RELIABILITY EVALUATION OF SOLAR POWER GENERATION

By

Zesizwe Prudence Ncane

In fulfillment of the Master of Science in Electrical Engineering, College of Agriculture, Engineering and Science, University of KwaZulu-Natal.

February 2020

Supervisor: Prof Akshay Kumar Saha

DECLARATION - PLAGIARISM

I …….Zesizwe Prudence Ncane……………., declare that

1. The research reported in this dissertation, except where otherwise indicated, is my original research.

2. This dissertation has not been submitted for any degree or examination at any other university.

3. This dissertation does not contain other persons' data, pictures, graphs or other information, unless specifically acknowledged as being sourced from other persons.

4. This dissertation does not contain other persons' writing, unless specifically acknowledged as being sourced from other researchers. Where other written sources have been quoted, then:

   a. Their words have been re-written but the general information attributed to them has been referenced,

   b. Where their exact words have been used, then their writing has been placed in italics and inside quotation marks and referenced.

5. This dissertation does not contain text, graphics or tables copied and pasted from the Internet, unless specifically acknowledged, and the source being detailed in the dissertation and in the References sections.

Signed　　　　　　　　　　　　　　　　Date

…………………………………… 　　　　2020-02-25 ……………………………………

As the candidate's Supervisor I agree/do not agree to the submission of this dissertation.

Signed　　　　　　　　　　　　　　　　Date

Akshay Kumar Saha　　　　25/02/2020

…………………………………… 　　　　……………………………………

DECLARATION 2 - PUBLICATIONS

DETAILS OF CONTRIBUTION TO PUBLICATIONS that form part and/or include research presented in this dissertation (include publications in preparation, submitted, *in press* and published and give details of the contributions of each author to the experimental work and writing of each publication)

Publication 1

Z.P. Ncane, A.K. Saha: "Characteristics of Solar Power Generation Plant" IEEE PES & IAS Power Africa Conference, 2018.

Publication 2

Z.P. Ncane, A.K. Saha: "Forecasting Solar Power Generation Using Fuzzy Logic and Artificial Neural Network" Southern African Universities Power Engineering Conference, 2019.

Signed

……………………………………

Date

……2020-02-25……………………

ACKNOWLEDGEMENTS

- I would like to express my gratitude to God for granting me with wisdom, courage, and the opportunity of education.
- A huge appreciation to my family (TA Ncane, GB Ncane, LL Mdlalose, PP Ncane, SM Ncane, BC Ncane, AA Mdlalose and MM Ncane) and loved ones for the continuous support and for motivating me to always do what I love.
- Thank you to my supervisor Prof AK Saha and my colleague Mr. VC Mathebula for the guidance and support provided throughout the research period.
- The University of KwaZulu-Natal is also acknowledged for providing facilities to conduct my research.

Abstract

Environmental challenges associated with greenhouse gases and limitations with fossil fuel that is used in the conventional generating plants have encouraged the usage and expansion of renewable energy sources. In substituting conventional energy sources, solar energy has emerged as the most popular approach compared to other renewable energy sources such as wind, hydropower and geothermal energy. A 30 MW grid connected solar photovoltaic (PV) plant located in the Upington area, Northern Cape, South Africa has been developed and presented in this dissertation. The plant has been modelled using MATLAB Simulink where one solar module is first simulated, followed by a string of series connected modules and an array of parallel connected strings for the purposes of obtaining the desired voltage levels and power. The plant was subjected to different ambient conditions (simulating the actual weather patterns that the plant would be subjected to), with the aim of studying its I-V and P-V characteristics.

As renewable energy sources are dependent on weather patterns, it is therefore crucial to predict when the output power will start to decay due to solar radiation decaying. Forecasting of solar PV plant output power is therefore vital in assisting the grid operators to effectively manage the electric balance between power supply and the demand. Methods of forecasting solar PV plant output power have been studied and developed i.e. fuzzy logic and artificial neural network (ANN), in order to effectively manage the effect of the abrupt fluctuations of environmental conditions. The fuzzy logic method to mimic the solar PV plant was successfully developed, the average percentage error obtained was 1.9 %. Similarly for ANN method the obtained average error was 2.6 %. The study has been conducted using MATLAB. Reliability evaluation of the plant is also studied and presented in this dissertation, looking into probability based indices and customer based indices to assess the performance of the plant. Hardware failure and solar resource intermittency have been considered in the evaluation of these reliability indices. For reliability improvement purposes, different possible configurations and considerations were evaluated and are presented in this dissertation.

Contents

List of Figures

List of Tables

Nomenclature

A:	Amps
AC:	Alternating Current
ANN:	Artificial Neural Network
ASAI:	Average System Availability Index
CAIDI:	Customer Average Interruption Duration Index
COPT:	Capacity Outage Probability Table
DC:	Direct Current
EENS:	Expected Energy Not Served
FIS:	Fuzzy Inference System
FOR:	Forced Outage Ratio
I-V:	Current Voltage
LOEE:	Loss of Energy Expectation
LOLE:	Loss of Load Expectation
LOLP:	Loss of Load Probability
MF:	Membership Function
MOSFET:	Metal Oxide Semiconductor Field Effect Transistor
MTBF:	Mean Time before Failure
MTTR:	Mean Time to Repair
MW:	Megawatts
p.u:	per unit
PV:	Photovoltaic
P-V:	Power Voltage
RBD:	Reliability Block Diagram
SAGC:	South African Grid Code
SAIDI:	System Average Interruption Duration Index
SAIFI:	System Average Interruption Frequency Index
SAWS:	South African Weather Service
SPWM:	Sinusoidal Pulse Width Modulation
V:	Volt

CHAPTER 1 - INTRODUCTION

Renewable power generators such as solar photovoltaic (PV) plants play a vital role in supporting the power system (with conventional fossil fueled generators connected) during normal conditions and during system emergencies. Solar PV systems utilize photovoltaic cells to produce electric power from solar irradiation conversion. These types of generators are therefore highly dependent on weather patterns which implies that their output varies as the weather conditions fluctuate [1]. To minimize the variations in the plant's output power brought about the varying weather patterns; some applications make use of energy storage methods to store power for use under unfavorable weather conditions.

Solar power generators are environmentally friendly and have an advantage of having reduced carbon emissions as there is no fuel source required to burn for power production. Customers require continuous power supply, with minimal interruptions. However, with an uncontrollable input resource of solar power generators, it is difficult to project how long these generators can continuously supply the loads when the demand is high. Solar power sources are also generally considered reliable when they can meet the load demand and can report if they cannot meet the demand any longer, to avoid detrimental effects to the grid [2]. The research is therefore aimed at assessing the plant's reliability and developing the forecasting techniques for an improved system planning and operation, as well as for grid stability. This chapter discusses the background and motivation behind the research topic, the key questions to be addressed in the study, main research objective, the feasibility study undertaken to assess the necessity and contribution of the research work to the industry and the assumptions made during the study.

1.1. Background

Despite the benefits with renewable energy sources, there are uncertainties with the power production from this technology which require methods and processes in place to manage the abrupt environmental fluctuations [3]. It is therefore of utmost importance to have a reliable forecasting system that allows for the prediction of the available solar power, so as to assist system operators with effective load management. System planning may include, but not limited to the following:

- Forecasting if the generated power from the solar PV plant will meet the demand. Short and long term forecasts are generally used by system operators e.g. hour-ahead and day-ahead forecasts.
- Scheduling maintenance outages on some connected renewable and conventional power generators, while maintaining minimal customer interruption.

- Notifying customers on time if there is a projected shortage of power from the connected generators.
- Planning the return to service of generators that are on outage such that supply to the customers is maintained

Furthermore, an analysis of the plant's reliability is also as important; as it assists in ensuring a reliable power system, selection of the most feasible configuration that would yield a high reliable plant, quantifying the annual system outages of the plant which is related to its performance and conducting life of plant planning which include the forecasted component replacement strategies.

1.2. Motivation

Electricity (specifically alternating current (AC) power) cannot be stored; if generated it has to be transmitted and used immediately. Generating more than the demand causes voltage instabilities in the grid and generating less than the demand may lead to the connected load being shed for safeguarding the network. Due to solar power being uncontrollable because of its input resource being intermittent, it makes it difficult to predict, control and maintain the balance between generated power and the demand [4]. Solar PV systems are highly reliable, however, with all the interfaces which incorporate power electronics, protection components, power transformers etc. for a complete functionality of the plant, the reliability is reduced which often results in plant breakdowns [5]. This research study takes these factors into account and it has been motivated by the following factors:

- The rise in the usage of this renewable energy technology in the energy sector, implying that more attention (e.g. research studies and plant improvements) needs to be given for a more efficient, cost effective and reliable technology.
- The dependency of the solar PV plant on the weather patterns and methods that can be employed to manage the plant's output variations.
- The ability to select the plant's optimum design and assess the plant's performance from the reliability analysis; and being able to proactively put measures in place to improve and/or maintain the plant's reliability throughout its life.

These considerations will enable an effective management system of the plant, such that the uncontrollable nature of the plant's behavior is not impacting the supply and demand. This will also assist in assessing the extent to which the solar PV plants can substitute conventional generators when necessary.

1.3. Key questions

To ensure that a comprehensive research on this topic is achieved, key questions to be addressed are as follows:

- How does climate change affect solar power generators and what is the impact of seasonal changes on solar power generation?
- What methods can be used to forecast a solar PV plant's output power?
- What methods can be used to analyze solar PV plant's availability and reliability?
- How can the reliability of the plant be improved?

1.4. Feasibility Study

The configuration of the solar PV generators can be for off-grid applications or it can be grid connected. Both these applications can have a battery energy storage system, depending on the requirements and objectives. Effective grid interface of renewable energy sources requires adequate assessment to ensure compatibility, stability and reliability of the network [5], [6]. The system can also be a large scale or small scale, which is determined by the application and size of the plant. The system under study is a 30 MW solar PV plant, aimed at being grid connected in order to substitute conventional power generators and other grid connected renewable sources in the event of network constraints or during plant break downs and scheduled maintenance. Fluctuations in output power can result in undesired voltage and frequency fluctuations in the network, which would interfere with the requirements for safe and stable operation of the grid.

Solar PV panels used for the study are monocrystalline silicon type which are fairly more efficient compared to polycrystalline and thin-film modules [7]. The data for a monocrystalline silicon module is therefore used for simulation purposes. For the purpose of this study, Upington area, located in Northern Cape, South Africa is chosen to be the location of the solar power plant under study. The province offers favorable solar radiation levels and has attracted the majority of solar PV projects in South Africa [1]. Data from the Upington area was provided by South African Weather Service (SAWS) which only included the solar irradiance and excluded the corresponding temperature readings; however the study makes assumptions with regards to the corresponding temperature values, for the purpose of this study.

Conventional power plants are not designed to ramp up and down quickly to make up for solar power's variability but are designed to generate base load energy [8]. It is therefore very important to ensure that effective system management and planning is done to avoid having to require conventional generators to ramp up and down as and when required. Due to the intermittent nature of the plant's performance it is vital to develop different systems that can be used to forecast solar PV plants' performance, such that should there be a decay in the forecasted output power the plan to bring back conventional generators can be done. The forecasting of the solar PV plant output power is crucial in assisting the grid operators to effectively manage the electric balance between power supply and the demand [9]. The solar plant can be used during the day especially if the design does not cater for energy storage systems. Advanced and comprehensive forecasting methods provide utilities with reliable production predictions and the opportunity to plan for additional power supply and conduct appropriate preventative maintenance strategies to minimize energy losses [4].

Some literature consider forecasting solar plant input variables and some consider the output power of the plant. Both methods are aimed at being able to perform system planning by ensuring that proactive actions are taken, to always minimize the interruption of customers and minimize the ramping up and down of other connected energy sources. Over and above the forecasting methods, the reliability of the plant needs to be taken into account. With the nature of the plant, the analysis of reliability needs to consider the varying resource and component failures.

1.5. Research Objective

The research undertaken and presented in this dissertation is aimed at studying the solar PV plant behavior under different weather conditions, with the main focus being on analysing the solar power generation system reliability and investigating forecasting techniques that can be employed. The following aspects need to be considered:

a) Solar PV Plant

In order to develop forecasting systems and analyse the plant's reliability, the first aspect to consider is the actual plant design. This is investigated by making use of MATLAB Simulink for the development of the plant model. This should therefore enable the study of the plant's behaviour under different weather patterns.

b) Forecasting

The understanding of the plant's behaviour when the solar resource is varied enables the forecasting system to be developed as the forecasting system should be as close as possible to the actual plant's behaviour for a more accurate and effective system planning. Investigation on the methods that can be used to forecast the solar PV plant's output power is required.

c) Reliability

The reliability of the plant needs to be assessed, taking into account the variations in solar resource and failure rates of the components employed in the system. Different reliability indices therefore need to be investigated and computed. Furthermore, the sensitivity analysis needs to be conducted, to ascertain the most contributing factors to component failures. The study further considers various techniques for reliability improvement.

1.6. Key Research Assumptions

There are assumptions which were made for the purpose of the research work; these assumptions were informed by experience and previously completed similar works from literature. Assumptions made in this research were the following.

- Due to the lack of temperature data received from the SAWS, the temperature was assumed in accordance to the time of the day and the corresponding irradiance, for the purpose of studying the solar PV plant behavior with varying solar resources.
- The load profile for studying the reliability of the plant was assumed based on a typical load profile i.e. during the day the demand is fairly low, compared to the night. This considers the fact that the plant under study is grid connected, therefore it follows the same load profile as the grid.
- For reliability assessment, the components/system failure rates were obtained using the stress factors for typical applications and not necessarily for an existing plant. Similar to the repair rates, the MTTR were assumed based on experience and available literature.

1.7. Dissertation Layout

The dissertation is presented in different chapters, where each chapter is focusing on a certain research aspect. The layout of the dissertation is as follows:

Chapter 2 discusses the literature review of similar works previously done, where research results of this study are compared with various literature to further confirm the validity of the findings. Furthermore, a different aspect and contributions brought about this research are highlighted in the chapter, which most literature did not take into account during the respective research work conducted.

Chapter 3 entails the methodology used in the study, which details the approach taken for the entire research work. The chapter discusses all the methods, configurations, modelling equations etc. used in the study.

Chapter 4 gives the preliminary research results of the studied solar PV plant; obtained from modelling and simulations. The results include the plant's dependency on solar resources, in order to aid the development of the forecasting techniques.

Chapter 5 looks at forecasting the solar PV plant output power using two methods, fuzzy logic and artificial neural network. The forecasting is aimed at assisting the planners with production forecasting for proper management of the system. The two methods are compared and the obtained results validate both methods and this therefore implies that both methods can be used for forecasting purposes.

Chapter 6 details the reliability analysis of the plant under study, considering two aspects of the plant i.e. solar resource variation and hardware failure. Probabilistic and customer based indices are discussed, as well as how the plant configurations and designs can be optimized to improve the reliability.

The dissertation is then concluded by Chapter 7 which highlights the conclusion of the study and associated findings. The shortfalls on the research work and findings presented in this dissertation is discussed and recommendations for future work are proposed.

CHAPTER 2 - LITERATURE REVIEW

2.1 Introduction

This chapter focuses on the reviewed literature of similar research work conducted and presented in this dissertation. There has been a variety of literature conducted on renewable energy systems, with the focus of this literature review being on solar PV systems and some related literature on hybrid systems which combine solar PV and wind power plants. The dependency of the solar PV plant on the solar resource variations is reviewed from literature and the conclusions made are all the same. This dependency on the solar resource variations necessitates the development of forecasting techniques to allow for power system planning. The available forecasting methods in literature have been reviewed and are discussed in this chapter. The methods of focus in the conducted literature review are fuzzy logic technique and artificial neural network which are utilized in this study. Literature review is also conducted on the reliability evaluation of the solar PV plant which calls for three possible methods that can be used to do the reliability analysis. Simulation methods, analytical methods and hybrid methods are some of the available methods that are utilized mostly in literature and this study makes use of the analytical method [10]. Different reliability indices are considered in literature and these are compared with the indices studied and presented in this dissertation.

2.2 Solar PV Plant

Solar systems are normally interfaced in the low voltage levels of the grid, depending on the size of the plant and the required voltage levels. M.E. Ropp and S Gonzalez developed a MATLAB Simulink model of a single phase grid connected solar PV plant [11]. The developed model took into account the anti-islanding requirements of the inverter, maximum power point tracker (MPPT) and the solar system response to grid fluctuations such as frequency and voltage. The authors compared the experimental results with the modelled results, for the model validation. This dissertation falls short in discussing the grid connection requirements such as the anti-islanding of the inverter which are covered in South African Grid Code and IEC standards. This is due to the objective of the research work being on the forecasting methods and reliability analysis of the plant.

Similar to [11], authors in [6] developed models for the solar PV plant which are used for simulation studies to determine the following:

- Solar PV plant’s performance when environmental conditions fluctuate,
- Ability to track the maximum power point of the plant,

- Importance of the battery system in mitigating the risks posed when there are power oscillations,
- Inverter requirements to enable grid connection of the plant.

A converter between solar PV array and the DC bus or inverter is used by the authors, to fulfil three purposes i.e. to step up the voltage of the solar PV array, to regulate the fluctuating solar PV array voltage caused by varying solar resource and for maximum power point tracking. The conclusions made are similar to other authors in literature [11], [12], [13] i.e. the plant is highly dependent on weather conditions; which is expected because the plant's main resource is affected by weather conditions. Solar PV plant characteristics observed were that at high ambient temperature the solar PV plant output power is reduced and at high insolation, the output power is increased. Furthermore, voltage regulation of the converter due to fluctuating resource is up to a certain level; it does not eliminate the voltage decaying of the plant when there is a drastic decay in the solar resource. The authors gave benefits of making use of the battery energy storage system, which amongst the most include sustaining voltage and frequency when the solar resource varies.

This dissertation omits the use of the DC-DC converter as the solar PV plant is already at a high voltage level that is governed by the maximum inverter input voltage for low voltage applications as per the IEC standards. The exclusion of a variety of components such as the converter, play a role in the improvement of the reliability of the plant as the transformer can perform the stepping up of the plant's voltage, thereby reducing the quantity of components in the plant. The converter omission is also supported by the conclusions made by the authors in [6] that the converter will not have much benefit as it can only boost the voltage up to a certain level, not eliminating the effect of the resource decay on the system voltage. The voltage and frequency can be sustained by the use of the battery energy storage system which is not part of the plant studied in the research work presented in this dissertation; the output voltage of the plant therefore varies as and when there are fluctuations in the input solar resource. This is managed by the forecasting models that are developed to plan ahead when there are predictions of voltage decaying.

2.3 Forecasting Solar Power Generation

This dissertation makes a comparison of two forecasting methods viz. fuzzy logic and artificial neural network, which were developed using data of the solar PV plant under study. Fuzzy logic is first developed, followed by the development of the artificial neural network (ANN), both developed using solar radiation data obtained from the SAWS. Different defuzzification controllers have been assessed to ascertain the most accurate method. Furthermore, triangular and Gaussian membership functions (MFs) were also compared, to distinguish the most accurate MF. The report further presents the results of the optimized fuzzy logic, for both temperature and irradiance varying, using normalized data. The results are then compared to the ANN results and the actual solar PV array output power.

A review of literature related to forecasting output power or input variables of a solar generation plant has been done. Authors in [14] focused on forecasting of the day-ahead hourly solar PV power using ANN, which is similar to the work presented in this dissertation. Authors in [14] and [15] emphasized the use of historical data of the specific solar PV plant as well as that of weather forecasts to properly train the network. This was considered in the development of the ANN model for this study.

Prediction of solar PV system output power on a small scale system has been studied in [16]. An observation made was that the volume of the historical data used in the learning phase has an impact on the accuracy of the ANN. The objective was to develop a PV system performance analyzer (PVSPA); the authors developed a generic model that can produce a projection for any PV system. This has an advantage of employing the same model for any plant without having to retrain the model for a specific plant. However the results from a generic model were the least accurate compared to the Specific model and Generic local model developed by the authors.

Authors in [17] developed an optimized solar prediction algorithm using ANN model with fuzzy logic pre-processing. The authors looked at an error correction factor which is based on the previous five minutes predicted values and used the error as an input such that the forecast error is minimized. A pre-processing toolbox was used to perform real time analysis of climate data such that it is factored in the prediction process. The main objective of the study was to show an improved forecast error by the introduction of fuzzy logic pre-processing, error correction factor and improved back-propagation algorithm. This is desirable as the aim is to always be as close as possible to the actual plant data. Unlike the authors in [17], fuzzy logic and ANN in this dissertation have been developed to be used independently, in a way that both methods can be utilized to do the forecasting as a way of validating the accuracy of the forecasted data.

Sobrina Sobri et al. studied and compared various techniques of solar PV power prediction with regards to characteristics and performance such as forecast method, measurement error, computational time etc. The authors looked at 3 techniques i.e. time series statistical techniques (e.g. ANN method), physical techniques and ensemble techniques. From the metrics assessment it was observed that artificial intelligence techniques minimize the error better than other arithmetic techniques [18].

