VOLTAGE PROFILE IMPROVEMENT AND POWER LOSS MINIMIZATION OF MINNA DISTRIBUTION NETWORK USING SOLAR PHOTOVOLTAIC GENERATION

BY

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A THESIS SUBMITTED TO THE POSTGRADUATE SCHOOL, FEDERAL UNIVERSITY OF TECHNOLOGY, MINNA, NIGERIA IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF MASTER OF ENGINEERING DEGREE (MENG) IN ELECTRICAL AND ELECTRONICS ENGINEERING (POWER SYSTEM OPTION).

SEPTEMBER, 2023

DECLARATION

I hereby declare that this thesis titled: **“Voltage Profile Improvement and Power Loss Minimization of Minna Distribution Network using Solar Photovoltaic Generation”** is a collection of my original research work and it has not been presented for any other qualification anywhere. Information from other sources (published or unpublished) has been duly acknowledged.

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CERTIFICATION

The thesis titled: **"Voltage Profile Improvement and Power Loss Minimization of Minna Distribution Network using Solar Photovoltaic Generation"** by MOHAMMED Haruna (MEng/SEET/2018/8521) meets the regulations governing the award of the degree of (MEng) of the Federal University of Technology, Minna and it is approved for its contribution to scientific knowledge and literary presentation.

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ABSTRACT

Distribution networks in Nigeria had suffered setbacks such as network losses, voltage deviation and inadequate power injection into substations compared to the net power delivered to the load. This study examines the impact of solar photovoltaic generation on Minna Town 33/11kV injection substation distribution networks. Distributed Generation (DG) is to minimize line losses and improve the voltage profile of the network. Solar Photovoltaic Generation (SPVG) is one of the DGs that is capable of supplying real and reactive power into an existing distribution network to increase its overall efficiency. The SPVG was optimally placed in the network for the case study by the use of the Particle Swarm Optimization (PSO) technique. The 11 kV Minna town distribution feeders of the Abuja Electricity Distribution Company (AEDC) used as a case study were modelled and simulated in PSAT and MATPOWER environment as a 17-node system. A capacitor bank of capacitive susceptance 0.5 per unit was used to validate the results obtained. Power flow analysis for the test network was performed to calculate the various voltage and power flow values in the distribution system. From the results, it was observed that the minimum voltage at node9 was 95.3% which was improved to 100% after optimization with SPVG. The right installation of SPVG indicated sufficient improvement in the voltage profiles and power transfer on the branch, as none of the nodes had a voltage drop exceeding 3% when the power flow analysis was carried out. The total voltage drops (or deviation) after optimization with SPVG and shunt capacitor bank placement were obtained as 2.7% and 3.6%, respectively. Also, the total losses associated with the active and reactive power were 1005.2kW and 508.1kVAr after optimization with the shunt capacitor bank on the test network. When SPVG was optimally placed on the network, the active and reactive power loss became 762.6kW and 387.1kVar. Hence, the power loss saving obtained with SPVG (PSAT model) was 433.8kW (36.26%).

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ABBREVIATIONS/SYMBOLS

AC	Alternating Current
AEDC	Abuja Electricity Distribution Company
G_{best}	Global best
DE	Differential Equation
DG	Distributed Generation
DISCOS	Distribution Companies
DN	Distribution Network
ECN	Electricity Corporation of Nigeria
EPSRA	Electricity Power Sector Reform Act
F	Power loss minimization objective function
FC	Fixed Capacitor
GA	Genetic Algorithm
GENCOS	Generation Companies
GUI	Graphical User Interface
HC-ACO	Hyper-Cube Ant Colony
I	Injected Bus Current
ICT	Information and Communications Technology
IPPs	Independent Power Producers
Km	kilometer
kV	kilovolt

MATLAB	Mathematical Laboratory
MVA	Mega Volt Ampere Reactive
MW	Mega Watt
NDA	Niger Dam Authority
NEBT	Nigerian Electricity Bulk Trader
NEPA	Nigerian Electric Power Authority
NIPP	National Integrated Power Projects
P_{best}	Personal best
PHCN	Holding Company of Nigeria
PSAT	Power Analysis Toolbox
PSO	Particle Swarm Optimisation
P	Real Power
Q	Reactive Power
R	Line Resistance
RE	Renewable Energy
REMP	Nigeria Renewable Energy Master Plan
SPVG	Solar Photovoltaic Generator
TCN	Transmission Company of Nigeria
TS	Transmission Substation
TVD	Total Voltage Deviation

V	Injected Node Voltage
ϑ	Phase Angle
Σ	Summation
n	Total number of nodes in the network.

CHAPTER ONE

1.0 INTRODUCTION

1.1 Background to the Study

Nowadays, electrical energy is the most efficient and popular form of energy in modern society. The electrical power system has three broad sub-systems. These are generation, transmission, and distribution systems. These sub-systems use a distribution system to distribute electric power to consumers for utilization purposes. The distribution system consists of feeders, distributors, and service mains. It is also classified according to the connection scheme as a radial, ring main, and inter-connected system (Molla, 2020).

