

Microgrid energy management system based on artificial intelligence

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Dissertation submitted in fulfilment of the requirements for the
degree *Master of Engineering in Electric and Electronic
Engineering* at the North-West University

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Graduation ceremony: May 2019

Student number: 22684956

Abstract

Microgrids provide the opportunity to combine various distributed energy resources to supply a local load independently from, or in parallel with the national grid. This allows the load to utilise renewable energy as much as possible while having the option to utilise energy storage or fossil fuel generators during times when renewable energy is not available. This provides robustness and quality of supply for the load. Due to the abundance of solar irradiation in Africa, the microgrid is seen as a solution to provide reliable, clean energy at affordable rates.

The aim of this study is to develop an energy management strategy for an industrial, low-voltage microgrid in Johannesburg, South Africa. The main objective for the energy management strategy is to reduce the electricity costs of the facility. Several objectives are identified as performance measures through which the savings can be achieved.

From literature, promising energy management strategies are identified. A simulation framework is developed in Simulink in order to simulate the operation of the energy management strategy. It is verified to be an accurate representation of how the actual system would work. An iterative design process is followed in order to develop, model and verify a truth-table based logic controller, as well as a fuzzy logic controller that both achieve the objectives set-out. An artificial neural network short term load forecasting approach is also investigated, which proved to be promising.

The truth-table based logic controller is converted to PLC-code and implemented on the physical microgrid controller. Field data is collected which serves to validate that the objectives defined, did in fact result in the expected savings.

Furthermore, the simulation framework in Simulink is utilised in conjunction with the fuzzy logic controller to investigate the effect that various sizing options of the distributed energy resources in the system might have on the cost savings. A more ideal configuration is also investigated, where the energy management system receives

an additional input from the solar-PV power production, which is not available in the system studied.

This study emphasizes the importance of simulating microgrid energy management algorithms and illustrates how the expected performance can be achieved through effective planning, design and simulation of an energy management algorithm. The study also illustrates the versatility of MATLAB and Simulink for microgrid-related work. This project shows that artificial intelligence techniques have promising potential when applied to microgrid energy management.

Keywords: Renewable energy, microgrids, distributed generation, energy management, fuzzy logic, artificial neural networks, energy storage

Acknowledgements

I would like to thank Eaton for funding this research and providing a working microgrid on which to test my algorithms.

I would also like to acknowledge the following people for their contributions during the course of my studies.

- My supervisors Prof. G. Van Schoor, Prof. K.R. Uren and Prof. A.P.J. Rens for their valuable guidance and inputs. I want to especially thank Prof. George van Schoor, my main supervisor, for his guidance and advice throughout the study.
 - Dr. Eugén Ranft at Eaton for his innovative idea to propose the study, his support and guidance throughout the study and for giving me the opportunity to work on the development of an actual microgrid.
 - Brian Lloyd, Nico Archer, Bunty Kiremire and Goolam Bux at Eaton for helping me to gather data from their systems, getting all the information I required and uploading my algorithms on the system.
 - My wife, Chirestie, for her unwavering love and support throughout the study.
 - My parents for all their love and support throughout my years of study.
-

"For God so loved the world, that he gave his only Son, that whoever believes in him should not perish but have eternal life." John 3:16

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List of Abbreviations

DER distributed energy resources

DG distributed generation

DS distributed storage

PV photovoltaic

AC alternating current

DC direct current

MGC microgrid controller

PMS power management system

EMS energy management system

SCADA supervisory control and data acquisition

BESS battery energy storage system

MILP mixed integer linear programming

MINLP mixed integer non-linear programming

ANN artificial neural network

FIS fuzzy inference system

SOC state of charge

MLP multilayer perceptron

RBF radial bias function

IS interconnection switch

TOU time of use

PLC programmable logic controller

AVR automatic voltage regulator

PCC point of common coupling

CSV comma separated value

STLF short term load forecasting

Chapter 1

Introduction

This chapter provides background information on microgrids in general and the control of microgrids. The problem statement is given, followed by the issues to be addressed and the methodology. A concise overview of the document is also presented.

1.1 Background

1.1.1 Microgrids

A microgrid is an electric power system consisting of distributed energy resources (DER), which may include control systems, distributed generation (DG) and/or distributed storage (DS). A microgrid is usually located at or near a local load and is capable of operating in parallel with, or independently from, the main power grid. When the microgrid operates independently from the grid, it is referred to as an island [1]. Loads and DERs in a microgrid system can be disconnected and reconnected when necessary with minimal disruption to local loads, thereby improving reliability. DG technologies contain a variety of energy sources and may include photovoltaic (PV) cells, wind generators, fuel cells, micro turbines, and reciprocating internal combustion engines with generators. A combination of fossil fuel and renewable DG technologies allow

the reduction of the load's carbon footprint, as well as to generate electricity more economically due to the continuing reduction in the price of renewable energy generation [1]. DS systems can be battery banks, super-capacitors or flywheels. Microgrids generally operate at low-voltage and medium-voltage levels, which corresponds to the operating voltages of equipment in industrial parks and households [5]. Another advantage of a microgrid is the reduction of costs and inefficiencies related to distribution and transmission of electricity over great distances, due to the fact that DG allows electricity generation to take place close to the load [1]. DG and DS systems are mostly connected to the microgrid through power electronic converters, isolation transformers, or both. The use of power converters at DG and DS branches serves the purpose of controlling power flows, stabilizing the microgrid voltage and frequency, conversion from alternating current (AC) voltage to direct current (DC) voltage and vice versa [6]. Figure 1 shows the two typical microgrid topologies, namely microgrids controlled by utilities and microgrids controlled by private or commercial facilities. The main interconnection switch (IS) labelled as IS-1 in figure 1, would be open for a utility microgrid, which would be actuated by the local utility. IS-2 would be open for an industrial or commercial microgrid, operated by the owner of the facility.

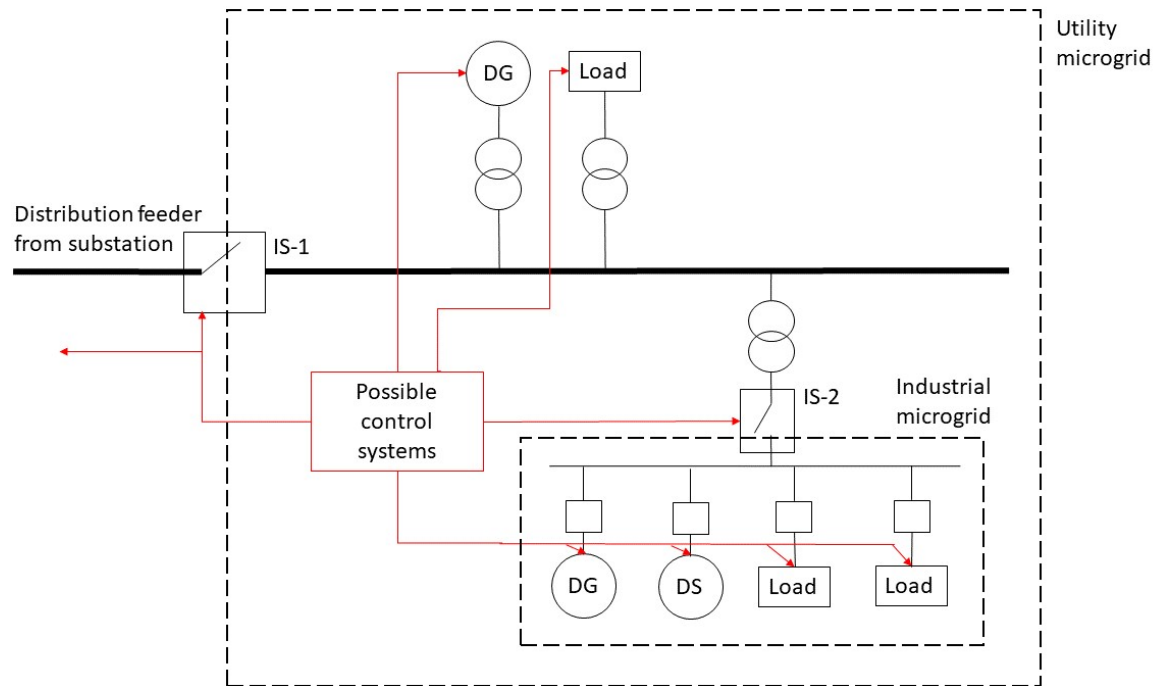


Figure 1: Typical microgrid topology [1]

In figure 1, the possible areas of use for control systems are indicated. The specific portions to be controlled would depend on the needs of the client, but may include control of interconnection switches, DG, DS and loads as indicated in figure 1.

Any microgrid implementation should be carefully planned due to the complexities that may arise. For microgrids to work properly in islanded mode, a switch must open and the DER must be able to carry the load on the islanded section. This includes maintaining suitable voltage and frequency levels for all islanded loads. Depending on the switch technology, momentary interruptions may occur during transfer from grid-parallel to islanded mode. If power is lost, the DER assigned to provide power to the intentional island should be able to restart and pick up the island load after the switch has opened. Power flow analysis of island scenarios should be performed to ensure that proper voltage regulation is maintained and establish that the DER can handle inrush currents from large loads. The DER must be able to follow the load by supplying sufficient power during islanded operation and sense if a fault current has occurred downstream of the switch location. When power is restored on the utility side, the switch must not close unless the utility and islanded portions are synchronised. This requires measuring the voltage and frequency on both sides of the switch to allow synchronization of the island and the utility.

1.1.2 Microgrid control

The control system of a microgrid is designed to safely operate the system in grid-parallel and stand-alone modes. Such a control system may be based on a central controller or embedded as autonomous parts of each distributed generator [1]. When the utility is disconnected, the control system should control the local voltage and frequency, provide (or absorb) the instantaneous real power difference between generation and loads, provide the difference between generated reactive power and the actual reactive power consumed by the load; and protect the internal microgrid [1]. Usually, there are three layers of hierarchical control, namely primary, secondary and tertiary. Primary control is responsible for the first, faster level of control. It is usually

an uncoordinated droop control that maintains voltage and frequency levels. Any remaining oscillations that may occur due to a serious disturbance in the system, can be compensated for by the actions of a secondary controller. Tertiary control is a higher level control responsible for scheduling regarding DER in a microgrid. The tertiary level, which is a supervisory control level, is referred to as a power management system (PMS) or energy management system (EMS).

A PMS is a supervisory control and data acquisition (SCADA) system that can implement specific algorithms or functions necessary to control a power system. The software usually runs on a microgrid controller (MGC) [7–9]. The PMS of a microgrid usually has several goals, but is dependent on the individual needs of the operator as well as the operator’s contract with the local utility company. Thus, these operational goals vary greatly between different microgrids. Typical goals are safety of the plant, reliable operation, power quality and peak demand shaving [10]. Additional goals like energy related cost savings and emissions reduction will typically also be controlled by the microgrid controller, but by a subset of the main control algorithms, called the EMS. The EMS focuses on the economic aspects of optimising the microgrid’s energy usage. The techniques with which this can be achieved are discussed in more depth in chapter 3. In order to achieve the microgrid’s specific goals, there are different functions that have to be implemented [11]:

Control and regulation: These functions are employed to ensure the safe and reliable operation of the microgrid when it is connected to the grid, in islanded mode or has to re-connect and synchronize with the grid. While performing these functions, the EMS has to optimize the energy efficiency as well as maximize renewable energy production and minimize the wear on internal combustion generators. This can be achieved through various energy management strategies, some of which include artificial intelligence that decides on preferable power outputs or inputs for DG and DS units.

Emergency management: The MGC will ensure that the correct measures are implemented in order to protect the system’s integrity in emergency situations. The emergency functions should ensure system stability and maintain power supply to critical loads

that might affect the safety of staff or the plant's integrity.

Other typical SCADA functions may also be employed by the MGC:

Supervision: Real time monitoring of system parameters and storing of data for analysis.

Alarms Management: The system collects and displays relevant alarms to the operator.

Back-up management: Increases the availability of the MGC.

All of these functions enable the MGC to control and supervise a microgrid in its relevant operating modes.

1.2 Problem statement

The purpose of this project is to develop an EMS algorithm for a low-voltage, industrial microgrid. Various techniques should be studied from literature and suitable techniques should be selected to implement on the system. Artificial intelligence techniques in particular have to be investigated. The artificial intelligence should allow the system to adapt to certain situations and choose the best course of action without human input. The single line diagram of the microgrid on which the project is based can be seen in figure 2. The system constitutes a 200 kW PV array, 200 kWh battery energy storage system (BESS) and a 400 kVA diesel generator, indicated as "GEN" in figure 2. The BESS has a 275 kW inverter. "B" represents a circuit breaker. The system powers an industrial facility and is controlled by a central MGC with local controllers on each component as indicated in figure 2.

The main objective of the EMS algorithm is to minimize the energy costs that the plant incurs by optimal usage of the PV array and BESS, during normal operating conditions. The diesel generator is for emergency use only and does not form part of the study. Essentially, only the charging and the discharging of the BESS will be controlled by the

EMS. The curtailment of the PV as well as opening and closing of the circuit breakers is managed by a separate programmable logic controller (PLC). The proposed EMS algorithm will be developed and verified in MATLAB after which the EMS algorithm will be implemented on the MGC's programmable logic controller (PLC)-based system in order to validate the proposed method.

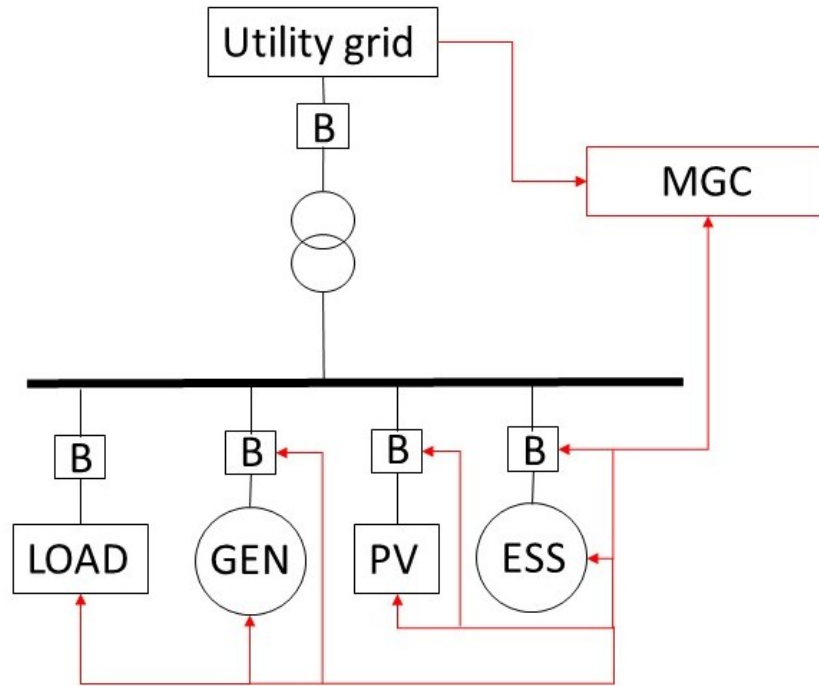


Figure 2: Microgrid single line diagram

Thus, the main objective for the study is to develop an EMS algorithm for a specific microgrid to ensure energy cost savings. This can be achieved through:

- Researching relevant energy management strategies for microgrids and selecting strategies from literature to apply to the specific problem
- Researching methods with which to simulate energy management algorithms and selecting a suitable option. This would serve to verify the energy management algorithm.
- Implementing an energy management algorithm on the physical microgrid. The field data collected from the implementation would serve to validate the energy management objectives identified for the specific microgrid.

-
- Researching and simulating other methods, i.e. artificial intelligence, in order to compare them with the method implemented on the microgrid

1.3 Issues to be addressed and methodology

EMS design process

In order to design an EMS for a microgrid, a comprehensive design process is essential. The objectives for the EMS has to be identified. An iterative design process can be followed to ensure the necessary objectives are met. Extensive research has to be done in order to select the most appropriate energy management approaches and techniques to achieve the performance measures. After development of the EMS, it has to be simulated in order to verify its effectiveness before implementation can occur.

System specification

The development of an EMS for a microgrid requires a detailed system specification as well as a list of performance measures. This will allow the designer to set specific, measurable goals and outcomes for the system to reach in order to determine its efficacy. The system specification for this project can be obtained by consulting the owner or operator of the microgrid. A detailed system diagram, equipment list and equipment ratings is required. The unique objectives and challenges for the microgrid can be defined by analysing the utility electricity tariff structure, assessing the available equipment in the microgrid and discussing the expectations and objectives that the owner or operator of the microgrid might have.

Data acquisition

Before the microgrid can be modelled, data on the actual system's performance has to be acquired. This will help to build an accurate model by comparing the theoretical results with that of the actual system. Dedicated measurement equipment is required on the physical system in order to retrieve the necessary data. Typical data required to develop an EMS would be load demand over several months or years, as well as PV or other DER power production data, if available. The load data can usually be retrieved from the utility or through on-site metering equipment. Most large PV inverters have the ability to provide power production data at various resolutions, which can be extracted directly from the inverter or from a web interface.

EMS Simulation

In order to verify the effectiveness of the proposed EMS, its performance has to be simulated first. A suitable simulation method has to be identified and implemented. To simulate the EMS, it has to receive inputs similar to that which the actual microgrid would provide. Thus, a detailed dynamic model can be developed to emulate the behaviour of the microgrid. Alternatively, if all the necessary real historical data is available, the microgrid can be represented by a set of data, which will serve as the inputs to the EMS. This data should include actual load demand as well as power production for any DER that might be active in the system. During simulation, the outputs of certain DER, for example an ESS, might be dependent on the outputs of the MGC that is being simulated. This means that historical data for these DER won't be usable, as the simulation should react in real-time to the set-points provided by the MGC. These methods had to be thoroughly researched in order to select the most applicable method. The simulation environment chosen was MATLAB and Simulink.

AI selection

After extensive research, the best artificial intelligence approach has to be selected. This selection has to be made by keeping in mind the system specifications and performance measures in order to ensure the most compatible solution for the specific problem. After reviewing the literature, it was decided to utilise fuzzy logic to control the charging and discharging of the ESS based on inputs from the load and pre-defined objectives. Utilisation of artificial neural network load forecasting will be studied in order to determine whether or not it will add value to the EMS.

Verification of EMS

Verification of the EMS's performance will be done by simulating it in MATLAB and Simulink and then analysing the results. In order to verify the performance of the EMS, it should perform as expected by analytic predictions as well as that of literature. The performance measures and objectives defined for the system has to be reached. This would typically be assessed by calculating the simulated savings on the facility's electricity bill.

Validation of EMS

Validation of the EMS will be by implementing it on the physical system and analysing its performance. The simulated EMS algorithm has to be converted to PLC-code that can be uploaded onto the physical microgrid controller. The EMS algorithm will be validated if it performs as it was intended to, as predicted by simulations. If the objectives defined did in fact result in the expected savings, the objectives that were defined for the EMS can also be validated.

1.4 Dissertation overview

Chapter 1 defines the objective of the study as developing an energy management algorithm for a specific microgrid.

Although the focus of the study is on energy management of a microgrid, a thorough understanding of microgrids in general and microgrid design has to be developed. Chapter 2 aims to set the foundation by discussing microgrid design considerations and guidelines from literature and relevant standards.

After microgrids are thoroughly defined and understood, chapter 3 looks at the literature around microgrid energy management and what techniques are typically used. From the literature, fuzzy logic and artificial neural networks are identified as promising techniques.

In chapter 4 the objectives for the energy management system are identified. A strategy is developed that would reach these objectives. The strategy is implemented through a standard logic control algorithm.

Chapter 5 discusses the development of a simulation framework in Simulink wherein the energy management algorithm can be tested and evaluated. The algorithm is verified through the simulations. The algorithm is then implemented on a physical microgrid controller and field data is collected. The field data then serves to validate that the objectives defined in chapter 4, do in fact reach the expected cost-saving goals as set out in chapter 4.

In chapter 6, the artificial intelligence techniques identified from the literature are developed to suit the specific microgrid defined in chapter 1. These techniques are implemented in the simulation framework developed and verified in chapter 5. It is found that the fuzzy logic control delivers good results. The short term load forecasting through the artificial neural network is found to be fairly accurate, but not as accurate as found in literature, due to reasons discussed in more detail in chapter 6.

The sizing of the DER in the microgrid is varied in chapter 7. The potential savings are discussed and compared with recommendations given. Simulated control is applied by the fuzzy logic controller developed in chapter 6.

In chapter 8 a more ideal configuration for the fuzzy logic controller is simulated. This entails adding PV power as an input to the fuzzy control, which was not available on the physical microgrid during the study. It is found that having PV power as an input provides definite cost-saving benefits.

Chapter 9 discusses future work, recommendations and concludes the study.

Chapter 2

Microgrid design considerations

This chapter aims to give a brief overview of the standards applicable to microgrids, as well as the project flow and aspects to consider with sizing, design, commissioning and testing of a microgrid. In chapter 1 it was mentioned that the focus of the study is microgrid energy management. However, it is important to gain a thorough understanding of the working principles of a microgrid before commencing with the energy management thereof. This chapter aims to provide that foundation.

2.1 Introduction

Microgrids provide the opportunity to ensure quality and reliability of supply with also potentially reducing the costs of energy. In order to achieve these objectives, effective planning, design and implementation is necessary. In the field of PV-array projects, thorough best practices and guidelines have been developed to guide design engineers. However, with the added dynamics of various types of DER connected together, some new challenges arise. Due to the relative novelty of microgrids, there aren't a great multitude of guidelines on the best practices and design processes to follow for microgrids yet. However, certain technical standards have discussed these practices before, but they have been found lacking. Therefore, the IEC and IEEE are working on

new microgrid-specific standards which will be discussed further in this chapter.

2.2 Microgrid standards

The only available, published, international standards relevant to microgrids that were available before 2017, are indicated in table 1.

According to [12], these standards are limited and not applicable to modern microgrids. Thus the IEC and IEEE worked on developing new standards that are more relevant to smart grids and microgrids. The IEC is developing the 62898 series of technical standards related to microgrids which are displayed in table 2. At the time of writing, only IEC 62898-1 has been published.

Institute	Published standards
IEEE	IEEE 1547.4: Guide for design, operation, and integration of DER island systems with electric power systems
IEC	IEC 62257-1: Introduction to rural electrification IEC 62257-9-1 Micropower Plants IEC 62257-9-2 Microgrids

Table 1: Pre-2017 standards applicable to microgrids

The IEEE is also working on new microgrid-related standards with the IEEE 2030 series of standards. It is described as the "Guide for Smart Grid Interoperability of Energy Technology and Information Technology Operation with the Electric Power System (EPS), and End-Use Applications and Loads." Table 3 outlines the contents of the standard, where 2030.7 and 2030.8 specifically focus on microgrid controllers. At the time of writing, 2030.8 was still in development.

Until all the new standards are finalised, the IEEE 1547 series of interconnection standards remain a reliable reference to ensure safe and effective microgrid installation.

Section	Description
IEC 62898-1	Guidelines for general planning and design of microgrids
IEC 62898-2	Technical requirements for operation and control of microgrids
IEC 62898-3-1	Technical requirements for protection in microgrids
IEC 62898-3-2	Technical requirements for microgrid EMS
IEC 62898-3-3	Technical requirements for self-regulation of dispatchable loads in microgrids

Table 2: IEC 62898 series of microgrid standards

Section	Description
IEEE 2030.1	Guide for electric-sourced transportation infrastructure
IEEE 2030.2	Guide for the interoperability of energy storage systems integrated with the electric power infrastructure
IEEE 2030.3	Standard for test procedures for electric energy storage equipment and systems for electric power systems applications
IEEE 2030.5	Standard for smart energy profile application Protocol
IEEE 2030.7	Standard for the specification of microgrid Controllers
IEEE 2030.8	Standard for the testing of microgrid controllers

Table 3: IEEE 2030 series of standards

There are numerous other standards that might also be applicable to microgrids, for example the IEC 61850 communication standards, which outlines how DER in a microgrid should communicate.

2.3 Microgrid design

From the IEEE 1547.4-2011 standard and literature [13], [14], [1] the following steps can be followed to plan and design a microgrid:

1. Purpose and objectives of new microgrid

First and foremost, the project team should reach consensus on why the microgrid is needed and what is expected from it in terms of performance measures. This will influence decision making throughout the rest of the project. The project team should also carry out an economic feasibility study.

2. Site survey

When a microgrid is planned, it is important to collect certain information of the proposed site, for example its current operating conditions and equipment already installed. The following information should be collected:

- Inventory of loads, DER, switching and protection devices and metering equipment installed
- Load characteristics and requirements
- DER characteristics, capabilities and requirements
- Utility and local system parameters i.e. system grounding, fault levels, source impedance, voltage regulation, automation scheme, protection scheme etc.
- Acceptable power quality ranges defined by the utility
- Available space for new installation of DER or other equipment

3. Load requirements

The microgrid should be able to meet the load's requirements in islanded mode. The load control scheme (if applicable) should be able to manage all the loads to perform functions like load shedding in the event that the DER cannot provide enough power. The DER should also be able to maintain the voltage and frequency within acceptable ranges during all expected load and DER changes.

A detailed load analysis has to be done to gain information on three-phase detail with regard to the load, historical demand profiles, power quality requirements and influence, loads with large starting currents and what those currents might be. A very important aspect to consider is load imbalance. Three phase voltage/current imbalance can cause damage to motors and cause inverter-based DER to put ripple currents on the DC bus. One form of load imbalance can be caused by large amounts of single-phase loads connected to one specific phase only, causing the current drawn in that phase to be higher than the other two phases. The load analysis will also determine the amount of reactive power required. Dynamic reactive power demand is an important consideration, for example during motor starts.

The inrush currents of transformers have to be analysed. When a transformer is energised, it can cause massive inrush currents which may cause protection equipment to trip. This is an important consideration if there are situations that require transformers to be de-energised and re-energised.

4. Utility requirements and planning

The following aspects with regard to the utility has to be taken into account:

- What are the local regulations regarding islanding
- Ensure that the grounding under normal and islanding conditions are adequate. More information on this is included in IEEE 1547.2
- The voltage regulation of the utility and the microgrid has to be coordinated. It is important that DER can be operated in voltage source mode during islanding and effectively re-synchronise with the utility for parallel operation. It is preferred to have inverter-based DER working in voltage source mode, as this closely emulates a synchronous machine and may improve power quality.
- Frequency regulation has to be considered to ensure that DER can support the frequency requirements of the system in islanded conditions.

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- The interconnection device (which switches the microgrid between parallel and islanded operation) should be capable of withstanding 220% of the rated system voltage.
 - The microgrid should be able to detect utility faults. Adequate protection equipment and schemes are required.
 - System monitoring, information exchange and control guidelines are set out in detail in IEEE 1547.3-2011

5. DER requirements

Effective planning is required to ensure that DER in a microgrid operate as expected and within required ranges. Coordination of various DER is an important consideration to ensure that the system as a whole operates effectively. Protection and trip settings of DER might have to be adjusted to ensure reliable operation during islanding. For example if a fault on the utility side, which causes voltage sag, is detected and islanding is actuated, inverter-based DER would preferably have to ride-through the dip instead of tripping due to the voltage sag. How the DER will control voltage during islanding has to be decided. The two available methods are voltage droop control and reactive power sharing. In order to control the frequency, the DER can use speed droop control or real power sharing. An alternative to droop control is isochronous control with a so called swing machine. In the isochronous speed control mode, the speed will return to the original speed set-point after a load has been applied or rejected.

6. System studies

When planning a microgrid, the project team has to conduct several system studies in each operating mode which includes detailed reviews of voltage profiles, circuit element loading, fault clearing, protection device operation and system stability. System studies are necessary to ensure quality of supply. The following studies need to be done:

- Generation capability planning

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- Load-flow studies
 - Short-circuit and protection studies
 - Stability of microgrid system in general
 - Small-signal stability study
 - Transient stability studies
 - Motor starting studies

7. Control system design

Once all the hardware considerations, planning and design has been finalised, the project team has to decide on the control strategy and the equipment required to implement it. The two main microgrid control schemes are centralised and decentralised [1]. In a centralised scheme, the microgrid is controlled by one central controller. In a decentralised approach, the microgrid would have multiple controllers, each controlling a specific aspect of the microgrid. When deciding on the control approach, the project team should consider existing hardware that is available for the project as well as the objectives of the microgrid.

In an industrial microgrid, the DER would most likely have their own controllers built-in. For example a large diesel generator would have its own engine governor and automatic voltage regulator (AVR) working together to keep the voltage and frequency within set ranges, without input from external controllers. Grid-tied inverters would follow the voltage forming source in the microgrid within set ranges. If the voltage forming source causes under-or over-voltage/frequency, these inverters would trip. This would happen without input from external controllers. With modern DER having their own controllers built-in, a modern industrial microgrid lends itself well to a centralised approach with one controller that coordinates power output from DER, as well as opening and closing switchgear and supervising synchronisation.

To make such a system work, the project team can follow these steps:

-
- Make an inventory of measurement and control equipment currently installed and document the communication protocols that can be used with each device.
 - Determine what additional equipment is needed.
 - Ensure that new equipment does have all the functionality required.
 - Ensure that all new and existing equipment can communicate with appropriate communication protocols.
 - Determine detailed control strategy, which includes conditions for islanding, synchronisation and switching back to grid-tied mode. This should include important control functionality like PV and ESS curtailment while the diesel generator is running to prevent back-feeding, grid-code compliance in terms of connecting and disconnecting from the grid as well as exporting power to the grid.
 - Determine energy management objectives and develop a detailed energy management strategy.

8. Additional planning

Once all the previously mentioned steps were taken, the project team should develop a detailed single-line diagram indicating connection of all new DER, measurement equipment, control equipment and switchgear to be installed. An additional drawing should be made to indicate cabling required for control and automation communication purposes. This can also be included on the overall single-line diagram, but the drawing might become cluttered with too much detail.

Additional safety measures should be evaluated, for example arc flash considerations. General operational and contingency planning should be conducted to assess reliability and availability of elements in the microgrid.

2.4 Microgrid DER sizing

During the planning phase, the project team would have to decide on the sizes of proposed new DER to be added to the system. By analysing the load profile, the optimal combination of PV and energy storage can be decided on. In some cases a diesel generator may have to be added for emergency purposes. There is software available to do this kind of analysis. A popular option is to use software developed by Homer Energy. This software can analyse load profile data and receive utility tariff structures as input in order to determine the optimal combination. The load profile can also be analysed by using MATLAB or similar software. MATLAB allows the user to easily visualise data and develop custom software to analyse a given load profile while keeping tariff structures in mind.

To install the optimal amount of DER in a microgrid isn't always an option. In some cases the installation can be restricted by capital expense limitations, so a certain approach might be to only get as much PV and storage as the budget permits.

In the case of an industrial grid-tied microgrid, it would usually only island if there is an outage from the utility. Most industrial facilities already have a diesel generator installed for back-up purposes. This means that in islanded mode, the generator will be able to support most or all of the load and sources like the PV and ESS would only have to support the generator. In this case the diesel generator will be the voltage forming source, which will give a reference voltage and frequency to the PV and ESS, which would otherwise have been grid-tied and only voltage following, not voltage forming. This topology means that when sizing the new DER, it would not be necessary to plan for PV and ESS capacities to support the full load of the facility during islanded operation, unless the objective would be to have the island operated by renewable sources and energy storage alone. This would however require considerable capital investment to ensure that the load demand will be satisfied at day and night and during any weather conditions.

Back-feeding considerations

Due to the stochastic nature of renewable sources, it is not common practice to rely on renewable sources alone to satisfy a microgrid's load demands during islanding [1]. The diesel generator is an important component of the islanding system, especially if the other DER is solely grid-tied. This however presents the danger of back-feeding to the diesel generator. If the load goes below the output of the PV array or ESS, these DER might start to feed into the generator. This could cause considerable damage to the generator. However, it can be easily mitigated by the use of PLC's to control the outputs of DER or the load demand itself. There are various methods employed to achieve this. The PLC can rather send some power from the PV to the ESS, if there is storage capacity available. Certain devices can also be switched on to consume more power. A common and effective method is to curtail the output of the PV or the ESS in the event that the load drops below the supply. Theoretically, when back-feeding starts, the voltage and frequency on the bus would increase and cause the PV array and ESS inverters to trip before real damage could occur. However, this is not safe practice and could still result in damage to the generator. This can be a common issue with microgrids, due to PV arrays being sized for peak power much higher than the actual load. This is to compensate for lower PV production in winter months and also to provide surplus energy that can be stored in the ESS. This however results in a potential back-feeding hazard, especially if the microgrid has to do a black-start in islanded mode. In such a situation, not all components in the load might be actively consuming power, due to manual restarts required. This could cause the PV output to be far greater than the load and start feeding the generator. Clearly, this is an important consideration. Luckily, this can easily be mitigated by modern control hardware and software.

2.5 Microgrid testing

Once the proposed microgrid has gone through the planning, design and installation phases, the commissioning and testing of the system shall serve as the final assessment of the system's robustness. Testing of microgrid components should adhere to applicable standards for each mode of operation, being grid-parallel and islanded modes, as well as transitioning between modes. Testing the system under all conditions will point-out any oversights in the planning, design and engineering phases. There are potential safety hazards if the microgrid has not been properly designed and tested.

It would also be valuable to test the microgrid's performance with high-resolution metering equipment in order to assess the power quality in the system. This may provide valuable insights into the quality of supply that the load will be consuming, in order to determine if any equipment is at risk of damage due to bad power quality. Specialised metering equipment would be required to measure at high enough resolutions. The results should be benchmarked against applicable standards, for example in South Africa, the NRS 048 standard provides quality of supply benchmarks.

2.6 Conclusion

This chapter served to gain a better understanding of the operating principles and considerations of physical microgrids, as well as what to keep in mind when designing a microgrid. As mentioned in the first chapter, this study focuses on microgrid energy management. Therefore, in the next chapter, a specific focus is placed on microgrid energy management. The available literature on the topic is discussed and analysed in order to enable effective microgrid energy management.

Chapter 3

Microgrid energy management literature study

This chapter aims to give the reader an overview of microgrid energy management. The chapter starts with an introduction on microgrid energy management, after which the energy management objectives of microgrids are discussed. The techniques used to model a microgrid and simulate the performance of the energy management system (EMS) are also discussed. Finally, a literature survey on the techniques used to develop and realise an EMS, is presented.

3.1 Introduction

The EMS of a microgrid is control software that allocates the power output among DER units and finds the most cost-effective manner in which to supply the load. This is done while taking safety, reliability and power quality into account. The EMS should not be confused with the main microgrid controller which does islanding, voltage and frequency control, etc. The main control software should be able to override any commands given by the EMS that could have potential negative effects on the system. Generally, a microgrid EMS has to coordinate a variety of DER, each with its own set

of constraints, in order to provide energy in a sustainable, reliable, environmentally friendly and cost-effective way. The EMS receives numerous inputs and then acts on the available information to achieve the objectives set out by the owner of the microgrid. Figure 3 is an illustrative overview of a microgrid EMS [2]. Typically, an EMS would have an interface between the control logic and the DER in the system that are being controlled or monitored, as well as an interface that gives information about the utility's status, the desired operating mode for the microgrid and optional extras, for example weather forecasts. The control logic would receive various other inputs as well, as indicated in figure 3. The control logic would then make decisions based on these inputs, in order to give commands to the various DER in the system. Forecasting and prediction algorithms can be included to further optimize the functionality of the EMS by providing it with data on future conditions, which might influence its current operation. Additional optimization algorithms might also be added to the EMS in order to achieve maximum monetary savings. The EMS might also make data available on a human machine interface, for easy inspection by operators and also allow for some manual controls to override automated EMS decisions or change operating modes. The EMS can usually also store data in a database for performance analysis and savings calculations by operators at a later stage.