Luyao Liu et al. and authors in [19] looked at a 2 stage model to measure the prediction intervals of solar output power. The results indicated that the 2 stage method outperforms the conventional prediction techniques with regards to forecasting of short term solar PV output power. Appreciating the variation intervals of the solar PV plant assists in the effective operation of the integrated energy system (IES), as the plant can be adjusted accordingly to satisfy the system demand [20],[19]. Authors in [19] developed a day ahead and 1 hour ahead average solar PV output power prediction model using extreme learning machine (ELM) approach which is a new training process for single hidden layer feedforward neural networks (SLFNs). The performance with regards to accuracy has been compared with other common forecasting techniques such as support vector regression (SVR) and feed forward ANN. The outcome of the comparison indicated that ELM provides improved accuracy and reduced computational time in predicting solar PV output power. M. Hossain et al. concluded that the network accuracy reduces with shorter duration/period considerations, as the accuracy is improved in a day ahead forecasting and reduced in an hourly ahead forecasting [19].

E.R. Muhammad et al. estimated the profile of a day ahead output power of a grid connected solar PV plant rated at 20 kW_p [14]. The authors used artificial neural network for the study, employing a two-layer feed-forward network which has been trained with Levenberg-Marquardt algorithm. The authors used the data for 35 days, which was normalized using the maximum output power of the considered days. The network's best performance was decided based on the values of Mean Squared Error (MSE) i.e. average squared difference between network output and target value. The performance was also measured against the Regression (R), which is the correlation between the network output and target value. The authors further assessed the network's performance based on computational time for the computer that was used for the ANN development which was found to be 2 minutes. The same authors published a similar research paper which focused on developing a network that could also be used for large scale plants, however it requires training using the specific plant's historical data for an improved accuracy [14], [16]. MSE was obtained to be between 0.019 and 0.025 for the day-ahead forecasting, which is fairly accurate.

The work done by the authors in [14] had a similar objective as the work presented in this dissertation which is to forecast the solar PV plant output power. The study in this dissertation makes use of the feed-forward network trained using the same algorithm used by these authors. The network performance presented in this dissertation is evaluated based on the MSE and regression, however the computational time was not looked at; this can form part of the future work for the optimization of the network results.

Authors in [21] used solar irradiation, ambient temperature and wind speed as inputs to the network to predict the maximum power of a PV module. The output power of a PV module also depends on the cell temperature which in turn depends on the ambient temperature and wind speed (as it cools down the solar PV modules). For the following day's planning, the predicted environmental conditions from weather services is required. The authors concluded that only two days data is required in the training of their proposed network. The network can be used to forecast the next day's output power using the weather forecast data for the day. Literature has indicated that it is vital to note that the more historical data available for training the network the more accurate the plant will be, however there needs to be a balance between computational time and the required accuracy.

Authors in [22] forecasted solar radiation at different weather conditions, using fuzzy logic and ANN. The solar radiation is affected by sky condition, temperature and time information. The sky condition checked if it is cloudy, sunny or rainy. The authors made use of the feed-forward network and a backpropagation learning method. They measured the performance of the network using Mean Absolute Percentage Error (MAPE) which shows the error between the actual radiation and a forecasted one. The work presented by the authors is different from the one presented in this dissertation, however the methodology is the same.

Fathia Chekired et al. developed an energy management system based on fuzzy logic of a solar PV powered home. The focus was to prioritize the loads to be supplied from the plant and be able to charge the batteries with excess power or feed surplus energy into the grid with the aim of reducing the energy consumption. The system monitored 3 parameters as input data i.e. solar PV plant power, load power demand and battery state of charge. The decision from these was therefore to prioritize the loads accordingly, the priority is to supply essential loads; when the battery is discharged, the priority is to charge it and switch off all non-essential loads. The authors made use of the Mamdani FLC method [23]. The work presented by the authors has a similar concept to the study conducted in the development and use of the fuzzy logic techniques.

From the considered literature, the observation made is that there is not much usage of fuzzy logic system as the solar PV power forecasting technique. Majority of authors make use of the ANN techniques. This dissertation therefore presents a more detailed approach of developing a fuzzy logic based forecasting technique for the solar PV plant. The method includes investigating a more accurate fuzzy inference system to be employed in the system for better results.

Authors in [24] employed ANN and Adaptive Neuro-Fuzzy Inference System (ANFIS) methods to forecast the output power from the solar PV plant. The ANN produced better results compared to ANFIS which was measured using Normalized Root Mean Square Error (NRMSE). From the reviewed literature, the use of ANN in the prediction of solar PV plant output is popular. This dissertation also makes use of this method and further compares the results with the fuzzy logic method. The comparison of the two methods is based on the percentage error obtained.

2.4 Reliability Evaluation

Authors in [25] evaluated the reliability performance of a grid connected solar PV plant. They considered the variations in input power to components and component failure rates which are based on ambient conditions. The authors considered each component failure rate e.g. for an inverter, IGBTs, diodes and capacitors were assessed. The emphasis on the consideration of the inverter configuration was made i.e. there are no parallel components, as failure of one component can result into a system failure; the inverter was then evaluated as a series system. Peng Zhang et al. further looked into the solar PV array reliability, making use of binomial distribution method to compute the probabilities of PV strings states (i.e. working state and out of service state. The binomial distribution method has been employed in this study for the reliability indices of the plant, as detailed in Chapter 6.

Energy and time oriented indices were looked at, which include Ideal Output Energy (IOE), Expected Output Energy (EOE), energy availability, time availability; de-rated, available and outage hours. The authors concluded that the reliability of a solar PV plant is reduced with the rise in temperature. This is supported in this dissertation as the failure rates of components are dependent on the environmental stress factor which incorporates temperature. Insolation rise which implies higher input power to the inverter, negatively affects the inverter reliability as this may increase the temperature of components. Solar PV plant degradation and aging failures need to be taken into consideration when doing the reliability evaluation; these two conditions cause decays in solar PV plant output power over the years, as depicted in Figure 2-1, where A_e represents energy availability and A_t being the time availability [25].

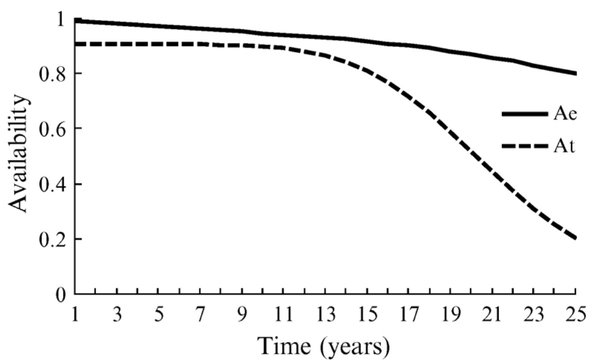

Figure 2-1: System reliability considering PV modules degradation and aging failures [25]

The availability and hence reliability of the plant can be improved over the years by conducting necessary maintenance, repairs, replacement etc. of critical components that are major contributors to the plant's availability.

The authors in [26] analyzed the system reliability of the off grid hybrid solar PV and wind power system using the probabilistic approach. They evaluated different indices such as LOLE, EENS, Energy Index of Reliability (EIR) and Expected Customer Interruption Cost (ECOST). The primary supply is the wind power plant and the secondary supply is the solar PV plant. The authors highlighted that the main advantage of using the analytical method of reliability evaluation is the reduced computational time compared to other methods such as Monte Carlo Simulations. This finding is, however, contradicting with the conclusions made in [10] where the authors conducted a review on the reliability evaluations that have been conducted in literature. They compared a simulation method, analytical method and a hybrid method; with the simulation method being the most preferred due to its fast computational time and random sampling of states.

The authors discovered that the seasonal reliability evaluation is more complex as compared to the hourly evaluation; and prediction of power is impossible when employing seasonal variations. Solar resource data used by the authors was assumed, due to the unavailability of the actual data, for the purpose of the reliability evaluation. The results indicated that the reliability is high in spring and low in autumn. The presence of the capacity storage system improves the reliability of the hybrid system. More energy sources that are added into the system improve the reliability of the plant. The same authors in [27] had an observation that the additional energy sources have a nonlinear relationship with the reliability, implying that the reliability will saturate at some point, regardless of the added energy sources; where other alternatives need to be explored for the reliability improvements. Similar to authors in [25] Nabina Pradhan and Nava Raj Karki concluded that the reliability decreases over the years due to various factors such as ageing of components [26].

M. Padma Lalitha et al. evaluated the reliability of wind power system and solar PV plant, considering component failure rates and the intermittency of energy resources. The authors made use of 50 solar PV arrays which make up a 30 MW solar PV plant. Both wind power system and solar PV plants were added to the Roy Billinton Test System (RBTS) which consists of 240 MW generated power and a load of 185 MW. LOLP and LOLE were obtained from the analysis. The authors made use of Markov models for the reliability which have reduced computation time and is comprehensive in the evaluation process. The reliability of the system with added wind farm is high, compared to a base RBTS; and the solar PV plant addition is even greater than the addition of wind farm with the same power rating, as seen from the obtained LOLP and LOLE indices [28].

Authors in [29] evaluated reliability of a stand-alone solar PV plant with and without battery storage and authors in [30], [31] evaluated the grid connected plant, all using Monte Carlo technique, which simulates the random behavior of components. LOLP index was evaluated, considering hardware failure of PV modules and solar irradiance variation [29]. The plant's reliability when considering solar irradiance variation is found to be less than when considering both resource variation and hardware failure. For a more accurate approach it is therefore necessary to consider hardware failures [29], [32]. The authors highlighted that the assumption of solar PV modules being 100 % reliable may give inaccurate results as this assumption is unrealistic. This dissertation excludes the solar PV modules in the reliability analysis as they are considered to be highly reliable with mean time before failure (MTBF) of 522 and 6666 years [33]. However, the PV array reliability is incorporated in the overall plant reliability when considering the fuses which interconnect the PV strings.

Authors in [34] developed the reliability and sensitivity analysis of a solar PV system. The reliability analysis focused on the components and various configuration of the solar PV system, using logic gate representation which is also employed in this dissertation. The authors made reference to the military handbook for the component failure rates, similar to this dissertation's approach. The sensitivity analysis focused on the variation of temperature and irradiation while observing the open circuit voltage and short circuit current of the solar PV cell. The findings align with the literature discussed in Section 2.2 and with the findings of this study which were obtained from MATLAB simulations. The authors further conducted the sensitivity analysis on the most contributors of component failure rates, with the aim of reducing the critical stress factors and ultimately improving the failure rates which therefore improves reliability. Three configurations were considered to check the most beneficial configuration i.e. off-grid, off-grid with battery and grid connected with battery. The obtained results show that the off-grid configuration has a low reliability and the grid connected with battery configuration has the highest reliability; which is due to the parallel configuration of two energy sources. The authors did not consider the fluctuations of the solar resource in the study, which also play a role in the overall reliability analysis of the plant.

Amir Ahadi et al. used a probabilistic approach in evaluating reliability, based on the varying solar resource [35]. LOLE and EENS were the evaluated indices. The renewable energy penetration improves the reliability of the system, however the reliability is noticeably improved with the addition of conventional energy sources with the same ratings, due to the renewable energy sources having intermittent resources.

This study makes use of analytical methods to evaluate the reliability of the plant under study. Similar to literature reviewed, the assessment takes into account the solar resource variation and component failures. With most of the literature considering probabilistic indices, the study brings in the aspect of customer based indices which are influenced by both failure of components and weather variations. The indices evaluated and presented in this dissertation are therefore probabilistic and customer based indices which includes indices such as LOLE, EENS, SAIFI, SAIDI, ASAI etc., as discussed in Chapter 6.

2.5 Conclusion

Reviewed literature on the solar PV plant development, forecasting methods and reliability evaluation of a solar PV plant all had similar considerations and conclusions. There are some contradictions between the findings, such as some authors concluding that the reliability of the PV modules is high and negligible, while other authors recommend consideration of the modules as well, which can improve the analysis results. This study assumed that the PV modules are highly reliable, based on literature and were therefore not considered in the reliability analysis. However, the inclusion of the modules can form part of the future work, to analyze how much the results are influenced by the modules' failure rates.

ANN is the mostly used forecasting method in the reviewed literature compared to fuzzy logic system. This dissertation presents a detailed development of the fuzzy logic system which can be used to develop a fuzzy logic system for other related plants. In addition to the ability to do the prediction of the plant's performance for system planning purposes, the study aims to optimize the renewable energy sector by assessing the solar PV plant performance and selecting the most optimum configuration of the plant during the planning/design phase, which would yield better reliability. This would also have a cost benefit in a way that customers or connected plant process are not highly experiencing power outages.

CHAPTER 3 - METHODOLOGY

3.1 Introduction

The solar PV plant studied is modelled and simulated using MATLAB Simulink. The simulation of the plant first made use of the input solar irradiance data as received from South African Weather Service (SAWS) with the assumed temperature of 25 ºC, due to the lack of temperature readings received; to validate the accuracy of the model. The plant was then subjected to a fixed solar irradiance while varying the temperature, to study the temperature effect on the plant. Similarly the temperature was fixed while varying the solar irradiance and the plant's behavior was observed.

The research further normalized the variables i.e. input (solar irradiance and temperature) and output (power), for the purpose of studying the forecasting techniques, such that the technique is easy to understand and can be utilized for any other plant. Two forecasting methods were studied and compared; which were also developed using MATLAB and reliability evaluation for the plant has been mathematically computed. The reliability evaluation of the plant considers two aspects of the plant i.e. failure of components and intermittency of the solar resource. Different indices reflecting the performance, availability and reliability of the plant are looked at.

3.2 Solar PV Plant

The system under study is a grid connected solar PV plant, modelled and simulated on MATLAB Simulink. The plant is designed such that the desired output power of 30 MW is obtained. Solar PV panels used for the study are monocrystalline silicon which are fairly more efficient compared to polycrystalline and thin-film modules, as indicated in Chapter 1 [7]. The data for a monocrystalline silicon module is therefore used for simulation purposes.

For a successful modelling and simulation of the plant, expressions representing solar PV cell configuration and behavior need to be obtained. An equivalent circuit of an ideal solar PV cell is therefore shown in Figure 3-1, which has components of shunt and series resistances; and a bypass diode. The expressions defining the I-V characteristics of the solar PV cell are derived from this equivalent circuit as depicted by Equation (3.1) to (3.10).

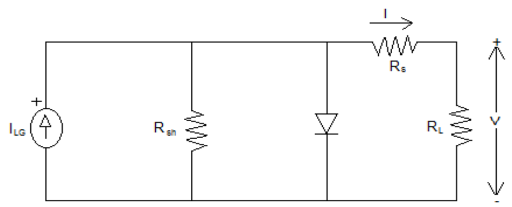

Figure 3-1: Ideal PV cell equivalent circuit

$$I = I_{LG} - I_D - I_{R_{sh}} \tag{3.1}$$

The bypass diode current characteristic and the current across the shunt resistance component are then substituted in Equation (3.1) to yield Equation (3.2).

$$I = I_{LG} - I_{os}\{\exp[\frac{q}{AkT}(V + R_s I)] - 1\} - \frac{V+R_s I}{R_{sh}} \tag{3.2}$$

Due to the complexity of obtaining the parameters related to the cell's temperature and radiation intensity, most parameters are available in a PV module's datasheets. The following equations define other unknown parameters, which are further defined in Appendix A, Table A1. The assumption $I_{SC} \approx I_{pv}$ is generally used in the modelling of PV arrays. Equation (3.3) shows the bypass diode saturation current which strongly depends on temperature. The bypass diode is used across each cell to avoid hot-spots in solar PV modules [12]. Photon current and PV cell output current are given in Equation (3.4) and (3.5), respectively.

$$I_{os} = I_{or}\left[\frac{T}{T_r}\right]^3 \exp\left[\frac{qE_{GO}}{Bk}(\frac{1}{T_r} - \frac{1}{T})\right] \tag{3.3}$$

$$I_{LG} = [I_{SCR} + K_I(T - 298)]\frac{S}{1000} \tag{3.4}$$

$$I = I_{SC}\{1 - C_1\left[exp\left(\frac{V}{C_2 V_{OC}}\right) - 1\right]\} \tag{3.5}$$

At the maximum power point, when V = V_m, I = I_m, Equation (3.5) is therefore expressed as:

$$I_m = I_{SC}\{1 - C_1\left[exp\left(\frac{V_m}{C_2 V_{OC}}\right) - 1\right]\} \tag{3.6}$$

Under normal temperature,

$$exp\left(\frac{V_m}{C_2 V_{OC}}\right) \gg 1$$

Therefore,

$$I_m = I_{SC}\left\{1 - C_1\left[exp\left(\frac{V_m}{C_2 V_{OC}}\right)\right]\right\} \tag{3.7}$$

$$C_1 = (1 - \frac{I_m}{I_{SC}})exp\left(\frac{-V_m}{C_2 V_{OC}}\right) \tag{3.8}$$

Substituting Equation (3.8) to (3.6) yields Equation (3.9).

$$0 = I_{SC}\{1 - (1 - \frac{I_m}{I_{SC}})exp\left(\frac{-V_m}{C_2 V_{OC}}\right)\left[exp\left(\frac{1}{C_2}\right) - 1\right]\} \tag{3.9}$$

Under normal temperature,

$$exp\left(\frac{1}{C_2}\right) \gg 1$$

$$C_2 = (\frac{V_m}{V_{OC}} - 1)/ln(1 - \frac{I_m}{I_{SC}}) \tag{3.10}$$

The aforementioned expressions show relationships of different parameters which make it possible to obtain the output power from the solar PV cell. These expressions are therefore used to model and simulate the solar PV plant. One solar PV module is first simulated, followed by a string of series connected modules and an array of parallel connected strings to yield an increased output. These were simulated under standard testing conditions (STC) i.e. cell temperature of 25 ºC and irradiance level of 1000 W/m^2 for the model validation.

The results of the 30 MW solar PV plant under study are detailed in Chapter 4; the configuration of the plant (e.g. quantity of modules in a string) took into account the fact that the plant should have as little components/systems as possible while minimising the risk of having a single point of failure. The plant is grid connected which requires an inverter and a transformer to achieve the grid connection. The study does not focus on the detail design of these systems and the associated auxiliary components; however, these systems are considered in the reliability evaluation, making use of the generic component data which is specific to the plant studied. The inverter is however simulated using MATLAB Simulink at a high level and is discussed in Chapter 4.

3.3 Forecasting

The simulated solar PV plant is then used in the study of forecasting techniques that can be employed in predicting the plant's behaviour under varying solar resource. Prediction techniques include forecasting what the output power of the plant would be at a particular solar irradiance and temperature. This is aimed at forecasting how long the plant would substitute conventional generators during outages.

Fuzzy logic and artificial neural network in MATLAB tool are used as the two forecasting techniques for the solar PV plant output power. These two techniques are widely used in the forecasting field and are fairly understandable and they yield accurate results if developed correctly. These methods only took account of one array which is rated at 1.61 MW, however, they can also be developed for a bigger plant. During the development of these forecasting techniques, the available solar plant data was normalised using the 1000 W/m^2 as the base and 30 ºC as the base for the temperature values. These bases were informed by the available data, i.e. the average highest irradiance and temperature. A comparison of the results from the two methods is done and it considers the percentage error between the desired results and the data used to develop the models.

3.3.1 Fuzzy Logic Method

Load and energy production forecasting has always been crucial for the effectiveness of power system planning and operation. Advanced forecasting techniques provide utilities with reliable production predictions and the opportunity to plan for additional power supply and conduct appropriate preventive maintenance strategies. The system under study is a grid connected PV plant, where variations in solar power can cause undesired voltage and frequency fluctuations in the network. Prediction of solar power is therefore of importance for efficient load management and operation of the system [4].

The fuzzy logic based load forecasting has an advantage of dealing with the nonlinear parts of the forecasted load curves and can deal with the abrupt change in the weather variables such as temperature and irradiance [36]. The data acquired from the solar PV plant simulations was used in the fuzzy logic system to yield the approximated PV plant output values. Figure 3-2 depicts a high-level block diagram which indicates how a fuzzy logic based load forecasting system interfaces with the entire solar PV plant.

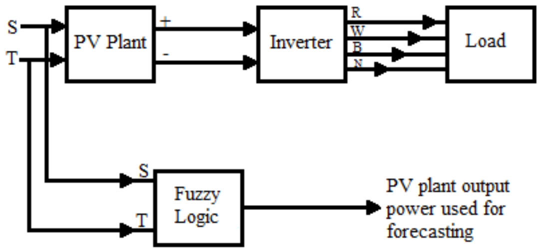

Figure 3-2: Block diagram for the integrated plant with fuzzy logic system

The inputs to solar PV plant block and fuzzy logic block are irradiance (S) and temperature (T), as shown in Figure 3-2. The output of the fuzzy logic block will be the input to the forecasting process for operation and planning. The PV plant DC output is the input to the inverter system which converts DC power to AC power for grid connection. The inverter is a 3-phase system that outputs 3 phases and neutral (R, W, B, N) which is then used by connected loads, via a step up transformer. This technique is developed using MATLAB and is detailed in Chapter 4 of this dissertation.

