \( \eta_C \) and \( \eta_D \) are the charging and discharging factors respectively. Storage device charging/discharging time is written as follow:

\[
T = \frac{SD}{IP_n} \quad (4.9)
\]

where \( SD \) is the theoretical capacity, \( I \) is current, and \( P_n \) is the Peukert number.

b) All updated velocities of the selected initial values of each generation unit must not exceed the capacity of the source itself:

\[
U_{Gmin} \leq U_G \\
S_{Gmin} \leq S_G \leq S_{Gmax} \\
G_{Gmin} \leq G_G \leq G_{Gmax} \quad (4.10)
\]

c) When each gen-set is covering 500 kWh, the nominated dispatch values maximise the spinning reserve utilisation from the running gen-sets. Therefore, the gas gen-sets dispatch cost is formulated as follows:

\[
G_{\text{lost}G} = \left( \left\lfloor \frac{G_G}{500} \right\rfloor + 1 \right) \cdot 500 - G_G \quad (4.11)
\]

d) The sum of all of the tested dispatch should always be greater or equal to the value of demand at the time of decision \( t \) in the managed microgrid:

\[
G_G(t) + S_G(t) + U_G(t) + W_G(t) + P_{hG}(t) \geq \text{Demand}(t) \quad (4.12)
\]

e) The cost function must consider the SDs operational status, which is represented by environmental and economic cost function indicators. This indicator is applied to switch the searching mechanism, and thus prioritise the utilisation of the storage devices when
they are ready for dispatch. Another cost indicator was integrated within the economic and the environmental cost functions, to indicate the charging-discharging status for SDs.

f) All velocity equation updates result in positive values to guide the searching towards selecting positive dispatch values:

\[ V_{i,j}^{k+1} = wV_{i,j}^k + (P_{\text{best},i,j}^k - X_{i,j}^k)C_1\text{rand}_1() + (G_{\text{best},i,j}^k - X_{i,j}^k)C_2\text{rand}_2() \]  

(4.13)

\[ X_{i,j}^{k+1} = \text{abs}(X_{i,j}^k + V_{i,j}^{k+1}) \]  

(4.14)

where \( V_{i,j}^{k+1} \) is the updated amount of the dispatched power (velocity) for each dispatch source \( j \) at iteration \( i \), \( C_1 \) and \( C_2 \) are the learning factors and \( w \) is the inertia weight. By referring to other people’s works [168, 169], in line with simple empirical studies applied to nominate PSO parameters, \( w \) has been set to 0.4, \( C_1 \) and \( C_2 \) have been set to 1.4 and \( \text{rand}_1() \) and \( \text{rand}_2() \) are random number generators, set to provide numbers between 0 and 1.

g) The update process is repeated based on a predefined number of iterations \( i \) as shown in the flow chart illustrated in Figure 4.10.
4.8 Results

We show in detail the microgrid's overall management performance within the proposed method. Accordingly, the integrated optimisation roles were tested by simulating the sys-
tem with the operational scenarios data. The results show that the initial proposed PSO successfully maximised the utilisation of the spinning reserve of the installed gas gen-sets. It also showed that the method could control the dynamic generation cost dispatch, with the intermittent generation from the renewable energy sources. Tables 4.5 and 4.6 illustrate the performance of the proposed PSO and Fuzzy-based Particle Swarm Optimisation (FPSO) method for a typical 12-hours daily operation. From both Tables 4.5 and 4.6, it is shown that this work was firstly successful in modelling the SDs attitude by reflecting the charging process in line with evaluating the variable $S_P$ as the SDs are charged. Secondly, the studies conducted on the microgrid’s operational conditions could identify the charging/discharging cost parameters. Eventually, controlling these parameters using FPSO could make the charging price cheaper as compared with the traditional PSO. These results highlight the robustness of the proposed adaptive optimisation method (FPSO) in switching its calculation mechanism based on the operational scenarios that were encountered. By following the charging process from hour 1 to 7, it is shown that while SDs is charged, their price is influenced by the local generation cost that results from evaluating the share of generation of each participant generator at time of charging. It is also shown, by comparison, that $S_P$ is relatively cheaper when the microgrid is ran by FPSO than it is with the traditional PSO. Although, the difference is tiny, but there will be a larger difference in the longer term of operation, and also a higher amount of participation, which in turn results in a lower cost for the power generation in the microgrid. The cost difference is further detailed in Table 4.7. The results also show that the interpreted cost function was successfully utilised to reduce the amount of lost reserve, by maximising the share of gas gen-sets and matching the number of active units with the power required by the microgrid. Hence the additional safety unit cost was divided over the amount of power supplied by the microgrid, and eventually considered in the local generation price.

Figure 4.11 shows the control for the SDs generation capacity during their charging and discharging times.

The results also proved that the SDs can play a substantial role in balancing the operation within a remote self-supplied microgrid. Moreover, the role can be utilised to enhance SDs efficiency. FPSO method was tested for its ability to control the charging/discharging of the SDs, based on monitoring their operational performance. The method was evaluated, based on its ability to increase the amount of SDs participation in the microgrid electricity power dispatch with the lowest possible generation cost. It was found to bring a range of benefits to the system in terms of Number of Participation (NOP), Supplied Power (SE),
### Table 4.5: Microgrid generation performance evaluation with FPSO

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<th>W</th>
<th>U</th>
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<th>SG</th>
<th>Price ($)</th>
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### Table 4.6: Microgrid generation performance evaluation with PSO

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<th>W</th>
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<th>Price ($)</th>
<th>U</th>
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<th>GNo.</th>
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<td>92</td>
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<td>0.0991</td>
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Achieved Profit (AP), and generation cost. The simulation results are discussed below. Table 4.7 illustrates the difference in the values resulting from adding the proposed fuzzy pricing method to the typical PSO.

From Table 4.7, it is shown that generally running SDs would result in a higher cost as compared with $U_P$ and $G_P$. However, due to the disparity of the $U_P$ and $G_P$, SDs can be smartly utilised to make a cheaper power dispatch as compared with $U_P$ and $G_P$. It is also shown that the traditional PSO could manage this uncertainty and could make the SDs profitable by selecting the suitable dispatch time to maintain optimum dispatch cost. However, the proposed fuzzy charging mechanism was successful to guide the traditional PSO towards making optimum decisions concerning the charging and discharging process.

Eventually our method has increased the NOP by 28.2%, SE by 4.5% and AP by 50%. These increments resulted from following the pattern of weekly prices around the
microgrid’s operation. Hence, investigating the best time domain for the prices change could be an optimisation problem to be addressed in future research. The performance results should prove to be attractive to potential investors in this sector.

4.9 Closing remarks

In this chapter the target was to test a novel optimisation method aimed to perform smart utilisation of the resources in generating electricity power for a typical autonomous microgrid. The proposed method is applied to control the charging process of the SDs through a fuzzy charging price threshold system. The proposed system included monitoring the microgrid’s local generation price, and the total amount of SDs dispatch in the most recent seven days of operation, to establish an optimum charging/discharging prices for SDs. The generated charging prices aim to maximise the opportunity to charge the SDs with low prices, thus maximising the likelihood of achieving cheaper dispatch throughout the SDs lifetime. After evaluating the charging price, a switchable PSO mechanism was applied to control the power dispatch, based on the dynamic generation cost of producing electricity within the microgrid. The results showed a higher amount of SDs participation, thus a higher amount of potential profit can be achieved with the proposed system. The higher profit in turn reduces the overall generation cost of the managed microgrid. Future research should investigate the demand response, and the ancillary services trade considerations, under a competitive prices environment; for the given optimisation method.
Chapter 5

Fuzzy Logic-Based Ancillary Service Adaptive Pricing System

This chapter details the third intelligent module in our management system. At this stage, we aim at performing two way power flow for our microgrid, and therefore, we have assumed that the microgrid has two-flow meters for importing and exporting electricity, from and to the utility grid. It is clearly understood that importing electricity was less problematic than exporting it, due to the complexity of markets, the capacity of dispatch, administrative fees and quality issues. Therefore, even if there is a chance of exporting electricity to the grid, it will always be sold at a lower rate. In this chapter, we are going to illustrate and analyse the possibilities of increasing the electricity export rate from microgrids with more competitive Ancillary Services (AS) pricing. The chapter will detail the pricing principles used for AS. In addition, it will look at the impact of adding appropriate Artificial Intelligence (AI) methods to increase the chance of market participation in the longer run. The proposed pricing mechanism aims at adapting fixed initial pricing rules to the microgrid’s past, present and future operational conditions. Accordingly, several levels of intelligence have been integrated with the proposed pricing module to enhance the efficiency of the applied rules. In this chapter, Section 6.1 introduces the types of AS, and detailing their role in maintaining safety and reliability in power systems. Section 5.2 studies the technologies and the methods utilised by research community to perform smart energy trading. Section 5.3 will detail the targeted research problems and the objectives aimed at this work. Section 6.4 will simply show the research assumptions that have been considered before performing our simulations. Section 5.5 will detail the exploration of the operational conditions in the microgrid. Section 5.6 will discuss the methods of extracting the adaptive pricing rules which includes: 1) subsection 5.6.1, where the main pricing equations are formulated, 2) subsection 5.6.2, where the relevant forecasting models are detailed, 3) subsection 5.6.3,
where a fuzzy rule base system based on correlating effective pricing variables to achieve satisfactory profit is detailed. Section 5.7 has covered the simulation tools utilised to create a virtual competitive market for testing the proposed pricing method. Section 6.6 will discuss the recorded results, and finally Section 6.7 carries the conclusions and the recommended future extensions of this work.

5.1 Background

The electricity rules force the market operators to ensure achieving safe and reliable operation for the power systems. In this context, the frequency and voltage profiles are the major considerable issues. Ancillary Services (AS) can play a major role in balancing the voltage and frequency profiles in the power system. AS are generally classified as: 1) Load Following - the power required to balance the amount of demand and generation, and ensures supporting the system when any of its scheduled generation units fails; 2) Dispatch Support - the ancillary power required to maintain the voltage level; 3) Load Rejection Reserve - the generators ability to reduce their dispatch when a load operational fault is encountered; 4) System Restart, the power that can be supplied from the running generators to black start additional generation unit without importing extra power from the transmission source; and 5) Spinning Reserve - is the power held as part of the generators capacity to respond to the network demand when any other generation unit experiences an outage. By considering our case study (microgrid), we targeted a combination of Load Following, Dispatch Support and Spinning Reserve types of AS that can be offered to the market. Specifically, two types of reserve was identified to be offered as AS to the market: 1) the fast reserve, which is the rapid and fast response active power supply that results from increasing the torque of the operational generation units, or from a planned load shedding within the managed microgrid; 2) standing reserve, which is the active power supply that can be obtained from extra synchronous or asynchronous generation units in the microgrid. However, AS can be integrated with the power grid after a set of negotiation between the grid and sellers. Depending on the amount required from the market (utility grid), and the amount offered to the market at any particular time, variable and competitive price might be encountered for the AS trading. Hence offering the reserve to the market becomes a challenging process. Therefore, our pricing rules aim at maximising the amount of AS trading with the market.

A comprehensive study for the market operation mechanism was needed to guide the development of the AS pricing. Generally in the electricity market, auctions are divided
vertically and horizontally. In the latter, the daily demand in a particular spot is partitioned by its duration, which is considered as a distinct lot for each time frame. Whereas in case of the vertical auction, the daily demand is divided into hourly demand lots, where each hour demand lot contains the full demand of that particular demand zone. In both types of auctions, our pricing equations were formulated based on two pricing rules: 1) the uniform rules, which allow the auction winners to pay the highest accepted bidding price; and 2) the discriminatory pricing rule, which allows the winners to pay their own proposed bids. However, although the uniform price auction is expected to achieve a higher number of transactions, which makes it a more efficient auction format [170], it is restricted to the amount of supply and demand for electricity in the market. The auction design has been tested with the ability of learning in the context, where symmetrically informed adaptive agents with common evaluations learn to bid for a good in [171]. The auction types (First-price Sealed-bid, Vickrey, English or Dutch), based on the complexity of the markets and the number of participant players, have been investigated by [172]. In Australia, the English type auction is the auction that electricity market operators use, where all the bidders use their best strategies to increase their bid until it reaches their minimum profitable capability. Essentially both sellers and buyers wish to maximise their profit, where the buyers look to buy from the cheapest selling price. The current Australian energy market relies on the Australian Energy Market Commission’s (AEMC) rules, which are applied depending on the place and the size of energy trade. In the eastern and southern Australian states, the Australian Energy Market Operator [167] is the pool that hosts the electricity generators’ bids to the retailers, who in turn sell the electricity to the end consumers. In the Northern Territory, electricity reforms have been introduced, but at present there is no competition in the generation or retail markets. By way of contrast, in the state of Western Australia, the Independent Markets Operator [173] operates both the Wholesale Electricity Market (WEM) and the Gas Information Services Project (GISP).