3.2 Energy management objectives

The energy management objectives in a microgrid depend on the user's preferences. The objectives are influenced by factors like geographical location, equipment installed, types of loads to be supplied, utility energy tariff structures, government regulations and energy storage and generation options in the microgrid. Due to the modular and highly customisable nature of a microgrid, each microgrid has a unique set of objectives. Generally the main objective of a microgrid is reducing operating costs by maximizing the savings of a microgrid through renewable energy, and minimizing the generation expenses [3]. Typical objectives are indicated in figure 4. Each category represents an objective, where the sub-categories represent aspects that might want to

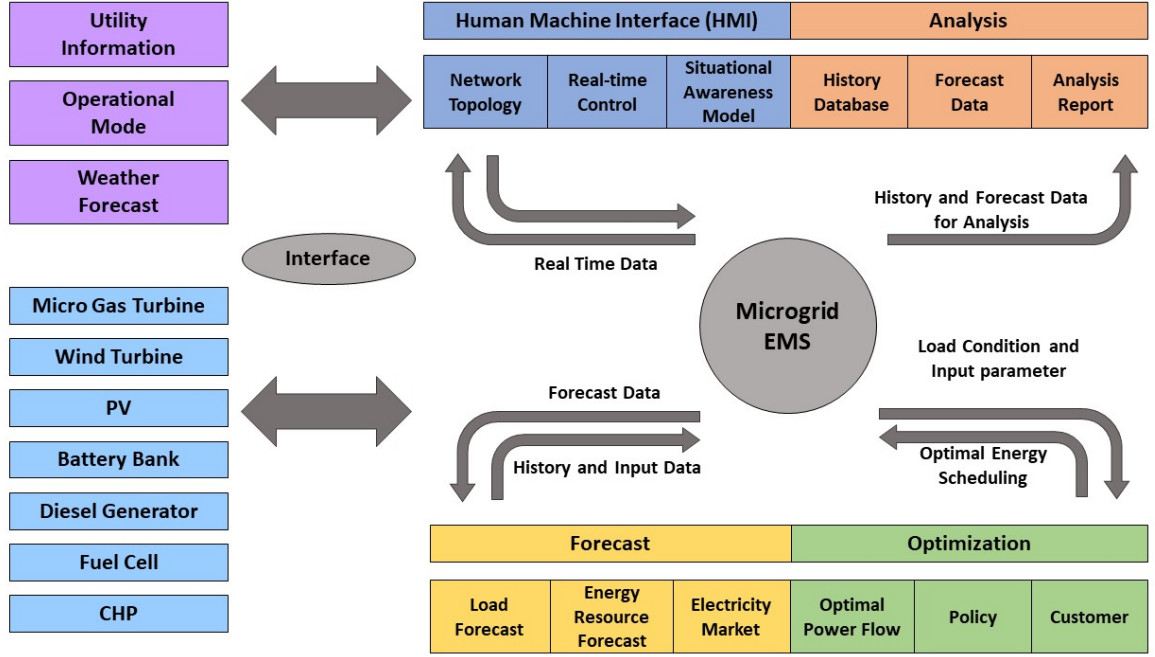


Figure 3: Illustrative microgrid EMS [2]

be minimized in order to achieve the objectives.

These objectives and possible challenges create optimization problems, which can be described by the use of analytic equations in the form of cost functions. For example in (1), the purpose of the function is to minimize the daily system operating cost and maximize the energy output from distributed energy resources [15]. This is an example of a complex system with multiple variables that need to be taken into account in order to minimize the operating cost (OC). Table 4 indicates the description of each variable in (1).

$$\begin{aligned}
 OC = & \sum_{t=1}^N \Delta T (F_{GB,t} + F_{ACC,t}) C_{bio} + \sum_{i=1}^N \sum_{g=1}^N (v_{g,t} SU + w_{g,t} SD) \\
 & + \sum_{t=1}^N \Delta T \left(OM_{ICE} \sum_{g=1}^M P_{g,t} OM_{GB} + P_{GB,t} + OM_{ACC} P_{ACC,t} + OM_{AR} P_{AR,t} \right) \\
 & + \sum_{t=1}^N \Delta T (C_{Grid} P_{grid,t}) \quad (1)
 \end{aligned}$$

Equation (1) can be generalised and applied to multiple use cases on various microgrid

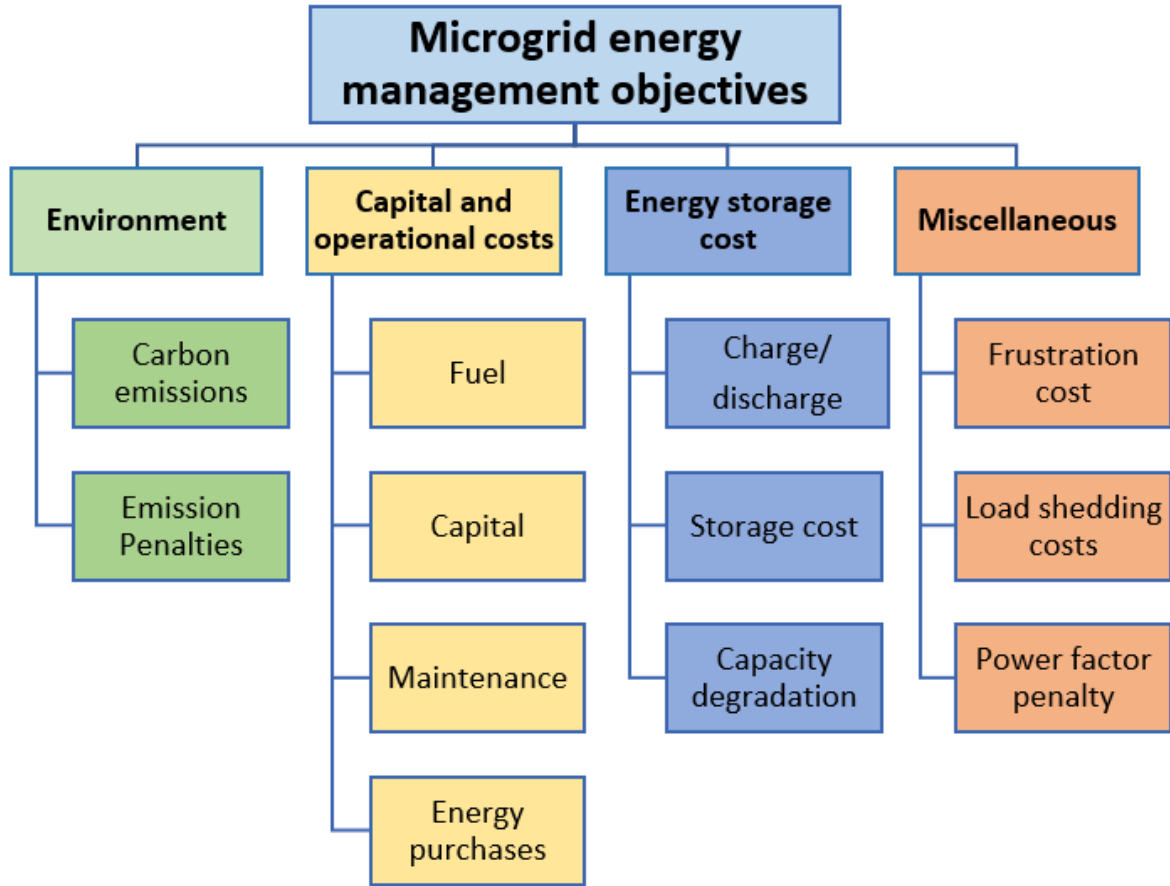


Figure 4: Microgrid energy management objectives [3]

systems with different energy resources. Energy storage can also be added [3]. From this equation and possible different combinations that every microgrid can have, it becomes clear that this is a multi-objective optimisation problem. The literature provides numerous techniques with which to solve these optimisation problems. These techniques will be discussed in more detail in section 3.4.

Additional objectives might include load shifting in order to reduce energy usage from the grid during certain time of use (TOU) periods. In the case of the microgrid that is being investigated for this study, the utility charges at higher rates for energy usage during peak TOU periods. Thus, the EMS should try to use energy storage during those periods to reduce the energy extracted from the grid.

The energy management objectives are accompanied by certain physical constraints that also need to be taken into account. Typical constraints are: Maximum and min-

Variable	Description
ΔT	time step
C_{bio}	cost of bio-gas in \$/Litre,
$F_{GB,t}$	fuel costs of gas-boiler (GB) at time t
$F_{ACC,t}$	fuel costs of absorption chiller (ACC) at time t
SU	start up cost in \$
SD	shut down cost in \$
$OM_{ICE,GB,ACC,AR}$	operational and maintenance costs of: combustion engines (ICE), gas boiler (GB), absorption chiller (ACC) and refrigerator (AR) in \$/kWh
$P_{GB,ACC,AR,t}$	power outputs of: gas boiler (GB), absorption chiller (ACC) and refrigerator (AR) at time t in kW
C_{Grid}	electricity cost from the grid in \$/kWh
P_{Grid}	power imported from the grid in kW

Table 4: List of variables in (1)

imum output power of DER units required for safe and economic operation, associated stochastic nature of renewable sources, operating limits of loads, charge and discharge rate limitations of storage systems, start up and shut down operational requirements with associated delays and real time energy sales pricing (only in certain countries) [3]. These constraints are central to the considerations of an effective microgrid EMS.

3.3 Microgrid modelling

Modelling refers to simulating a process, concept, or the operation of a system, commonly with the aid of computer software. In order to test and simulate the performance of the EMS, some sort of model would be needed that represents the actual behaviour of the microgrid. This will allow the developer of the EMS to verify the performance of the EMS before uploading it to the actual controller. There are numerous methods with which to model microgrids. This section discusses the two main methods used, namely dynamic (electromagnetic transient) and data-driven modelling. A common approach found in literature to test an EMS after the simulation has been verified, is to do hardware-in-the loop testing. This serves as an additional stage of verification for the EMS.

Dynamic Modelling

For studies concerned with microgrid control where a controller is responsible for voltage and frequency control, dynamic modelling is essential in order to assess the effects of control algorithms on component level performance in a microgrid. A dynamic model can also help to prove regulatory compliance to certain standards like IEEE 1547 or local grid code. Dynamic modelling usually employs software packages to select ready-made component models or create unique models in a wide variety of software packages. Another approach is traditional mathematical modelling, where components are modelled from first principles. The following examples from literature illustrate some mathematical models of microgrid DER.

Solar array

There are several methods with which to model the performance of a PV system. From first principles, the model of a single PV cell can be derived from its equivalent circuit [16] as:

$$I = I_{PH} - I_s \left[\exp \left(\frac{q(V + IR_s)}{kT_c A} \right) - 1 \right] - \frac{(V + IR_s)}{R_{SH}}, \quad (2)$$

where I is the total output current, I_{PH} is the photo-current defined as a function of the cell's solar insulation and working temperature, I_s is the saturation current, q is the electron charge, k is the Boltzmann constant, T_c is the cell's working temperature, A is the ideal factor which is dependent on the PV technology, R_s and R_{sh} is the series and parallel resistance in the circuit, respectively. After simplification, an equivalent model of a solar panel can be written as:

$$I_{RS} = \frac{I_{SC}}{\exp \left(\frac{qV_{OC}}{N_s k A T_c} \right) - 1}, \quad (3)$$

where I_{RS} is the cell's reverse saturation current, I_{SC} is the cell's short circuit current, V_{OC} is the open circuit voltage and N_s is the number of series cells.

A different approach is to directly model the output power, P_{PV} of a PV module [17]:

$$P_{PV} = P_{STC} \frac{G(\beta, \alpha)}{G_{STC}} \left[1 + \gamma(T_c - T_{STC}) \right], \quad (4)$$

where P_{STC} is the output power in kW of the module under standard test conditions, $G(\beta, \alpha)$ is the incident irradiation in the plane of the panels, G_{STC} is the incident irradiation under standard test conditions, γ is the power temperature coefficient, T_{STC} is the temperature under standard test conditions and T_c is the cell temperature.

Another approach is to calculate the output power of a PV module, $P_{PV,t}$ at time t , which is given by [15]:

$$P_{PV,t} = \eta_{PV,t} A_{PV} G_{\beta,t}, \quad (5)$$

where $\eta_{PV,t}$ is the efficiency at time t , A_{PV} is the total available area for PV modules in m^2 and $G_{\beta,t}$ is the incident irradiation in Wh/m^2 at time t .

Battery state of charge

In the literature, a battery bank's state of charge (SOC) can be determined as a percentage of available capacity, from which the actual energy available can be easily calculated. In some cases the hourly available capacity of the battery, $P_{batt,t}$ is calculated as [15]:

$$P_{batt,t} = P_{batt,t-1} + E_{cha,t} \eta_{cha} - \frac{E_{dis,t}}{\eta_{dis}}, \quad (6)$$

where $E_{cha,t}$ is the hourly charging energy that flows into the battery in kWh, $E_{dis,t}$ is the hourly discharging energy extracted from the battery in kWh, η_{cha} is the charging efficiency of the battery and η_{dis} is the discharging efficiency of the battery. This method calculates the energy levels in the battery at a specific moment, from which the SOC can be calculated.

[18] uses the following equations to describe the battery's SOC:

$$SOC(h+1) = SOC(h) + (h_{step} \{ P_{ESS}^{ch}(h) - P_{ESS}^{dis}(h) \}) / E_{ESS} \quad (7)$$

$$SOC(h) \in [SOC_{min}, SOC_{max}], \quad (8)$$

where $SOC(h)$ is the battery's state of charge at each time step h_{step} bounded by an upper limit SOC_{max} and a lower limit SOC_{min} . E_{ESS} denotes the battery capacity in kWh. The charging (discharging) power of an ESS is also bounded according to the following constraints:

$$P_{ESS}^{ch}(h) \leq P_{max}^{ch} \eta_{ch} u_{ESS}(h) \quad (9)$$

$$P_{ESS}^{dis}(h) \leq P_{max}^{dis} (1 - u_{ESS}(h)) / \eta_{dch}, \quad (10)$$

where P_{max}^{ch} (P_{max}^{dis}) is the battery's maximum charging (discharging) power; η_{ch} (η_{dis}) is the battery's charging (discharging) efficiency; u_{ESS} is a binary variable that denotes the charging (1) or discharging (0) status at each time step.

Similar methods are used in [19], [20] and [21]. It is important for the EMS to know the battery's SOC, in order for it to decide whether or not to charge or discharge the battery under the current conditions.

Data-driven modelling

The DER in microgrids generally have accurate measurement devices on them or in the system, which can accumulate performance data over long periods of time at variable resolutions. This allow researchers to develop data-driven microgrid models. It is worth noting that this is usually steady-state data from normal operation. However, the researcher can inject faults into the data if necessary in order to test how the EMS might react. Due to the data being readily available from metering equipment in microgrids, this is a popular modelling technique [22–25]. This technique allows the usage of historical data to simulate the generation of specific DER in a microgrid and then test the performance of the EMS based on the available data of the system performing under normal conditions. In a conventional EMS, it would receive load and energy generation data and make decisions based on the values of the data. The

EMS thus only takes into account the immediate power generated by the DER and consumed by the load. This is why data-driven modelling is a popular and effective tool to test EMS algorithms, as power/load profile data is easy to come by. This method might rather be referred to as EMS simulation, rather than microgrid modelling, as the data gathered, simulates the behaviour of the microgrid in order to assess the response of the EMS control algorithm.

Mathematical models are sometimes incorporated into data-driven models where a DER's performance is dependent on the output of the EMS, for example battery banks. Usually the charge and discharge rates and scheduling is totally controlled by the EMS, where PV arrays produce their power independently from the EMS's commands, unless curtailment is actuated. Thus, the charge and discharge commands from the EMS has an effect on the battery's state of charge. In this case, the method to estimate the SOC of the battery, as discussed in the previous sub-section, can be used in the data-driven model. In certain situations, data driven models are included in dynamic models. For example, if accurate load data is available, then a file containing load samples would simulate the load that interacts with dynamic models of the PV or storage inverters, instead of modelling each component in the load, which can be a tedious process.

3.4 Literature survey of microgrid energy management strategies

The objectives of a microgrid EMS, as discussed in the previous section, can be achieved by solving a cost-function (also referred to as an objective function) or implementing other techniques like artificial intelligence. There are various methods discussed in the literature to achieve this. This section aims to give a brief overview of some popular techniques used in literature to develop an EMS by solving a cost-function, implementing artificial intelligence, heuristic programming, exact programming or other techniques.

Linear programming

In order to deal with problems that have a linear objective function and linear constraints, but no non-linear constraints, mixed integer linear programming (MILP) can be used. In [26] a multi-objective problem is discussed where minimizing the total cost of transferring the electricity from/to the grid, the cost of operation of DER and start-up and shut-down cost, is achieved by using a MILP method. According to this research, the MILP problem can be solved by commercial software like CPLEX, which is an optimization software package. In [27], a MILP method for solving a power scheduling problem is discussed. The intermittent nature of renewable energy sources due to weather conditions as well as possible renewable energy curtailment is addressed. The authors also mention that the problem can easily be solved by CPLEX. Typically researchers would define objective functions and constraints in the same manner as in (1) and then use a software package or one of the solution techniques that will be discussed in the next section [10].

Non-linear programming

For optimization problems with objectives and constraints that have continuous or discrete variables or non-linear functions, mixed integer non-linear programming (MINLP) is used. In [15], a combined cooling, heating and power microgrid model was built to improve the energy efficiency of a dairy farm and optimise animal waste treatment by means of multi-objective optimisation. Animal manure produces biogas, which is used to fuel an internal combustion generator. The fuel consumption rate of the internal combustion engine is expressed by the following quadratic equation:

$$F_{g,t} = a_g + b_g P_{g,t} + c_g P_{g,t}^2, \quad (11)$$

where $P_{g,t}$ is the power output of generator, g , in kW at time t . The coefficients a_g, b_g, c_g can be calculated from the machine's datasheet. This equation is an example of a non-

linear function that can be solved with MINLP through the use of an optimisation software package. This is only one of a multitude of applications for MINLP applied to microgrid energy management [10], [3].

Stochastic programming

The stochastic nature of renewable energy sources require a unique approach to scheduling and optimisation problems. Stochastic linear programming is a well known approach for scheduling problems, according to [28]. A typical approach is to have variables split into different stages, which refer to different moments of decision. Two stages can be considered, where the distinction is made depending on whether the values of the variables have to be known before a specific scenario or not. Variables independent on scenarios are first stage and dependent variables are in the second stage, which reflects the uncertainty of the problem. In [28], a system with a solar array, battery energy storage and a molten carbon fuel cell requires a charge and discharge schedule for the battery bank one week in advance, without knowing whether or not the fuel cell will be available to provide energy. The fuel cell's uncertainty is related to technical issues with its reliability. Charging and discharging of the battery will be the first stage variables of the problem. Second stage variables such as electricity purchases, will depend on the availability of the fuel cell. This approach allows battery scheduling to be calculated by taking future uncertainty into account.

Heuristic approach

A heuristic approach can be classified as a practical method which is not necessarily optimal, but sufficient enough to reach immediate goals [29]. In [30], a centralised microgrid EMS which uses a heuristic approach is proposed. It considers the use of a fuel cell, the state of charge of a battery bank, the variable stochastic output of a solar array, a variable load profile and electricity tariff. The goals are economic operation of the system and power quality. In this case the EMS firstly determines whether or not the

power output from the PV array is larger than the load or not. If it is larger, the battery should charge. If the PV production is lower than the load, the EMS checks what the current tariff is. For low tariffs, the battery is charged, for high tariffs the battery is discharged, with the rate depending on the SOC. This approach reaches the goals of discharging during expensive tariff periods and charging during cheaper periods or when there is surplus PV power. However, it is not optimal, as the system might fully charge the battery during cheaper periods just before a surplus of PV power might occur, resulting in a loss of "free" energy that cannot be absorbed.

Multi-agent system

An agent-based framework facilitates power trading among elements in a microgrid. This approach finds a way to utilize energy availability from certain DER which are better suited for the specific situation by implementing a bidding process between energy resources in order to determine the most effective option for the current situation. This method requires high speed communication between DER in a microgrid and thus requires modern infrastructure to be installed. According to [8] the multi-agent system proposed provides more robust and high-performance controls than the conventional central EMS.

Evolutionary approach

The evolutionary approach is a popular, yet diverse topic in microgrid energy management research. The evolutionary approach has its own range of options and subsets. The purpose of evolutionary optimisation is to mimic behaviour seen in nature in order to find the optimal way of doing something. Swarm optimisation is a subset of the evolutionary approach, but it also has different options. For example in [31], a glow worm swarm optimisation is applied to solve the optimisation problem of sizing DER in low or medium voltage microgrids. In [32] a particle swarm optimisation approach is proposed to harvest energy from traffic in a city. Then multi-objective particle swarm

optimization is also an option [3].

The ant colony optimization algorithm is also a common method to use when optimising energy dispatch in a microgrid. In [33], ant colony optimisation is used for DER dispatch control. According to the authors it is a rather heuristic approach, but aids in solving the complex problem of DER dispatch.

The genetic algorithm is a well-known method for solving optimisation problems. It is used for solving constrained and unconstrained problems that are based on natural selection, which drives biological evolution. This algorithm repeatedly modifies a population of individual solutions. There are numerous examples in literature where genetic algorithms are used to optimise microgrid energy management [3, 10, 19, 34].

Model predictive control

Model predictive control is a method of process control where certain constraints need to be satisfied. A dynamic model of the system is usually used in order to achieve immediate objectives, but also take possible future events into account. As mentioned before, microgrids have specific constraints that need to be adhered to. In [35, 36], MILP is used for optimisation and then solved by model predictive control. The authors claim that this approach is more effective than a static energy management approach.

Exact algorithms

An exact algorithm passes inputs through a sequence of states to produce exactly the desired output. Exact algorithms can also be referred to as deterministic algorithms. They are very popular and can be run on real machines efficiently. However, deterministic algorithms can be combined with heuristics, which won't result in exact outputs. Examples of exact programming are truth-tables and state machines. These are common approaches used to develop industrial control and automation algorithms. However, in order to develop an exact algorithm, the developer should be able to ac-

count for any input possibility or condition in the software. Where heuristics on the other hand should generally be able to provide a “close-enough” approximation of the desired output.

Fuzzy logic

Fuzzy logic uses a set of rules to approximate human logic. Fuzzy logic rely on degrees of truth, rather than normal Boolean logic, which is only 0 or 1. If certain expert knowledge of a microgrid system is available, a collection of rules can be set-up to dictate how an EMS should react to certain scenarios. Fuzzy logic is a very popular solution method for microgrid energy management [34,37–40].

In [21], the authors developed a low-complexity fuzzy logic controller to control the charge and discharge rates of a BESS. The requirements of the controller are to optimise the load profile, by reducing peaks drawn from the utility, as well as maintain the battery’s SOC within acceptable levels. The performance goals were defined by a pre-determined set of goals. As mentioned earlier, the goals of each microgrid are different, due to its unique constraints, location, energy mix and contract with the utility, which results in unique challenges for every microgrid. In [40], a fuzzy controller is proposed to control the energy dispatch of an off-shore industrial facility. The controller makes decisions based on generation capacity, load demand, storage capacity and water levels of a desalination plant. The authors conclude that the fuzzy approach resulted in a highly efficient EMS for the microgrid. They also mention that this approach eliminates the need of accurate models. In [41], a fuzzy load demand forecasting approach is proposed. A stable Takagi & Sugeno fuzzy model was implemented to forecast the load demand. The authors found that the fuzzy model performed better than an adaptive neural network. They also mention that large amounts of training data, rather than increased training frequency, is necessary to achieve high enough accuracy. This approach is not a common one in the literature, as most fuzzy systems in microgrids are used for EMS control [37,42–45].

Neural network

An artificial neural network (ANN) is generally used in microgrid applications to forecast the load and the availability of energy resources in various intervals, ranging from hourly to yearly [3]. Typically historical data will be used to train an algorithm to make predictions based on the historical data. This method is usually combined with some other solution methods like fuzzy logic [42,46] or swarm optimisation [3].

When it comes to microgrids, ANNs have been employed successfully to optimise energy management [47–49]. In [49], the authors employ two different types of ANNs, namely multilayer perceptron (MLP) and radial bias function (RBF) to develop a short-term load forecasting model. 80% of historical data was used for training and 20% for testing. The Levenberg-Marquardt training method was used. The authors found that the RBF method performed the best. However, the prediction accuracy was not satisfactory. This was attributed to the dataset being too small for sufficient training. In [48], a recurrent neural network was employed to forecast the available energy from a solar array, as well as the load demand for the next 15 minutes. This information is then used to allow the EMS to make decisions in advance based on the predictions. Once the future values are determined, they are used to solve the optimisation problems that might have been defined for the microgrid. The authors conclude that this method proves to have significant benefits and aids in microgrid energy management optimisation. In [50], the authors also use a recurrent neural network to forecast solar energy generation. The results were good, but not satisfactory. Again the authors mentioned that the dataset of only one month was not sufficient. In [51], an ANN was employed to predict the load demand and solar production for a small microgrid in Tanzania. The load prediction proved ineffective, due to stochastic power usage that cannot be predicted. This is a clear drawback of load prediction when applied to non-commercial problems where there are no set schedules. In [52], the authors applied ANN-based load and solar generation forecasting on a microgrid in Japan to successfully optimise energy management for a small microgrid. In [53], the authors also successfully employ ANNs to forecast load demand and generation.

3.5 Critical review

This chapter discussed various methods with which to realise microgrid energy management and how to test such an algorithm through modelling and simulation. From the literature, an energy management approach and a simulation technique has to be selected. The following two paragraphs will discuss the methods that were selected to be used during the rest of the study and also explain how this selection was made.

Energy management

From the literature it is clear that there is a great multitude of options for realising a microgrid EMS. Some methods are more effective than others, but all achieve the goals within satisfactory parameters. When selecting the correct method, the topology of the microgrid and its specific objectives need to be taken into account. The microgrid that is used in this study, is relatively simple when compared to microgrids found in research. There is really only one DER to be controlled in this microgrid, namely the BESS. From the research, it can be concluded that fuzzy logic is a very popular method, due to its relative simplicity, but very good results. When combined with an ANN-based forecast system, the results are improved even further. This removes the need for complex cost-functions to be developed and solved. From the research, it can be concluded that the relative simplicity of the microgrid in this study, lends itself well to a simpler energy management strategy like fuzzy logic. There are enough known variables to ensure that the desired objectives are met sufficiently. Thus, a heuristic algorithm would not be the best option. In addition, due to the system's relative simplicity, the efficacy of the EMS can be compared by developing an exact algorithm based on a truth-table or state machine. Such a classical PLC-based algorithm can be implemented on the microgrid controller with relative ease and should serve as a good benchmark for the AI-based EMS algorithm.

EMS simulation

The EMS to be developed for this specific microgrid, will only operate under normal

conditions in grid-parallel mode in order to reduce utility charges. The EMS will not play a role during emergency islanding, as there will be other objectives to address by the control system. The EMS will not be responsible for voltage or frequency control. Thus, the EMS would only need to receive power output data from the DER and power consumption data from the load. Therefore, the EMS can be simulated by developing a data-driven model that feeds power data to the control logic. This method is supported by literature and should be an effective tool to test the EMS's performance before deployment on the actual controller. MATLAB and Simulink are readily available for this purpose and are more than capable to provide the necessary functionality to develop and simulate a microgrid EMS strategy.

3.6 Conclusion

After studying and reviewing the available literature, it was decided to first develop a traditional truth-table-based exact EMS algorithm, that will be used as a benchmark for the simulation and implementation of the fuzzy logic EMS algorithm. The use of ANN short-term load forecasting will also be investigated, as the literature supports its use. MATLAB and Simulink will be used to develop and simulate the EMS algorithms. The next step is to proceed with the actual development, testing and implementation of the EMS algorithms. Therefore, the following chapters thoroughly document this process.

Chapter 4

EMS algorithm development

4.1 Introduction

This chapter contains the detailed design of the EMS algorithm for the microgrid. Firstly, the design process for the algorithm is explained, followed by system specifications and the definition of the objectives for the EMS. The objectives play an important role in how the algorithm is developed and evaluated. This is followed by the development of the truth-table-based EMS logic.

4.2 Design process

A microgrid EMS involves data acquisition, processing and decision-making in order to achieve certain power and energy related objectives as defined by the operator of the microgrid. This specific EMS design entails a classical structured-text PLC-based control logic which is aimed at satisfying certain objectives. This is done in order to create a benchmark to verify the effectiveness of other EMS topologies like artificial intelligence (AI). The PLC-based algorithm can also be implemented on the actual system with relative ease.

Note that the design process mentioned in this chapter would occur as part of, or after the design of the microgrid in general.

The iterative design process that was followed to develop the EMS can be seen in figure 5. The first step is to complete a system specification. From the system specification, it can be determined which DER are available in the system, the nature of the load to be served, what metering and control equipment is available and what the overall objectives for the microgrid would be, based on tariff structures and operational needs.

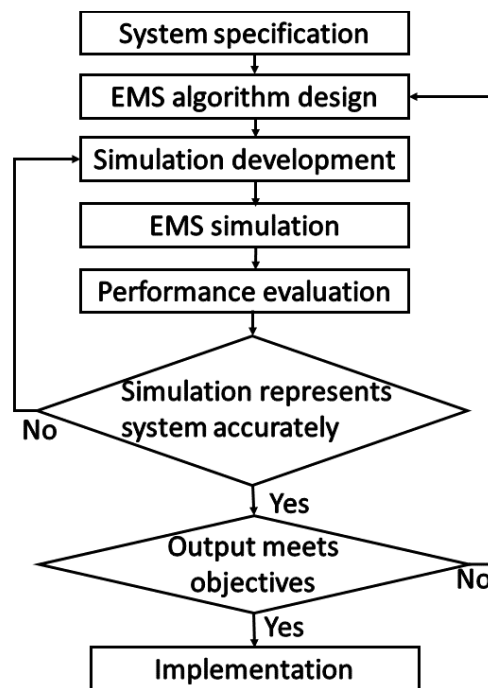


Figure 5: Design process

Once the system and the objectives are clearly defined, the EMS design can begin. Firstly a comprehensive literature study must be completed in order to determine the best approach to realise an EMS, based on the system characteristics and objectives. A suitable technique can be chosen from literature and development of the actual algorithm can commence. Once the algorithm has been developed, the focus can shift to the simulation thereof.

The behaviour of the EMS has to be tested by means of simulation in order to ascertain its efficacy. A suitable simulation environment has to be selected in order to test the algorithm. A custom means of simulation has to be developed, as there is no ready-

made EMS control logic simulator available. Thus the simulation framework has to feed the EMS control logic the same kind of data that the actual microgrid would. Once the development of the simulation framework has been verified, the performance of the control logic itself can be evaluated. If the outputs are not desirable, the algorithm can be adjusted and refined until it meets the objectives set-out. Once the algorithm is verified by simulation, it can be deployed on the actual system. The sections that follow aim to give detailed information on each step of the design process.

4.3 System specification

A microgrid EMS has to be developed that has the main objective of decreasing the electricity charges of the plant. This requires an effective method to simulate the EMS as well.

4.3.1 Research outcomes

The operator of the microgrid is developing a business model towards providing microgrid solutions. They are interested in developing an efficient EMS that could be adapted for other microgrid topologies and also develop competent microgrid engineers. Another student has created a dynamic model of the microgrid as part of the research project.

Developing and optimising an EMS for a microgrid can become a complex task. The following areas of research were identified:

- General microgrid functionality
- Artificial intelligence
- Microgrid modelling/simulation

The EMS is designed keeping microgrids in general in mind. This implies that the EMS will be easily adaptable to different topologies and objectives, especially due to the simulation method chosen which allows for rapid modifications, testing and PLC-code generation to be done.

4.3.2 Main area of focus

Information gathered from research and discussions with the microgrid operator indicated that the main area of focus should be to develop an efficient EMS for the microgrid that reduces the plant's monthly electricity bill.

An EMS has to be developed and an effective simulation method must be employed to ensure that the EMS meets the objectives. TOU periods, PV-generation and maximum power demand are taken into account in order to reduce utility charges as much as possible.

The diesel generator in the system is utilised for back-up purposes and does not form part of the cost-saving functionalities of the microgrid, thus it will not be considered by the EMS. The EMS will also only focus on energy management and will not be responsible for islanding, protection or synchronisation activities.

4.3.3 Specification of EMS objectives

The EMS objectives are primarily dependant on utility electricity charges. Other considerations are grid code compliance and battery lifetime.

Electricity charges

The tariff structures need to be analysed carefully in order to determine what the exact objectives of the microgrid are in terms of cost savings. The plant's electricity bill consists of 6 types of charges. These charges are listed in table 5.

The energy charges are dependent on the season of the year, the day of the week and the time of day. Winter months are defined as June, July and August. The rest of the months of the year are summer months. The time of day determines whether it is a peak, standard or off-peak time. These are called time of use (TOU) periods. Figure 6 shows the TOU periods for weekdays.

Charge	Description
Peak-hour energy charges	Charged per kWh at R 1.5352 in summer and R 5.0478 in winter
Standard-hour energy charges	Charged per kWh at R 1.0079 in summer and R 1.4417 in winter
Off-peak-hour energy charges	Charged per kWh at R 0.7563 in summer and R 0.85 in winter
Maximum demand power charge	Charged per kVA at R 65.65 for maximum instantaneous power consumption at any point during peak or standard hours in a month
Network access charge	Charged per kVA at R 40.35 for the average highest demand registered over a 12 month period
Fixed charge	charged at R 2530.19

Table 5: Monthly electricity charges for microgrid site

It can be seen in figure 6 that in the winter, the early morning hours are off-peak, followed by three hours of peak tariffs. From 09:00 there are standard tariffs for most of the day, followed by two peak-hours, three standard hours and then off-peak tariffs again. In the summer, the peak-hour periods just shift one hour later. On weekends, Saturdays have standard hours from 07:00 to 12:00 and from 18:00 to 20:00. The rest of the time on Saturdays are off-peak. The whole of Sundays are off-peak. Public holidays that are in the week, are charged according to the TOU periods of Saturdays.