Nevertheless, in this thesis radial distribution system will be considered. As a result of load growth and /or inappropriate size of distribution transformers, inadequate power injection, and frequent distribution network expansion without a corresponding increase in power supply, most injection substations' transformers and feeders are overloaded and cannot effectively dispatch energy to meet the increasing load demand of the electricity consumer (Okorie *et al.*, 2021). This may affect the performance of operating loads and may result in blackouts. In an attempt to mitigate the above challenges, the electricity distribution company resorted to unplanned load-shedding, rationing the power supply as an alternative, and yet the above solution could not satisfy customers' needs (Amesi *et al.*, 2017). Therefore, many households and commercial organizations now run their independent power generator to complement their power needs to meet the daily electricity demand. Two options could improve the performance of the distribution system, namely, (a) Installation of a new injection substation for better service delivery and (b) Integration of distributed generations (DGs) into an existing grid. However, as suggested above, the first option involves high costs and is time-consuming. The second option is the most economical and convenient (Jain *et al.*, 2017).

The objectives of this research work are based on the setback suffered by distribution networks, such as inadequate power injection into substations compared to the net power delivered to the load. So, deploying Distributed Generations (DGs) is a means to enhance the distribution network for better performance regarding voltage profile improvement within its acceptable limit, reduction in transformers' working stress, and network losses. In addition, the optimal placement of the DGs will significantly improve the power quality delivered.

The following attributes characterize' a good and reliable distribution system: it has maximum reliability of power delivery; minimum maintenance and operation cost; minimum duration of interruption; voltage drop at consumer's inlet is within 5% of nominal voltage; efficiency is not less than 95%.

1.2 Statement of the Research Problem

The distribution network is expanded in radial form, and the generation cannot reach the existing load; additional power must feed the electric network in the loading part, which is taken from distributed generation units (DG). DGs will affect the distribution system by changing the power flow of the distribution feeders (Saleh *et al.*, 2019). However, the reverse power flow due to an excessive DG size may increase total circuit losses, and a network's power delivery elements can be overheated, which can decrease its efficiency (Zain ul Abideen *et al.*, 2020). Research has confirmed that there are many feeders at the distribution whose voltage levels were below the standard voltage deviation (0.95pu - 1.05pu), consequently leading to high power loss. As a result, a voltage not at its limit causes voltage instability and blackout. For loss reduction, the optimum DG size can play a significant role. So, to improve the voltage profile and minimize power loss, a scientific solution is highly required. Thus, this thesis introduces distributed generation Solar Photovoltaic Generation (SPVG) at the feeder to achieve this purpose. The feeder lines under consideration are Bosso, Maitumbi, Piggery, Tunga, GRA, Dustan Kura, Hajj camp, Feeder 4, Tudun Fulani, Maikunkele, and Airport 11kV feeder lines.

1.3 Aim and Objectives

The aim of this research is voltage profile improvement and power loss minimization of Minna distribution network using solar photovoltaic generation.

The objectives are as follows:

i. Model base case study network using Power System Analysis Toolbox (PSAT) and MATPOWER in MATLAB environment.
ii. Carry out power flow analysis on the base case study network to determine the steady-state performance of the system and identify weak nodes.
iii. Determine the optimal placement of SPVG on the base case study using the Particle Swarm Optimization technique.
iv. Evaluate the network's performance before and after the installation of SPVG in the base case study network and validate the results by incorporating a capacitor bank for a given set of loading conditions of the feeder.

1.4 Scope of the Research

This research work covers $2\times15MVA$, $2\times7.5MVA$, $15MVA$ and $33/11\ kV$ lines with eleven (11) outgoing feeders from Minna Town Injection Substation to minimize power loss and improve voltage profile.

1.5 Significance of the Research

Since the power distribution system loss will cause a considerable cost for an electric utility, its evaluation and reduction are very important. The decrease and increase in the voltage profile of a certain node out of the acceptable limit will cause the system's total collapse. Therefore, this thesis has significance in avoiding such conditions on the selected power system as a case study.

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1 Review of the Distributed Generation Concept

Distributed generation, also known as embedded generation, on-site generation, dispersed generation, decentralized generation, or distributed energy, is a small plant that generates electricity close to the end user of electric energy. The capacity of Distributed Generations (DGs) is less than 100MW (Saleh *et al.*, 2019). It is developed using cogeneration units, renewable energy systems, or traditional power generation.

Some DGs were installed at the customer's premises and connected to the customer's side to supply electricity directly. Others were connected to the distribution network to supply multiple customers with electricity. The use of DG in distribution networks can play a key role in building sustainable energy infrastructure (Mishra *et al.*, 2021)

Nowadays, the need for more quality electric supply has become a priority for the consumer. They are aware of the value of a reliable electric supply. Distribution networks are associated with high power losses due to a higher value of R/X . Consequently, apart from the large voltage drops to near zero, the consumer can also suffer from smaller voltage deviations (Kumar *et al.*, 2015). For example, in radial networks, bus voltages happen to decrease as the distances from the distribution transformer increase and may become lower than the minimum voltage permitted by the utility (Taiwo *et al.*, 2017). Distributed generations can be classified as illustrated in Figure 2.1.