5.2 Related works

Price modelling has been extensively covered by researchers in both engineering and economics research fields. A new price modelling approach has been presented in [174] to construct noisy supply and demand processes, and then equate them to find an equilibrium price. An accurate pricing model that combines social, technical, environmental, and economic aspects using an analytic network process to show the impact of the renewable energy pricing has been discussed in [175]. Integer-programming [176] and non-linear
programming [177] have been introduced respectively to formulate prices, based on unit commitment of electric power generators, and to maximise the retailer’s profit under a deregulated electricity market. Generic mixed integer linear programming mode has been proposed to resolve residential microgrid generation cost in [178] by involving a predictive control method to reduce the generation cost and cope with the uncertainty of installed DERs under different market pricing rules.

Various marketing strategies for the microgrid power market, such as spot marketing and pricing, which can be applied to forecast and ensure its economic viability, have been addressed in [179, 180]. A buy-back program that incorporates the compensations and the setup cost over finite planning horizons has also been modelled in [181]. The strategy of the spot market price of microgrids and the new pricing formulae have been detailed in [179] to show how the microgrid can foster an efficient market. Microgrids AS market participation has been represented as an optimisation problem in [182], which has been modelled using fuzzy sets concept to allocate three AS types among microgrid agents in electricity markets. As a result, the commercialisation of the microgrid generation in context of smart, economic and market participant generation was the major identified challenge. Various marketing strategies, such as bidding, spot marketing, and pricing, for ensuring economic viability of a microgrid scenario have been investigated in [183].

Developing an energy management system that relies on the spot electricity market in its optimum decisions has been proposed in [184]. [185] has investigated a case where microgrids are considered as market competitors for generation companies in Fort Collins. The operation of microgrid as part of Colombian energy market has been investigated in [186], where a linear programming algorithm has been proposed to perform an optimum operation for microgrids under the uncertainty of electricity market participation. A market-based mechanism which allows a single microgrid operator to control the behaviour of the internal loads, has also been indicated in [187, 188].

By considering the dynamic electricity demand changes and monitoring the factors that influence prices, different approaches can be utilised to build smart integration for the local generation units within the utility grid. A pricing mechanism for supplying the microgrid electricity in a competitive electricity market, participating in the bidding process, and settling the market-clearing price has been proposed in [189]. A price-based open-loop control signal to facilitate enhanced penetration by distributed energy resources in the power system; by coordinating their participation in electricity markets while also maintaining the local system energy balance, has been considered in [190]. In addition, having
the right method to generate competitive bids in a competitive market environment can increase the range of electricity trades for the managed power system. [191] has proposed an electricity market oriented tool that creates bidding strategies in a competitive market environment by combining fuzzy logic and deterministic approaches, while [192] has proposed a pricing analyser and generator to initiate competitive bids in electricity markets. Microgrid market participation with distribution system has been investigated under different market policies and pricing rules in [193]. Accordingly, to increase the performance of efficiency of the microgrid’s DER and increase market participation, this problem has been solved using PSO. A novel fuzzy modelling approach, to generate strategic bidding to handle uncertainty in market parameters, such as load demand, generator bidding, power dispatch, price, cost, revenue, and profit, has been detailed in [194]. In this section, we have critically reviewed the methods and technologies utilised in trading the AS with the markets. Hence in this work we will also refer to the pricing method utilised by [194] to develop our pricing method supported by the operational conditions forecasts. Ultimately this will build more efficient pricing method that suits our case study and also the market rules. Finally, our pricing rules will be implemented to cope with the problems discussed in the literature, and also to reflect our strategic ideas relating to selling AS to the market. The rules will be implemented and tested in this chapter as an independent seller, which tries to sell the AS in a competitive market. The rules will also be implemented as a bigger management system that consider other operational conditions in the decisions, which will be covered in Chapter 6.

5.3 Research objectives and challenges

Selling the AS to the market requires advanced network infrastructure, which in turn results in political restrictions due to the high cost of development and implementation. Therefore, justifying the substantial economic and environmental benefits will help attract investment when building a more reliable grid like the Smartgrid [195, 196, 197]. In the meantime, researchers and engineers seek solutions for solving this problem, either by finding alternatives or by utilising intelligence in the power grid in order to cut these expenses. By aligning our research with other researchers and engineers, we are targeting the following objectives by proposing our AS pricing rules:

1. Identifying the operational scenarios that maximise the chance of market participation.
2. Maximising the level of market participation through minimising the selling price in the longer term.

3. Maximising the amount of power offered to the market through the achieved market participation.

5.4 Research assumptions

The assumptions that we are relying on at this stage of our investigations are:

1. The microgrid negotiation is connected directly to the market and not to retailers or any other third party.

2. We are targeting the $U_P$ as the indicator of the market balance point for buying and selling electricity.

5.5 Possible scenarios and rule base system

Controlling the microgrid’s resources under the complexity of manipulating multiple sources of dispatch, is the art of selecting the appropriate management strategy. Therefore, a comprehensive analysis of the system’s operational conditions is needed before nominating the right strategy. Our approach aims at classifying the expected operational conditions based on the cost of generation. However, due to the complexity and the variety of sources; including the installed onsite renewable energy sources, with dynamic demand, utility and gas/diesel dispatch price, we related the amount of demand within the microgrid to the variable generation cost that results from the intermittent generation and dynamic utility price. Based on the extracted operation scenarios, a suitable pricing equation is set for each operational scenario. Hence the complexity of the rules increases when the SDs are considered in operation in the case study; due to the uncertainty of charging/discharging price and time. The multiple sources of generation within the case study are initially classified based on three different demand levels: 1) less than the available renewable energy sources dispatch; 2) more than the renewable energy sources dispatch and less than the renewable energy sources together with the SDs dispatch; 3) more than the renewable energy sources together with the SDs dispatch. After classifying the operation scenarios based on the demand levels, we then sub-classify the operation at each level based on the generation cost for each generation unit: $G_P$, $S_P$ and $U_P$. Eventually these dynamic cost factors would complicate the problem and increase the number of rules that are required.
Figure 5.1: The decision tree for the classified demand levels as compared with renewable energy sources and storage devices generation capacity scenarios

Depending on the importance of each of the generation sources to the case study, the rules are developed based on comparing gas generation cost with the utility generation cost, and comparing the gas generation price with SDs generation price. As a result, a suitable pricing that aims at maximising the benefits and cutting the generation cost was initially generated for each operation scenario.

The extracted decision tree for the expected operational scenarios from the case study is illustrated in Figure 5.1.

Table 5.1 was utilised to represent the relationship between the demand levels and the expected generation cost scenarios illustrated in Figure 5.1.

where $RE$ is the total amount of $Ph_G$ and $W_G$ generation. The relationship identified in this table will be utilised in the next section to formulate the initial pricing rules for the AS.
Table 5.1: Possible expected operation cost scenarios; with regards to the level of expected demand in the managed microgrid

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<td>E</td>
<td>K</td>
<td>Q</td>
</tr>
<tr>
<td>$S_P &lt; U_P &lt; G_P$</td>
<td>F</td>
<td>L</td>
<td>R</td>
</tr>
</tbody>
</table>

5.6 Decisions mechanism and Ancillary Services pricing equations formulation

Our proposed pricing mechanism initially reflects our trading attitude, which will set an initial sale price and monitor the further opportunities for generating more competitive prices based on the market and the microgrid operation conditions. Since the ability to change the sale price is typically needed to cope with these conditions, we have considered different three implementation stages to build the proposed pricing system. In the following subsections, we describe the pricing rules in detail, along with their ability to adapt to external conditions.

As weather conditions and energy prices are highly correlated [198, 199, 200], the first effective parameters identified regarding the prices for the case study the amount of $S_G$, $P_{hG}$, $W_G$ and $Dmnd$. Evaluating the amount of these factors will result in counting the amount of $RdyFrSLElec$ (reserve). To increase the scope for monitoring the operational conditions, forecasting models and optimisation techniques have been utilised to estimate the limits of the pricing factors in the decision making. Forecasting the generation parameters has been considered as a substantial factor for increasing the net earning of the generation in [201], and the future electricity price classification forecasts have been utilised in the decision-making process in [202]. To estimate the long term risks in the electricity markets, a swarm-intelligence, meta-heuristic, optimisation technique have been proposed in [203]. Our optimisation technique is aimed at estimating operational conditions based on the weather and prices forecasts. Figures 5.2 and 5.3 illustrate our proposed adaptive pricing mechanism with its relative operation sequence. Basically, the proposed pricing mechanism starts by reading the information about the renewable energy sources, the utility price, the weather conditions, and the time and the date of the pricing. The forecasting module then starts forecasting $W_S$, $SLR_I$, and $U_P$ for up to 4 iterations (two hours) in advance. 2) Since $S_G$, $S_P$ and $LG_P$ are strongly related to the information supplied to the
forecasting module, the PSO is called from the Power Generation Management and Storage Control System (PGMSCS), which was discussed in Chapter 4 to utilise these forecasts in order to estimate $S_G$, $S_P$ and $LG_P$ throughout the four-iterations forecasting horizon. Figure 5.3 illustrates $S_G$, $S_P$ and $LG_P$ estimation sequence in a specified forecasting horizon. 3) The estimates and forecasts are then utilised by the third computation stage (the fuzzy adaptation) to adapt the initial sale price, which is resulted from the decision tree that has been developed in Sub-section 5.6.1, based on the operational scenarios explained in Section 5.5. Subsequently, the final price value will be fed back to the PSO in line with forecasts to estimate $S_G$, $S_P$ and $LG_P$ in the subsequent iterations.

5.6.1 Pricing equations

The developed pricing equations are the core of our pricing mechanism. Basically, the pricing equations were developed to suit every possible operational scenario that holds a $RdyFsLElec$ (reserve) in the case study. Just like any successful business, the pricing rules were developed to make a profit, by evaluating the cost of the product and the possible sale value derived from the perceived market affordability.

Firstly, we discuss the formulation of the $LG_P$ equations. These were developed after: 1) studying the decision making rules at each operational scenario; 2) evaluating the amount of participation for each of the generation units; and 3) assessing the percentage
Figure 5.3: Proposed pricing adaptation process
contribution of each of the generation units in supplying the power required to match the demand in the microgrid. By giving consideration to the use of renewable energy sources in $LG_P$ would always result in it being cheaper than $UP$ and $GP$.

In case of evaluating the amount of reserve that is proposed for sale ($RdyFrSLElec$), the evaluation was always based on the condition that $LG_P$ is less than $UP$, by subtracting the demand value from the amount of local generation at each operational scenario. Hence the value of $RdyFrSLElec$ depends mainly on the demand in the case study; along with the type of utilised cost function e.g., economic, environmental, or economical-environmental. In this work the proposed pricing method was tested with economic, environmental, and economic-environmental operation in the case study in section 6.6.

Finally, $SL_P$ rules were simply developed from the logic of achieving profit by evaluating the $LG_P$ and $UP$, and making a fair decision about setting a competitive price between these values. Although $SL_P$ was proposed to be adaptive, as an initial value, we have set it to start from the half difference between the two prices: $LG_P$ and $UP$. Since this initial pricing point is aimed to make $SL_P$ competitive and profitable.

To relate the operational scenarios with their assigned pricing rules, we have utilised the identified operational scenarios in Table 5.1, to list the pricing rules, as illustrated in Table 5.2.

