DEVELOPMENT OF A HYBRID FUZZY LOGIC AND LINEAR PROGRAMMING ALGORITHM FOR OPTIMAL LOAD SHEDDING IN ISLANDED MICROGRID

JOSIAH TEYAH MAROKO

MASTER OF SCIENCE IN

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Development of a Hybrid Fuzzy Logic and Linear Programming Algorithm for Optimal Load Shedding in Islanded Microgrid

Josiah Teyah Maroko

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DECLARATION

This thesis is my original work and has not been presented for a degree in any other University.

Signature…………………………………… Date……………………………………

Josiah Teyah Maroko

This thesis has been submitted for examination with our approval as the University Supervisors:

Signature…………………………………… Date……………………………………

Prof. David Kinyua Murage, PhD (Deceased)

JKUAT, Kenya

Signature…………………………………… Date……………………………………

Prof. Peterson Kinyua Hinga, PhD

JKUAT, Kenya

DEDICATION

I dedicate this research work to my family for their unwavering moral support.

My heartfelt love and gratitude to the Almighty God.

ACKNOWLEDGEMENT

I would like to thank our almighty God for this far He has brought me, His mercy, care, knowledge and abundant grace. Goodwill wishes to my supervisors, the late Professor D.K. Murage and Professor P.K. Hinga. Through their guidance, critics, suggestions and recommendations I was able to complete this work. I am also greatly thankful to Jomo Kenyatta University of Agriculture and Technology for providing a serene environment for the entire period of my research work. I am also indebted to the chairman, dean of electrical and electronic engineering and the director of postgraduate studies for the administrative support accorded me throughout my research journey.

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ABBREVIATIONS AND ACRONYMS

AI	Artificial Intelligence
BFOA	Bacteria Foraging Optimization Algorithm
BOA	Bisector of Area
CIGRE	Conseil International des Grands Réseaux Électriques
COG	Centre of Gravity
COGS	Centre of Gravity Method for Singletons
DGs	Distributed Generations
DR	Distributed Resource
DSs	Distributed Storages
FIS	Fuzzy Inference System
FLC	Fuzzy Logic Controller
FLP	Fuzzy Linear Programming
FLS	Fuzzy Logic System
FT	Fourier Transform
FVSI	Fast voltage stability index
GA	Genetic Algorithm
GHG	Green house gas
HGAPSO	Hybrid of Genetic Algorithm and Particle Swarm Optimization

IEEE	Institute of Electrical and Electronics Engineers
IMG	Islanded Microgrid
kW	Kilowatt
LM	Leftmost Maximum
LP	Linear Programming
LPP	Linear Programming Problem
LS	Load Shedding
MDP	Markov Decision Process
MG	Microgrid
MHP	Micro Hydro Power
MOM	Mean of Maxima
NN	Neural Network
PCC	Point of Common Coupling
PID	Proportional Integral Derivative
PLC	Programmable Logic Controller
PSO	Particle Swarm Optimization
PV	Photovoltaic
RES	Renewable Energy Source
RHS	Right Hand Side

RM	Rightmost Maximum
ROCOF	Rate of Change of Frequency
SCADA	Supervisory Control and Data Acquisition
US	United States
UVLS	Under Voltage Load Shedding
VSI	Voltage Stability Indicators

ABSTRACT

The islanded microgrid (IMG) entirely depends on Distributed Generations (DGs) like Micro Hydro Power (MHP), solar photovoltaic (PV), wind, and fuel cells among other sources of energy. The stochastic nature of solar PV, wind and local loads creates an imbalance between generation and the loads. These disturbances can plunge the IMG into an emergency power crisis which can lead to a cascaded blackout if no remedy strategy is brought on board to restore the power to a balance. To avert the power crisis in the IMG load shedding (LS) is done as a last resort after all control mechanisms have been exhausted. The conventional methods of LS used in grids perform poorly when applied to the IMG because of low convergence and settling time. Recent researchers have found that adaptive methods for LS specifically the hybrid method perform optimal LS to curb the power system from collapsing in times of contingencies. The hybrid method of LS using a Fuzzy Logic Controller (FLC) and Linear Programming (LP) was used to optimize the amount of LS in the IMG. In this method, the objective function was formulated and solved by the Fuzzy Linear Programming (FLP) algorithm. The inputs to the controllers are power generated and power demand of the IMG. The loads were classified according to priorities using fuzzy membership functions while optimization of loads shed was achieved by the LP algorithm. The simulations consisted of generation contigencies, power demand in which 10 overload contingencies were simulated, voltage profiles and power losses. The results depict FLP algorithm finds the best steady-state operating point with a minimal amount of load curtailment. The scheme minimizes loading at the buses until total load demand matches generation to restore power balance within a single LS step. In comparison to GA 77.04%, ABC-ANN 84.03%, PSO-ABC 85.50% the proposed FLP algorithm was able to shed optimal amount of load quantities resulting in 86.10% voltage profile recovery. The developed algorithm was tested by performing simulations on IEEE 14 bus systems on a Matlab Simulink platform.

CHAPTER ONE

INTRODUCTION

1.1 Background of Study

The volatility of prices for conventional sources of energy (like fossil fuels) has led to the shift of focus to Renewable Energy Sources (RES) which are environmentally friendly and sustainable in the long run. However, the intermittency of the RES has hampered the direct coupling to the main grid due to stability and harmonic issues (Marnay &. Venkataramanan, 2006). The flexible nature of the microgrids (MG) has opened up the connection of RES to the grid as they can be synchronized to the grid and islanded when instabilities strike (Mohammad, 2018; Long &. Phung, 2021). The MG benefits the distribution system by providing network support in times of severe faults (Fu, Hamidi, Nasiri, Bhavaraju, & Krstic, 2014).

The MG is a promising frontier for future smart grids; its present application is acting as a bridge since power is produced, circulated, consumed and controlled in a confined scale (Gandoman, 2018; Conteh, Tobaru, Lotfy, Yona, &. Senjyu, 2017). The application of MG ensures the whole power system becomes more distributed, more connected and interactive.

A microgrid is a power system with low voltage that integrates various DGs, Distributed Storage (DSs), and loads which may include the utility grid (Mahmoud, Habibi, & Bass, 2012). The MG is capable of operating in grid-connected mode or islanded mode from the main grid. An IMG refers to a MG disengaged from the power grid because of one of the following reasons; regular maintenance, occurrence of faults in the interconnected grid or geographical isolation (Kim, Kinoshita, Shin, . & Engineering, 2010).. The IMG mainly depends on power generated from its DGs which are located close to the local loads which reduce line losses.

The increasing demand for energy both for industrial and domestic use due to the increase in population has encouraged the increased research and use of RES to satisfy the growing energy demand (Raju & Milton, 2016). Green energy plays a vital role in building a clean and sustainable environment by reducing greenhouse gas (GHG) emissions which contributes greatly to global warming. Additionally, there is a correlation between GHG emissions and electricity use, with the one-degree rise in temperature owing to emissions translating into a growth in electricity consumption of between 0.45% and 0.75% (Sarwar, et al., 2020; Mogaka, Nyakoe, & Saulo, 2020).

To meet this growing energy demand crisis in the world; solar, wind, fuel cells and other renewable energy sources are the main solutions Bower, Bower, Llc, Reilly, .&. Associates, 2014). When the IMG is coupled to the grid power balance is maintained by exchanging with the grid however, the IMG has to depend only on the power from its DGs (Kim, Kinoshita, & Lim, 2014). In case of a disturbance from the grid, the outstanding feature of the IMG is its ability to island itself from the main grid and completely depend on its DGs (Kim, Suharto, &. Daim, 2017).

Distributed Generation refers to small power generations which are less than 10MW and are usually located close to load centres to avoid the need to expand transmission and distribution networks (Sapari, Mokhlis, Laghari, Bakar, & Dahalan, 2018). The MG system acts like a plug-and-play power unit in that it has advanced controllers that can detect grid disturbances, isolate itself at the Point of Common Coupling (PCC) and continue to supply its loads. In the IMG frequency is considered a system-wide phenomenon that is used to indicate the balance or imbalance of active power while voltage is considered a local feature used to determine reactive power balance Nair, Member,. &. Ancell, 2012; Abazari, &. Zahedi, 2016).

Bulk electrical power is very expensive to store hence its generated and consumed almost instantaneously. Power system operators must ensure that generation and load are balanced however, with ever-increasing demand it becomes very challenging. If the available generation cannot meet the available demand, then system operators are compelled to load shed excessive load to balance the power system. In an emergency in the MG occasioned by shortage of power generation, frequency and voltage will reduce below the required threshold Zadeh, (2012). If the system governor cannot bring spinning reserve on time, then the under frequency LS is activated as the last resort to ensure the system is restored to a normal state.

Load shedding is the selective reduction of load according to a preplanned schedule when power shortage occurs (Wang, Mei, Dong, Chen, & Zhu, 2020). Optimal LS thus refers to the amount of load that should be removed almost instantly to maintain the stability of the remaining part of the system (Lim, Kim, Park, . & Kinoshita, (2021). LS can be triggered by several factors including insufficient generation, transmission or distribution line constraints, equipment failures and extreme weather conditions (Fotis, Vita, & Maris, 2023). LS can be classified into two categories namely; planned and unplanned. The first one is usually scheduled for, as the anticipated generation shortage is predictable and thus prepared for in advance while the latter is due to an abrupt loss of generation (Mohammad, 2018; Long &. Phung, 2021; Kaewmanee, . Sirisumraaukul, . & Menaneanatra, 2013).This type of LS is unpredictable because when there is a loss of generation, the outcome is a reduction of frequency below the standard stipulated value.

LS has two approaches namely centralized LS and decentralized LS. In centralized LS, all components operate for a collective objective which is the maximization of system efficiency by the Microgrid Operation and Control Centre (MGOCC). The MGOCC determines the amount of load to be dropped at each phase until the system attains equilibrium. In the decentralized LS approach scheme, the components in the MG possess different owners and operating policies. In this scheme, several decisions from several components should be taken autonomously on the amount of load shed (Hong, Hsiao, Chang, Der Lee, & Huang, 2013).. In an islanded mode, when there is a power supply shortage LS is a control measure to lower loads to restore power balance.

In the past research, LS has been addressed by evolutionary methods such as ANN, GA and PSO which to a great extent have helped avert instabilities and blaclouts in IMG (Kisengeu, Muriithi, & Nyakoe, 2021, Hagh, &. Galvani, 2011). The conventional controllers for LS when applied to IMGs offers poor control and do not perform optimal LS. The IMGs are often fed with RES that are intermittent in nature and have low inertia or innertialess generators. This can plunge the IMG to instability when the available generation cannot meet the load demand. Thus IMG requires a reliable and robust controller to optimally curtail loads when the demand exceeds the available generation in IMG.

Despite the merits of IMG highlighted, the IMG face critical challenges due to the dependence on intermittent RES and low inertia generators. Bulk power connot be stored, thus supply and demand must be balanced in real time. Any deficit in generation leads to an overload if uncontrolled may cascade and result to a blackout. In such case LS is used as a last line of defence to preserve IMG stability.

Conventional LS have been used widely in power system and are not suited for IMG application. This is because in interconnected grid has high inertia and has spinning reserve thus governors act to restore system equilibrium. In contrast in IMG power fluctuations are fast and sudden and conventional LS methods leads to excessive shedding or suboptimal LS. Heuristic and metaheuristic approaches like artificial intelligence (fuzzy logic, neural networks, genetic algorithm and particle swarm optimization) and hybrid methods have been used to achieve fastes and optimal LS in IMG yet this methods still face challenges in real-time implementation and scalability.

This study focuses on the development of a hybrid method of fuzzy linear programming controller for load shedding in an islanded microgrid. The research investigated the application of FLP algorithm for load shedding under varying generation and load conditions. The proposed approach aims to improve IMG stability and reduce the amount of load shed.

1.2 Problem Statement

An IMG is more vulnerable than a conventional power grid such that a small disturbance can lead to a loss of stability that can cause overloading leading to a cascaded blackout. When the IMG is linked to the grid, the system power balance is determined by connected synchronous generators; however, when the IMG is operating in islanded mode, it is mostly fed with generators with low inertia (mini hydros, wind turbines) or inertialess generators like solar PV and fuel cells.

In times of severe power imbalance due to an overload in IMG LS is applied as a last resort to reduce the load to match the available generation. The existing LS techniques are not effective in estimating the amount of power imbalance, which leads to under-shedding or over-shedding, which can plunge the IMG into a cascaded blackout (Karimi, Mohamad, Mokhlis, & Bakar, 2012). This work developed a FLP algorithm to optimally shed minimal loads to stabilize the frequency in IMG.

1.3 Justification

Contingencies such as generation deficiencies, load fluctuations and equipment failures. Conventional LS applied to power grids for LS are often rigid and deterministic in nature Sarwar, (2020).. While these methods have provided corrective action to solve power mismatch, they are limited in handling uncertainties inherent in IMGs with RES.

To address these challenges a hybrid method of fuzzy logic and linear programming is proposed. The fuzzy logic is effective in handling uncertainties common with RES, which have intermittent behaviours and LP is incorporated for optimization to minimize the amount of load to shed. Optimized LS reduces operation losses and minimizes the down time. Optimal LS contributes to improved grid stability, voltage regulation and system reliability. The models in this study will help in enriching the existing literature and provide an insight for further studies in the future.The fuzzy logic and linear programming (FLP) provides a robust algorithm that leverages the strengths of both techniques to perform optimal LS in IMG.

1.4 Research Objectives

1.4.1 Main Objective

To develop a hybrid method of fuzzy logic and a Linear programming algorithm for optimal load shedding.

1.4.2 Specific Objectives

i. To model the IEEE 14 bus test system and incorporate the islanded microgrid

ii. To formulate the objective function for load shedding and optimize it using heuristic FLP algorithm

iii. To test the performance of the FLP algorithm developed using IEEE 14 systems.

1.5 Scope of Study

The research was limited to the development of a heuristic method of FLP algorithm for optimal LS on an IMG with hybrid renewable energy (solar of 100MW, mini hydro of 50MW and wind of 50MW) and the developed algorithm was tested by running simulations on a modified IEEE 14 bus test system.

1.6 Contribution of this Research

This research developed a novel algorithm that hybridized fuzzy logic model and linear programming for optimal LS in IMG. The developed model used priority of loads, power demands and available generations as inputs to make adaptive LS decisions.

1.7 Thesis Organization Structure

The thesis is structured with the following five chapters, Chapter one is the introduction which contains the background of the study, the problem statement, Justification, objectives, scope and the contribution. Chapter two gives the literature review, here the fuzzy logic controller and linear programming architechures are discussed, past LS methods are reviewed and research gap is heighlighted. Chapter three deals with the development of the fuzzy linear programming algorithm. Chapter four presents research results and discussions. The research is finally summarized in chapter five with conclusions and recommenndations.

CHAPTER TWO

LITERATUREREVIEW

2.1 Introduction

This chapter provides an in-depth review of existing literature related to microgrid architecture and load shedding. Operation modes of microgrids and load shedding techniques are discussed including conventional methods of undervoltage and underfrequency. Advanced hybrid method of fuzzy logic and linear programming are introduced. Previous research contributions and limitations are analyzed to identify research gap.

2.2 Microgrid Overview

A microgrid is a small-scale electricity system consisting of DGs, loads and control centre. It can operate independently or when coupled to a larger grid. The proliferation of MG around the world is quite encouraging and their growth prospect in the future is quite promising (Takase, Kipkoech, & Essandoh, 2021). Currently, the research trend is skewed towards exploring renewable energy for sustainable development to reduce dependence on fossil fuels in the generation of electricity (Gholami, Shekari, & Sun, 2018).

The fact that Kenya is richly endowed with an abundance of solar and wind resources has opened up their application along with other conventional power sources (Ainah & Folly, (2015). However, the intermittency and small capacity have hampered the direct coupling with the existing grid. The concept of instability and unpredictability has reduced the chances of RES participating largely in real-time power production, thus the concept of MG has been embraced to incorporate RES. MGs operation modes are; direct connection to the main grid without jeopardizing stability or islanded with DGs close to the loads (Lee, Vu, Zafar, Hwang, & Chung, 2021). Power sources in IMG include solar PV systems, Wind, fuel cells and other sources.

The islanded microgrid is an occurrence where a section of the electrical grid consisting of DGs and loads gets disconnected and has to entirely depend on its local generations as illustrated in Figure 2.1 (Jain, Gupta, Masand, Agnihotri, & Jain, 2016). The island can be triggered by faults at the grid which makes isolation to be effected at the isolating switch.

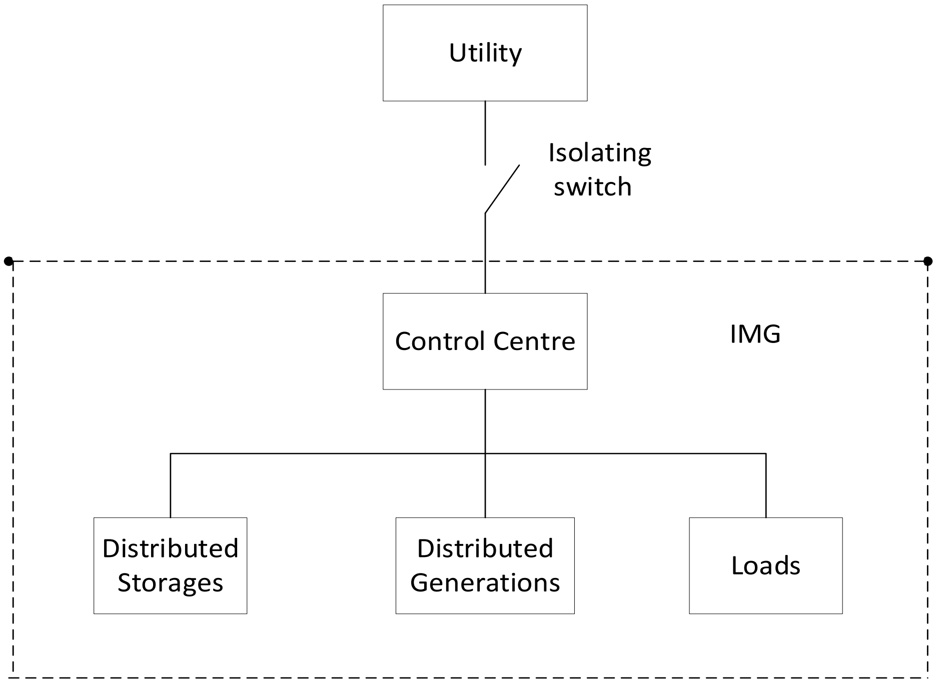


Figure 2.1: Islanded Microgrid Architecture

The classification strategies of MGs based on the amount of RES used for power generation are quantified as a percentage (Lee, Vu, Zafar, Hwang, & Chung, 2021) whereby <10-14% falls in the category of low penetration, 15-49% is the medium penetration category while >50% is the high penetration as illustrated in Figure2.2.