From the billing and TOU analysis, it can be concluded that the ESS would be useful

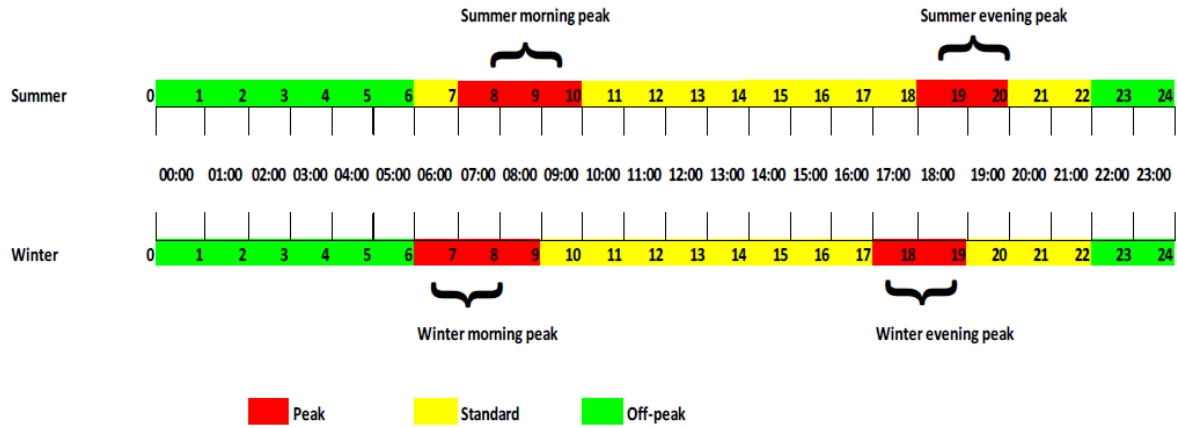


Figure 6: Weekday TOU periods

during peak TOU hours, as those hours are charged at much higher rates than in other periods, especially in the winter. Thus, energy arbitrage could be an effective strategy to save money on the plant's energy usage from the utility. Another consideration could be to reduce the maximum demand charges by implementing peak shaving. The maximum demand is a considerable monthly charge due to it being charged at R 65.65 per kVA. With a maximum demand of around 400 kVA, this amounts to around R 25 000 per month for the maximum demand charge alone. The ESS would probably not be able to effectively reduce the maximum demand charges and the peak TOU energy. Thus, a comprehensive cost comparison has to be done in order to determine the best course of action and define the objectives for the EMS.

Grid code

At the moment the plant is not allowed to export power to the local utility grid. This has to be taken into account when developing the EMS.

Battery lifetime

From literature, it became evident that the cycle life of lithium batteries can be increased four-fold by limiting the depth of discharge of the battery to 50% [54]. This could increase the lifetime of the battery, ensuring savings over a longer period of time. This should be balanced with short-term return on investment objectives and also considerations on future technology that might be much more affordable than now. This

aspect has to be analysed in more detail when defining the objectives of the EMS.

4.4 EMS objectives

As mentioned in the previous section, deeper analysis has to be done on the electricity bill and the load profile in order to decide on the prioritisation of energy arbitrage or peak shaving. Energy arbitrage refers to the practice of purchasing and storing electricity during off-peak times, or with surplus PV power, and then utilizing that stored power during periods when electricity prices are higher. The grid code requirements and battery lifetime would also have to be considered.

Electricity charges

By looking at an extract from the plant's electricity bill, more insights can be gained on what to focus on. Figure 7 is an extract from the bill for March 2017 when the PV array was not installed yet. March is during summer months. Note that even though energy usage during peak hours is lower than in standard and off-peak periods, the total amount billed was still higher than that of off-peak hours. This clearly indicates that there is money to be saved by discharging the ESS during peak hours.

Tariff	Description	Units	Rate	Amount
ELECTRICITY - Primary Supply				
Peak (LS)	Total 12,655,221.840 kWh	22701.6 kWh	R 1.5068	R 34,206.77
Standard (LS)	Total 12,655,221.840 kWh	57105.6 kWh	R 0.9893	R 56,494.57
Off-peak (LS)	Total 12,655,221.840 kWh	30400.8 kWh	R 0.7423	R 22,566.51
Max Demand (LS)	0.885 pf 2017-03-16 15:00:00	401.511 kVA	R 64.44	R 25,873.35
Network Access		567.639 kVA	R 39.60	R 22,478.50
Fixed Charge		1 month	R 2483.39	R 2,483.39
Total consumption: 110,208 kWh			Utility Total	R 164,103.10

Figure 7: March 2017 electricity bill extract

Figure 8 is an extract from the electricity bill for July 2017, which is in winter months. The PV array has been installed by this time and the difference in energy usage between March and July can be seen clearly. Note that the energy usage in standard hours has dropped from 57 105.6 kWh in March to 29 940 kWh in July. Peak and off-peak energy has also been reduced. Despite these savings, the plant has been billed more in July than in March. This can be ascribed to the exceptionally high charges during peak

hours (refer to table 5 and 6 for tariff structure). From figure 8 it is clear that there is big room for savings to be made during peak hours in winter.

Tariff	Description	Units	Rate	Amount
ELECTRICITY - Primary Supply				
Peak (HS)	Total 12,940,673.040 kWh	14774.4 kWh	R 5.0478	R 74,578.22
Standard (HS)	Total 12,940,673.040 kWh	29940 kWh	R 1.4417	R 43,164.50
Off-peak (HS)	Total 12,940,673.040 kWh	19773.6 kWh	R 0.8500	R 16,807.56
Max Demand (HS)	0.929 pf 2017-07-10 08:30:00	377.037 kVA	R 65.65	R 24,752.47
Network Access		522.87 kVA	R 40.35	R 21,097.80
Fixed Charge		1 month	R 2530.19	R 2,530.19
Total consumption: 64,488 kWh			Utility Total	R 182,930.74

Figure 8: July 2017 electricity bill extract

The case for energy arbitrage is self-explanatory. The case for maximum demand peak shaving has to be investigated as well. With the addition of the 200 kW PV array to the plant, much of the energy usage during standard TOU hours will be reduced. The plant's maximum power demand usually occurs during business hours, which means that there is usually good solar irradiation, hence the PV will decrease the maximum demand charges as well. This can be seen when the extracts from the plant's electricity bill are compared. Figure 9 is an extract from the bill for March 2018, which was after the PV array was installed. It can be seen in figure 7 that the max demand is indicated as 401 kVA, where in figure 9, the max demand is indicated as 286 kVA. This is a considerable saving due to the PV.

Tariff	Description	Units	Rate	Amount
ELECTRICITY - Primary Supply				
Peak (LS)	Total 13,376,381.040 kWh	13024.8 kWh	R 1.5352	R 19,995.67
Standard (LS)	Total 13,376,381.040 kWh	28855.2 kWh	R 1.0079	R 29,083.16
Off-peak (LS)	Total 13,376,381.040 kWh	25118.4 kWh	R 0.7563	R 18,997.05
Max Demand (LS)	0.855 pf 2018-03-07 10:00:00	286.476 kVA	R 65.65	R 18,807.15
Network Access		401.511 kVA	R 40.35	R 16,200.97
Fixed Charge		1 month	R 2530.19	R 2,530.19
Total consumption: 66,998 kWh			Utility Total	R 105,614.18

Figure 9: March 2018 electricity bill extract

In order to determine whether or not it would be possible to reduce the maximum demand further, the load profile of the plant would have to be analysed more closely. In figure 9, the utility has indicated that the maximum demand occurred on the seventh of March. Figure 10 indicates the load demand over the 24 hour period of 7 March 2018. In this figure, the large peak in demand in the middle of the day, can be attributed to low PV penetration. This was probably due to heavy cloud cover. This can be confirmed by looking at figure 11, which is the load demand for the sixth of March 2018.

In this figure it is clear that there was good PV penetration for that day due to the large indent in load demand from around 09:00 to 15:00. Referring back to table 5 it becomes clear that the maximum demand charge is difficult to minimise. This is due to the fact that the maximum demand tariff is charged for the maximum instantaneous power drawn at any time during the month. So if there is one instance in a month where there is an unexpected peak in power drawn from the utility due to cloud cover and the ESS is empty, that fee would have to be paid for the whole month. This effectively nullifies any other peak shaving efforts made earlier in the month.

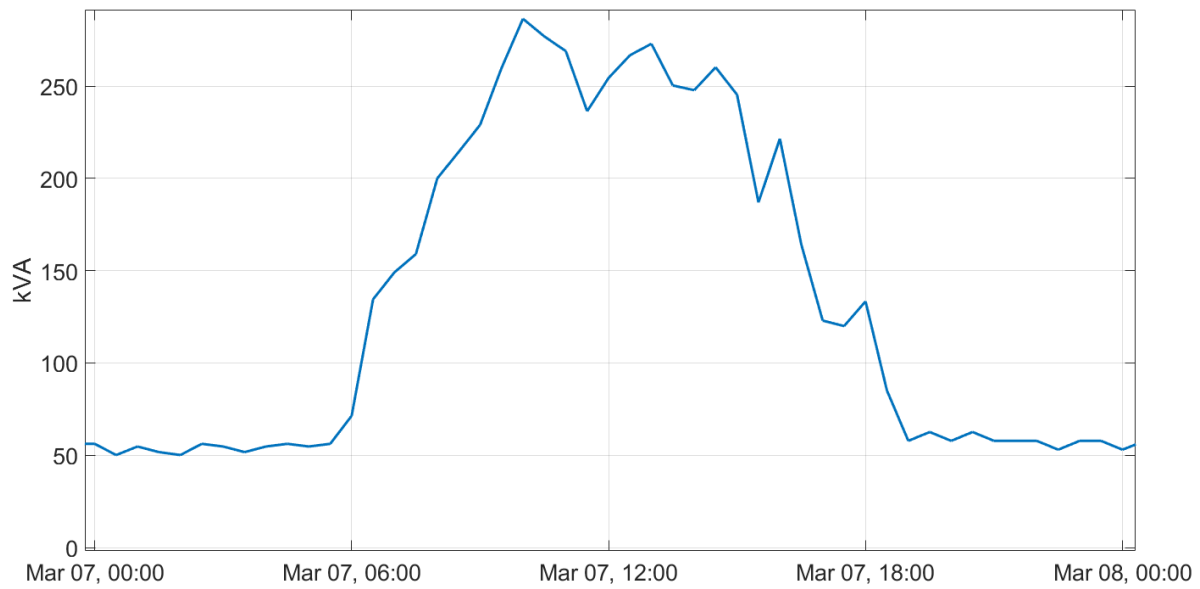


Figure 10: Load demand for 7 March 2018 in kVA

The practicality of reducing the maximum demand can be assessed by doing a case study of typical scenarios that are present in this facility's load profile. The month of March 2018 will be used again. Figure 12 represents the load demand for March 2018 in kVA. The red horizontal line represents a relatively conservative target for peak shaving at 200 kVA. From figure 9, the maximum demand for March 2018 was billed at 286.48 kVA. So if the target of 200 kVA could be maintained for a whole month, there would be a reduction of 86.48 kVA for the month. This would result in a saving of R 5 677.41. By looking at figure 12, it is evident that the ESS would have to discharge for 18 days of the month in order to keep the maximum demand below the target.

To determine how much energy the ESS would have to provide per day, the seventh

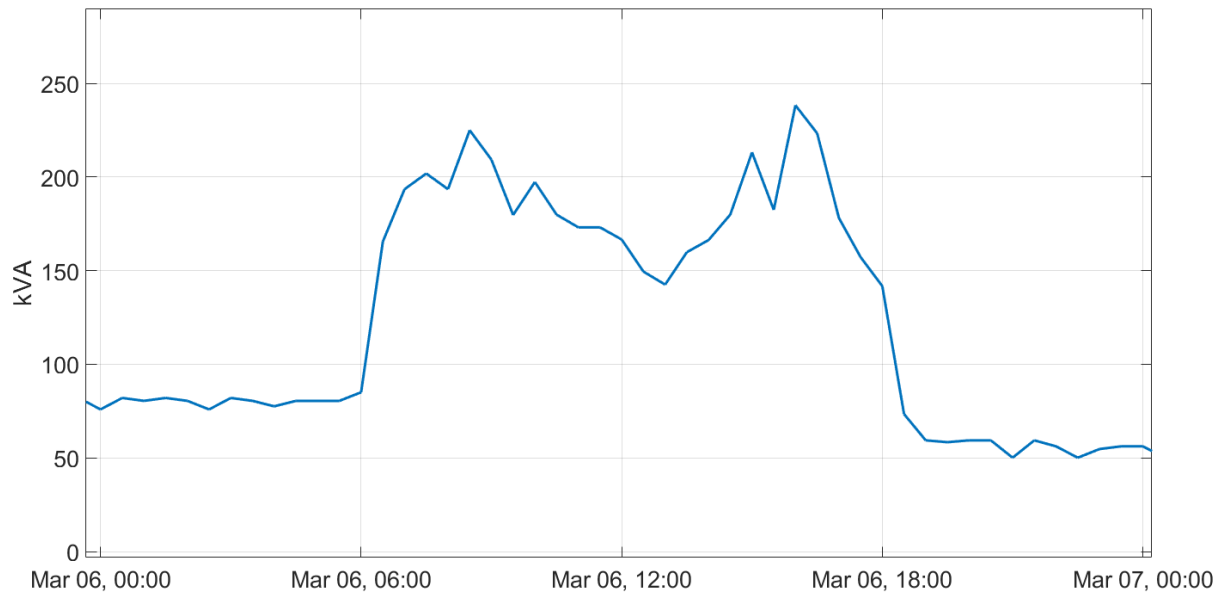


Figure 11: Load demand for 6 March 2018 in kVA

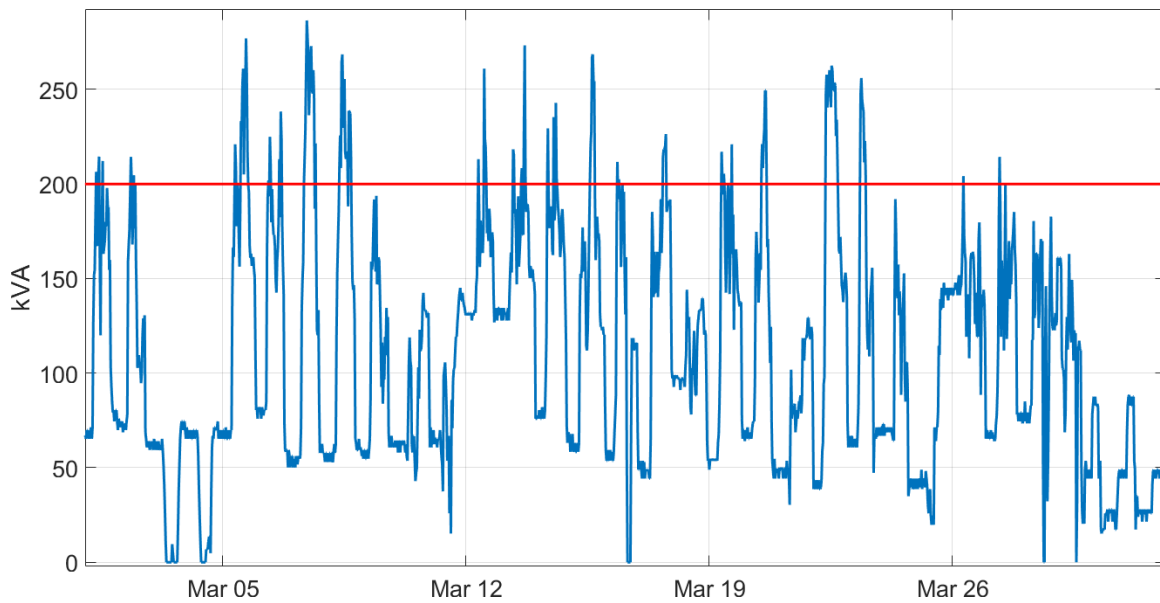


Figure 12: Load demand for March 2018 in kVA

of March can be analysed again. Figure 13 shows the load demand of the seventh of March with the peak shaving target added at 200 kVA. The area above the red target line would be how much energy the ESS would have to provide for this day. MATLAB can be used to calculate the amount of kWh that the ESS would have to provide to keep the maximum demand below the target value. The power factor of 0.885 indicated in figure 9 was used to do the calculations. The ESS would have to provide 316.78 kWh of

energy to keep the maximum demand below the target. This means that the facility's 200 kWh ESS would not be sufficient to keep the maximum demand below a target of 200 kVA.

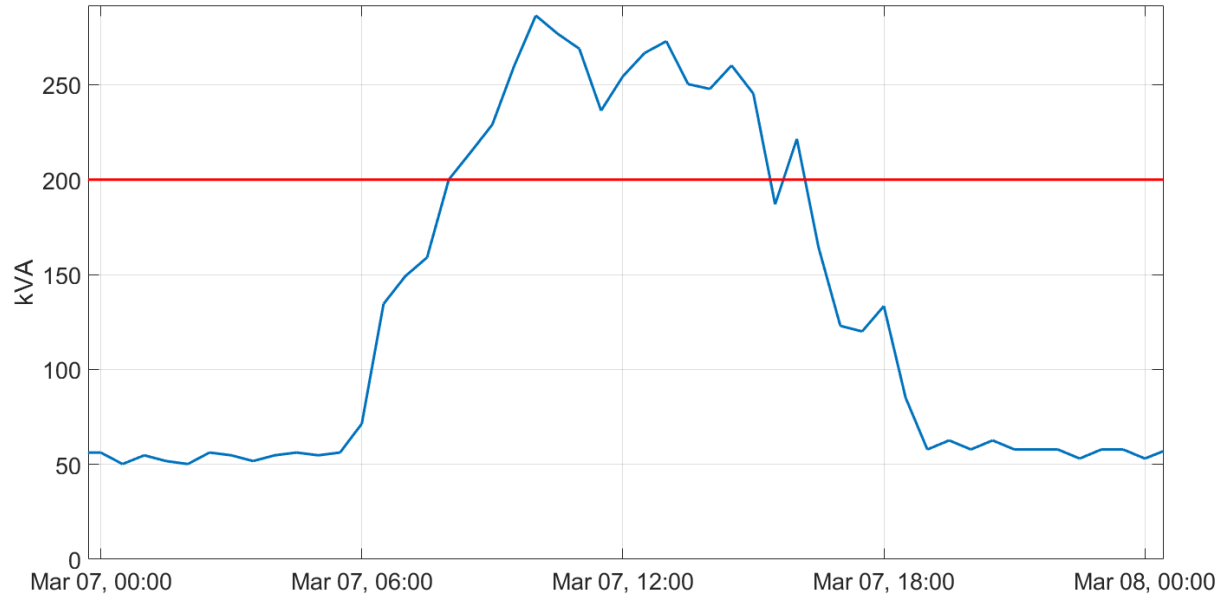


Figure 13: Load demand for 7 March 2018 in kVA with peak shaving target

It is clear that reducing the maximum demand is not a realistic objective. An argument can be made to use the diesel generator to augment the peak shaving ability of the ESS. This will also not be a realistic endeavour, due to the expensive operating costs of a diesel generator. The saving of R 5 677.41 that would be made by reducing the maximum demand to 200 kVA, would be off-set by fuel costs of the diesel generator.

However, reducing the energy usage during peak TOU hours can result in large monetary savings that have no uncertainties like that of the maximum power demand. From the bill extracts in figures 7 and 8, it can be seen that there are large potential savings to be made. The peak TOU hours only occur on business days. A typical month would have around 20 business days. With the ESS being able to provide 200 kWh of energy per day, it would be able to provide 4 000 kWh of energy during peak hours per month. By taking the tariffs indicated in table 5, it can be concluded that in the summer months the potential savings of a 4 000 kWh reduction in peak-hour energy consumption would be R 6 140. In winter months the potential saving would be a much larger R 20 191. The costs of charging the ESS at off-peak hours would have to

be deducted from these amounts. Which means nett savings are around R 3 115 per month in the summer and R 16 791 in the winter. These savings can be increased with discharging during standard hours on weekends and charging with surplus PV energy during weekends. When taking these aspects into account, the potential nett savings per year are around R 80 000 for this facility. By referring back to figure 9, it can be seen that the 4 000 kWh that the ESS can provide per month during peak TOU hours is not nearly enough to satisfy the monthly usage during this period. Which means that a larger ESS would be able to provide even more monetary savings. However, the operator of the microgrid would have to decide if the savings justify the capital expense.

From the analysis in this section, it can be concluded that the main objective of the EMS would be to reduce energy usage during peak hours as much as possible while charging the ESS during off-peak hours or when surplus PV power is available.

Grid code

This microgrid is not allowed to export power to the local utility grid. So during normal operation, excess PV power should not be exported to the grid and in the event of an outage on the utility side, the microgrid must isolate itself before it can power-on. At the time of writing, the logic that controls the output of the PV array is not controlled by the EMS. The PV is curtailed automatically by an independent PLC. The islanding and synchronisation is also controlled by independent PLCs. Thus, grid code compliance is not applicable to the EMS in the configuration of the microgrid at the time of writing.

Battery lifetime

As mentioned earlier, the battery's lifetime can be increased four-fold by limiting the depth of discharge to 50% [54]. This strategy would result in less savings per year, but it would potentially increase the long-term savings. On the other hand, utilising the full depth of discharge would provide bigger savings per year in the short-term.

After discussions with an engineer from the company operating the microgrid, it became evident that planning for a much longer lifetime has many unknowns. For example it is expected that energy storage prices will be reduced drastically over the next ten years due to large increases in production. This might make energy storage technology much cheaper in the future. The current ESS installed has a five year warranty for one full cycle per day. After the five year period, the ESS will still be functioning, at a smaller capacity, but it would still be able to provide a considerable amount of energy. It was decided that to plan for a very long term of usage is not realistic. The storage can rather be utilised as much as possible within warranty ranges in order to achieve a faster return on investment and possibly invest in newer, more affordable technology in the future. Thus, the depth of discharge of the ESS will not be limited to 50%. It will be assumed that the ESS will have usable energy between the SOC ranges of 90% and 15%. It will also be assumed that the SOC is linear.

The objectives of the EMS algorithm can be summarised accordingly:

- Discharge ESS during peak hours
- Keep SOC between 90% and 15%
- Only charge during allocated times:
 1. Off-peak periods during weekday evenings, excluding Friday evenings or evenings before a public holiday
 2. Standard hours during business days, only to increase SOC by 25%
 3. Off-peak periods during weekends or public holidays when there might be surplus PV power
- Do not charge if power measured at the PCC is above 200 kW

These objectives will also serve as performance measures to assess verification and validation of the EMS algorithm.

4.5 EMS design

4.5.1 EMS algorithm design considerations and performance measures

In the previous section, peak shaving has been eliminated as an objective. The main objective was clearly defined as being the reduction of energy usage during peak hours. In order to achieve this, detailed control logic would have to be developed. The data inputs that are available to the EMS from the microgrid is:

- The active power usage of the load measured at the point of common coupling (PCC), i.e. the power consumption that the utility would see.
- The SOC of the ESS.
- The month of the year.
- The day of the month.
- The day of the week.
- The hour of the day.

The EMS will use this data, run it through a control algorithm and decide whether or not to charge or discharge the ESS and at what rate.

The main consideration of the algorithm would be the current time. This would determine the course of action based on the TOU tariffs as set-out by the utility. An additional consideration would be the power measured at the PCC. There are two main aspects to consider with regards to the power measured at the PCC:

- The ESS should not charge when the power consumption at the PCC is above a certain limit. This would cause the maximum power demand seen by the utility to be higher. By analysing the monthly electricity bills, the ideal maximum

demand, during a month with good PV penetration, can be determined to be around 270 kVA. Typically the maximum demand is much lower during most days due to good PV penetration. However, the ESS should preferably not charge during a time that it can potentially increase the maximum demand. Therefore, the EMS algorithm should restrict charging only to situations where the active power measured at the PCC is below 200 kW. At a worst case power factor of 0.8, this is 250 kVA.

- Currently the PV curtailment is activated by a PLC that cannot be controlled by the EMS. The curtailment is set to keep the power drawn at the PCC above 20 kW in order to prevent exporting power to the local utility grid. Thus, the EMS should not discharge in situations where the power measured at the PCC is close to this level. This will cause the PV (if any) to be curtailed more, which will result in a loss of renewable energy. This should be avoided by the EMS.

The algorithm should thus consider the month of the year (in order to determine seasonal tariffs), the day of the month (to identify public holidays), the day of the week and the time of the day, as well as the power measured at the PCC and then decide on the course of action in terms of charging and discharging.

Charging and discharging set-points

The EMS algorithm would have to decide at what rate the ESS should charge or discharge, if necessary. These set-points have to be defined in the logic. The set-points should aid in achieving the objectives and also prevent possible undesired situations as mentioned.

The main objective is to discharge the battery during peak hours. There are three peak-hours in the morning and two peak-hours in the afternoon. It was also mentioned that it is assumed that the ESS would operate within 90% and 15% SOC. This means that 25% of the daily energy allowance is not being used. To compensate for that, the ESS could discharge 60% during the morning peak-hours, which takes the SOC down to 30%. Then the ESS could charge the additional 25% during standard-hours, which

increases the SOC to 55%. Finally, the remaining 40% of the day's energy allowance can be discharged during the afternoon peak-hours, which should decrease the SOC to its lower limit of 15%.

To achieve this, the ESS could discharge at a set-point of 40 kW during peak-hours. In the three morning peak-hours, that would deliver 120 kWh of energy to the load. This also corresponds to the targeted 60% discharge, because the total capacity of the ESS is 200 kWh. During the final two peak-hours of the day, if the ESS is discharging at 40 kW, it would provide 80 kWh of energy to the load. Which corresponds to 40% of the SOC. Which results in one full cycle for the day. This is the only discharging set-point required in the logic.

For charging, there are two TOU periods in which charging would occur and three separate conditions. The three conditions permitting charging are described in the following list:

- Weekday charging during standard-hours. This would only occur between the two peak TOU periods of the day to add the required 25% of energy to the ESS before the final discharge of the day.
- Weekday off-peak TOU charging. This will occur at night during off-peak TOU periods in order to recharge the ESS for the next morning's discharge during the peak TOU period.
- Weekend PV surplus charging. On weekends the facility has lower power consumption, which results in surplus power from the PV that is available for storage in the ESS.

The first condition requires the restriction mentioned earlier with regard to the maximum demand. This requires that the ESS does not charge when the power measured at the PCC is above 200 kW. Additionally, if the power measured at the PCC is below 200 kW, say 195 kW, the power drawn by the ESS should not potentially exceed the desired maximum demand limit. These requirements necessitate conditional adaptive

set-points. The proposed set-points are to charge the ESS at 30 kW when the power measured at the PCC is below 170 kW. If the power measured at the PCC is above 170 kW and below 200 kW, the ESS should charge the balance. For example, if the power measured at the PCC is 185 kW, the ESS should charge at 15 kW. An additional constraint for this charging period is the SOC. The SOC should not go above the 55% target. Thus the EMS should stop charging once this target is reached.

The second condition does not require any specific restrictions other than the SOC target of 90%. Charging under these conditions would typically occur at night from 22:00 to 06:00, which is eight hours. This means that there is enough time to fully charge the ESS at a moderate rate. A charging power of 30 kW will be able to provide enough energy to fully charge the battery in less than seven hours, but also provide some time for the last 10% to be trickle-charged as this may take longer.

The third condition requires some ingenuity, as the EMS in the actual microgrid could not read PV power output data at the time of writing. The PV curtailment also takes place independently of the EMS, which means that even if the EMS could read the PV output power, it would not know how much surplus there actually is, it would only read the curtailed output. On weekends, there usually is a surplus of PV power due to reduced loads. Due to the PV power not being readable, a different method would be required to utilise the surplus PV power. It was decided to charge at a fairly low-rate during off-peak hours that are in daylight hours of non-working days. For example, on a Saturday, Sunday or public holiday, the ESS will charge from 12:00 to 16:00. This time period is during off-peak hours for Saturdays, Sundays and public holidays. It is also during a time when solar irradiation is normally good. In the event of cloud cover causing reduced PV output, this strategy will still charge the ESS, but at off-peak tariffs which it would have charged at anyway during the night. Thus, this strategy will be able to utilise surplus PV power in most cases and not cause unnecessary expenses of charging during standard-hours. It was decided to set the charging power at 20 kW. This would allow the ESS to charge 80 kWh on a Saturday and 80 kWh on a Sunday, which means that a total of 160 kWh will be charged over a weekend, with a large portion being from the PV. This is equal to 80% of the total capacity of the ESS. With

the SOC limits set at 90% and 15%, the 160 kWh will be more than enough to bring the ESS to a 90% SOC level.

Additional considerations

Due to the fact that there would possibly be surplus PV power over weekends and public holidays, the logic should foresee this by not charging during the evening off-peak periods before a weekend or public holiday. During the week, the standard approach would be to charge the ESS at night in off-peak TOU hours. Additional savings can be made by postponing charging on the night before a weekend or public holiday to allow for possible charging from the PV during the next day. Thus, in addition to determining whether the current day is a workday or not, it should also be able to determine whether or not the following day is a workday or not in order to decide on charging during the evening.

4.5.2 EMS algorithm flowchart

In order to conceptualise the proposed EMS algorithm, a flowchart of the algorithm can be generated. Figure 14 displays the flowchart for the proposed EMS algorithm.

Firstly the algorithm checks what season of the year it is, then whether or not the current day is a workday. The algorithm will then apply the TOU tariff applicable to the current time i.e. standard, peak or off-peak. Then the algorithm will decide whether to charge or discharge. As explained in the previous sections, the ESS will only discharge during peak hours, so that would be the only condition that actuates a discharge command. If the SOC of the ESS is acceptable, the ESS will discharge at a rate of 40 kW, otherwise there will be no charging or discharging and the ESS will be in idle mode.

If the TOU periods warrant charging, the algorithm will check if the SOC of the ESS allows for energy to be absorbed. If not, the ESS will enter the idle mode. If the ESS can absorb energy, the algorithm will determine what the current charging condition

is. If it is off-peak hours during the week, the ESS will charge at 30 kW, if it is off-peak hours during a weekend or public holiday, the ESS will charge at 20 kW. If the current TOU time is during standard-hours of the week, the algorithm will activate charging if the load is below 200 kVA, otherwise the ESS will enter idle mode. If the load is below 200 kVA, but above 170 kVA, the ESS will charge the difference between the 200 kVA target and 170 kVA. If the load is below 170 kVA, the ESS will charge at a maximum rate of 30 kW.

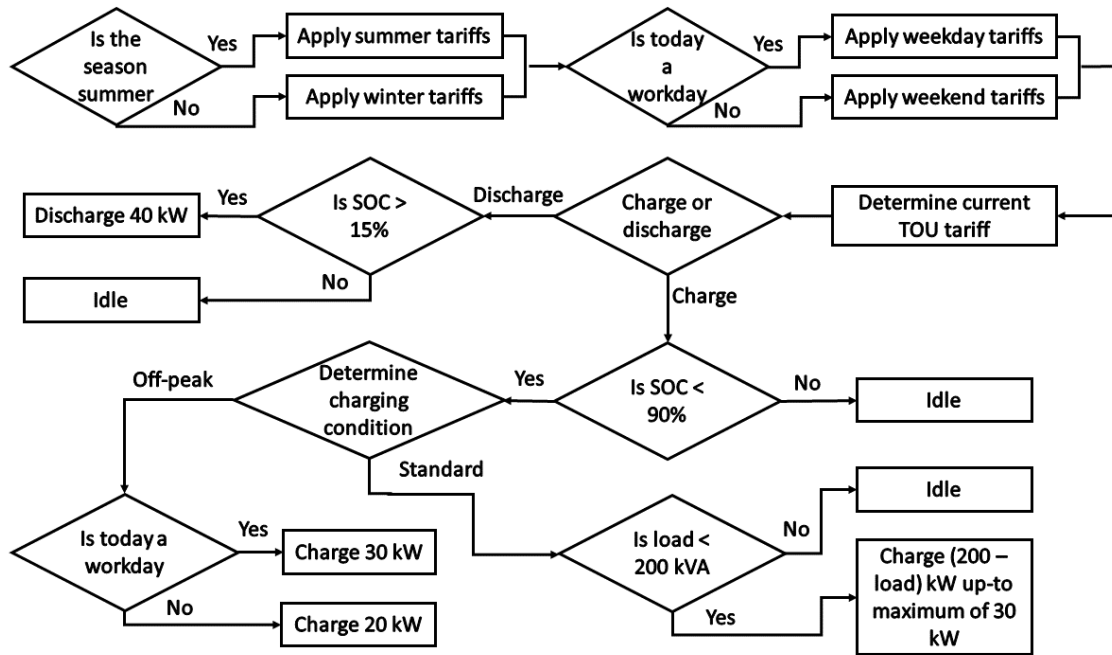


Figure 14: EMS algorithm flowchart

The flowchart in figure 14 can be used to aid in the development of the logic that will realise the proposed algorithm.

4.5.3 EMS algorithm logic

In order to realise the algorithm as shown in figure 14, specific logic has to be defined and coded. Several approaches are available to do this. The deterministic nature of the algorithm with three distinct states, namely charge, discharge and idle, would lend itself well to a state-machine or a truth-table. Due to the relative simplicity of the

algorithm, a truth-table approach should suffice.

A truth table is a mathematical table used for logic operations. It usually consists of a table with conditions and a table with actions depending on the Boolean state of the conditions. An action may depend on the Boolean state of various conditions in order for the action to be executed by the logic. Table 6 shows the conditions that were defined for the proposed algorithm in figure 14.

Condition	State				
Currently peak hour	T	F	F	F	-
Currently standard hour	F	T	F	F	-
Currently off-peak hour	F	F	T	T	-
Today is a workday	T	T	T	F	-
Power at the PCC is less than 200 kVA	-	T	-	-	-
SOC is above 15%	T	-	-	-	-
SOC is below 90%	-	T	T	T	-
SOC is below 55%	-	T	-	-	-
Corresponding rows in action table	A1	A2	A3	A4	A5

Table 6: Truth table conditions

Each condition has a set of Boolean states, where "T" represents a true state, "F" represents a false state and "-" represents indifference to a specific state. At the bottom of the table, the corresponding actions from table 7 are shown. For example, in order to execute action A1, the current hour must be during peak hours, the current day must be a workday and the SOC must be above 15%. If all these conditions are met, the action designated as A1 in table 7 will be executed. The same holds for the rest of the conditions and corresponding actions. If the current inputs do not warrant either one of actions A1-4 to be executed, the ESS will enter idle mode.

Implementing the truth table method as set-out in tables 6 and 7, will allow the EMS to reach the objectives and performance measures that were defined earlier. From the

Designation	Action
A1	Discharge ESS at a rate of 40 kW
A2	Weekday standard hour charge. If load is more than 170, charge at 200 - load. Otherwise, charge at a rate of 30 kW
A3	Weekday off-peak hour charging. Charge at a rate of 30 kW
A4	Weekend off-peak charging. Charge at a rate of 20 kW
A5	Idle

Table 7: Truth table actions

conditions in table 6, it is clear that the truth table requires four inputs: the current TOU period, whether the current day is a workday or not, the power measured at the PCC and lastly the SOC.

4.5.4 Data pre-processing

TOU function

In order to determine the current TOU period and whether or not today is a workday, requires some additional data processing and detailed knowledge of the utility tariff structure. The TOU period is dependent on three time variables, namely the month of the year (which indicates the season), the day of the week and the time of day. The truth table as defined in tables 6 and 7, should not be concerned with these variables, as it adds unnecessary complexity to the truth table. Instead, the time variables mentioned can be pre-processed in order to provide the truth table with a value between 1 and 3, which indicates one of the three TOU periods. A simple function can be coded that allocates a TOU period to the current time and feeds the period to the truth table. Additional safety measures can be programmed into the code. For example standard hours on weekdays in the winter start at 09:00 and end at 17:00. To reduce the risk of increasing the maximum power demand, standard tariffs can be defined from 11:00 to 15:00, which is during maximum PV penetration. Thus the truth table would not

consider charging outside of those hours.

Workday function

An additional consideration is whether or not the current day is a workday. This is dependant on the day of the week, as Saturdays and Sundays are not workdays, and also on the day of the month, because public holidays are not workdays. A function can be coded that checks if the current day is a workday and just provide the truth table with a binary input. This input can also be relayed to the TOU function, which needs to know if the current day is a workday. In addition, the workday function should determine whether or not the next day is a workday, because this will influence the behaviour of the logic on the current day. This function can also relay the workday status of the next day to the TOU function, which would then assign a TOU period based on that condition as well. For example, if it is a Friday evening, the TOU function will not assign an off-peak period to the current time, in order to ensure that the truth table does not charge, but rather waits for the next day that might have surplus PV power. The MATLAB code for these two functions can be found in Appendix A.