To evaluate the robustness of the proposed pricing rules, we have conducted a simple simulation test with the operational scenarios in the January demand pattern of the case study. For simplicity we have presented seven working days for the operation profile. Figure 5.4 illustrates the range of generated sale prices over that week.
Table 5.2: Formulated equations that evaluate the possible amount of Ancillary Services in every operation scenario

<table>
<thead>
<tr>
<th>Sc.</th>
<th>$RdyFrSLElec$</th>
<th>$SL_P$</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>$G_G + Ph_G + W_G - Dmnd$</td>
<td>$(U_P - (G_G + HrfrSLElec + Dmnd))$</td>
</tr>
<tr>
<td>B</td>
<td>$G_G + S_G + Ph_G + W_G - Dmnd$</td>
<td>$U_P - (U_P - (U_P - (G_P + S_P + Dmnd + W_G + W_G + S_P + G_P + S_P + S_P + G_P))$</td>
</tr>
<tr>
<td>D</td>
<td>$Ph_G + W_G - Dmnd$</td>
<td>$S_P - (G_P + S_P + Dmnd + W_G + W_G + S_P + G_P + S_P + S_P + G_P) - 0.02$</td>
</tr>
<tr>
<td>E</td>
<td>$Ph_G + W_G - Dmnd$</td>
<td>$S_P + (G_P + S_P + Dmnd + W_G + W_G + S_P + G_P + S_P + S_P + G_P) - 0.02$</td>
</tr>
<tr>
<td>F</td>
<td>$S_G + Ph_G + W_G - Dmnd$</td>
<td>$S_G + (G_P + S_P + Dmnd + W_G + W_G + S_P + G_P + S_P + S_P + G_P) - 0.02$</td>
</tr>
<tr>
<td>G</td>
<td>$G_G - G_{SG}$</td>
<td>$U_P - (U_P - (G_P + S_P + Dmnd + W_G + W_G + S_P + G_P + S_P + S_P + G_P))$</td>
</tr>
<tr>
<td>H</td>
<td>$G_G - G_{SG} + S_G$</td>
<td>$U_P - (U_P - (G_P + S_P + Dmnd + W_G + W_G + S_P + G_P + S_P + S_P + G_P))$</td>
</tr>
<tr>
<td>J</td>
<td>0</td>
<td>/</td>
</tr>
<tr>
<td>K</td>
<td>0</td>
<td>/</td>
</tr>
<tr>
<td>M</td>
<td>$G_G - G_{SG}$</td>
<td>$U_P - (U_P - (G_P + S_P + Dmnd + W_G + W_G + S_P + G_P + S_P + S_P + G_P))$</td>
</tr>
<tr>
<td>N</td>
<td>$G_G - G_{SG} - S_G$</td>
<td>$U_P - (U_P - (G_P + S_P + Dmnd + W_G + W_G + S_P + G_P + S_P + S_P + G_P))$</td>
</tr>
<tr>
<td>O</td>
<td>$G_G - G_{SG}$</td>
<td>$U_P - (U_P - (G_P + S_P + Dmnd + W_G + W_G + S_P + G_P + S_P + S_P + G_P))$</td>
</tr>
<tr>
<td>P</td>
<td>0</td>
<td>/</td>
</tr>
<tr>
<td>Q</td>
<td>0</td>
<td>/</td>
</tr>
<tr>
<td>R</td>
<td>0</td>
<td>/</td>
</tr>
</tbody>
</table>
Figure 5.4 shows that as long as there is a $RdyFrSLElec$, the generated $SL_P$ is always found between $LG_P$ and $U_P$, which proves the success of the initial pricing rules in creating beneficial $SL_P$ under all operational conditions in the case study. Subsequently, decisions are subject to the forecasting conditions as shown in sub-section 5.6.2, which will finally be evaluated by calling the (PGMSCS).

### 5.6.2 Pricing factors forecasting

The second part of the smart pricing mechanism was forecasting the operational conditions that affect pricing in a competitive market environment. The first effective parameter in the case study was the power demand. Therefore, we called the Demand Forecasting Model (DFM), that has been introduced in Chapter 3, to provide this system with demand information. To estimate the profit, and to balance it with the amount of $RdyFrSLElec$ to generate competitive prices, there is a need to estimate $LG_P$ and to forecast $U_P$. To support our proposed pricing mechanism, which depends on the short-term forecasting for the operational scenarios, we have introduced a forecasting model for each pricing factor. We have used different modelling approaches for these parameters, depending on the non-linearity of each model. The proposed forecasting models are to perform short term forecasting, and to align the forecasting output with the instantaneous real-time parameters.
change. Therefore, we have developed three forecasting models for $W_S$, $SLR_I$, and $U_P$. For $W_S$ and $SLR_I$, we obtained four years of historical records from the Australian Bureau of Meteorology [3]. In order to deal with the high nonlinearity of the recorded $W_S$ and $SLR_I$, we implemented the models by dividing the generation times into different zones: 1) in case of forecasting $W_G$, we utilised the $W_S$ model to forecast the expected amount of generation from the nominated wind turbines on the project location as explained in Chapter 4; 2) in case of $Ph_G$, we did the same, except that solar panels are expected to have zero generation from sunset to sunrise, which will make the $SLR_I$ model less complicated than that for the $W_S$. In both models, we have also utilised the instantaneous real-time measured values, in line with the date (hour/day/month) values, as a base for the short term forecasting.

For many forecasting horizons, Artificial Neural Network (ANN) has been proved to be a robust multi-step forecasting [204]. We have used ANN with a Backpropagation learning algorithm. In all developed ANN models, we proposed one hidden layer network, with a bi-polar log-sigmoid activation function in the hidden layer, and a bi-polar linear type activation function in the output layer. Table 5.3 details the design of the proposed forecasting models. Figure 5.5 shows that the forecasting accuracy for the developed models is relatively high, due to forecasting alignment with the real-time values.

The $RdyFrSLElec$ estimate was then evaluated by calling the PGSMCS, based on utilising the $W_S$, $SLR_I$ and $U_P$ forecasts. Hence the most challenging part of estimating the factors in the forecasting horizon for the case study were, $S_G$ and $S_P$; due to the uncertainty of charging/discharging time and cost as explained in Chapter 4. As a result, the Power Generation and Storage Management Controller Agent would return the $RdyFrSLElec$ estimates for the near future as specified by the forecasting horizon, which would be eventually considered in the final $SLp$.

### 5.6.3 Adaptive pricing rules fuzzy system

To utilise the factors forecast in our pricing mechanism, we proposed a fuzzy system that reflects our experience in generating competitive prices within a competitive markets en-
Figure 5.5: $W_S$, $Ph_G$ and $U_P$ forecasting models performance in a typical one week of operation
Table 5.4: Pricing adaptation fuzzy rule base system

<table>
<thead>
<tr>
<th>IncandDec(+)</th>
<th>SLp</th>
<th>RdyFrSLElec</th>
<th>S</th>
<th>M</th>
<th>L</th>
</tr>
</thead>
<tbody>
<tr>
<td>S</td>
<td>S</td>
<td>S</td>
<td>M</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M</td>
<td>S</td>
<td>M</td>
<td>L</td>
<td></td>
<td></td>
</tr>
<tr>
<td>L</td>
<td>M</td>
<td>L</td>
<td>L</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>IncandDec(−)</th>
<th>SLp</th>
<th>RdyFrSLElec</th>
<th>S</th>
<th>M</th>
<th>L</th>
</tr>
</thead>
<tbody>
<tr>
<td>S</td>
<td>S</td>
<td>S</td>
<td>M</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M</td>
<td>S</td>
<td>M</td>
<td>L</td>
<td></td>
<td></td>
</tr>
<tr>
<td>L</td>
<td>M</td>
<td>L</td>
<td>L</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

environment. Our proposed fuzzy system was utilised to adapt the pricing rules to the microgrid’s operational conditions. In the design, we related the amount of RdyFrSLElec to the simultaneously rule based generated SLp, to have an adaptive SLp, thus keeping it advantageous and competitive. The other input to the proposed fuzzy system is the direction of IncandDec (increment/decrement) of the effective pricing factors in the forecasting horizon, whether the estimation results in an increment/decrement in the pricing factors. The direction of parameters change (increment/decrement) was evaluated from the values difference at each iteration in the forecasting horizon. However, to evaluate the slope of the increment/decrement, the values were compared with their next and previous forecasts. The proposed Fuzzy rule based system was extracted and illustrated in Table 5.4. In the same table, the increment/decrement were represented by (+/-).

To introduce the nominated fuzzy inputs, we normalised the first input (SLp) by relating it to the UP:

\[
FLSLp = \frac{(UP - SLp)}{UP} \tag{5.1}
\]

and the second input (FLRdyFrSLElec) to the amount of full generation capacity (3000 kWh) in the case study (without considering the standby 0.5MW gen-set):

\[
FLRdyFrSLElec = \frac{(3000 - RdyFrSLElec)}{3000} \tag{5.2}
\]

The proposed membership functions that represent the normalised input values and the range of increment/decrement for the effective pricing parameters are illustrated in Figure 5.6. In this work, we have utilised two types of fuzzy membership functions, the triangular and the trapezoidal, to suit the objectives of the proposed fuzzy system. The final sale price NewSaleprice was evaluated by multiplying the value of PriceAdjustment
by the difference between $LG_P$ and $U_P$ as explained in the following equation:

\[ \text{NewSaleprice} = ((U_P - LG_P) \times \text{PriceAdjustment}) + LG_P \] (5.3)

### 5.7 Market simulation

The proposed negotiation mechanism is built to start the trading process by registering the participant agents within the pool under a common predefined service. In this work we have defined the common service in the MAS framework as “ElectricityTrade”, where each pool participant must be registered under this service to receive the appropriate information messages. The implementation details of MAS technology on this system will be covered in Chapter 6. Thereafter, the buyer was designed to look for the participant sellers in the framework’s Yellow Pages. Messages with Call For Proposal (CFP) type are sent to the identified agents asking them to submit a proposal for their registered service. When CFP is received, the sellers will reply with messages of INFORM type that carries
either acceptance or rejection, based on their predefined pricing analysis. In the case of acceptance, the agreed seller’s proposal should include informative details about the proposed offer. Figure 5.7 illustrates the proposed negotiation software sequence. Our simulation also allowed for one of the sellers to receive a rejection of their proposal, where the ability to regenerate more competitive prices within a strict time frame was attached to the seller’s pricing mechanism. At this stage, this mechanism was not discussed, but can be extended as future work arising from this thesis.

Our pricing system has been tested using MAS technology, where a virtual market was created and tested under both the uniform and discriminatory pricing rules. In the created market, each player was represented by a smart agent that has the ability to negotiate and perform smart trading decisions based on its pricing rules. For the buyer agents, we proposed that they have randomly generated CFPs based on their predefined settings that reflect the market’s attitude at that point of time. In addition, each buyer was programmed to select the winning seller based on the uniform and discriminatory pricing rules. In this work, we used Java Agent DEvelopement Framework (JADE) [2] to simulate the proposed agent system, since JADE-based MAS technology role has already been evaluated through implementing electronic markets on a real test sites [82, 83]. Hence the data for the simulated markets have been collected from [167]. Figure 5.8 illustrates
5.8 Results

To evaluate the robustness of our pricing method, we have conducted several simulation studies for a month of operation time on our case study. Specifically, we have selected January operational data for the simulation, as it contains different demand patterns that reflect public holidays, normal working days, and weekends. Therefore for simplicity and clarity of results, our figures show a one week of operational time results, while our tables show the whole month of operational time results. In this section, we will show the impact of adding each of the intelligent modules to the agents that carry the main pricing rules. So we will test the system based on its level of intelligence. In the simulation we have used three sellers, where the first seller enters the market and generates proposals with the initial pricing rules. The second seller enters the market and generates proposals based on the fuzzy system adaptive pricing rules. The third seller enters the market with initial pricing rules in line with a fuzzy adaptation mechanism based on forecasting the very near future operational conditions; making the proposals adventurous, though more competitive in the longer term.

The simulation studies start with the initial pricing rules under the economic, environmental, and economic-environmental cost considerations in the case study. These cost considerations based decisions are generated by the PGSMCS. The simulation studies have
been conducted using JADE to act in an electronic competitive market as explained in section 5.7; where the case study has been represented as a competitive seller, who tries to achieve a maximum profit with a reasonable amount of transactions. From the simulation, we found that the programmed buyer reflecting the predefined trends for the actual market attitude, was generating different CFP signals to the sellers. Eventually, based on the nature of the released CFP, we found our pricing agents offering different amounts at different times and prices. Therefore, the robustness of each of the tested pricing rules depends on their response to the generated CFP in a specific simulation time frame. In fact, the developed initial pricing rules were found to achieve a set of transactions, and thus a range of achieved profit, and exchanged electricity with the utility through these successful transactions. Tables 5.6 and 5.7 identify different numbers of transactions and different amounts of achieved profit in a month of simulation time. At each operational cost consideration there were different $SLp$ and $RdyFrSLElec$, depending on the assigned number and the type of generation units for the local generation at that operational cost mode. Comparing these results with the adaptive fuzzy based rule results, we can identify a higher amount of participation under the uniform pricing rules for the fuzzy adaptation based pricing system. Thereafter, when we added the forecasting considerations to the pricing rules, we also found a higher amount of participation in the economic cost consideration under the uniform pricing rules. The proposed fuzzy system has been tested to evaluate its range of adaptation, which was found to actively increase and decrease the sale price based on the evaluated amount of $SLp$ and $RdyFrSLElec$ as shown in Figure 5.9.

Moreover, the final results proved that this logic was successful in making more profit even with less amount of participation than with the initial pricing rules. This is because the fuzzy system was acting when a higher amount of $RdyFrSLElec$ was available, to generate more competitive prices. This was based on the logic that when the amount was increased, a sufficient price reduction can make more profit. That will eventually compensate the missed transactions that occurred when a high $SLp$ was offered with a low amount of $RdyFrSLElec$. The main reason for increasing the prices with a low amount of $RdyFrSLElec$, was to try selling the small amount at a higher price; based on the low probability of “there are no other sellers offering cheaper services at that time”. When comparing the amount with the possibility of participation, we found that it was worth trying to sell at these high prices.