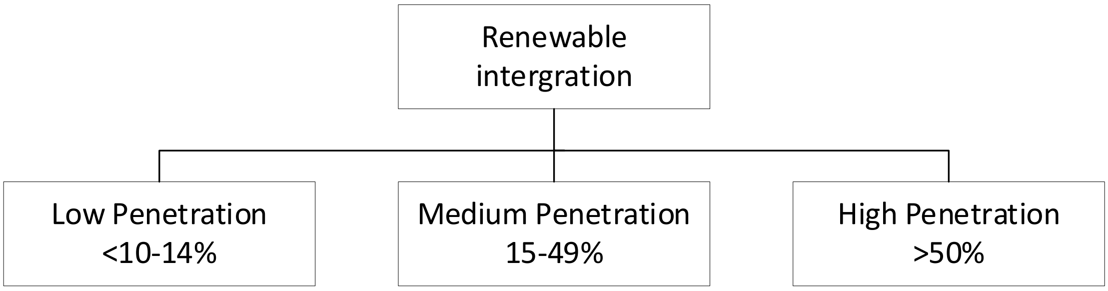


Figure 2.2: RES Penetration Classification

The CERT laboratory results on MG provided an ideal platform for the integration of RES into the grid without affecting its stability (Jain, et al., 2016). However, due to the economic crisis in the year 2000 and 2001, its progress was slowed down (Ergun, Dik, Boukhanouf, &. Omer, 2025). In Lasseter *et al.*(2011). MG testbed made a positive breakthrough with the following objectives; effective switch from grid and islanded mode, Protection scheme for MG components and Effective frequency and voltage control in an islanded mode. The IEEE 1547.4 provides a guide for the design, operation and integration of DG resources islanded with the grid. Table 2.1 shows IEEE microgrid standards, description and status (Shareef, Khamis, & Mohamed, 2015).

Table 2.1: Microgrid IEEE Standards and Descriptions

IEEE Standard	Description
1547- 2003	IEEE standard for interconnecting distributed resources (DR) with the electric grid.
1547.4 - 2011	IEEE 1547.4 Guide for the design, operation and integration of distributed resource islanded systems with electric power systems.
1547.7	IEEE P1547.7 Draft guide to conducting distributed impact studies for distributed resource interconnection (Approved Sept 2013).
P1547.8	IEEE P1547.8/D5.0 Draft recommended practice for establishing methods and procedures that supplemental support for implementation strategies for expanded use of IEEE 1547 (Clause 8 recommended practice for DR islanded systems).
P1547a– amendment 1	IEEE 1547a Standard for interconnecting distributed resources with electric power sources amendment 1 (The amendment is limited to address three topics for change i). Voltage regulation ii). Voltage ride through and iii). Frequency rides through. Recirculation Dec 2013).
1547 Revision	PAR December 2013; working group Jan 2014.

2.2.1 Advantages of Microgrids

The MGs have the following advantages compared with conventional power sources located in remote areas (Ongondo Mogaka, Murage, & Saulo, 2015). They promote the use of sustainable energy resources to help in solving the power crisis, reduce line losses by locating DGs close to load or demand, congestion mitigation, and reduce greenhouse gas (GHG) emissions inherent in conventional sources like coal plants and crude oil plants, and lessens the strain on the main grid through load shedding when the demand is high and reduces the need for costly upgrading of the central grid to cater for the additional generation (Barker . & De Mello, 200). A larger system serving more customers is cheaper per Kilowatt (kW) than a smaller unit for an individual R. S. A. L. carbon Africa Limited, (2015) and a typical microgrid of between 20-500 kW can serve 10-1000 customers. The fact that RES has a high upfront cost it’s in the long run cheaper when compared with diesel generation (Baurzhan . & Jenkins, 2017).

2.2.2 Disadvantages of Microgrids

Among the major challenges faced in the MG are; the problem of sharing the loads among the available DGs, maintaining the voltages, frequency and power quality within acceptable standards, and the challenge of storing electrical energy in battery banks which requires a lot of space, costly, inefficient and difficulty in resynchronization with the utility grid (Ojo, Saha, & Srivastava, Lee, Vu, Zafar, Hwang, & Chung, 2025)..

2.2.3 Islanded Operation of Microgrids

The MGs can be operated in islanded mode due to the following: in remote areas in arid and semi-arid areas not yet served by the conventional grid. During grid disturbances, disconnection is recommended to prevent impacting loads in the microgrid (Casals-Torrens, Martinez-Velasco, Serrano-Fontova, & Bosch, 2020). When the grid experiences a blackout, islanding is necessary to ensure local loads have power supply from local generators. The MG can also enter an islanded state to shield the primary grid from faults and disturbances that occur within the IMG.

Islanding as discussed in chapter one can either be intentional or unintentional. The challenge immediately after an island has been initiated is to regulate the voltage and frequency response. The effect of frequency and voltage immediately after unintentional islanding when plotted versus time is displayed in Figure 2.3. Sarwar, (2020).

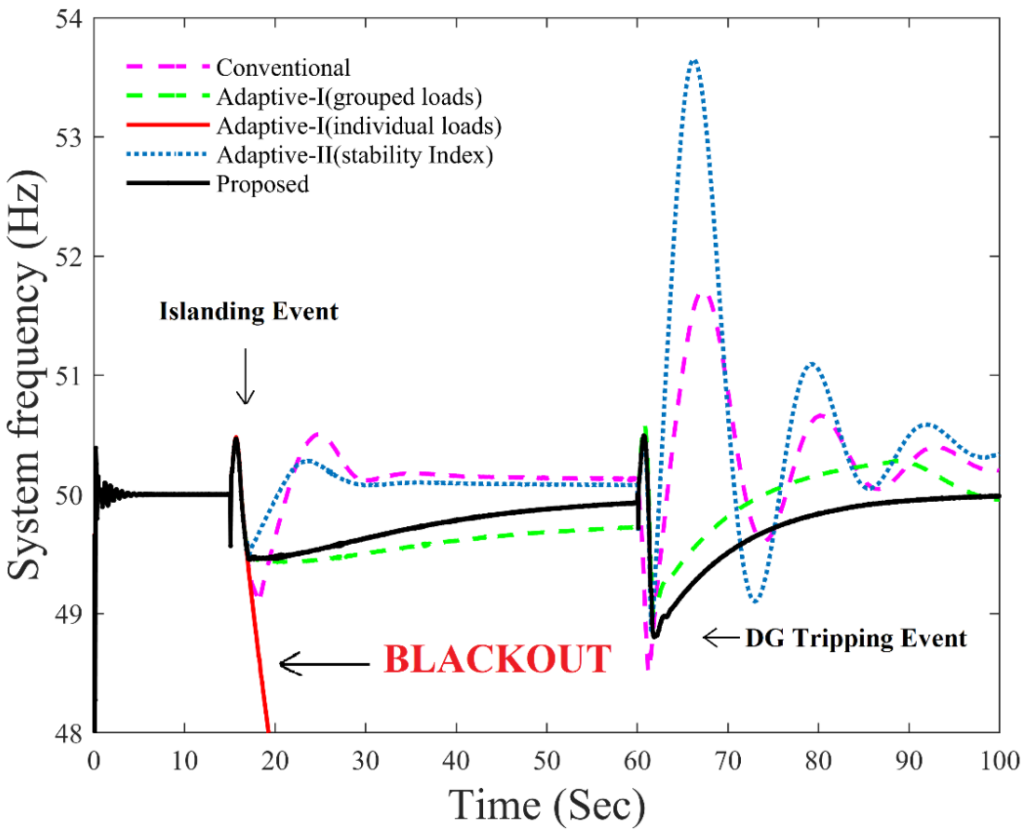


Figure 2.3: Frequency Response During Islanding

There is a growing interest in LS in the mini version of the larger grids and various researchers worldwide have explored various ways to ensure the optimal LS is done in unstable MG.

In reference Yujin, Hak-man, and Tetsuo, (2014). presented a distributed LS in an autonomous MG using a multiagent system. The components in the MG distribute the information among the agents and the power allocation is done through the bidding process. The algorithm was tested on a distribution scheme; however, the challenge with the scheme was finding the optimal bidding to maximize the profit on the remaining connected loads. The multiagent LS was presented in Wu, Jiang, and Lu, (2014). the distributed scheme used the average consensus theorem to mine data from neighbouring agents and incorporated the plug-and-play operation which was not common in the centralized scheme.

Two fuzzy-based load shedding algorithms were suggested in (Sasikala & Ramaswamy, 2011). The two algorithms prevent voltage collapse by using voltage stability indicators (VSI). The first algorithm locates the most appropriate position for the loads to be shed whereas the second algorithm envisages the number of loads to be released from the buses. The simulated results demonstrate that the method is appropriate in a power network of any size. In Mokhlis, Laghari, Bakar, and Karimi, (2012). presented an under-frequency LS using fuzzy logic in a mini hydro DG connected in an islanded distribution network. In the proposed method, fuzzy LS controller and LS controller modules were modelled. The scheme was tested on response and event-based scenarios and simulated results demonstrated that the scheme was able to shed optimal load to stabilize the system.

The Talmud rule was presented in Kim, Kinoshita, and Lim, (2014) for autonomous operation for a multiagent system in islanded MG. The system was tested in an agent-based MG and the LS was approached as a bankruptcy problem. The results obtained indicated that the processing time was short and acceptable for real-time applications however, the multiagent scheme was not much detailed for MG operation.

In reference Xu, Liu, Chen, and Gao, (2016) a dynamic LS was presented in an IMG with limited generation capacity, focusing on adaptive control on uncertainity. Intermittent energy and load demand uncertainties, as well as limited generation resource are considered The LS was envisioned as a random optimization problem in which the uncertainties from sporadic renewable energies were incorporated and modelled using Markov decision process (MDP) and numerical simulations showed that the system was effective in LS in optimal time.

Optimization technique of Cuckoo and fuzzy controller was presented in Einan, Torkaman, and Pourgholi, (2017) for an IMG for power control for solar PV, battery control, wind turbine and fuel cell. The outcomes were contrasted using particle swarm optimization (PSO) and genetic algorithm (GA) (Larik, Mustafa, Aman, Jumani, Sajid, & Panjwani, 2018). Among the three systems, COA exhibited high efficiency giving 59% and 68% fewer errors compared to GA and PSO.

A hybrid method is performed in Tamilselvan and Jayabarathi, (2016). for optimal LS that used a combination of GA and neural network (NN). GA was used to model the optimization and generate data for the NN heuristic LS model. The buses on which LS was done were selected using minimum eigenvalues of Jacobian load flow. The developed system achieved voltage stability with minimum LS.

In reference Tyagi, Kumar, and Chanana, (2012). proposed an adaptive LS using the proportional, integral and derivative controller (PID) in an isolated system. The LS steps are determined by initial ROCOF considering the impact of the PID and the results were compared to the controller with and without a controller. The results for LS with PID controller displayed fewer steps to stabilize the system than without the controller. A new intelligent fuzzy logic LS was presented in Ben Hessine, Jounini, and Chebbi, (2014) where LS was estimated in real-time and the FLC generated the command vector for LS, which was a precalculated potion of load to restore power balance.

Research Ojaghi, Azari, and Valujerdi, (2014). put forward under-voltage load shedding (UVLS) using a hybrid of GA and Particle Swarm Optimization (HGAPSO). The problem was formulated as a multi-objective function of active power losses, minimum customer interruption and highest level of voltage stability. Cost of customer disruption was modelled to quadratic function and the strength of the presented system was tested on the IEEE57 bus. In Çimen and Aydın, (2015) presented an optimal LS in Selcuk university medical facility with DG using fuzzy logic LS system. The quantity of LS was chosen by fuzzy logic centered on acquired data from PV generation and load demand. The results indicated that optimal load was shed to regain system reliability.

An improved LS scheme that considers DG was presented in Das, Nitsas, Altin, Hansen, and Sorensen, (2017), where new UFLS was proposed that utilizes directional relays, power flows, PV and wind measures to choose the feeders in the best way possible to shed. The researcher used Monte Carlos simulations to verify the effectiveness in all possible scenarios. A two-stage LS was presented in Zhou, Li, Wu, & Shahidehpour, (2018) to cope with severe power deficits. The initial phase was tasked to tame high frequency decline and local frequency measurements were used to guide LS levels until a steady state was reached. The second stage was activated to shed loads according to priorities.

The bacterial foraging optimization algorithm (BFAO) was presented in Estrada, (2012)., the target function consisted of overall electric losses, cumulative shaded load costs and the voltage stability index. The framework was validated using IEEE 30 bus architecture and the outcomes proved that BFAO gave good results.

2.3 Load Shedding Techniques

Numerous LS methods have been developed, ranging from traditional or conventional methods, to adaptive intelligent and optimized methods. Figure 2.4: illustrates LS techniques that are employed by power system operators (Najihah, Bakar, Yusri, Fani, Na, &. Khamis, 2016)..

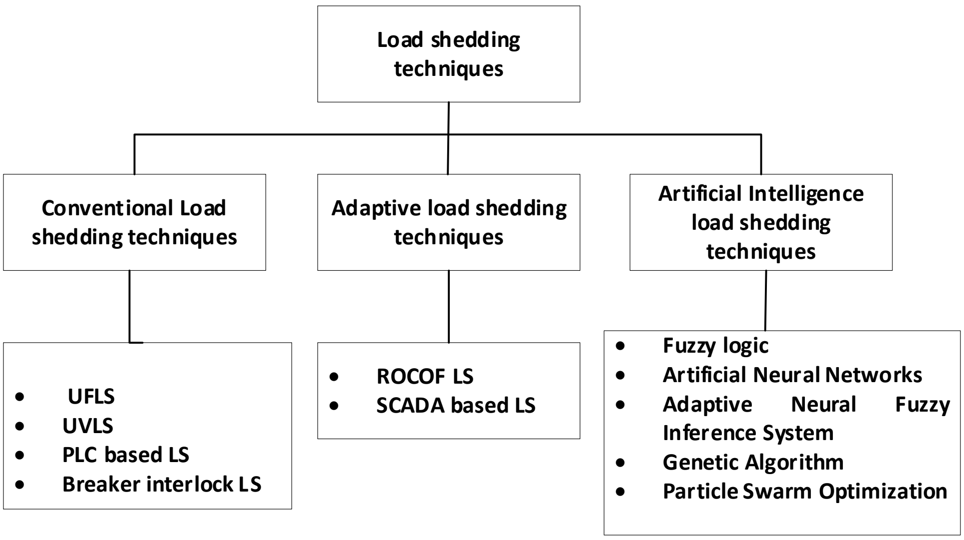


Figure 2.4: Load Shedding Techniques

2.3.1 Conventional Load Shedding Methods

These methods are referred to as traditional methods because they use a preset frequency values approach to shed loads from overload buses. The preset values are usually determined from simulations and experience.

2.3.1.1 Under-Frequency Load Shedding

The frequency decreases when the existing load exceeds the power being generated and it increases when the available generation is more than the existing load. In this system, a fixed amount of load is curtailed at fixed system frequency blocks (Khaki & Kouhsari, 2010). The quantity of load to shed at each step is estimated by Equation 2.1 (Choi, Lim, & Kim, 2017). This is after the expiry of a predefined time delay; the circuit breaker receives signals from the frequency relays to shed the loads. The cycle is repeated until the system frequency is restored (Rafinia, Rezaei, & Moshtagh, 2020; Acosta, *et al.*, 2020). The system however suffers from the following drawbacks: it has a slow response time since it is iterative until the desired frequency is attained, minimum load shedding is through trial and error method and excessive load shedding is possible as the order in which circuit breakers operate might not be ideal.

$$LS = \frac{\frac{L}{1+L} - d\left(1-\frac{f}{f_o}\right)}{1-d\left(1-\frac{f}{f_o}\right)} \qquad (2.1)$$

Where

L- is the pu overload

f- minimum permissible overload

f_o- Nominal frequency

d- load reduction factor

The level of disturbance is estimated using ROCOF. The LS should be performed fast enough to curb the frequency from deteriorating to an unacceptable level (Paramo & Bretas, 2023). The ROCOF is estimated using Equation 2.2. The negative value depicts a reduction in frequency, while a positive value shows an increase in frequency.

$$ROCOF = \frac{pL(f_1 - f_2)}{H\left(1 - \frac{f_1^2}{f_0^2}\right)} \tag{2.2}$$

Where;

ROCOF- Rate of change of frequency in Hz per second

p- Power factor

L- per unit overload = (Load- Power input)/(Power output)

f_0- initial frequency in Hz

f_1- final frequency in Hz

f_2- lower frequency limit in Hz

H- Inertia constant of machines

The initial stage in UFLS is to curb rapid frequency deterioration as depicted in portion AB in Figure 2.5. This will allow the frequency to temporarily settle at point B. Further LS is triggered to get rid of the extra load, the frequency improves to a safer value at point C. Additional LS will trigger the frequency to be restored to D which is the recommended rated value (Zhou, Li, Wu, & Shahidehpour, 2018)..

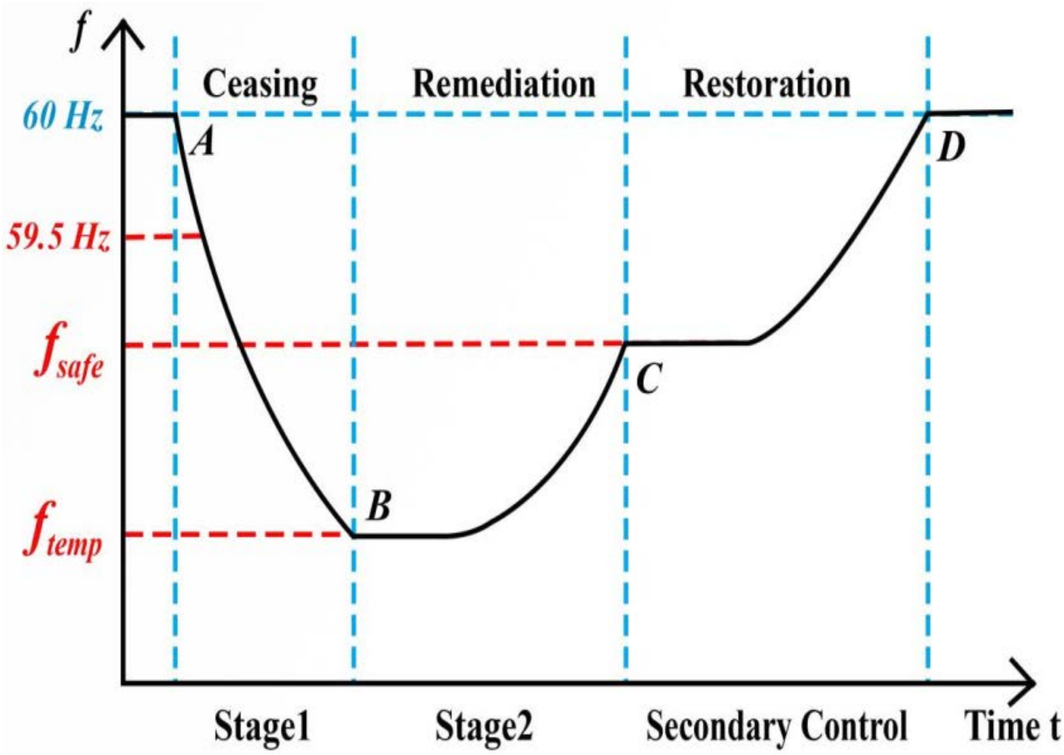


Figure 2.5: Frequency Response During Load Shedding

2.3.1.2 Undervoltage Load Shedding

Undervoltage LS (UVLS) is an effective method of handling voltage instability issues in power systems to prevent voltage collapse (Pourghasem & Seyedi, 2019). It works by disconnecting a fixed amount of load from a given system with a fixed time delay .