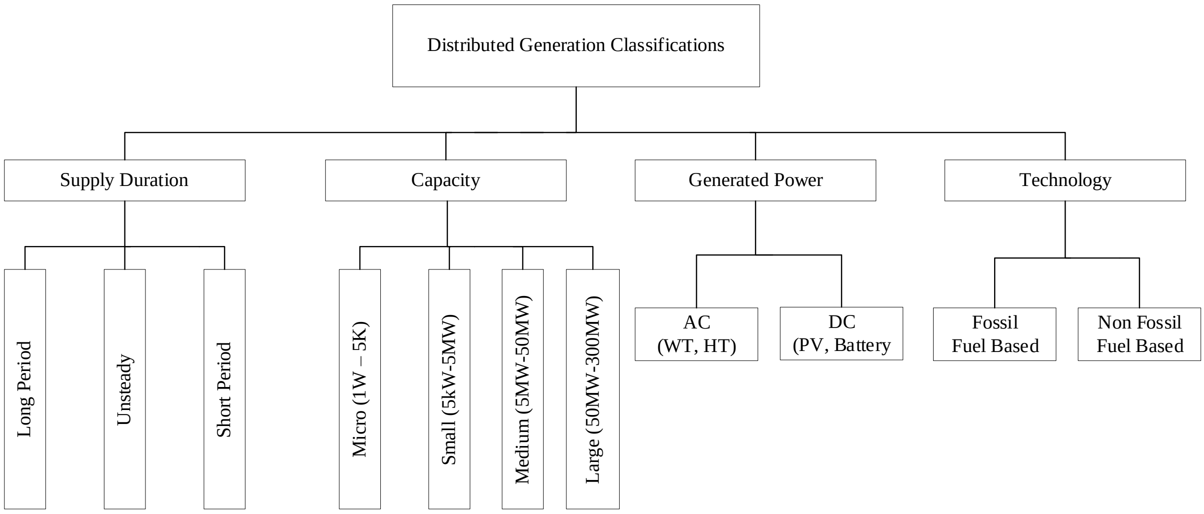

Figure 2.1: Classification of Distributed Generation (Rini *et al.*, 2017)

The introduction of DGs to distribution systems can significantly impact the flow of power and voltage conditions at customers and utility equipment. Depending on the distribution system operating characteristics and DG characteristics, these impacts may be either positive or negative (Berrada *et al.*, 2021). Positive impacts are generally called "system support benefits" and include: loss reduction, improved utility system reliability, voltage support and improved power quality, transmission and distribution capacity release, deferments of new or upgraded transmission and distribution infrastructure, easy and quick installation on account of prefabricated standardized components, lowering cost by avoiding long-distance high voltage transmission and, environment friendly where renewable sources are used (Kifle *et al.*, 2018) and (Rodriguez-Diaz *et al.*, 2016).

2.2 Nigeria Electricity Power Industry

With the present estimated population of about 200 million people, Nigeria is the most populous country in Africa (Otobo, 2022). It is located in West Africa and is divided into 36 states and a Federal Capital Territory. Electricity generation in the country dates back to 1896 when the first hydro Dam generator was commissioned at Kainji Dam. Since then, the Nigeria electricity power system has undergone several transformations both in physical structure and organization. The transformation started with the established Electricity Corporation of Nigeria (ECN) in 1951 and the Niger Dam Authority (NDA) in 1962. The ECN and NDA were merged through Degree 24 of 1972 to form the Nigerian Electric Power Authority (NEPA), which later metamorphosed into the Power Holding Company of Nigeria (PHCN) (Ayamolowo *et al.*, 2019). PHCN was a vertically integrated utility with the sole custodian of generation, transmission, distribution, and electricity sales in the country before the opening up of the electric power sector to competition through the Electricity Power Sector Reform Act (EPSRA) of 2005. As a result of the Act, PHCN was unbundled into 18 successor companies, including 11 Distribution Companies (DISCOS), 6 Generation Companies (GENCOS), many Independent Power Producers (IPPs), a Transmission Company of Nigeria (TCN) and Nigerian Electricity Bulk Trader (NEBT). The function of the NEBT is mainly to support the initial take-off of the competitive electricity market during the transitional period. NEBT buys generation from the GENCOS and resells the same to the DISCOS. The much-anticipated better services, lower prices, and reliable and efficient power supply expected from the deregulation of the electricity market have not been felt by Nigerians. The reverse is the case; electricity demand is far more than the generation, and the transmission wheeling capacity is insufficient to evacuate the available generation to the electricity consumers. The distribution system is also confronted with a multitude of problems. Access to the grid presently stands at only 40% of the population. Even the available electricity capacity is insufficient to meet the existing power demands of less than 40% who have access to the national grid (Wimalaratna *et al.*, 2022).

Consequently, the connected population faces most of the power problems (Ayamolowo *et al.*, 2019). This makes a large segment of Nigerians rely on alternative power sources, mostly fossil fuels, for their daily energy needs. The reliance on fossil fuel-based generators (centralized large-scale and small diesel generators) contributes significantly to carbon footprints compared to Power generated from freely available Renewable Energy (RE) sources such as solar, wind, hydro, biomass, geothermal, and any other forms of renewable energy. Considering the abundant RE resources in the country, it is envisioned that the electric power system in Nigeria will undergo tremendous changes in the near future to overcome the present electricity challenges in the country. Therefore, the country needs to diversify its energy supply mix using RE to support its socioeconomic and technological development with an immediate impact on job creation, crime reduction, sustainable energy, and a clean environment for all. Diversification of the energy supply mix requires a thorough knowledge of the existing power system.

2.2.1 Generation and load

Electricity supply in Nigeria started in 1896 when two small (60kW) generating sets were installed to serve the erstwhile Colony of Lagos. However, an imbalance between the electricity generation capacity and load demand emerged in 1978, thus leading to frequent power outages. This prompted the establishment of the Niger Dams Authority (NDA), under whose scheme three hydro and three thermal generating plants were constructed (Ayamolowo *et al.*, 2019).