The number of transactions under the uniform pricing rules, was evaluated from the
number of successful electricity exchanges based on the condition that the sellers provide equal or less than the expected price (market balance point). Eventually that was also depending on the CFP signal generation trends from the buyers. In case of the discriminatory rules, the number of transactions was evaluated from the number of successful electricity exchanges based on the conditions: 1) that the seller records lowest price among the participants; and 2) the seller records an equal or lower price than that expected by the buyer. Based on our studies of performing a smart sale decision making process, we would like to test our extended strategy which adds the forecasting module, to achieve a higher rate of successful transactions. Adding the forecasting module will act to generate more competitive prices by considering the near future operational conditions; and possibly make more profit in the longer term. To verify the robustness of adding the forecasting module to the pricing mechanism, we investigated the future forecasting horizon, based on the number of iterations with 30-minutes based samples. However the major problem that resulted from adding forecasting to the pricing decisions, was the forecasting error; which resulted from the lack of accuracy in the developed forecasting models. Increasing the percentage of error would eventually reduce the accuracy of the pricing decisions. Table 5.5 illustrates the importance of adding the forecasting to the pricing system under different operating cost modes; by showing the number of transactions, money value, and amount of exchanged electricity with the buyer. From the same table we can relate the percentage of forecasting error to the evaluated pricing performance.
Table 5.5: Pricing performance analysis

<table>
<thead>
<tr>
<th>Forecasting horizon</th>
<th>0.5</th>
<th>1</th>
<th>1.5</th>
<th>2</th>
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<tbody>
<tr>
<td>Cost</td>
<td>PE %</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Economic ETP</td>
<td>89</td>
<td>91</td>
<td>93</td>
<td>93</td>
</tr>
<tr>
<td>Economic TV $</td>
<td>15724</td>
<td>15123</td>
<td>15778</td>
<td>16670</td>
</tr>
<tr>
<td>Environmental ETP</td>
<td>55</td>
<td>63</td>
<td>61</td>
<td>65</td>
</tr>
<tr>
<td>Environmental TV $</td>
<td>11011</td>
<td>12032</td>
<td>11249</td>
<td>12302</td>
</tr>
<tr>
<td>Eco-Environmental ETP</td>
<td>90</td>
<td>85</td>
<td>71</td>
<td>71</td>
</tr>
<tr>
<td>Eco-Environmental TV $</td>
<td>18918</td>
<td>16921</td>
<td>13363</td>
<td>13534</td>
</tr>
</tbody>
</table>

Table 5.6: Performance analysis for discriminatory pricing rules

<table>
<thead>
<tr>
<th>Cost consideration</th>
<th>Results</th>
<th>NPR</th>
<th>FLAPR</th>
<th>ANN - FLAPR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Economic</td>
<td>ETP</td>
<td>9</td>
<td>15</td>
<td>91</td>
</tr>
<tr>
<td></td>
<td>SLDElec kW</td>
<td>13770</td>
<td>24960</td>
<td>160700</td>
</tr>
<tr>
<td></td>
<td>TV $</td>
<td>5777</td>
<td>10545</td>
<td>15123</td>
</tr>
<tr>
<td>Environmental</td>
<td>ETP</td>
<td>50</td>
<td>2</td>
<td>63</td>
</tr>
<tr>
<td></td>
<td>SLDElec kW</td>
<td>42550</td>
<td>1823</td>
<td>58100</td>
</tr>
<tr>
<td></td>
<td>TV $</td>
<td>273</td>
<td>473</td>
<td>12032</td>
</tr>
<tr>
<td>Eco-environmental</td>
<td>ETP</td>
<td>43</td>
<td>1</td>
<td>85</td>
</tr>
<tr>
<td></td>
<td>SLDElec kW</td>
<td>35920</td>
<td>542.5</td>
<td>80870</td>
</tr>
<tr>
<td></td>
<td>TV $</td>
<td>169</td>
<td>135</td>
<td>16921</td>
</tr>
</tbody>
</table>

We subsequently tested the pricing system under different operation cost considerations for both pricing rules. To evaluate the importance of adding the stages of intelligence to the pricing system, we created three sellers, each carrying the proposed pricing system with different levels of intelligence. We also created a buyer that searches for the cheapest prices in this simulated environment. As discussed before, we have utilised JADE to represent MAS in performing this simulation, and have created an agent for each of the three sellers and the one buyer. The recorded amount of successful ETP, SLDElec and TV are illustrated in Table 5.6.

In the simulation studies, we used January operational data to simulate this spot virtual market based on the relevant operational conditions for the case study. In the simulation it is assumed that all sellers have the same generation capacity and operational conditions. However they are also assumed to have different pricing mechanisms. The results showed that in a month of simulation time the economic operation mode recorded 115 transactions, 199.43 MW of sold electricity, and eventually $AUD 31445 of the total achieved money value. It is notable that adding the forecasting to the system led the seller to take 79% of the achieved transactions, 80% of the exchanged amount of electricity, and 48% of the total transactions money value. In addition, the initial pricing rules that did not include the forecasting in their decisions could achieve 33% of the total money value for all of
the 115 transactions. This means that the highest efficiency was achieved with the initial rules and the fuzzy adaptation system. However the forecasting was still needed to cover those critical pricing regions in the operational conditions, where the initial pricing rules and the adaptation fuzzy system lack the ability to do so. Thus the initial basic pricing rules could achieve only 18% of the total transactions money value. The 33% and 18% of the achieved money values mean that although the forecasting and the fuzzy system could generate more competitive prices in the markets; they were still missing those transactions due to the careful considerations about maximising the profit. The number of the missed transactions can be reduced by applying an online optimisation technique to the generated prices, by monitoring the success rate of the trade with the buyer in the competitive environment, and trying to adjust the prices accordingly. This part is recommended as a future research undertaking arising out of this work. From analysing the results along with other cost considerations, we have set the forecasting zone to one hour, when it carried a precision error of 4.8%, and took about 48% of total achieved money value in the simulated time frame. However, the results showed the same rates of improvement with environmental and economic-environmental cost considerations, except that in these cases there was a higher initial local generation cost due to the environmental concerns. Thus a fewer number of trade participations was expected, as shown in Table 5.6. Hence there was a noticeable state in the results where the fuzzy based pricing system recorded a very low number of transactions, compared with the initial pricing rules and the forecasting based pricing rules. However, it was also clear from the table that although the initial pricing rules recorded a higher number of transactions, the recorded total money value was also higher. Therefore, although there might be no transactions from the fuzzy based pricing rules for a certain trading time frame, these missed transactions can be compensated by few higher price ones when there is a higher demand in the market. The results showed that the proposed pricing system was robust in maximising the profit, by exploiting some of the possible opportunities, and logically reducing the sale price to increase the chance of participation.

In the uniform pricing rules we had a higher amount of transactions from the participant sellers, as the rules were applied to buy all the available electricity in the market; as long as the offered prices were below what the buyer expected. Therefore, we expected to have closely related values from all sellers. The simulation studies using JADE presented a buyer agent who generates CFP signals based on predefined random function settings; and three sellers, who analyse their operational conditions and generate their sale prices
Based on the tested pricing system, with different levels of intelligence. It was also assumed that all sellers share the same generation capacity and operational conditions. Table 5.7 records the resulting values achieved from testing the pricing system with different levels of intelligence, under three operation cost considerations with the uniform pricing rules.

The results showed that the economic cost considerations recorded 315 transactions from the three participant sellers, where each seller had a closely related amount of participation. Eventually these results led to the same ratio of total amount of sold electricity for the total value of money. The difference in the number of participations results from the amount of price reduction achieved by the adaptation system. Since it was expected that the buyers would always buy the electricity as long as the sale price is below the buying price; reducing the price can lead to less profit, although a higher number of participations can be achieved. However the proposed logical price adaptation has proved its success with a large number of transactions, and achieved profit in doing so.

### 5.9 Conclusion

In this chapter we developed adaptive pricing rules that aim at generating competitive AS sale prices for a typical autonomous microgrid. The pricing rules were developed in a way that reflects the business strategies in achieving a maximum possible profit from successful transactions with the grid. The pricing rules have been developed with three levels of intelligence. First, the initial pricing rules were developed using linear programming, and a derived decision tree that details the operational scenarios in the case study. Second, a fuzzy system was added to adapt the initial rules based on monitoring the microgrid $SLp$ and the availability of $RdyFrSLElec$. Third, a forecasting module was added to enlarge the monitoring horizon and include the near future scenarios in the careful prices adaptation. The developed pricing rules have been simulated with a virtual competitive market.

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environment, where different amount of transactions have been recorded, and estimated money values have also been recorded. The results highlighted the importance of adding each level of intelligence to the pricing rules. By using MAS, we have simulated the intelligent behaviour of the electronic negotiation between the three microgrids (sellers), and the utility (buyer) in a competitive market pool. The results provided different numbers of transactions and different amounts of exchanged electricity, and thus different total money values. The results also proved that the proposed pricing strategy was largely successful, yet it has encompassed few limitations such as the lack of forecasting modules' accuracy and the difficulty to cope with other seller's changable strategies. Overcoming these challenges can be achieved through the inclusion of a monitoring strategy that can adapt the pricing strategy to the changable pricing parameters accordingly. This piece of intelligence can be included as a future extension to this work.
Chapter 6

Agent-Based Implementation of Energy Management Systems for Microgrids

In this chapter, we investigate the economic and environmental impacts of the intelligent utilisation for the microgrid resources, through a set of strategies which are invoked, depending upon the microgrid’s operational conditions. The purpose of these strategies is to maintain a secure, and low economic and environmental cost generation for our case study. In this chapter we describe how we applied agent-based technology to model the proposed management strategies. The proposed management strategies aim to provide feasible decisions concerning power generation, in order to cope with the problems which arise from: 1) the uncertainty of demand; 2) weather conditions; and 3) electricity markets. Hence testing the proposed management strategies includes testing of the software components which perform the agent-based modelling. These software components are installed on distributed machines and are connected via a standardised communication protocol to allow for future extension. The proposed Multi-Agent System (MAS) implementation aims to reflect the human factors involved, when making team-decisions based on the observed operational conditions around the managed microgrid. In addition, the proposed MAS implementation provides several emergency operational modes, which are activated when any of the distributed software components fails. Dealing with the uncertainties of the operational modes has been successfully achieved by having a dynamic management system structure, which is autonomously configured to cope with the variable operational conditions. Although all the software components are needed in order to provide full system functionality, testing of each of the components was conducted in turn, in order to evaluate the individual importance of each of them. In this chapter, Sections 6.1 and 6.2 address the role the energy management systems in improving the power systems performance, and introduce the current challenges encountered with this process. Section 6.3 details the
targeted research problems and the objectives aimed at in this work. Section 6.4 briefly shows the research assumptions considered before performing the simulation. Section 6.5 utilises a case study to address the proposed management strategies for the smart utilisation of the multiple sources of dispatch; and in addition, it details the modelling procedure for implementing the proposed management system. Finally sections 6.6 and 6.7 present the results which have been captured, and conclude the research outcomes of this chapter respectively.

6.1 Background

Power systems are required to apply efficient solutions to reduce the generation cost for both generators and consumers. So far, Energy Management Systems (EMS) have shown to be key in the power systems development, and has had a significant role in improving the power systems efficiency. This is mainly through providing planning and security solutions at the High Voltage (HV) level networks; and optimising the power flow and the generators scheduling at the Low Voltage (LV) level networks of the power systems. Therefore, EMS development has been investigated in this research, based on the fact that EMS includes two major research topics in the electrical engineering field: 1) Supervisory Control And Data Acquisition (SCADA) system to monitor and control the network; 2) and the specific strategies embedded in the management systems advised to optimise the performance of the power systems. This chapter has targeted the second component of the EMS, which is the strategies required to perform low cost generation; more specifically, the chapter has investigated the role of this technology in managing the power generation of our case study.

From both the economic and the environmental perspective, microgrids have proved their reliable performance by reducing the generation cost [145]. In this context, building a reliable EMS for a microgrid encounters the challenge of incorporating multiple sources of dispatch; with the attendant problems of uncertainty of generation cost and availability of the participant generators. In addition to this challenge, it is necessary that the generation facility performs successfully in a market under competitive pricing conditions.

As a result, the process of identifying the cost factors for generating the electric power highlights the challenges being faced, which go far beyond simply performing low cost generation. Thus, identifying the cost factors of generation helps to guide the strategies being embedded within the EMS design, orienting it more towards providing a practical solution for this problem. Hence dealing with more than one complex problem simultaneously requires the deployment of a real-time distributed management system. Microgrids’ EMS can
be implemented by having real-time distributed management system. Such a deployment allows the network operators to optimise the use of distributed generation resources, and enables real-time communication between customers and utility service providers in order to allow optimisation and balancing of energy usage. It is only possible to improve the flexibility and control of the distribution network in this way if the control center operator has very accurate knowledge of the real-time situation of the network [205]. EMS and distributed decision making systems have been widely used for providing power flow management and economic dispatch solutions for microgrids. The details of the technologies which have been deployed, and the applied strategies, are explained in the next section.