These two functions will operate outside of the truth table and will serve to pre-process time data for the truth table logic. The next step is to implement the logic and test it by means of simulation.

4.6 Conclusion

In this chapter the performance measures and objectives for the microgrid EMS algorithm were defined. In order to achieve these objectives, a truth-table was set-up in order to develop the necessary logic that will be used in the algorithm. Now that the logic has been developed, the next step is to simulate it, verify its performance, implement it on the physical system and validate that the objectives that were chosen, does in fact achieve the desired results. This will be discussed in the next chapter.

Chapter 5

EMS algorithm evaluation

5.1 Introduction

In this chapter, the truth-table that was developed in the previous chapter will be implemented in Simulink and its performance will be simulated. The development of the EMS simulation framework will also be discussed. The verification of the algorithm and the implementation thereof on the physical system will be addressed. Then, the results are analysed and the validation of the objectives are investigated.

5.2 EMS simulation

It was decided to utilise Stateflow to implement the truth table logic. Stateflow, developed by MathWorks, is a control logic tool used to model reactive systems via state machines and flow charts within a Simulink model. Stateflow allows the user to simulate logic operations with models created in Simulink. Thus, after creating the Stateflow object and defining the logic, the inputs to the Stateflow object can be fed by data from Simulink. This data can be generated by a dynamic model in Simulink or from a database of historical data. Then, the output of the control logic can be compared with

the input data in order to verify that the control logic is functioning as expected.

The EMS of the actual microgrid would only receive the active power at the PCC, the SOC of the ESS and time as inputs and would not be responsible for anything other than energy management. Thus, the EMS would not be responsible for protection, islanding or synchronisation. Therefore, it was deemed unnecessary to develop a dynamic model of the microgrid in order to simulate the operation of the control logic. It was decided to simulate the microgrid by using historical data. Thus, a database would represent the normal operating conditions of the load requirements in the microgrid and feed real historical data to the control logic, upon which the control logic would react. This will allow for sufficient verification of the control logic and is also supported by literature, as discussed in chapter 3. The block diagram in figure 15 represents the main components in the Simulink simulation. $T(t)$ is the time and date at time-step t . $P_{PCC}(t)$ is the power measured at the PCC at time t . $P_{ESS}(t)$ is the power output of the ESS at time t . It can be seen that the current time, power measured at the PCC and the SOC of the ESS is fed as inputs to the control logic, which then decides at what rate to charge or discharge the ESS, if necessary. It can also be seen that the output of the ESS is subtracted from the power measured at the PCC. This is because the power measured at the PCC will depend on the ESS output.

5.2.1 Data acquisition

Load data

In order for a database to be developed that represents the normal load requirements of the microgrid, load data and PV production data are required. The only load data that was available for the facility during 2017, was 30-minute kWh aggregate samples. This data is measured at the PCC. The data that the EMS receives, is power samples measured in kW, at the PCC. In order to convert the 30-minute energy aggregate samples in kWh, to average 30-minute power drawn samples in kW, the energy samples can be divided by the corresponding time period, in this case 30 minutes or half an hour, as

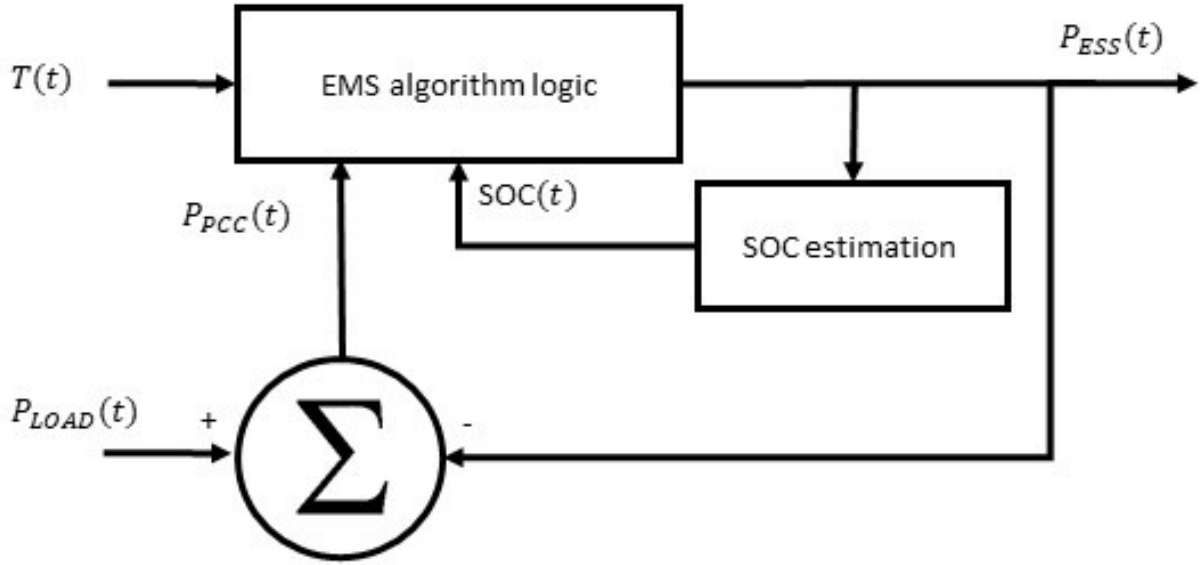


Figure 15: EMS simulation block diagram

indicated in (12), where $P_{average}(t)$ is the desired average power sample in kW at time t , T is the sampling period in hours, which is half an hour in this case, $E(t)$ is the energy sample in kWh at time t . This equation can be simplified to multiplying every energy sample by 2.

$$P_{average}(t) = \frac{E(t)}{T} = \frac{E(t)}{0.5} = 2E(t) \quad (12)$$

The data is available in comma separated value (CSV) format from the utility. The data was processed with the help of MATLAB. In order to increase the resolution of the data, linear interpolation was applied. By adding a sample between every two samples, which is the average between the first and second sample, the data resolution was increased to 15 minute samples. Higher resolution data would give a more accurate representation of how the actual system would work. Ideally, resolution in the range of seconds would be preferred, but that data is not available.

PV data

The PV energy production data was retrieved from the inverters connected to the PV-

array. Each inverter provides a daily spreadsheet that indicates the total energy in kWh produced and also the power in Watts delivered per 5-minute sample. This data had to be converted into the same format as the load data. A MATLAB script was compiled to do the conversion for hundreds of data sets. The algorithm in 13 was used to process the data.

$$\sum_{n=1}^{48} E(n) = \sum_{i=i+1}^{i+6} \frac{\left(\frac{P(i)}{60} \times 5 \right)}{1000} \quad (13)$$

where $E(n)$ is the energy produced during the n -th 30-minute sample by an inverter in kWh. $P(i)$ is the 5-minute power delivered sample in Watts. This algorithm iteratively converts each power sample to a kWh sample, assuming the same amount of power was delivered for 5 minutes, then adds the samples together to create a 30-minute energy sample, which has to be repeated 48 times in order to generate the solar energy production for one day in the same format as the load data. The variable i starts at 0 and every time it reaches a multiple of 6, the n variable has to be incremented. This process had to be repeated to process 60 days worth of data from four inverters. The results of each day were compared with the inverter's daily total energy production and the error was within 2%.

The PV array was commissioned in June 2017, which affected the power measured at the PCC. In order to get data of the actual load for the remainder of the year, the PV data has to be added to the load data obtained from the utility. During weekends, there is usually a surplus of PV power. This causes the load measured by the utility to drop to zero, even though the PV array is actually exporting power to the utility. The data over weekends would thus have to be manually edited to represent weekends similar to that which was observed prior to the PV installation. Simply adding the PV data to the load data would not suffice for weekends, as not all the PV power delivered by the inverters was consumed by the load.

In 2018 PV curtailment was added to the plant, as well as a data historian which records the power measured from the PV, ESS and the power demand measured at the PCC.

This makes it easier to determine the actual load demand, however, at the time of writing the system was still under testing and not fully functional.

Time data

The logic will receive time data from the PLC. As mentioned earlier, the time inputs that are required is the month of the year, the day of the month, the day of the week and the time of the day. The logic will receive this data as numeric inputs. These four inputs and their corresponding ranges are listed in table 8.

Time data	Value
Month	Between 1 and 12
Day of the month	Between 1 and 31
Day of the week	Between 0 and 6, with Sunday being 0
Hour of the day	Between 0 and 24

Table 8: Time inputs

The four inputs in table 8 and the load data will be the only inputs that the EMS algorithm receives. The logic will thus make its decisions based on these inputs alone. The load data from the utility has corresponding time-stamped samples for each energy sample. These samples were also interpolated with the use of MATLAB to generate 15-minute time samples.

Database

The time-stamp samples provided by the utility requires the extraction of the four individual components listed in table 8 to serve as the four inputs. By utilising MATLAB these four elements were extracted from every time-stamp and stored in separate vectors. These four vectors and the load data were individually allocated to five columns in an Excel spreadsheet which shall serve as a database. These five columns in the database will then serve as five individual inputs that the EMS algorithm will receive. Referring back to figure 15, the database is represented by the first block in the diagram.

5.2.2 SOC estimation

The SOC has to be estimated after each time-step in Simulink. The SOC is dependent on the output of the ESS, which is dependent on the output of the control logic, which means that the SOC percentage would have to be estimated in some manner. To do this, the method discussed in section 3.3 can be employed. This method requires the power output at each time step to be converted to an energy value, which will then be added or subtracted from the SOC of the ESS. In the actual microgrid, the EMS will receive an SOC value as input from the ESS. The SOC can be estimated in Simulink by graphically implementing the SOC estimation algorithm from (7) which is indicated in figure 16. The estimator receives the output power from the ESS as input, which passes through an initial condition of 0. This is just to ensure that the loop has an initial value on start-up. Afterwards the initial condition block just lets any data pass through unaltered. The power output is then divided by 8. This is to convert the 15-minute power average sample to a 15-minute energy sample as a percentage of total ESS capacity. Equation (14) explains the simplification made, where $P(t)$ is the power output of the ESS in kW at time-step t , T is the sampling time which is a quarter of an hour in this case and E is the capacity of the ESS in kWh.

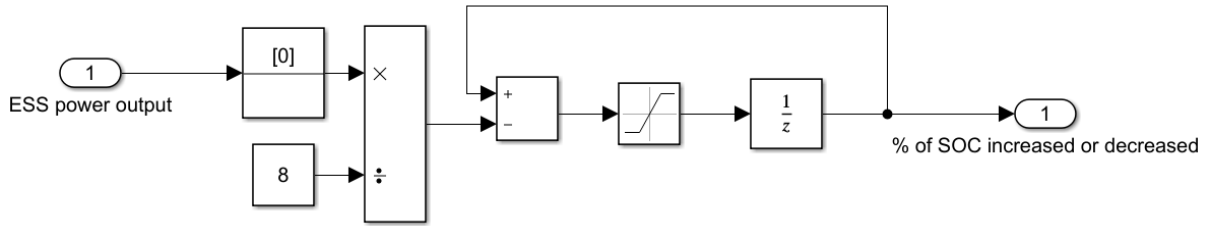


Figure 16: Simulink SOC estimation

$$SOC\% = \left(\frac{P(t)T}{E} \right) (100) = \left(\frac{P(t)(0.25)}{200} \right) (100) = \frac{P(t)}{8} \quad (14)$$

In the case of the ESS charging, the power output will be negative and if the ESS is discharging, the output will be positive. This energy sample, that has been converted to a positive or negative SOC percentage, is then subtracted from the previous value

calculated for the SOC. Thus, if the ESS is charging, the power output would be negative, which would then be added to the SOC, due to the double negative. The opposite holds for discharging.

This method provides a linear SOC estimation, which is not how the actual ESS will react, but it is a close approximation. The purpose of the estimation is for the simulated logic to have a reference SOC to work with. In the actual system, the logic would receive the SOC from the ESS. It can be concluded that if the logic responds to specific SOC limits in the simulation, it would do the same in the actual system.

5.2.3 Simulink simulation

In order to simulate the behaviour of the EMS algorithm, Simulink will be employed to feed data from a database as well as an SOC estimation block as inputs to the control logic implemented in Stateflow. Stateflow allows the user to construct a truth table by defining inputs, outputs, conditions and actions. This greatly simplifies the process for the user, as there is no need to generate low-level code. It is however possible to add low-level code to actions in a Stateflow truth table. For example, action A2 in table 7, requires an if-statement to be employed. Stateflow allows the user to write standard MATLAB code in actions. This gives the user the opportunity to add any complex code to an action's execution, if need be.

Referring back to the simplified block diagram in figure 15, the central block contains the control logic. The implementation of this block in Stateflow and Simulink can be seen in figure 17. The inputs 1 - 4 are from the database and input 5 is from the SOC estimation. Input 6 is from the database, but the power output of the ESS has been subtracted, as can be seen when referring back to figure 15. The two function blocks named "TOU period" and "Workday determination" contains custom MATLAB code that executes the pre-processing of the time data as discussed in section 4.5.4. The large block named "Truth table" contains the truth table logic as defined in tables 6 and 7. The output named "Battery Out" is the charge or discharge rate command that the

control logic sends to the ESS.

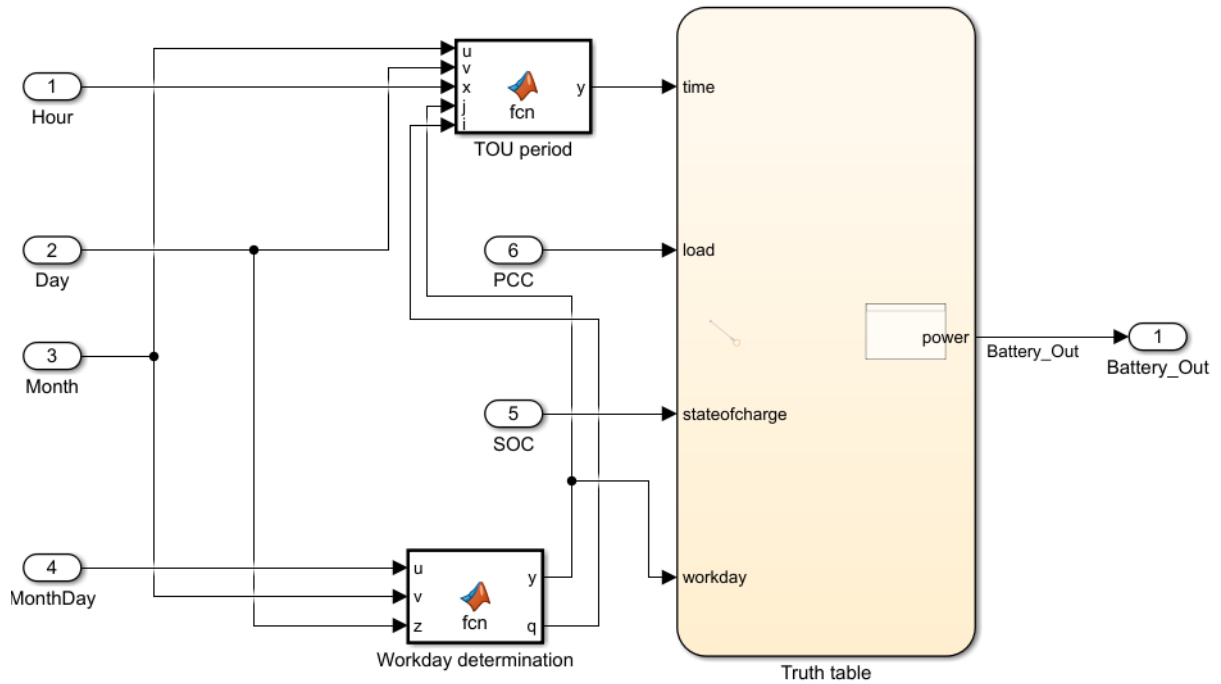


Figure 17: Control blocks in Simulink and Stateflow

This system can now be simulated in Simulink in order to verify the effectiveness of the proposed simulation method and EMS algorithm.

5.3 Verification

Verification of simulation method

Firstly, the simulation method has to be verified. This can be done by feeding a limited amount of data into the model and verifying that it is functioning as expected. It was decided to use data from July 2017 for verification purposes. In figure 18, the simulation output from a limited set of data from 10 July can be analysed. A section of data has been extracted from the database to test the simulation platform that has been developed. Three step inputs of ESS discharge/charge was injected to test the simulation's response. In figure 18, it can be seen that the simulation starts at 00:00 on 10 July. The legend shows the colours of the individual signals in the plot.

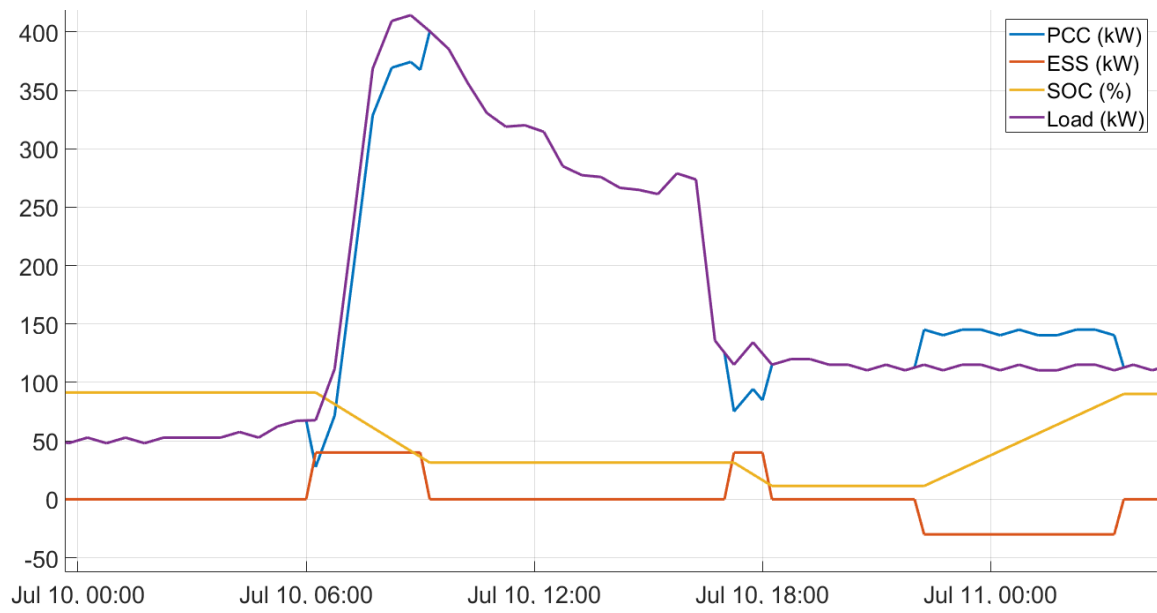


Figure 18: Simulation testing data from 10 July 2017

The purple line, designated as "Load" is the power measured at the PCC that is provided by the database, where the blue line, designated as "PCC" is the "Load" subtracted by the output of the ESS. This would then serve as the input to the truth table. At 06:00, the ESS delivers 40 kW for 3 hours. The effect of the discharge can be seen in the difference between "Load" and "PCC". The effect on the SOC can also be noticed. At 17:00, the ESS delivers 40 kW again for 4 samples, which equals 1 hour, after which the SOC reaches the lower limit and discharging stopped. The effect on the power measured at the PCC can be seen again due to the difference between "Load" and "PCC". At 22:00, the ESS charges at a rate of 30 kW, hence the negative value in the plot. Once again, the effect on the power measured at the PCC can be seen. It can be concluded that the power measured at the PCC due to the output of the ESS is accurately represented with this simulation. Next the SOC estimation has to be verified. Referring back to the first ESS discharging block and analysing the corresponding change in SOC, it is observed that over the three hour period, the SOC drops from 90% to 30%. This 60% reduction in SOC corresponds well with the three hours of discharging at 40 kW, which is 120 kWh and 60% of total ESS capacity. The same is observed with the other discharge and charge blocks in the data observed. It can thus be concluded that the simulation method is verified, as it is performing as expected.

Verification of EMS algorithm

In order to verify the effectiveness of the EMS algorithm, it has to be determined whether or not the objectives and performance measures that were set out in section 4.5 are met. To do this, all the data for the month of July 2017 was used in the simulation. The objectives defined in section 4.5 are:

- Discharge ESS during peak hours
- Keep SOC between 90% and 15%
- Only charge during allocated times:
 1. Off-peak periods during weekday evenings, excluding Friday evenings or evenings before a public holiday
 2. Standard hours during business days, only to increase SOC by 25
 3. Off-peak periods during weekends or public holidays when there might be surplus PV power
- Do not charge if power measured at the PCC is above 200 kVA

The output of the simulation can be inspected to iteratively check whether each objective has been met. The objectives should hold for any and all conditions that could arise during the month. Figure 19 shows the simulation output for the entire month of July.

Even though PV production is not taken into account by the EMS, it is shown in the figure to give an idea of the renewable energy available to the microgrid and the effect that it has on the power measured at the PCC.

Verification that the ESS is in fact discharging during peak hours can be confirmed by looking at any individual weekday of the month. Thus, for verification purposes, the data in figure 19, will be zoomed into on individual days for closer inspection. In order to verify that the EMS is functioning as expected on business days, every day should be inspected for any anomalies. For the sake of brevity, only two days will be discussed

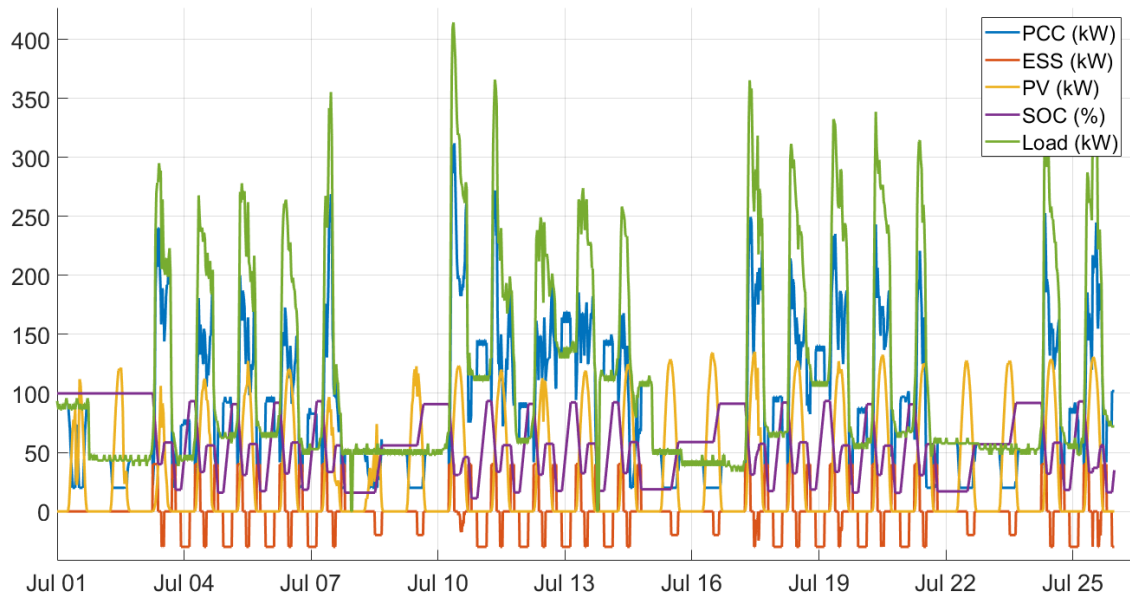


Figure 19: Simulation output for the month of July 2017

in order to determine whether or not the objectives with regard to business days were met. The 18th of July was arbitrarily selected to inspect. In figure 20 the data starts at 00:00 on 18 July and ends at 00:00 on 19 July.

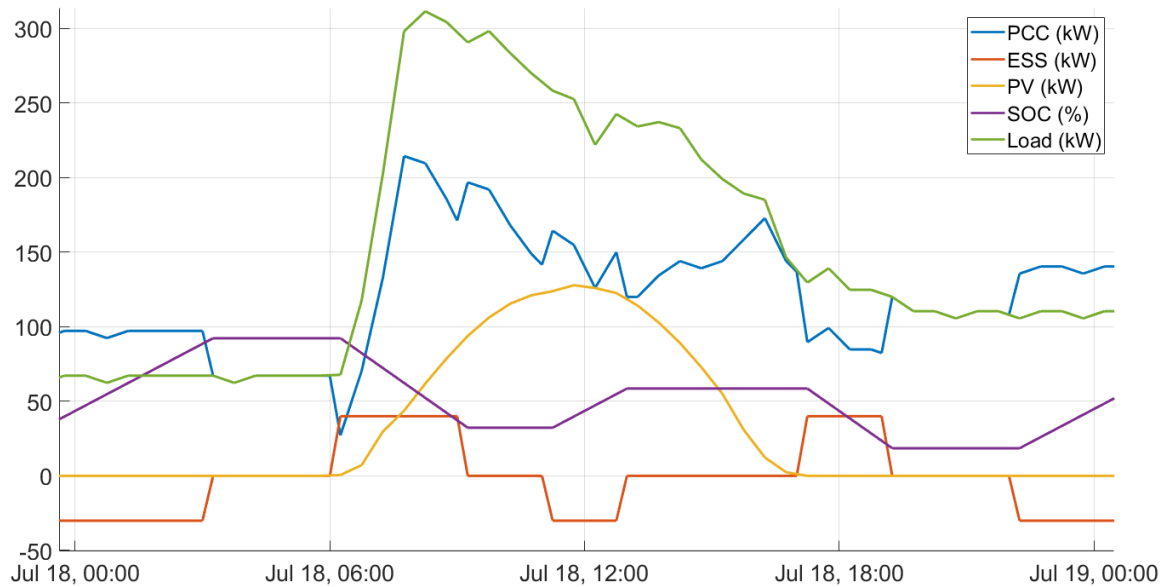


Figure 20: Simulation output for 18 July 2017

At 06:00 discharging commences at 40 kW. The discharging terminates at 09:00. At 11:00, the ESS starts to charge at a constant rate of 30 kW until it reaches an SOC of 55%. The ESS waits in idle mode until it starts to discharge again during peak hours at

17:00 until 19:00. This also depletes the ESS and it goes into idle mode, waiting for off-peak hours to arrive to charge again. The ESS starts to charge at 22:00 and continues to do so until it reaches full capacity the next morning. This can be seen in figure 21, where the simulation output for 19 July 2017 is displayed. It can be seen that the charging terminates once the SOC reaches 90%. Through inspection it follows that the EMS algorithm performed exactly as expected on 18 July.

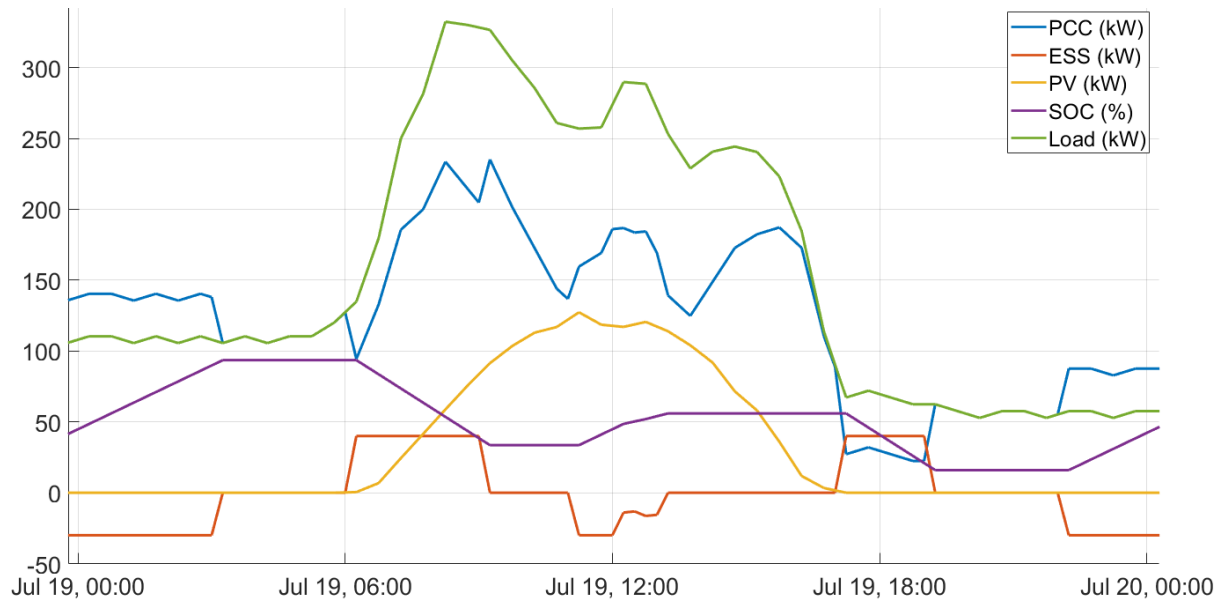


Figure 21: Simulation output for 19 July 2017

The simulation output for 19 July starts exactly as expected. During the middle of the day it can be noticed that the rate of charge is varying. This is due to the condition defined which states that the ESS shall not charge if the power measured at the PCC is above 200 kW. If the power measured at the PCC is above 170 kW, it shall only charge the difference between the power measured at the PCC and the 200 kW target. It can be seen in figure 21 that the ESS reacts as expected, keeping the power measured at the PCC well below the 200 kW target. For the remainder of 18 July, the algorithm seems to function as expected. By manually inspecting the rest of the days of July 2017, it was verified that the algorithm meets its objectives set-out for weekdays.

It has now been verified that the algorithm keeps the SOC within acceptable ranges and charges and discharges as expected during weekdays. Next it has to be confirmed whether the algorithm meets the objectives set-out for weekends and public holidays.

The same methodology will be followed, by inspecting individual days for any anomalies. It was decided to inspect the weekend of 14 July - 16 July. Figure 22 displays the simulation output for the weekend. It can be noted that after the afternoon discharge from 17:00 to 19:00 on Friday, the ESS does not charge for the remainder of the night. Instead, it waits for the following day's daytime off-peak hours to arrive and starts to charge at 12:00 on Saturday. It charges for the allocated time of 12:00 to 16:00 and then waits for the same hours to arrive on Sunday. Then the ESS charges until it reaches an SOC of 90%. This indicates that the algorithm performed exactly as expected. Through inspection of the other weekends in the dataset, it was confirmed that the algorithm functioned as expected on every weekend.

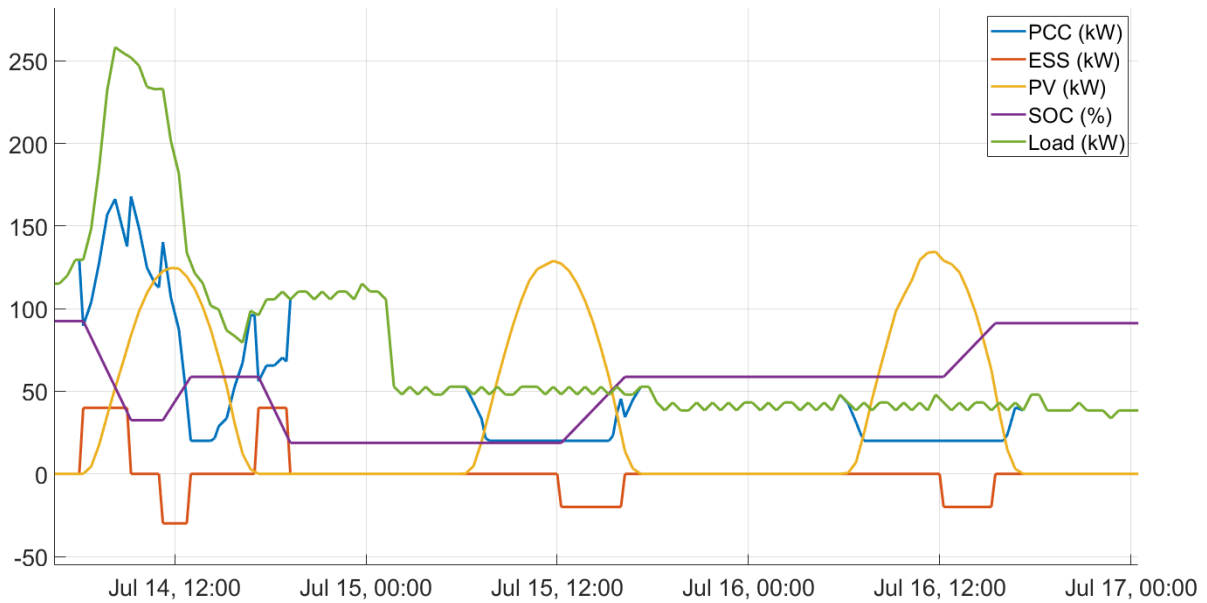


Figure 22: Simulation output for 14-16 July 2017

It can now be concluded that the EMS algorithm satisfies all objectives that were set-out. The algorithm has therefore been verified. The next steps are to implement the algorithm on the actual system and validate the objectives.

5.4 Implementation

In order for the EMS algorithm to be implemented on the physical system, the control logic blocks as indicated in figure 17 have to be converted to PLC-code. This includes the TOU and workday function blocks as well.

The physical system utilises the CODESYS environment in which ladder logic or structured text PLC programs can be implemented. Structured text was generated from the control blocks in figure 17. Please see the structured text code in Appendix A.

The code was uploaded to the microgrid controller on 14 September 2018 and ran on the system until 21 September. The field data was collected from the system's historian. This data can be used to validate the performance of the EMS algorithm. The field data contains a weekend and a full work week, thus the data should be sufficient to validate the performance of the EMS in various conditions. However, before the algorithm was uploaded, several hardware and software issues with the physical microgrid system were identified. As the system was still under development at the time, some of the microgrid's components were not fully operational yet. These issues may affect the results:

- It was found that three battery strings in the ESS was out of order. This reduced the capacity of the ESS by 25%.
- The algorithm used by the BMS of the ESS to determine its SOC, had some technical issues. The SOC would typically not go above 90% or below 17%, although it sometimes does. The SOC value would also drift up and down when the ESS is in idle mode. This could affect the functioning of the logic and has to be taken into account when analysing the results.
- The historian caused some errors in the data at times, where constant rates for PV power would occur over several hours. This however should not affect the operation of the EMS algorithm, as PV power is not an input for the algorithm.

The operator of the microgrid aims to solve the issues with the three inactive strings and the SOC in the short term, thus it was decided not to alter the developed logic to account for the changes in system behaviour. However, these issues need to be taken into account when analysing the data. It must also be kept in mind that these issues are not caused by the EMS algorithm.

5.5 Validation

The EMS algorithm was uploaded to the microgrid controller on 14 September at 09:00. Figure 23 shows the field data gathered by the microgrid's historian for 14 - 21 September. It can be seen that the ESS discharges on Friday 14 September for a short period of time. This is expected, as the algorithm was only uploaded at 09:00, thus it discharged from 09:00 to 10:00, which is during peak-TOU hours in the summer. The discharging stops and the ESS enters idle mode, as the ESS is still quite full due to the short discharge. During the afternoon peak-hours, the ESS discharges again. However, it does not charge during the evening off-peak hours. This is because it is a Friday and it is preferred that the ESS charges the following two days when there is possibly a surplus of PV power. It can be seen that the ESS then charges on Saturday 15 September and Sunday 16 September, in a similar fashion than what was seen in the simulations.