3.3.2 Artificial Neural Network

The use of artificial intelligence techniques to predict complex and uncertain models has gained popularity due to their ability to work on complex and nonlinear systems [3]. ANNs are based on the operation of biological neural networks and supposedly possess the ability of a human-like learning process. The ANN structure consists of an input layer (which receives data), a hidden layer (processing the information between input and output layers) and an output layer (which sends computed information). Each layer consists of neurons that process the input signals and produce an output while connections between layers have a weight factor as depicted in Figure 3-3 [37].

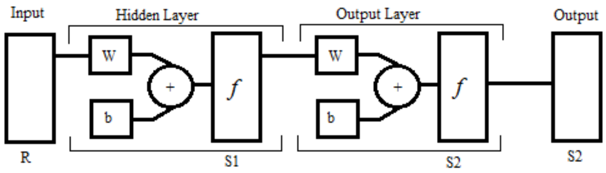

Figure 3-3: ANN structure

All or a fraction of neurons in a layer are connected with all or a part of neurons of the previous and the next layer through the adaptable synaptic weights according to the chosen architecture. The number of hidden layers and the total number of neurons of each layer depend on the specific model, convergence speed, generalization capability, the physical process and the training data that the network will simulate [3]. The relationship of each layer to the previous or next layer is given by Equation (3.11).

$$a = f(W + b) \tag{3.11}$$

Where: a – output vector of hidden layer

f – transfer function in a layer

W – weight matrix

b – bias vector

The input layer consists of input data the network needs to use in the learning process; this data includes target data that the network needs to mimic. For optimum results the weights are adjusted during the training process; Figure 3-4 depicts this phenomenon.

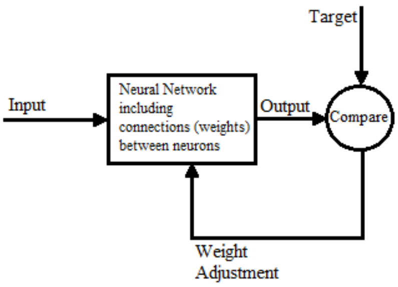

Figure 3-4: ANN training process overview

Input and target vectors used in the network are randomly divided into three sets:

- 60% used for training.
- 20% to validate that the network is generalizing and to stop training before overfitting or to halt training when generalization stops improving.
- 20% used as a completely independent test of network generalization. This has no effect on training and so provide an independent measure of network performance during and after training.

These sets can be adjusted to suit each application. Mean squared error (MSE) is calculated during the training process; this is the average squared difference between outputs and targets. Lower values are better and zero means no error, which is desirable for an optimum performance of the network. Regression (R) values are also observed which measure the correlation between outputs and targets. A regression value of 1 means a close relationship and 0 means a random relationship which is not desired.

There is a strong relationship between the forecasting process and the reliability of the plant. The forecasted output takes into account the varying solar resource, the failure of components is taken care of in the reliability evaluation study of the plant. The system planning process should therefore consider the plant's reliability to get a clear picture on the probability of the plant's availability.

3.4 Reliability

The study further evaluates the reliability of the 30 MW solar PV plant studied. Two different approaches of reliability evaluation have been looked at, one looks at the probabilistic reliability indices and one considers customer based indices. The two approaches are related in a way that the customer based indices are impacted by the probabilistic indices, for example, customer interruptions will either be experienced due to failure of components or due to unavailability of solar resource, as a minimum.

Reliability is defined as the probability of the system performing its intended use for a defined duration. The reliability evaluation techniques in literature can be categorized in analytical techniques and simulation techniques. Analytical methods represent the system with mathematical equations and evaluate the reliability indices through numerical solutions. On the other hand, simulation methods estimate the reliability indices by simulating the actual plant and random behavior of the plant [29]. This study only considers the analytical method of analyzing the reliability; in a form of reliability block diagrams (RBD) and logic gate diagrams.

The plant under consideration has been represented as per the configuration in Figure 3-5. Fuse switches for protection and isolation have been fitted for every 40 PV strings and each PV array is fitted with the DC circuit breaker which then feeds to an inverter; implying that each PV array has one DC circuit breaker and an inverter with a filter. The AC output of each PV array's inverter is then connected to the AC circuit breaker which feeds to the transformer via a junction box. The overall plant has a single transformer which is used for grid connection. All these components constituting the overall plant are analyzed in terms of their reliability.

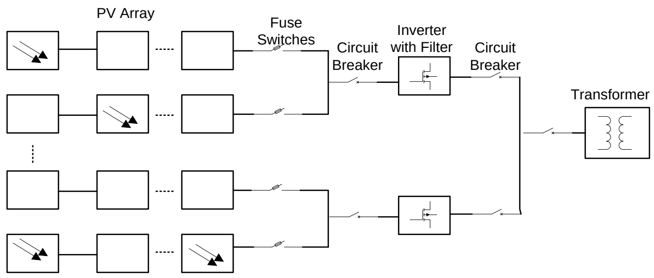

Figure 3-5: 30 MW Solar PV Plant Overview

3.4.1 Reliability Analysis Methods

Reliability block diagrams (RBD) technique is one of the widely used techniques in reliability evaluation. This technique involves developing a reliability block diagram which is success oriented, showing the logical connections of components which are required to satisfy the intended function of the system [38], [39]. Logic gate representation of the system is also used for the analysis of the plant's reliability. The RBD has been derived from Figure 3-5 and is depicted in Figure 3-6. The components/system configuration can be viewed as being all series connected, taking into account the intended objective of the plant i.e. to achieve the full rated output. All the components are required to achieve the overall plant's full output rating or capability.

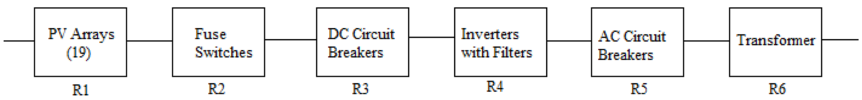

Figure 3-6: Reliability Block Diagram for a 30 MW solar PV plant

The RBD also shows the logical connection of components needed to fulfil a specified system function; this is depicted in Figure 3-7, where the components required to perform a function are put in series in a form of an AND gate and the redundant components are put in parallel [34]. In this case there are no redundant components, all components/ systems are seen as series connected. If the failure of a component fails the system, it should be modelled with the series blocks which is what has been represented.

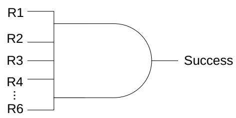

Figure 3-7: Logic diagram for a grid connected 30 MW solar PV plant

The RBD and logic gate representation assist in realizing the correct formulas to use to compute the reliability of the overall plant for a correct evaluation of the system. The series components and parallel components use different formulas to compute the reliability and these are discussed in Chapter 6, Section 6.2.3.

The study first looks at the hardware reliability i.e. it considers the failure rates and repair rates of the components and sub systems that make up the 30 MW plant under study as discussed. The reliability evaluation is studied considering different configurations (e.g. such that there is a reduced quantity of components), as a way to optimise the reliability; as the objective is to have the reliability as close as possible to unity. The study further looks at the varying solar resource; this is also related to the forecasting of the solar plant's output power as the anticipated solar output power should take into account the probability of the deterioration of the solar resource.

SAIFI, SAIDI, LOLE, LOEE etc. are the reliability indices evaluated when using the customer based indices approach, for the plant studied. For the reliability evaluation purposes, the plant has been further sectioned to three solar PV plants, rated at 13 MW, 17 MW and 10 MW. This was for the purpose of studying and computing the reliability indices.

3.5 Conclusion

Expressions used for modelling the solar PV plant have been studied and discussed. These expressions were used for a single PV module, strings, arrays and the overall 30 MW plant. A solar PV plant is modelled with the aim of studying its behaviour under different solar resource conditions, to further develop techniques for forecasting its output power under varying solar resource conditions. The forecasting techniques developed are fuzzy logic and ANN which are then compared to each other for the validity of the two techniques and the accuracy of these techniques. The forecasting capability of the system is heavily related to the reliability of the plant as the forecasted power should take into account the plant's actual reliability. This then gives a clear indication on how long a solar PV plant can support the system demands on a daily basis. The reliability of the plant is evaluated and discussed in depth in Chapter 6. The methodology used in the study is the reliability block diagram and logic gate diagrams which were used to determine the correct expressions to use to compute the reliability of the plant. Different reliability indices are also evaluated with possible ways to improve the plant's reliability which will also improve these indices.

CHAPTER 4 – SOLAR PV PLANT SIMULATIONS

4.1 Introduction

This chapter entails preliminary research results of the system under study. As indicated in Chapter 3, MATLAB Simulink is used to model the solar photovoltaic (PV) plant and to simulate the I-V and P-V characteristics under different solar conditions. This chapter further focuses on the study of solar PV plant behaviour when varying both solar irradiance and temperature. A solar module, string and array results are presented in this chapter, with the behaviour studied when the input resources are varied. The chapter further discusses the inverter used for DC-AC conversion for the purpose of grid connection of the plant.

4.2 System under study

The equations detailed in Chapter 3, Section 3.2 were employed in developing the solar PV model, looking into the solar PV module, string and array. The input to the models is the data as obtained from the SAWS for the Upington area.

4.2.1 Preliminary results

A single PV module that was employed in [12] was modelled and simulated using MATLAB Simulink. The objective was to initially compare the obtained results with those of [12] to prove the credibility of the model before adopting it to the system under study. The PV module used for this purpose is rated as shown in Table 4-1; and was modelled under STC. Figure 4-1 and 4-2 show the simulation results obtained for this PV module.

Table 4-1: Parameters of a PV module employed in [12]

Parameter	**Symbol**	**Value**
Voltage at maximum power	V_m	35.20 V
Current at maximum power	I_m	4.95 A
Open circuit voltage	V_{oc}	44.20 V
Short circuit voltage	I_{sc}	5.20 A

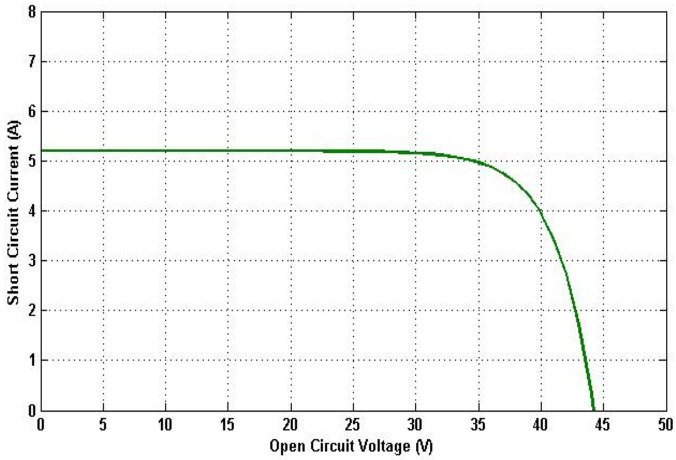

Figure 4-1: I-V characteristics of a single PV module [12]

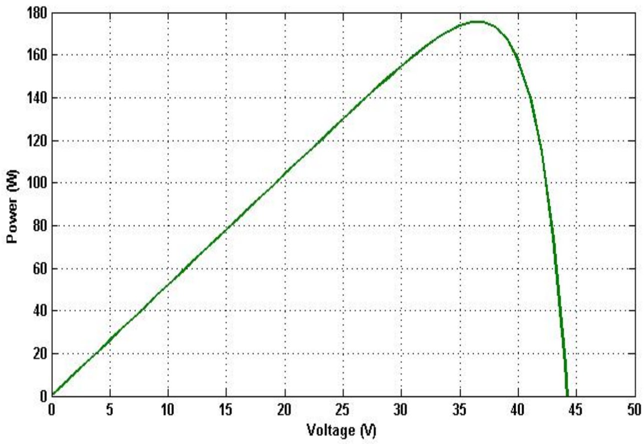

Figure 4-2: P-V Characteristics of a single PV module [12]

Figure 4-1 and 4-2 depict the characteristics of the PV module as per the expected results. The graphs show an open circuit voltage of 44.2 V DC i.e. with no load connected to the module; and a voltage of 35.2 V DC at maximum power of 174.24 W. The current at maximum power can be observed from Figure 4-1 to be 4.95 A as per the PV module data. The obtained results imply that the model can be adopted to simulate the 30 MW plant under study.

4.2.2 Solar cell characteristics

For a 30 MW solar power plant under study, the employed PV module is a Sunmodule make and its data is given in Table 4-2 [40]. A single module was first simulated, followed by a series connected modules called strings and parallel connected strings called arrays. Only 1 out of 19 PV arrays is modelled in this chapter, which consists of 40 series connected cells and 161 parallel strings.

Table 4-2: 30 MW solar power plant parameters [40]

Parameter	Specification
PV panels total output power	30 MW
System voltage	1500 V DC
PV Module	
Cell type	Monocrystalline silicon
Open circuit voltage	37.8 V
Short Circuit current	8.28 A
Maximum power point voltage	31.1 V
Maximum power point current	8.05 A
Module efficiency	15.7%
Maximum power rating	250 W
TC I_{sc} (A)	0.004 %/K
TC V_{oc} (B)	-0.30 %/K
TC P_{mpp}	-0.45%/K
Operating temperature	-40 ºC to 85 ºC

Figure 4-3 and 4-4 show simulation results for a single PV module employed in a 30 MW solar power plant. The results demonstrate the characteristics of the module, which indicate short circuit current, open circuit voltage and maximum output power. A short circuit current is obtained when the voltage is 0 V i.e. when module terminals are short circuited and the open circuit voltage is obtained from the module terminals at no load. The useful current and voltage (i.e. when there is load connected) yield maximum power that can be produced by the module.

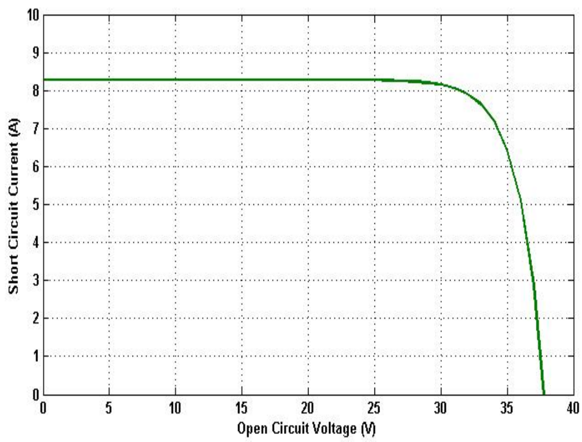

Figure 4-3: I-V characteristics of a single PV module for a 30 MW plant under study

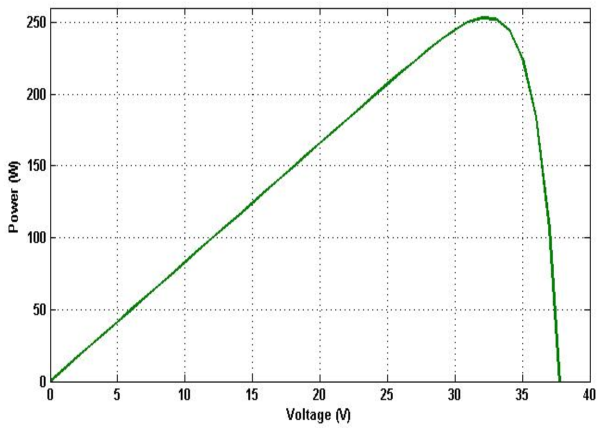

Figure 4-4: P-V characteristic of a single PV module for a 30 MW plant under study

The type of module used in the study has an advantage of producing higher maximum power compared to that employed in [12], which means fewer modules can be used to obtain the same required power. The string and array were then modelled and simulation results are outlined in Section 4.2.3 and 4.2.4, respectively.

4.2.3 Solar PV string characteristics

To expand on the model conducted for a single module, a simulation of series connected cells to yield higher voltage was conducted. The assumption made is that all modules are identical, which in practice is not the case. Certain parameters may vary due to the manufacturing process of each individual module. Furthermore, different operating conditions may exist in different parts of the entire plant e.g. cleanliness, shading effect on some modules etc. [41]. The string and array model assumes that the modules used are identical. To obtain an increased desired output voltage of the plant, 40 PV modules were connected in series. This configuration keeps the system current the same as that of a single PV module and only increases the voltage to 1500 V DC. Figure 4-5 and 4-6 was obtained with 40 modules connected in series.

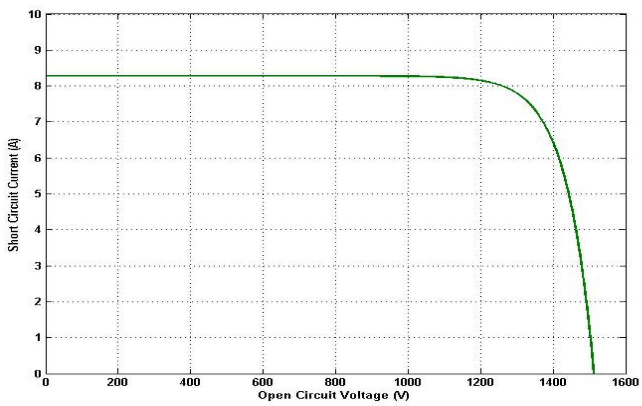

Figure 4-5: I-V characteristics of a single string at 1500 V DC

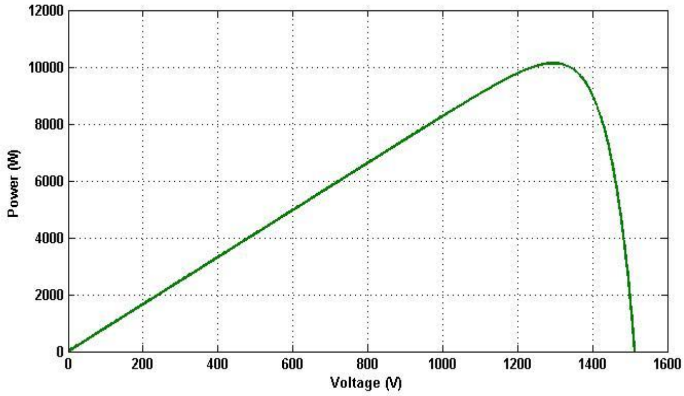

Figure 4-6: P-V characteristics of a single string at 1500 V DC

The short circuit current can be observed to have remained unchanged with the series connection of modules, while the open circuit voltage increased to 1500 V DC. The maximum output power shown in Figure 4-6 is 10.014 kW as per the expected string power; with maximum power point voltage of 1244 V DC and maximum power point current of 8.05 A. The obtained results prove that with the series connection of PV modules, power will slightly increase because of an increased system voltage. However; to get a higher increase in power, both current and voltage must increase. The extent to which the system voltage was increased to, took into consideration the inverter input voltage which was guided by the requirements of the IEC standards. The IEC standards specify a maximum DC voltage of 1500 V for low voltage systems [42].

4.2.4 PV array characteristics

For increased system output current, the strings were then connected in parallel which keeps the voltage at 1500 V DC and increases the short circuit current to 1333 A. The model was updated to include 40 series connected cells and 161 parallel connected strings, the obtained results are shown in Figure 4-7 and 4-8.

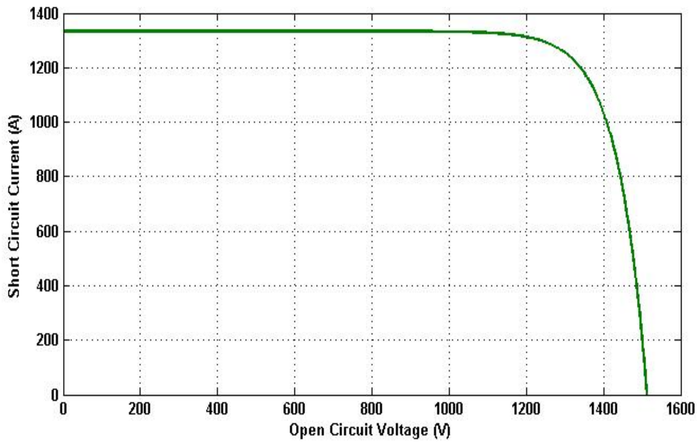

Figure 4-7: I-V characteristics of 1 array at 1333 A and 1500 V DC

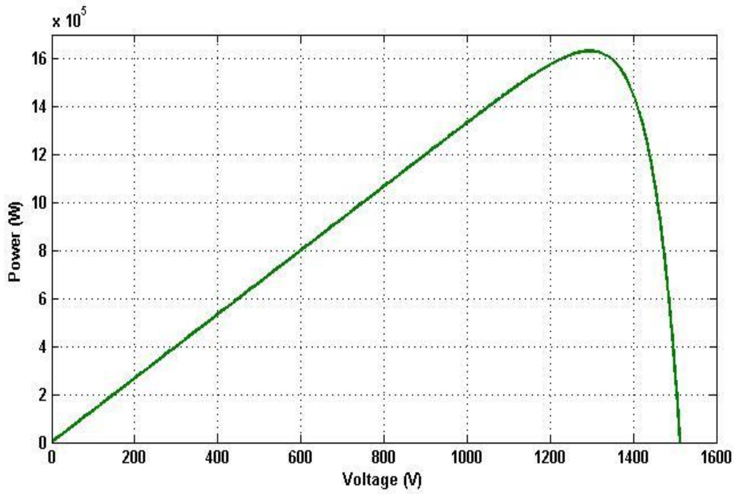

Figure 4-8: P-V characteristics of 1 array at 1333 A and 1500 V DC

With both current and voltage increased, the maximum power that can be produced by one array is 1.612 MW as depicted in Figure 4-8. To obtain this maximum power, the maximum current of a single array is 1296 A and maximum voltage is 1244 V DC. For a complete plant model, 19 PV arrays are used to obtain 30.6 MW output power. The plant modelled in this chapter will then be used to evaluate its reliability, when subjected to different conditions and the forecasting techniques will be developed to forecast the plant's output power under varying input sources.