6.2 Related works

In recent times, investigating the impact of EMS on reducing the economic and environmental costs for microgrid-based power generation has been active research topic. A survey of various existing microgrid energy management strategies has been presented in [75] to highlight researchers’ opinion on microgrids’ energy management systems. AC and DC microgrid systems have been compared in [206] in terms of the main features and the control methods utilised to maintain their optimum operation. Furthermore, a comprehensive review of the control and operation management strategies utilised in both microgrid systems has been presented in [207, 208]. In terms of the economical, technical, and environmental benefits, microgrid operation has been comprehensively reviewed in [208]. Ultimately, microgrid operation management problem has been considered as a reliability problem in [209], which has also been considered as a multi-objective self scheduling optimisation problem. Thus, microgrids performance has been identified to be mainly dependent on the robustness of the management strategy and the level of intelligence required to achieve the optimum operation.

EMS development has been considered within an economic analysis of distributed supply in [210], while a determinist EMS for a microgrid, including advanced photovoltaic generators with embedded storage units and gas gen-sets, has been proposed in [211]. A new method of mesh adaptive direct search has been employed to minimise the cost function of managing the operation of a microgrid designed for residential application in [149].

The literature has addressed the challenges of managing microgrid resources encountered by the system operators, and has also nominated the technologies and the design standards required to tackle these challenges.
Therefore, the integration of distributed decision making systems has been identified as a successful method for optimising the performance of the microgrid generation. A distributed control framework for the integration of distributed wind turbines and solar panels has been previously addressed [212]. Multi-Agent technology was found to be a viable solution for implementing and/or simulating the distributed control systems in order to optimise the performance of the microgrids. The capabilities of Multi-Agent System (MAS) technology in performing the microgrids generation management has been presented in [105]. MAS has also been used as a solution for managing a distributed hybrid renewable energy generation system in [213], and performing a microgrid power management in [214]. MAS-based control architecture, for achieving microgrids power management objectives, has been proposed in [215, 216]. A decentralised MAS, and a hybrid algorithm, combined with an Evolutionary Algorithm (EA) and a Linear Programming (LP) have been developed to manage a power distribution system in [217].

For market participant-based microgrid management systems, agent technology has also been widely utilised due to their social and autonomous characteristics. In addition, due to agent’s learning characteristics such as creating behaviours and following specific rules in making decisions, they have been proved to be a right modelling tool to model the high uncertainties of various market factors [201]. Eventually, agent technology has been proved as one of the most applicable modelling techniques, and has been successfully utilised in modelling power systems, in order to foster their integration into the electricity market in [218, 219, 220, 221], and also in [222], where it has been used to model the UK market mechanism. For Smartgrid research, agents have been proposed for use when modelling and automating Smartgrid markets in [223]; taking into consideration power dispatch limits, generation and transmission constraints, and spinning reserve requirements.

By considering the environmental issue in the market participation, agent-based planning systems for distributed energy management have been proposed in [224] in order to process energy trading based on energy decisions, with application to market oriented programming for controlling CO2 emissions. Finally, it has been realised that implementing smart management strategies to perform microgrid optimum performance is a timely research topic, and it has been increasingly targeted by power engineering research communities. In this context, MAS technology has been identified as one of the most successful tools for modelling and simulating power systems. However, some critical issues, such as integrating interactive demand forecasting in the decisions, and dynamically configuring the proposed management system based on the operational scenarios, have not been covered.
in literature yet, and hence introducing a new method that overcomes these limitations would have a high impact in this field.

6.3 Research objectives and challenges

The aim of this research is to evaluate the potential of the intelligent management systems in reducing the economic and environmental generation costs. Concurrently, MAS technology has been found to be a successful solution to model the power system management systems; and therefore, we will utilise this technology in the implementation of the proposed system. Hence Artificial Intelligence (AI) is also needed in the implementation. Ultimately, our research will contribute to the knowledge by presenting a novel and adaptive MAS-based microgrid management system, which is implemented as distributed AI-based modules in order to achieve low economic and environmental generation costs.

The major identified challenges in implementing this system are:

1. Reducing the complexity of the system and the high computation resources required to implement it.
2. Managing the difficulty of synchronising the operation of the distributed intelligent software components.
3. Implementing a hierarchy of decision levels in order to prioritise the decisions based on the operational scenarios.
4. Enabling a remote access and control for the proposed management system and the distributed generation units.

6.4 Research assumptions

The assumptions that were considered in the investigations are:

1. Renewable energy sources are assumed to experience a dramatic drop in price in the coming years, whereas electricity and gas prices are expected to increase rapidly.
2. Negotiations for microgrid market participation are conducted directly with the market itself and not with the retailers or any other third party.
3. The market balance point is considered to be an indicator of $U_P$ when buying and selling electricity, by assuming that the market operator is a non-profit body.
4. The nominated generation units for this project are assumed to have the highest efficiency, in comparison with the other products in the market.
5. It was assumed that the weather conditions test data are valid for the simulations in this work.

6. It was hypothesised that the simulation data will accurately reflect the nature of the near future interaction between the utilities and their customers.

6.5 Agent-based technology for implementing the proposed management strategies

The management system for this work was developed in order to implement agent-based applications, so that the performance of the microgrid power generation can be optimised, and can enable the microgrid generation to be integrated with the power markets. The proposed architecture was enriched with ideas for increasing the intelligence of the system, thus increasing its operational proficiency. By analysing the operational scenarios in the targeted microgrid, we found that it was essential to consider the demand values in all of the computation stages, when optimising the microgrid’s performance. Consequently, a demand forecasting model was also required as part of the proposed management strategy. Furthermore, after studying the possibilities of running multiple sources of dispatch, other issues were subsequently identified. These issues centre around the uncertainty of generating electricity from renewable sources; and the difficulty of forecasting the generation cost for SDs, unless a proper control technique is applied to control the charging and discharging process. As a result, it became clear that an alternative optimisation model was necessary in order to optimise the microgrid’s performance. Finally, the microgrid power generation includes lost reserve power generation capacity that can be utilised, if it can be delivered to potential buyers in a timely and cost effective fashion. While exploring an opportunity to sell this reserve to the grid under competitive market environment, it became clear that there is a need to include a smart bidding strategy that can integrate with other models in the overall management strategy, to facilitate selling the electricity to the grid. After identifying the critical operational issues concerning the provision of optimum dispatch for the microgrid, the challenge becomes building a strategy that successfully integrates these models in order to synthesise a solution delivering the optimum performance.

The proposed strategy was designed around a 30-minute operational life-cycle, which ensures that a new decision is made every 30 minutes. The implementation of the proposed management architecture is based on a real case study data from Edith Cowan University (ECU), where the on-campus power network with its everyday load profile was utilised.
in the simulation of this work. The weather conditions throughout the year in the city of Joondalup have been studied over the previous 5 years, and formed the basis of the weather data employed within the case study. In the actual simulation, the MAS was utilised to perform the required generation management objectives on the case study. As the demand values must be included in all of the computation stages of this strategy, the operation cycle starts by forecasting the demand. The process of creating the demand forecast begins by reading the information about the demand of the microgrid, such as time, date and real time demand. After the demand has been forecast, it is then sent to the subsequent computation stages for further processing. The next computation stage is the creation of the power generation schedule and the SDs control. During this stage, all of the information concerning the operational conditions of the microgrids are supplied every 30 minutes, and are then employed to determine the optimum decisions for scheduling the power generation within the microgrid. Once a decision has been made during this stage, all the results are sent to the third computation stage, where the bids are generated to participate within markets under competitive prices. Hence the power generation is planned, and the resource utilisation is based on economic and environmental cost considerations.

This sequence of operation highlights the need for the computational stages to be controlled by superior decisions. The proposed MAS has multiple levels of advanced decision making capability, which helps in prioritising the specific decision making process within the microgrid. The implementation of the proposed agents was based on four major decision making objectives: 1) master controller decisions; 2) demand forecasting; 3) generation and storage management; and 4) bids analysis and generation. In addition to this structure, various external units are also present; representing the grid with other generators, and other microgrids that represent the market competitors. Consequently a network of control agents, that achieve the detailed management objectives, was subsequently proposed. The MAS that has been developed includes three main sections: 1) processing; 2) communication; and 3) input/output interface (monitoring and control). Figure 6.1 illustrates the overall MAS structure.

Generally, the implementation of all agents in this system encompasses the following:

1. Service Registration: At this stage, after the agents are created, named and addressed, they are also registered under the framework's Yellow Pages. This allows agents to identify each other by the services they provide. In this work, the agents were registered under various types and names, depending on the task they assigned to do.
Figure 6.1: The developed Multi-Agent System structure
2. Behaviour setup: During this stage, all of the behaviour parameters for each of the agents are set. More specifically, cyclic behaviours are applied to perform repetitive operations, which unfortunately, also have the drawback of being extremely CPU extensive. In order to reduce the CPU workload, the action() and block() methods were added under the same behaviour class. The action() and block() methods cause the the behaviour cycle to be marked as being blocked; and no longer available for agent processing. The behaviour can be over-ridden if the agent receives a message instructing it to undertake the processing.

A typical pattern for receiving messages code looks like this [2]:

```java
public void action() {
    ACLMessage Message= BidsGeneratorAgent.receive(mt1);
    if (msg!=null){
        // If message recieved, process it!
    } else block();
}
```

3. Message template: This is a predefined messaging communication template that is used to classify the received messages type. For instance, if the template carries a: 1) performative type “REQUEST”, then the message carries a request to the receivers; 2) an “INFORM”, then the message carries information to the receivers; 3) either a “PROPOSE” or “CALL FOR PROPOSAL (CFP)”, then it is either proposing or is calling for a proposal. More details about FIPA complaint message template types can be found in [2, 78]. A message template creation sample looks like the following:

```java
MessageTemplate
mt1 = MessageTemplate.MatchPerformative(ACLMessage.INFORM);
```

The specific content of messages sent between the agents and the environment, or within the agents themselves, were discussed in section 6.5. More specifically, agent structures depend on the complexity of their tasks, and therefore, different structures have been proposed for the agents.

4. Ontology: This is a predefined messaging vocabulary; shared among all the participant agents to code/decode the information exchanged within the agents framework. Building ontologies in our proposed system allows both the information senders and receivers to categorise the content of the messages based on the role they assigned to do.
The ontologies also allow the agents to exchange a set of details simultaneously. In this work, the information exchange is depicted in Figure 6.4. More information about JADE ontologies and their implementation methods can be found in [2].

Finally, the proposed MAS has been configured to run in three connection modes, which results in a different operation strategy for the distributed agents. For the Connecting mode, the microgrid is connected to the utility grid; while for Islanding and Emergency modes, the microgrid is disconnected from the utility grid and is self supplied from its integrated distributed generators. Each of the operational modes has its own individual processing and communication scenario. Figure 6.2 shows the direction that messages take when being sent between the agents, for each of the three operational modes. The specific strategy to be applied is chosen because of its connection mode.

In Connecting mode, the sequence of operations begins by forecasting the demand. This step is followed by the creation of a report of the demand value, along with the status and cost of the other generators, including the utility grid supply, which is sent to the Generation and Storage Management agent (GSM). Once a decision has been made by this agent, the results are then reported to each of the Master Controller (MC) agent, Bidding Analysis and Generation (BAG) agent, and to the generators; for scheduling the generation. The BAG agent may analyse and generate bids, and then send them to the grid agent after receiving information from: 1) the GSM agent stating the amount of power that is ready for sale; 2) weather conditions; 3) generators status; 4) utility and gas generation cost; and 5) a CFP from the grid agent for bidding. When the grid agent responds to this unit with acceptance or rejection, another analysis stage is commenced and other reports are sent to the GSM agent, the MC agent, and the utility grid agent to prepare the system export the power to the grid in the next 30 minutes of operation; providing that there is an agreed deal between the grid and the BAG agents. At that time another processing cycle commences.

In case of Islanding mode; the operation sequence starts by forecasting the demand and reporting the demand value with other generator’s status and costs, including the grid, to the GSM agent for final decision about the generation scheduling. Thereafter, the results are reported to the generators for operation, and to the MC agent for updating the microgrid operation status. Meanwhile, the MC agent will report the operational status to all the processing agents to keep or change the management scenario on the microgrid. Finally, in Emergency mode, the operation can be categorised under Islanding-Emergency mode or Connection-Emergency mode. In both cases the operational decisions...
Figure 6.2: The messaging direction between agents in all operation modes
will be generated from the GSM agent, without considering the demand value to run full
generation capacity from the distributed gas gen-sets (in Islanding mode), or from the grid,
in Connecting mode. At this time, the MC agent will be updated with the microgrid’s
operational status from the GSM agent.

Based on the outcome of the decision concerning the microgrid’s connection mode
and status, four layers of strategies, resulting in multi-level of decisions priority, have
been proposed to cope with operational conditions around the managed microgrid: 1) basic
management strategy; 2) utilising demand in the generation scheduling strategy;
3) advanced management strategy; and 4) market participation strategy. It is proposed
that the MC agent makes the high priority decisions for the microgrid’s operation, based
on three operational modes: 1) Connecting mode; 2) Emergency mode; and 3) Islanding
mode. In addition, it was proposed to include the basic management strategy that runs
other strategies, based on the microgrid’s operational conditions. The priority of the
decisions, and their related strategies based on the operational conditions, are depicted in
Figure 6.3.