There is a strange spike in ESS charge visible on 17 September. A closer look at this phenomenon is taken in figure 24. This occurrence can be attributed to the inaccuracy of the SOC algorithm as mentioned in section 5.5. Charging of the ESS stopped on 16 September when the SOC reached 90%. By looking at the SOC value, a gradual decline in SOC percentage is noted. It can be seen that at around 00:00 the ESS was discharged at 30 kW for 15 minutes. At the instant when the ESS was triggered to charge, the SOC value was at 79%. This is a reduction of 11% of capacity within 8 hours without the ESS being discharged at all. After the 15 minutes of charging at 30 kW took place, the SOC can be seen to jump up to 90% again. This is not mathematically possible as a 30 kW charge for 15 minutes only provides 7.5 kWh of energy. Thus, it is impossible

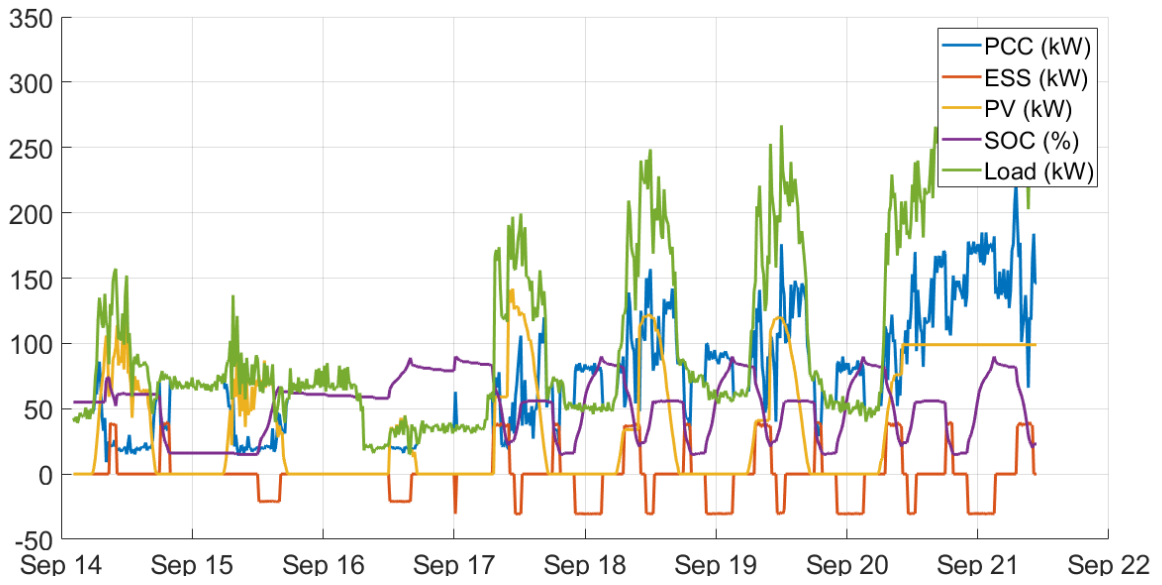


Figure 23: EMS algorithm field data for 14-21 September 2018

to add 11% of capacity to the ESS. The spike in the data can be attributed to the SOC algorithm being defective, which incorrectly causes the logic to try and charge the ESS, while it is in fact, full.

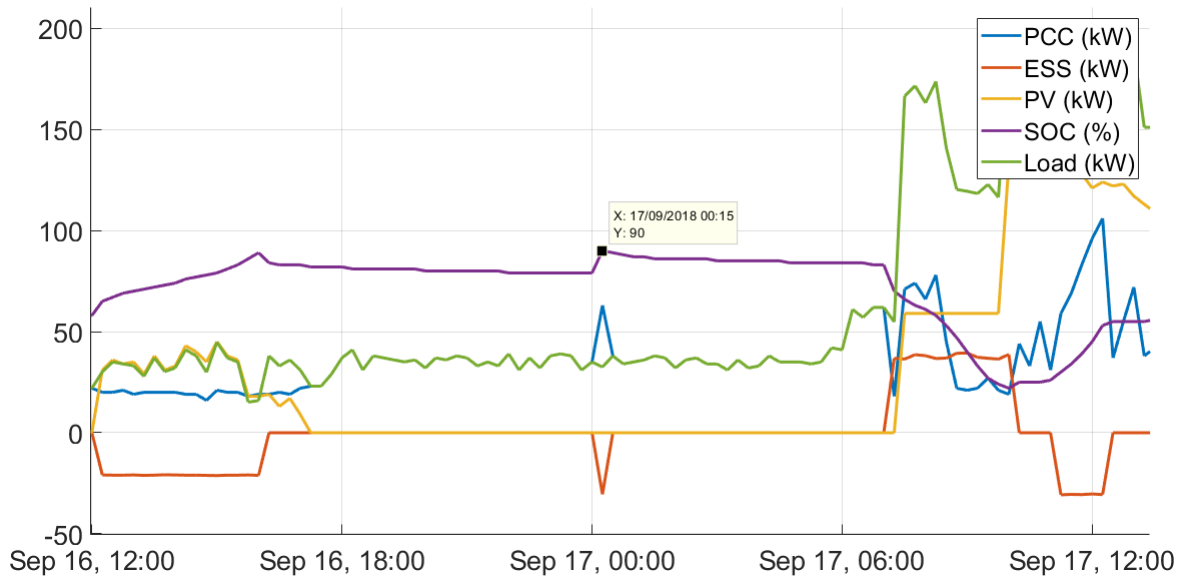


Figure 24: Spike in validation data

In order to further inspect the data for validation purposes, a full day cycle will be extracted and analysed. In figure 25, the results of 18 September can be observed. The data in the figure starts at 06:00. It can be seen that the ESS is discharged from 07:00 to 10:00, which is the first summer peak-TOU period. It is observed that the SOC drops to

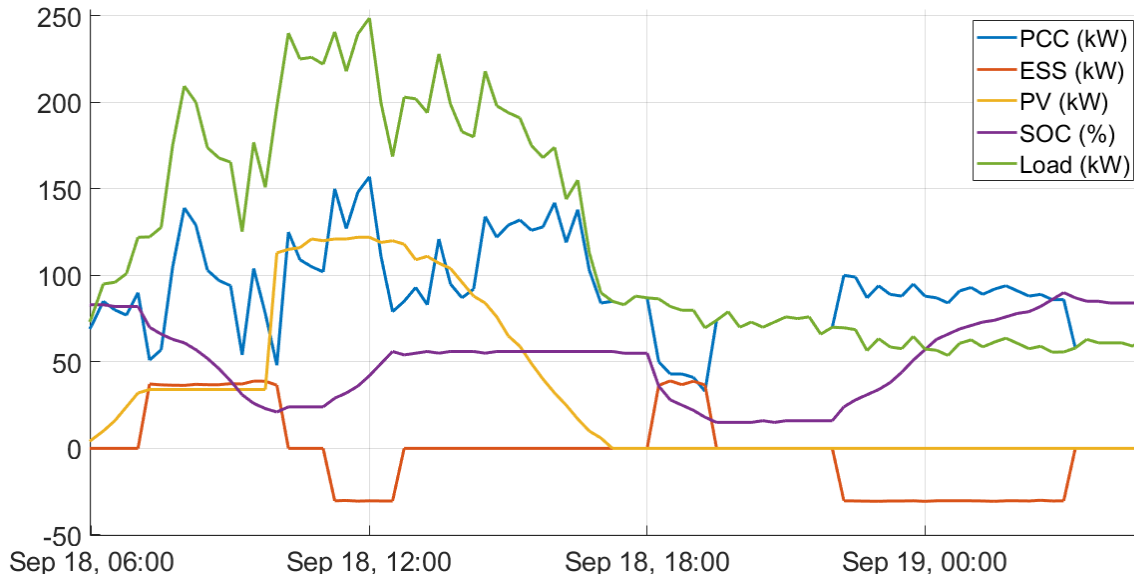


Figure 25: Field data for 18 September

21%, which is lower than what is observed during the simulations. This is due to the three inactive strings of the ESS reducing the effective capacity of the ESS. Following the morning discharge, the ESS goes into idle mode and starts to charge at around 11:00 until the SOC target of 55% is reached. The ESS then goes into idle mode again and discharges during the afternoon peak-TOU period from 18:00. However, the ESS was depleted by 19:15 and discharging stopped at an SOC of 15%. The EMS algorithm then put the ESS into idle mode while it waited for the off-peak-TOU period to arrive at 22:00, when charging commenced. It can be seen that the ESS was charged at 30 kW until the SOC reached 90% and charging ceased. The constant rate of PV power in figure 25 from 07:30 to 10:00 can be attributed to an error with the historian. The other days in the data followed the same pattern as can be seen in figure 23.

In section 4.5.1, the charging over weekends was discussed. It was mentioned that it is desirable to charge with the surplus solar power that is available over weekends, however the PV power is not available as in input to the EMS algorithm. Thus, it was decided to charge during off-peak hours on weekends, which is after 12:00. This means that even in the event of no surplus PV due to cloud cover, the charging would still take place at off-peak rates. Thus, when there is surplus PV power, that would be an added bonus. This strategy can be assessed by having a closer look at the weekend of 15-16

September in figure 26. It can be seen that on Saturday 15 September, the charging starts at 12:00. The power at the PCC remains fairly the same at around 20 kW, which means the curtailment of the PV has been decreased to provide for the extra power drawn by the ESS. As the time goes on and the PV production naturally reduces, the power drawn at the PCC steadily increases. The same is evident for Sunday. However, by looking at this figure, it can be noted that further optimisation could be done to utilise the PV more effectively. For example, by starting to charge an hour earlier. It is a risk to possibly charge at standard tariff rates if there is no surplus PV, however, this would be very rare. Nonetheless, the EMS algorithm has performed as expected in this scenario.

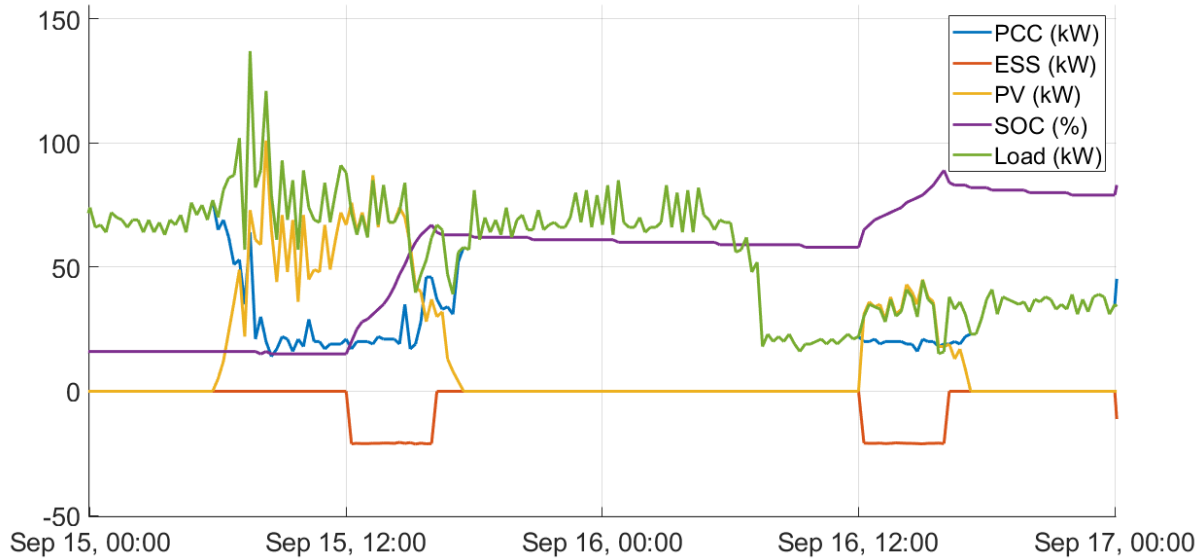


Figure 26: Field data for 15-16 September 2018

In order to validate that the objectives identified for the EMS algorithm do in fact achieve the expected savings, the savings can be calculated from the data retrieved from the historian. The data samples provide the average power consumption at a resolution of 15-minutes. This means that the energy used for every 15 minutes can be approximated by simply multiplying the power sample with the time period, as indicated in (15), where P represents the 15-minute power sample, E represents the energy used and t is the time period, which is a quarter of an hour in this case.

$$E = P \times t = P \times 0.25 = \frac{P}{4} \quad (15)$$

To determine the actual savings, a full discharge/charge cycle will be analysed. With the capacity reduced by 25%, theoretically, 150 kWh of capacity remains to be used in the ESS. September qualifies as a summer month in terms of the tariff structure, thus if all 150 kWh could be discharged during peak hours, that would result in a saving of R 1.5352 multiplied by 150 kWh, which is R 230.28. The objectives defined in chapter 4, require that the ESS be charged 25% during standard hours at R 1.0079 per kWh, in order to utilise the full daily energy allowance of the ESS. Thus, with 25% of 150 kWh being 38 kWh, this would cost R 38.30 extra. The ESS would then have to be fully charged at off-peak hours for R 0.7563 per kWh. If only 75% of the capacity is available for charging (90%-15%), that means that only 112 kWh will be charged during off-peak hours. This would cost R 84.71. These calculations do not take into account the efficiency of the charging and discharging, which would increase the costs in reality. Thus, the total nett saving per day, for an ideal situation would be R 230.28 - R 84.71 - R 38.3, which is R 107.27. This saving is expected to be lower due to conversion inefficiencies. The 24 hour period from figure 25, namely 18 September will be analysed. By applying (15) to every power sample, and aggregating the results, the following was found:

TOU period	Charge (kWh)	Discharge (kWh)	Savings
Off-peak	151.85	0	-R 114.84
Standard	45.5	0	-R 45.86
Peak	0	158.45	R 243.25
		Total savings:	R 82.55

Table 9: ESS performance 18 September

This table confirms that if the additional charging during standard hours did not take place, the total 150 kWh of the ESS would not have been used. This confirms that the objective to increase the SOC by 25% during standard hours in order to use the full en-

ergy allowance for the day, is indeed valid. It is interesting to note that in total, 197.35 kWh was charged, but only 158.45 kWh was discharged. This results in a conversion efficiency of 80%. This apparent loss of energy can however not only be attributed to conversion losses. The ESS system has to power its cooling system, battery management system and control system. This might explain the 10% decline in capacity overnight, which might be due to the ESS powering the peripheral components in the system. Thus, the conversion efficiency is likely much higher than the perceived 80%.

It has to be kept in mind that these savings would be significantly higher during the winter months, due to the higher peak TOU tariffs. The EMS algorithm functioned as expected through all scenarios and achieved the expected savings. Therefore, the EMS objectives, algorithm and the simulation method used, can be deemed to be validated.

5.6 Conclusion

In this chapter, the EMS algorithm was evaluated by firstly simulating it, then verifying the simulation method and the algorithm's performance. Thereafter, the implementation of the algorithm on the physical system was discussed. The objectives and the performance of the algorithm were validated after obtaining results from the implementation. There were some hardware challenges with the physical microgrid, which affected the results obtained from the trial run. However, with the issues kept in mind, the functionality of the algorithm could still be analysed and it was deemed to have performed exactly as expected under the circumstances.

Chapter 6

AI-based EMS

6.1 Introduction

In this chapter, the two artificial intelligence approaches identified in chapter 3, are developed, tested and discussed. Firstly a fuzzy logic controller is developed, then an ANN load forecasting model is developed. The results are discussed at the end of the chapter.

6.2 Fuzzy logic controller

From literature, the fuzzy logic approach was identified as a promising method with which to develop an EMS for a microgrid. Fuzzy logic is a superset of Boolean logic. The difference with Boolean logic being that the system can consider values between 0 and 1, thus values that are not completely true or completely false. Fuzzy systems allow subjective human knowledge to be translated to a mathematical framework. A fuzzy logic controller can be regarded as a non-linear static function that generates outputs based on inputs that are processed by a rule base [37]. The rules of a fuzzy logic system are linguistic if-then statements. For example: If the TOU period is peak

and the ESS is not empty, then discharge the ESS.

The conditions of the rules depend upon membership functions defined for each input. The membership function describes the degree to which something belongs to a fuzzy set. Fuzzy sets describe vague concepts, therefore membership functions are required. For example, Friday can be considered as a weekend day, but not completely a weekend day, nor completely a weekday. The degree to which an object belongs to a fuzzy set is described by a membership value between 0 and 1. For example Friday is a weekend day to the degree of 0.7, or whatever the operator of the system deems sufficient. A membership function associated to a fuzzy set, maps an input value to its appropriate membership value. Thus, it is a curve that defines how each point in the input space is mapped to a degree of membership between 0 and 1.

The knowledge gained on the system and the objectives pointed out in chapter 4, can be used to define membership functions for each input and output, as well as define linguistic rules that ensure that the objectives are met.

6.2.1 Fuzzy logic controller development

Once again MATLAB will be employed to develop the desired controller. In this case the Fuzzy Logic Designer application will be used to develop the fuzzy inference system (FIS). The designer allows the user to graphically define inputs and outputs and assign membership functions. The linguistic rules can then be defined, after which the rule-viewer can be used to verify the functionality of the FIS. Once the FIS has been deemed sufficient, it can be substituted into the simulation framework that was developed in chapter 5. The truth table logic controller can simply be removed and replaced with the fuzzy logic controller. There is no need to adjust the inputs, as the inputs already simulate the data that the actual EMS would receive from the microgrid. Once the fuzzy logic controller has been verified through simulation, it can be converted to PLC-code and deployed onto the microgrid controller. The functions that preprocess the data shall thus also remain in the simulation. These functions drastically

reduce the complexity of the controller. They are however converted to PLC-code together with the truth table or fuzzy logic controller, as they form part of the overall EMS algorithm.

Membership functions

The inputs of the system were determined in chapter 5 as the TOU period, the power measured at the PCC, the SOC of the ESS and whether or not the current day is a workday. For the fuzzy logic controller, the range of each input and its membership functions have to be defined.

TOU

The TOU periods are divided into three categories namely, peak, standard and off-peak. Each category is assigned a distinct value by the TOU function as explained in chapter 4.5.4. Thus, the range of the TOU input shall be between 1 and 3 with three membership functions corresponding to each period. Figure 27 is an extract from Fuzzy Logic Designer, which displays the membership functions defined for the TOU period.

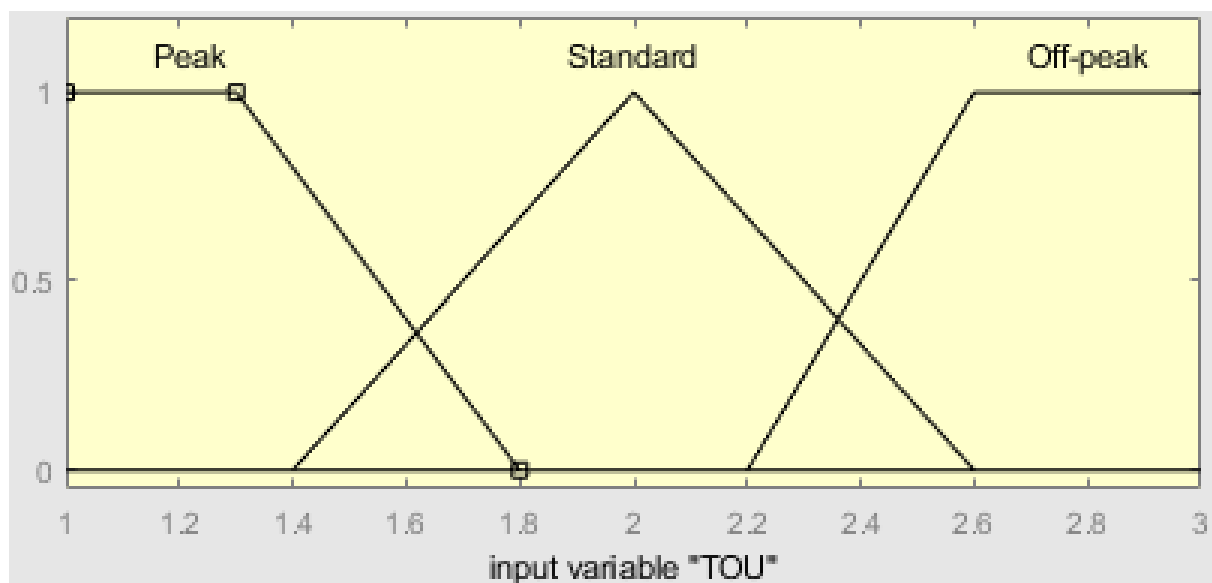


Figure 27: TOU periods membership functions

The TOU input will have distinct inputs, either 1, 2 or 3. There will be no decimals involved. Thus the degree of membership for any input shall be 1. for example if the input is 2 on the x-axis, the degree of membership will be 1 on the y-axis.

PCC

The power measured at the PCC is only relevant during standard TOU periods. When charging, the power drawn from the utility should not exceed 200 kW. To this end, two membership functions have been defined for this input. The first membership function is when the power measured at the PCC is relatively low, i.e. below 160 kW, in this case the ESS should discharge at a constant rate. This membership function can be trapezoidal, as a constant degree of membership is desired. The second membership function should be triangular, so that the degree of membership increases as the input decreases. This is to charge the difference between the 200 kW target and the current load. A third membership function, "High", has been defined for future use. Figure 28 displays the membership functions defined for the PCC input in Fuzzy Logic Designer.

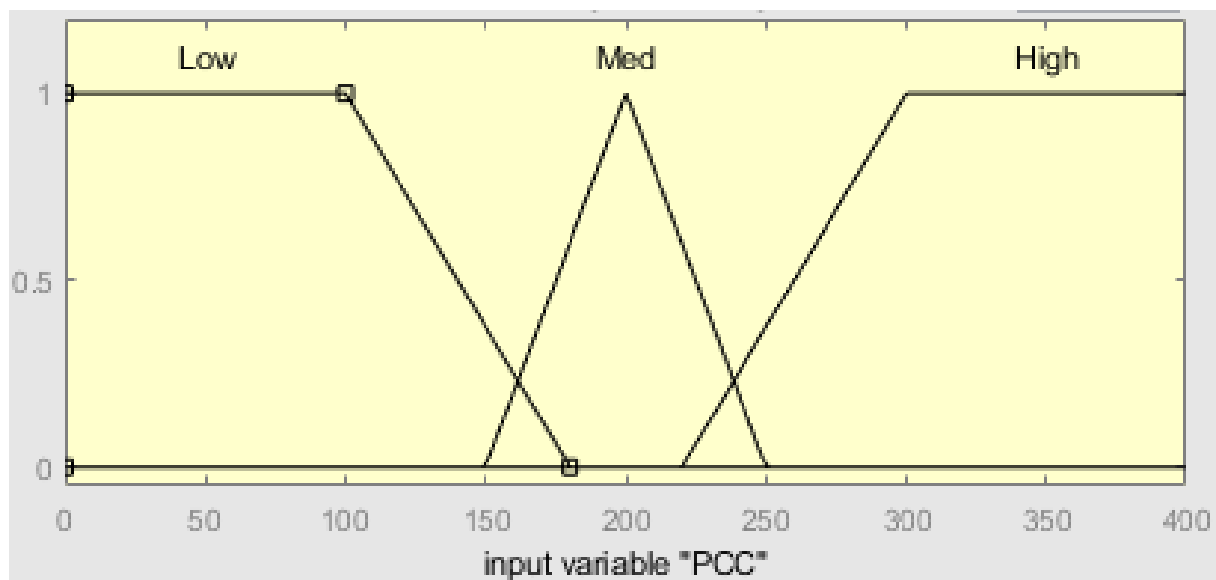


Figure 28: Power measured at PCC membership functions

SOC

The SOC input has three important zones. Two of which is the upper and lower limits at 90% and 15%. The other limit is the charge limit at 55% during standard TOU times.

Therefore three membership functions were defined. Empty, Medium and Full. They are trapezoidal membership functions, as a uniform degree of membership is desired in order to maintain constant charging or discharging levels at all times. In the future this might be adjusted to allow for slower charging when the ESS is near full capacity. Figure 29 displays the membership functions that were graphically defined.

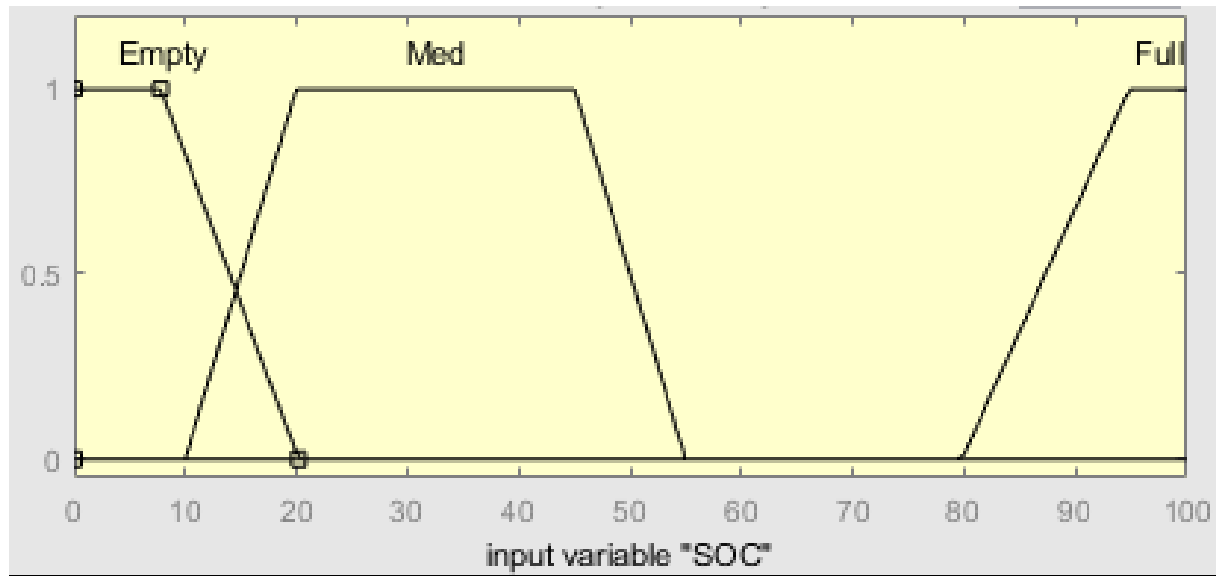


Figure 29: SOC membership functions

Workday

The workday input has two distinct inputs, namely 0 or 1. There are no possible values in-between. Thus, as can be seen in figure 30, only two membership functions were declared namely workday (W) and not a workday (NW).

ESS output

The FIS only has one output, namely the ESS power output. This output has a range of 40 to -30. Where a negative value indicates charging. The objective of the system is to discharge at a constant rate of 40 kW during time periods when discharging is desirable. For charging, constant rates have also been identified. During off-peak hours charging should be at 30 kW, except for weekends and public holidays where it should be 20 kW. During standard times charging should be at 30 kW, if the load is below 170 kW. If the load is above 170 kW, the difference between 200 kW and 170 kW should

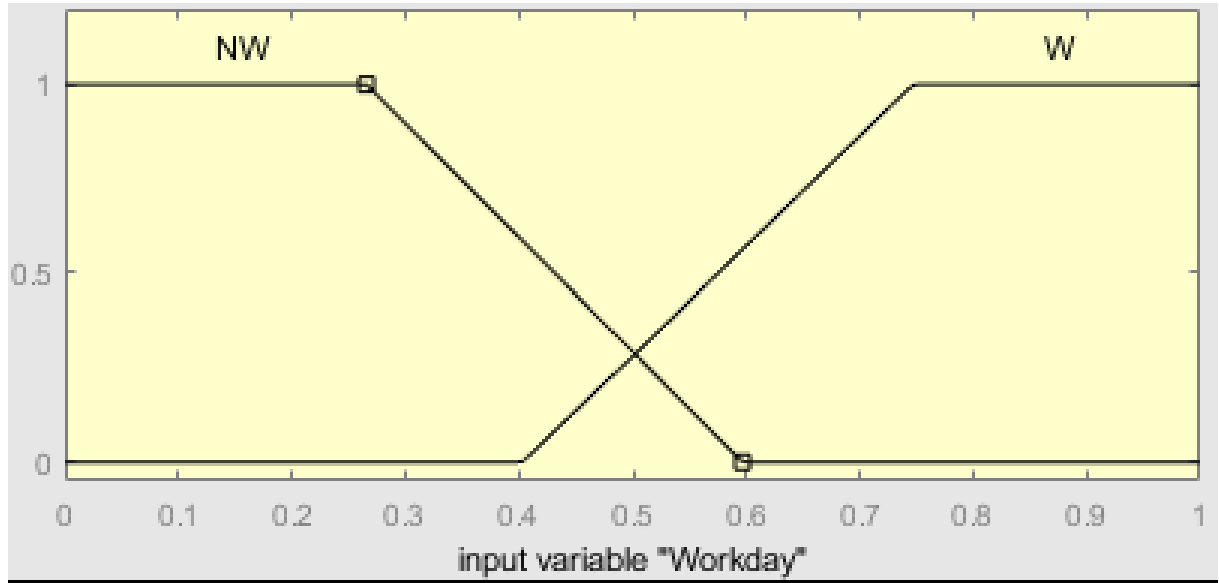


Figure 30: Workday membership functions

be charged. Consequently, three membership functions were defined, namely charge, slow charge (SC) and discharge. Figure 31 shows the membership functions that were defined. The range was defined as 40 to -40, even though the maximum charge would be -30. This is to ensure that if no rules are applicable to the current input conditions, the output would automatically be set to the mean value in the range, which is 0. This eliminates the need to define various rules to ensure that the ESS goes into idle mode. With this approach only the necessary rules need to be defined, for any other conditions the output would be 0.

Rules

A set of linguistic rules need to be defined in order to allow the FIS to make decisions according to desired outcomes. The rules for a fuzzy logic controller are defined by creating a set of if-then statements. The rules defined for this controller are displayed in table 10. The first rule would allow the ESS to discharge during peak TOU times only if the ESS still has energy left. The second rule states that the ESS would charge during off-peak hours as long as the ESS is not full and it is a workday. If it is not a workday, rule 3 dictates that the ESS should charge at a reduced rate (SC). This is for weekends.

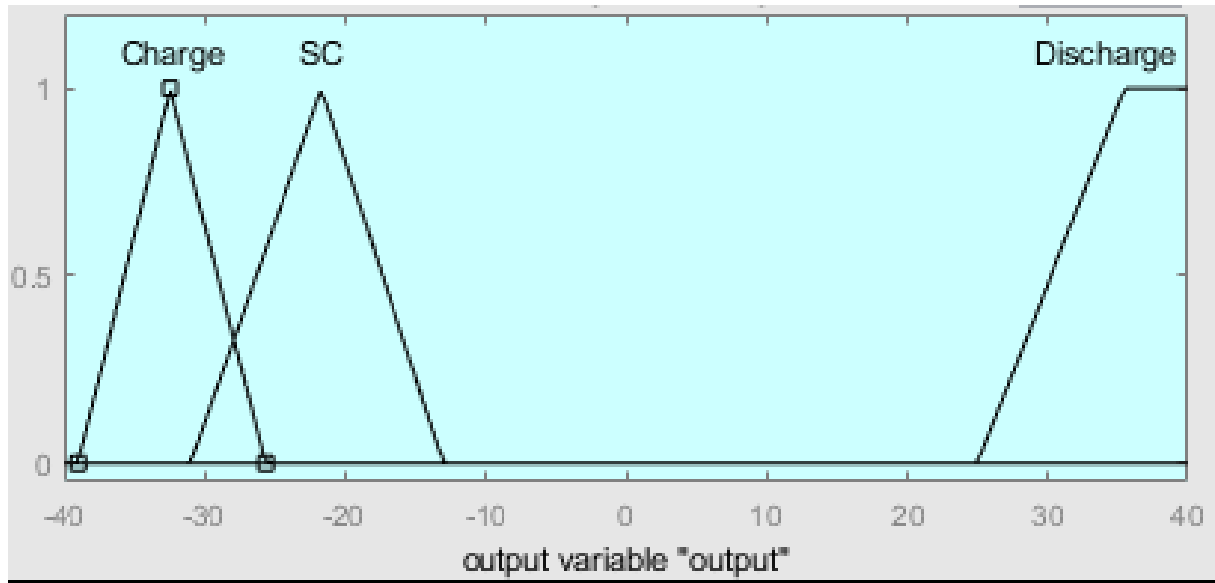


Figure 31: Output membership functions

The fourth rule would charge the ESS if the PCC is at medium range, and the SOC has not surpassed the 55% limit, but at a reduced rate (SC). The fifth rule would charge the ESS at a constant rate if the PCC is low and the SOC has not surpassed the 55% mark.

IF TOU is:	AND PCC is:	AND SOC is:	AND Workday is:	THEN Output is:
1. Peak	-	NOT empty	W	Discharge
2. Off-peak	-	NOT full	W	Charge
3. Off-peak	-	NOT full	NW	SC
4. Standard	Med	Med	W	SC
5. Standard	Low	Med	W	Charge

Table 10: Fuzzy logic controller rules

It is worth noting that, if it were not for the functions that pre-processes the time data and allocates it to TOU periods, the rules for the fuzzy controller would have been significantly more.

6.2.2 Simulation results

The fuzzy logic controller's performance was validated by substituting the controller into the simulation framework that was developed in chapter 5. Figure 32 displays the connection of the controller to the inputs. It was decided to use the same dataset of July 2017 to test the controller with. This should also serve as a reliable comparison to the truth table logic that was implemented. The simulation output data was collected and visualised with MATLAB.

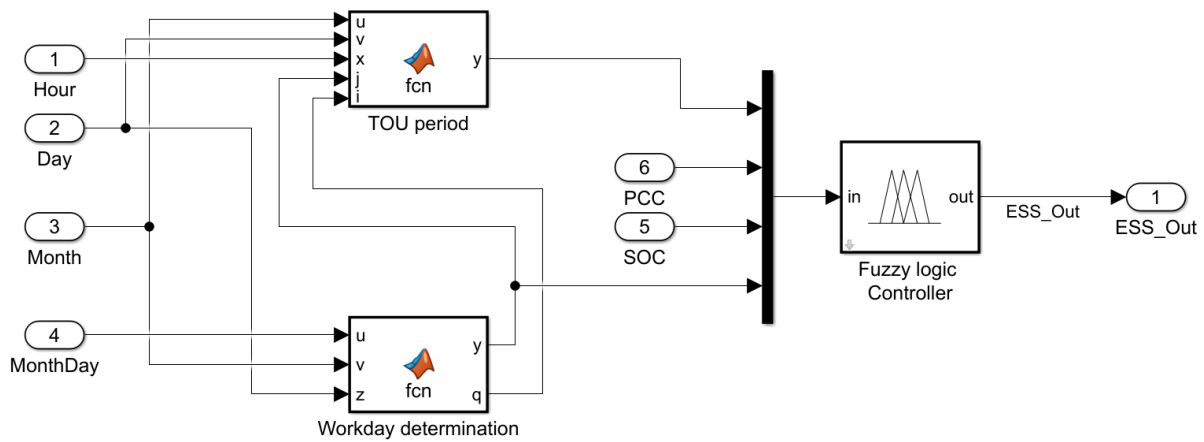


Figure 32: Fuzzy logic controller Simulink implementation

In figure 33, the simulation output can be seen for July 2017. If this figure is compared with the truth table simulation output in figure 19, it can be seen that the profiles look very similar. A closer look at the data should provide some insights into whether the fuzzy logic controller does in fact meet all of the objectives.