2.3.1.3 Programmable Logic Controller Based Load Shedding

The logic compares the available generation and total load or state of under frequency and is programmed to send signals to trip preset loads until frequency returns to normal. A PLC load shedding scheme offers many merits just to mention a few, it offers automated load relief to restore the system to stability as well as the use of the distributed system in load management. It suffers from a long response time which occurs during the transient disturbances that take long time making more loads to be shed.

2.3.1.4 Breaker Interlock Load Shedding

In this method, circuit breakers are arranged to operate on a inbuilt trip signal from generator trip or intertie circuit breakers. This method is used when the speed of LS is of utmost importance. This is because the tripping of loads is tied to breaker interlocks without relying on the central controller or wireless communication (Baiceanu, Ivanov, Beniuga, Neagu, & Nemes, 2023). The breakers of the loads are interlocked to the generator breakers electrically or mechanically such that when generator trips, it disconnects a number of predefined loads. However, the system suffers the following drawbacks; often more load is shed that its necessary, LS is achieved on one step and its very expensive to do modifications and upgrading of the system.

2.3.2 Adaptive Load Shedding

This approach reduces the load automatically according to the severity of the disruption and the system behaviour at each stage Toro-Mendoza, et al., (2023). Adaptive LS occasionally makes use of the swing equation to predict how much load to shed.

2.3.2.1 Rate of Change of Frequency (ROCOF)

The power imbalance and the inertia of a power system both affect the ROCOF after an interruption. Prior to the disturbance in power system, spinning reserve, active power consumption and turbine governor change in active power as a result of voltage and frequency deviation due active power deficit.

2.3.2.2 SCADA System

SCADA systems are preferred because they offer high reliability in LS solution without requiring data transfer over the communicatin lines. It has wide application in LS for medium sized or big industrial facilities. SCADA based LS has a faster computational time and no specific relays need to be installed and has a faster reaction time in times of power imbalances compared to frequency-based LS schemes.

2.3.3 Computer Intelligent LS Techniques

Computational intelligence LS techniques are modern methods used to perform LS in power systems and IMGs. The adaptability, predictiveness and optimization capabilities of these methods makes them ideal for application in IMGs and smart grids with high penetration of RESs.

2.3.3.1 Fuzzy Logic Load Shedding

Fuzzy logic has been used for LS in power systems and IMGs. In Hong and Hsiao, (2022) used Fuzzy and PSO for UFLS in a standalone powers system using 81L relay system. Two set of fuzzy rules were implemented to tune the inertia weight leaning in the PSO. The proposed system can be used for event based UFLS which disregards frequency response. UFLS based on Fuzzy logic has been presented in (Małkowski, 2020). The work demonstrated efficacy in using frequency for dropping loads during small and large disturbances in contrast to conventional methods. In Li, Wei, and Ma, (2018) presented fuzzy logic LS considering solar PV fluctuation and voltage stability. In Hanzala, et al., (2024). presesented fuzzy logic decentralized power management for residential buildings. The decentralized controller was used to maximize energy output from the solar and battery storage. The load shifting and load shedding was achieved through fuzzy logic controller. Application fuzzy logic and hierarchy process algorithm was presented in Le, Quyen, and Nguyen, (2016). Fuzzy was used to reduce the load profiles for load shedding. The simulation results showed that less amount of load was shed though the recovery time was a bit longer. In Gain, Hassan, Rahman, and Jisan, (2025) presented an AI- fuzzy logic load shedding to enhance power system stability in Banngladesh. The results showed that the AI- fuzzy controller outperformed classical methods of load shedding in terms of voltage and frequency stability.

Fuzzy logic when used for LS has the following merits: It can handle uncertainities in load demand, RES sources and system disturbances. It can also process fuzzy inputs faster and initiate LS quickly to avert the occurrence of a blackout (Nghia, Quyen, & Do, 2016). It can also produce optimal results when inputs are noisy or imprecise. Fuzzy logic can be adapted to reflect dynamics of the MG like load priorities such that more critical loads are left online. The demerits of fuzzy logic include: for large system the fuzzy, the rules are many which makes the sytem complex to design which may end up with results which are not optimal. There is also lack of standardization making the fuzzy system dependent on the membership functions chosen.

In contrast to the clear membership of traditional binary logic, fuzzy logic uses mathematical principles to express knowledge dependent on the degree of membership. It addresses approximate reasoning as opposed to fixed or accurate reasoning and a fuzzy logic controller (FLC) resembles the human decision-making method. It deals with vague (large, small) and imprecise information. Figure 2.6 illustrates a block diagram of an FLC. It helps in solving real-world problems based on the degree of truth rather than the usual true or false used in classical binary logic. It uses a range of logical values from 0 to 1.

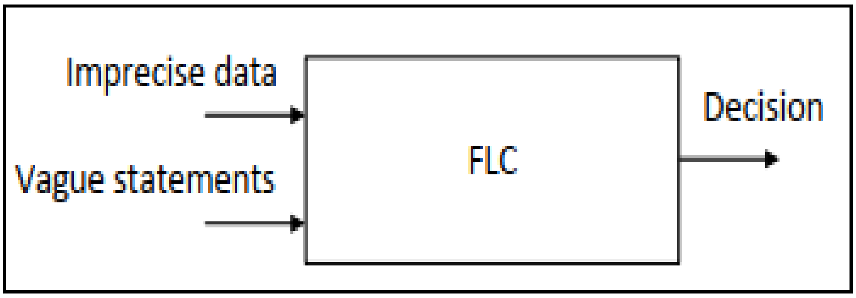


Figure 2.6: Fuzzy Logic Controller

Fuzziness is best described by its membership function (MF). The MFs are often represented by graphical forms. In other words, the MF is a curve that shows the correlation between each point and the membership value. There are distinct MF forms such as; trapezoidal, triangular, Gaussian, piecewise linear and singleton. The MFs are used in the fuzzification and defuzzification in the FLS. Figure 2.7 illustrates the trapezoidal MF of a fuzzy set.

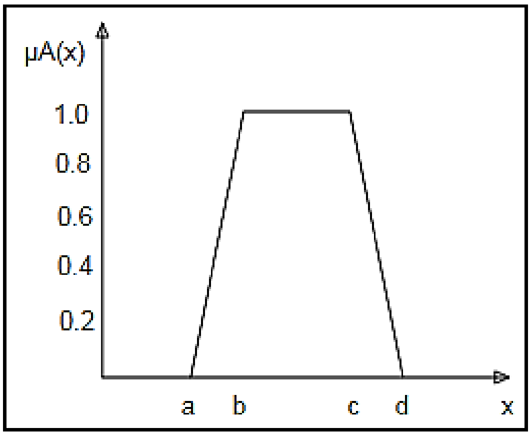


Figure 2.7 Membership Function with Trapezoidal Shape

Trapezoidal MF is determined by four parameters, lower limit of a, lower support limit of b, upper support limit c and upper limit of d. Where a < b < c < d. Mathematically trapezoidal MF (x; a, b, c, d) is expressed in Equation 2.3 below.

$$\mu_{A(x)} = \begin{cases} 0 & (x < a) or (x > d) \\ \dfrac{x-a}{b-a} & a \le x \le b \\ 1 & b \le x \le c \\ \dfrac{d-x}{d-c} & c \le x \le d \end{cases} \quad (2.3)$$

Ftuzzy logic has an outstanding feature of simplicity, and robustness in transforming nonlinear problems into linear. LS is nonlinear as the rate of change of frequency df/dt is a continuously varying problem. Additionally, it handles greater ambiguities in the signal under study. As a result, the superior property of approximation of fuzzy over crisp classifier renders it useful in real-time application in algorithms with uncertainties.

When fuzzy systems are used as the controllers, they are known as Fuzzy logic controllers (FLCs). The functional block of FLC consists of the following components; fuzzifier, Rule base, inference and fuzzified. Figure 2.8 illustrates how the FLC components are interrelated (Larguech, Aloui, Pages, El Hajjaji, & Chaari, 2015). The FLC is designed based fuzzy system process model. Fuzzy control incorporates heuristic and human expertise in the form of IF- Then rules and the controllers are designed based on these rules.

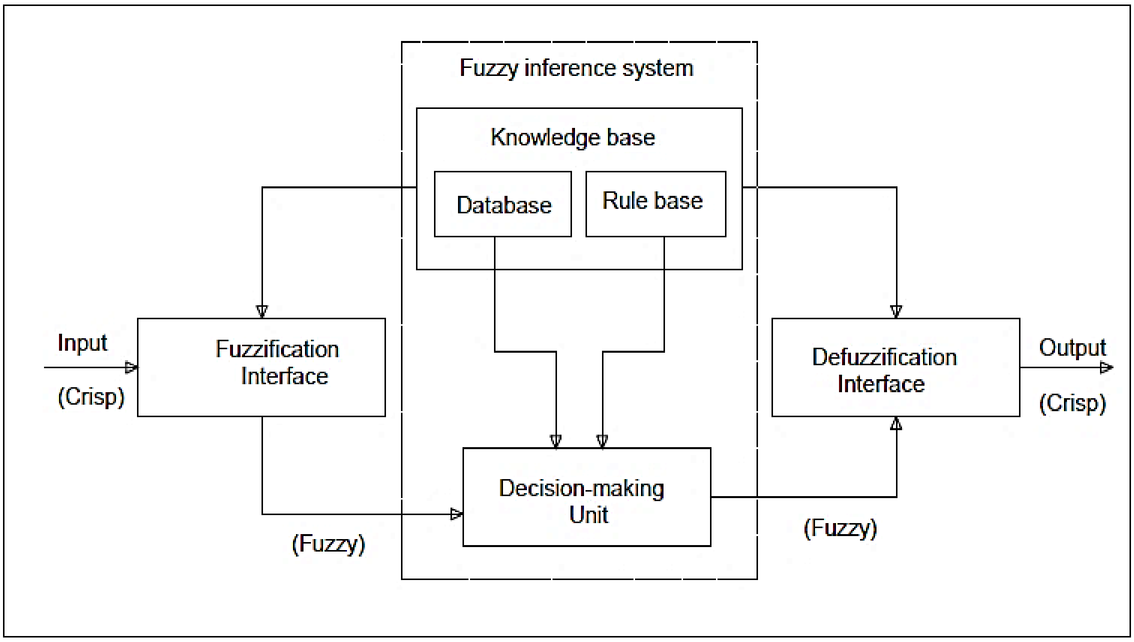


Figure 2.8: Architecture of a Fuzzy Logic Controller

The basic building block of a FLC consists of a fuzzification interface that converts crisp inputs to fuzzy followed by a knowledge base that defines all the variables (membership function of linguistic terms) and parameters of the system. Then this block is followed by a decision-making unit, in which all the reasoning is done and perfect decisions are arrived at. The final block is the defuzzification interface whose main purpose is to transform the fuzzy outputs to definite crisp values for a control system to effect the respective commands. It involves finding a value that best represents the information contained and evaluated in the inference system.

The available methods of defuzzification are; centre of gravity (COG), the centre of gravity method for singletons (COGS), the weighted average method, bisector of area (BOA), mean of maxima (MOM), leftmost maximum (LM) and rightmost maximum (RM). The weighted average method is a less computationally intensive method and is used with output membership functions that are symmetrical. The defuzzified value is depicted in Equation 2.4;

$$W = \frac{\sum_{i=1}^{n} \mu_{(x)} . x}{\sum_{i=1}^{n} \mu_{(x)}} \tag{2.4}$$

Where;

W is the weighted average value

μ_x is the membership degree of each output rule.

x is the weight associated with each rule

n is the number of rules

The advantage of this method of defuzzification is that it is computationally fast and provides accurate results that are sent to the plant to perform the required function.

2.3.3.2 Linear Programming Load Shedding

Linear programming (LP) is also known as linear optimization. LP is a mathematical technique that optimally allocates scarce resources, such as limited generation, based on given criteria of optimality (Kunwar & Sapkota, 2022). The criteria can be maximization or minimization of the objective function. LP has been used to perform optimal LS in power system in cases where the load demand exceeds the generation. A mixed integer LP for optimal LS in IMGs was presented in Sarwar, 2020; Ceja-Gomez, Qadri, & Galiana, 2012; Javadi, & Amraee, 2018; Babagana, et al., 2025). The proposed system incorporates frequency to calculate the power imbalance and optimises it through mixed integer LP to yield the best shedding plan. In Bio Gassi and Baysal, (2022) has utilized LP for energy management in MG. The model minimizes vector value decisions by taking consideration of current, energy storage and forecasted demand in the MG. The scheme considered, penalty costs of LS and operating cost are taken into consideration and the system is tested on IEEE 28 and 69 bus systems. In Hagh, and Galvani, (2011) presented a hybrid of LP and PSO for minimization of LS during contingency in a large power system. Power rescheduling was implemented to mimize the effect of LS in the IEEE 14 bus system.

2.3.4 Linear Equation

Equations and inequalities in LP must be linear, having the following form of Equation 2.5;

$$c_1x_1 + c_2x_2 + c_3x_3 + \ldots c_nx_n = 0 \tag{2.5}$$

In general, c's represent the coefficient of the equation which on most occasions are referred to as the parameters. The coefficients of LPP are fixed values based on the nature of the problem being solved. The x's are usually called the variables of the equation and take on a range of values defined by the constraints.

2.3.5 Decision Variable

Variables in LPP are a set of quantities that need to be determined to solve the problem Subject to the following set of linear constraints. The decision variables are usually represented as x_1, x_2 x_3……x_n. The decision variables must be determined to find the best optimal solution in a LP problem. In power system the decision variables can be interpreted as generator outputs.

2.3.6 Objective Function

This in LPP indicates how much each variable contributes to the value to be optimized when solving the problem. The desired largest or smallest value of the objective function is usually called the optimal value. In LPP the objective function defines the optimality criteria of a problem under study. It normally takes the following form of Equation 2.6;

$$min\ or\ max\ z = c_1x_1 + c_2x_2 + c_3x_3 + \cdots c_ix_i \tag{2.6}$$

Where

Min – minimize

Max- maximize

c_i - objective function coefficient corresponding to an i^th^ variable

x_i - is the i^th^ decision variable

In LP canonical form Equation (2.5) can be written using a summation sign as

$$\min or \max z = \sum_{i=1}^{n} c_i x_i \tag{2.7}$$

2.3.7 Constraints

In a LPP constraints define the possible values that the LPP may take. They usually show the resource constraints or the minimum or maximum quantity. These can also be conceptualized as mathematical expressions that combine the variables to express the limitations on possible solutions. These are used to define the domain of feasible solution, they take the general form depicted of Equation 2.8 (Hillier & Lieberman, 2021). In LPP the constraints are used to define the domain of feasible solutions. Mathematically inequalities are written with less than or equal to depict the decision variables as non-negative.

$$Subject\ to \begin{Bmatrix} a_{11}x_1 + a_{12}x_2 + ... + a_{1n}x_n \le b_1 \\ a_{21}x_1 + a_{22}x_2 + ... + a_{2n}x_n \le b_2 \\ . \\ . \end{Bmatrix} \tag{2.8}$$

In a compact form, Equation 2.8 can be represented in Equation 2.9;

$$\sum_{i=1}^{n} a_{ij} x \le b_j \tag{2.9}$$

Where; j= 1, 2… m i=1,2….. n

x_i- is the i^{th} decision variable

a_{ij} – is the coefficient on x_i in constant j

b_j- is the right-hand side (RHS) coefficient on constant j

2.3.8 Non Negativity Constraints

The variables in LP must be greater than or equal to zero as expressed in Equation 2.10a and 2.10b (i.e. they must always take non negative values zero or positive values). Non negativity constraints are part and parcel of LPP formulation and must therefore be included (Inayatullah, et al., 2019).. However, some LP can have negative values which usually make the problem very complex to solve.

$$x_i \geq 0 \qquad (2.10a)$$

$$c > 0 \qquad (2.10b)$$

Or the variables may be specified by the lower and upper limits as expressed in Equation 2.11

$$x_i^{\min} \leq x_i \leq x_i^{\max} \quad i = 1 \ldots n \qquad (2.11)$$

2.3.9 Slack Variable

Slack variables are used to convert inequality to equality. In solving LPP the first step is to convert the RHS of Equation 2.8 to a positive constant term. Slack variable expresses inequalities as an equation that can be solved by the iteration method Inayatullah, et al., 2019).. For a constraint of "≤" we add a slack variable while for a constraint of "≥" we subtract the slack variable as shown in Equation 2.12. Applying slack variables to Equation (2.8) yields;

$$
\left\{
\begin{array}{l}
a_{11}x_1 + a_{12}x_2 + ... + a_{1n}x_n + s_1 = b_1 \\
a_{21}x_1 + a_{22}x_2 + ... + a_{2n}x_n + s_2 = b_2 \\
. \\
.
\end{array}
\right\} \quad s_i \geq 0 \tag{2.12}
$$

Where s_1, s_2,….. s_n are the slack variables

2.3.10 Linear Programming Formulation

LPP is formulated using the following basic steps;

a) Identification of decision variables.
b) Formulation of the objective function.
c) Formulation of constraints and define non-negativity constraints.
d) Introduction of slack variables to convert an inequality to equations.

The optimal solution in LP means the minimum or maximum value of an objective function. The objective function, decision variables and constraints must all be linear functions. A feasible region is a set of points where the power flow equations can be solved and system parameters i.e. line flows and bus voltages are within acceptable ranges. Typically, this is where the IMG system works normally (Wang, & Kang, 2022). The set of points where the power flow has a solution but one or more limits are exceeded is the infeasible region. This is not recommended and can lead to system collapse; however, the system may be operated in this area temporarily (Kanimozhi & Balaji., 2014).