In Figure 6.3, it is shown that the operational strategies are configured in such a
manner that the operation is sustained, even in the case of faults occurring in one of the
processing agents. To involve the microgrid with market participation requires that all
other agents must provide their solutions before generating bids. At the same time, the
advanced management strategy, which is operated as the GSM agent, is not permitted to
operate without identifying the demand in the microgrid. Finally, the basic management
strategy (bias) is essential for running all the subsequent decision agents, including running
basic utility and gas gen-sets generation scheduling.
The roles of each agent were described previously in Chapters 3, 4 and 5, however a simplified description concerning the connection and the exchanged messages among the proposed agents, are illustrated in Figure 6.4. The figure also shows the exchange of data between the environment and the agents in the proposed management framework. The figure clearly details the framework for processing the information about the operational conditions of the microgrid; including the attached learning and adaptation mechanisms that were incorporated within the agents. The same figure also illustrates the MC agent role, which is crucially important when reconfiguring the agents structure, based on the specific operational conditions. It also controls the microgrid grid-connection, based on the received results from other agents in the framework.

The management system relies on the utility in supplying the power to the microgrid, as this will provide relatively more secure back-up for the microgrid. Figure 6.5 illustrates the initialisation of the strategy program that runs all agents. To perform the sequence control operation of the proposed management system, messages are to be sent between the agents and external data sources. The purpose of the sequence of operations is to control the conversations needed by the agents, both within and outside of the framework. Several conversations and negotiations must occur before the final decision is made. In Figure 6.5 it is shown that the system supplies all of the electricity demand from the utility, until decisions about optimising the generation have been made. Finally, the decisions are made by the GSM agent, which is also the interface between the management system and the resources. The connection modes with their operation strategies have been firstly tested using JADE as shown Figures 6.6, 6.7, and 6.8.

The implementation of the agents, including their interaction with external data sources and software, is described next.

6.5.1 Demand Forecasting Model agent

The Demand Forecasting Model (DFM), which was explained in detail in Chapter 3, was inter-connected to the proposed MAS through a safe and reliable middle ware, as shown in Figure 6.1. This integration will enable this model to interact with other agents in the proposed management system, as the agent will be considered as a buffer for the forecast values. In addition, the forecast values can also be encrypted and/or modified based on the operational requirement, before they are sent to other agents. Ultimately, this agent development encompassed the following issues:

1. Data streaming - in this part, the data are to be supplied to the model from the date
Figure 6.4: Information exchange between the proposed agents in Connecting mode
Figure 6.5: Framework initialisation sequence
Figure 6.6: Agents communication in Connecting mode
Figure 6.7: Agents communication in Islanding mode
and load metering agents, based on 30-minute intervals of operation, which can be a future extension of this work. In this work the data was supplied from the database. However, the superior decisions are proposed to be received from the MC agent. The streaming data consists of date, time, type of the day (working day or holiday) and real-time demand.

2. Forecasting process - at this stage the model will process the month, day, hour, temperature, and the real-time load data to estimate the next 30-minute demand value in the case study.

3. Data beaming - finally, the demand forecast values are beamed to the targeted agents for further processing stages.

This agent is registered as demand forecasting model agent under “OptimumGenerationPerformance” type, and “DemandForecastingAgent” name in the framework’s Yellow Pages of the proposed management system. There is also a synchronisation setting between the forecasting model in Matlab and the forecasting agent in JADE. This setting allows the agent to read the amount of demand from the model, in a predefined and timely manner. A timing setting for reading information from the model, is essential for all further stages of calculations in the proposed management system.

6.5.2 Generation and Storage Management agent

This agent is the integration of the PGMSCS with other modules in the proposed system. This agent’s role depends mainly upon the information exchanged with other agents. It
will initially acquire the information about the demand and the generators’ status from the DFM agent, and also from the generators’ agents. Thereafter, it will proceed with the required optimisation calculation. Ultimately, the results will be sent to other agents as explained in Section 6.5. The implementation of this agent includes the following:

1. Data streaming - in this part the data is sourced from other agents based on 30-minute intervals of operation. The streaming data consists of the generators’ status and costs; in addition to the superior decisions that are generated from the MC agent.

2. Processing - all received data are processed with the proposed optimisation technique explained in Chapter 4.

3. Data beaming - all results of the optimisation and the decision making should be beamed to other agents as explained in Section 6.5.

This agent will be registered under “OptimumGenerationPerformance” type, and “GenerationStorageManagement” name in the framework’s Yellow Pages. The type and the name will help the seeker agents identify their specific targets for information exchange.

### 6.5.3 Bids Analysis and Generation agent

This agent will connect the Fuzzy Logic-Based Ancillary Service Adaptive Pricing System (FLASAPS) with other intelligent modules in the proposed system. The implementation of this agent considers the competitiveness when selling electricity in a spot market pool. Therefore, building this agent included:

1. Data streaming - the data are sourced from other agents based on 30-minute intervals of operation. The streaming data consists of weather conditions, demand, generators’ status and cost, markets Call For Proposal (CFP) requests, availability and readiness for selling electricity; in addition to the superior decisions that are generated from the MC Agent.

2. Processing - all received data are processed with the proposed pricing and bidding methods explained in Chapter 5. Receiving orders from the market and GSM agent as discussed in Chapter 5.

4. Data beaming - all results of the pricing decisions are beamed to the markets agents, and to other agents in the framework as discussed in Section 6.5.
6.5.4 Master Controller agent

The implementation of this agent involves setting the type and the sequence for the signals generated from this agent for the purpose of controlling other agents in the framework. Hence these signals are generated based on the operational conditions (connection modes) of all the active agents at the time of decision. The agents connection modes, and the messaging directions created in these modes, are illustrated in Figure 6.2. The MC agent development included:

1. Data streaming - the data are sourced from other agents to indicate their operation status based on 30-minute intervals. The streaming data consists of the decisions generated from the GSM agent and BAG agent; in addition to the grid agent that reports the connection status.

2. Processing - all received data are processed with the proposed operational condition rules. The processing includes running the basic management strategy in emergency modes, and setting the orders to other agents to run the advance management strategy in normal operation modes.

3. Data beaming - all decisions applied on the microgrid’s agent operation strategies and messaging directions are beamed to all other agents in the framework as discussed in Section 6.5.

6.6 Results

In this section, the significance of using the proposed strategy with MAS for managing resources in an autonomous microgrid was presented. Ultimately, the results target two main issues for the microgrid operation management: 1) the importance of the proposed strategy in reducing the generation cost in the targeted case study; and 2) the role of agents technology in modelling the proposed strategy. In both considerations, the results cover the economic and the environmental costs throughout a year of simulation time. The subsections below evaluate the impact of the agents on reducing the generation costs.

6.6.1 The role of forecasting in the proposed management strategy

The demand forecasting was integrated with the proposed management system, to maximise the utilisation of generation reserve and to schedule the operation of the generators as explained in 3. In the basic management strategy, the demand forecasting is utilised in order to manage the operation of utility and gas gen-sets. Accordingly, the demand was
fully supplied from gas gen-sets in Islanding modes. The Islanding modes are assumed to be activated in emergency cases, and when the $G_P$ becomes less than $U_P$. Ultimately, full generation capacity is supplied to the load, thus 6 gas gen-sets run all the times in these modes. Hence the environmental cost is evaluated based on the following function:

$$ EnviCost = (G_G + G_{lostG}) * G_E $$

(6.1)

In the economic cost function, there are additional variable and fixed costs for each dispatch source, added to the main cost function: $(MoV)$ variable maintenance and starting and shutting down cost, and $(MoA)$ annual maintenance and insurance cost. The economic cost is evaluated based on the following function:

$$ EconCost = (G_G + G_{lostG}) * (G_P + MoV_G + MoAnG) $$

(6.2)

The Islanding mode is achieved when the following condition becomes true:

$$ (((G_G + G_{lostG}) * G_E) + ((G_G + G_{lostG}) * (G_P + MoV_G +
MoAnG))) > (((U_G) * U_E) + ((U_G) * (U_P))) $$

based on this condition, Figures 6.9 and 6.10 show the impact of utilising the demand values in reducing the economic and environmental costs throughout the year. In the simulation, the microgrid’s mode of operation was switched automatically between Connecting and Islanding modes, based on the variation of economic and environmental costs. The evaluation of economic cost was evaluated from the $G_p$ and $U_p$ data. To evaluate the environmental cost, modern gas and steam turbine power plants were found to emit 435 kg (960 lb) CO2/MWh, while coal-fired power plants were found to emit 900 kg (1980 lb) CO2/MWh [225]. Figures 6.9 and 6.10 show that by taking the forecasting into consideration, the economic and environmental costs would be reduced by 25%.

In both Figures 6.9 and 6.10, it is shown that in Islanding mode, the full generation capacity is identified; which results in a variable amount depending on the month. Therefore, when considering the demand, the system would be more effective in winter, when a low demand profile is identified.
Figure 6.9: Demand forecasting impact on reducing the economic cost ($\) of the electricity supply in the case study.

Figure 6.10: Demand forecasting impact on reducing the CO\textsubscript{2} emission (Kg) of the electricity supply in the case study.
6.6.2 The role of Generation and Storage Management agent in the proposed strategy

The role of this agent was evaluated according to its ability to maintain low economic and environmental generation costs throughout the year. The most challenging part in performing optimum power generation in this agent, is determining $S_p$. This agent was also evaluated according to its ability to control the SDs, in order to perform a beneficial charging/discharging process. The failure of this agent will result in activating the emergency operation mode, that runs based on the basic management strategy. In the basic management strategy, the load is supplied from the utility only at the Connecting mode, and from the full capacity of the installed gas generators in Islanding mode. This fact will result in a huge difference in the generation cost when the advanced management strategy is enabled. Furthermore, operating the microgrid without controlling the storage devices’ charging/discharging process will result in the SDs running continuously, which will result in a higher generation cost that includes the operating cost and the cost incurred by the utility and gas generation prices. In Figures 6.12 and 6.13 and Table 6.1, the results illustrate the role of this unit in controlling $S_G$, reducing the overall cost and increasing the utilisation of reserve over all types of connection modes. Hence the wind turbines and the solar panels generation cost over the 25 years of operation, with the estimated maintenance and insurance cost can be added to the overall achieved costs. The renewable energy sources’ maintenance and insurance costs were estimated by [4, 226]. These estimates have been reflected in our case study’s generation cost by considering the size of the generation units in line with their number of operation hours. The ratio of supplied energy from wind turbines and solar panels is illustrated in Figure 6.11 as compared with demand values throughout the year.

Finally, the economic and environmental costs are compared, based on the utilisation of the advanced management strategy by the GSM agent over the basic management strategy by the MC agent. Figures 6.12 and 6.13 compares the evaluated economic and environmental costs under Islanding and Connecting modes, with basic management strategy and both connection modes with the advanced management strategy.

The results show that the evaluated costs under all microgrid connection modes are mainly dependent on the demand in each month. The maximum demand was identified in February during the summer time, with full load utilisation in the university; differing from December and January, as these two months usually encounter public holidays, which would result in a low power consumption. The lowest demand values can be identified during
Figure 6.11: The ratio of the renewable energy sources generation to the demand values throughout the year in the case study.

Figure 6.12: Economic generation costs in ($).
the winter season from June till September, as shown in Figures 6.12 and 6.13. Tables 6.1, 6.2 and 6.3 compare the utilisation of resources in the basic management system and the advanced management system under all types of connection modes. After evaluating the average \(U_P\) and \(G_P\), which are 0.28 $/kWh and 0.2 $/kWh respectively, we found that although \(U_P\) is greater than \(G_P\), \(U_G\) has more penetration due to its cheaper operating cost, and the fact that it does not waste reserve.

In Table 6.1, it is also noted that SDs utilisation was controlled, by monitoring cost variation in \(U_G\) and \(G_G\) to have optimum amount and time for charging/discharging, to maximise their efficiency for both economic and environmental costs. Running the SDs without controlling them would result in a big economic and environmental loss, due to \(U_G\) and \(G_G\) cost variation; in addition to their operating cost. Ultimately, GSM agent could save these losses, making the SDs of benefit to the efficient running of the system.