In the verification section of chapter 5, the days of 18 and 19 July were inspected in order to verify the effectiveness of the truth table logic. The same days will be used to verify the effectiveness of the fuzzy logic controller. Figures 34 and 35 display the simulation outputs for these two days. It can be seen that the fuzzy logic controller's output for 18 July is exactly the same as that of the truth table controller's output in figure 20.

By comparing the fuzzy logic controller's output for 19 July in figure 35 with that of the truth table controller's output in figure 21, it can be seen that the output is almost

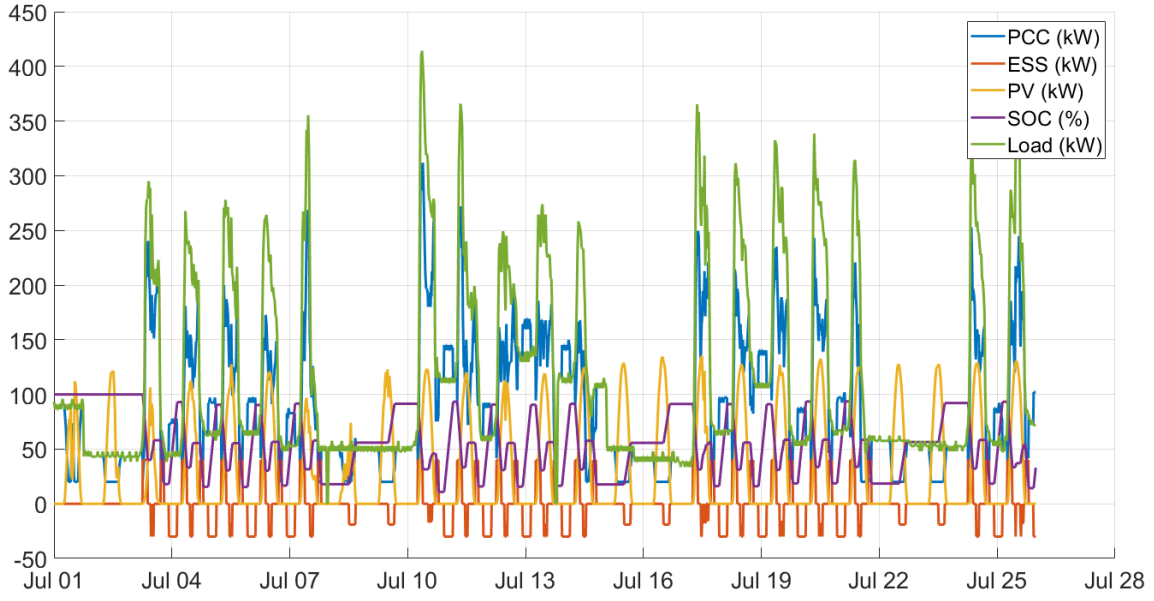


Figure 33: Fuzzy logic controller simulation output July 2017

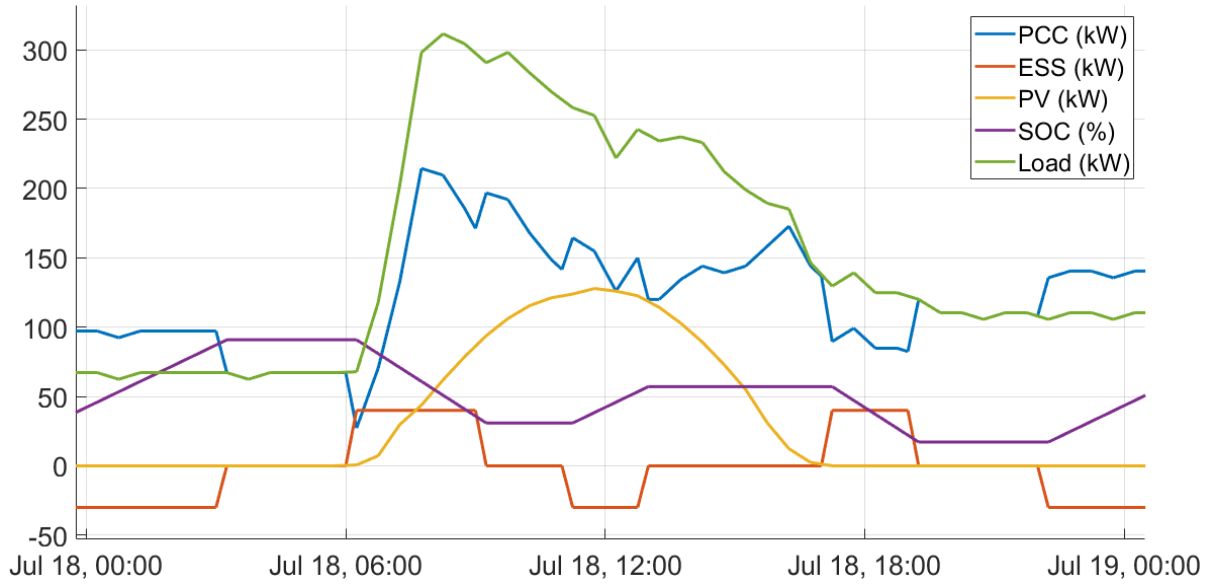


Figure 34: Fuzzy logic controller simulation output 18 July 2017

exactly the same. A slight difference in the charging rate at 12:00 can be noticed. This is only due to the non-exact output of the FIS. The effect on the PCC is still well within the desired range.

The same process was followed to verify the fuzzy logic controller's output over weekends. It was found that the controller performed exactly as expected under all conditions with charging rates closely correlating with that of the truth table controller.

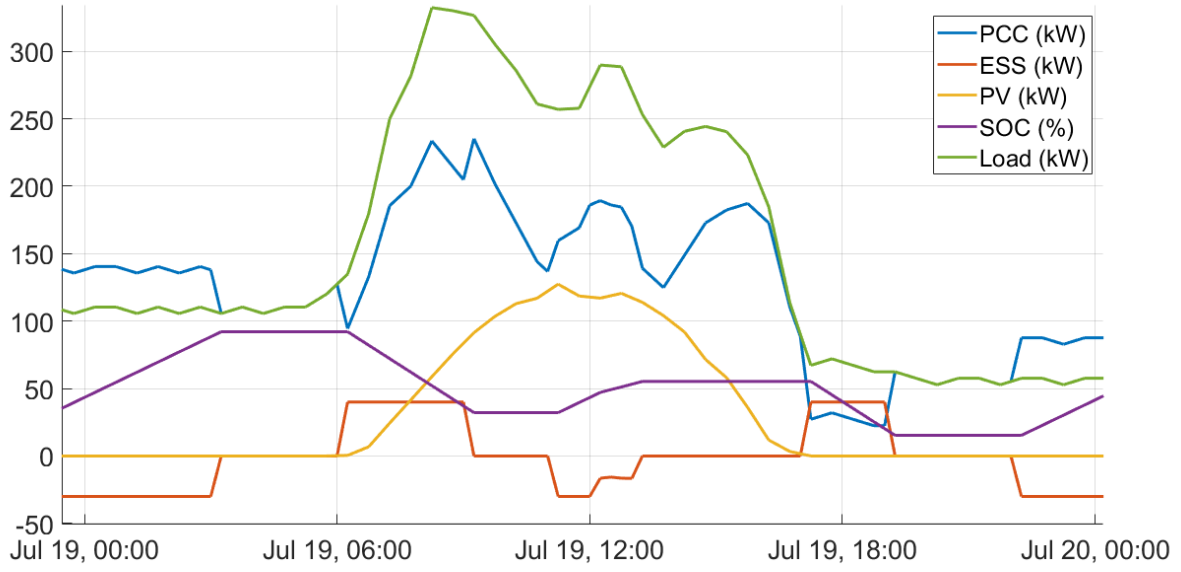


Figure 35: Fuzzy logic controller simulation output for 19 July 2017

6.3 Artificial neural network forecasting

ANN short term load forecasting (STLF) was identified in chapter 3 as a promising method with which to add value to a microgrid EMS. In this section an ANN load forecasting model will be developed and evaluated.

6.3.1 Overview of ANN methodology

The traditional ANN is a computational model of the human brain that can do pattern recognition, data fitting and machine learning. A neural network is trained by providing it with a set of training data as inputs and a target output. The properties that need to be defined before training a neural network include: (i) training method, (ii) stop criteria to prevent over-fitting and (iii) complexity, i.e. number of inputs, hidden layers and neurons in each layer. Training refers to tuning parameters until the prediction is as accurate as possible by evaluating some cost function. In this case the mean squared error (MSE) function is used. Equation (16) gives the MSE function.

$$MSE = \frac{1}{N} \sum_{s=1}^N e_s^2, \quad e_s = y_{t,s} - f_{MLP}(X_s, \theta), \quad (16)$$

where N is the number of input-target measurement pairs, e is the neural network model error, $(X_s, y_{t,s})$ is the s -th input-target pair, f_{MLP} is a mathematical function that describes the neural network and θ is a vector of neural network parameters.

To prevent over-fitting the training data is divided into training, validation and testing data. When there is no improvement of the cost function occurring on the validation data set, the training is stopped and the best performing parameters are used.

Once again MATLAB will be employed to develop, train, test and validate the ANN. A gradient-based Levenberg-Marquardt algorithm will be used.

6.3.2 ANN properties, data preparation and input variable selection

During the design of a neural network, the amount of hidden layers and neurons per layer has to be selected. A small number of neurons might not produce good results, while a large number of neurons and hidden layers might be too complex and demanding for the algorithm. Literature shows that for STLF purposes, one hidden layer with 20 neurons is sufficiently accurate [55], [56], [57].

Load data from the facility is available in 30-minute energy samples from as far back as 2015. However, the load has changed significantly from 2016 to 2017 due to operational changes. Thus, load data from January 2017 to July 2017 shall be used to train the ANN. Literature indicates weather data, specifically temperature data, can be a good indicator of load fluctuations. Historical weather data was acquired for the facility from Weather Underground by requesting the data for a specific day from their servers via their API. A MATLAB script was developed to sequentially poll the API for every day in 2017. The data was then stored with timestamps in an Excel spreadsheet. The data from Weather Underground was then interpolated assuming linear change between samples in order to convert the weather data to the same amount of

samples as the load data.

The time of day is also indicated in literature as a good predictor of load demand. Thus, MATLAB was employed to divide each time sample into the day of the week (value between 1 and 7) and the hour of the day (value between 0 and 24). A MATLAB script was also developed to determine whether or not each day is a workday, similar to the function discussed in chapter 4.5.4. This algorithm checks whether a day is a normal weekday, a weekend day or a public holiday and assigns a binary workday value to each time-stamp. An additional consideration is that the facility ran night-shifts or overtime on weekends, which increased the load above normal levels during evenings or over weekends. Through inspection over-time was identified and the specific day was assigned a binary value to determine whether or not there is overtime for that day.

Additionally, from literature, historical data at specific times are indicated as good predictors of future load. Thus, it was decided to add as inputs, the load from the previous week and the previous 24 hours at the same time-step and the load from the previous sample as inputs. Therefore, the inputs that were selected to train the ANN are: (i) the day of the week, (ii) the hour of the day, (iii) workday, (iv) over-time, (v) temperature, (vi) previous week's load, (vii) previous 24 hours load, (viii) previous sample's load. These eight inputs will be used to train the neural network which will have the actual load at the specific time-step as the target output.

The ANN will thus attempt to predict the load 30-minutes in advance.

The topology of the proposed neural network can be seen in figure 36, where it has eight inputs, one hidden layer with 20 neurons and one output layer. The standard approach of using 70% of the data for training, 15% of the data for testing and 15% for validation was used.

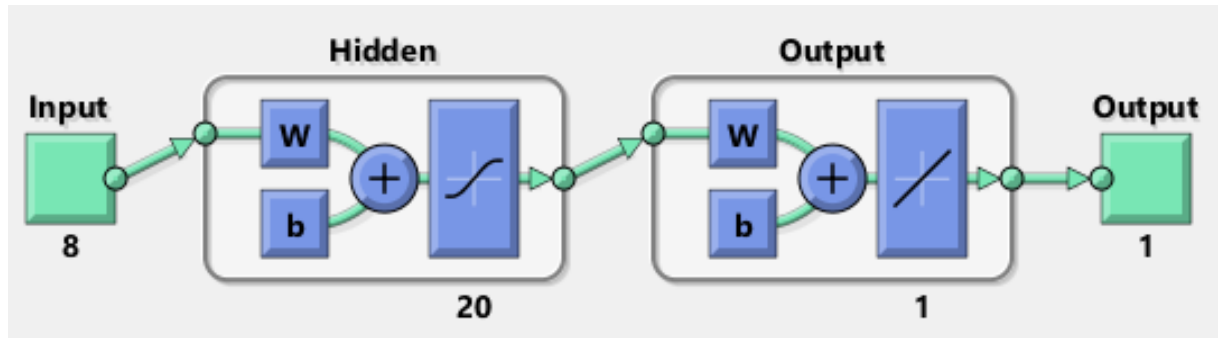


Figure 36: ANN topology

6.3.3 STLF results

The proposed ANN was implemented with the Neural Fitting Tool application in MATLAB. In figure 37, a week's data is visualised. It can be seen that the difference between the actual load and the predicted load is fairly small.

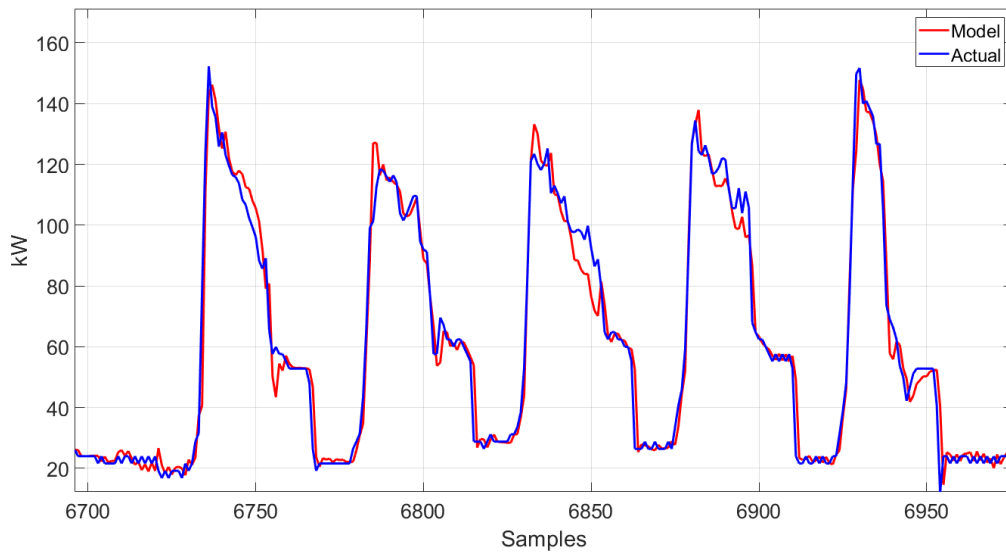


Figure 37: ANN prediction results for a week

A closer look at an arbitrary day is given in figure 38, which serves as a good example of the possible accuracy of the ANN developed in MATLAB.

The error in the prediction can be inspected more closely by looking at the error histogram in figure 39. The x-axis represents the error range by calculating the difference between the actual load and the predicted load. The y-axis presents the amount of in-

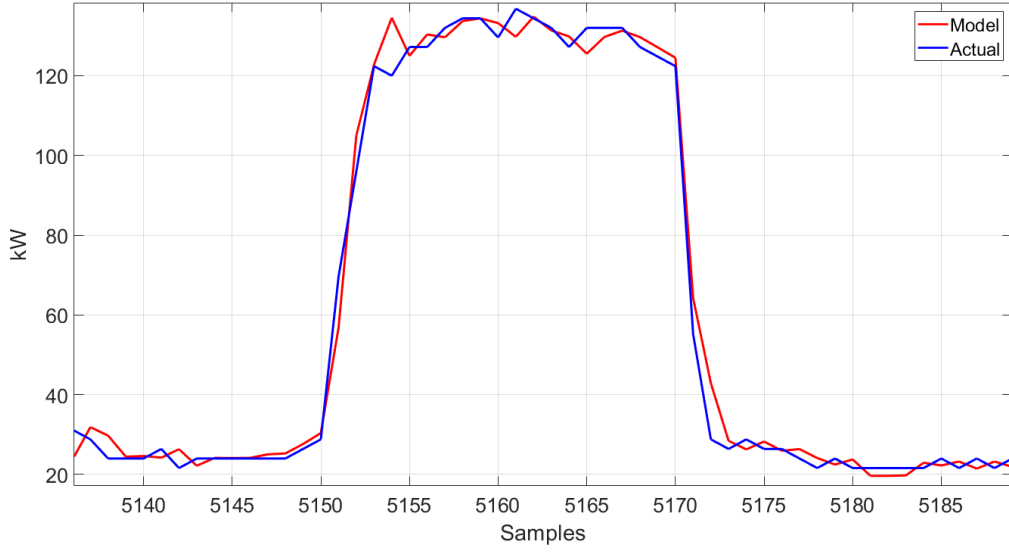


Figure 38: ANN prediction results for an exemplary day

stances of errors occurring in the specific error range. It can be seen in figure 39 that the typical prediction error is around - 2.7 kW and 2.9 kW.

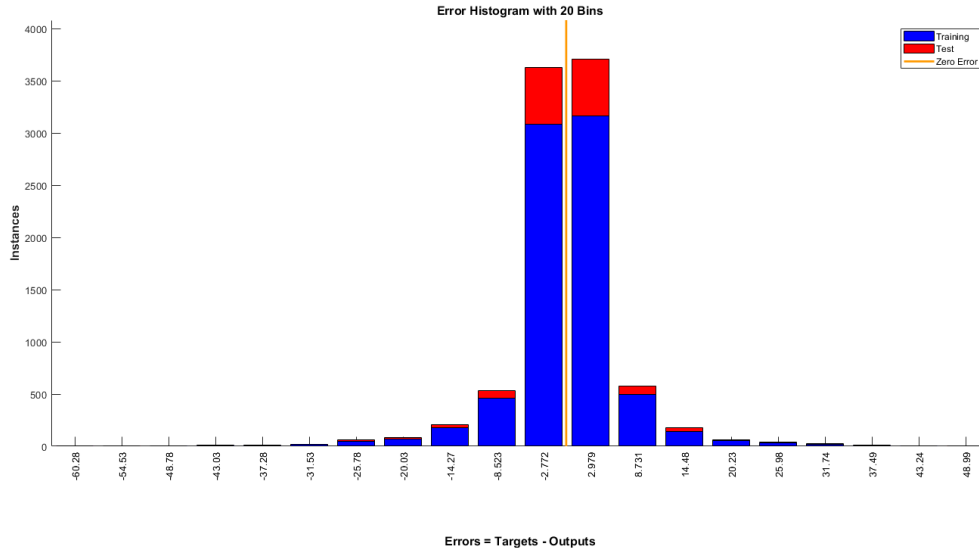


Figure 39: ANN prediction error histogram

An additional performance measure commonly used in literature is the mean absolute percentage error (MAPE) [55]. The MAPE is calculated by using equation 17, where A_t is the actual value and F_t is the forecast value. The difference between A_t and F_t is divided by the actual value A_t again. The absolute value in this calculation is

summed for every forecast point in time and divided by the number of fitted points n . Multiplying by 100 makes it a percentage error.

$$M = \frac{1}{n} \sum_{t=1}^n \left| \frac{A_t - F_t}{A_t} \right| \times 100 \quad (17)$$

Implementing equation (17) the MAPE of the developed ANN was calculated to be 7.9%. Having too many inputs can negatively affect the accuracy of the ANN. By iteratively removing certain inputs and re-training the ANN, it can be determined if certain inputs are not good predictors and possibly only generating noise. The MAPE will be used as performance measure. The following operations were done to determine the effect of certain inputs on the prediction accuracy.

Remove temperature input

MAPE stays the same, thus temperature is not a good predictor of this facility's load.

Remove over-time input

Increased MAPE to 8.28%. Thus, not a very good predictor, but adds some value. This is probably due to the low amount of times in the 7 month period that actually had over-time or night-shifts.

Remove workday input

Increased MAPE to 8.48%. Thus, not a very good predictor, but adds some value. This is probably due to the day input providing enough information to predict the load on weekends. Public holidays are also a small occurrence in the data, which results in relatively small changes in prediction accuracy.

Remove temperature, workday and over-time as inputs

Increased MAPE to 8.38%.

It can thus be concluded that temperature can be excluded from the ANN, as it is not

a good predictor. Workday and over-time can be included, as they add some value, however not much. Excluding temperature will make the model simpler and allow it to converge faster.

6.4 Conclusion

Fuzzy logic controller

After analysing the results from the simulation of the fuzzy logic controller developed in this chapter, it can be concluded that the fuzzy logic approach is highly effective. It satisfies the pre-set goals. The development of a fuzzy logic controller is fairly simple due to the linguistic nature of rule declaration, especially if detailed knowledge of the plant and desired outputs are available. Furthermore, the development of the fuzzy logic controller was comparatively faster than the development of the truth table logic in chapter 4. The results of the fuzzy logic controller is also exactly on par with that of the truth table. It can thus be concluded that a fuzzy logic controller is a very effective tool with which to develop control logic algorithms for a microgrid EMS.

ANN STLF

The ANN that was developed is fairly accurate. However, in literature, many load prediction studies are based on large residential microgrids in the range of megawatts. With these microgrids, the MAPE is often times lower than 2% [58], with some studies reporting accuracy lower than 1% [59]. It is worth noting that these studies usually have multiple years of data available for training. The MAPE for the ANN developed in section 6.3, which is around 8%, correlates well with studies of smaller microgrids. For example in [53], the MAPE is around 13%. The accuracy of the prediction depends on various factors. A small microgrid may have a higher level of uncertainty due to small differences in human behaviour potentially causing large changes in the load at unpredictable times. Furthermore, in literature, STLF is primarily used for peak demand management, which, in chapter 4, has been excluded as an objective for the

facility in this study. Thus, implementing ANN STLF on the current microgrid will not add any value. However, if the ESS is expanded in the future and load data over a longer period is available, this might be an option with which to add value to the microgrid's EMS.

Chapter 7

Variable microgrid DER sizing

7.1 Introduction

The simulation method developed in chapter 5, can also be used to assess the effect that different DER sizes can have on the power drawn from the utility. With this data, the savings due to the changes can be approximated fairly accurately. Changes to the size of the PV array as well as to the ESS are simulated and investigated in this chapter. In order to simulate the operation of the ESS under these conditions, the fuzzy logic controller developed in chapter 6 will be adapted to achieve new objectives that are influenced by DER size changes.

7.2 Cost savings calculations

The method used to calculate the savings has to be verified by calculating the utility bill from the load profile generated by the simulation and then comparing the calculations with that of the actual bill. Once this method is verified, it can be applied to the data simulation results. Data from June 2017 will be used for verification purposes.

A similar script in MATLAB was developed to divide each sample into the correspond-

ing TOU period in order to assign a tariff with which to multiply the energy sample with. The utility provides reactive energy usage data as well, so an estimate of the maximum demand charge can also be made. The extract in figure 40, is the utility bill for June 2017, which will serve as the benchmark with which to compare savings. This bill includes the effect of the 200 kW PV array.

Tariff	Description	Units	Rate	Amount
ELECTRICITY - Primary Supply				
Peak (HS)	Total 12,876,185.040 kWh	15364.8 kWh	R 4.9545	R 76,124.90
Standard (HS)	Total 12,876,185.040 kWh	29577.6 kWh	R 1.4150	R 41,852.30
Off-peak (HS)	Total 12,876,185.040 kWh	18004.8 kWh	R 0.8342	R 15,019.60
Max Demand (HS)	0.913 pf 2017-06-28 08:30:00	294.37 kVA	R 64.44	R 18,969.17
Network Access		567.639 kVA	R 39.60	R 22,478.50
Fixed Charge		1 month	R 2483.39	R 2,483.39
Total consumption: 62,947 kWh			Utility Total	R 176,927.88

Figure 40: Utility bill for June 2017

The load data was processed and found to be closely related to the bill. The processed data produced 14 239 kWh peak-TOU energy usage, 29 270 kWh standard-TOU energy usage and 16 629 kWh off-peak-TOU energy usage. Comparing this with the bill's 15 365 kWh, 29 578 kWh and 18005 kWh respectively, it is noted that the standard-TOU energy usage is fairly accurate. However, the off-peak energy and peak energy has an error of 7.6%. In table 11, the simulated calculations are compared with that of the raw data and the actual bill. It can be noted that the values for the peak-TOU energy that was calculated from the raw data and the simulated data are exactly the same. This points to a measurement difference between the utility's billing and actual meter. The standard energy and off-peak energy calculated from the raw data, correlates closely with the bill. The difference in the simulated values can be attributed to the method used for calculating the PV energy as outlined in chapter 5. The calculation method therefore produces a small error.

TOU period	Bill	Raw data	Simulated data
Peak	15 365	14 239	14 239
Standard	29 578	30 648	29 270
Off-peak	18 005	18 041	16 629

Table 11: Comparison of energy usage calculations (kWh)

The 7.6% error will be taken into account when considering energy related cost-saving projections.

The raw data from the utility also provides the amount of reactive energy used per 30-minute sample. It can be attempted to estimate the maximum power demand in kVA from this data. However, the maximum power demand is charged at any moment that the instantaneous power drawn exceeds the previous maximum for the month. Thus, without high resolution power samples, the actual spikes in power demand might be lost within the 30-minute energy samples. That said, a decent idea can be gained of the typical power drawn. The energy samples will be converted to power samples and then (18) will be used to calculate the apparent power.

$$S_{kVA} = \sqrt{Q_{kVAR}^2 + P_{kW}^2} \quad (18)$$

Firstly, the calculation from the raw data will be compared with the value indicated in figure 40 as 294.37 kVA. This method has produced a very accurate result of 294.37 kVA. Secondly, the calculation from the simulated data will be compared. The maximum apparent power demand calculated from the simulated data is exactly the same as that calculated from the raw data. Thus, this method should provide an accurate estimate of the possible savings to be made on maximum demand charges.

Savings already achieved

By using the cost savings calculation method developed, it is possible to use the simulation to calculate what the actual load is and quantify the savings due to the PV installation. The energy that would have been consumed from the utility, if there were no PV installed in June 2017 would be:

Peak-TOU: 15 619 kWh Standard-TOU: 44 834 kWh Off-peak-TOU: 19 334 kWh

The projected maximum demand without the PV array was calculated to be 367.98 kVA.

These values can be compared with that of the utility bill in figure 40 to calculate the approximate savings for June 2017.

Table 12 outlines the savings made. The final column indicates the savings made in South African Rand by calculating the difference between the value indicated on the utility bill and the simulated values for the actual load and then multiplying the difference with the tariffs for 2017.

Tariff type	Bill	Load	Savings (ZAR)
Peak-TOU energy (kWh)	15 365	15 619	R 1 258.44
Standard-TOU energy (kWh)	29 578	44 834	R 2 1587.24
Off-peak-TOU energy (kWh)	18 005	19 334	R 1 108.65
Maximum demand (kVA)	294.37	367.98	R 4 743.43
Total			R 28 697.76

Table 12: June 2017 cost savings due to PV

Table 12 shows that the bulk of the savings due to the PV is during standard-TOU periods. This is typically when the sun is shining during the day. This table also further illustrates the value that an ESS can provide by reducing energy usage during peak-TOU periods. Additionally, the PV should reduce the network access charge over time, due to this charge being dependant on a 12-month average maximum demand. It can be seen by looking at the utility bill for May 2018 in figure 41, where the network access charge has dropped to 378.105 kVA, compared to the 567.639 kVA billed for June 2017 in figure 40. This adds to the savings incurred due to the PV over time.

Tariff	Description	Units	Rate	Amount
ELECTRICITY - Primary Supply				
Peak (LS)	Total 13,517,875.440 kWh	16917.6 kWh	R 1.5352	R 25,971.90
Standard (LS)	Total 13,517,875.440 kWh	35820 kWh	R 1.0079	R 36,102.98
Off-peak (LS)	Total 13,517,875.440 kWh	28303.2 kWh	R 0.7563	R 21,405.71
Max Demand (LS)	0.897 pf 2018-05-31 13:00:00	369.226 kVA	R 65.65	R 24,239.67
Network Access		378.105 kVA	R 40.35	R 15,256.54
Fixed Charge		1 month	R 2530.19	R 2,530.19
Total consumption: 81,041 kWh			Utility Total	R 125,506.99

Figure 41: Utility bill for May 2018

7.3 PV sizing

In this section, the size of the PV array will be adjusted in the simulation by multiplying the output of the measured PV data with a certain factor. The effect on the power drawn from the utility can then be assessed and the possible savings can be quantified. The current PV installation has a rated peak power output of 200 kW. No ESS functionality will be simulated in this section.

Figure 42 shows the power drawn from the utility at the PCC as well as the power produced by the PV array for June 2017. This data will be used to compare the simulation results. In figure 43, an exemplary day of 8 June 2017 was selected, which will serve as a comparison day for the simulation results.

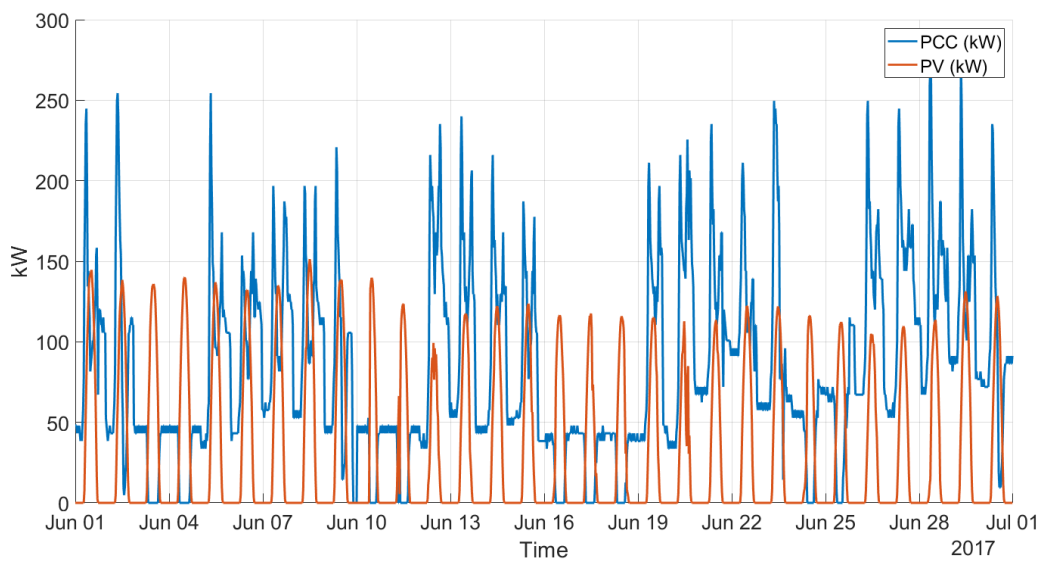


Figure 42: June 2017 actual PV production and utility power draw

As mentioned earlier, PV curtailment is actuated by a PLC controller in order to prevent surplus PV power to be exported to the utility grid. The current PV curtailment set-point is at 20 kW. This means that the PV will be curtailed to keep the base power draw from the utility at 20 kW. This curtailment set-point will be set at 0 to simulate an ideal maximum saving. The curtailment was only introduced in 2018. Therefore, in data from 2017, the power drawn from the PCC would typically go down to 0 if there is enough PV power.

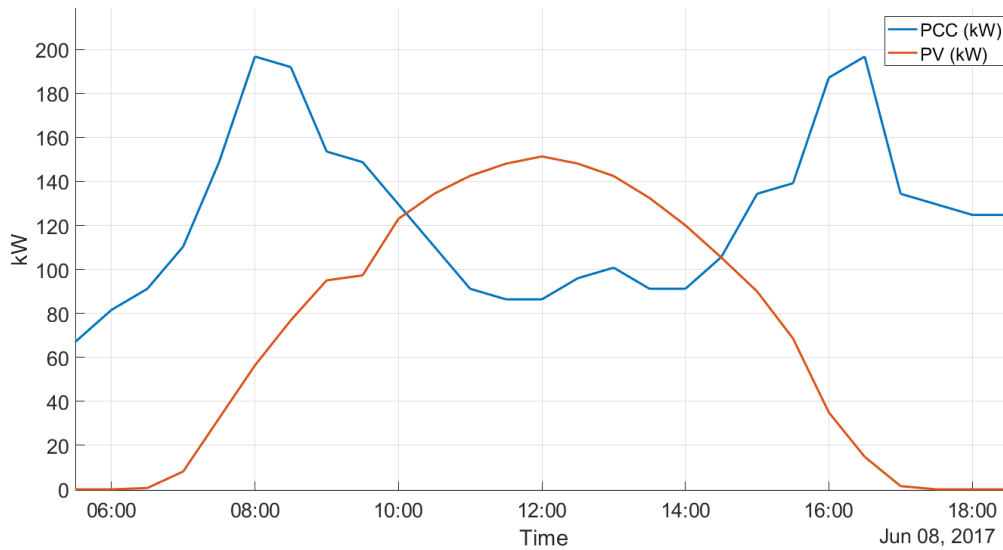


Figure 43: 8 June 2017 actual PV production and utility power draw

Addition of 100 kWp PV

The addition of 100 kW of PV will be simulated by multiplying the PV data with a factor of 1.5 in Simulink, bringing the total installed peak power capacity to 300 kW.

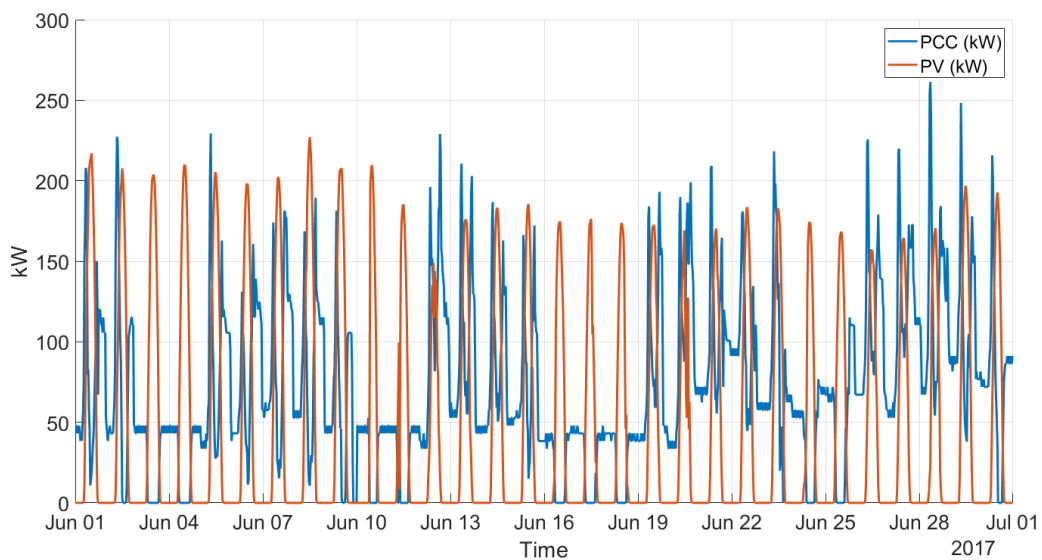


Figure 44: June 2017 simulated PV production and utility power draw due to 100 kWp increase in PV power

Figure 44 shows the overall effect of the increase for June 2017. It can be seen that there is an increase in PV production and a decrease in the overall power drawn from the

utility. However, it can be seen that on 28 June, there is still a considerable spike in power demand. This is probably due to cloud cover on that day.