2.4 Fuzzy Linear Programming

Fuzzy linear programming (FLP) has the same structure as the classical LP. It incorporates fuzzy logic to deal with imprecise data and uncertainities. The difference comes about in that in the classical LP approach the values and operators used are crisp while in the FLP approach some or all the parameters take fuzzy characteristics as shown in Equation 2.13a,b and c Nasseri, Zavieh, & Mirmohseni, 2017; Hosseinzadeh & Edalatpanah, 2016). FLP is efficacious in solving optimization problems because it uses fuzzy set theory and when modelled properly it can lead to a great reduction in computation time. This property makes it to be preferred for application in real-time power system operations.

$$\min z(x)=\sum_{i=1}^{n}\tilde{c}_i\tilde{x}_i \;\tilde{\leq}\; z^0 \tag{2.13a}$$

$$Subject\,to \sum_{i=1}^{n}\tilde{a}_{ij}\tilde{x}_i \;\tilde{\leq}\; b_i \tag{2.13b}$$

$$\tilde{x}_i \;\tilde{\geq}\; 0 \quad \ldots.. \tag{2.13c}$$

The symbols $\tilde{\leq}$ and $\tilde{\geq}$ represents the fuzzified version of $\leq$ and $\geq$ they are read as approximately less than and approximately greater than respectively. In FLP, the objective function and constraints are expressed as fuzzy linear inequalities or equations.

FLP controller has many merits outstanding one being that the designer does not need to know the system complex model when developing the controller, and also there is much freedom in choosing system parameters for the controller (Bhat, Vaz, & Meza, 2013). The real-world problems that are subject to vagueness and uncertainties need not be presented using sharp crisp boundaries but require soft and flexible boundaries. In such scenarios fuzzy comes in handy to help in modelling the system. It is also easy to write new rules, modify the existing or remove the rules from the knowledge base.

2.5 Load Management

2.5.1 Load Model

The stability of an islanded microgrid depends on the ability of available generating units to meet the electrical demand of the loads. Load modelling in any bus is very complicated because it can consist of motors, discharge lamps, furnaces, cookers etc.

Estimating the exact load thus becomes very complicated, however, loads are classified into two categories that are static and dynamic load models. In a static model, the active and reactive power depict the frequency and voltage at that instant hence it represents steady state operating condition of a power system.. Considering that the load is voltage dependent, a polynomial model is proposed. The following model Equations 2.14a and 2.14b depicts the dependence of load on frequency and voltage. The frequency parameter for different loads is shown in Table.2.2. (Das, et al., 2017).

$$P = P_o \left[p_1 \overline{V}^2 + p_2 \overline{V} + p_3 \right] \left(1 + K_{pf} \Delta f \right) \tag{2.14a}$$

$$Q = Q_o \left[q_1 \overline{V}^2 + q_2 \overline{V} + q_3 \right] \left(1 + K_{qf} \Delta f \right) \tag{2.14b}$$

Where

P = is the active power at a node

Q = is the reactive power at a node

$$\overline{V} = \frac{V}{V_0}$$

V = is the actual voltage understudy

Vo = is the rated voltage understudy

K_{pf} = is the frequency sensitivity factor for active power and ranges from 0.0 to 3.0

K_{qf} = is the frequency sensitivity factor for reactive power and ranges from -2.0 to 0.0

Δf = is the frequency variation of the system.

Table 2.2: Typical Load Frequency Parameters

Load type	Frequency parameters	
	k_{pf}	k_{qf}
Residential		
Electrical heating	1	-1.7
Non electrical heating	0.8	-1.7
Commercial		
Electrical heating	1.7	-1.1
Non electrical heating	1.7	-0.9

2.5.2 Classification of Loads

The loads connected to the microgrid are classified using the priority criteria to ease load management. The major classification employs three clusters; (i). secured vital loads (ii). non-secured vital loads and (iii). non-secured non-vital loads (Salmasi & Hosseinzadeh, 2015). All loads classified as vital loads are non-shedable irrespective of the amount and cost of generation. The loads classified as non-vital loads will be scheduled for LS to achieve the economic operation of the microgrid (Guo, Sha, & Liao, 2014).

2.6 Renewable Energy Sources

2.6.1 Micro Hydropower

MHP is harnessing water on a small scale from a small head over the running river. According to session paper number 4 on the energy of 2004 MoE, (2004), MHP generates power up to a maximum of 100KW. Its renewable energy in the sense that it has minimal effects on ecology and it can be erected on the run of the river. It has a simple design and maintenance because it does not require a dam when compared to large hydropower plants and can also be integrated with other renewable energy sources like solar and wind (Sapari, Mokhlis, & Laghari, 2017). In Kenya, hydropower plants are usually classified according to their capacity as shown in Table 2.3.

Table 2.3: Classifications of Hydropower Plants

Category	Power range
Pico Hydro	<5 kW
Micro Hydro	>5kW – 100 kW
Mini Hydro	>100 kW – 1 MW
Small Hydro	>1MW – 3 MW
Medium Hydro	>3MW-30MW
Large Hydro	>30MW

The energy available from the hydro power is given by equation 2.15 and is proportioned to the volume flow rate and the pressure.

$$P = 9.81\rho\eta QH \times 10^{-3} kw \tag{2.15}$$

Where P is power generated, ρ is the water density (1000kg/m^3) η is the overall efficiency of the plant, 9.81 is the acceleration due to gravity, Q is the water flow rate (m^3/s), H is the water head in meters.

A MHP mainly consists of a small reservoir, canal or dam as depicted in Figure 2.9. The water is relayed to the generator turbine via the penstock. When the water strikes the turbine, it converts the hydraulic energy of water into mechanical energy. The turbine is coupled to the generator which converts mechanical energy to electricity. Water flowing to the turbine is controlled by the governor, which controls the speed of the generator and helps in maintaining a constant frequency (Mogaka, Nyakoe, & Saulo, 2020). The gate valve of the turbine is controlled by the servomotor which adjusts the rate of water flow to the turbine in response to the load connected.

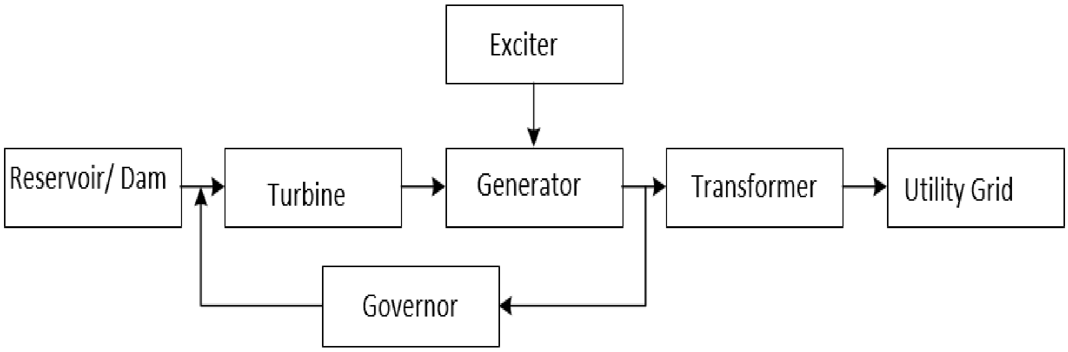


Figure 2.9: Layout of Micro Hydropower Plant

2.6.2 Wind Power

Wind power provides mechanical power that turns the turbine to produce electrical energy. The power produced is given by equation 2.14. A German scientist Albert Betz discovered that no wind turbine can convert more than 59.3% of its kinetic energy of wind into mechanical energy Jiang *et al.*, (2025). This is what is usually included in the power formula of wind and is referred to as the power coefficient.

$$P = \frac{1}{2}\rho A V^3 C_p \qquad (2.16)$$

Where P - wind power in watts

ρ – density of air (1201 g/m^3)

A – swept area (m^2)

V – velocity of air (m/s)

Cp – power coefficient

Wind as a source of power is attractive in that it is available in plenty, does not pollute the environment and is non-exhaustible. The major drawback of harnessing power from wind is its intermittency and not dependability however constant power can be generated with varying wind speeds with the advent of technology. It is also used for power generation together with other sources to ensure continuity and reliability (Kothari & Nagrath, 2008). There are three types of operations for wind power generations as shown in Table 2.4.

Table 2.4: Wind Power Generation Operation Classifications

Classification	Description
Small (0.5-10 kW)	For isolated single premises
Medium (10-100 kW)	For communities
Large (>1.5 kW)	For connection to the grid

2.6.3 Solar Photovoltaic

A solar PV system converts photons of light into electrical energy with the help of solar PV modules. The solar cell constitutes the basic building element of the PV. The energy produced by the solar is estimated by Equation 2.17. The solar panel produce power commensurate with the total area covered by the irradiance of that location and the efficiency of that module.

$$P_{pv} = PV_{rating} x(1 - P_1) x T_2 x N_i \tag{2.17}$$

Where P_{pv} is the dc power from the PV modules

P_1 is the percentage power loss of 0.5% per degree rise in temperature

T_2 is the ambient temperature (^{o} C)

N_i is the number of solar modules.

The energy from energy obtained from the DGs like solar PV has to be converted by dc/dc boost converter to harness maximum power from the renewables. The dc power is then converted to ac through a dc/ac inverter then stepped up by a transformer and fed to the ac distribution network (Akbari, Golkar, & Tafreshi, 2011). A PSO solution for improved voltage stability of a hybrid ac-dc microgrid,”.

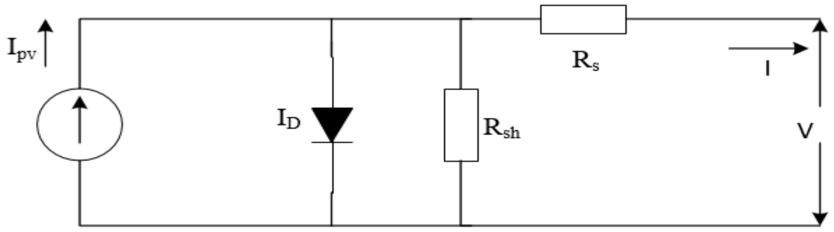


Figure 2.10: Equivalent Circuit of a PV Module

The equivalent circuit model of PV is depicted in Figure 2.10, it consists of a current source I_{pv} which is produced by the photoelectric effect. R_s represents series resistance and R_{sh} represents the shunt resistance. The load current of the solar PV panel in figure 2.10 is given by Equation 2.18a to 2.18d);

$$I_{PV} = I + I_D \quad (2.18a)$$

$$I = I_{PV} - I_D \quad (2.18b)$$

$$I = I_{PV} - I_o \left[exp \left(\frac{V + IR_s}{\alpha} \right) - 1 \right] \quad (2.18c)$$

$$I_{PV} = \frac{\psi}{\psi_{ref}} \left[I_{PV,ref} + \mu I_{sc} \left(T_c - T_{c,ref} \right) \right] \quad (2.18d)$$

Where I_{pv} is the light current

I_o is the saturation current

R_s is the series resistance

V is the output voltage

T_c is the PV cell temperature

Ψ is the irradiance level (W/m^2)

α is the thermal factor

2.7 Power System Frequency Ranges

Frequency is perceived as a global parameter in synchronous electrical power systems. At a glance, it indicates the system state of power balance between generation, the load demand and power disturbances. Under normal operating conditions, the Kenyan synchronous frequency should be balanced at 50 Hz and shall be maintained between 49.50 Hz and 50.50 Hz (±0.5).

Table 2.5 Frequency Limits in the Kenyan Electric Power System

Frequency limits	**Duration**
49.50 Hz – 50.50 Hz	Continuous normal operation
49.00 Hz – 51.00 Hz	For a duration of at least 60 minutes
48.00 Hz – 51.50 Hz	For at least 30 minutes
47.50 Hz – 51.50 Hz	For a duration of at least 30 minutes
<47.50 Hz or > 51.50 Hz	For a duration at least 20 seconds

Depending on the severity of the disturbance, the power system is required to operate within a specified frequency band for a given duration of time [92]. For frequencies below 47.50 Hz, the power system can operate for 20 seconds, while for frequencies above 52.00 Hz the power system must disconnect as indicated in Table 2.5, above. The frequency is a global indicator of the state of the power system. Table 2.6, shows the frequency changes and their respective effects. From the table, it’s evident that the decrease in frequency can lead to power system collapse. It is also noted that in severe system disturbance the frequency deviates more from the nominal value of 50Hz which progressively reduces the fault ride through time.

Table 2.6: Effect of Generation and Load on Frequency

Power systems	**Effect on frequency**	**Action**
Generation > demand + Losses	Frequency increase	Reduce generation
Generation = demand + Losses	Frequency remains constant	No action
Generation < demand + Losses	Frequency decrease	Load shedding

2.8 Summary and Research Gap

The reviews of the past researchers have embraced techniques such as conventional controllers, proportional integral derivative (PID), artificial intelligence and hybrid methods have been able to offer optimal load shedding in power systems however, some controllers have the disadvantages of having a long settling time and high overshoots. The use of evolutionary algorithms like GA and PSO offers favourable results but they suffer from low convergence speed (Hagh, &. Galvani, 2011).

The convention algorithms offer poor control and cannot perform optimal LS when applied in islanded MG. Both the power generation and load profiles are constantly changing due to intermittency from renewables, generator outages, or overloads; yet, the relays have a single point for all scenarios. Therefore, a need exists to develop an adaptive system that can respond to the system conditions. Thus, the application of the hybrid method of FLP will greatly improve the control performance of the FLC to achieve optimal load shedding in the IMG. This is because fuzzy logic is capable of solving a problem with imprecise data while LP has strength in solving resource allocation problems. This research designed a FLP controller to optimal shed loads in the IMG.

The significant features of the FLP controller are: - it’s able to converge in a minimum number of iterations, it’s able to solve linear optimization problems formulated for the minimization of LS and it has the capability of obtaining feasible solutions in terms of the optimal amount of load to be shed.

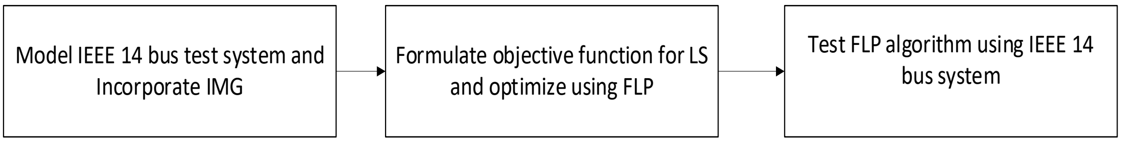
CHAPTER THREE

METHODOLOGY

3.1 Introduction

This chapter presents the methodology used to develop and validate a fuzzy linear programming load shedding approach for IMG. The study begins with modelling of the IEEE 14 bus system integrated with distributed generations in MATLAB/SIMULINK. An objective function for optimal load shedding is formulated and optimized by linear programming. The developed FLP is implemented and tested on a modified IEEE 14 bus system. The system performance is evaluated under generation loss and overload contingencies.

3.2 Objectives Overview



shows how the different objectives are interlinked. It begins by modelling the IEEE 14 bus system and connecting with IMG to simulate realistic grid scenarios. This is followed by objective two, which is the formulation of the objective function, incorporating relevant constraints and parameters. The third objective is the validation of the performance of the FLP by subjecting it to the modified IEEE 14 test system.

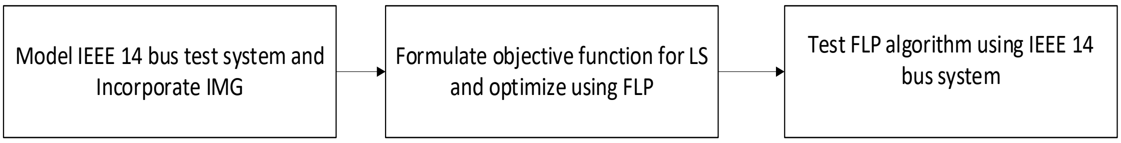


Figure 3.1 Integration of Objectives

3.3 Modelling of IEEE 14 Bus System and Incorporating IMG

This entailed the development of the modified IEEE 14 bus test system in Matlab Simulink. The developed system is then intergrated with IMG components including DGs and loads. The power generations considered for powering the IMG are; solar PV generation, with efficiencies of 16% to 20% and a solar insolation of between 400 kWh/m^2 to 1000 kWh/m^2. The solar farm has a capacity of 100 MW. However, due to intermittency, the solar radiation varies throughout the day which also affects the PV output. The sytem under study is illustrated in Figure 3.2.

Figure

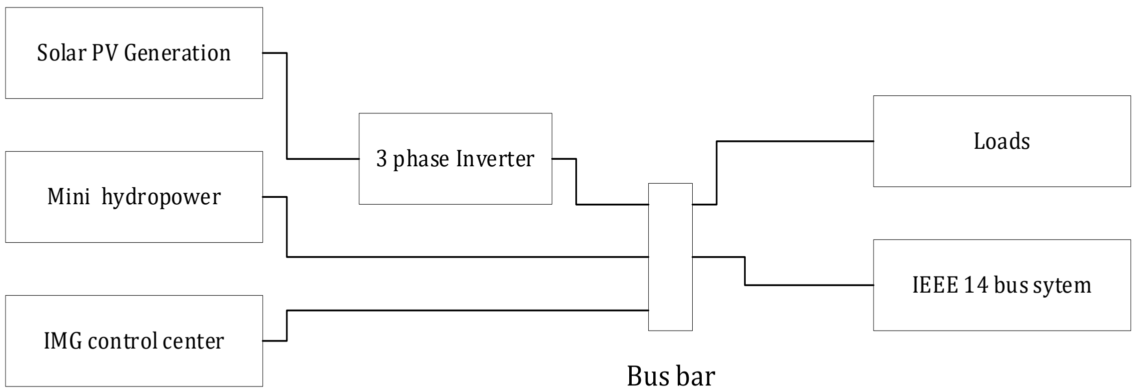


Figure 3.2: Islanded Microgrid System

The system is also fed with a micro-hydro that has a turbine efficiency of 0.8 - 0.95 and generates 50MW. At islanding the main feeder breaker breaks at the PCC, prevent back feeding of the electric power to the main grid for safety reasons. After islanding, the IMG has to entirely depend on its DGs to supply loads within the island. Under normal operation the system DGs are able to meet the load demand. When a fault occurs such as generation loss or a sudden large load is switched on the system checks for power balance and in case of an overload then optimal load shedding is initiated.. The Simulink model of IMG is illustrated in Figure 3.3. The system measurement detects the power imbalance and the FLP controller evaluates the severity of the disturbance. The load shedding action is initiated to drop non critical loads to stabilize the power in the IMG.