4.3. Discussion of Solar PV Plant Results

4.3.1. Temperature Dependence

In an array model, temperature was varied between 15-55 ºC in steps of 10 ºC, while keeping irradiance constant at 1000 W/m^2. This was aimed at studying the behavior of a solar PV plant under varying temperature conditions. Figure 4-9 depicts the obtained P-V characteristics.

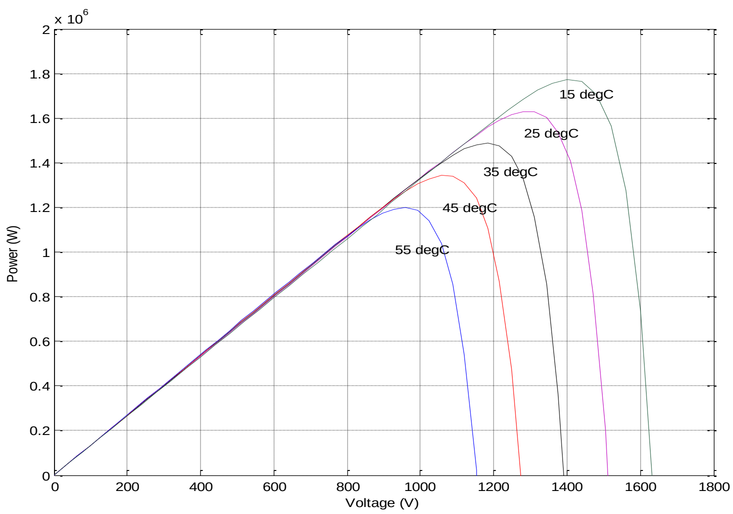

Figure 4-9: P-V characteristics at varying temperature

When the ambient temperature is varied, it can be observed that as the temperature rises, the open circuit voltage is reduced thereby reducing the output power. This is due to the temperature coefficients of the modules that impact on the modules output power when the temperature is varied.

4.3.2. Irradiance Dependence

Varying irradiance while keeping the temperature constant at 25 ºC was observed and results are depicted in Fig. 4-10. The results prove that the solar PV plant is highly dependent on the irradiance. The plant produces less power at low irradiance levels and it increases as irradiance levels are raised.

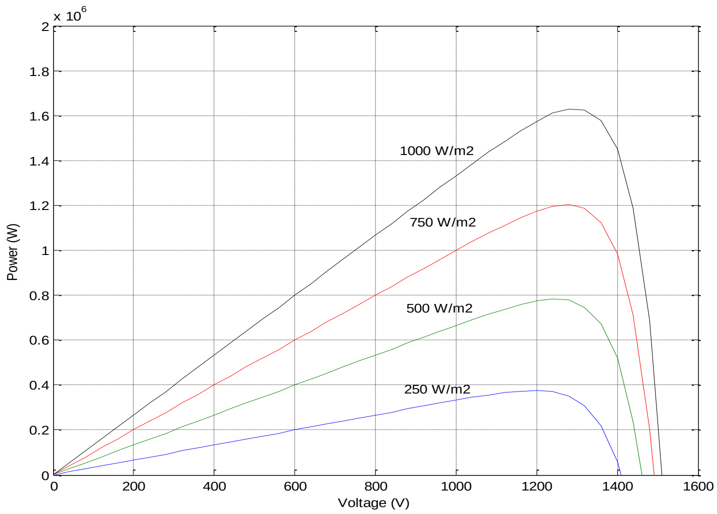

Figure 4-10: P-V characteristics at varying solar irradiance

4.3.3. Solar PV performance in Upington Area

Upington real data as obtained from the South African Weather Service was used for simulations to compare monthly data of the area, for the purpose of evaluating the plant's reliability. Upington data obtained was limited to solar irradiance; therefore temperature was kept at 25 ºC, for the purpose of this study. Figure 4-11 highlights the performance of the plant under different seasons, showing power obtained from the plant in different months. With daily average irradiance levels per month for the area varying from 629.27 W/m^2 in December to 304.39 W/m^2 in June, it can be observed that the plant performs better during summer seasons and decays during winter seasons.

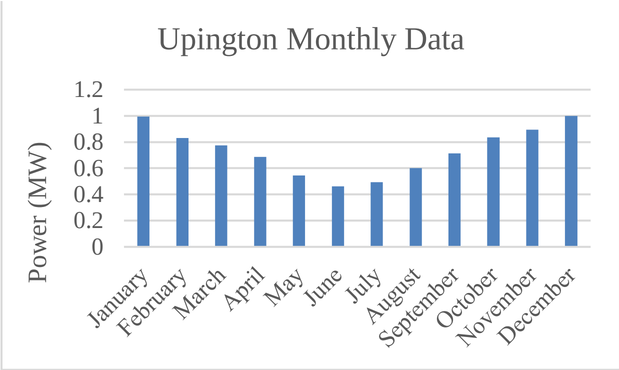

Figure 4-11: Solar PV plant monthly performance for Upington area

The plant performance shown in Fig. 4-11 is also tabulated in Table 4-3, showing the actual obtained maximum power per month.

Table 4-3: Output power obtained for solar PV plant in Upington area

Month	**Daily Irradiance Average (W/m^2)**	**Power (MW)**
January	627.425	0.996
February	528.415	0.831
March	494.535	0.775
April	442.373	0.688
May	354.587	0.544
June	304.386	0.463
July	323.425	0.494
August	389.000	0.600
September	458.359	0.714
October	530.785	0.835
November	566.789	0.895
December	629.266	0.999

4.4. Three phase DC-AC Inverter

Inverters play a vital role in grid connected solar PV power plants; to convert DC output power to AC power. Sinusoidal Pulse Width Modulation (SPWM) technique is used in the inverter model simulated using MATLAB Simulink. The carrier frequency (f_s) and fundamental frequency (f_1) used in the SPWM are related as per Equation (4.1) [43].

$$m_f = \frac{f_s}{f_1} \tag{4.1}$$

Where: m_f is the frequency modulation ratio.

The modulation ratio of 21 was employed and was chosen to be an odd number in multiples of 3 to eliminate even harmonics. The carrier frequency of 1050 Hz was selected such that it eliminates interference with audible frequency range. Equation (4.2) shows a relationship between the amplitude of 3 sinusoidal voltage waves displaced 120 ° apart and that of a triangular waveform, used in the comparison [43].

$$m_a = \frac{V_{control}}{V_{tri}} \tag{4.2}$$

The modulation ratio of 0.8 has an impact on the output rms voltage of the inverter and was chosen to be below 1 for the inverter to operate in a linear region. The relationship of the modulation ratio to the line-to-line rms voltage is given by Equation (4.3) [43].

$$V_{LLrms} = \frac{\sqrt{3}}{2\sqrt{2}} m_a V_d \tag{4.3}$$

Where: V_d is the input DC voltage.

The inverter will therefore reduce the overall rating of the plant due to the losses experienced during switching and the modulation ration as depicted by Equation (4.3).

4.4.1. Sinusoidal Pulse Width Modulation

The triangular waveform used in the SPWM has an amplitude of 1 at 1050 Hz switching frequency. Sinusoidal waveforms have an amplitude of 0.8 at a fundamental frequency of 50 Hz to achieve the modulation ratio of 0.8 as per Equation (4.2) and a frequency modulation ratio of 21 as per Equation (4.1). Figure 4-12 depicts this comparison.

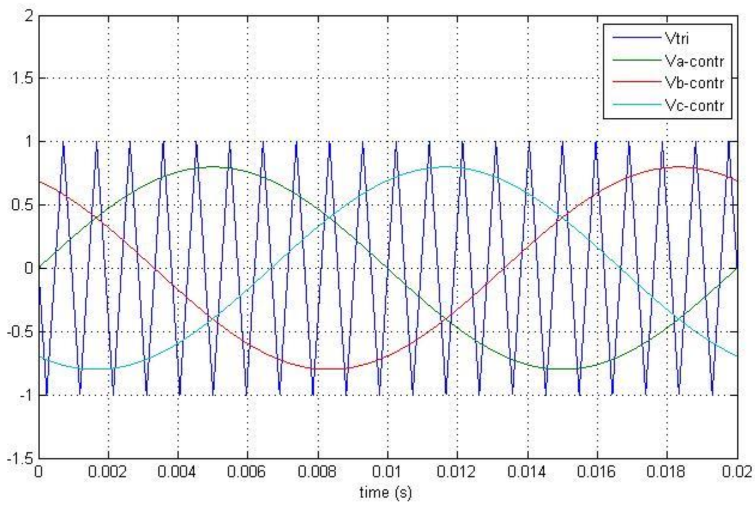

Figure 4-12: SPWM triangular and sinusoidal waveforms comparison

The comparison results of Figure 4-12 are pulses that are used as inputs to the gates of MOSFETs semiconductor switches employed in the inverter circuit. The inverter circuit used is shown in Figure 4-13.

4.4.2. Inverter simulation results

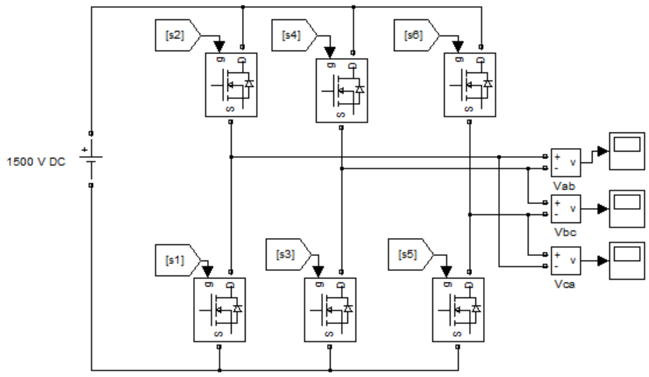

Figure 4-13: Solar PV power plant inverter circuit

With the solar PV plant output voltage of 1500 VDC, which is the input to the inverter; the inverter unfiltered output voltage is also 1500 V DC as expected. Figures 4-14, 4-15 and 4-16 indicate a single cycle of each modified line-line voltage waveform.

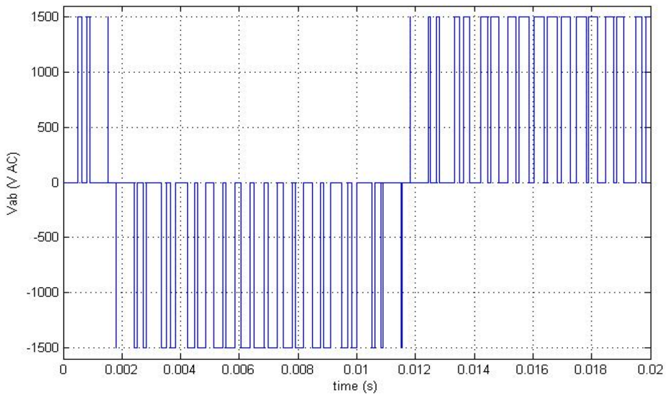

Figure 4-14: Vab modified sinusoidal wave

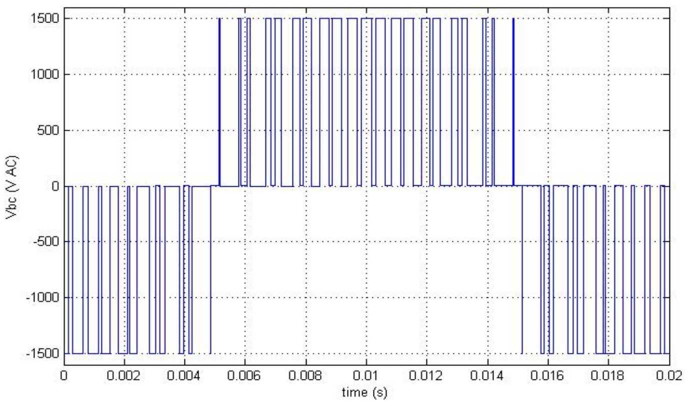

Figure 4-15: Vbc modified sinusoidal wave

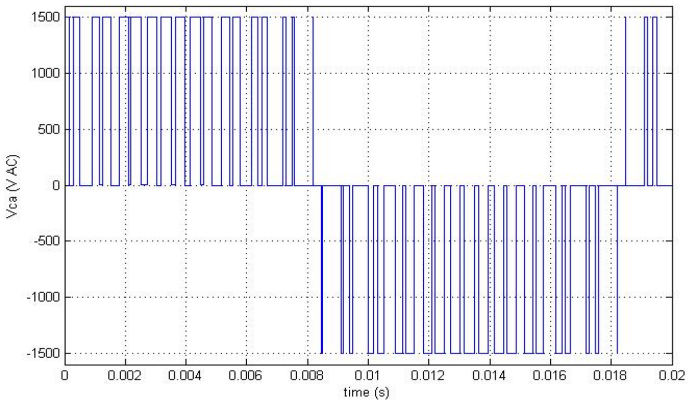

Figure 4-16: Vca modified sine wave

The output line-to-line rms voltage is as depicted in Figure 4-17. The results do not give a true reflection of the theory given by Equation (4.3). This is due to the fact that the modified waveforms have not been filtered to smoothen the output waveforms.

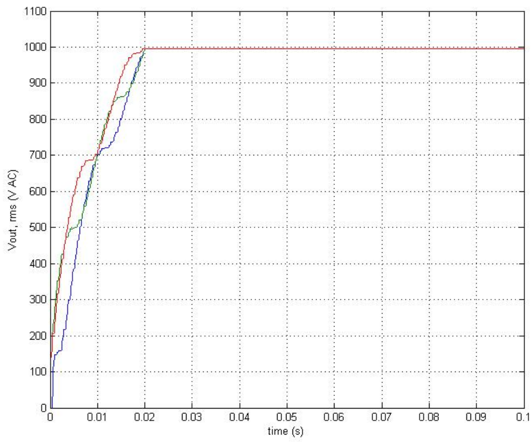

Figure 4-17: Inverter line-to-line rms voltage

The inverter is then used to interface the solar PV plant to the transformer, to make the grid connection possible. The modelling and simulation of the inverter assists in knowing the output power of the plant after the inverter, as there are losses expected due to the switching losses of the MOSFETs employed, efficiency of the inverter etc. The modeling of the plant also ensured that the components used are also utilized to specify the failure rates for the reliability evaluation purposes.

4.5. Conclusion

Modelling and simulation of a photovoltaic system was presented and its performance under various irradiance and temperature conditions was observed. The study revealed that solar PV plant performance is dependent on both ambient temperature and solar irradiance. When the ambient temperature is varied while keeping the irradiance constant, it can be observed that as the temperature rises, the output power of the plant is reduced. When the solar irradiance is varied, while keeping the temperature constant, the plant produces less power at low irradiance levels. The discussion of when both irradiance and temperature are varied at the same time, is given in Chapter 5 where the forecasting techniques are developed and are to therefore resemble the true environmental conditions. SPWM inverter was also designed and simulated, with the obtained results as expected i.e. conversion of DC-AC for the purposes of interfacing with the transformer. The components used in the inverter design will then be used in the reliability evaluation of the plant where components failure rates are assessed.

CHAPTER 5 – SOLAR POWER FORECASTING

5.1 Introduction

This chapter focuses on the fuzzy logic method, which attempts to combine the imprecision associated with natural events with computational power of the computer to produce highly intelligent, robust and flexible reasoning systems [44]. The objective is to predict the output power from the solar PV plant which will be used in evaluating the reliability of the solar PV plant and forecast the duration to which the plant would continuously supply the loads.

This chapter further looks at the artificial neural network (ANN) method employed in this study, aimed at forecasting the generated power from the 30 MW solar PV plant through its capabilities of machine learning and pattern recognition. The comparison study will then be conducted between the ANN and fuzzy logic methods and the more accurate and feasible method will be employed for the reliability evaluation study of the plant. In this chapter a neural network is trained to produce a certain output i.e. output power based on inputs i.e. irradiance and temperature.

5.2 Fuzzy Logic System

Fuzzy logic method was modelled using data depicted in Figure 5-1, which was obtained from the solar PV plant simulated in MATLAB Simulink by varying the irradiance while keeping the temperature constant at 25 ºC. Section 5.2.2 further details the results obtained when varying both temperature and irradiance.

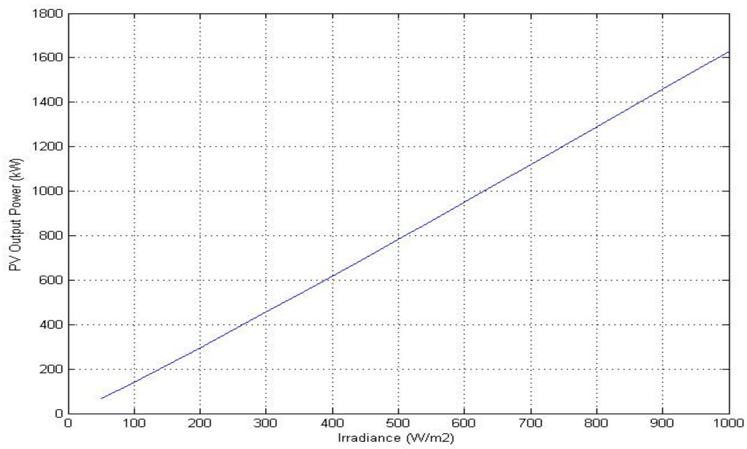

Figure 5-1: Solar PV plant output power at varying irradiance and constant temperature

The behavior of the PV plant as depicted in Figure 5-1 is that at constant temperature, the increase in the solar irradiance increases the solar PV plant output power. The fuzzy logic system is expected to match this behavior; this is detailed in the Section 5.2.1.

5.2.1. Varying Irradiance at Constant Temperature

Fuzzy logic is made up of 3 systems viz. fuzzification, inference and defuzzification. Fuzzification system measures the value of input variables and converts input data into suitable linguistic values or fuzzy inputs based on subsets called membership functions (MFs). Inference system processes fuzzy inputs according to the set rules and produces fuzzy outputs. The fuzzy control rules in the inference system have been set up using a set of IF-THEN statements [45]. The fuzzy rule base is the heart of the fuzzy logic predictor. Each fuzzy rule is derived from the knowledge and expertise of the system operator. In this case, full information about the system to be controlled is required. Defuzzification converts a fuzzy output to a crisp real value [46]. Different defuzzification methods have been studied in this chapter and comparison with each method has been conducted; the most accurate method has been selected for use in the forecasting system of the PV plant under study.

5.2.1.1. Fuzzy Inference System

For this study, MATLAB tool was used to develop the load forecasting system which is based on fuzzy logic method. The system is a 2 input, 1 output Mamdani model which represent solar irradiance, ambient temperature and output power; respectively as shown in Figure 5-2. Out of Mamdani and Sugeno methods available, the Mamdani is widely used for decision support applications due to its interpretable and intuitive nature. It also allows interpretation of the expertise in more human-like manner [47].

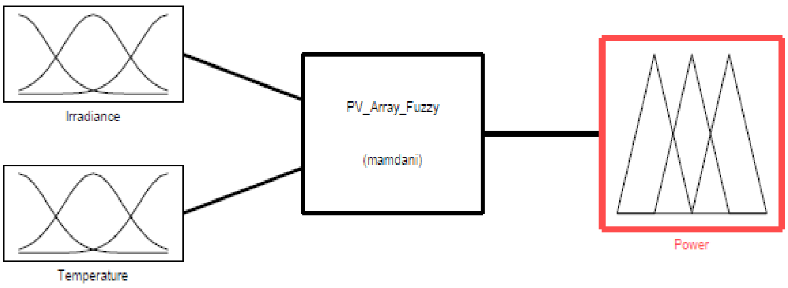

Figure 5-2: FIS Editor for the fuzzy logic system

Each variable (inputs and output) has its own membership functions which are defined according to the information given in Table 5-1 which shows the rule base of varying irradiance at constant temperature. Two types of membership functions viz. triangular and Gaussian, were used and the comparison between the 2 types is discussed. The first discussion is with the irradiance input variable having 21 triangular MFs (50 - 1000 W/m^2), temperature input variable having 3 triangular MFs (0 – 30 °C) and the power output variable having 21 triangular MFs (67.6 - 1629.6 kW). The plant was simulated under constant temperature of 25 °C which is in the range of 20 – 30 ºC.