The other identified cost parameter is the gas gen-sets lost generation reserve. The proposed GSM agent aimed to utilise the generation reserve in accordance with the safety requirements for the microgrid’s power supply. In the Connecting mode under the basic management strategy, the demand is fully supplied from the utility. In this scenario, the lost reserve that was incurred by the microgrid as shown in Table 6.2 will not take place; instead, the lost reserve is incurred by the utility generators, an outcome which is not
Table 6.1: The cost of running the advanced management system for the resources utilisation throughout the year

<table>
<thead>
<tr>
<th>Month</th>
<th>$S_G\ kW$</th>
<th>$U_G\ kW$</th>
<th>$G_G\ kW$</th>
<th>Lost Reserve kW</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>AP</td>
<td>$CO_2$ (Kg)</td>
<td>$CO_2$ (Kg)</td>
<td>$CO_2$ (Kg)</td>
</tr>
<tr>
<td>Jan</td>
<td>466</td>
<td>4659</td>
<td>3.14</td>
<td>313860</td>
</tr>
<tr>
<td>Feb</td>
<td>825</td>
<td>3887</td>
<td>2.67</td>
<td>395380</td>
</tr>
<tr>
<td>Mar</td>
<td>694</td>
<td>4621</td>
<td>3.11</td>
<td>324230</td>
</tr>
<tr>
<td>Apr</td>
<td>323</td>
<td>4577</td>
<td>2.92</td>
<td>239644</td>
</tr>
<tr>
<td>May</td>
<td>519</td>
<td>2071</td>
<td>3.12</td>
<td>361093</td>
</tr>
<tr>
<td>Jun</td>
<td>561</td>
<td>4582</td>
<td>2.99</td>
<td>322910</td>
</tr>
<tr>
<td>Jul</td>
<td>664</td>
<td>2081</td>
<td>3.04</td>
<td>402363</td>
</tr>
<tr>
<td>Aug</td>
<td>824</td>
<td>4854</td>
<td>3.07</td>
<td>291522</td>
</tr>
<tr>
<td>Sep</td>
<td>751</td>
<td>4606</td>
<td>2.83</td>
<td>234080</td>
</tr>
<tr>
<td>Oct</td>
<td>614</td>
<td>4763</td>
<td>3.00</td>
<td>369004</td>
</tr>
<tr>
<td>Nov</td>
<td>1152</td>
<td>4455</td>
<td>2.92</td>
<td>214040</td>
</tr>
<tr>
<td>Dec</td>
<td>673</td>
<td>4602</td>
<td>3.16</td>
<td>25799</td>
</tr>
</tbody>
</table>
Table 6.2: The cost of running the basic management system for the resources utilisation under Connecting mode

<table>
<thead>
<tr>
<th>Month</th>
<th>$</th>
<th>$CO_2(Kg)</th>
<th>Gg</th>
<th>Lost Reserve</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jan</td>
<td>572976.5</td>
<td>1144.6875</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Feb</td>
<td>758705</td>
<td>1388.0545</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Mar</td>
<td>579256.5</td>
<td>1176.9185</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Apr</td>
<td>524867.5</td>
<td>1064.4255</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>May</td>
<td>632015.5</td>
<td>1213.1575</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Jun</td>
<td>637223</td>
<td>1270.1615</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Jul</td>
<td>683871</td>
<td>1318.1785</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Aug</td>
<td>532442</td>
<td>1001.007</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Sep</td>
<td>498206.5</td>
<td>963.5535</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Oct</td>
<td>640246</td>
<td>1235.546</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Nov</td>
<td>523229</td>
<td>970.2705</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Dec</td>
<td>469999</td>
<td>960.446</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 6.3: The cost of running the basic management system for the resources utilisation under Islanding mode

<table>
<thead>
<tr>
<th>Month</th>
<th>$</th>
<th>$CO_2(Kg)</th>
<th>Gg</th>
<th>$CO_2(Kg)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jan</td>
<td>0</td>
<td>826800</td>
<td>1003.2185</td>
<td>373295</td>
</tr>
<tr>
<td>Feb</td>
<td>0</td>
<td>746099</td>
<td>906.105</td>
<td>191856</td>
</tr>
<tr>
<td>Mar</td>
<td>0</td>
<td>826800</td>
<td>1003.2185</td>
<td>359594.5</td>
</tr>
<tr>
<td>Apr</td>
<td>0</td>
<td>800867</td>
<td>970.811</td>
<td>378248.5</td>
</tr>
<tr>
<td>May</td>
<td>0</td>
<td>826800</td>
<td>1003.2185</td>
<td>345609</td>
</tr>
<tr>
<td>Jun</td>
<td>0</td>
<td>800867</td>
<td>970.811</td>
<td>293225</td>
</tr>
<tr>
<td>Jul</td>
<td>0</td>
<td>826800</td>
<td>1003.2185</td>
<td>300975.5</td>
</tr>
<tr>
<td>Aug</td>
<td>0</td>
<td>826800</td>
<td>1003.2185</td>
<td>429250</td>
</tr>
<tr>
<td>Sep</td>
<td>0</td>
<td>800867</td>
<td>970.811</td>
<td>416939.5</td>
</tr>
<tr>
<td>Oct</td>
<td>0</td>
<td>826800</td>
<td>1003.2185</td>
<td>330060.5</td>
</tr>
<tr>
<td>Nov</td>
<td>0</td>
<td>800867</td>
<td>970.811</td>
<td>416360.5</td>
</tr>
<tr>
<td>Dec</td>
<td>0</td>
<td>826800</td>
<td>1003.2185</td>
<td>443804.5</td>
</tr>
</tbody>
</table>

considered in this study at this stage. In Islanding mode under the basic management strategy, it is assumed that the demand is fully supplied from the distributed gas gen-sets. In this sense, the generation will result in a spinning reserve, which is incurred by the gas gen-sets. This lost reserve is found in the advanced management strategy, but with relatively small amount. By comparing the results in Tables 6.1 and 6.3 it is shown that the advanced management strategy could utilise up to 6% of the total lost reserve throughout the year.
Table 6.4: Comparing the amount of reserve sold with the amount of the reserve offered in the market

<table>
<thead>
<tr>
<th>RdyFrSLElec kW</th>
<th>SLDElec kW</th>
<th>Month</th>
<th>30 days</th>
<th>31 days</th>
<th>28 days</th>
</tr>
</thead>
<tbody>
<tr>
<td>240196</td>
<td>117621</td>
<td>Feb</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>331950</td>
<td>138730</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>363319</td>
<td>134030</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>397058</td>
<td>170177</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>411850</td>
<td>63231</td>
<td>Jun</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>458499</td>
<td>104766</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>526950</td>
<td>217790</td>
<td>Aug</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>709219</td>
<td>315927</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>905687</td>
<td>425920</td>
<td>Sep</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>936272</td>
<td>428840</td>
<td>Apr</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1259486</td>
<td>174973</td>
<td>Nov</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2863598</td>
<td>288030</td>
<td>Jun</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

6.6.3 The role of Bids Analysis and Generation agent in the proposed strategy

It is intended that this agent performs electronic negotiations to sell the generated electricity to the utility under various competitive pricing rules. Although the amount of electricity actually sold will be based initially on the amount of generated, CFP signals from the utility, and the offered proposals from the sellers; the system proved its ability to attract the attention of the market, when tested with other sellers under same operational conditions. Due to unexpected markets and the behaviour of other sellers, it was easier to test this unit under the uniform pricing rules, so that the offered proposals can be accepted when they become lower than the market balance point. Table 6.4 compares the amount of the sold reserve with the amount of the total reserved offered to the market by considering the type of the month.

In Table 6.4, it is shown that the amount of reserve mainly varies depending on the season, in addition to the type of the month (31 days, 30 days or 28/29 days). In winter, a relatively low amount of demand is encountered, when the distributed generators can offer higher amount of reserve, except in July, as the demand will be higher when more activities are expected to take place in the university as the semester starts. In contrast to summer, a lower amount of reserve is offered to the market as shown in the Table 6.4. Generally, the demand is high in summer; however, the wind speed and the solar irradiation are also high, which makes the amount of reserve ranked in the middle. Having the semester break as in summer will also help increase the amount of reserve. The results show that February
has the lowest amount of reserve in this study. Since February has 29 days of operation, in addition to the extensive utilisation for load in this month due the starting of semester activities around the campus. However, in February, there is still some amount of reserve that can be offered to the market. This is due to the high amount of solar generation encountered at that particular period as shown in Figure 6.11 in line with the temperature drop at the second half of the month. In case of both seasons: spring and autumn, there will be higher difference between the demand and the full generation capacity of the microgrid, especially in semester breaks as in April, September and November. This is due to the fairness of the ambient temperature in these seasons, which reduces the amount of power required to run the air-conditioning. This difference has been indicated by the amount of reserve offered to the market in Table 6.4. The other considerable result is the relationship between the amount of the transactions and the money value achieved out of selling the power to the market. Figure 6.14 compares the amount of money achieved with the total amount of transactions. By comparing the results illustrated in Figure 6.14 and Table 6.4, it is shown that the higher amount of power sold to the market is encountered in accordance with the high amount of reserve. Figure 6.14 also shows a non-linear relationship between the amount of money and the transaction achieved out of selling the power to the market. This is mainly due to the variation between the local generation price and the market price; in addition to the adaptation in the sale price which reduces the amount of money achieved in the favour of increasing the amount of sold power in a competitive market environment.
From the results in Table 6.4 and Figure 6.14, it was found that the system could sell 27.8% of the offered amount for sale in the market throughout the year with an average price of 0.13 $/kWh. As comparing this price with the $P_0$, which is of an average of 0.28 $/kWh throughout the year, we found that offering the electricity with 46% of the market balancing price will only sell 27.8% under the uniform pricing rules. This value can be changed, depending on the market conditions, accuracy of the pricing method that cope with the markets requirement, and the variation between the market and the microgrid’s operational conditions. In this work we assumed that the market is ready to buy all the offered electricity from the microgrid, if its generated bid was accepted.

6.7 Conclusion

In this chapter we presented the design and the development of a management strategy, that encompasses distributed intelligent systems for optimising the generation cost in a
typical microgrid. The strategy was tested so that the importance of cutting the cost of generation could be evaluated; where the simulation data was based on actual historical operational conditions. As was discussed in the literature, the MAS was effective in modelling intelligent systems and participating systems with markets under different competitive pricing rules. Eventually the MAS was widely applied to the management of power systems. Therefore, it was utilised to model the proposed management strategy, and integrate it with a simulated market environment to show the effectiveness of the intelligent systems that we developed. In this chapter we presented the development of the proposed management system, which included the integration of MAS technology with AI. The results showed that the proposed layers of strategies were effective in performing optimised economic and environmental generation cost, and also providing remote monitoring, access and control for the intelligent systems under various operational conditions. Furthermore, it proved that the proposed strategies can run under different modes, and the proposed MAS has the ability to reconfigure the strategies to add or remove agents to or from the system depending on the operational conditions. Ultimately, adding MAS characteristics to the proposed management strategy, provided flexibility for system maintenance and upgrade; which overcomes the limitations of the traditional management systems. As verified by the realistic operational conditions data, the MAS was efficient, and could achieve the humanisation management of the microgrid power generation. As a future work, AI can be embedded in the generator’s agents, to increase the quality for the generated electricity and optimise the dispatch for the microgrid. Since this work required a set of software licenses to implement the proposed strategy, using MAS technology to build a system with less number of licenses by directing all the distributed system requests to a one licensed server agent, can be implemented as a future extension of this work. In addition, it is intended that a suite of smart agent-based Android applications be developed, that can provide remote mobile and instantaneous access, monitoring and control for the management system.
Chapter 7

CONCLUSION

This thesis has introduced a new management strategy for power generation within a microgrid, where there are multiple sources of dispatch. The proposed management strategy is based on the deployment of multiple intelligent software modules, which have been developed to perform individual management tasks simultaneously. The intelligent modules undertake decision making, in order to achieve the lowest possible economic and environmental costs, for power generation within a microgrid. The requirement for integrating this level of intelligence into the management system, in order to operate the microgrid’s resources, has been established by analysing the microgrid’s operational conditions, and by critically reviewing the recommendations of other researchers in this field. Short term demand forecasting has been identified as an essential part of the proposed system, as it provides the other stages of analyses, with the necessary information concerning the requirements for power generation in the microgrid. Due to the uncertainty of both user behaviour and weather conditions, obtaining an accurate demand profile has become a challenging process. Therefore, it is crucial that an advanced modelling technique that incorporates an adaptation of the demand forecasts be deployed, which can provide the instantaneous operational conditions to the model. The implementation of a novel adaptive demand forecasting model which meets this criteria, has been illustrated in this thesis.

The second major issue we were confronted with when attempting to optimise power generation within the case study, was in controlling the attitude of the SDs under complex operational scenarios. This problem has been addressed in this thesis by introducing a novel charging/discharging process, which aims to improve the operation of the storage devices. After optimising the operation of multiple sources of dispatch in the microgrid, another cost effective factor has been identified, the generation reserve. A further stage of investigation and analysis became essential in order to successfully incorporate this factor when optimising the generation cost. Offering the reserve for sale to the grid became the
next challenge, the process also needing an extensive pricing analysis. Before implementing
the required pricing algorithm to optimise the bidding, it was also essential that the mar-
kets policies and the bidding rules were studied in detail. Ultimately, adaptive pricing rules
have been added to the proposed management system to respond to the competitiveness of
the market, and also to ensure that the amount of power offered at a competitive price is
maximised. Finally, since the proposed management system is needed to achieve reliable,
safe, and low cost generation for the microgrid; MAS technology has been implemented
to operate the distributed intelligent modules in a reliable manner. To ensure reliability
in the management decisions, the management system has been set to run the intelligent
modules in a complementary fashion, where all the modules are dependent upon each other
when making the final and optimum decisions. In addition, the management system struc-
ture included a number of active agents that work together to support the system when
it encounters an operational fault. In this case, a reconfigurable management strategy is
activated to run the remaining agents in a different operating mode. The simulation results
illustrate the generation cost under different operational conditions, proving the success of
MAS technology to model the proposed management strategy with distributed processing
stages. This chapter summarises the findings and the contributions of this thesis in Sec-
tion 7.1, and suggests several research directions that can be undertaken as future works
in Section 7.2.