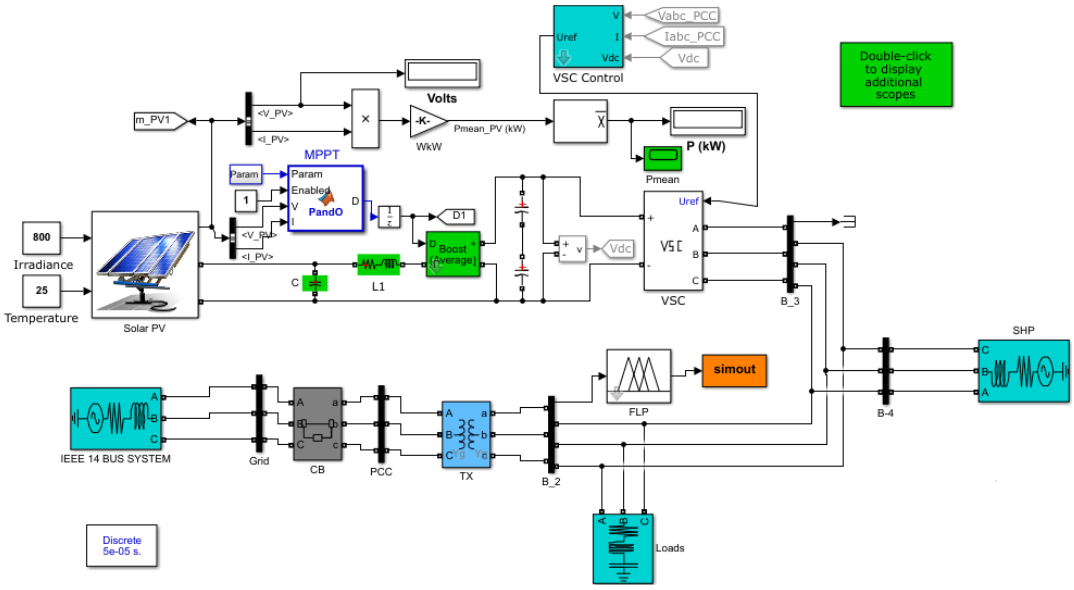


Figure 3.3: Simulink Model of IEEE 14 Bus Connected to IMG

3.4 Formulation of Objective Function

The objective function Equation 3.1 was formulated based on the load priorities and the amount of load to be shed in the IMG.

$$Min\ F = \sum_{i=1}^{NB} (P_{ri} P_{shi}) \tag{3.1}$$

Where;

NB is the number of buses,

F is the objective function representation,

p_{ri} refers to the priority of the load,

$P_{shi} = \sum(P_{gi} - P_{di})$ is the amount of load to shed at bus i,

p_{gi} - is the active power and reactive power generated from the DGs,

p_{di} refers to active and reactive power demanded.

The load connected to the IMG keep on varying at any given time, the LS problem was formulated to satisfy the load priority and to minimize the total amount of loads to shed. The following constraints were incorporated when solving the objective function: The voltage must satisfy the inequality in Equation 3.2.

$$v_{i\,\min} \le v_i \le v_{i\,\max} \qquad (3.2)$$

The V_i is the voltage at the node of i^{th} bus and should be within 10% of the nominal voltage allowed Ćetković, Žutolija, . & Komen, (2024). The range should be within 0.9 - 1.05 pu. The nominal voltage is taken to be 1 pu, as shown in Equation 3.2; hence, a voltage of less than 0.9 pu is considered an undervoltage (voltage dip), while a voltage of more than 1.05 pu is considered an overvoltage with an exception of a slack bus 1.06pu. The frequency in Equation 3.3 should satisfy the inequality.

$$f_{i\,\min} \le f_i \le f_{i\,\max} \qquad (3.3)$$

The generator active power should be within the minimum and maximum values as shown in Equation (3.4a). The reactive power of the i^{th} generator in Equation (3.4b) is within the limits.

$$P_{Gi\ \min} \le P_{Gi} \le P_{Gi\ \max} \qquad (3.4a)$$

$$Q_{Gi\ \min} \le Q_{Gi} \le Q_{Gi\ \max} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3.4b)$$

The total generated power must be able to meet the total demand of available loads and the losses as stipulated in Equation (3.5a). The total generated reactive power should satistify inquality Equation (3.5b).

Also $$\sum_i P_{Gi} = \sum_i (P_{Di}) + P_L \tag{3.5a}$$

$$\sum_i Q_{Gi} = \sum_i (Q_{Di}) + Q_L \tag{3.5b}$$

Where P_L and Q_L are system real and reactive power losses. Any significant change in the balance of Equation (3.5a) will cause a change in the frequency of the power network. Power loss is given by Equation 3.5.

$$P_{Loss} = Min\sum_{k=1}^{N} G_k \left(V_i^2 + V_j^2 - 2V_iV_j \cos\alpha_{ij}\right) \tag{3.5}$$

Where G_k is the conductance of the k^{th} branch connected in the i^{th} and j^{th} buses.

The Newton Raphson power flow method was used and its equation for real power flow is shown in Equation 3.6. The equation helps in detecting imbalances and predicting overloads. In polar form real power injected at bus i is given as;

$$P_i = |V_i| \sum_{\substack{k=1 \\ k \neq i}}^{n} |V_k||Y_{ik}| \sin(\delta_i - \delta_k) \tag{3.6}$$

Where Y_{ik} is the total admittance between i^{th} bus and k^{th} V_i and V_k is the voltage magnitudes at bus i, k and δ_i ,δk represent the voltage angles.

3.5 Fuzzy Linear Programming Algorithm

Fuzzy linear programming algorithm is one of artificial intelligence method in which the input data is imprecise and applies concepts of fuzzy logic. In contrast to conventional binary, which utilizes discrete values. The following steps are followed when designing the FLP algorithm.

i). Initialization process

- Define the linguistic variables
- Construct the MFs

- Formulate the rule base

ii). Convert crisp input data to fuzzy values (Fuzzification)

iii). Evaluate the rules in the rule base (inference)

iv). Combine the results of each rule (inference)

v). Convert the output to non-fuzzy values (defuzzification)

The fuzzy logic LS was modelled in a matlab simulink platform. In this case, the LS rules were formulated in the fuzzy logic toolbox. The inputs to a FLP controller for the LS consisted of two inputs which are the power generated and power demand as shown in Figure 3.4 FLP controller design. FigureThe output is the optimal amount of load to be shed to ensure the frequency remains within the threshold value.

Figure 3.4: FLP Controller Design

The power generated linguistic variables input to the controller are; Extremely very low (EVL), extremely low (EL), very low (VL) and low (L). The load demand linguistic variables input to the controller is represented by; high negative (HN), low negative (LN), low positive (LP) and high positive (HP). The linguistic variables for the output of the LS controller are; very small shed (VSS), small shed (SS), big shed (BS) and very big shed (VBS). These variables are summarized in Table 3.1.

Table 3.1: Linguistic Variables

Time(minutes)	**Power (MW)**	**Voltage (pu)**
0	100	1.05

5	90	1.04
10	80	1.03
15	70	1.02
20	60	1.01

3.5.1 Power Generated Membership Functions

The fuzzy membership function ranges from 0.0 to 1.0 in fuzzy logic the membership function maps how an input value belongs to a specific set as shown in Figure 3.5. The power generation varies from 200 to 350 MW. The power generated linguistic variables input to the controller are; Extremely very low (EVL), extremely low (EL), very low (VL) and low (L).

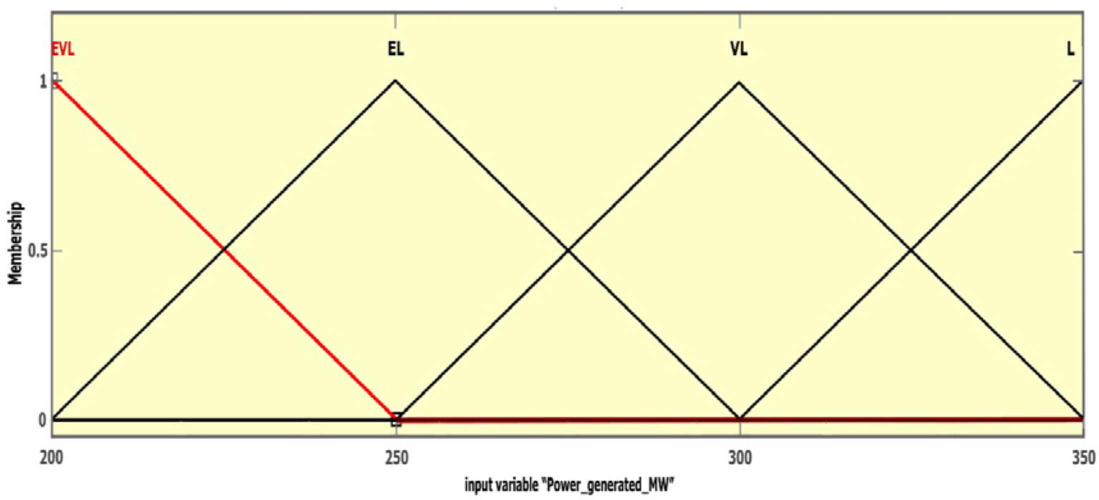


Figure 3.5: Power Generation Membership Functions

3.5.2 Power Demanded Membership Functions

Figure 3.5 depict membership functions for a typical load demand levels. The triangular membership functions are used to convert the MW values into degree of membership (0 to 1). The low demand is at 340MW, medium demand at 370MW and high demand occurs at 390MW. For instance at 370MW the system has a membership function of 0.5 in low demand state (LN) and 0.5 membership function in nominal demand (LP) state. The load demand linguistic variables input to the controller is represented by; high negative (HN), low negative (LN), low positive (LP) and high positive (HP).

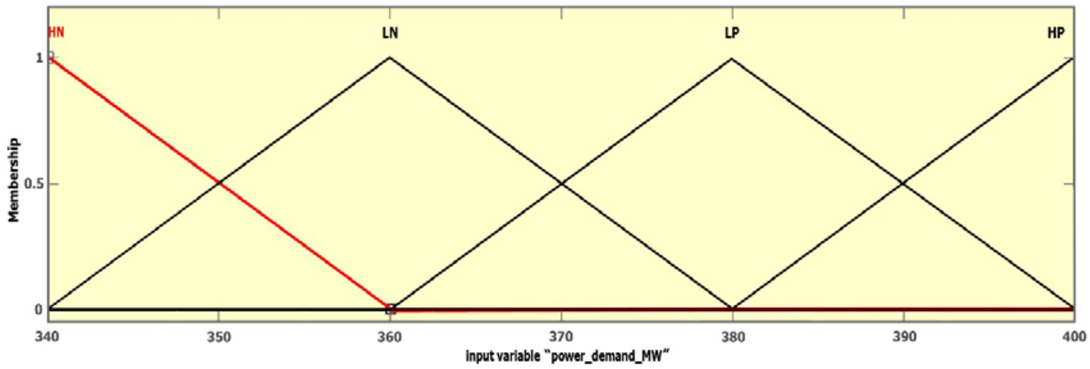


Figure 3.6: Power Demand Membership Functions

3.5.3 Membership Functions for Load Shedding

The LS is done when the inference engine evaluates rules which are defuzzified through a centroid method. A typical aggregated fuzzy rule is shown in Figure 3.7, with a membership functions. These membership functions allows the FLP algorithm to avoid sudden or excessive load cuts. They help the controller to translate the numerical MW value into quantitative actions, allowing the FLP system to intelligently decide how much load to shed under varying conditions. The linguistic variables for the output of the LS controller are; very small shed (VSS), small shed (SS), big shed (BS) and very big shed (VBS).

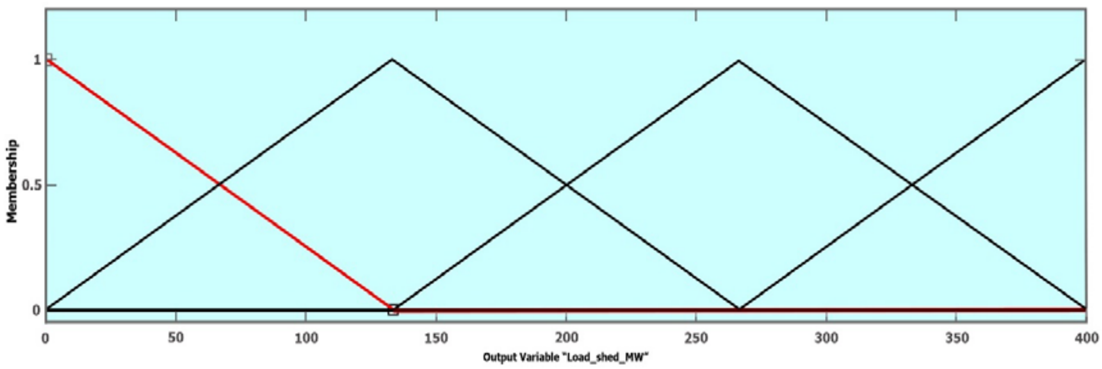


Figure 3.7: Load Shedding Membership Functions

3.5.4 Surface Plots of Load Shedding

The surface plot of the LS strategy is illustrated in 3D in Figure depicting the power demand in the x axis, power generated in the y axis and amount of load to be shed in z axis. From the graph on the right hand side of the surface shows higher generation values and the amount of load shed decreases as shown in the blue region. On the other hand as the power demand increases towards the left side (x axis), the amount of load shed increases as shown the yellow region. It can be deduced that the blue region represents the minimum LS thus representing the optimal LS conditions. The 3D surface plot shows how the FLP responds to LS across a wide operating scenarios.

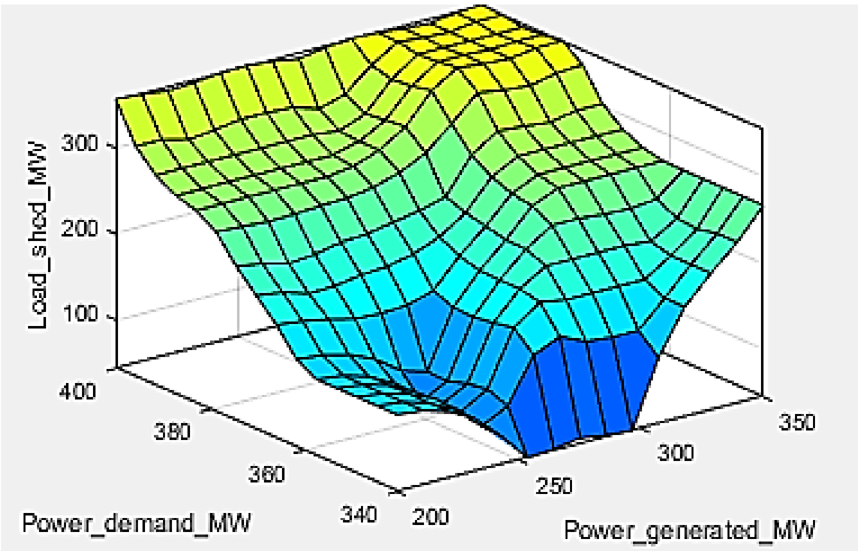


Figure 3.8: Surface Plot of Load Shedding

3.5.5 The Test System for the FLP Algorithm for Load Shedding

To validate the result of FLP load shedding, IEEE 14 bust test system is used as shown in Figure 3.9,. Appendix I contains complete raw data for the IEEE 14 bus system. It consists of 5 generators, 14 buses, 20 branches, 11 loads and 3 transformers. If the power generated meets the power demand there is no LS, however, if the demand exceeds the generation then LS is initiated to ensure the stability of IMG. LS is applied considering the priority of the loads with fewer priority ones being shedded first while critical loads remain in operation. The objective function for LS from bus 1 to bus 14 is as shown in Equation 3.7;

$$MinF(x) = P_{r_1} P_{sh_1} x_1 + P_{r_1} P_{sh_2} x_2 + P_{r_3} P_{sh_3} x_3 + \ldots\ldots P_{r_{NB}} p_{sh_{NB}} x_{NB} \tag{3.7}$$

Where ; NB- Refers to number of buses

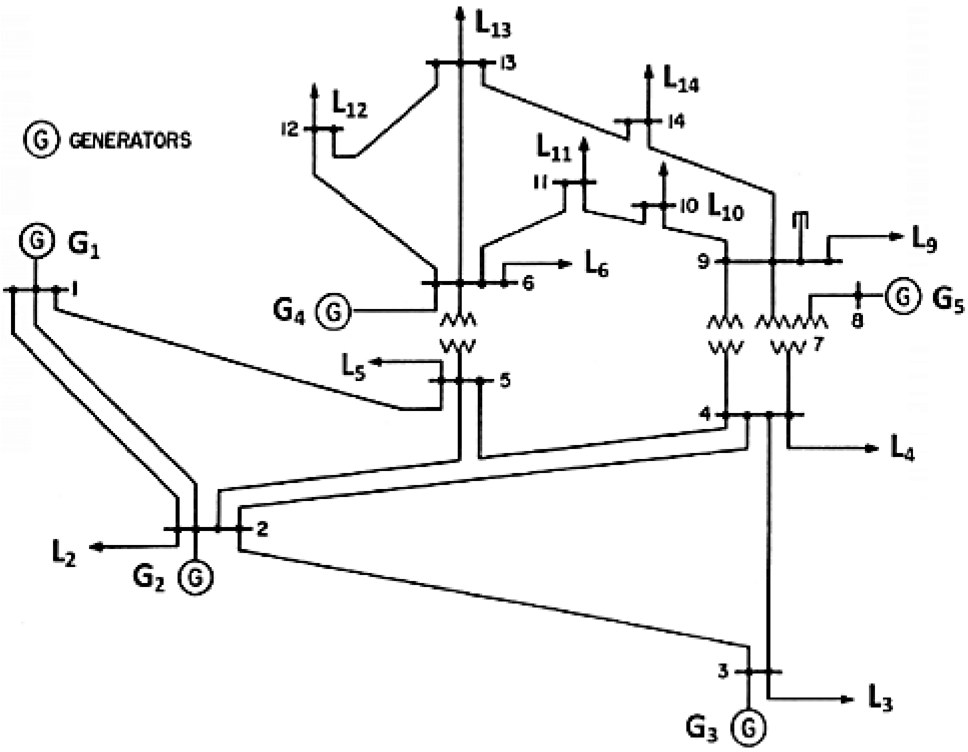


Figure 3.9: IEEE 14 Bus Modified Test System

3.5.6 Determination of Weak Buses for Load Shedding

The fast voltage stability index (FVSI) was used for the identification of weak buses that are susceptible to voltage collapse. The results for FVSI the IEEE 14 bus system at 100 % loading is shown in Figure 3.10. From the graph the weakest buses whose lines were having a value exceeding 0.6 (high index approaching value 1, which signifies that a power system is near voltage collapse). In this case, it was lines 3 and 9, however, since the system is at base loading no LS was done.