In 1980, Nigeria's total population increased to 73.7 million, but its available Power was pegged at 783MW. Subsequently, in 1988, available power was increased to 1273 MW. By 1992 her population had grown to about 80 million; however, the total available power was 3,000 MW (Sule, 2010). In 2001, the existing generating plants were already depreciating due to poor maintenance; this further caused a dip in the available generated power. In search of a remedy, the Independent Power Producers (IPPs) and National Integrated Power Projects (NIPP) were established to combat the power shortage challenge. As of 2005, Nigeria has only approximately 6,861 MW of installed electric generating capacity (Ayamolowo *et al.*, 2019). Presently, Nigeria has only seventeen functional grids connected to generating plants; eight (8) were owned by the Federal Government with an installed capacity of 6,256MW with just 2,484MW available, while nine (9) were from both the NIPP and IPP projects with total designed capacity of 2,809MW, however, with an available capacity of 1,336.5MW (Oladimeji *et al.*, 2019).

Furthermore, it was revealed that a larger percentage of Nigeria's generation plants are thermal-driven; this accounts for 83% (4,116MW) of Nigeria's total available generation capacity. In comparison, Nigeria's present power demand with generated Power revealed that the actual electricity supply has been significantly less than the load demand. This clearly indicates that there is no corresponding increase in electricity generation as the population increases (Klug *et al.*, 2022).

2.2.2 Power distribution section

The power distribution system comprises medium voltages classified as primary and secondary distribution voltage. The primary distribution voltage is 33kV, whereas the secondary distribution (feeder) voltage is rated at 11kV. The distribution sector comprises distribution substations, transformers, distribution lines or feeders, and sub-feeders mentioned but few. Both 33kV and 11kV are 3-phase, 3-wire systems (for balanced load). On the other hand, the tertiary distribution section constitutes a 3-phase, 4-wire system (for unbalanced load) (Idoniboyeobu *et al.*, 2017). If the industries (manufacturing, production) are to be fed from the distribution networks, the connection is from the 33kV side before stepping the voltage down to 11kV. This is because most of their electric machines/motors run at this voltage. Most times, the consequence of using these machines and some loads in residential areas result in distorting the power quality, increasing power losses, generating harmonics, voltage swells, and flickering. Such devices that cause these distortions include arcing devices, induction motor starting, Information, and Communications Technology (ICT) equipment/facilities, electromagnetic radiations, cables, and embedded generation (Dembra and Sharma, 2014).

Typical Nigeria distribution network has the following characteristics as at the time of carrying out this research, and they include:

i. Consistent overloading of the distribution installations (distribution lines and transformers)
ii. Lack of system network upgrade
iii. Prolonged abandonment of the distribution network
iv. Deviation/not adhering strictly to engineering ethics, standards and practices.

In an attempt to reform the power sector, the FGN privatized the Distribution Companies (Discos) through the national council on privatization and the bureau for public enterprise in 2005 (Joseph and Olorunkanmi, 2014). This reformation is to improve the power quality and overall efficiency. The transformation in the distribution sector has resulted in the creation of eleven (11) distribution companies in the country. These include Ibadan, Kaduna, Port Harcourt, Jos, Benin, Eko, Ikeja, Kano, Yola, Abuja, and Enugu.

2.3 Faults in Power System

A fault in the distribution system is inevitable for many uncontrollable factors, such as animals and weather-related factors (Awasarmol *et al.*, 2020). Different kinds of fault causes have similar fault features. The fault causes can be identified by the fault feature analysis, which is useful for fault-finding and fault-clearing when a fault happens. It has been investigated that a fault causes most power outages in the distribution system. 60%

of faults were found in the distribution system for large distribution lines in complex environments.

A large Electric Power Research Institute (EPRI) study was done to characterise distribution faults in the 1980s at 13 utilities monitoring 50 feeders. The fault causes are classified into 11 types: lightning, tree contact, equipment failure, animal, wind, dig-in, vehicle accident, ice/snow, vandalism, construction activity, and others (Wang, 2016). The power outage was grouped into 8 possible causes, which are animal, faulty equipment/human error, planned, unknown, vehicle accident, weather/trees, theft/vandalism, and over demand (Eaton, 2014). It should be noted that not all power outage is caused by a fault. European Network of Transmission System Operators for Electricity (ENTSOE) classified the fault causes into 7 types: lightning, other environmental causes, external influence, operation and maintenance, technical equipment, and other and unknown. The underground utility system fault causes are classified into excavating equipment, vehicles hitting transformers, and pedestals mentioned but few.

2.3.1 Distribution system losses

Energizing the distribution system at the connection of a load with the resistance of all connecting conductors results in many losses (Adeoye and Ekejuiba, 2014). When current flows through cables and other electrical devices (e.g., transformer,) there is bound to be a power loss denoted as I^2R. Thus, this power loss is known as technical loss, and the losses that do not involve the physical power system but rather are related to electric theft and errors due to billing and metering systems, bypassing the meter, unpaid electricity bills, vandalization of power line were all counted as non-technical losses. A report published by Idoniboyeobu *et al.* (2017) declared that 26 - 30% of power losses occurred in transmission and distribution systems with a voltage variation of up to 10% of the rated value. However, in their report, they opined those non-technical losses are due to the ageing of equipment of power system, human errors in measurements of a kilowatt-hour (KWh) on energy meters, and the theft of electricity.