7.1 The contribution of the thesis

The main contributions of this thesis are concluded as follows:

- Introducing a novel modelling method that performs adaptive demand forecasting
  for the case study. The modelling method that has been developed, has been im-
  plemented to perform short term demand forecasting for the case study, by reading
  the information relating to the forecasts such as: the air ambient temperature, date,
  type of day, and time of forecasting. This combination has been nominated to suit
  a university type demand profile after studying the demand patterns in the case
  study. It has been identified that the demand profile is affected by individual and
  correlated factors. After these factors have been identified, they have been included
  in the model, though not through the traditional modelling training methods. The
  factors have been included through an adaptation method, that tunes the forecasts
  based on the knowledge about the real effect of the correlated parameters. This
adaptation mechanism has been implemented via Fuzzy Logic (FL) with a rule base system, developed to impose the effect of these parameters on giving more accurate forecasts. We have also made note of the influence that our experience in modelling has, when attempting to set the correct membership functions and universe of discourse settings. (These functions and settings are in turn applied to the fuzzy tuning system in order to enhance forecasting accuracy). Apart from the main forecasting model, another intelligent component has also been added to the model; to return the real-time demand values to the model’s forecasts, through an optimum tuning process that aims to achieve the highest forecasting accuracy. This part of the modelling includes another adaptation method; to ensure that the system can react to unexpected changes in the real-time demand, based on optimum adaptation values achieved with low optimisation searching times. The optimisation method utilised in this model was developed by training the Artificial Neural Network (ANN) to react to changes by providing suitable tuning values. The results obtained from testing have enabled the conclusion to be drawn that the proposed demand forecasting model achieves more accurate forecasting in comparison to the traditional model. In addition, the results have also proved that the adaptation mechanism we added, was a viable solution for utilising the forecasts with the generation scheduling problem in the case study; when further analysis and studies involved.

- Implementing a new optimisation method, to optimise the performance of the microgrid’s power generation, while being supplied from various types of distributed generators. The implementation of the proposed method was undertaken to cope with the variations in the cost of generation that result from: variable utility tariff ($/kWh), variable gas generation cost ($/kWh), dynamic demand profile (kWh), intermittent solar and wind generation (kWh), unexpected SDs charging/discharging price ($/kWh), and eventually the unpredicted SDs generation capacity (kWh). Operating wind turbines, solar panels, SDs, gas gen-sets, and utility supply simultaneously would result in high generation costs; unless a robust management system is involved to track the dramatic changes to the cost of generation, and match the supplied power to the level of demand being experienced in the microgrid. To cope with these challenges, our proposed optimisation technique is comprised of a combination of intelligent methods, applied to optimise the performance of the microgrid power dispatch. Traditional Particle Swarm Optimisation (PSO) has been applied, to ensure that optimum decision-making is occurring when scheduling the power gener-
ation in the microgrid. However, to deal with the challenging SDs operation, a price monitoring mechanism has been integrated with the PSO to enable making profitable charging/discharging decisions, while maintaining optimum performance for other resources. Since utility supply and gas gen-set power generation are the main supply points for the microgrid, their prices have been nominated as being the index for the charging/discharging process. The method updates the charging/discharging price threshold, by employing a daily price change trend; following this, a weekly average of price change trends is calculated, which in turn becomes the charging price for the utility supply or gas generation. This value has been considered in parallel with the amount of storage device SDs participation in the microgrid dispatch, to ensure that their profitable operation time is maximised. In order to include these factors for consideration when optimising the decision-making, a hybrid PSO-FL structure has been implemented. In this instance, the results are accumulated in a daily pattern so that the cost variations can be analysed, and then a rule base system is invoked, to correlate the price variation with the amount of SDs utilisation. Finally this method has been compared with the traditional PSO, giving consideration to the overall generation cost achieved, and also to the SDs’ level of operational efficiency. As a result, this method has demonstrated that it can achieve both lower costs, and a better operational efficiency.

- Developing novel pricing rules for offering the microgrid’s spinning, and non-spinning generation reserve, as AS to the electricity market. This part of the thesis includes a basic economic analysis to place beneficial, yet also competitive reserve prices, so that both its prospects of market participation can be increased, and that the amount of reserve sold to the market can be maximised. The pricing rules have been built to reflect the strategic thinking of a seller, who might adjust his/her prices according to his/her operational circumstances, in parallel with the market conditions. The rules have also been designed to include the near future operational conditions in the pricing. It has been suggested that this strategy may have a better outcome in the longer term, than that which is possible from the fixed pricing rules. The proposed pricing mechanism is comprised of four stages of processing: 1) the decision tree stage, 2) the forecasting stage, 3) the estimation stage, and 4) the adaptation stage. At each stage of processing, a proper AI method is invoked to achieve the objectives required by the stage itself. In the main part of the pricing, i.e. the decision tree, the initial pricing rules have been devised in such a way, that they can evaluate the
difference between the microgrid’s local generation cost point, and the market balancing point. Depending on the operational scenarios, variable local generation price is often encountered, thus variable prices ($SLp$) are also expected from the microgrid. In order to maximise the profit and increase the chance of market participation, the initial prices have been set so that they are midway between the two points. It was proposed that the middle point move between the market balancing and the local generation cost points, as the operational conditions are explored; looking for possibilities to maximise the profit and the chance of market participation. To this end, a simple forecasting module has been implemented; to forecast the near future weather conditions (wind speed and solar irradiation), the utility supply tariff and gas generation cost, and to include these estimates in the final prices. The proposed forecasting models have been built to consider the real-time operational conditions in the forecasting, which would benefit from having accurate short term forecasts. To utilise these forecasts in the pricing, the third processing stage has been designed to estimate the operation of the microgrid resources, based on the forecast values. PSO has been incorporated in the design, to utilise the forecasts when estimating the optimum operation profile for the microgrid. This estimation was necessary for building predictions about the reserve conditions, to make the pricing more strategic. These estimates are utilised by the fourth processing stage, to adapt the initial prices and make them market competitive. Basically, the adaptation is subject to three elements that adjust the prices in the appropriate direction: the amount of reserve offered for sale $RdyFrSLElec$, the evaluated microgrid local generation price $SLp$, and the future direction of price change $IncorDec$ (up/down). These factors are correlated through a fuzzy system that operates according to a predefined rule base, to reflect the desired decisions, corresponding to each operational scenario. MAS technology has been utilised to simulate a competitive market environment, that represents three competitive sellers, including our case study, and a one buyer (utility grid). The proposed pricing method has been tested under various market policies, where the proposed method has consistently sold a higher amount of reserve.

- Implementing a Multi-Agent based management System (MAS) that holds strategic behaviours, to maintain reliable, secure, and cost effective operation for the case study. Initially, the system was implemented as a collection of distributed intelligent agents, controlled via a central agent, and working together to achieve the management system objectives. The distributed agents were centrally controlled to
keep them running in a timely fashion under predefined strategies. Furthermore, the operational structure of the agents was set to be reconfigurable, depending on the scenarios of the microgrid and the management system. The system that we have implemented, is comprised of four levels of increasing sophistication of decision making; so that the microgrid can be operated under different economic and environmental cost levels. The decision levels are enabled, according to the information supplied about the case study, and the distributed agents status. The proposed agents were implemented within three major categories: Input/output interface, communication, and processing. Within each category, agents were assigned to deal with the operational scenarios, reacting to changes in the operating conditions, so that they provide the optimum decision. The system implementation has proved its success in running low cost generation for the microgrid, under different operational scenarios. The simulation studies have also proved that the proposed strategy was successful, in making the microgrid participate appropriately under different market policies.

From the reliability perspective; implementing MAS based technology for managing resources, could overcome the traditional management systems, by including the flexibility in maintenance and upgrade when required. The system has been verified with detailed operational conditions data, which have been derived from a set of engineering assumptions. In conclusion, the MAS was able to reflect the human strategic behaviour, in managing the power of generation for a microgrid with multiple sources of dispatch.

7.2 Future works

The possible future extensions of this work can be undertaken in the following areas:

7.2.1 Developing adaptive membership function demand forecasting models

Our proposed demand forecasting has been implemented via an intelligent adaptive model that adapts the forecasts to the operational conditions. By analysing the operation of the models that we developed, several opportunities for investigating how to improve the adaptation performance have been identified. The first possible research direction of this work, can be the fuzzy model membership functions update based on the demand accuracy. In this case, the demand accuracy can be represented as the cost of a function, that
encompasses the shape and the range of discourse of the fuzzy model’s membership functions. The rationale being that this approach will build a dynamic modelling structure, capable of coping with the uncertainties of the variable modelling parameters. The other research direction extended from this work, can be implementing an optimisation technique to tune the feedback fuzzy tuning parameters, based on the operational conditions in the microgrid. In this case, the modelling accuracy will be represented by a cost function, for the feedback adaptation membership functions of the fuzzy system. In both cases, the demand forecasting accuracy will be the index for updating the model’s parameters. Yet, the limitation of implementing the optimisation technique to tune the model’s parameters, is the searching time that should match with demand forecasting intervals.

7.2.2 Considering power quality and market participation in optimising the microgrid performance

In the second intelligent module, we have presented a novel optimisation method, for optimising the microgrid performance with various types of distributed generators. In this context, four distinct research investigations can be launched from this chapter. 1) Modelling the generation price change pattern for the microgrid resources. 2) Considering the microgrid market participation in prioritising the operation of the resources in the microgrid. For instance, making the SDs operation attractive to the market; or including forecasting modules, to guide the optimisation technique towards estimating the operational conditions, required to prioritise the operation of the resources. 3) The traditional PSO utilised in this chapter has been implemented with fix searching parameters, however there is an opportunity for including online parameters adaptation, that adjusts the searching mechanism, according to the operational scenarios. This part of the work will help improve the traditional PSO performance, which would result in a lower generation cost. Adapting the PSO parameters has been addressed using FL in [148] on managing microgrid resources. The future work arising from this chapter is in teaching the PSO how to select its best searching parameters, based on the historical values of the achieved cost, using Artificial Neural Networks (ANN). 4) Considering the voltage and frequency droop control, in line with the economic and environmental dispatch in the power management strategies, to improve the reliability and efficiency of the power generation in microgrids.
7.2.3 Implementing adaptive pricing rules that aim to sell the power reserve in a limited time frame

In this work, we have implemented an adaptive pricing mechanism that adjusts both the initial prices offered to the market, and the microgrid’s operational conditions. The successfullness of the method was tested under a variety of different market rules. However, in all the market rules, the power trade is made after a set of electronic negotiations are conducted; resulting in either the acceptance or rejection of the bids which were previously placed. This was made in a fixed transaction time frame. The first instance of a possible future work, is to investigate the application of adaptive pricing rules to find the optimum deal within the market, after receiving a market rejection for the microgrid’s initial bid; while utilising the lowest possible negotiation time. This can be implemented by converging the price change towards the lowest expected market price, in order to achieve the least possible negotiation time. The second possible extension to our research work is in adjusting the current implemented pricing factors, by monitoring the rate of successful transactions achieved by the pricing parameters. Accordingly, adjusting these parameters by making the maximum number of transactions, is the cost for the pricing parameters function. This would help maximise the number of successful power trade transactions. The investigation would also include an analysis of the specific optimisation methodology which would be most appropriate for this research.

7.2.4 Investigating the role of agent technology in implementing a mobile distributed energy management system using the Android operating system

It has been demonstrated that the MAS with distributed AI, is successful in reflecting the human attitude in making strategic decisions for optimising the microgrid’s power generation performance. As a future work, the MAS implementation can be extended to include sensors, relays, and generators; enabling remote access, a greater degree of control over the devices, and providing for a more sensitive management system. Furthermore, AI can be deployed on the generator’s agents, in order to provide a multi-objective optimisation functionality that includes power quality control. In this case, we are expecting high amount of computation resources required by the intelligent distributed systems. Ultimately, investigating the role of MAS technology in reducing the amount of these resources can be another extension to this work. MAS technology can be utilised in building a centralised system that directs all the distributed agents’ tasks to a centralised server agent. This
agent by its turn can be developed to process the requests sent from the distributed systems in a timely fashion, thus ensuring systematic operation for the distributed agents. Further extensions could also include the design of control systems capable of coping with voltage and frequency instabilities in the dispatched power. It is also possible to extend the mobile-based agent technology to Android devices, allowing for more flexible remote access capabilities for controlling the system.
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