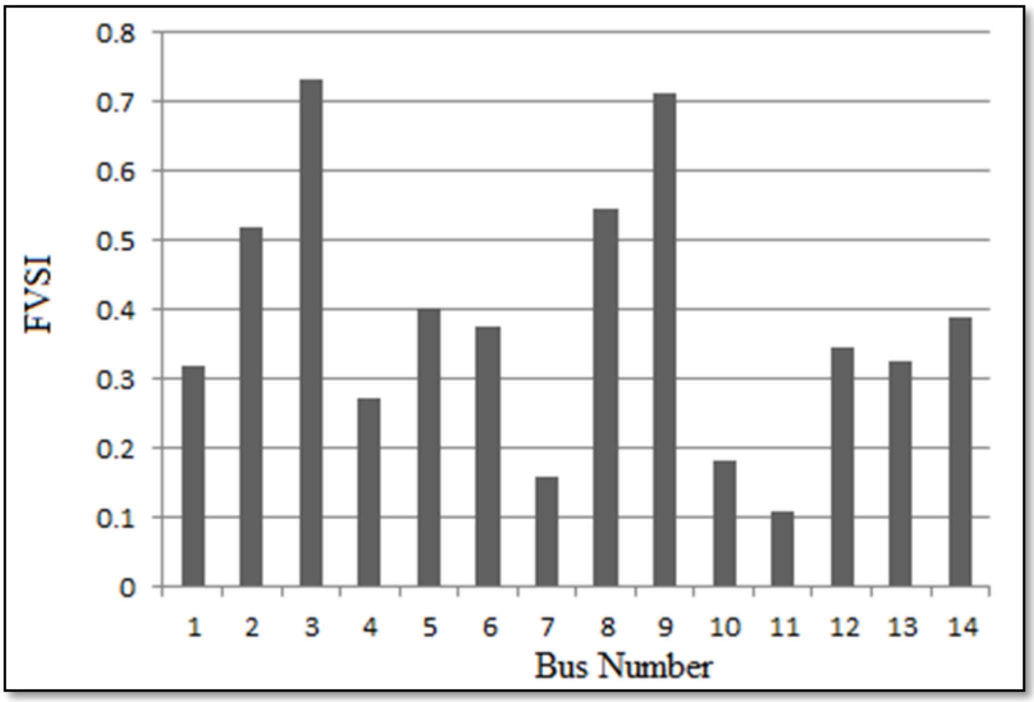


Figure 3.10: FVSI of Lines at Base Loading

3.5.7 Fuzzy Linear Programming

Fuzzy linear programming algorithm is a feasible solution only if the objective function satisfies the constraints of the problem, the optimal solution means that the solution is feasible, thus the proposed method is summarized as a flowchart Figure 3.11.

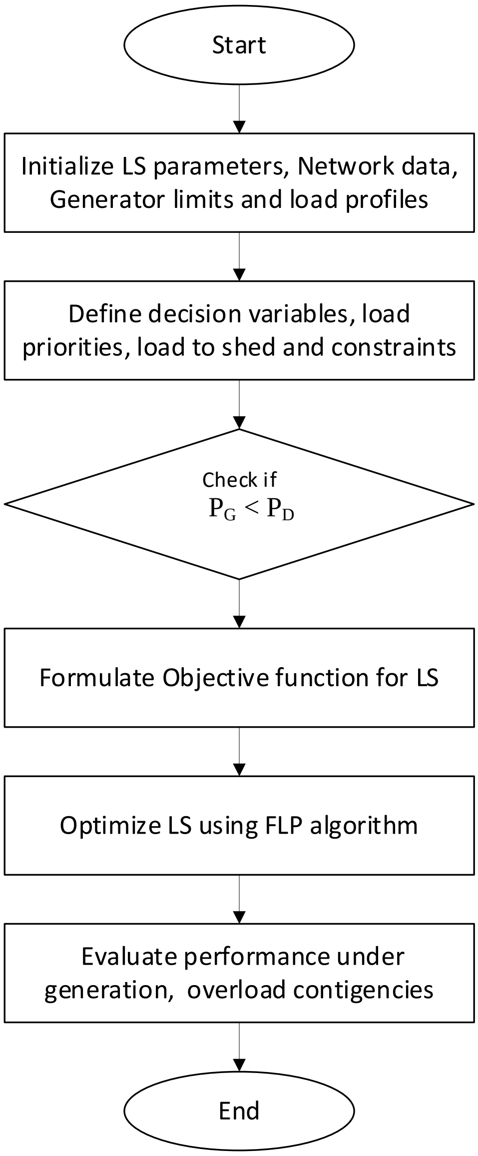


Figure 3.11: Load Shedding Algorithm

3.5.8 Bus Ranking

Bus ranking helps in maintaining sanity when performing LS such that when there is a power deficit the weakest buses are given priority. The fast voltage stability index (FVSI) was used to classify the buses for LS is illustrated by Equation 3.6 (Hamid, Musirin, Othman, and Al, 2013).. The FSVI is defined as;

$$FVSI = \frac{4Z^2 Q_j}{V_i^2 X} \tag{3.6}$$

Where Z is the impedance of the line

Q_j is the receiving end reactive power

X is the reactance of the line.

V_i is the sending end voltage

The value evaluated by FVSI shows how close or far that line is from collapsing. A value close to 1.0 indicates the line is close to its stability limit. Thus for a stable system, it should be less than 1.0, while a bus with more than 1.0 indicates the system voltage is likely to collapse and thus becomes the potential bus for LS. The FVSI algorithm for ranking buses is shown in figure 3.12.

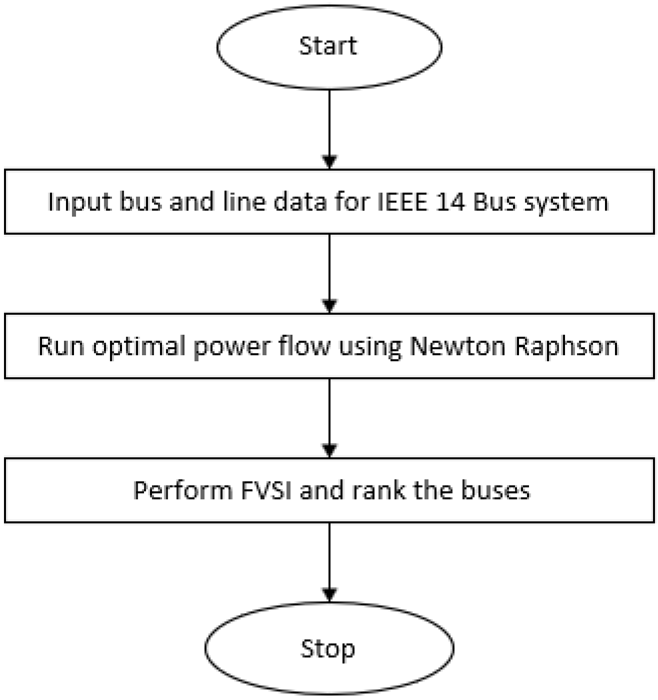


Figure 3.12: FVSI Algorithm

The IMG is dynamic in nature hence is prone to a lot of disturbances and failures. Since all the disturbances were not simulated, this research was limited to disturbances of loss of generation and overload contingencies. The following events were simulated to justify the effectiveness of the optimal FLP LS algorithm.

3.5.8.1 Loss of Distributed Generation

The DG disconnection was triggered during islanded operation to create generation. The resulting imbalance between available generation and connected was evaluated by FLP algorithm. The algorithm priotized loads in IMG which consist of both critical and non-critical, less critical loads were shed to ensure contuinity to critical loads.

3.5.8.2 Overload on a Feeder

To evaluate the effectiveness of the proposed LS strategy, feeder overloading was simulated by progressively increasing load demand at bus 5 and bus 9 which depicted critical load buses under study. The overload condition on the feeder was introduced by load increment in steps of 5%, 10%, 15%, 20%, 25%, 30%, 35%, and 40% above the base loading. This intentional loading was to stress the feeder and replicate a realistic operating conditions where sudden demand may exceed the available generation. Once the feeder loading exceeded its rated capacity, the voltage limits and frequency thresholds begin to deteriorate and can plunge the IMG to a complete blackout.

These overload scenarios provides a systematic framework for assessing the capability of the FLP Load shedding algorithm. The FLP main function is to detect the stressed feeder and initiate timely LS thereby ensuring system stability and prevent cascaded failures within the IMG.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents and discusses the simulation results obtained from the implementation of the hybrid FLP algorithm. The IEE14 bus system was used to test the FLP algorithm, and it consists of 5 generators, 14 buses, 20 transmission lines and 11 loads. The FVSI was used in ranking the buses. The chapter further evaluates the algorithm under load prioritization, overload contingencies, voltage profiles, line flows and generator performance. Finally, the FLP was validated for effectiveness by comparing with existing literature.

Table 4.1: Ranking of Buses at Base Loading

Line number	FVSI value	Ranking	From bus	To bus
3	0.7339	1	12	13
9	0.7140	2	14	13
8	0.5457	3	9	14
2	0.5204	4	6	12
5	0.4038	5	6	11
14	0.3902	6	1	5
6	0.3755	7	11	10
12	0.3457	8	3	2
13	0.3260	9	3	4
1	0.3183	10	2	5
4	0.2710	11	6	13
10	0.1818	12	7	9
7	0.1595	13	9	10
11	0.1084	14	1	2

Buses with the highest FVSI are priotized for LS because they represent lines which are near their voltage collapse point. At base loading, line 3 (buses 12-13) has the highest FVSI at 0.7339, which signifies that it’s a heavily loaded line. It is followed by line 9 (buses 14-13), which has an FVSI of 0.7140. This ranking helps in making decisions about which buses LS to be applied to relieve the system from overloads. In this case, LS has to be applied to buses 14 and 13 to releave lines 3 and 9.

4.2 Load Shedding Considering Load Prioritization

Load prioritization provides a means of classifying the loads in terms of importance. Loads are classified as vital loads, semi-vital loads and non-vital loads. When load shedding non-vital loads are shed first and if the frequency does not stabilize semi vital loads are shed to curb the frequency from decaying any further. The vital loads like military installations and hospitals are not shedded.

Table 4.2: Load Shedding Considering Load Priorities

Power Generated (MW)	Power Losses (MW)	Amount of load shed (MW)	Buses to shed
265	0.2349	5.0246	14 & 13 & 12
270	0.2348	4.7993	14 & 13
275	0.2349	4.5497	14 & 13
280	0.2350	4.3004	14 & 13
285	0.2353	4.0516	14 & 13
290	0.2360	3.8032	14 & 13
295	0.2365	3.5553	14 & 13
300	0.2365	3.3079	14
305	0.2371	3.0609	14
310	0.2378	2.8143	14

Each load bus in the system is categorized as critical and non-critical. The order of priority is in ascending order from bus 1 through to bus 14, thus LS is initiated from bus 14 being low priority bus. If the shedding of bus 14 does not stabilize the IMG, then LS in bus 13 is initiated. This is done to keep the frequency of IMG in the acceptable range. Thus, it can be deduced from the Table 4.2, that when the power shortage is large, then the amount of LS involves more buses. However, when the load demand and generation mismatch is less then LS is minimal and is limited to one bus.

4.3 Overload Contingency

The overload contingency simulation validates the system operational response and confirms the effectiveness of the applied LS control strategy under the N-1 contingency conditions. The system was subjected to an overload scenario where the generation was fixed at 340MW and the demand was increased incrementally by 5MW. The results presented in Table 4.3, clearly indicate that the system demand increased from 345MW to 395MW, and both power losses and LS increased with the increase in power mismatch. This pattern confirms that LS algorithm dynamically adjusted the system stability by proportionally shedding low priority loads.

Table4.3: Overload Contingency

Power demand	Power loss	Load to shed	Buses to shed
345	0.2446	3.5980	14 & 13
350	0.2805	4.0279	14 & 13
360	0.2963	4.3569	14 & 13
365	0.3179	4.7146	14 & 13
370	0.3394	5.0720	14 & 13
375	0.3630	5.4400	14 & 13
380	0.3627	5.8388	14 & 13
385	0.3725	6.1378	14, 13 & 12
390	0.3845	6.4475	14, 13 & 12
395	0.3951	6.7507	14, 13 & 12

Table 4.4: Generators Output Before and after Load Shedding

Parameter	Before load shedding	After load shedding
Bus voltage (pu)	1.0605	1.0597
Line flow (MW)	145.0	132.7
Generator 1 output	232.4	232.4
Generator 2 output	40.0	40.0
Generator 3 output	0.0	0.0
Generator 4 output	125.0	75.0
Generator 5 output	50.0	0.0

The generator output data in Table 4.4, support the technical validity of the LS control action. Before LS, high line flow (145MW) and high outputs from generators 4 and 5 indicate that the system was nearing its thermal and voltage stability limits. After LS implementation, the line flows of generator 1 reduced to 132.7MW, reflecting a measurable alleviation of transmission stress and confirming that overload was effectively mitigated.

Notably, the output of generators 1 and 2 maintained their output at 232.4MW and 40MW respectively indicating that the generation stability was preserved. The output of generators 4 and 5 experienced output reductions from 125MW to 75MW and 50MW to 0MW respectively. This demonstrates that the LS strategy effectively redistributed generation demand, reducing overload and enhancing overall system stability.

The minimum change in bus voltage from 1.0605pu to 1.0597pu further validates that the system voltage profile remained stable throughout the contingency. The negligible voltage deviation indicates that the LS method achieved balance restoration without introducing reactive power instabilities at bus 9. Bus 9 represents load centres and at the IMG and is a further from the generations thus was chosen for study of overload contigencies. Overall, the simulation confirms that the LS scheme successfully mitigated overloads, preserved generator stability, reduced line overloads and maintained acceptable voltage margins demonstrating robusteness of LS control logic under increasing demand conditions.

4.4 Bus Voltages Before and After Load Shedding

The optimal LS has been able to improve voltages at every bus. In bus 1 the voltages remained the same at 1.05pu because it is a slack bus and is used to maintain the system at balance, while from bus 2 to bus 5 are usually the generator bus (PV buses), which maintain the voltage close to 1.0 pu. Buses 6 to bus 14 are the load buses (PQ buses) here is where most of the loads are connected and the voltage is below 1.0 pu due to too much load demand and the fact that the buses are far from the generators (Maroko, Murage, & Hinga, 2024).. After application LS, there was an improvement in the voltage in the buses from bus 2 to bus 14, as shown in Table 4.5. The lowest voltage in bus 14 of 0.917pu rising to 0.970pu after LS. This consistent upward shift demonstrates that the shedding of non critical loads effectively reduced the reactive power burden and active power demand, thereby improving overall voltage stability and power quality.

Table 4.5: Bus Voltages Before and After Load Shedding

Bus	Voltage without load shedding (pu)	Voltage with load shedding (pu)
1	1.05	1.05
2	0.981	1.02
3	0.97	1.01
4	0.961	1.00
5	0.953	0.996
6	0.946	0.991
7	0.943	0.988
8	0.94	0.986
9	0.936	0.983
10	0.933	0.981
11	0.925	0.976
12	0.922	0.974
13	0.919	0.972
14	0.917	0.970

Table 4.6: Load Shedding on Bus 5

Time(minutes)	Power (MW)	Voltage (pu)
0	100	1.05
5	90	1.04
10	80	1.03
15	70	1.02
20	60	1.01

Table 4.6, depicts LS on bus 5 in an interval of 5 minutes. Bus 5 is chosen because it is a generation bus and acts as a connection point of DGs The system settles at 1.010 pu after 20 min, comfortably above the typical under-voltage threshold of 0.95 pu. Active power shed from 100 to 60 MW causes a 3.8 % voltage drop (1.050 → 1.010 pu). The voltage slightly decreased after load shedding because some loads which were responsible for reactive power compensation were shed. This demonstrates that the LS achieved a stable operating point without triggering secondary instabilities.

4.5 Line Flows Before and after Load Shedding

A Newton-Raphson power flow analysis was conducted for the IEEE 14-bus system, and the results are tabulated in Table 4.7.

Table 4.7: Line Flows Before and after Load Shedding

Line	Flow without load shedding (pu)	Flow with load shedding (pu)
1-2	0.657	0.650
1-5	0.304	0.302
2-3	0.476	0.472
2-4	0.402	0.400
2-5	0.251	0.250
3-4	0.237	0.236
4-5	0.413	0.410
4-7	0.245	0.255
4-9	0.251	0.249
5-6	0.262	0.260
6-11	0.381	0.377
6-12	0.523	0.518
6-13	0.393	0.389
7-8	0.238	0.244
9-10	0.288	0.285
9-14	0.284	0.282

LS has reduced the line flows in most of the lines, as depicted in Table 4.7, including lines 4-7 and 7-8, where the limits were exceeded before LS was implemented. The results overscores a decrease in line flows, signifying a slight decrease in load demand following load LS. A decrease in line flow indicates that overload has been mitigated.

Specifically, the reductions in line flow magnitudes such as from 0.657pu to 0.650pu (line 1-2) and 0.523pu to 0.518pu (line 6-12) demonstrates the algorithm's ability to rebalance the power network by curtailing demand at lower priority buses. The most significant improvement occurred in lines that were previously close to exceeding their limits i.e. lines 4-7 and 7-8. After LS, these lines displayed stabilized flow values (0.245-0.255 and 0.238-0.244pu), this results display the redistribution of power and mitigation of local congestion. The slight increase in line flows (e.g. in lines 4-7 and 7-8) is technically acceptable, as it mya result from network reconfiguration after LS. This due to the fact that power my be rerouted to less reloaded paths to maintain continuity of supply to other buses.

4.6 Validation of the Hybrid FLP Algorithm

The FLP algorithm was validated by comparing with similar works in [11] and Tamilselvan, (2020). This is shown in Table 4.8, the voltage before and after LS is performed is tabulated.