Jayaprakash *et al.* (2016) highlighted that the losses mentioned above would reduce the overall system's efficiency, thereby increasing the operational cost of service delivery and the high cost of electricity to end users. According to (Ugwu *et al.*, 2022), transmission and distribution losses account for a good portion of the power losses in any power system. If the real power losses are greater than the demand, the distribution companies will be adversely affected. Hence, the system engineers need to put in place the necessary mechanism.

2.3.2 Reducing distribution system losses

Several measures can be taken to reduce the power loss of a distribution network. Some of these measures are (Hassan *et al.*, 2022):

i. Feeder capacity optimization by network reconfiguration
ii. Optimize the capacity and size of transformers
iii. Load balancing among all phases
iv. Appropriate coordination of voltage control devices
v. Reactive power compensation
vi. Improvement of voltage profile by DG placement
vii. Subsequently, a few of these techniques are discussed briefly:

2.3.2.1 Optimal network reconfiguration

Network reconfiguration is a process or technique for altering a distribution network's topological structure by opening and closing its switches (Sambaiah and Jayabarathi, 2020). Generally, two types of switches exist in a distribution system: open and closed. Closed switches connect the line segments, and open switches connect the tie-line between two feeders. These switches were used for network protection. By optimally operating these switches, power loss can be significantly reduced. (Landeros *et al.*, 2019). Traditionally, network reconfiguration has been performed to reduce loss and relieve network overloads. Generally, network reconfiguration algorithms have been based on different heuristic and meta-heuristic methods (Jafar-Nowdeh *et al.*, 2020). One heuristic method, based on the minimum branch current in a system, proposed by (Abdulkareem *et al.*, 2020), was also applicable to online feeder reconfiguration applications. Another meta-heuristic method, in which a discrete GA was used to perform branch exchange, was proposed by (Mokhtarzadeh *et al.*, 2021). The method in (Mokhtarzadeh *et al.*, 2021) was compared with another evolutionary algorithm, simulated annealing (SA). For power loss minimization, a method based on the Hyper-Cube Ant Colony (HC-ACO) algorithm was proposed by (Abdelaziz *et al.*, 2012), who adopted the Hyper-Cube Ant Colony (HC-ACO) algorithm method based on modifying the local heuristic rule by applying the standard state transition rule instead of the probabilistic choice criterion for network reconfiguration problem for 32-bus, 69-bus and 118-bus systems and the results showed that a significant reduction in power losses from 1294.68 kW loss to 855.322 kW with 33.1% power loss reduction was recorded when tie switches were changed to obtain a final configuration and most of the node voltages have been improved after reconfiguration.

The impact of network reconfiguration on power loss was discussed (Shaheen *et al.*, 2021). The proposed method by (Shaheen *et al.*, 2021) was based on the fuzzy multi-objective approach, while Mixed-Integer Convex Programming is used for loss minimization by (Jabr *et al.*, 2012). All these methods improve the voltage profiles of a network by significantly reducing its losses.

According to Okereafor *et al.* (2017), a combination of network reconfiguration and installation of synchronous generators or distributed generators (DGs) along the network directly or indirectly to the utility's power distribution network can enhance power loss reduction and provide adequate power supply to end users.

2.3.2.2 Optimal capacitor placement and voltage dynamic restorer

Shunt capacitors are widely used for network power loss reduction. Besides, it improves the voltage profiles by controlling the voltage level supplied to the customer. However, shunt capacitors cannot adequately achieve these benefits without proper reactive power compensation. On the other hand, the extreme size of capacitors at an unplanned location may create overloading, which causes power loss and premature failure of these compensation devices. Therefore, it is necessary to determine the optimum locations or sites and their ratings for benefit maximisation and reduce the utility's operating costs and losses.

Different methods based on analytical approaches, heuristic, and meta-heuristic algorithms have been used to solve this research problem. Here some of the recent progress is discussed briefly. First, a method based on a Genetic Algorithm (GA) was proposed by (Kwon *et al.*, 2020). The fuzzy logic and immune-based algorithm for placing and sizing shunt capacitor banks are discussed (Ebrahimi *et al.*, 2020). This fuzzy-GA-based method successfully reduces the cost and loss of a system. This algorithm also shows its superiority over only fuzzy and only GA-based methods. A method based on non-linear programming (NLP) was proposed by (Eajal and El-Hawary, 2010) to reduce the cost of power loss in a system. This method is applied in the IEEE 13 bus network, where power loss is reduced significantly. A method has been proposed for the placement of fixed and switched capacitors considering uncertainty and time-varying load (Lotfi, 2022). Based on optimal capacitor placement, these methods reduce the system loss significantly.