The effect of the increase of PV power on the utility power draw for 8 June can be seen in figure 45. In comparison to figure 43, it can be seen that the peaks during the morning and afternoon have been reduced slightly, but that there is a big decrease in utility power drawn during the middle of the day. However, there is no surplus PV power.

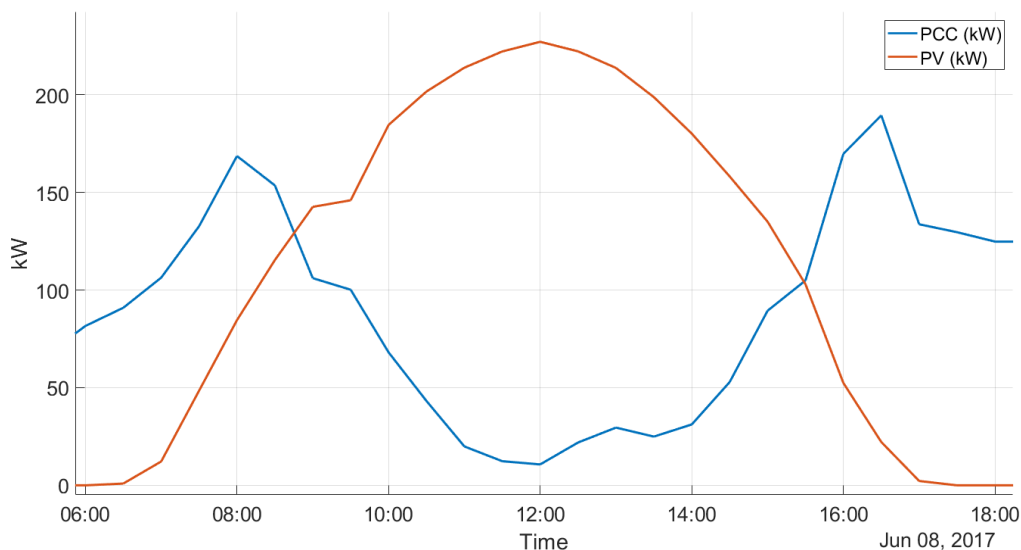


Figure 45: 8 June 2017 simulated PV production and utility power draw due to 100 kWp increase in PV power

In order to quantify the savings, the simulated power drawn from the utility will be billed according to the TOU periods. Table 13 outlines the savings made. In the second column the actual bill from the utility, which includes the 200 kWp PV production is compared with the simulated savings due to a 100 kWp increase to 300 kWp.

It can be noted that only a small decrease in energy usage during peak-TOU periods was caused by the PV, however, this translates to a large monetary saving due to the high tariff for peak-TOU periods. The savings during standard hours only increased by about 50%, which is expected. The maximum demand however, was not decreased by much. This is due to the maximum demand probably occurring on a cloudy day, which

Tariff type	200 kWp PV	300 kWp PV	Savings (ZAR)
Peak-TOU energy (kWh)	15 365	13 549	R 8 997.37
Standard-TOU energy (kWh)	29 578	22 127	R 10 543.17
Off-peak-TOU energy (kWh)	18 005	16 421	R 1 321.37
Maximum demand (kVA)	294.37	287.63	R 434.33
Total			R 21 296.24

Table 13: June 2017 cost savings due to 300 kWp PV

rendered the PV ineffective. It is interesting to note that the total savings due to the 100 kWp addition is R 21 296.24, where the savings due to the initial 200 kWp installation was R 28 697.76 from table 12. This large increase in savings due to the addition of only 100 kWp PV production, can mostly be attributed to the large monetary savings due to the slight peak-TOU energy usage decrease.

Addition of 200 kWp PV

The addition of 200 kWp of PV will be simulated by multiplying the PV data with a factor of 2 in Simulink, bringing the total installed peak power capacity to 400 kWp.

For the sake of brevity, only the data for 8 June shall be shown in figure 46. By comparing this figure with the 100 kWp addition in figure 45, it can be seen that the power drawn from the utility during peak-TOU periods has been reduced slightly. It can also be noted that the power drawn from the utility from about 10:00 to 14:30 is zero. This is during standard-TOU periods. This means that there is surplus PV power, which can be used to charge the ESS.

In table 14, the savings due to the 200 kWp addition of PV power is compared with that of the 100 kWp addition. It can be seen that the savings gained due to the 200 kWp is smaller than that from the 100 kWp addition in table 13. This is due to the large peak-TOU savings being reduced due to reduced solar irradiation during those times of the day. Thus, it seems that optimal savings may be achieved by adding only 100

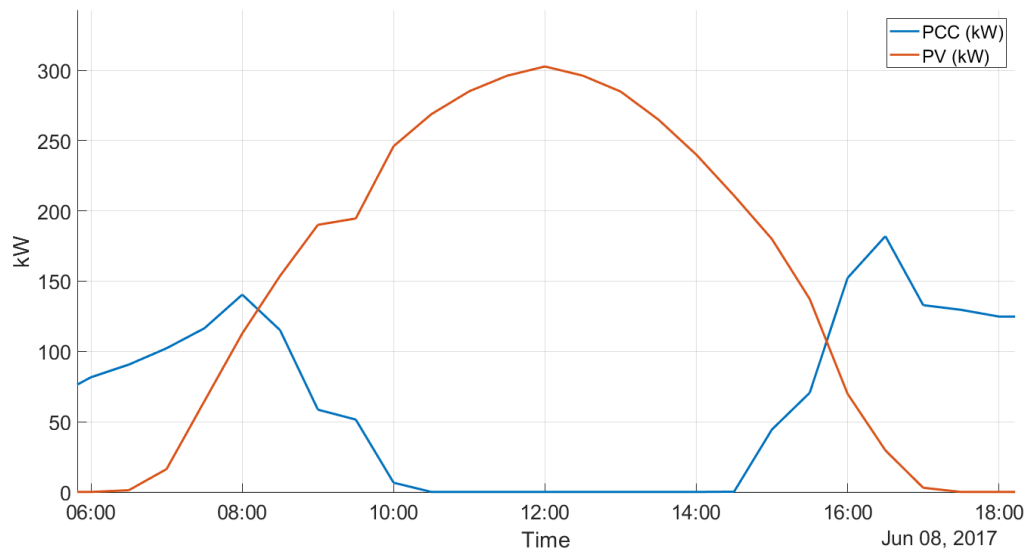


Figure 46: 8 June 2017 simulated PV production and utility power draw due to 200 kWp increase in PV power

kWp of PV to the current system. However, the 200 kWp addition allows for surplus PV power to be available. This can be used to charge the ESS in order to reduce the power drawn from the utility during peak-TOU hours. This will be investigated in the following section.

Tariff type	300 kWp PV	400 kWp PV	Savings (ZAR)
Peak-TOU energy (kWh)	13 549	12 860	R 3 413.65
Standard-TOU energy (kWh)	22 127	16 212	R 8 369.73
Off-peak-TOU energy (kWh)	16 421	16 322	R 82.59
Maximum demand (kVA)	287.63	280.93	R 431.75
Total			R 12 297.72

Table 14: June 2017 cost savings due to 400 kWp PV

7.4 ESS sizing

In this section, the effect of changing the ESS size will be studied. Changing the size of the ESS will also influence the objectives of the EMS algorithm. The fuzzy logic controller developed in chapter 6 will be employed to test the functionality of a larger ESS. This means that the membership functions and rules of the controller would have to be adjusted. The SOC estimator in the simulation would also have to be adjusted in order to provide for the additional capacity.

By referring back to chapter 4, the objectives for the EMS algorithm was identified to mainly be to reduce energy usage during peak-TOU periods. Once the peak-TOU energy drawn from the utility has been reduced to zero, only then would it be worthwhile to consider peak shaving to reduce maximum demand charges. By looking at the utility bill for June 2017 in figure 40, it can be seen that the total energy used during peak-TOU periods was 15364.8 kWh. For the 21 business days of June 2017, this translates to 731.66 kWh per day. This means that the capacity of the ESS should be larger than 750 kWh in order to consider other objectives than reducing peak-TOU energy usage.

800 kWh ESS and standard 200 kWp PV

For this combination, it is safe to say that the objective would be to reduce the energy usage during peak-TOU periods to zero, while charging only in off-peak times. In this ideal situation, the possible gross savings for June 2017 would be R 76 124.9, from the utility bill in figure 40. The energy charged during off-peak times would have to be subtracted from this, resulting in a nett saving of about R 63 000. The maximum demand would also be significantly decreased automatically, due to the maximum demand peaks commonly occurring during peak-TOU periods when solar irradiation is low. In order to approximate the savings due to maximum demand reduction, the 800 kWh ESS can be simulated. This capacity is a fourfold increase of the existing installation. Thus, the range of the output membership function of the fuzzy logic controller will be adjusted by a factor of four. This will bring the maximum discharge

power to 160 kW and the maximum charging power to 120 kW. For this simulation, the SOC limitations will be relaxed in order to simulate a more ideal situation. Thus, the SOC will be operated between 5% and 98%. To this end, the SOC membership functions had to be adjusted as well. The rules were adjusted to remove the charging during standard hours and to remove the slower charging rate over weekends and replace it with the normal charging rate. The following figure shows the simulation for a week in June.

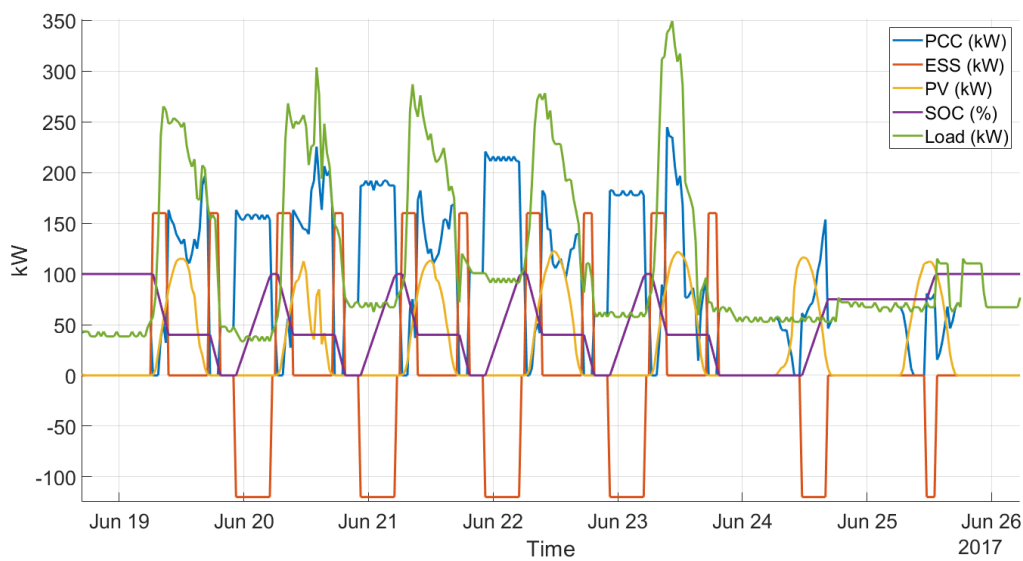


Figure 47: Simulation of a week in June with an ESS capacity of 800 kWh

It can be noted in figure 47 that the high charging rate during the evenings, especially on 22 June, increases the power drawn from the utility significantly. This is however not a threat to possibly increase the maximum demand charge, as maximum demand charges do not take off-peak-TOU periods into account. On the utility bill in figure 40 the maximum demand was stipulated as 294.37 kVA and that the peak occurred at 08:30 on 28 June. The simulation shows that this peak was greatly reduced due to the ESS discharging at a high rate. However, the simulated maximum demand only decreased slightly, to 268 kVA. This instance however, occurred during standard-TOU times, when the ESS was not discharging. In order to reduce that peak, additional PV would have to be installed, or additional energy storage. However, due to the abundance of solar irradiation during standard-TOU times, PV should be the logical

option.

800 kWh ESS and 300 kWp PV

In this section, the combination of an 800 kWh ESS and a 100 kWp addition to the PV array will be simulated in order to analyse the effect on the maximum power demand. In figure 48, it can be noted that the overall peaks of power measured at the PCC has been reduced. However, there are slightly lower peaks prevalent in the early mornings or late afternoons when solar irradiation is lower. Thus, the maximum demand might at times still be quite high.

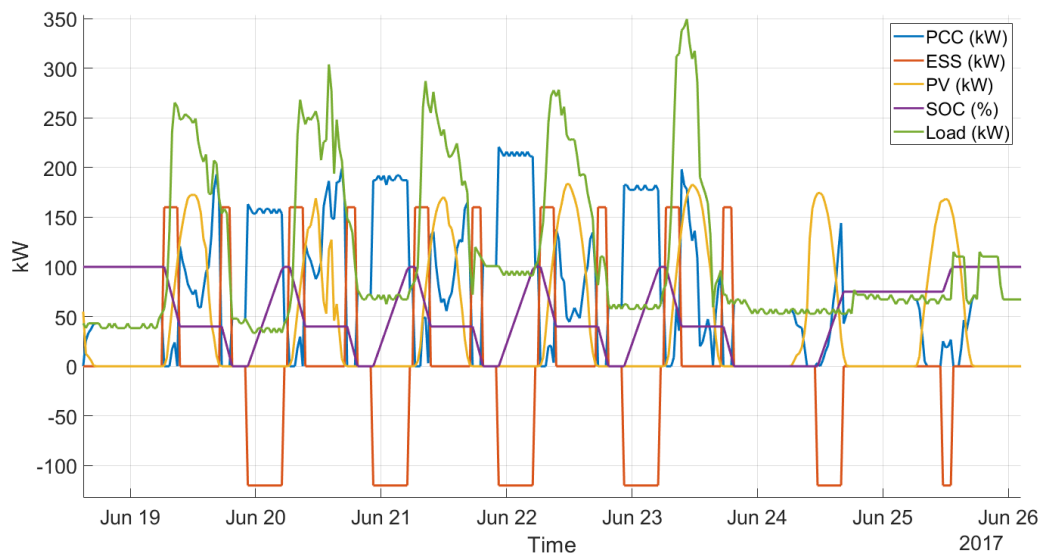


Figure 48: Simulation of a week in June with an ESS capacity of 800 kWh and additional 100 kWp of PV

By analysing the simulation output, it was found that the simulated maximum demand is 263 kVA. That is a reduction of only 5 kVA from that of the 800 kWh ESS alone. This maximum demand peak occurred at 16:00, which means that the solar irradiation was low at that time. The only way to mitigate this is by using the ESS for peak shaving. However, the large capital investment would not be justified by the relatively small savings. The amount of energy required to keep the peaks at a certain level during the entire month, is significant, as was discussed in chapter 4.4.

7.5 Conclusion

In this section several DER size scenarios were investigated. By increasing the ESS capacity, the savings due to energy arbitrage can be greatly increased. However, due to the high costs involved with acquiring additional ESS capacity, it is highly recommended to rather add additional PV capacity to the current system. 100 kWp seems to provide the most savings, however a 200 kWp addition would allow the ESS to charge with surplus PV power during normal business days, slightly increasing the savings. In the next chapter, the effect of having PV power as an input to the system is investigated.

Chapter 8

Ideal system configuration simulation

8.1 Introduction

As mentioned in section 4.5, the microgrid that this study is based on, does not have the ability to use the PV power as input for the energy management algorithm. This means that the EMS algorithm would not know if there is a surplus of PV power. It could assume that there is a surplus due to the power measured at the PCC being lower than the base load, but even then the EMS would not know exactly how much PV power is available. However, a fairly effective workaround for this problem was developed in section 4.5. In this chapter, the fuzzy logic controller will be expanded to accept PV as an input. This would slightly increase the complexity of the fuzzy logic controller and also allow the system to fully utilize any surplus PV power. This would be especially valuable in situations where there is more PV and ESS capacity available, as simulated in the previous chapter. Therefore, this chapter will first assess the performance of the standard system with the PV added as an input to the fuzzy controller and then inspect the performance of a larger system. All of this will be done in the same Simulink environment developed in chapter 5, with the PV size, ESS size and fuzzy membership functions and rules adjusted according to the specific scenario. These simulations will also provide the opportunity to display the functionality and

efficacy of a fuzzy logic controller for these applications.

In this chapter it will be assumed that the PV curtailment will be very accurate and will be able to keep the power drawn from the utility above 5 kW, in order to avoid back-feeding into the grid. It will also be assumed that the full capacity of the ESS will be usable. The fuzzy logic controller would still have to keep the SOC within acceptable ranges.

8.2 Standard sizing

In this section, the standard sizing of the physical microgrid will be used in the simulation. The only difference being that the PV power will be available as an input to the fuzzy logic controller. This means that membership functions for the PV input have to be defined. Figure 49 indicates these membership functions. Three membership functions were defined, namely Low, Medium and High. Although the PV array has a rated peak power output of 200 kW, the data retrieved shows that the array rarely produces that much power. Due to the static mounting of the PV panels, the array rarely produces more than 140 kW in the winter. Therefore, the "High" membership function reaches its maximum amplitude at around 130 kW.

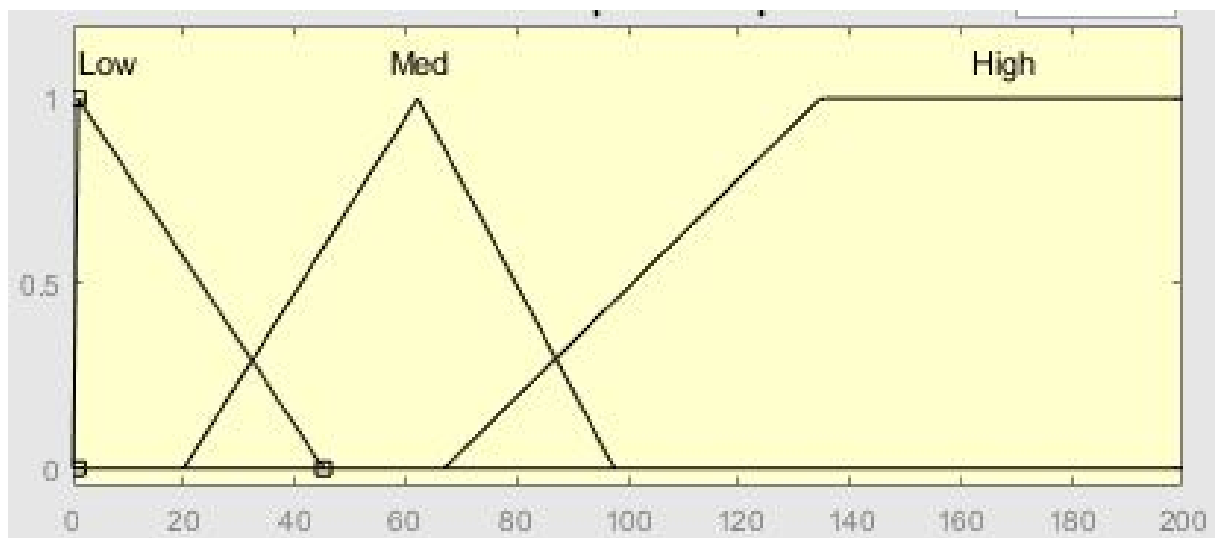


Figure 49: Membership functions for PV power input

The ESS output also required an additional membership function to be added, namely very slow charging. This is because certain situations may require the ESS to charge at a very slow rate between 5 and 15 kW. Figure 50 shows the added membership function indicated as "VSC". The discharge membership function will stay the same, as the constant discharge rate is still desirable.

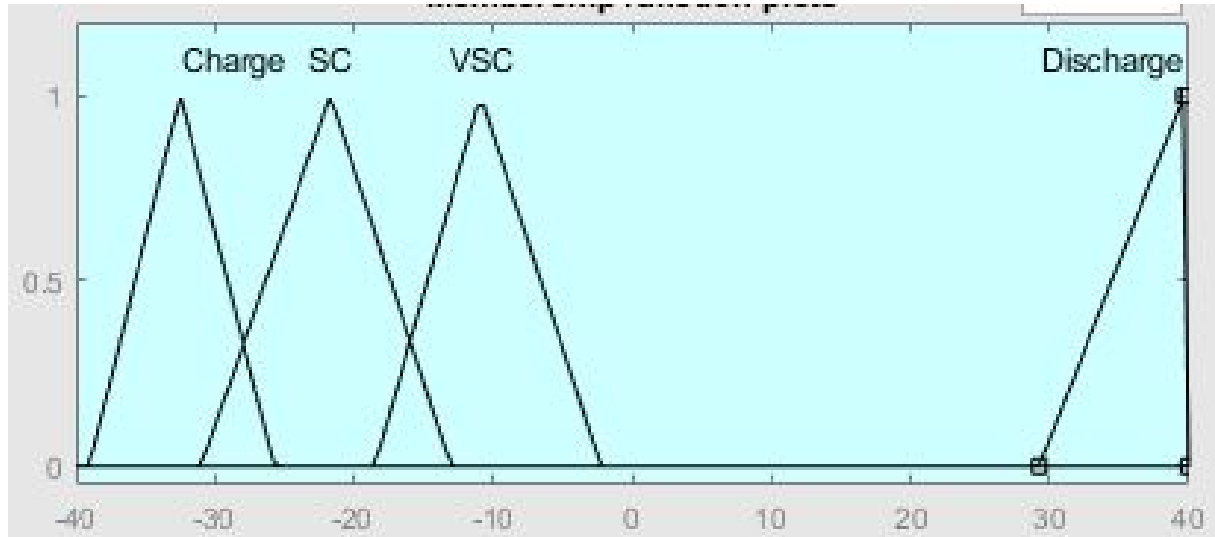


Figure 50: Membership functions for ESS power output

A new membership function for the PCC input has to be defined as well. This membership function would be below the base load, which would allow the FIS to believe that there is a possible surplus of PV power available. Therefore the additional membership function, very low (Vlow), was defined, as seen in figure 51.

Additionally, new rules would have to be defined. Referring back to table 10, the first three rules will be kept as is, with the last two rules being removed. These last two rules are not necessary, due to the full capacity of the ESS being assumed to be available. This removes the need to charge the additional 25% capacity during standard TOU periods. Additional rules need to be added to define charging in the event of a surplus of PV power. The rate of charging also need to be dictated by these rules. For the standard system sizing, it is known that the PV output would not be large enough to result in a surplus of PV power during business days. Therefore, typically a surplus of PV power would occur only on weekends and public holidays. Thus, the fuzzy logic controller will be configured to only charge off solar surplus solar PV during off-peak periods.

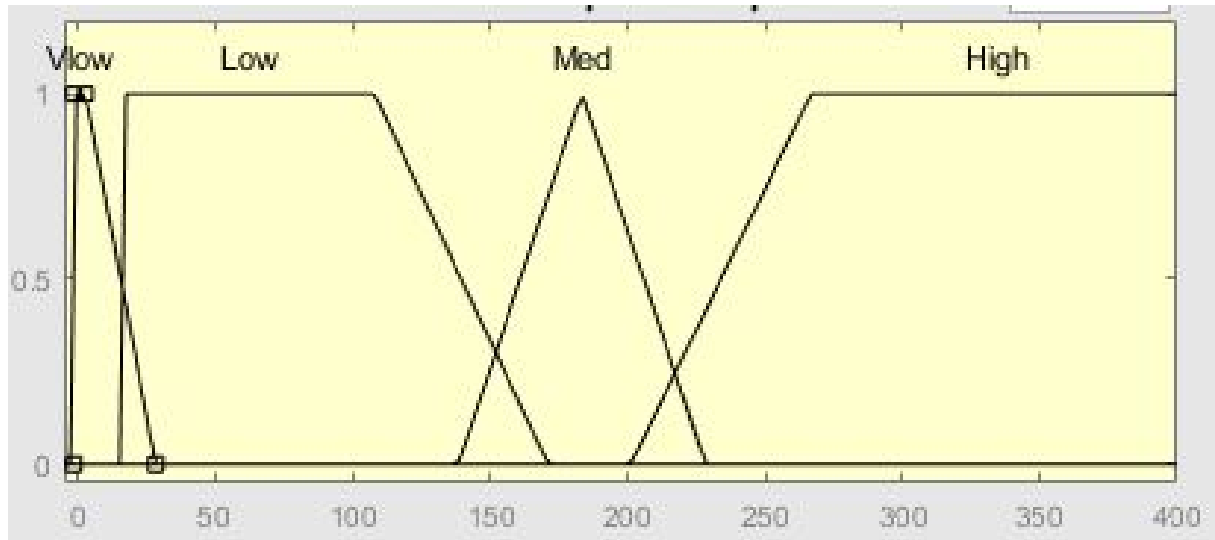


Figure 51: Membership functions for PCC input

The definition of a surplus PV power would typically be that the power measured at the PCC is below the base load of roughly 50 kW and the PV production is fairly high. However, these conditions could occur during peak hours when the ESS is discharging. The discharging of the ESS could cause the power measured at the PCC to be very low, which could cause the FIS to think that there is a surplus of PV power. Thus, the rules need to restrict PV charging to off-peak TOU periods. Table 15 outlines the rules defined to achieve these objectives. As can be seen, three additional rules were added. These rules basically dictate the rate of charge based on the level of the PV power, if the power measured at the PCC is below a certain level.

IF TOU is:	AND PCC is:	AND SOC is:	AND Workday is:	AND PV is:	THEN Output is:
1. Peak	-	NOT empty	W	-	Discharge
2. Off-peak	-	NOT full	W	-	Charge
3. Off-peak	-	NOT full	NW	-	SC
4. Off-peak	Vlow	NOT full	-	High	Charge
5. Off-peak	Vlow	NOT full	-	Med	SC
6. Off-peak	Vlow	NOT full	-	Low	VSC

Table 15: Fuzzy logic controller rules with PV as additional input

In figure 52, the output of the simulation for July can be seen. The performance of the FIS in terms of the power output and off-peak charging remains unchanged to that of the original simulations in chapter 6. For this simulation, the real difference comes in situations where there is a surplus of PV power on weekends. A closer look at these weekends can be taken in order to assess the performance of the FIS in these situations.

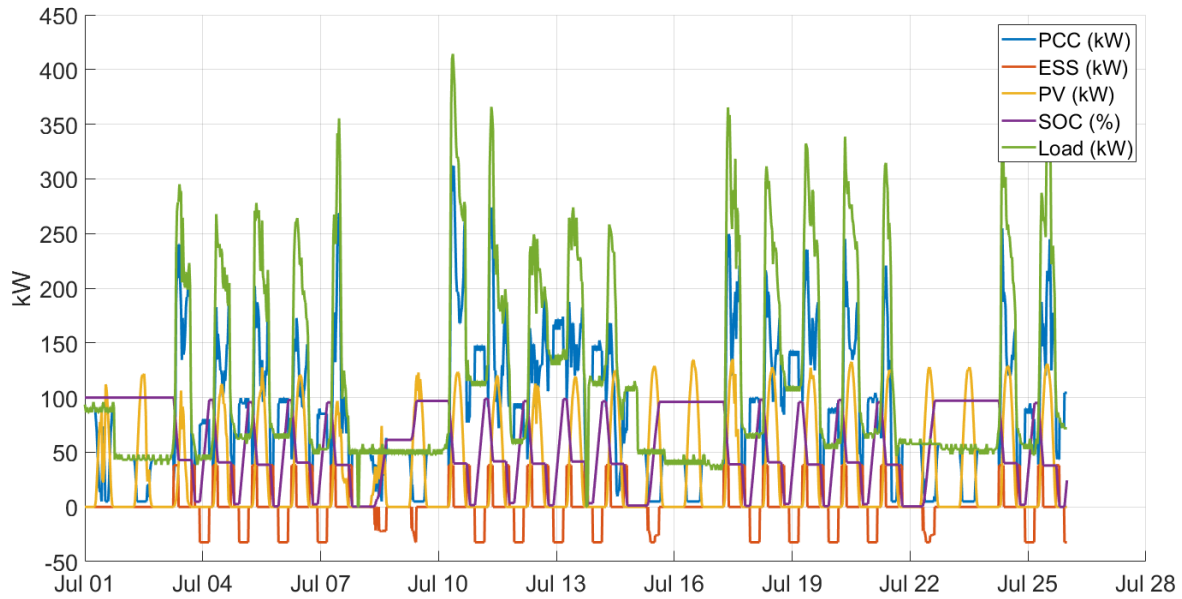


Figure 52: Simulation output for July 2017 with PV as EMS input

In figure 53, it can be seen that the Friday of 14 July has the typical, normal business day discharge pattern, with no off-peak charging on Friday evening, as the FIS waits for possible PV surplus on Saturday. Then on Saturday the ESS starts to charge once the PCC reaches a low level and continues to charge at rates that depend on the PCC and the PV. It can be seen that the ESS is fully charged by surplus PV power alone. The charging rates also do not increase the power drawn from the utility. From this data it is evident that the FIS performs well in this situation.

In figure 54, it can be seen that there is very little PV power available on Saturday 8 July. The ESS charges a fair amount, with the additional capacity being charged on Sunday 9 July. This is also an indication that the system works well in situations where the PV production is stochastic.

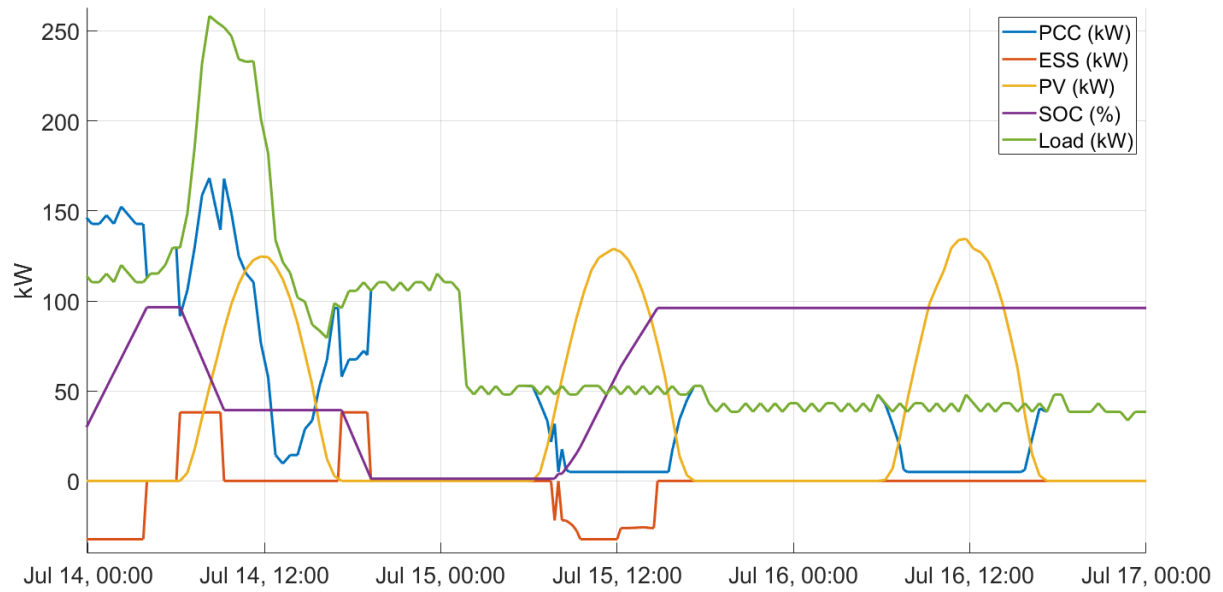


Figure 53: Simulation output for weekend of 15 July 2017

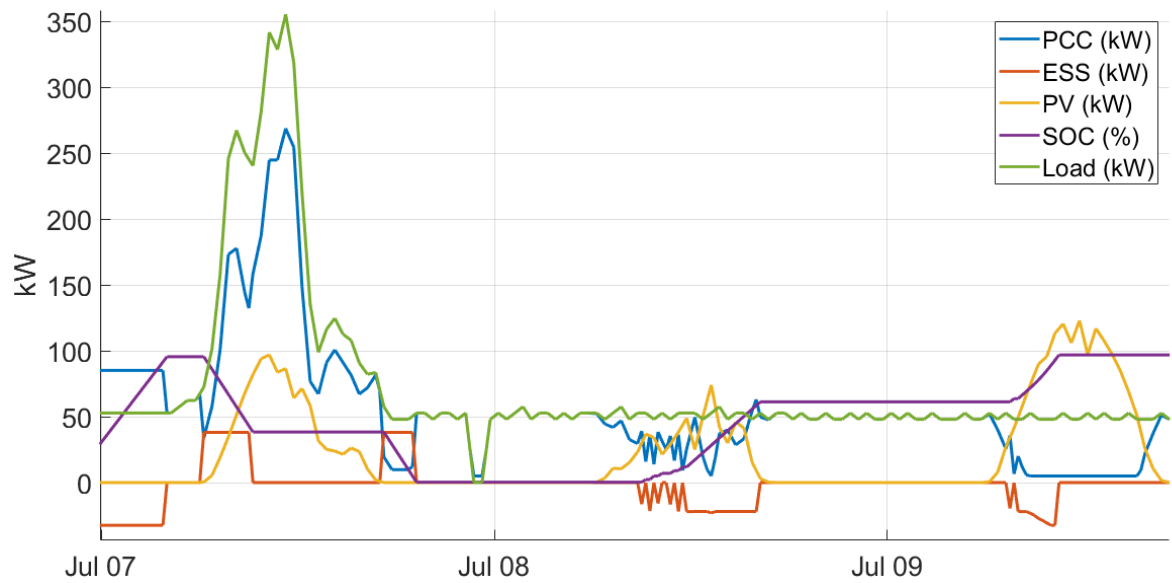


Figure 54: Simulation output for weekend of 8 July 2017

8.3 300 kWp PV and 800 kWh ESS

In this section, the size of the PV array has been increased to 300 kWp and the size of the ESS has been increased to 800 kWh. From chapter 6, it is known that there would still not be a surplus of PV power during a normal business day, thus for this simulation, the rules defined in table 15 can remain the same for this simulation. The ranges of the membership functions for the PV and the power output of the ESS just have to be

adjusted accordingly. Figure 55 indicates the simulation output for July 2017. From this figure, it is evident that the ESS could generally still be fully charged on Saturdays alone, in the event of high PV production. The rest of the results are similar to that discussed in the previous chapter.