Table 4.8: Comparison of Load Shedding Methods

Bus number	Normal Voltage	After the generation change	GA	GA-ANN	ABC-ANN	Hybrid FLP
1	1.0600	1.0600	1.0600	1.0600	1.0600	1.0600
2	1.0450	1.0450	1.0450	1.0450	1.0450	1.0450
3	1.0100	1.0200	1.0150	1.0100	1.0100	1.0100
4	1.0000	1.0199	1.0186	1.0105	1.0250	1.0167
5	1.0000	1.0228	1.0195	1.0115	1.0267	1.0175
6	1.0700	1.0700	1.0600	1.0500	1.0700	1.0700
7	1.0000	1.0530	1.0524	1.0422	1.0564	1.0609
8	1.0900	1.0900	1.0900	1.0800	1.0900	1.0900
9	1.0000	1.0362	1.0356	1.0254	1.0405	1.0550
10	1.0000	1.0346	1.0329	1.0225	1.0383	1.0502
11	1.0000	1.0485	1.0430	1.0328	1.0505	1.0564
12	1.0000	1.0537	1.0392	1.0251	1.0539	1.0551
13	1.0000	1.0475	1.0244	1.0033	1.0482	1.0502
14	1.0000	1.0229	1.0123	0.9966	1.0257	1.0349

The hybrid FLP displays the lowest voltages across all the buses for instance, bus 5 is 1.0175pu, bus 7 is 1.0609pu, bus 11 is 1.0564pu, and bus 14 is 1.0349pu. These results show that the FLP algorithm sheds just enough load to stabilize the system without leaving voltages too high. It avoids the overshoot displayed in the ABC-ANN, where the voltages exceed the desired value. The FLP stands out as the most conservative method as it maintains the voltage close to 1.000pu and is most stable for weak buses 9 -14 displays clear improvement.

4.7 Iteration Characteristics

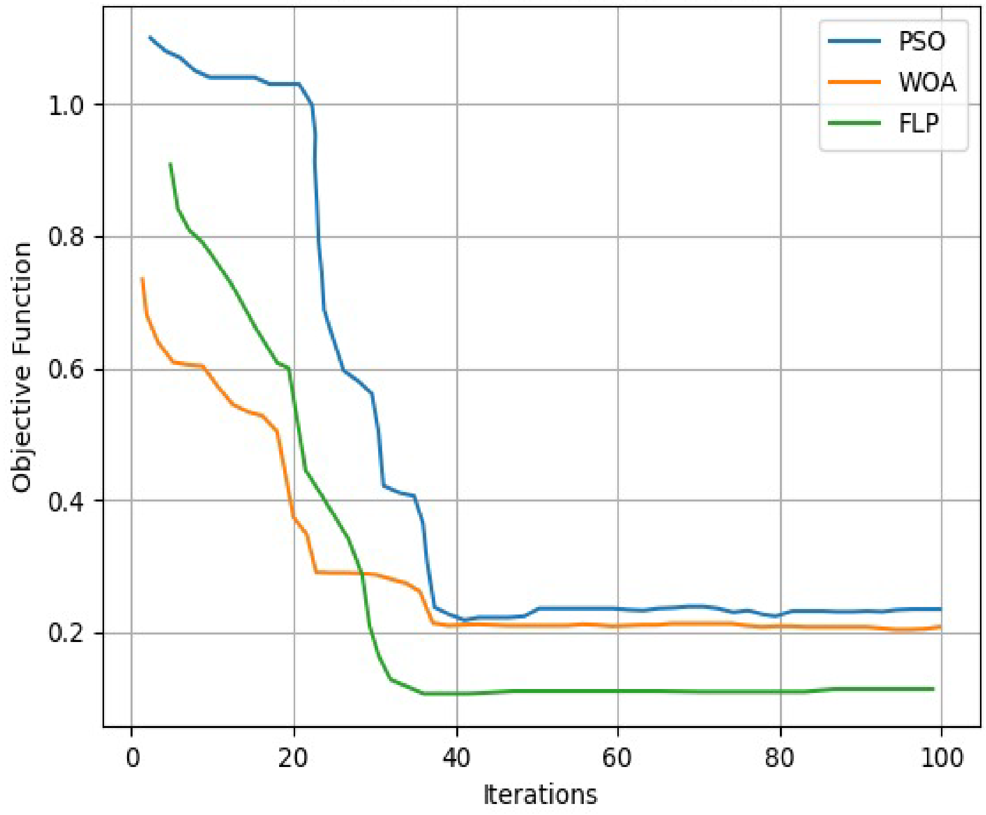


Figure 4.1: Iteration Convergence

The convergence behaviour illustrated in Figure 4.1 demonstrates the computational efficiency and stability of the implemented FLP algorithm. It achieves convergence after 33 iterations. The WOA performs moderately well while the PSO converges slower and gets trapped at a higher objective value. The FLP outperforms both PSO and WOA with convergence speed and quality of solution. Thus it can be deduced that the algorithm possesses fast dynamic response and robust optimization capability, which are critical features for real-time LS in IMG.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

In this study optimal LS in IMG has been achieved using a combination of FLP techniques in line with the objective function. The IEEE 14 bus system was used for validating the results. As depicted from the results, the proposed FLP algorithm was applied satisfactorily for LS in IMG. The LS was executed for generation contingencies and overload contingencies. For all the scenarios optimal LS was performed to ensure the operating constraints are not violated in the IMG. From the simulated results it can be conclude that the proposed LS scheme was able to stabilize the frequency through optimal shedding of loads.

The IMG has a low proportionate inertia therefore a small disturbance sustainable in nature could result into a significant frequency variation that if not corrected can plunge an IMG to total collapse. The LS objective function is formulated as an approximate model because the sources in IMG are highly stochastic. Thus, the fuzzy logic controller took care of the vagueness to process and fire correct rules for load shedding. The optimization aspect of LS was achieved via the linear programming. The inequality constraints of defined the feasible solution of the LS objective function. In comparison to GA 77.04%, ABC-ANN 84.03%, PSO-ABC 85.50% the proposed FLP algorithm was able to shed optimal amount of load quantities resulting in 86.10% voltage profile recovery. According to the results, if IMG becomes overloaded owing to contingencies, the least amount of load is shed in order to prevent frequency and voltage collapse.

5.2 Recommendation and Areas for Further Studies

The FLP algorithm for LS once adopted, will maximize the exploitation of IMG using renewable energy as the main source of power. The LS process put forth in this research will guarantee optimal LS to avert the occurrence of a blackout during severe power imbalances.

The following areas were not covered in this thesis and thus are subject for further investigation. Future researchers should explore;

i. Rota LS as opposed to LS based on priorities of the customers.
ii. Continous refining of LS methods by assimilating more variables and advanced machine learning algorithms.
iii. LS considering reactive power demand of each bus.
iv. LS in IMG integrated with energy storage system.

REFERENCES

Abazari S. &. Zahedi, B. (2016).“Combinational load shedding with tracing reactive power and using genetic *algorithm,. 61*, 325–330.

Acosta, M.N. (2020). “Optimal under-frequency load shedding setting at Altai-Uliastai regional power system, Mongolia,” *Energies*, 13(20), 1–18, , doi: 10.3390/en13205390.

Ainah P.K. & Folly, (2015). “Development of micro-grid in Sub-Saharan Africa: An overview,” *Int. Rev. Electr. Eng.*, *10*(5), 633–645, doi: 10.15866/iree.v10i5.5943

Akbari, M. Golkar, M.A. & Tafreshi, S. M. M. (2011). A PSO solution for improved voltage stability of a hybrid ac-dc microgrid,” *2011 IEEE PES Int. Conf. Innov. Smart Grid Technol. ISGT India 2011*, 352–357. doi: 10.1109/ISET-India.2011.6145340.

Babagana, A. Jimoh, I.A. Seferi, Y. & Burt, G. (2025). “A Timer and Mixed Integer Linear Programming Load Shedding Scheme for Resilient DC Microgrids,” *IEEE Access*, vol. 13, pp. 6632–6642, doi: 10.1109/ACCESS.2025.3525975.

Baiceanu, F.C. Ivanov, O. Beniuga, R. C. Neagu, B.C. & Nemes, C.M. (2023). “A Continuous Multistage Load Shedding Algorithm for Industrial Processes Based on Metaheuristic Optimization,” *Mathematics*, 11(12), 1–19, doi: 10.3390/math11122684.

Barker P.P. & De Mello, R.W. (200).“Determining the impact of distributed generation on power systems. I. Radial distribution systems,” 1(5), 1645–1656, doi: 10.1109/pess.2000.868775.

Baurzhan S. & Jenkins, G.P. (2017). “On-Grid Solar PV versus Diesel Electricity Generation in Sub-Saharan Africa : Economics and GHG Emissions,” *Sustainability*, 9(3), 1–15, doi: 10.3390/su9030372.

Ben Hessine, M. Jounini, H. & Chebbi, S. (2014).“Load Shedding Strategy Application Using Fuzzy Logic,” *Int. J. Sci. Res.*, 3(6), 2012–2015

Bhat, H.S. Vaz, G.J. & Meza, J.C. (2013).“Fast Solution of Load Shedding Problems via a Sequence of Linear Programs,” in *IEEE International Conference*, pp. 1–6.

Bio Gassi K. & Baysal, M. (2022). “Analysis of a linear programming-based decision-making model for microgrid energy management systems with renewable sources,” *Int. J. Energy Res.*, 46(60, 7495–7518, doi: 10.1002/er.7656.

Bower, W. Bower, W. Llc, L. Reilly, J.&. Associates, R. (2014). “The Advanced Microgrid Integration and Interoperability,”. March, 1–56.

Casals-Torrens, P. Martinez-Velasco, J.A. Serrano-Fontova, A. & Bosch, R. (2020). “Assessment of unintentional islanding operations in distribution networks with large induction motors,” *Energies*, *13*(2), 1–25, doi: 10.3390/en13020345.

Ceja-Gomez, F. Qadri, S.S. & Galiana, F.D. (2012). “Under-frequency load shedding via integer programming,” *IEEE Trans. Power Syst.*, vol. 27, no. 3, pp. 1387–1394, 2012, doi: 10.1109/TPWRS.2012.2186156.

Ćetković, D. Žutolija, J. & Komen, V. (2024). “Voltage Rise Mitigation in Medium-Voltage Networks with Long Underground Cables and Low Power Demand,” *Energies* , *17*(13).

Choi, Y. Lim, Y. & Kim, H. (2017). “Optimal Load Shedding for Maximizing Satisfaction in an Islanded Microgrid,” *Energies*, vol. 10, no. 45, pp. 1–13, 2017, doi: 10.3390/en10010045.

Çimen H. & Aydın, M. (2015). “Optimal Load Shedding Strategy for Selçuk University Power System with Distributed Generation,” *Procedia - Soc. Behav. Sci.*, *195*, 2376–2381, doi: 10.1016/j.sbspro.2015.06.218.

Conteh, F. Tobaru, S. Lotfy, M.E. Yona, A & Senjyu, T. (2017). "An effective Load shedding technique for micro-grids using artificial neural network and adaptive neuro-fuzzy inference system," *Energy*, *5*(July),814–837, doi: 10.3934/energy.2017.5.814.

Das, K. Nitsas, A. Altin, M. Hansen, A.D. & Sorensen, P.E. (2017). "Improved Load-Shedding Scheme Considering Distributed Generation," in *IEEE Transactions on Power Delivery*, pp. 515–524. doi: 10.1109/TPWRD.2016.2536721.

Einan, M. Torkaman, H & Pourgholi, M. (2017). "Optimized Fuzzy-Cuckoo Controller for Active Power Control of Battery Energy Storage System, Photovoltaic, Fuel Cell and Wind Turbine in an Isolated Micro-Grid," *Batteries, 3*(3), 23, doi: 10.3390/batteries3030023.

Energy Regulatory Commission, (2016), *Energy Regulatory Commission* Nairobi: Kenya National Grid code.

Ergun, S. Dik, A. Boukhanouf, R. &. Omer, S. (2025)."Large-Scale Renewable Energy Integration: Tackling Technical Obstacles and Exploring Energy Storage Innovations," *Sustain.*, 17(3), 1–31, doi: 10.3390/su17031311.

Estrada, M.T.A. (2012). "Bacterial Foraging Optimization Algorithm for," *Int. J. Innov. Comput.*, *02*(1), 8–14, doi: 10.13140/RG.2.2.10053.24803.

Fotis, V. Vita, G & Maris, T.I. (2023). "applied sciences Risks in the European Transmission System and a Novel Restoration Strategy for a Power System after a Major Blackout," *Appl. Sci.*, *13*(83), 1–32.

Fu, B.Q. Hamidi, A. Nasiri, A. Bhavaraju, B & Krstic,S.B (2014). "The Role of Energy Storage in a Microgrid Concept," *IEEE Electrification Magazine*, February, 21–29, 2014.

Gain, B. Hassan, M. Rahman, A. & Jisan, S.R. (2025). "AI-Based Fuzzy Logic Approach for Load Shedding Scheme for Enhanced Power System Stability in the Barishal , Bangladesh," *Int. J. Res. Sci. Innov.*, *12*(9), 3919–3928, 2025, doi: 10.51244/IJRSI.

Gandoman, F.H. (2018)."Review of FACTS technologies and applications for power quality in smart grids with renewable energy systems," *Renew. Sustain. Energy Rev.*, *82*(August), 502–514. doi: 10.1016/j.rser.2017.09.062.

Gholami, A. Shekari, T.& Sun, X.A. (2018). "An Adaptive Optimization-Based Load Shedding Scheme in Microgrids," in *Proceedings of 51st Hawaii International conference on system science,* PP 2660–2669.

Guo, Z. Sha, D. & Liao, X. (2014)."Energy management by using point of common coupling frequency as an agent for islanded microgrids," in *IET Power Electronics*, pp. 2111–2122. doi: 10.1049/iet-pel.2013.0564.

Hagh, M.T &. Galvani, S, (2011)."Minimization of load shedding by sequential use of linear programming and particle swarm optimization," *19*(4), 551–563, , doi: 10.3906/elk-1003-31.

Hamid, Z. Musirin, M. M. Othman, M. & Al, E.T. (2013). "Utilizing Stability Index Tracing for Precise Load Buses Identification in Load Shedding Problem," *Sci. Res.*, 2013(January), 168–173, doi: 10.4236/eng.2013.51b031.

Hanzala, M. Memon, Z. Hussain,M. I. Azeem, F. Shahzad, N. & Kim, J. (2024). "Fuzzy-Logic-Based Cascaded Decentralized Control and Power Load Management," *Buildings*, *14*(9), 1–23.

Hillier F.S. & Lieberman, G.J. (2021). *Introduction To Operations Research*, (11th ed.). Boston: McGraw-Hill.

Hong Y.Y. & Hsiao, C.Y. (2022) “Under-Frequency Load Shedding in a Standalone Power System With Wind-Turbine Generators Using Fuzzy PSO,” *IEEE Trans. Power Deliv.*, vol. 37, no. 2, pp. 1140–1150, doi: 10.1109/TPWRD.2021.3077668.

Hong, Y.Y. Hsiao, M.C. Chang, Y.R. Der Lee, Y. & Huang, H.C.(2013). “Multiscenario underfrequency load shedding in m Microgrid consisting of intermittent renewables,” in *IEEE Transactions on Power Delivery, 2013*, 1610–1617. doi: 10.1109/TPWRD.2013.2254502.

Hosseinzadeh A. & Edalatpanah, S.A. (2016). “A New Approach for Solving Fully Fuzzy Linear Programming by Using the Lexicography Method,” *Hindawi Publ. Corp.*, vol. 2016, 1–7.

Inayatullah, S. Rani, A. Siddiqi, T.A. Zaheer, H. Imtiaz, M. & Jafree, H.A. (2019). “An Efficient Method for Pivoting Free Variables in Linear Programming : A Computational Approach,” *Eur. Sci. J.*, 15(9), 1–17. doi: 10.19044/esj.2019.v15n9p1.

Jain, M. Gupta, S. Masand, D. Agnihotri, G. & Jain, S. (2016).“Real-Time Implementation of Islanded Microgrid for Remote Areas,” *J. Control Sci. Eng.*, *2016*, doi: 10.1155/2016/5710950.

Javadi, M. & Amraee, T. (2018).“Mixed integer linear formulation for undervoltage load shedding to provide voltage stability,” *IET Gener. Transm. Distrib.*, vol. 12, no. 9, pp. 2095–2104, doi: 10.1049/iet-gtd.2017.1118.

Jiang G. *et al.*, (2025). “Operational Flexibility Assessment of a Power System Considering Uncertainty of Flexible Resources Supported by Wind Turbines Under Load Shedding Operation,” *Energie*, *13*(11), 1–17.

Kaewmanee, J. Sirisumraaukul, S. & Menaneanatra, T (2013).“Optimal load shedding in power systems using Fuzzy Decision Algorithm,” China, 2013.

Kanimozhi S.K . & Balaji K.M., (2014) “Multi-objective approach for load shedding based on voltage stability index consideration,” *ALEXANDRIA Eng. J.*, 2014, doi: 10.1016/j.aej.2014.09.005.

Karimi, M. Mohamad, H. Mokhlis, H. & Bakar, A.H.A. (2012).“Under-Frequency Load Shedding scheme for islanded distribution network connected with mini hydro,” *Int. J. Electr. Power Energy Syst.*, *42*(1), 127–138, doi: 10.1016/j.ijepes.2012.03.017.

Khaki B. & Kouhsari, S.M. (2010). “Proper setting of underfrequency load shedding relays in industrial plants,” in *2010 9th Conference on Environment and Electrical Engineering, EEEIC 2010*, pp. 198–201. doi: 10.1109/EEEIC.2010.5489970.

Kim, H Kinoshita, T. & Lim, Y. (2014).“Talmudic Approach to Load Shedding of Islanded Microgrid Operation Based on Multiagent System Talmudic Approach to Load Shedding of Islanded Microgrid Operation Based on Multiagent System,” *J. Electr. Eng. Technol., March 2011*, 25–54, doi: 10.5370/JEET.2011.6.2.284.

Kim, H. Kinoshita, T Shin, M. & Engineering, S. (2010).“A Multiagent System for Autonomous Operation of Islanded Microgrids Based on a Power Market Environment,” *Int. J. Adv. Eng. Technol.*, vol. 3, no. 20, pp. 1972–1990, 2010, doi: 10.3390/en3121972.

Kim, J Suharto, Y &. Daim, T.U. (2017). “Evaluation of Electrical Energy Storage (EES) technologies for renewable energy : A case from the US Paci fi c Northwest,” *J. Energy Storage*, *11*, 25–54, doi: 10.1016/j.est.2017.01.003.

Kisengeu, S. M. Muriithi, C.M. & Nyakoe,G.N (2021). “Under voltage load shedding using hybrid ABC-PSO algorithm for voltage stability enhancement,” *Heliyon*, *7*(10), e08138, doi: 10.1016/j.heliyon.2021.e08138.

Kothari, I.J. & Nagrath, D.P. (2008). *Power System Engineering*, Second. New Delhi: Tata McGraw-Hill Publishing Company Limited, 2008.

Kunwar R. & Sapkota, H.P. (2022). "Introduction to Linear Programming Problems with Some Real-Life Applications," *Eur. J. Math. Stat.*, *3*(2), 21–27, doi: 10.24018/ejmath.2022.3.2.108.