Table 5-1: Rule base used for fuzzy logic system

Temperature (°C) / **Irradiance (W/m²)**	**20-30**
0 - 50	67.6 kW
50 - 100	141.6 kW
100 - 150	218.1 kW
150 - 200	296.4 kW
200 - 250	375.3 kW
250 - 300	455.9 kW
300 - 350	536.9 kW
350 - 400	617.9 kW
400 - 450	700.6 kW
450 - 500	783.7 kW
500 - 550	866.8 kW
550 - 600	949.9 kW
600 - 650	1033 kW
650 - 700	1118.3 kW
700 - 750	1203.5 kW
750 - 800	1288.7 kW
800 - 850	1374 kW
850 - 900	1459.2 kW
900 - 950	1544.4 kW
950 - 1000	1629.6 kW

5.2.1.2. Membership Functions and Rules

A. Triangular Membership Functions

The membership functions of both inputs and output variables are represented by symmetric triangular functions and defined in actual range as opposed to a normalized range i.e. (-1,1), to give a true representation of the PV plant under study. A normalized set of data is used in Section 5.2.2. To study the effect of the use of triangular functions, all the FIS variables had triangular membership functions. These membership functions within the variables (Irradiance, Temperature and Power) were defined in accordance with the data provided in Table 5-1 e.g. if the solar irradiance is between 50 -100 W/m^2 and the temperature is between 20 – 30 °C then the output is 141.6 kW. Input variable membership functions were defined as shown in Figure 5-3 and 5-4 i.e. for solar irradiance levels between 0 – 50 W/m^2, between 50 – 100 W/m^2 etc. and temperature levels between 0 – 10 ºC, 10 – 20 ºC and 20 – 30 °C.

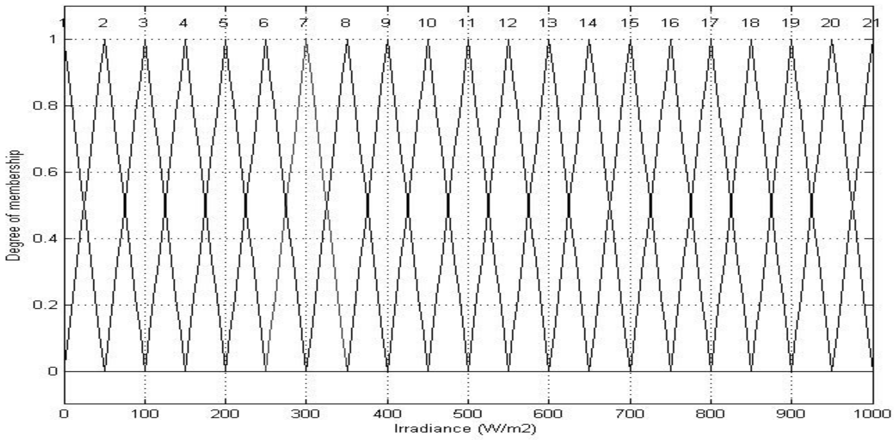

Figure 5-3: Membership function for input variable (Irradiance)

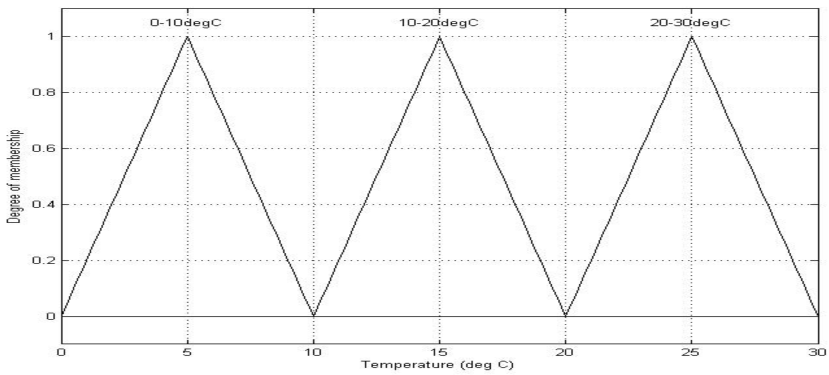

Figure 5-4: Membership function for input variable (Temperature)

The output variable membership functions were then defined as per Figure 5-5; interpreting the data in Figure 5-1 as highlighted in the rule base in Table 5-1. From the solar PV plant simulations conducted, the output power for irradiance levels below 0 - 50 W/m^2 was always below 67.6 kW at a temperature of 25 ºC. For irradiance levels between 800 - 900 W/m^2, the output power was above 1288.5 kW but less than 1459.2 kW. This data was then used in the development of the rules, for the fuzzy logic system to interpret and yield the desired output power. Rules defining the desired operation of the system are defined in the Rule editor of the system. The rules have been defined to align with the actual plant performance.

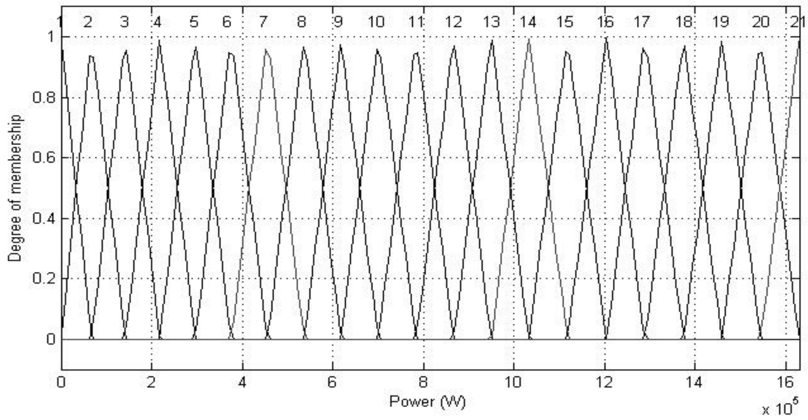

Figure 5-5: Membership function for output variable (Power)

Different defuzzification methods were used to calculate the associated output; these controllers are Mean of Maximum (MOM), Centroid, Bisector, Small of Maximum (SOM) and Large of Maximum (LOM). The objective was to study the effect of using each method and select the most accurate of them all. The obtained comparison results are discussed in Section 5.2.1.3.

B. Gaussian Irradiance and Power

The irradiance membership functions were converted to Gaussian shapes for comparison with the triangular function and for studying both functions to observe the one with more accurate results. The comparison results are discussed in Section 5.2.1.3. The Gaussian irradiance is shown in Figure 5-6; the temperature and power remained unchanged when triangular MFs were used, as indicated in Figure 5-4 and 5-5.

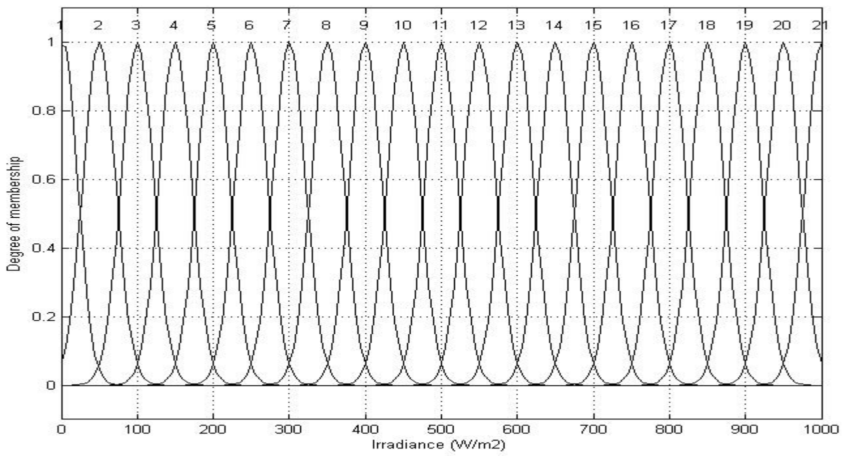

Figure 5-6: Gaussian Irradiance MFs with Triangular temperature and power MFs

The observed behavior of the output power after changing the MF types for the irradiance variable indicated some minor changes compared to the triangular irradiance. Following this observation, the input irradiance was reverted to a triangular MF and the output was changed from triangular MFs to Gaussian MF. Figure 5-7 shows the Gaussian membership functions for the output power.

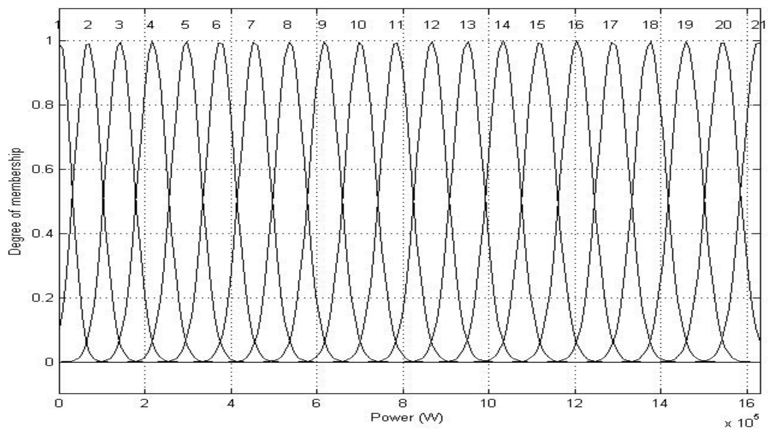

Figure 5-7: Gaussian Power MFs with input variables having triangular MFs

5.2.1.3. Discussion of Results

The inputs were varied to check the behavior of the output power from the fuzzy logic system if it corresponds to the expected power of the solar PV plant. Results obtained from all fuzzy methods are depicted in Figure 5-8 to 5-12. Centroid defuzzification method for input and output variables having triangular MFs gives the least percentage error compared to Gaussian membership types employed. Changing the membership functions from triangular to Gaussian type had a negative impact on the obtained results as the percentage error was high. The percentage error values were calculated using Equation (5.1). Figure 5-8 to 5-12 show the PV plant output power and fuzzy logic system output power plotted against the input irradiance. The results shown in these figures are only using a triangular MFs on all inputs and output variables.

$$\%\, error = \frac{PV\ Plant\ Output - Fuzzy\ Logic\ Output}{PV\ Plant\ Output} x100 \tag{5.1}$$

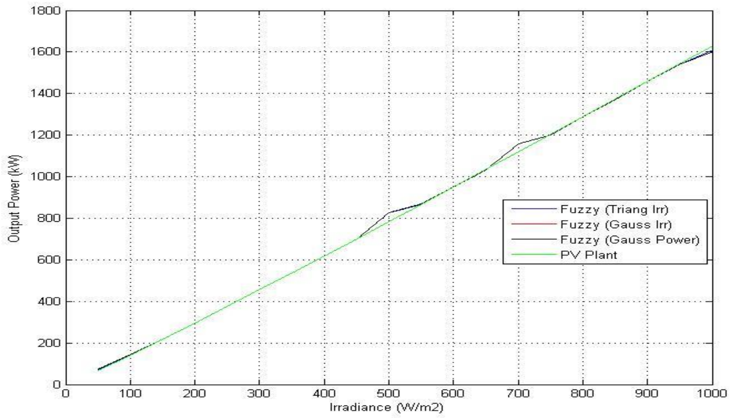

Figure 5-8: Comparison of PV plant output with Fuzzy logic output for Centroid method

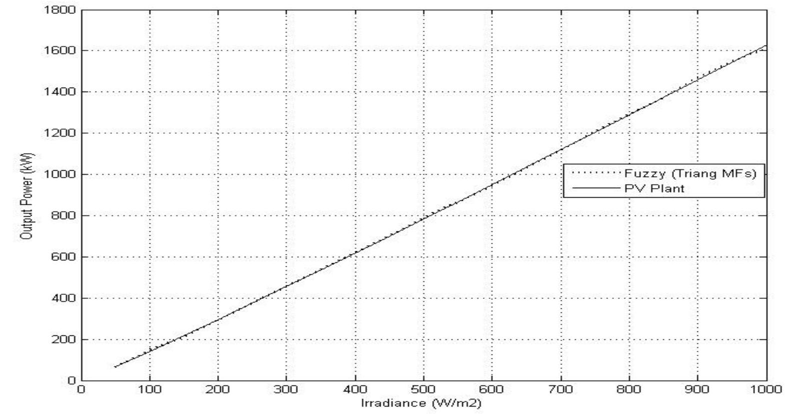

Figure 5-9: PV Plant and Fuzzy Logic System Output Power for Bisector method

The bisector defuzzification method as shown in Figure 5-9 is aligned with the PV plant output. The average error from this is 0.247 % which is slightly more than that of the Centroid method. This is a low percentage error, however the Centroid method is still the lowest which is what is required as the more the accurate the fuzzy logic system is, the more accurate the reliability evaluation will be.

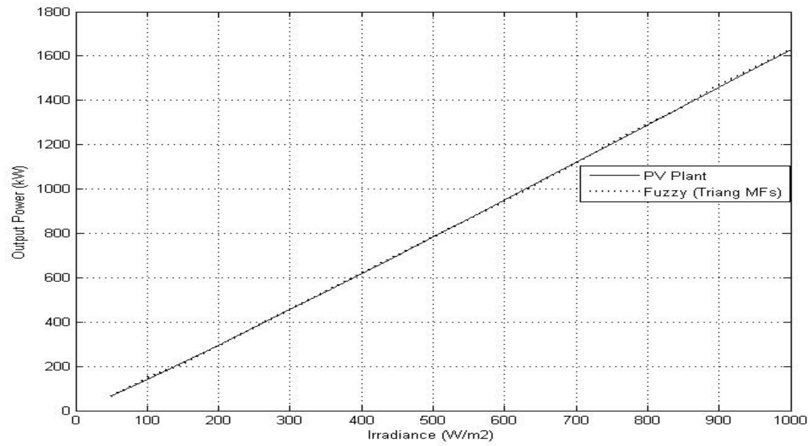

Figure 5-10: PV plant and Fuzzy Logic Controller Output Power for MOM method

The mean of maximum (MOM) method used yields Figure 5-10 which shows the fuzzy logic system output compared to the PV plant output power. The fuzzy logic system output is aligned to the PV plant output with an average error of 0.2955 %.

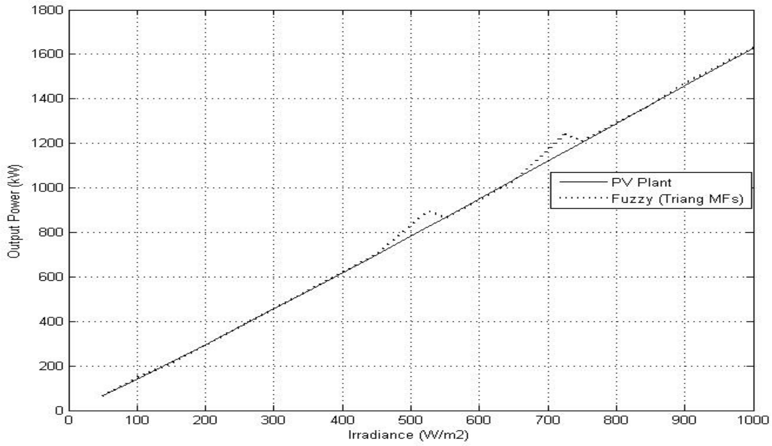

Figure 5-11: PV plant and Fuzzy Logic Controller Output Power for LOM method

Figure 5-11 shows the LOM method output results to be aligned to the PV plant output, with a noticeable change of output power in irradiance levels of 525 and 725 W/m^2. The average error obtained with this method is -0.497 %.

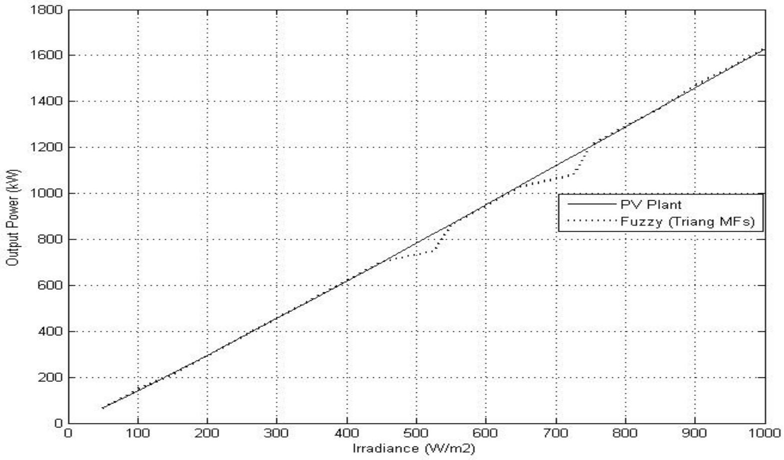

Figure 5-12: PV plant and Fuzzy Logic Controller Output Power for SOM method

Figure 5-12 shows the output results of the fuzzy logic system using SOM defuzzification method and is compared to the PV plant output results. There is a noticeable deviation between the two plots at solar irradiance values of 525 W/m^2 and 725 W/m^2. The obtained average error with this method is 1.082 %. The obtained results show that with the developed fuzzy logic system, the output power obtained is close to the expected results i.e. from the solar PV plant. Triangular membership functions can be seen to be more accurate compared to the Gaussian method. Centroid defuzzification is also observed to be more accurate when used with triangular membership functions compared to other studied methods. Centroid method gives the least percentage error compared to all other defuzzification methods studied. The fuzzy logic system was then improved to represent the solar PV plant with both irradiance and temperature varying; this is detailed in Section 5.2.2.

5.2.2. Irradiance and temperature varying

In practice, the solar PV plant experiences changes in both irradiance and temperature which both have influence on the output power of the plant. This section focuses on the fuzzy logic system for these conditions. The solar PV plant was simulated with irradiance and temperature values varied and the obtained results are as highlighted in Table 5-2 which shows the rule base of the system. The solar PV plant data used was normalized to be between 0 and 1. Irradiance values were normalized using the STC of 1000 W/m^2, temperature normalized using 35 °C and output power normalized using 1629.6 kW.

Table 5-2: The rule base for varying both the temperature and irradiance

Irradiance (pu)	**Temperature (pu)**			
	0.43-0.57	0.57-0.71	0.71-0.86	0.86-1
0.1 – 0.15	0.09	-	-	-
0.15 – 0.2	0.14	-	-	-
0.2 – 0.25	0.19	-	-	-
0.25 – 0.3	0.24	-	-	-
0.3 – 0.35	-	0.29	-	-
0.35 – 0.4	-	0.34	-	-
0.4 – 0.45	-	0.39	-	-
0.45 – 0.5	-	0.43	-	-
0.5 – 0.55	-	0.48	-	-
0.55– 0.6	-	-	0.53	-
0.6 – 0.65	-	0.59	0.58	-
0.65 – 0.7	-	-	0.63	-
0.7 – 0.75	-	-	0.68	-
0.75 – 0.8	-	-	0.72	-
0.8 – 0.85	-	-	0.77	0.8
0.85 – 0.9	-	-	0.81	0.8
0.9 – 0.95	-	-	-	0.86
0.95 – 1	-	-	-	0.9
1	-	-	1	0.94

Lower values of irradiance were limited to a varying temperature range of 0.43-0.57, approximating the actual environmental conditions i.e. it is not expected that the irradiance levels be lower while the temperature is high. From 0.3 – 0.55 irradiance, the temperature range used was 0.57-0.71, for irradiance values between 0.55 – 0.8, the temperature variations used were between 0.57-0.71 and 0.71-0.86. The higher irradiance values were limited to varying temperature values of 0.57-0.71 (which only included the output power at Standard Testing Conditions (STC)) and 0.86-1. The input temperature variable in the fuzzy logic system was defined as shown in Figure 5-13, using the aforementioned argument.

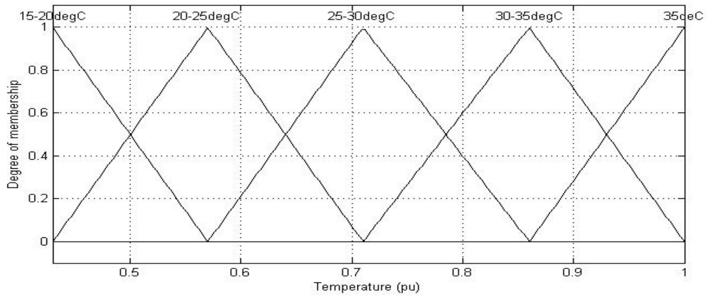

Figure 5-13: Input Temperature membership functions

The temperature was defined such that it starts from 0.43 to 0.57 as per Figure 5-13, considering the Upington area used for locating the solar PV plant. It was sectioned to align with the rule base in Table 5-2 and has 5 membership functions. Similarly, the 20 membership functions shown in Figure 5-14 for the input irradiance were defined according to the rule base in Table 5-2.