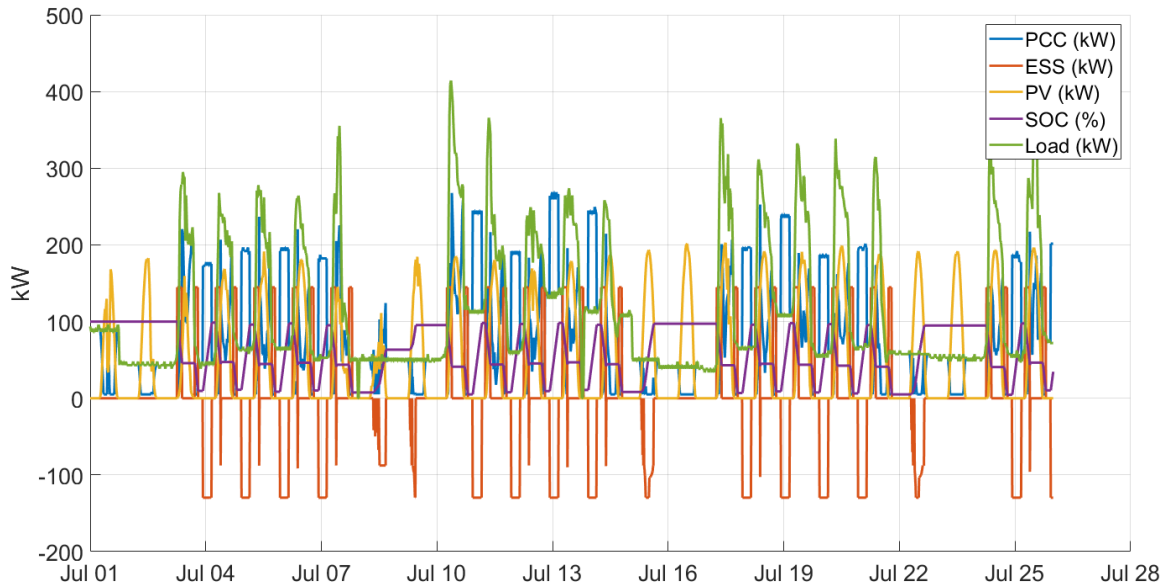


Figure 55: Simulation output for July 2017 with PV as input and variable sizes

8.4 500 kWp PV and 800 kWh ESS

In this section a PV size of 500 kWp will be investigated. This would most likely result in a surplus of PV power during business days. This would allow the ESS to charge from the surplus PV power in the day, rather than the off-peak utility power at night. This would provide additional savings. To achieve this, additional rules would have to be defined to allow the ESS to charge during standard TOU periods. This would essentially mean that the FIS would look to charge from surplus PV at all times except during peak hours. However, the charging would take place at a lower rate than usual, as the surplus during business days would generally be fairly small. Therefore, the rules in table 15 can be supplemented by adding rule number 7 in table 16. This rule dictates that in the event of a surplus of PV power during standard TOU periods, the ESS will charge at the “very slow” rate.

IF TOU is:	AND PCC is:	AND SOC is:	AND Workday is:	AND PV is:	THEN Output is:
1. Peak	-	NOT empty	W	-	Discharge
2. Off-peak	-	NOT full	W	-	Charge
3. Off-peak	-	NOT full	NW	-	SC
4. Off-peak	Vlow	NOT full	-	High	Charge
5. Off-peak	Vlow	NOT full	-	Med	SC
6. Off-peak	Vlow	NOT full	-	Low	VSC
7. Standard	Vlow	NOT full	-	High	VSC

Table 16: FIS rules with 500 kWp PV, 800 kWh ESS and PV as input

Figure 56 shows an extract of the simulation results for 20 and 21 July 2017. It can be seen that the ESS is charging around mid-day on both days. This results in a higher capacity at the end of the day, which means that less energy has to be imported to the ESS during the evening, which would save money.

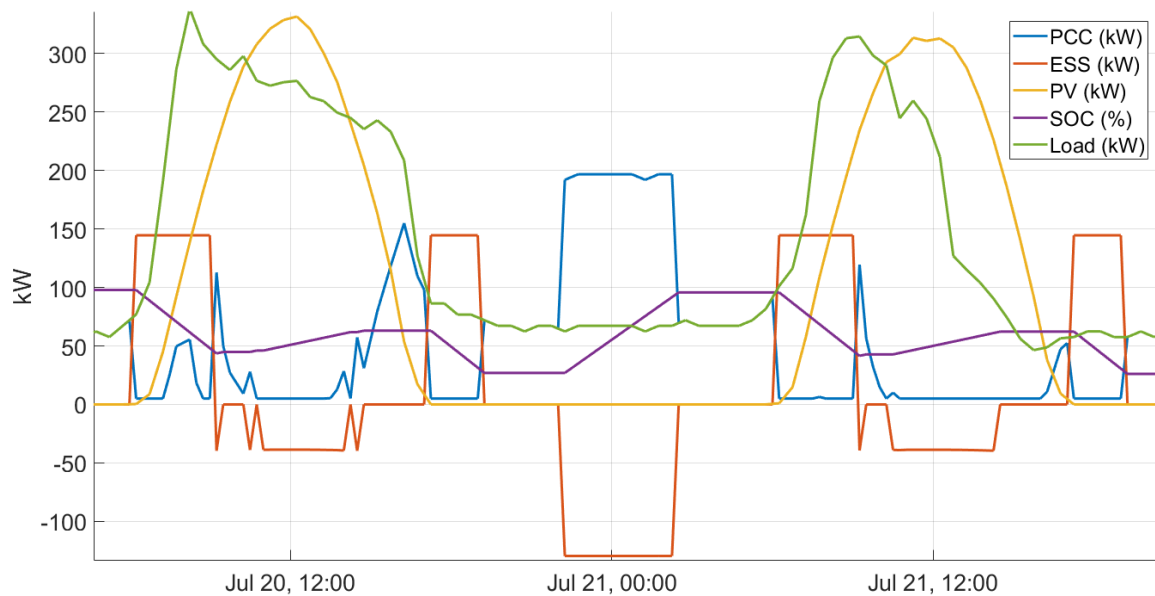


Figure 56: Simulation output for 20 and 21 July 2017

8.5 Conclusion

In this chapter the PV power was added as an input to the FIS. Adding the PV power as an input to the FIS provides clear benefits. Especially if the PV and ESS sizes are increased. The results do show some room for improvement. Charging and discharging rates can be fine-tuned for the specific sizing combinations. An additional concern is some hysteresis that is prevalent during some conditions that were simulated in the 500 kWp sizing variation. This can be seen in figure 57 where there is clear hysteresis taking place around mid-day. A more in-depth investigation into this occurrence should provide insight on whether this is due to a shortcoming of the FIS or the simulation method used. However, the findings of the results from the FIS-based EMS algorithm are predominantly good and easily achieve the desired objectives.

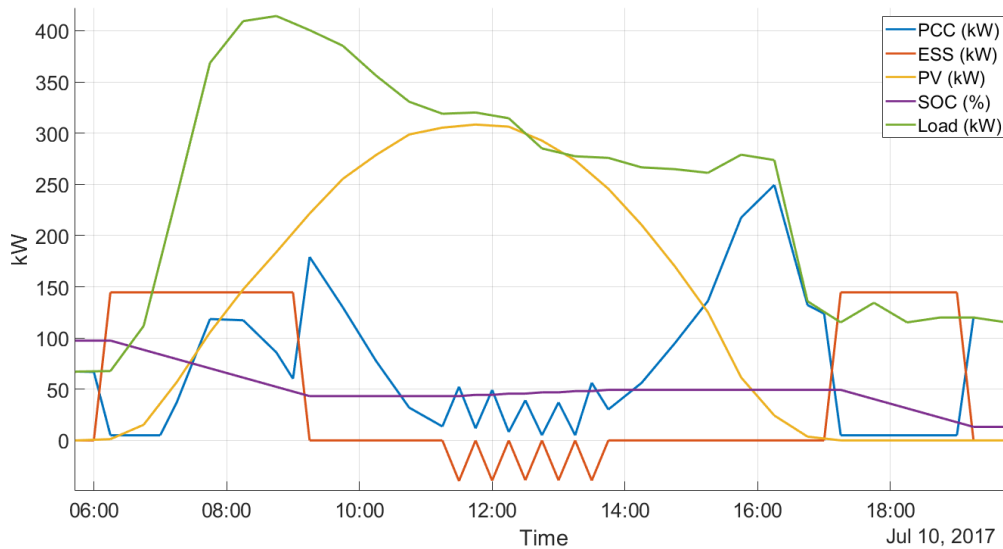


Figure 57: Hysteresis in simulation output

Chapter 9

Conclusion and recommendations

This chapter aims to conclude the document by connecting with chapter 1 in order to confirm that the necessary objectives were met. The chapter starts with a reflection on the research objectives as set-out in chapter 1. Then the refinement of the MATLAB simulation is discussed. Possible future work is also discussed. Finally, some recommendations are made and the chapter ends with a conclusion.

9.1 Reflection on research objectives

In the problem statement in chapter 1 it was stated that the purpose of this project is to develop an EMS algorithm for a low-voltage, industrial microgrid. The main objective was identified to be electricity cost savings. In order to achieve this, certain objectives were defined in chapter 1. These objectives are reviewed and discussed in the following paragraph.

- *Research relevant energy management strategies for microgrids and select strategies from literature to apply to the specific problem.*

The methods identified, developed and simulated were fuzzy logic control, artificial neural network short term load forecasting and a traditional crisp logic

algorithm.

- *Research methods with which to simulate energy management algorithms and select a suitable option.*

MATLAB and Simulink were identified as suitable options and proved to be very effective. The simulations served to verify the energy management algorithms that were developed.

- *Implement an energy management algorithm on the physical microgrid.*

The crisp algorithm was realised by means of a truth-table, converted to PLC-code and implemented on the microgrid controller. Field data were collected and the data served to validate the energy management objectives defined in chapter 4.

- *Research and simulate other methods, i.e. artificial intelligence, in order to compare them with the method implemented on the microgrid.*

The fuzzy logic and ANN STLFF methods were developed, simulated and the results were analysed. The results indicated that these techniques hold great potential. However, for energy arbitrage only, a crisp logic algorithm would be sufficient. Artificial intelligence techniques seem to be more valuable for a situation where non-exact charging/discharging rates are required or load and generation forecasting are required, typically for peak-shaving applications.

- *Additionally, the effect of various system configurations on the energy cost savings were investigated.*

System sizing and configuration variations were simulated, discussed and recommendations were made.

9.2 Simulation refinement

After analysing the field data from the EMS algorithm that was implemented on the microgrid, it became evident that there is a difference between the simulation and the field data. The biggest difference being the rate of charging, which affects the SOC curve. Additional deviations in the field data caused by the efficiency of the system should also be taken into account. It was mentioned in chapter 5, that an ideal system will be simulated, so it was expected that there would be some differences between the field data and the simulation. However, it is possible to take these factors into account in the simulation in order to predict more accurate savings.

Rate of charge

A Li-Ion battery typically charges quite fast until it reaches an SOC of around 80%, after which the charging speed decreases significantly. Figure 58 illustrates the charging characteristics of a typical Li-Ion cell from a datasheet [4]. It can be seen that the rate of charge significantly decreases when the cell nears full capacity. It can also be seen that the current drawn by the cell greatly decreases. This means that the EMS algorithm could take these characteristics into account when giving charging commands. This would require that the EMS algorithm be aware of the typical rate of charge for the battery system. This can be implemented with data from a datasheet and a simple look-up table to dictate charging speeds for the EMS algorithm based on the SOC of the battery system.

SOC curve

In the validation section, it was noticed that the SOC curve is non-linear. This should be fixed by applying the rate of charge instructions as mentioned in the previous section. However, it was also noticed that the SOC rapidly drops soon after the battery has

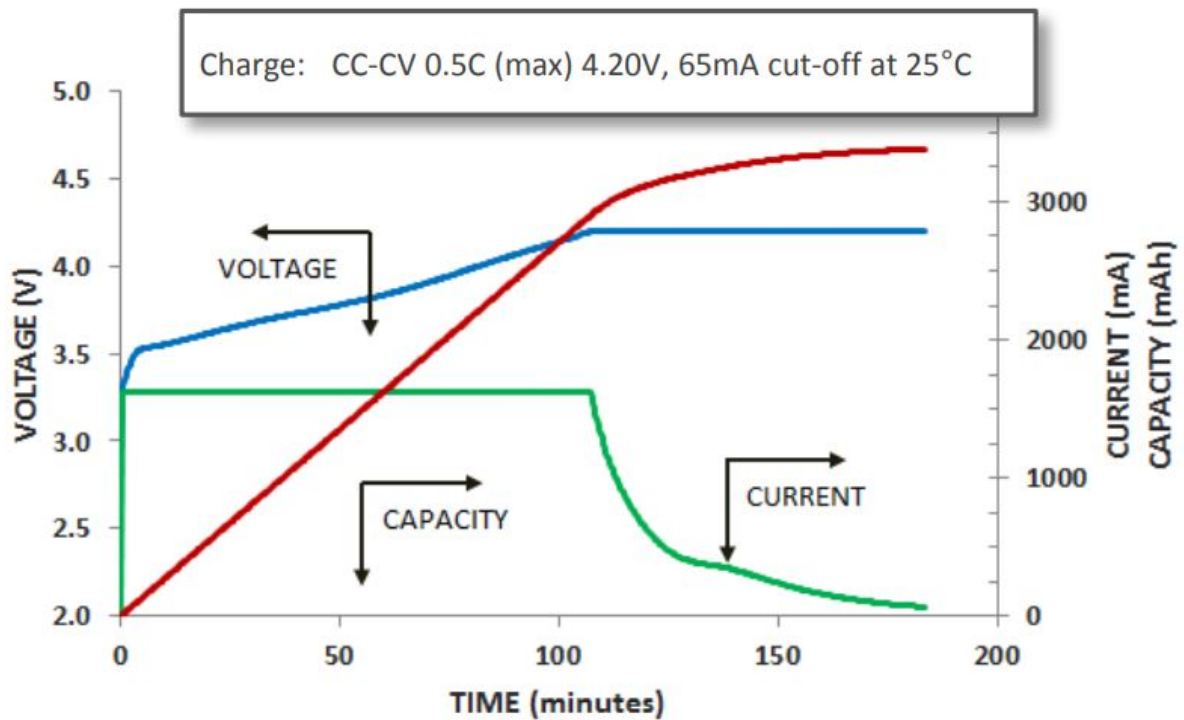


Figure 58: Charging characteristics of a Li-Ion battery [4]

been fully charged. This can be implemented in the simulation in order to gain a better idea of the available energy after the battery has been in idle mode during the night. It was mentioned that the SOC is reduced by around 10% during the night. This would have a definite effect on the savings estimations if not taken into account.

System efficiency

The issues with the SOC curve is most likely related to the efficiency of the system. This might be due to the auxiliary systems of the ESS that are drawing power. As mentioned in the validation section, the cooling of the batteries might be responsible for the sharp drop in SOC after it has been fully charged. This is likely because the batteries are at a higher temperature immediately after charging and requires effective cooling, which in turn drains the batteries again. These inefficiencies can be programmed into the simulation in order to have more accurate predictions.

9.3 Future work

STLF integration with fuzzy logic

In chapter 4 it was found that peak shaving is not an objective for the current tariff structure and topology of the microgrid. However, from literature and the results in chapter 6, it was found that STLF does hold potential benefits when peak shaving becomes an objective. Therefore, future work can be done to integrate the STLF with the fuzzy logic controller for scenarios where peak shaving would be a priority.

STLF refinement

As the data for the microgrid becomes more over time, there is an opportunity to increase the accuracy of the ANN STLF model. Adding higher resolution metering equipment would also assist the ANN STLF to become more accurate as it is trained over time.

Weather forecast integration

Along with the STLF, weather forecasting would also add value to the system. This would allow the system to be aware of adverse weather conditions in advance, which would reduce PV power output. The system could then analyse the weather forecasts and adjust the optimisation goals accordingly.

9.4 Recommendations

In chapters 7 and 8, significant time was spent on analysing various sizing and set-up scenarios for the specific microgrid. Certain recommendations were given regarding

PV and ESS sizing. It was mentioned that adding an additional 100 kWp of PV would result in large monetary savings. Adding more than that would result in additional savings, however, there would be surplus energy that the ESS would not be able to absorb, resulting in the surplus energy going to waste. Increasing the size of the ESS is not recommended due to the high capital expenditure coupled with the current tariff structure that only allows for high savings during the three winter months. It is however recommended to provide PV power as an available input to the EMS, as this would result in optimal utilisation of surplus PV power.

9.5 Conclusion and critical analysis

In chapter 1, the purpose of this study was defined to be the development of an EMS algorithm for a low-voltage, industrial microgrid. The main objective of the EMS algorithm was defined as reducing electricity charges as much as possible.

Various microgrid energy management techniques were studied and a truth-table based logic controller was developed and implemented on the actual microgrid. A microgrid energy management algorithm simulation framework was developed in Simulink and verified as an accurate representation of the actual system.

Artificial intelligence techniques were developed and tested in the simulation environment.

The results collected from field data and simulations show that the objectives were achieved.

The cost savings on energy usage for this microgrid from energy arbitrage with the ESS might seem relatively small. Energy storage is not a viable option to compete with utility grid pricing at the time of writing. However, if this facility were to heavily rely on diesel generators, then the energy storage and PV combination would definitely make economic sense, due to the high cost of diesel fuel.

The work done during the research process provides technical insight into the development of a microgrid control algorithm. These algorithms can provide large monetary savings to the end-user, therefore there is a lot of value in investigating different approaches. However, in this study the fuzzy logic approach does not add any real value, as a crisp logic algorithm can achieve the same objectives while having a lower complexity. Through this research, it has become evident that machine learning techniques like artificial neural networks could potentially add value to peak-shaving problems and could therefore be studied in more depth.

Appendix A

Software

All of the MATLAB code, Simulink models and Structured Text code developed for this dissertation is available on a cloud-based server accessible from the following link:

<https://nextcloud.nwu.ac.za/index.php/s/0w7e03mvq99dlzj>

The files are sorted into five main folders namely: Data processing, Truth Table, Fuzzy Logic, ANN STLF and Dissertation. Each folder contains the relevant MATLAB, Simulink and Excel files used in the study. The following sections describe the files and folders in each main folder.

Clarification of file types in the folders:

.slx - Simulink model

.fis - Fuzzy inference system developed with Fuzzy Logic Designer

.xlsx - Excel files used for the databases

.csv - Comma separated value Excel files used for the databases

.m - MATLAB code file

.txt - Text file

.png - used for pictures and figures in the dissertation

.jpg - used for pictures and figures in the dissertation

.tex - LaTeX document

.bib - LaTeX bibliography database

A.1 Data processing

The data processing folder contains all the raw and processed data for the load and PV production, as well as the MATLAB code developed to process the data.

A.2 Truth Table

The truth table folder contains the Simulink model developed to simulate the controller. The Simulink model contains the MATLAB code for the data pre-processing. In the folder, there is a MATLAB code file used to visualise the outputs of the Simulink simulation. This folder also contains the PLC code generated in order to implement the truth table logic on the actual controller. The field data used for validation can also be found in this folder.

A.3 Fuzzy Logic

This folder contains the Simulink models and FIS-files used in chapters 6,7 and 8. It contains the files for the standard set-up and the ideal set-up.

A.4 ANN STLF

This folder contains the MATLAB code generated to train the ANN STLF model discussed in chapter 6. It also contains the training data used by the MATLAB code.

A.5 Dissertation

This folder contains the dissertation with the LaTeX file and all the original figures.

Bibliography

- [1] B. Kroposki, R. Lasseter, T. Ise, S. Morozumi, S. Papathanassiou, and N. Hatziargyriou, "Making microgrids work," *IEEE Power and Energy Magazine*, vol. 6, no. 3, pp. 40–53, 2008.
- [2] S. Wencong, Jianhui. Wang, "Energy Management Systems in Microgrid Operations.pdf," *The Electricity Journal*, vol. 25, no. 8, 2012. [Online]. Available: http://ac.els-cdn.com/S104061901200214X/1-s2.0-S104061901200214X-main.pdf?{_}tid=3c37dc52-2b39-11e3-aa7f-00000aacb362{&}acdnat=1380701237{_-}28b23a4df5e6888be036441a076d95e7
- [3] A. Ahmad Khan, M. Naeem, M. Iqbal, S. Qaisar, and A. Anpalagan, "A compendium of optimization objectives, constraints, tools and algorithms for energy management in microgrids," *Renewable and Sustainable Energy Reviews*, vol. 58, pp. 1664–1683, 2016. [Online]. Available: <http://dx.doi.org/10.1016/j.rser.2015.12.259>
- [4] Panasonic Datasheet, "Lithium-Ion NCR18650B," p. 18650. [Online]. Available: <https://www.batteryspace.com/prod-specs/NCR18650B.pdf>
- [5] D. M. Bui, K.-Y. Lien, S.-L. Chen, X.-Y. Cheng, and M.-S. Lin, "Standards Commonly Used for MicrogridsA Research Project to Develop an Industry Microgrid Standard in Taiwan," *Electric Power Components and Systems*, vol. 44, no. 19, pp. 2143–2160, 2016. [Online]. Available: <https://www.tandfonline.com/doi/full/10.1080/15325008.2016.1216203>

-
- [6] J. M. Guerrero, P. C. Loh, T. L. Lee, and M. Chandorkar, "Advanced control architectures for intelligent microgridsPart II: Power quality, energy storage, and AC/DC microgrids," *IEEE Transactions on Industrial Electronics*, vol. 60, no. 4, pp. 1263–1270, 2013.
- [7] H. A. Gabbar and A. A. Abdelsalam, "Microgrid energy management in grid-connected and islanding modes based on SVC," *Energy Conversion and Management*, vol. 86, pp. 964–972, 2014.
- [8] M. Reyasudin, B. Khan, R. Jidin, and J. Pasupuleti, "Multi-agent based distributed control architecture for microgrid energy management and optimization," vol. 112, pp. 288–307, 2016.
- [9] M. E. Gamez, E. N. Sanchez, and L. J. Ricalde, "Optimal operation of an electrical microgrid via recurrent neural network," *World Automation Congress (WAC)*, 2012, no. 1, pp. 1–6, 2012.
- [10] M. N. Naz, M. I. Mushtaq, M. Naeem, M. Iqbal, M. W. Altaf, and M. Haneef, "Multicriteria decision making for resource management in renewable energy assisted microgrids," *Renewable and Sustainable Energy Reviews*, vol. 71, no. December 2016, pp. 323–341, 2017.
- [11] P. Pinceti, M. Vanti, C. Brocca, M. Carnesecchi, and G. P. Macera, "Design criteria for a power management system for microgrids with renewable sources," *Electric Power Systems Research*, vol. 122, pp. 168–179, 2015. [Online]. Available: <http://dx.doi.org/10.1016/j.epsr.2015.01.010>
- [12] B. Zhaohong, "REVIEW ON MICROGRID STANDARD AND INTRODUCTION," *IEC TC8/WG7*, 2015.
- [13] L. Hadjidemetriou, L. Zacharia, E. Kyriakides, B. Azzopardi, and S. Azzopardi, "Design Factors for Developing a University Campus Microgrid," *2018 IEEE International Energy Conference (ENERGYCON)*, pp. 1–6, 2018.

-
- [14] M. Sonnenberg, E. Pritchard, and D. Zhu, "Microgrid Development Using Model-Based Design," *2018 IEEE Green Technologies Conference (GreenTech)*, pp. 57–60, 2018. [Online]. Available: <https://ieeexplore.ieee.org/document/8373602/>
- [15] X. Zhang, R. Sharma, Yanyi He, and Y. He, "Optimal energy management of a rural microgrid system using multi-objective optimization," *Innovative Smart Grid Technologies ...*, pp. 1 –8, 2012. [Online]. Available: <http://ieeexplore.ieee.org/ielx5/6170475/6175527/06175655.pdf?tp={&arnumber=6175655{&}isnumber=6175527{}}5Cnhttp://ieeexplore.ieee.org/stamp/stamp.jsp?tp={&arnumber=6175655{}}5Cnhttp://ieeexplore.ieee.org/xpls/abs{ }all.jsp?arnumber=6175655{}}5Cnhttp://ieeexplore.ieee>
- [16] L. Roiné, K. Therani, Y. S. Manjili, and M. Jamshidi, "Microgrid energy management system using fuzzy logic control," in *2014 World Automation Congress (WAC)*, Waikoloa, HI, USA, 2014, pp. 462–467.
- [17] D. Arcos-Aviles, F. Guinjoan, P. M. Marietta, J. Pascual, L. Marroyo, and P. Sanchis, "Energy management strategy for a grid-tied residential microgrid based on fuzzy logic and power forecasting," in *IECON 2016 - 42nd Annual Conference of the IEEE Industrial Electronics Society*, 2016, pp. 4103 – 4108.
- [18] A. Anvari-Moghaddam, A. Rahimi-Kian, M. S. Mirian, and ..., "A multi-agent based energy management solution for integrated buildings and microgrid system," *Applied Energy*, vol. 203, pp. 41–56, 2017. [Online]. Available: <http://www.sciencedirect.com/science/article/pii/S0306261917307572>
- [19] M. Elsied, A. Oukaour, T. Youssef, H. Gualous, and O. Mohammed, "An advanced real time energy management system for microgrids," *Energy*, vol. 114, pp. 742–752, 2016.
- [20] D. Arcos-Aviles, J. Pascual, F. Guinjoan, L. Marroyo, P. Sanchis, and M. P. Marietta, "Low complexity energy management strategy for grid profile smoothing of a residential grid-connected microgrid using generation and

-
- demand forecasting,” *Applied Energy*, vol. 205, no. May, pp. 69–84, 2017. [Online]. Available: <http://dx.doi.org/10.1016/j.apenergy.2017.07.123>
- [21] D. Arcos-Aviles, J. Pascual, L. Marroyo, P. Sanchis, and F. Guinjoan, “Fuzzy Logic-Based Energy Management System Design for Residential Grid-Connected Microgrids,” *IEEE Transactions on Smart Grid*, vol. 3053, no. c, pp. 1–1, 2016. [Online]. Available: <http://ieeexplore.ieee.org/document/7454775/>
- [22] L. Oneto, F. Laureri, M. Robba, and F. Delfino, “Data-Driven Photovoltaic Power Production Nowcasting and Forecasting for Polygeneration Microgrids,” pp. 1–12, 2017.
- [23] J. Queiroz, P. Leitão, and A. Dias, “Predictive Data Analysis Driven Multi-agent System Approach for Electrical Micro Grids Management,” pp. 738–743, 2016.
- [24] A. E. Thanos, S. Member, M. Bastani, S. Member, N. Celik, C.-h. Chen, and S. Member, “Framework for Automated Control in Microgrids,” vol. 8, no. 1, pp. 1–10, 2015.
- [25] M. Pyne, S. Member, and S. Yurkovich, “Data Driven Modeling and Simulation for Energy Storage Systems,” *IEEE Conference on Control Applications (CCA)*, pp. 1306–1311, 2016.
- [26] Duong Tung Nguyen and Long Bao Le, “Optimal energy management for cooperative microgrids with renewable energy resources,” *2013 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, pp. 678–683, 2013. [Online]. Available: <http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6688037>
- [27] D. T. Nguyen and L. B. Le, “Optimal energy trading for building microgrid with electric vehicles and renewable energy resources,” *Isgt 2014*, pp. 1–5, 2014. [Online]. Available: <http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6816461>
- [28] G. Cardoso, M. Stadler, A. Siddiqui, C. Marnay, N. Deforest, A. Barbosa-Póvoa, and P. Ferrão, “Microgrid reliability modeling and battery scheduling using
-

-
- stochastic linear programming," *Electric Power Systems Research*, vol. 103, pp. 61–69, 2013. [Online]. Available: <http://dx.doi.org/10.1016/j.epsr.2013.05.005>
- [29] E. Ippoliti, *Heuristic Reasoning*. Springer, 2015, vol. 16. [Online]. Available: <http://link.springer.com/10.1007/978-3-319-09159-4>
- [30] J. B. Almada, R. P. Leão, R. F. Sampaio, and G. C. Barroso, "A centralized and heuristic approach for energy management of an AC microgrid," *Renewable and Sustainable Energy Reviews*, vol. 60, pp. 1396–1404, 2016. [Online]. Available: <http://dx.doi.org/10.1016/j.rser.2016.03.002>
- [31] M. L. Di Silvestre, G. Graditi, and E. Riva Sanseverino, "A generalized framework for optimal sizing of distributed energy resources in micro-grids using an indicator-based swarm approach," *IEEE Transactions on Industrial Informatics*, vol. 10, no. 1, pp. 152–162, 2014.
- [32] N. Milanese and V. L. Masa, "AN INNOVATIVE DEVICE FOR ENERGY HARVESTING IN SMART CITIES UP Underground Power Via Garibaldi 144 Francesco Grimaccia and Marco Mussetta Politecnico di Milano , Dipartimento di Energia," pp. 39–44, 2012.
- [33] C. M. Colson, M. H. Nehrir, and C. Wang, "Ant colony optimization for microgrid multi-objective power management," *2009 IEEE/PES Power Systems Conference and Exposition, PSCE 2009*, pp. 1–7, 2009.
- [34] E. De Santis, A. Rizzi, and A. Sadeghian, "Hierarchical genetic optimization of a fuzzy logic system for energy flows management in microgrids," *Applied Soft Computing Journal*, vol. 60, pp. 135–149, 2017. [Online]. Available: <https://doi.org/10.1016/j.asoc.2017.05.059>
- [35] A. Hooshmand, B. Asghari, and R. Sharma, "A novel cost-aware multi-objective energy management method for microgrids," *2013 IEEE PES Innovative Smart Grid Technologies Conference, ISGT 2013*, pp. 1–6, 2013.
- [36] A. Parisio, E. Rikos, and L. Glielmo, "A Model Predictive Control Approach to Microgrid Operation Optimization," *IEEE Transactions on Control Systems*
-

-
- Technology*, vol. 22, no. 99, p. 1, 2014. [Online]. Available: <http://ieeexplore.ieee.org/xpl/articleDetails.jsp?tp={&}arnumber=6705582{&}matchBoolean{&}3Dtrue{&}26rowsPerPage{&}3D30{&}26searchField{&}3DSearch{&}All{&}26queryText{&}3D{&}28{&}22A+Model+Predictive+Control+Approach+to+Microgrid+Operation+Optimization{&}22{&}29{&}5Cnfile:///Users/Ric>
- [37] H. S. Lee, B. G. Koo, S. W. Lee, W. Kim, and J. H. Park, "Optimal control of BESS in microgrid for islanded operation using fuzzy logic," in *Proceedings - International Conference on Intelligent Systems, Modelling and Simulation, ISMS*, vol. 2015-Sept, 2015, pp. 468–473.
- [38] L. Ji, B.-B. Zhang, G.-H. Huang, Y.-L. Xie, and D.-X. Niu, *Explicit cost-risk tradeoff for optimal energy management in CCHP microgrid system under fuzzy-risk preferences*. Elsevier B.V, 2018. [Online]. Available: <http://linkinghub.elsevier.com/retrieve/pii/S0140988318300252>
- [39] L. G. Marin, L. G. Mar, F. Valencia, and S. Doris, "Prediction interval based on type-2 fuzzy systems for wind power generation and loads in microgrid control design Prediction interval based on type-2 fuzzy systems for wind power generation and loads in microgrid control design," no. July, 2016.
- [40] X. Fang, Q. Yang, and W. Dong, "Fuzzy decision based energy dispatch in offshore industrial microgrid with desalination process and multi-type DGs," *Energy*, 2018. [Online]. Available: <http://linkinghub.elsevier.com/retrieve/pii/S0360544218302135>
- [41] F. Ávila, D. Sáez, G. Jiménez-estévez, L. Reyes, and A. Núñez, "Fuzzy demand forecasting in a predictive control strategy for a renewable-energy based microgrid," *2013 European Control Conference (ECC)*, no. 1, pp. 2020–2025, 2013.
- [42] D. O. Elamine, E. H. Nfaoui, and B. Jaouad, "Multi-agent system based on fuzzy control and prediction using NN for smart microgrid energy management," in *2015 Intelligent Systems and Computer Vision, ISCV 2015*, 2015.
-

-
- [43] D. Q. Oliveira, A. C. Zambroni de Souza, M. V. Santos, A. B. Almeida, B. I. Lopes, and O. R. Saavedra, "A fuzzy-based approach for microgrids islanded operation," *Electric Power Systems Research*, vol. 149, pp. 178–189, 2017.
- [44] M. Serraji, J. Boumhidi, and E. H. Nfaoui, "MAS energy management of a microgrid based on fuzzy logic control," in *Intelligent Systems and Computer Vision (ISCV)*, 2015, pp. 1–7.
- [45] W. L. Woo and K. Abidi, "Fuzzy Logic Control of Energy Storage System in Microgrid Operation," 2016.
- [46] S. Darvish Kermany, M. Joorabian, S. Deilami, and M. A. Masoum, "Hybrid Islanding Detection in Microgrid with Multiple Connection Points to Smart Grids using Fuzzy-Neural Network," *IEEE Transactions on Power Systems*, vol. 8950, no. c, pp. 1–1, 2016. [Online]. Available: <http://ieeexplore.ieee.org/document/7592429/>
- [47] F. Pilo, G. Pisano, and G. G. Soma, "Neural implementation of MicroGrid central controllers," in *IEEE International Conference on Industrial Informatics (INDIN)*, vol. 2, 2007, pp. 925–930.
- [48] M. E. Gamez Urias, E. N. Sanchez, and L. J. Ricalde, "Electrical Microgrid Optimization via a New Recurrent Neural Network," *IEEE Systems Journal*, vol. 9, no. 3, pp. 945–953, 2015.
- [49] D. Otilia and D. Florin, "Integrated solutions based on neural networks for optimizing energy management in a microgrid," *Electrical and Electronics Engineering (ISEEE), 2013 4th International Symposium on*, pp. 1–6, 2013.
- [50] E. Corsetti, A. Guagliardi, and C. Sandroni, "Recurrent neural networks for very short term energy resource planning in a microgrid," in *Mediterranean Conference on Power Generation, Transmission, Distribution and Energy Conversion (MedPower 2016)*, pp. 1–9.
- [51] M. Mauri, M. Carmeli, M. Merlo, C. Brivio, and M. Mbuya, "Neural Network based Load Forecasting and Fuzzy Logic EMS for Ngarenyuki School microgrid,"
-

-
- International Symposium on Power Electronics, Electrical Drives, Automation and motion*, pp. 321–326, 2016.
- [52] M. Koyama, T. Takeda, and K. Yukita, “Operation Method of Microgrid Using the Forecast Method by Neural Network,” in *2015 IEEE International Telecommunications Energy Conference (INTELEC)*, 2015, pp. 1 – 6.
- [53] J. Llanos, S. Member, D. Sáez, S. Member, and A. Núñez, “Load Profile Generator and Load Forecasting for a Renewable Based Microgrid Using Self Organizing Maps and Neural Networks,” *International Joint Conference on Neural Networks*, pp. 10–15, 2012.
- [54] T. Guena and P. Leblanc, “How depth of discharge affects the cycle life of lithium-metal-polymer batteries,” *INTELEC, International Telecommunications Energy Conference (Proceedings)*, 2006.
- [55] M. Gulin, M. Vasak, G. Banjac, and T. Tomisa, “Load forecast of a university building for application in microgrid power flow optimization,” *ENERGYCON 2014 - IEEE International Energy Conference*, pp. 1223–1227, 2014.
- [56] J. Ma and X. Ma, “State-of-the-art forecasting algorithms for microgrids,” *ICAC 2017 - 2017 23rd IEEE International Conference on Automation and Computing: Addressing Global Challenges through Automation and Computing*, no. September, pp. 7–8, 2017.
- [57] H. Hasan, M. R. Munawar, and R. H. Siregar, “Neural network-based solar irradiance forecast for peak load management of grid-connected microgrid with photovoltaic distributed generation,” *Proceedings - 2017 International Conference on Electrical Engineering and Informatics: Advancing Knowledge, Research, and Technology for Humanity, ICELTICs 2017*, vol. 2018-Janua, no. ICELTICs, pp. 87–90, 2018.
- [58] F. Liu and Z. Wang, “Electric Load Forecasting Using Parallel RBF Neural Network,” no. 1, pp. 531–534, 2013.
- [59] P. H. Cheah, H. B. Gooi, S. Member, and F. L. Soo, “Quarter-hour-ahead load forecasting for microgrid energy management system,” *2011 IEEE Trondheim*
-

PowerTech, pp. 1–6, 2011. [Online]. Available: <http://ieeexplore.ieee.org/document/6337027/>