2.3.2.3 Optimal DG placement

DG allocation studies are like capacitor allocation; the difference is that they can supply real power. Many research works on DG sizing and allocation based on power loss minimization with different analytical methods have been done, and the trend of power loss with the DG capacity variation is a quadratic function. So, power loss is a function of power generation from DG (Malik *et al.*, 2020). Optimum DG capacity can be obtained by determining the DG capacity that produces a minimum power loss profile with time-varying loads (Khasanov *et al.*, 2023). Minimizing power loss by finding the optimal size, location, and operation point of the DG unit was suggested by (Anderson *et al.*, 2020). A sensitivity analysis relating to the power loss with respect to DG-unit current injection was used to identify the DG-unit size and operation point. The proposed method was tested for constant impedance. One of the test systems assumed that loads were uniformly distributed, which was rare in practical feeder systems. The location of the DG unit was based on the assumption of downstream load buses, which may not be appropriate for different feeder configurations. GA-based methods have been proposed by (Petinrin and Shaaban, 2019), which also improve the voltage profiles of the system. An artificial bee colony algorithm has been used (Abu-Mouti and El-Hawary, 2011) for the loss reduction of a balanced distribution network. PSO-based algorithms have been used for loss reduction by (Prommee and Ongsakul, 2011). DG placement and sizing studies described by (Al-Ammar *et al.*, 2021) were based on the balanced test system. In (Dugan and Mcdermott, 2002), the optimal size and location of DG-unit (for planning purposes) based on a predetermined power loss reduction level (up to 25%) were proposed. The objective of the method was to reach that level with minimum net DG-unit cost (i.e., DG-unit cost subtracted from savings). The maximum number and size of the DG units were found to be two and 40% of peak loads, respectively. The solution was achieved using sequential quadratic programming. Also, (Asif *et al.*, 2022) discussed the maximization of the voltage support in radial distribution feeders using a DG unit. The method used a voltage sensitivity index to determine the DG unit's optimal location. Then, the DG-unit active and reactive powers were adjusted to obtain maximum voltage support. The weakest bus was identified using Thevenin's theorem. The results showed that the network's real and reactive power significantly improved.

Power loss minimization considering an unbalanced test system has been presented by (Anwar and Pota, 2011). Here, the placement and sizing of a single DG unit have been considered. Besides, the comparison among different DG technologies is not addressed here. These issues were considered later by (Anwar and Pota, 2012), where multiple DG placement and sizing were discussed for two unbalanced multi-phase distribution networks. In all the research studies, optimum DG planning makes the system more efficient by significantly reducing the loss.

(Sayed *et al.*, 2019) have discussed a load response-based economic operation strategy for post-contingency power systems incorporated with DGs after islanding. According to the authors, the system instability is limited to a minimum region as soon as possible by the optimized operation scheme for islands considering power quality, system efficiency, and transmission security criterion.

From previous research, many However, this thesis focuses on the optimal placement and sizing of DG on a distribution network case study of the 11 *kV* feeder "Minna town injection substation" using an artificial intelligent technique (Particle Swarm

Optimization) for feeder loss minimization and validation of results obtained with DG and Fixed Capacitor (FC) bank.

2.4 The Challenges and Future Perspectives

It is evident that available generated Power falls short of the load demand in Nigeria primarily due to ever-increasing energy demand resulting from an increasing population. This is a clarion call for diversification into other renewable energy sources to alleviate the inadequacies of power generation. Renewable energy sources such as Solar, Wind, and hydro can be harnessed optimally. With the current global trend towards Renewable Energy Sources (RES), it is expected that RES demand and utilization will skyrocket due to environmental concerns and the harmful effects of traditional fossil fuels. However, in the case of an oil-rich nation like Nigeria, RES utilization for national power generation will be gradual. The Federal Ministry of Environment in Nigeria, with the assistance of the United Nations Development Programme (UNDP), is currently implementing a policy called Nigeria Renewable Energy Master Plan (REMP), intending to intensify the contribution of RES to account for at least 10% of the total energy consumption by the year 2025 (Oladimeji *et al.*, 2019). The Master Plan conveys the national vision while setting the road map for RES increase to attain sustainable development.

CHAPTER THREE

3.0 RESEARCH METHODOLOGY

This thesis on the optimal location and sizing of Solar Photovoltaic Generation (SPVG) on Distribution Network to minimize power losses and improve voltage profile will be implemented using Power System Analysis Toolbox (PSAT) and MATPOWER in MATLAB environment. An electric power Distribution Network (DN), typically a low-voltage network, is vital to the energy supply chain. Almost 70% of total energy losses occur in this section (Akram *et al.*, 2020). Therefore, voltage drops and power losses are expected to be as low as possible in the distribution area to enhance the system's efficiency and stability. Also, the importance of a distribution system's efficiency evaluation has increased recently because industries and regulatory bodies focus on their environmental impacts, energy efficiency, and smart-grid capabilities (Rathor and Saxena, 2020). Therefore, it is necessary to use effective and efficient planning methodologies to increase a network's efficiency by managing loss reduction in its distribution system. The following measures can be considered to identify loss reduction techniques and improve system efficiency.

i. Advanced metering and improved communication and control measures.

ii. Optimal planning of network equipment and devices, including network reconfiguration and DG planning.

This chapter focuses on the efficiency enhancement of a distribution system based on an appropriate DG size and location planning using Artificial Intelligence (AI); (particle swarm optimization techniques). Since voltage stability is also highly dependent on the capacities of the DG units and the locations of their integration, it is necessary to identify the optimum DG capacity and location for voltage profile improvement.

3.1 Data Collection and Analysis

The data used in this work were collected from the public utility service provider known as Abuja Electricity Distribution Company (AEDC) Minna Region, Nigeria, during visitation to the injection substations. The Company provides Power to four (4) states in Nigeria: Federal Capital Territory (FCT), Niger, Kogi, and Nasarawa. Recorded data collected from the substation for Power, voltage and current at various buses for peak load conditions was reported in Table 3.1.