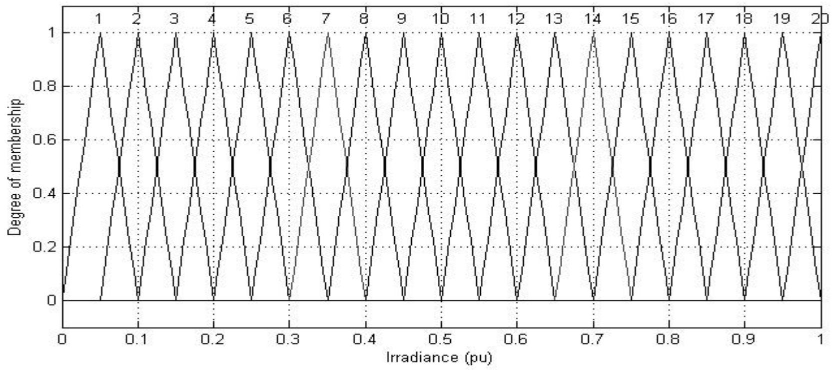

Figure 5-14: Input Irradiance membership functions

The output power has 20 membership functions as shown in Figure 5-15 which were also defined according to the rule base in Table 5-3. All the MFs were of triangular and the defuziffication method used was centroid, as per the conclusion made in Section 5.2.1.3.

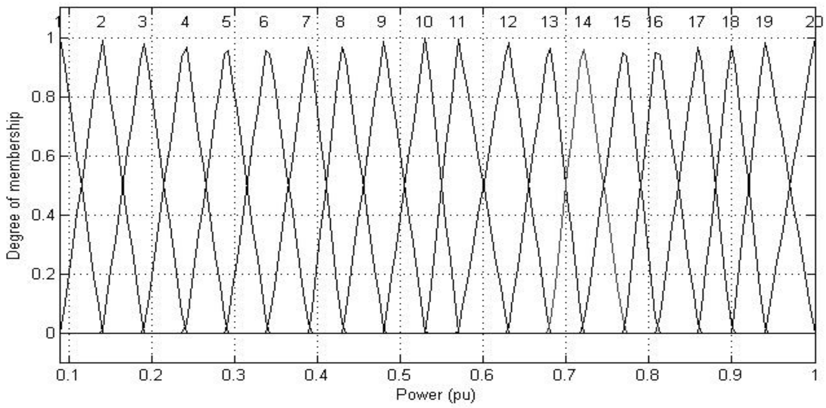

Figure 5-15: Output Power membership functions

The fuzzy logic system obtained results are as shown in Figure 5-16, where the comparison with the solar PV plant is done. The percentage errors between the two obtained results yielded an average error of -1.114 % which is fairly low and acceptable. The system accuracy will be taken into account in the reliability evaluation study.

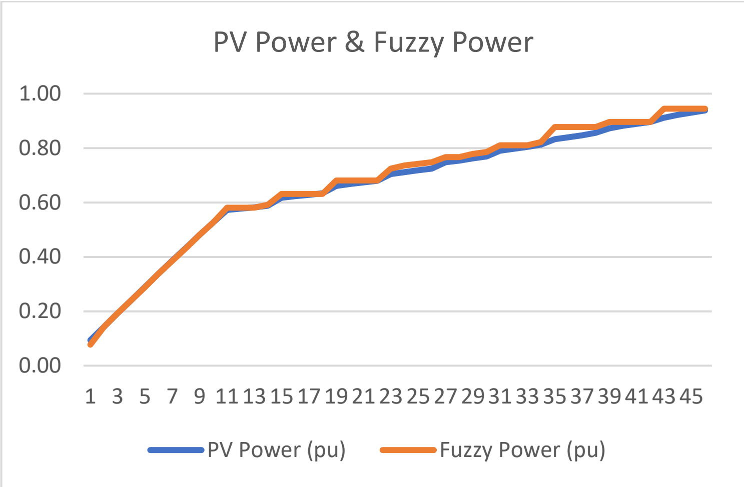

Figure 5-16: PV plant and fuzzy logic output power comparison

The average percentage error obtained in this scenario is slightly higher than when the temperature was kept constant. When the irradiance and temperature are varied, the system requires optimization by redefining the membership functions such that all possible cases are covered and the accuracy can be further improved. The overall fuzzy logic system developed is a representation of the actual solar PV plant; in a way that it makes approximation of what the output power should be, based on the rules set out using the membership functions defined. This fuzzy logic method will be compared to the artificial neural network (ANN) method to evaluate a more accurate method which will be used for the integrated system, in the reliability evaluation study.

5.3 ANN method - Backpropagation Network

A multilayer backpropagation network trained with Levenberg-Marquardt algorithm is employed in this study due to its ability to learn nonlinear and linear relationships between input and outputs. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between input and output vectors. Properly trained backpropagation networks tend to give reasonable answers when presented with inputs that they have never seen. Typically, a new input leads to an output similar to the correct output values obtained for input vectors used in training. This is desired in this study as the network needs to be able to predict the output power even when the inputs are different from the ones used during network training. The network was therefore trained until it had learned the relationship between the inputs and targets.

A feed-forward network usually has one or more hidden layers of log-sigmoid neurons, followed by an output layer of linear neurons. The output layer can be changed from using a linear function to using a log-sigmoid transfer function for the purposes of constraining the outputs of a network between 0 and 1. The number of neurons used in one hidden layer was limited to 30. More neurons require more computation but allow the network to solve more complicated problems. More layers require more computation but might result in the network solving complex problems more efficiently [3]. With the number of neurons used, the acquired mean squared error (MSE) was still acceptable.

5.4 ANN Training Results

Solar irradiance and temperature have been used as input data and the simulated PV plant output power used as target data. All the data used was normalized where irradiance values were normalized using the STC of 1000 W/m^2, temperature normalized using 35 °C and output power normalized using 1629.6 kW as discussed in Section 5.2. The normalized input and target data used for the network is as depicted in Figure 5-17; which includes the temperature and irradiance as input data and solar PV output power as target data. The neural network results are also presented as normalized values.

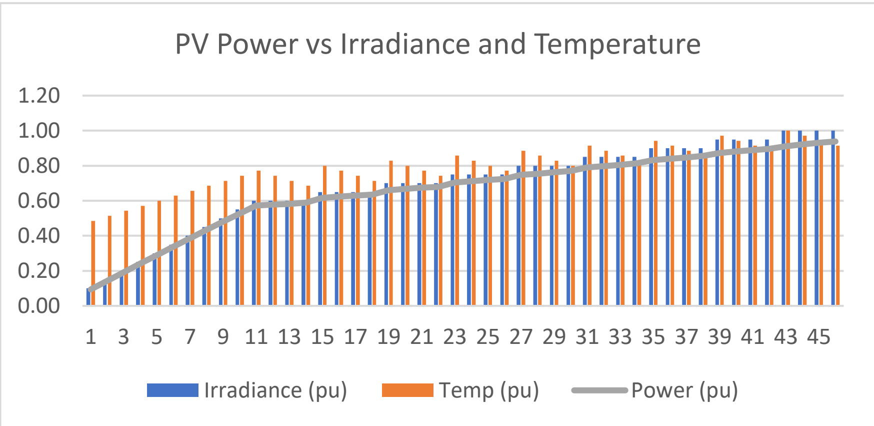

Figure 5-17: Input ad target data used in the ANN

Using neural network fitting tool in MATLAB with number of neurons being 30 at 60%, 20% and 20% sets, Figure 5-18 was obtained. The architecture employed was a feed-forward backpropagation which was developed using data in Figure 5-17.

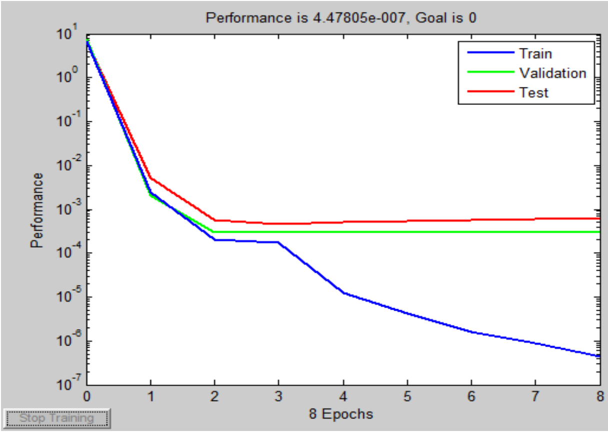

Figure 5-18: ANN performance using three sets

Figure 5-18 depicts the relationship between the 3 sets of data used during network training. It can be observed that the performance is close to 0 as expected, which implies that the network was optimized.

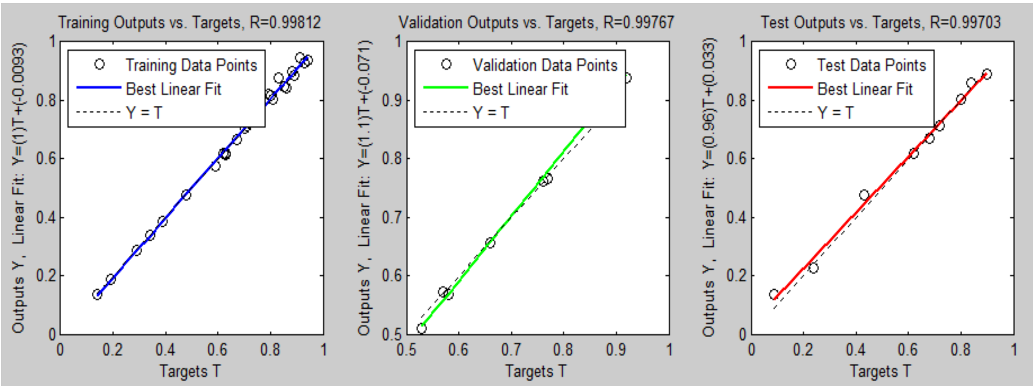

Figure 5-19: Regression analysis of outputs and targets

Figure 5-19 indicates that the network output tracks the target satisfactorily as the regression value is above 0.99 which is close to the desired value of 1. Comparison of target values to the obtained values from the ANN is shown in Figure 5-20.

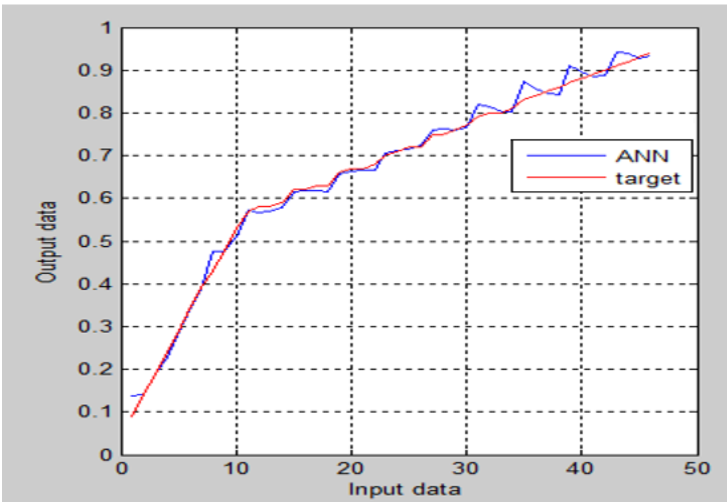

Figure 5-20: ANN results comparison to target data

There is a close relationship between ANN results and solar PV plant as shown in Figure 5-20, which implies that the network was successfully trained to follow the target data which is the solar PV plant output power. Similarly, ANN and fuzzy logic methods were both compared to the solar PV output power and the outcome is depicted in Figure 5-21.

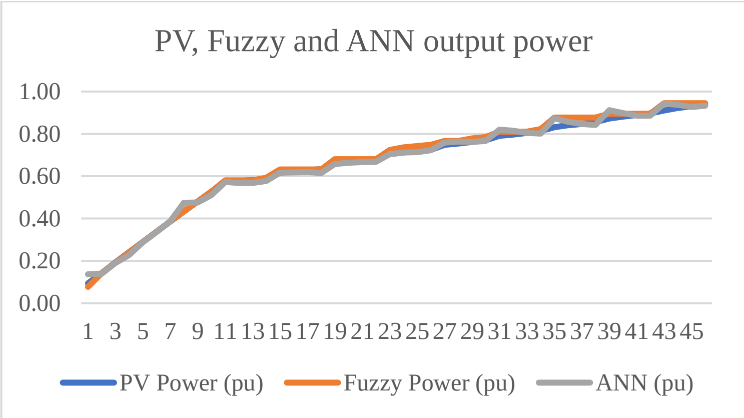

Figure 5-21: Comparison of fuzzy logic and ANN methods to PV power

It can be observed that both methods were successfully developed to mimic the solar PV plant behavior. Error values on both these methods were fairly acceptable. The average error obtained from the fuzzy logic method is 1.924 % and that of the ANN method was found to be 2.626 %. Both methods are not far off from the actual solar PV array and results can be improved by optimizing these methods. The accuracy of both methods gives an indication that the methods can be reliably employed in the forecasting process and for efficient load management.

5.5 Conclusion

The solar PV array data has been used to develop forecasting methods using fuzzy logic and artificial neural network. Triangular membership functions with centroid defuzzification were observed to yield more accurate results compared to other membership functions and were therefore employed. Both fuzzy logic and ANN methods proved to have been successfully developed as their results follow the actual solar PV array signature. These methods can therefore be used for forecasting of the solar PV plant's output power. Reliability evaluation of the plant is studied in Chapter 6, which has an effect on the forecasted output power as the forecasting should take into account the plant's reliability.

CHAPTER 6 - SOLAR PV RELIABILITY EVALUATION

6.1 Introduction

This chapter discusses the reliability evaluation conducted for the 30 MW solar PV plant under study. Two distinct classes of failure in a PV system are outage and impairment; where the former happens when the system is unavailable due to various causes such as breakdown or planned maintenance. The impairment class is when there is continuity of supply however the performance is below expectations. The impairment class is more related to the availability than reliability of the plant, where the plant can generate, however not meeting the intended use of supplying its full rated capacity for a defined duration. These two classes are crucial in analyzing the PV system performance; this chapter considers both classes. The effect of the unreliability of the plant is realized in the cost incurred during inability to produce and the cost of repairs; over and above loss of supply to customers and grid instabilities [48].

Analysis of each component in terms of failure rates and thereafter reliability has been conducted. Furthermore, the chapter looks at the repair rates of these components which then assist in evaluating availability and unavailability of the system/plant and for further computing different reliability indices that indicate the plant's performance. The overall plant reliability is also studied considering the intermittent source of the solar system; possible improvements for the overall reliability have been proposed. The study therefore covers reliability evaluation looking at both failure of components and intermittency of the solar resource i.e. irradiance and temperature.

6.2 Hardware Based Reliability

6.2.1 Components Analysis

The reliability of each component is evaluated taking into account the quantity and configuration (series or parallel connection) of the components in the overall plant, as discussed in Chapter 3. Component failure rates (λ) and repair rates (μ) play a vital role in the reliability evaluation study and are therefore studied in this chapter. Reliability of a component is represented by Equation (6.1) [34].

$$R = e^{-\lambda_p t} \tag{6.1}$$

where: λ_p is the actual failure rate, after considering base failure rates and stress factors; and t is time in hours over a year i.e. 8760 hours.

The components that are evaluated in this study are discussed in the following subsections. These components exclude the PV modules as they have a fairly low failure rate with mean time between failure (MTBF) of 522 and 6666 years, as indicated in Chapter 3 [33].

6.2.1.1 *Fuse Switches and Circuit Breakers*

There is a very little correlation between the fuse replacements and actual fuse failures. The need to replace these components is realized when a fault happened in the circuit and the fuse performs as per the design [49]; this analysis also applies to the circuit breaker. These protection devices have a relatively high reliability and their failure rates are expressed as per Equation (6.2) and (6.3). The failure rate of each component considers stress factors which the components are subjected to.

Fuse failure rate:

$$\lambda_P = \lambda_b \times \pi_E \tag{6.2}$$

Circuit Breaker failure rate:

$$\lambda_P = \lambda_b \times \pi_C \times \pi_U \times \pi_Q \times \pi_E \tag{6.3}$$

The stress factors experienced by the fuses and circuit breakers are environment factor π_E, configuration factor π_C, use factor π_U and quality factor π_Q as per the given equations. λ_b is the base failure rate of the components.

6.2.1.2 *Inverter*

The inverter is considered as one of the components which have a major contribution to the failure of PV systems. The inverter consists of MOSFETs and diodes; these have failure rates define as per Equation (6.4) and (6.5).

MOSFET failure rate:

$$\lambda_P = \lambda_b \times \pi_T \times \pi_A \times \pi_Q \times \pi_E \tag{6.4}$$

Diode failure rate:

$$\lambda_P = \lambda_b \times \pi_T \times \pi_S \times \pi_C \times \pi_Q \times \pi_E \tag{6.5}$$

The stress factors experienced by these components are temperature factor π_T, application factor π_A, quality factor π_Q, environment factor π_E, electrical stress factor π_S and contact construction π_C.

6.2.1.3 Filter

The filter is coupled to an inverter and consists of a capacitor and an inductor. Similarly to the inverter, a capacitor is recognized as one of the most contributors in the failure rate of the PV system whereas an inductor has a very low failure rate.

Capacitor:

$$\lambda_P = \lambda_b \times \pi_T \times \pi_C \times \pi_V \times \pi_{SR} \times \pi_Q \times \pi_E \qquad (6.6)$$

Inductor/transformer:

$$\lambda_P = \lambda_b \times \pi_T \times \pi_Q \times \pi_E \qquad (6.7)$$

The stress factors on these components are temperature factor π_T, capacitance factor π_C, voltage stress factor π_V, series resistance factor π_{SR}, quality factor $\times \pi_Q$ and environment factor π_E.

6.2.2 Components Reliability Computation

The military handbook [49] gives different base failure rates and stress factors for each component evaluated; these are highlighted in Table 6-1 and are used to compute the failure rates of each component, expressed in failures per million hours. Mean Time before Failure (MTBF) expressed in hours is then calculated from the obtained failure rates. The MTBF determines the expected time before failure of a component/system can occur. The values of the different stress factors used are specific to the PV plant under study, in terms of the plant conditions and component ratings; comparison with failure rates and MTBF from [34] is also done and is shown in Table 6-1.

Table 6-1: Components failure rates and MTBF

Item	**Component**	**Failure Rate & Stress Factors**	**Failure Rate [34]**	**Component MTBF**	**Component MTBF [34]**
1	Capacitor	$\lambda_b = 0.00037$ $\pi_T = 1.6, \pi_C = 1.6, \pi_V = 10.31,$ $\pi_{SR} = 0.66, \pi_Q = 10, \pi_E = 10.$ $\lambda_P = 0.644$	$\lambda_P = 0.1245$	1.553×10^6	8.032×10^6
2	Inductor/ transformer	$\lambda_b = 0.00003$ $\pi_T = 1.4, \pi_Q = 1, \pi_E = 6$ $\lambda_P = 0.000252$	$\lambda_P = 0.00152$	3.968×10^9	6.578×10^8
3	Fuse	$\lambda_b = 0.01$ $\pi_E = 2$ $\lambda_P = 0.02$		5.0×10^7	
4	Circuit Breaker	$\lambda_b = 0.34$ $\pi_C = 3, \pi_U = 2.5, \pi_Q = 1, \pi_E = 2,$ $\lambda_{PAC} = 5.1.$ $\lambda_{PDC} = 3.4$		AC CB: 0.196×10^6 DC CB: 0.294×10^6	
5	MOSFET	$\lambda_b = 0.012$ $\pi_T = 1.6, \pi_A = 10, \pi_Q = 8, \pi_E = 6$ $\lambda_P = 9.216$	$\lambda_P = 3.48$	0.109×10^6	0.287×10^6
6	Diode	$\lambda_b = 0.001$	$\lambda_P = 0.271$	6.135×10^6	3.690×10^6

		$\pi_T = 2.2, \pi_S = 0.77, \pi_C = 2, \pi_Q = 8, \pi_E = 6$ $\lambda_P = 0.163$			

The obtained failure rates are then used to compute the reliability of components, arrays and thereafter the overall plant. The system reliability considers the configuration of the components i.e. if they are configured in series or in parallel. Reliability of a series system $_s$(t) and that of a parallel system $_p$(t) are given by Equation (6.8) and (6.9), respectively [34].

$$s(t) = \prod_{i=1}^{k}[i(t)\,]; i = 1, \dots \dots, k \quad (6.8)$$

$$p(t) = 1 - \Pi[1 - i(t)]; i = 1, \dots \dots, k \quad (6.9)$$

where (t) is the reliability of the component/system.

As discussed in Chapter 3, the plant under study is configured in series, therefore Equation (6.8) is utilized to compute the reliability. The array is considered first; using Equation (6.1) and (6.8) to compute the reliability of an array, the obtained reliability is 0.72005. The reliability of the 30 MW plant with 19 inverters (each array having an inverter) is 0.001983 which is very low. In an attempt to improve the reliability of the overall plant, different configurations were considered i.e. when the 30 MW plant is configured with 2 inverters for the overall plant the reliability improved to 0.309. With only a single inverter in use for the entire plant the reliability is improved to 0.4159. When the quantity of inverters reduces, the AC circuit breakers also reduce, this contributes to the reduction of number of components in the system which in turn improves the reliability.