Larguech, S. Aloui, S. Pages, O. El Hajjaji, A. & Chaari, A. (2015). "Adaptive Type-2 Fuzzy Sliding Mode Control for MIMO nonlinear systems: Application to a Turbocharged Diesel Engine," in *2015 23rd Mediterranean Conference on Control and Automation, MED 2015 - Conference Proceedings*, pp. 203–210. doi: 10.1109/MED.2015.7158751.

Larik, R.M. Mustafa, M. W. Aman, M. Jumani, T.A. Sajid, S. Panjwani, M.K. (2018). "An Improved Algorithm for Optimal Load Shedding in Power Systems," *Energies*, *11*(7), 1–16, doi: 10.3390/en11071808.

Lasseter, R.H. 2011). "CERTS microgrid laboratory test bed," *IEEE Trans. Power Deliv.*, *26*(1), 325–332, 2011, doi: 10.1109/TPWRD.2010.2051819.

Le, T.N. Quyen, H. A. Nguyen, N.A. (2016). "Electrical Power and Energy Systems Application of fuzzy-analytic hierarchy process algorithm and fuzzy load profile for load shedding in power systems," *Int. J. Electr. Power Energy. Syst.*, *77*, 178–184, 2016, doi: 10.1016/j.ijepes.2015.11.044.

Lee, H. Vu, B.H, Zafar, R. Hwang, S. & Chung, I (2021)."Power System Performance and Economic Efficiency," *Energies*, *14*(2), 1–29.

Li, S. Wei, Z & Ma, Y. (2018). "Fuzzy load-shedding strategy considering photovoltaic output fluctuation characteristics and static voltage stability," *Energies*, *11*(4), 1–18, 2018, doi: 10.3390/en11040779.

Lim, Y. Kim, H. Park, J. & Kinoshita, T. (2021). "A Load-Shedding Scheme Using Optimization for Proportional Fairness in the Islanded Microgrid," in

Control and Automation, and Energy System Engineering, *2011*, 235–236.

Long B &. Phung, N. (2021).“Load Shedding in Microgrids with Consideration of Voltage Quality Improvement,” *Eng. Technol. Appl. Sci. Res.*, *11*(1), 6680–6686.

Mahmoud, T.S. Habibi, D. & Bass, O. (2012).“Fuzzy Logic for Smart Utilisation of Storage Devices in A Typical Microgrid,” in *International Connference on Renewable energy Research and application (ICRERA)nference on Renewable energy Research and application (ICRERA),* Japan, *2012,* 1–6.

Małkowski, R. (2020).“Underfrequency Load Shedding : An Innovative Algorithm Based on Fuzzy Logic,” *Energies*, *13*(6), 1–16.

Marnay C &. Venkataramanan, G. (2006). “Microgrids in the evolving electricity generation and delivery infrastructure,” *Power Eng. Soc. Gen. Meet. 2006. IEEE*, 5 p., 2006, doi: 10.1109/PES.2006.1709529.

Maroko, J.T. Murage, D.K. & Hinga, P.K. (2024). “Load shedding in islanded microgrid using fuzzy linear programming,” *Int. J. Appl. Power Eng.*, *13*(3), 637 - 644.

MoE, (2004). “*Sessional Paper No . 4 on Energy*,” Nairobi: MoE.

Mogaka, L.O. Nyakoe, G.N & Saulo, M.J. (2020). “Power Prioritization and Load Shedding in an Island with RESs Using ABC Algorithm,” *J. Eng. (United Kingdom)*, *. 20*, 1–10 , doi: 10.1155/2020/8131952.

Mohammad, D (2018). “Analysis of The Frequency and Voltage Changes While Load Shedding in The Multimachine System,” in *2018 International Seminar on Intelligent Technology and Its Applications (ISITIA),* IEEE, 45–49.

Mokhlis, H. Laghari, J.A. Bakar, A.H.A & Karimi, M. (2012).“A fuzzy based under-frequency load shedding scheme for islanded distribution network connected with DG,” *Int. Rev. Electr. Eng.*, 7(4), 4992–5000, doi: 10.1016/j.ijepes.2012.03.017.

Nair, N.C.C. Member, S. &. Ancell, G. (2012).“Automatic Under-Voltage Load Shedding :,” in *power and energy society*, 2012.

Najihah, N. Bakar, A. Yusri, M. Fani, M. Na,M &. Khamis, A.(2016). “Microgrid and load shedding scheme during islanded mode : A review,” *Renew. Sustain. Energy Rev.*, December, 0–1, 2016, doi: 10.1016/j.rser.2016.12.049.

Nasseri, S.H. Zavieh, H & Mirmohseni, S.M. (2017).“A Generalized Model for Fuzzy Linear Programs with Trapezoidal Fuzzy Numbers,” *J. Appl. Res. Ind. Eng.*, *4*(1), 24–38, doi: 10.22105/jarie.2017.49602.

Nghia, L.T.. Quyen, H. A. & Do, H.K. (2016). “Load Shedding based on Fuzzy Logic and AHP Algorithm,” *IJERT*, *5*(04), 395–402.

Ojaghi, M. Azari, M. & Valujerdi, C.A. (2014).“Robust UVLS scheme to improve transmission line performance considering interruption cost and voltage stability index,” in *Proceedings of the IEEE International Conference on Industrial Technology*, pp. 541–546. doi: 10.1109/ICIT.2014.6894955.

Ojo, K.E. Saha, K.A. Srivastava, Lee, H. Vu, B.H, Zafar, R. Hwang, S. & Chung, I (2025). “Review of Advances in Renewable Energy-Based Microgrid Systems: Control Strategies, Emerging Trends, and Future Possibilities,” *Energies*, *18*(14), 1–26, doi: 10.3390/en18143704.

Ongondo Mogaka, L. Murage, D.K. & Saulo, J. (2015). “Rotating Machines Based Islanding Detection Using Fuzzy Logic Method Analysis,” *Int. J. Energy Power Eng.*, *4*(5), 311, doi: 10.11648/j.ijepe.20150405.21.

Paramo G. & Bretas, A. (2023) “Proactive Frequency Stability Scheme : A Distributed Framework Based on Particle Filters and Synchrophasors,” *Energies, 16*(11), 1–19.

Pourghasem P. & Seyedi, H. (2019). “An under-voltage load shedding scheme to prevent voltage collapse in a microgrid,” in *International Conference on Protection and Automation of Power System, IPAPS 2019*, IEEE, 2019, pp. 12–16. doi: 10.1109/IPAPS.2019.8641952.

R. S. A. L. carbon Africa Limited, (2015).“Kenya Market Assessment for Off-Grid Electrification,” Nairobi, Retrieved from https://www.renewableenergy.go.ke/asset_uplds/files/ERC IFC mini-grids - final report - Final(1).pdf

Rafinia, A. Rezaei, N. & Moshtagh, J. (2020). “Optimal design of an adaptive under-frequency load shedding scheme in smart grids considering operational uncertainties,” *Int. J. Electr. Power Energy Syst., 121*(February), 2020, doi: 10.1016/j.ijepes.2020.106137.

Raju L. & Milton, R.S. (2016).“A novel approach for optimization of smart microgrid using multiagent reinforcement learning,” *Int. J. Adv. Eng. Technol., VII*(II), 27–32.

Salmasi F.R. & Hosseinzadeh, M (2015). “Power management of an isolated hybrid AC/DC micro-grid with fuzzy control of battery banks,” in *IET Renewable Power Generation*, pp. 484–493. doi: 10.1049/iet-rpg.2014.0271.

Sapari, N. Mokhlis, H. & Laghari, J.A. (2017). “Load shedding scheme based on frequency and voltage stability for an islanding operation of a distribution network connected to mini-hydro generation,” *Energies, 25*(3), 1852–1863, 2017, doi: 10.3906/elk-1601-111.

Sapari, N.M. Mokhlis, H Laghari, J.A. Bakar,A.H & Dahalan, M.R.M. (2018). “Application of load shedding schemes for distribution network connected with distributed generation: A review,” *Renew. Sustain.*

Energy Rev., *82*(January 2016), 858–867, 2018, doi: 10.1016/j.rser.2017.09.090.

Sarwar, S (2020). “A mixed integer linear programming based load shedding technique for improving the sustainability of islanded distribution systems,” *Sustain.*, *12*(15), 1–23, doi: 10.3390/SU12156234.

Sasikala J. & Ramaswamy, M. (2011). “Fuzzy based load shedding strategies for avoiding voltage collapse,” *Appl. Soft Comput. J.*, 11(3), 3179–3185, doi: 10.1016/j.asoc.2010.12.020.

Shareef, H. Khamis, A. & Mohamed, A. (2015). “Islanding detection and load shedding scheme for radial distribution systems integrated with dispersed generations,” *IET Gener. Transm. Distrib.*, *9*(15), 2261–2275, 2015, doi: 10.1049/iet-gtd.2015.0263.

Takase, M. Kipkoech, R. & Essandoh, P.K. (2021)“A comprehensive review of energy scenario and sustainable energy in Kenya,” *Fuel Commun.*, *7,* 100015, doi: 10.1016/j.jfueco.2021.100015.

Tamilselvan V. & Jayabarathi, T. (2016). “A hybrid method for optimal load shedding and improving voltage stability,” *Ain Shams Eng. J.*, 7(1), 223–232, doi: 10.1016/j.asej.2015.11.003.

Tamilselvan, V. (2020). “A hybrid PSO-ABC algorithm for optimal load shedding and improving voltage stability,” *Inderscience Publ.*, *34*(6), 577–597

Toro-Mendoza, M.A. Segundo-Ramirez, J. Esparza-Gurrola, A. Visairo-Cruz, N. Guitierrez, C.A N. & Perez-Negron, C. (2023). “Toward Adaptive Load Shedding Remedial Action Schemes in Modern Electrical Power Systems,” *IEEE Access, 11*(October), 111011–111033, doi: 10.1109/ACCESS.2023.3322657.

Tyagi, D. Kumar,A. & Chanana, S. (2012). “Load shedding via PID controller for an isolated power system,” in *2012 IEEE 5th Power India Conference,* *PICONF 2012*, India, 2012. doi: 10.1109/PowerI.2012.6479461.

Wang, C. Mei, S. Dong, Q. Chen, R.& Zhu, B. (2020).“Coordinated Load Shedding Control Scheme for Recovering Frequency in Islanded Microgrids,” *IEEE Access, 8,* 215388–215398, doi: 10.1109/ACCESS.2020.3041273.

Wang, S.Y.K. & Kang, L. (2022). “Considering Distribution Network Reconfiguration,” *Energies*, *15*(22), 1–18.

Wu, X. Jiang, P. & Lu, J. (2014).“Multiagent-based distributed load shedding for islanded microgrids,” *Energies*, *7*(9), 6050–6062, doi: 10.3390/en 7096050.

Xu, Y. Liu, C.-C. Chen, Y. &. Gao, H. (2016). “Dynamic load shedding for an islanded microgrid with limited generation resources,” *IET Gener. Transm. Distrib.*, *10*(12), 2953–2961, doi: 10.1049/iet-gtd.2015.1452.

Yujin, L. Hak-man, K. & Tetsuo, K. (2014). “Distributed load-shedding system for agent-based autonomous microgrid operations,” *Energies*, *7,* 385–401, doi: 10.3390/en7010385.

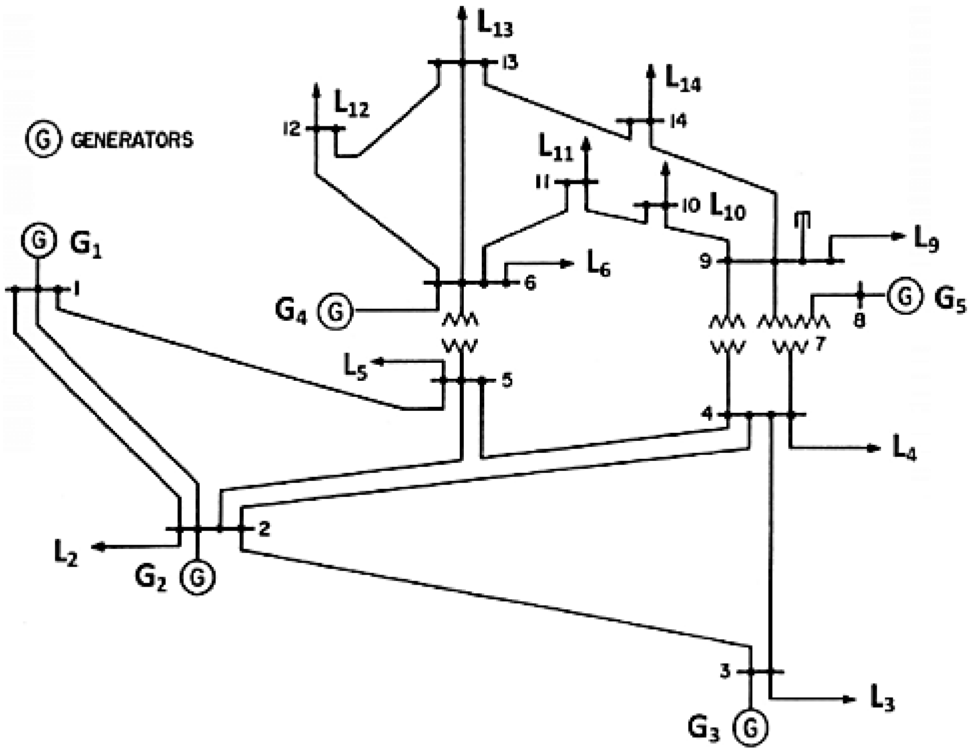
Zadeh, S.G.(2012).“New approaches to load shedding problem in islanded situation in distribution networks with distributed generation,” in *Cired workhop, Lisbon, 2012.*

Zhou, Q. Li, Z. Wu, Q. & Shahidehpour, M. (2018).“Two-Stage Load Shedding for Secondary Control in Hierarchical Operation of Islanded Microgrids,” in *IEEE Transactions on Smart Grid*, pp. 1–8. doi: 10.1109/TSG.2018.2817738.

APPENDICES

Appendix I : IEEE 14 Bus System

The data provided is on 100MVA base.



Appendix II: IEEE 14 Bus Data

IEEE 14 bus test system - bus data							
Base MVA = 100							
Bus number	**Bus type**	**P (demand)**	**Q (demand)**	**Voltage magnitude**	**Voltage angle**	**Voltage limits**	
[i]	**1-PQ 2-PV 3-Slack**	**[MW]**	**[MVAr]**	**[p.u.]**	**[rad]**	**max**	**min**
1	3	0	0	1.06	0	1.061	0.95
2	2	21.7	12.7	1.045	0	1.05	0.95
3	2	94.2	19	1.01	0	1.05	0.95
4	1	47.8	-3.9	1.00	0	1.05	0.95
5	1	7.6	1.6	1.00	0	1.05	0.95
6	2	11.2	7.5	1.05	0	1.051	0.95
7	1	0	0	1.00	0	1.05	0.95
8	2	0	0	1.05	0	1.051	0.95
9	1	29.5	16.6	1.00	0	1.05	0.95
10	1	9	5.8	1.00	0	1.05	0.95
11	1	3.5	1.8	1.00	0	1.05	0.95
12	1	6.1	1.6	1.00	0	1.05	0.95
13	1	13.5	5.8	1.00	0	1.05	0.95
14	1	14.9	5	1.00	0	1.05	0.95

Appendix III: IEEE 14 Bus Line Data

IEEE 14 bus test system - branch data						
Line number	**From bus**	**To bus**	**Resistance R [p.u.]**	**Inductance X [p.u.]**	**Susceptance (B/2) [p.u.]**	**Transformer tap ratio**
1	2	5	0.057	0.1739	0.034	1
2	6	12	0.1229	0.2558	0	1
3	12	13	0.2209	0.1999	0	1
4	6	13	0.0662	0.1303	0	1
5	6	11	0.095	0.1989	0	1
6	11	10	0.0821	0.1921	0	1
7	9	10	0.0318	0.0845	0	1
8	9	14	0.1271	0.2704	0	1
9	14	13	0.1709	0.348	0	1
10	7	9	0	0.11	0	1
11	1	2	0.0194	0.0592	0.0528	1
12	3	2	0.047	0.198	0.0438	1
13	3	4	0.067	0.171	0.0346	1
14	1	5	0.054	0.223	0.0492	1
15	5	4	0.0134	0.0421	0.0128	1
16	2	4	0.0581	0.1763	0.0374	1
17	5	6	0	0.252	0	0.932
18	4	9	0	0.5562	0	0.969
19	4	7	0	0.2091	0	0.978
20	8	7	0	0.1762	0	1

Appendix IV : Generator Data for IEEE 14 bus

IEEE 14 bus test system - generator data							
Bus no.	**P (gen)**	**Q (gen)**	**Q (max)**	**Q (min)**	**V (gen)**	**P (max)**	**P (min)**
[i]	**[MW]**	**[MVAr]**	**[MVAr]**	**[MVAr]**	**[p.u.]**	**[MW]**	**[MW]**
1	232.4	-16.9	10	0	1.06	332.4	0
2	40	42.4	50	-40	1.045	140	0
3	0	23.4	40	0	1.01	100	0
6	0	12.2	24	-6	1.05	100	0
8	0	17.4	24	-6	1.05	100	0

Appendix V: Conference Proceedings and Journal

1. SRI conference: A review of methods of optimal load shedding in islanded microgrids integrated with DGs.
2. JKUAT Scientific, Technological and Industrialization Conference. Challenges and opportunities of smart grids in developing countries.

Appendix VII : Certificate of Participation

CERTIFICATE

OF PARTICIPATION

This is to certify that

Josiah Maroko

Has participated in the 16th JKUAT Scientific, Technological and Industrialization Conference from 24-25th March 2022.

Dr. Rehema Ndeda
Chair, Organising Committee

Prof. Mary Abukutsa-Onyango, PHD., EBS
DVC, Research, Production and Extension

Appendix VIII: Publication


Intelektual Pustaka Media Utama

iaes Institute of Advanced Engineering and Science

Scopus® indexed

OPEN ACCESS

International Journal of Applied Power Engineering (IJAPE)

CERTIFICATE OF ACCEPTANCE

The manuscript (IJAPE-20947) titled:

Load shedding in islanded microgrid using fuzzy linear programming

Authored by:

Josiah Teyah Maroko, David K. Murage, Peterson Kinyua Hinga

was Accepted in IJAPE (ISSN 2252-8792) on

2023-12-18

20 March 2024

Prof. Dr. Chandima Gomes

Editor-in-Chief

https://ijape.iaescore.com

Journal

Josiah Teyah Maroko, David K. Murage and Peterson Kinyua Hinga, load shedding in islanded microgrid using fuzzy linear programming. ISSN 2252-8792, vol.13, September 2024, pp. 637-644, DOI: 10.11591/ijape.v13.i3.pp637-644