Table 3.1: The minna 33/11 kV injection substation feeders

S/No	Feeder Name	Rating (MVA)	No of Distribution Transformer	Peak Load Current (A)	MW
1	Bosso	15	52	402	6.7
2	Tunga	15	81	318	5.3
3	Maitumbi	15	98	450	7.5
4	Piggery	15	37	210	3.5
5	Tudun Fulani	7.5	49	288	4.8
6	Maikunkele	7.5	31	96	1.6
7	Airport	7.5	9	12	0.2
8	GRA	15	17	90	1.5
9	Dutsan kura	15	67	270	4.5
10	Hajj camp	15	28	204	3.5
11	Feeder 4	15	9	1.8	0.03

3.1.1 Base case study network description

Minna electricity network is composed of a 132/33 kV transmission substation and is mesh-connected to the national grid by two high-voltage circuits, Shiroro-Minna 132 kV Line I and Shiroro-Minna 132 kV Line II. Minna circuits emanate from Minna 132 kV transmission sub-station connected to the 330/132 kV Shiroro transmission station at North-South Hydropower Generation Station, Shiroro, in Niger state. The Shiroro-Minna Transmission Station (TS) consists of 150MVA, 132/33 kV transformers with a total installed capacity of 150MVA. Table 3.2 also shows the number of 11kV "feeder" lines and associated injection substations.

Table 3.2: The 33/11 kV Injection Substations (Minna Metropolis)

Transformer Capacity	Injection Substation Name	Capacity	No of Feeder (outgoing)
15MVA	Power House	$2 \times 15MVA(33/11kV)$	4
15MVA	Zarumai	$1 \times 15MVA(33/11kV)$	4
7.5MVA	Maikunkele	$2 \times 7.5MVA(33/11kV)$	3

Source: *Abuja Electricity Distribution Company Minna Region 2021.*

3.1.1.1 Determination of node operating voltage

The bus voltage sensitivity index determines the percentage of bus operating voltage. The bus voltage limits of less than 95% are considered under-voltage, whereas those above 105% are considered over-voltage. Thus,

$$\% \text{ operating voltage} = \sum_{i=1}^{Np} \left(\frac{V_i}{V_i^{sp}} \right) \times 100 \tag{3.1}$$

Where: V_i is the bus voltage magnitude at the i^{th} bus; V_i^{sp} is the specified (rated) voltage magnitude at the i^{th} bus; N_P is the number of buses in the system.

3.1.1.2 Evaluation of peak loads for the injection substations

Using base case study injection substation feeders, for example, Bosso feeder. Thus, we shall compute the various distribution substation's peak loads of the networks using equations (3.2) and (3.3)

$$At\,Peak\,load, MVA = \sqrt{3I_L}V_L X10^{-6} \tag{3.2}$$

Where Peak load at Bosso: P.f. = 0.8 lagging, $I_L(A)$ = 402, Voltage magnitude V_L = 11 kV

$$\text{But } MW = MVA \times \cos\phi \tag{3.3}$$

Therefore, $Peak\,load = MV = 7.659 \times 0.8 = 6.13MW$

3.1.1.3 Determination of overloaded transformer

The apparent power performance index is used to determine the percentage loading of the transformers in the network. Based on the principle of loading distribution transformers, 70% of the design rating is considered. A transformer with loadings above 70% is considered overloaded; therefore, precautions should be taken to avoid overloading a transformer in continuous operation. The percentage loading of each distribution transformer was calculated, thus,

$$\%loading = \sum_{i=1}^{NT}\left(\frac{S_{MVA}}{S_{MAX}}\right) \times 100 \tag{3.4}$$

Where S_{MAX} is the MVA rating of the transformer, S_{MVA} is the operating MVA from power flow calculation, and N_T is the number of transformers. Considering the power transformer of the base case network, TR1, rated 15MVA, now operates at 16MVA. The system loading can be evaluated, thus,

% *Loading* of TR1= $\frac{16MVA}{15MVA}\times 100 = 106.7\%$. (Operating beyond the rated capacity)

3.3 Simulation Tools

Power System Analysis Toolbox (PSAT) and MATPOWER were the MATLAB simulation tools used to analyse the various loading conditions and determine the node operating voltages on the base case study network. PSAT is an open-source software that supports Graphical User Interface (GUI) and a Simulink-based library that provides a user-friendly tool for network design. It includes power flow, continuation power flow, optimal power flow, small signal stability analysis, and time domain simulation. The main advantage of PSAT with respect to other tools is its implementation in MATLAB and Simulink, which makes it easy to understand, customize and extend. PSAT is used worldwide for teaching and research and is considered a benchmark reference for the dynamic analysis of power systems. Therefore, it was used to model the network under consideration and run the power flow. MATPOWER is also a free, open-source package; it uses MATLAB-language M-files for solving steady-state power system simulation and optimization problems, such as power flow (PF), continuation power flow (CPF), unit commitment (UC), and stochastic secure multi-interval OPF/UC. This research used it to run Particle Swarm Optimization codes for optimal location and sizing of SPVG. Installation of the Capacitor bank was then used to validate the optimization results obtained with SPVG. Figures 3.1 and 3.2 schematically illustrated the Simulink interface of the PSAT.