The obtained reliability is fairly low, as the desired reliability should be close to 1; this is due to the number of components constituting the 30 MW plant. A single array reliability is fairly high, compared to the overall plant, however it is still low due to the quantity of components used in the array and the fact that they are series connected. With the obtained reliability considering different configurations the conclusion that can be made is that the more components there are in the overall plant the lesser the reliability. In addition, the plant under study does not have any parallel components, all the systems utilized are series connected for the required objective to be met. The reliability can be improved by introducing a storage system or a similar plant connected in parallel. The reliability can also be improved by reducing/minimizing the stress factors that the components are subjected to, de-rating of components etc. Section 6.4 discusses possible improvements on the reliability of the plant under study.

6.2.1.4 Repair Rates

Each component has been further assessed in terms of its repair rate. The repair rate for fuses and circuit breakers considers catastrophic failures only, not operations due to their intended purpose of protecting. Bollen, M.H.J [50] as well as industry experience have been employed in determining the repair times of different components. Repair times of small components (excluding a transformer) takes into account the call out times of maintenance personnel, failure preliminary analysis/ investigations, spares etc. [50]. All components/ systems repair times assume that replacement will be conducted and repairs done offline; to minimize the plant or system outage. From the repair times i.e. mean time to repair (MTTR) expressed in hours, repair rates expressed in per million hours were computed. These were further used to calculate the availability (A) and unavailability (U) of the plant which are evaluated using Equation (6.10) and (6.11). Table 6-2 lists the computed availability and unavailability of the system.

$$A = \frac{\mu}{\mu+\lambda} = \frac{\text{Uptime}}{\text{Uptime+Downtime}} \tag{6.10}$$

$$U = \frac{\lambda}{\mu+\lambda} = \frac{\text{Downtime}}{\text{Uptime+Downtime}} \tag{6.11}$$

where λ is failure rate and μ is repair rate.

Table 6-2: Component Repair times and System MTBF

Item	Component	Repair Time (hrs)	Repair Rate	System Availability	System Unavailability
1	Capacitor	4	0.25	0.2796	0.7204
2	Inductor	4	0.25	0.9990	0.0010
3	Transformer	100	0.01	0.9754	0.0246
4	Fuse	3	0.33	0.9434	0.0566
5	AC Circuit Breaker	3	0.33	0.0614	0.9387
6	DC Circuit Breaker	3	0.33	0.0893	0.9107
7	MOSFET	4	0.25	0.0264	0.9736
8	Diode	4	0.25	0.6053	0.3947

The obtained data further assists in computing the reliability indices which indicate the overall reliability level of the plant. These indices are discussed in Section 6.3.

6.3 Hardware and Intermittent Source Based Reliability

6.3.1. Probabilistic Reliability Indices

The reliability evaluation of the solar PV plant needs to also consider the intermittency of its source i.e. solar irradiance and temperature. The first part of this chapter took into account the reliability of the system considering the hardware part of the plant i.e. components failure rates. This section focuses on computing the reliability indices taking into account both hardware and solar resource variations. The probabilistic method of reliability indices is first looked at. This method includes indices such as Loss of Load Expectation (LOLE) given in hours/year or days/year, Loss of Load Probability (LOLP) and Expected Energy not Served (EENS) given in Wh/year which have been considered in this study. These indices are widely used and are effective methods in the reliability study [35].

LOLE is the average number of days or hours in a given period in which the daily/hourly load is expected to exceed the available generating capacity. LOLE does not indicate the severity of the deficiency nor the frequency or duration of loss of load [51]. LOLP is not commonly used as it merely indicates the probability of a system failure, however the study considers this index [35]. A third reliability index used is EENS; which indicates the energy in MWh/year not supplied to the system due to failure rate of the components or due to change in temperature and solar irradiance, resulting in the PV plant output supply being less than the demand.

Solar PV plant can supply base and peak load demands, as well as provide some spinning reserve capacity. Base and peak capacity supply often take place during the day when the solar PV output is maximum. The solar PV supply profile corresponds well with the load profile, i.e. the demand is high during the day when the solar PV is at its maximum [52]. The basic reliability assessment approach for the solar PV plant consists of the generation and load models to form a risk model. The point of interest is the risk of generation capacity being less than the load demand. The assumption made is that the peak load will last for the whole day [53]. A generating plant is usually redundant as there are other interconnected power plants in a grid to supply customer’s demands. The incorporation of the solar PV plant into the grid often raises concerns of power supply reliability issues; due to the energy uncertainties associated with weather factors, geographical areas and reliability of PV units. Figure 6-1 shows the PV supply profile for a day in summer and a day in winter. As discussed in Chapter 4 the PV plant output power is reduced in winter due to seasonal changes that causes a reduction in solar irradiance.

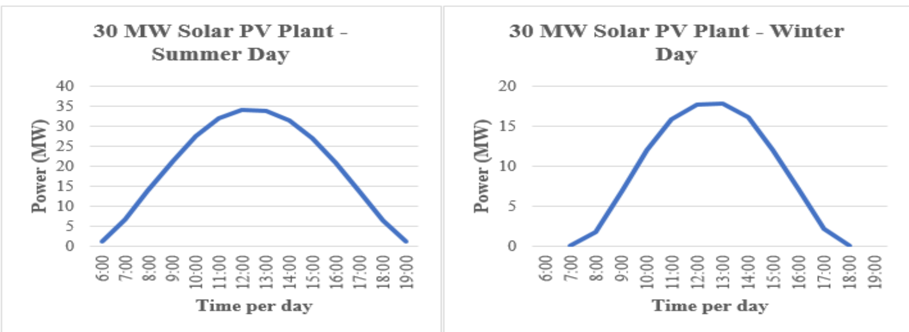

Figure 6-1: PV Plant generation profile over summer and winter days

Figure 6-2 and Figure 6-3 show the supply profile and load profile over a year, respectively; from the relationship depicted the indices are then computed. The load distribution curve in

Figure 6-3 shows the daily peak loads which have been arranged in a descending order from the peak load demand to the lowest, throughout the year.

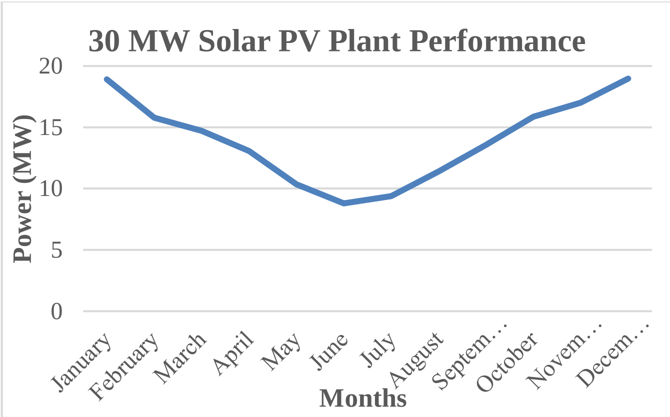

Figure 6-2: PV Plant generation profile over a year

The overall plant profile is seen to produce maximum 18.97 MW when taking into account the average solar irradiance over a month. The maximum output power is experienced during summer seasons as expected. The lowest output is 8.8 MW which is obtained in the winter season.

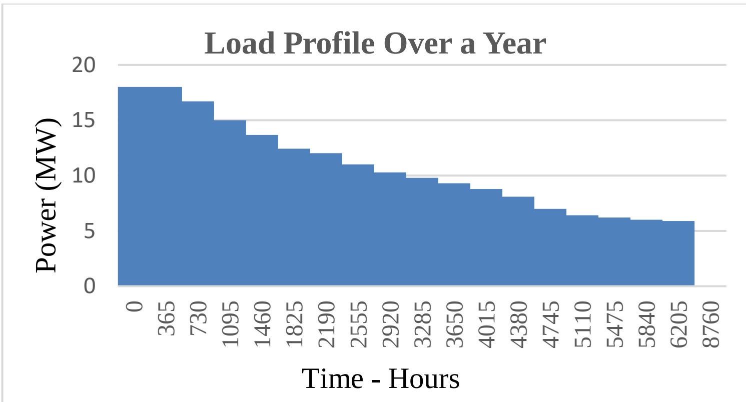

Figure 6-3: Load profile over a year

The 30 MW plant is divided into 3 plants for the purpose of demonstrating the reliability evaluation method that will yield these indices. The three plants are divided into 13 MW, 10 MW and 7 MW systems operating to supply an 18 MW peak load which is seen as the maximum demand in Figure 6-3.

As part of the evaluation of the reliability indices one other important aspect that requires development is capacity outage probability table (COPT). The COPT indicates the probabilities of the plant going on outage, where the sum of probabilities shall be equal to 1. The calculation involves combining the load profiles and the scheduled generator outages with the probability of the generator outage, to determine the expected number of days/ hours in a year when the shortage might occur [54]. The Forced Outage Rate (FOR) also known as the unavailability of the plant calculated over a year is used to develop the COPT. The forced outage rate takes into account the unavailability of solar irradiance at some hours in a day i.e. at late hours of the night and early hours in the morning.

The three plants considered have 2^n capacity states; for this particular study, 8 states are observed with associated probabilities. Since the plants are all positioned at the same Upington area the FOR and availability is the same for all plants when considering the intermittence source however they are different when considering component failure rates [29]. The indices are evaluated considering hardware failure rates and considering the solar resource variations. Table 6-4 gives the availability and unavailability of the overall plants. The obtained values when considering the hardware failure depend on the components used to make up the plant's rating e.g. the 7 MW plant has fewer components compared to the 13 MW plant and the availability relates to that relationship.

Commonly a recursive algorithm is used however there are other methods that can be employed such as the one employed in this study, the binomial distribution. The indices are computed using binomial distribution method$(U + A)^n$. When expanded, the resultant of the binomial distribution as follows:

$$(A_1 + U_1)(A_2 + U_2)(A_3 + U_3)$$

$$= A_1A_2A_3 + A_1A_2U_3 + A_1A_3U_2 + A_2U_3U_1 + A_1U_2U_3 + A_2U_1U_3 + U_1U_2A_3 + U_1U_2U_3$$

where: A_i represents the availability of the plant and U_i represents the unavailability (i representing the plant in a descending rating order).

Table 6-3: Availability and unavailability values of the 13 MW, 10 MW and 7MW plants

Plant Rating (MW)	**Factor**	**Considering Intermittence Source**	**Considering Hardware Failures**
13	U_1	0.458	0.447
10	U_2		0.417
7	U_3		0.401
13	A_1	0.542	0.553
10	A_2		0.583
7	A_3		0.599

Equation (6.12) and (6.13) show the LOLE and EENS, respectively in relation to the probabilities obtained from the COPT. The COPT is shown in Table 6-4 and 6-5 and has been expanded to include the LOLE and expected load loss (ELL) obtained for the plant considering the resource intermittency and hardware, respectively.

$$LOLE = P_{oi} \times T_{oi} \tag{6.12}$$

where: P_{oi} is the probability of capacity outage and T_{Oi} is the time of capacity outage

$EENS = \sum_{i=1}^{n} P_{oi} \times E_{oi}$ (6.13)

where: P_{oi} is the probability of capacity outage and E_{oi} is the energy not supplied due to the capacity outage [52].

Table 6-4: COPT and Indices for the plants considering solar resource intermittency

Capacity Available	**Capacity Outage**	**Binomial Distribution**	**State Probability**	**Cumulative Probability**	**LOLE (days/year)**	**ELL (MW)**
30	0	$A_1A_2A_3$	0.15922	1	-	-
23	7	$A_1A_2U_3$	0.134544	0.84077991	-	-
20	10	$A_1A_3U_2$	0.134544	0.70623600	-	-
17	13	$A_2U_3U_1$	0.134544	0.57169209	-	-
13	17	$A_1U_2U_3$	0.113692	0.43714818	41.498	0.568
10	20	$A_2U_1U_3$	0.113692	0.32345609	-	0.910
7	23	$U_1U_2A_3$	0.113692	0.20976400	-	1.251
0	30	$U_1U_2U_3$	0.096072	0.09607191	-	1.729

The ELL in the COPTs represents the expected load loss over a year, which is used to compute the EENS; this is the sum of all the load losses expected which is 4.458 MW. The EENS for data in Table 6-4 consider the hours where there is solar irradiance available and not the 8760 hours for the whole year. The EENS obtained is 21.149 GWh/year.

Table 6-5: COPT and Indices for the plants considering hardware failures

Capacity Available	**Capacity Outage**	**State Probability**	**State Probability**	**Cumulative Probability**	**LOLE (days/year)**	**ELL (MW)**
30	0	$A_1A_2A_3$	0.193117	1	-	-
23	7	$A_1A_2U_3$	0.129282	0.80688300	-	-
20	10	$A_1A_3U_2$	0.13813	0.67760100	-	-
17	13	$A_2U_3U_1$	0.1561	0.53947100	-	-
13	17	$A_1U_2U_3$	0.092471	0.38337100	33.752	0.462
10	20	$A_2U_1U_3$	0.104501	0.29090000	-	0.836
7	23	$U_1U_2A_3$	0.111653	0.18639900	-	1.228
0	30	$U_1U_2U_3$	0.074746	0.07474600	-	1.345

The obtained ELL for the plant considering the hardware is 3.872 MW and the EENS obtained is 18.37 GWh/year.

6.3.2. Customer Based Reliability Indices

There are reliability indices which can be used as key performance indicators (KPIs) that quantify the loss of supply to customers, in terms of the frequency, duration of interruptions etc. The reliability indices that were considered in this study are System Average Interruption Frequency Index (SAIFI) expressed in times per customer per year, System Average Interruption Duration Index (SAIDI) expressed in hours per customer per year, Average Service Availability Index (ASAI) expressed in percentage and Customer Average Interruption Duration Index (CAIDI) which indicates the required time to restore service.

These are represented as per Equation (6.12) – (6.15) and are used to further analyze the reliability of the solar PV plant [10], [55].

$$SAIFI = \frac{\sum N_i}{N_T} \tag{6.12}$$

$$SAIDI = \frac{\sum r_i N_i}{N_T} \tag{6.13}$$

$$ASAI = 1 - \frac{SAIDI}{8760\ (hours)} \tag{6.14}$$

$$CAIDI = \frac{\sum r_i N_i}{\sum N_i} = \frac{SAIDI}{SAIFI} \tag{6.15}$$

where N_i is the total number of customers interrupted (which incorporates the failure rate of the load point), r_i is the yearly interruption, N_T is the total number of customers served. To compute these indices for the purpose of this study, the total number of customers connected are assumed to be 10, three of which are contracted to be supplied 3 MW each, 2 contracted at 2 MW and the rest contracted at 1 MW. These load points are each connected via AC circuit breakers with auto reclose functionality [27]. Table 6-6 lists the computed indices for the plant under study, which were computed over a period of a year. The data represents the average interruptions in a year which is due to solar resource variations and failure of the plant, respectively (i.e. first column and second column under indices).

Table 6-6: Reliability Indices for a 30 MW solar PV plant considering solar resource

Date	**Cust.**	**Duration (hrs)**		**Customer-hours**		**SAIDI**		**SAIFI**		**CAIDI**		**ASAI**	
Jan	4	83	67.5	332	270	33.2	27	0.18	0.35	181.05	76.94	0.996	0.997
Feb	6	83	67.5	498	405	49.8	40.5	0.28	0.53	181.05	76.94	0.994	0.995
Mar	5	83	67.5	415	337.5	41.5	33.75	0.23	0.44	181.05	76.94	0.995	0.996
Apr	4	83	67.5	332	270	33.2	27	0.18	0.35	181.05	76.94	0.996	0.997
May	6	83	67.5	498	405	49.8	40.5	0.28	0.53	181.05	76.94	0.994	0.995
June	3	83	67.5	249	202.5	24.9	20.25	0.14	0.26	181.05	76.94	0.997	0.998
July	2	83	67.5	166	135	16.6	13.5	0.09	0.18	181.05	76.94	0.998	0.998
Aug	4	83	67.5	332	270	33.2	27	0.18	0.35	181.05	76.94	0.996	0.997
Sept	5	83	67.5	415	337.5	41.5	33.75	0.23	0.44	181.05	76.94	0.995	0.996
Oct	4	83	67.5	332	270	33.2	27	0.18	0.35	181.05	76.94	0.996	0.997
Nov	3	83	67.5	249	202.5	24.9	20.25	0.14	0.26	181.05	76.94	0.997	0.998
Dec	2	83	67.5	166	135	16.6	13.5	0.09	0.18	181.05	76.94	0.998	0.998

These obtained indices indicate that the plant under study is reliable as the obtained SAIFI results are closer to zero which indicates that no frequent interruptions occur, if they do occur the duration is not prolonged as indicated by the SAIDI values. The ASAI obtained results indicate that customers did receive power over 99 % of the time over the defined reporting period. The obtained results tabled in Table 6-6 are depicted graphically in Figure 6-4 and 6-

5 where a comparison is made between indices when considering solar resource intermittency and hardware failure rates.

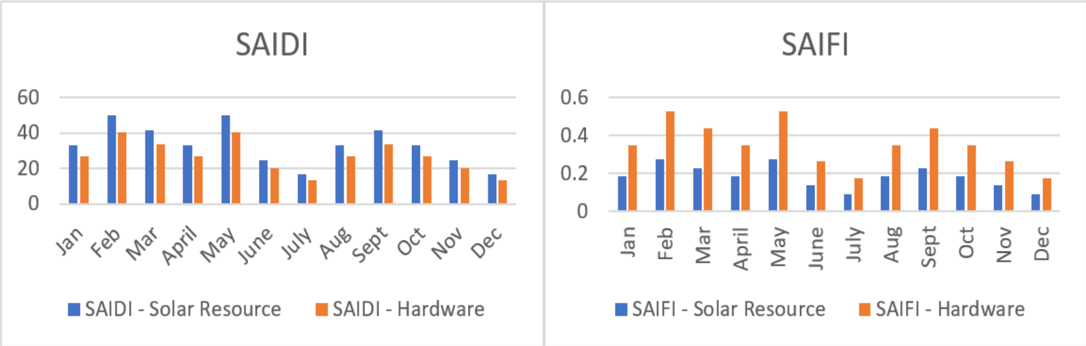

Figure 6-4: SAIDI and SAIFI considering solar resource and hardware

The SAIDI and SAIFI shown in Figure 6-4 compare the two conditions considered where the overall observation indicates that the customers will experience more interruptions due to loss of power caused by the unavailability of solar irradiance than due to failure of components. This is unavoidable as there is no control over the solar resource however there are some improvements that can be implemented to ensure that when there is less solar irradiance affecting the customers, there is reserve power supply to supplement during the shortage.

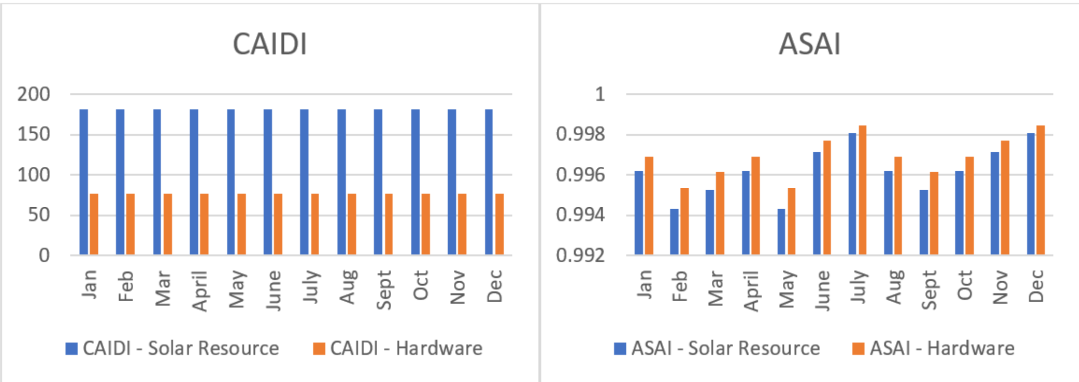

Figure 6-5: CAIDI and ASAI considering solar resource and hardware

Similarly to SAIDI and SAIFI indices, CAIDI in Figure 6-5 shows that the average interruption of customers is mostly due to the solar resource variations than hardware failures. This is expected as this index is dependent on the SAIDI and SAIFI indices which showed the same relationship. The average service availability index is fairly high for both cases however the solar resource has more impact on the unavailability of supply as seen on the discussed indices. These indices and the reliability of the plant are an indication of the performance of the solar PV plant under study which can be improved in various ways as discussed in the next section.

6.4 Reliability Improvement

Sensitivity analysis of the stress factors is required when attempting to improve the reliability of the solar PV plant. Figure 6-6 depicts the sensitivity analysis of the components looking at the stress factors. The capacitor is seen to be most sensitive to the voltage, environment and quality stress factors. Critical stress factors which MOSFETs are most sensitive to are application, quality and environment. The improvement of failure rates focuses on reducing the critical stress factors.

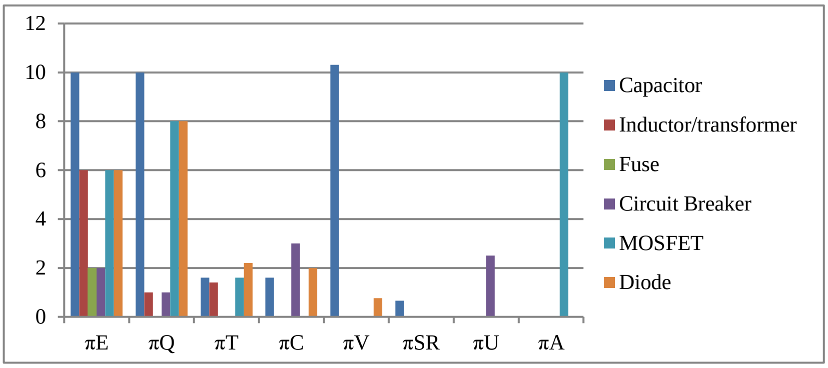

Figure 6-6: Stress factor sensitivity analysis

Stress factors that have a major impact in the reliability of the plant can be minimized in various ways. The quality stress factor can be minimized by improving the packaging quality of components. The voltage stress factor can be minimized by de-rating the components. The environmental stress factor can be reduced by ensuring that the components are used in their designed environmental conditions [38]. After reducing the dominant stress factors, failure rates and therefore reliability of the components and the system studied can be improved.

For improved reliability a redundancy approach can also be employed; this involves a creation of new parallel paths. The reliability has more significance compared to the cost spent in investing for a second redundant system as the gains on a high reliable plant is realized in a long run whereas the capital cost will be spent once. For hot standby redundancy systems, a redundant system is continuously in operation with the primary system whereas in cold standby redundancy systems the redundant system is only brought in operation when the primary system fails. The designer can decide on which redundancy system can be applied for improved reliability [39].

For the purpose of the study, possible parallel systems are considered for reliability improvements. A second 30 MW solar PV plant has been connected in parallel with the primary 30 MW plant. Two redundant methods have been looked at i.e. system redundancy and component redundancy. System reliability obtained with component redundancy is in general higher than that achievable with subsystem redundancy. Component redundancy is when the same component is found in the primary system and in the redundant system; such that when there is a failure in one component it can be replaced by the corresponding component from a second system. The interchangeability of components can be achieved by, as an example, employing couplers between systems such that the component can be bypassed while fully meeting the plant's objective [56]. The reliability of the plant when considering component redundancy can be represented as per Equation (6.16) and that of system redundancy is as per Equation (6.9).

$$p(t) = \prod_{i=1}^{l}[1-(1-i(t))^{k}\ ]; i = 1, \dots \dots, l \tag{6.16}$$

Where *l* is the number of components in parallel, *k* is the number of systems in parallel and *(t)* is the reliability of a component. The obtained improved results are shown in Table 6-7. As depicted in the table, the reliability is improved when considering component redundancy, this is due to the parallel configuration of the redundant systems i.e. the more parallel paths created in a system, the more improved the reliability.

Table 6-7: Improved reliability with redundancy employed

Reliability of a 30 MW Plant with one inverter	**Improved reliability considering system redundancy**	**Improved reliability considering component redundancy**
0.4159	0.659	0.933

Another method of improving reliability can be the introduction of a capacity storage system in a form of a battery; the logic gate diagram changes from that discussed in Chapter 3 to as shown in Figure 6-7. The battery will assist in improving the reliability when considering the solar resource variation as it will sustain the supply during solar irradiance decay.

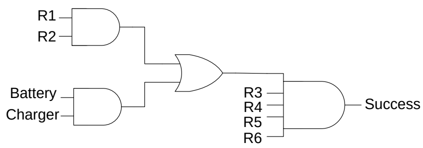

Figure 6-7: Solar PV plant logic diagram with battery storage

Since there is some level of redundancy introduced with the battery storage system in place, the overall reliability can be improved. It is crucial to note that the plant will not be in operation on its own, it's a substituting plant in case of emergencies and to support the conventional generators during the day; and therefore the overall reliability is improved as the conventional power plant is seen to be in parallel with the solar PV plant under study.

6.5 Conclusion

This chapter looked at the reliability of the 30 MW solar PV plant. The reliability indices were considered for two cases, considering the intermittence source and component failures. In the components assessed, the PV panels were excluded from the reliability due to their low failure rates. The reliability of the plant was improved when the number of components were reduced i.e. the most contributors to the failure rates which are inverters.

Probabilistic indices considered were computed using binomial distribution methods. The obtained results indicated that the LOLE index is high when considering the solar resource intermittency than when considering hardware failure. This implies that the supply is more affected by the solar resource variations than due to failure of components. This is also demonstrated by the customer based indices obtained. Various ways of improving reliability over and above reduction of components have been proposed and looked at. System redundancy and component redundancy have been studied as methods of improving reliability, with the component redundancy configuration yielding a higher reliability compared to when system redundancy is employed. It is crucial to also note that the reduction of components, aiming at improving redundancy, should attempt to avoid a single point of failure as far as practically possible and creating more parallel paths in a system improves the reliability.

CHAPTER 7 – CONCLUSION

7.1 Solar PV Plant

The work conducted and presented in this dissertation includes the modelling and simulation of a 30 MW solar PV plant which is grid connected and located in the Upington area in Northen Cape Province. The plant was modelled using MATLAB Simulink, with the aim of studying its characteristics under different weather conditions. South African Weather Services were approached for the actual historical solar radiation data for the area; this was used in the model and the plant's characteristics were observed. The data received from SAWS lacked the temperature readings and these were assumed and varied according to the time of the day, corresponding to the solar irradiation readings. The type of PV modules employed in the study is monocrystalline silicon which is one of the efficient modules with a higher rating, such that fewer modules are utilized to yield the desired output power of the plant.

The model first considered a single cell followed by a string, an array and the overall plant. The I-V and P-V characteristics were observed and the conclusion made was that the output power is highly dependent on the solar irradiance compared to the ambient temperature. The output power is seen to be highly affected by the change in irradiance, as for a single array rated at 1.61 MW the power obtained at 1000 W/m^2 is 1.61 MW and at 250 W/m^2 the obtained power is 0.4 MW whereas the power obtained at an ambient temperature of 55 °C is 1.2 MW and at 15 °C it is 1.7 MW. The plant's output power is reduced at high temperatures but it increases when the solar irradiance is high.

7.2 Forecasting Techniques

The plant's behavior under different weather conditions necessitated the development of the forecasting techniques that can be used by system operators to predict the plant's behavior and do the planning accordingly. The idea is to make use of the weather forecasted data as input to the forecasting models and observe the plant's output power. Should the results indicate the shortage of energy then alternative sources can be brought to service for an effective management of the supply and demand. The techniques developed were based on the fuzzy logic method and artificial neural network, both developed using MATLAB. Both the methods were developed using a single array.

7.2.1 Fuzzy Logic based method

The fuzzy logic based technique developed is a 2 input, 1 output Mamdani model which made use of the centroid defuzzification method for input and output variables using triangular membership functions. This was observed to yield the least percentage error of the forecasted data and the actual plant data compared to other methods that were studied. The forecasted data when compared to the actual plant data had an average error of 1.9 %. This implies that the model has been developed well, however further optimization of the model can be done to yield even more accurate results.

7.2.2 Artificial neural network technique

A second forecasting method employed in the study was based on ANN technique. The technique was a backpropagation network trained using a Levenberg-Marquardt algorithm which had been developed using MATLAB. Literature demonstrates the benefits of making use of historical data of the plant to train the network which yields more accurate results; the more historical data used in the training the more accurate the network is. For this study, the data used in the development of the network was the data obtained when simulating the plant. For optimization and a more accurate network, the study can make use of the existing plant and use the data to train the network. This will form part of the future work. With the data used in this study, the obtained average error was 2.6 %.

7.3 Reliability Evaluation

The plant was further analyzed in terms of its reliability. The objective is for effective planning of the system, selecting an optimal configuration of the plant and for an appreciation of the plant’s performance to effectively plan for future projects i.e. refurbishment, replacements or upgrades in order to improve or maintain the system’s reliability. The reliability evaluation took into account the hardware failure and repair rates; and further considered the solar resource variations since the resource is intermittent in nature. Probabilistic and customer based indices were therefore computed. The average SAIFI and SAIDI over a year when considering intermittency of solar resources was obtained to be 0.183 and 33.2, respectively; when considering failure of the plant the SAIFI and SAIDI were obtained to be 0.352 and 27, respectively. The obtained LOLE when considering solar resource intermittency is 41.498 days/year and when considering hardware failures it was obtained to be 33.752 days/year. The observation made is that when considering the hardware failures there is more customer interruptions however the duration of the interruptions is less than when considering the intermittency of the solar radiation. One of the contributors in achieving the reduced duration is the plant configuration selected. When considering the solar resource intermittency, the frequency of interruptions is reduced however the duration of the interruptions is high compared to that of hardware failures due to the number of days/hours when there is minimal solar radiation.

For improving the reliability, different considerations were highlighted i.e. reducing the stress factors of components used, reconfiguration of the plant and battery energy storage system or second plant that can be connected in parallel with the primary or main plant. The expressions studied prove that the parallel systems have a higher reliability compared to the series connected systems.

7.4 Research Contributions

In addition to the results obtained and the methods developed to forecast the plant's output power and evaluate its reliability, this dissertation presents a more detailed approach of developing a fuzzy logic based forecasting technique for the solar PV plant. Most literature make use of the ANN as the forecasting method. This research study can therefore be useful when developing the fuzzy logic system for any solar PV plant as more accurate fuzzy logic functions have already been assessed. Furthermore, the research work shows an aspect of computing reliability indices that can be evaluated for the plant; these include probability based indices and the plant's KPIs, considering two aspects that affect the plant's performance i.e. hardware and solar resource. The obtained results have addressed the key questions of the research and the objective, which is to be able to predict the plant's output power and assess its reliability, however there are improvements that can be done for a more optimum system.

7.5 Recommendations for Future Work

The grid connection requirements as per the SAGC and IEC standards for the inverter can be considered as part of future work. In this study there is no major effect observed by not considering these requirements, as the main focus was to conduct the reliability evaluation of the plant. However, to have a holistic appreciation of a grid connected solar PV plant it is vital to understand all aspects such that the plant studied is as close as possible to practical plants. The study can be adopted to the existing plants and use the parameters of the actual components.

Some of the components that are necessary in the plant are a maximum power point tracker and dc-dc converters which sustain the DC link voltage and therefore reduce the fluctuations in voltages when there are fluctuations in the solar radiation. Similarly the inclusion of the battery energy storage system can be looked at for an improved reliability and availability. This however requires some feasibility study for large scale applications as it may become impractical to have energy storage systems with sufficient back-up time. Should the outcome of the feasibility study indicates that these would be impractical, a good forecasting model and reliability analysis of the plant can be useful instead, as they will allow for proper planning.

Shading effect, cleanliness of the panels, panel reliability, wind speed, manufacturing defects etc. as seen from literature are some of the important factors that can be further looked at to get to an even more accurate reliability and output power from the solar PV plant. The approach and concept in the reliability analysis remains the same, it just requires the consideration of these factors. It can be noted that the obtained reliability indices were independent of each aspect considered i.e. the resultant indices when taking into account both solar resource variations and hardware failures were not computed. Forecasting of the plant can also incorporate the reliability of the plant, such that the forecasted power is more realistic, as the developed forecasting methods were independent of the plant's reliability; this will form part of the future work.

REFERENCES

[1] DoE, GIZ; “State of Renewable Energy in South Africa”, Dep. of Energy, South Africa, September 2015.

[2] M.S. ElNozahy and M.M.A. Salama, “Technical Impacts of grid-connected photovoltaic systems on electrical networks – A review”, Canada, 30 May 2013.

[3] E.R. Muhammad et al., “Artificial Neural Network Predictor for grid-connected solar photovoltaic installations at atmospheric temperature”, Trivandrum, December 2014.

[4] F. Grimaccia et al., “Neuro-fuzzy predictive model for PV energy production based on weather forecast”, Energy department, Italy, June 2011.

[5] Sumant G. Kadwane and Jyoti M. Kumbhare, “A Matlab/Simulink Modeling for Reliability Analysis of Inverter Applied to MPPT Based PV System”, India, 2015.

[6] P.I. Muoka et al., “Modeling, Simulation and Hardware Implementation of a PV Power Plant in a Distributed Energy Generation System”, Australia, 2013.

[7] Chapter 5 Solar Photovoltaics [online]. Available: www.uprm.edu/aret/docs/Ch_5_PV_systems.pdf.

[8] M.A Gonzalez-Salaza et al., “Review of the operational flexibility and emissions of gases and coal-fired power plants in a future with growing renewables”, Garehing, July 2017.

[9] A. Dolara et al., “PV hourly day ahead power forecasting in a micro grid context”, Department of Energy, Milano, Italy, 2016.

[10] P. Zhou et al., “Reliability and economic evaluation of power system with renewables: A review”, Nanjing, China, 2016.

[11] Michael E. Ropp, “Development of a MATLAB/Simulink Model of a Single-Phase Grid-Connected Photovoltaic System”, 2009.

[12] S.I. Rasel et al., “Design & Simulation of Grid Connected Photovoltaic System using Simulink”, Bangladesh, December, 2015.

[13] Md. Shohag Hossain et al., “Modeling of Solar Photovoltaic System Using MATLAB/Simulink”, KUET, Bangladesh, December, 2016.

[14] E.R Muhammad et al., “Day-Ahead Prediction of Solar Power Output for grid-connected solar photovoltaic installations using Artificial Neural Networks”, Barat Heavy Electricals Limited Tiruchrappalli, India.

[15] E. Ogliari et al., “Neural Forecasting of the Day-Ahead Hourly Power Curve of a Photovoltaic Plant”, Dipartimento di Energia, Italy, 2016.

[16] R.T.S. Rodrigues et al., “Development of an ANN Model to Predict the Electricity Produced by Small Scale Roof-top PV systems in Madeira Island”, University of Coimbra, Portugal, 2017.

[17] B. Sivaneasan et al., “Solar Forecasting using ANN with Fuzzy Logic Pre-processing”, Nanyang Polytechnic, Singapore, 19-21 July 2017

[18] Sobrina Sobri et al., “Solar photovoltaic generation forecasting methods: A review”, King Adulaziz University, Malasia, 1 December 2017.

[19] M. Hossain et al., “Application of extreme learning machine for short term output power forecasting of three grid-connected PV systems”, Malaysia, 2017.

[20] Luyao Liu et al., “Prediction of short-term PV power output and uncertainty analysis”, Beijing University of Posts and Telecommunications, China, 6 July 2018.

[21] Takashi Hiyama, “Neural Network Based Estimation of Maximum Power Generation from PV Module Using Environmental Information”, Japan, September 1997.

[22] S.X. Chen et al., “Solar radiation forest based on fuzzy logic and neural networks”, Singapore, 2 June 2013.

[23] F. Chekired et al., “Fuzzy logic energy management for a photovoltaic solar home”, Greece, 5-7 July 2017.

[24] K.R Kumar and M.S. Kalavathi, “Artificial intelligence based forecast models for predicting solar power generation”, India, 2018.

[25] P. Zhang et al., “Reliability Evaluation of Grid-Connected Photovoltaic Power Systems”, July 2012.

[26] N. Pradhan and N.R. Karki, “Probabilistic Reliability Evaluation of Off-grid Small Hybrid Solar PV-Wind Power System for the Rural Electrification in Nepal”, Nepal, 2012.

[27] N. Pradhan et al., "Reliability Evaluation of Small Standalone Hybrid Solar PV -Wind Power System", Nepal, 2012.

[28] M.P Lalitha et al., "Reliability Evaluation of Wind and PV Energy Penetrated Power System", India, 2014.

[29] S.S. Singh and E. Fernandez, "Reliability Evaluation of a Solar Photovoltaic System with and without Battery Storage", India, 2015.

[30] H. Li et al., "Reliability evaluation of PV power systems with consideration of time-varying factors" China, 3 November 2017.

[31] Abdullah Altamimi, "Reliability Performances of Grid-Integrated PV Systems with Varying Climatic Conditions", University of Birmingham, UK.

[32] S. Tao et al., "Operational Risk Assessment of Grid-connected PV System Considering Weather Variability and Component Availability", Tianjin, China, 18-20 October 2017.

[33] A. alferidi and R. Karki, "Development of Probabilistic Reliability Models of Photovoltaic System Topologies for System Adequacy Evaluation", University of Saskatchewan, Canada, February 2017.

[34] N Gupta et al., "Sensitivity and reliability models of a PV system connected to grid", Delhi Technological University, India, November 2016.

[35] A Ahadi et al., "Probabilistic Reliability Evaluation for Power Systems with High Penetration of Renewable Power Generation", University of Newfoundland, Canada, 2017.

[36] B. Yasmeena and G. Tulasi Ram Das, "Fuzzy set theory applications for FACTS devices in grid connected renewable power systems", EEE Department, India, 2016.

[37] E.G. Kardakos et al., "Application of Time Series and Artificial Neural Network Models in Short-term Forecasting of PV Power Generation", Aristotle University of Thessaloniki, GREECE.

[38] S Roostaee et al., "Reliability Comparison of Various Power Substation Automation based on IEC61850", Jamia Millia Islamia, India, 2017.

[39] Sunil Gupta, "Reliability Analysis of IEC 61850 Substation Communication Network Architectures", Maharaja Surajmal Institute of Technology, 2016.

[40] Sunmodule; “SW 250 mono/ Version 2.0 and 2.5 Frame Technical specifications”, Solar world.

[41] Tomas Markvart, Solar Electricity, 2nd ed, Wiley, 2000, 1994.

[42] R. Inzunza et al., “Development of a 1500Vdc photovoltaic inverter for utility-scale PV power plants”, Toshiba Mitsubishi-electric industrial systems corporation, Tokyo, Japan, 2015 IEEE.

[43] N. Mohan, T.M. Undeland and W.P. Robbins, Power Electronics, Converters, Applications and Design, John Wiley & Sons, Inc., 3rd ed, chapter 8, 2003

[44] S. Mohamad Nawi et al., “A fuzzy logic application for identification of harmonics disturbances sources”, University Technology of MARA, Bangi, Malaysia, 2003.

[45] F.A.O Aashoor and F.V.P. Robinson,”Maximum power point tracking of photovoltaic water pumping system using fuzzy logic controller”, University of Bath, UK.

[46] K.L. Lo and M.O. Sadegh, “System method for the design of a full-scale fuzzy PID controller for SVC to control power system stability”, Dept EEE, UK, May 2003.

[47] T. Vanker et al., “Comparitive analysis of PI and fuzzy control for a dual input DC/DC converter in hybrid energy application”, Kerala, India, 2017.

[48] A Golnas, “PV System Reliability: An Operator’s Perspective”, SunEdison/MEMC, Beltsville, USA, January 2013.

[49] Reliability Prediction of Electronic Equipment. Military handbook 217-F. Arlington, VA: Dept. Defense; 1991.

[50] Bollen, M.H.J. Literature Search for Reliability Data of Components in Electric Distribution Networks; Eindhoven University of Technology: Eindhoven, the Netherlands, 1993.

[51] L.H. Koh et al., “Reliability Evaluation of Electric Power Systems with Solar Photovoltaic & Energy Storage”, Nanyang Technology University, Singapore, 2014.

[52] A.A. Chowdhury and D.O. Koval, “Impact of photovoltaic power sources on a power system’s capacity reliability levels”, University of Alberta, Canada, 2005.

[53] H.F. Boroujeni *et al.*, “Calculation of generation system reliability index: Loss of Load Probability”, Islamic Asad University, Iran, 2012.

[54] Methods to Model and Calculate Capacity Contributions of Variable Generation for Resource Adequacy Planning, NERC, March 2011.

[55] *IEEE Guide for Electric Power Distribution Reliability Indices*, IEEE Std 1366, 2003.

[56] E. Udwadia, "A Note on the Reliability of Redundant Systems", University of Southern California, Elsevier North Holland, Inc., 1981.

APPENDIX A

Table A-1: Symbols used in the equations defining the I-V, PV characteristics [12]

Symbol	**Description**
V	PV Cell output voltage (V)
I	PV Cell output current (A)
I_{LG}	Photon current (A)
I_{OS}	Reverse saturation current of PV cell (A)
T	Operating temperature of PV cell (°K)
Q	Charge of an Electron =$1.6*10^{-19}$ C
K	Boltzmann’s constant =$1.38*10^{-23}$ J/°K
K_l	Temperature coefficient
I_{SC}	Short circuit current (A/°K)
S	Operating solar radiation (W/m2) Short circuit current at STC (A)
E_{GO}	Band gap energy of the semiconductor (J)
A, B	Ideality constant between 1 and 2
T_r	Absolute temperature at Standard Test Condition of PV cell = 301.18°K
I_{OR}	Reverse saturation current of PV cell at temperature Tr (A)
R_{Sh}	Intrinsic parallel resistance of PV cell (Ω)
R_S	Intrinsic series resistance of PV cell (Ω)