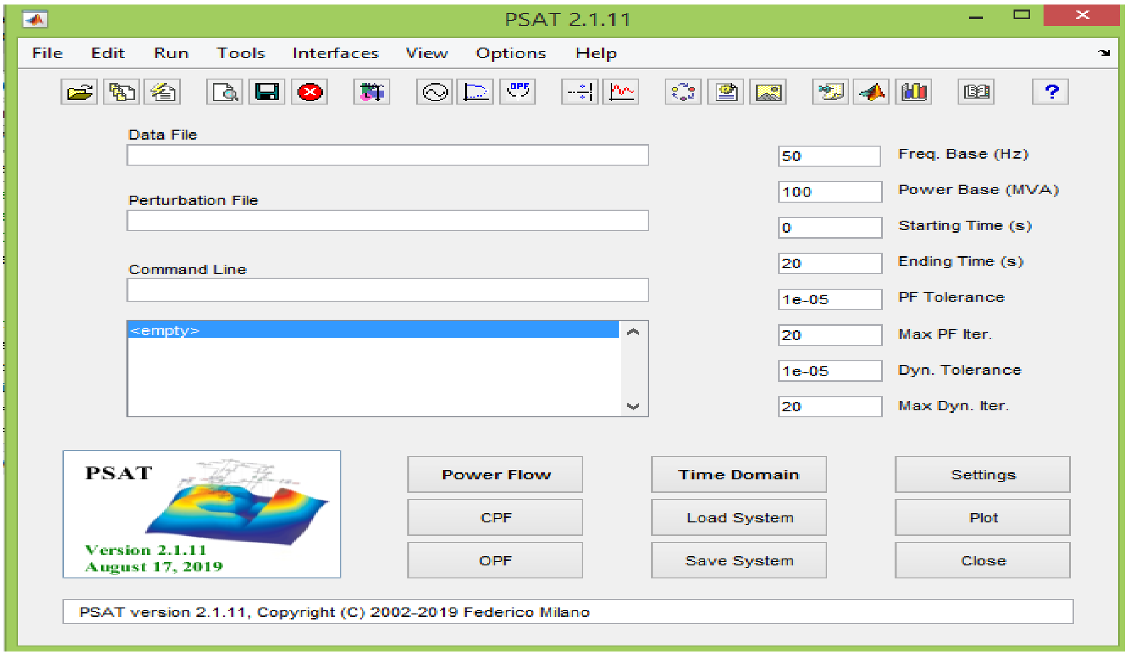

Figure 3.1: PSAT GUI Model

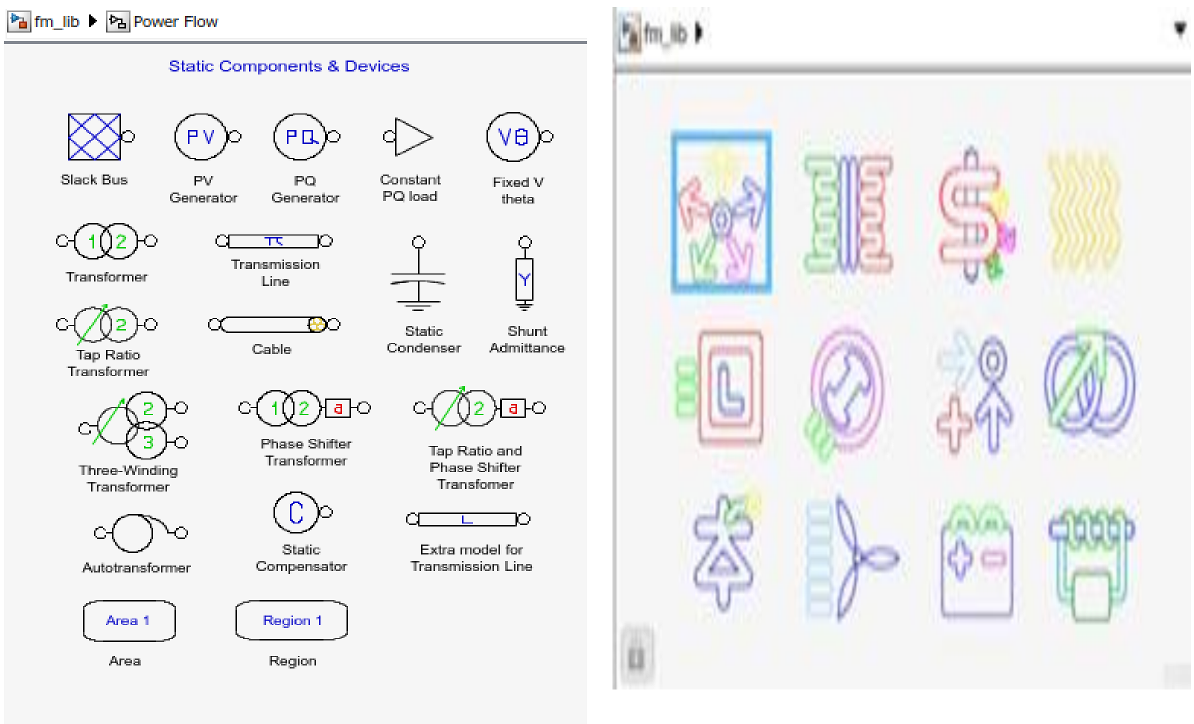

Figure 3.2: The PSAT Simulink model library

Figure 3.3 represents one-line diagram of 33/11kV Minna Injection Substation using Power System Analysis Toolbox (PSAT) software.

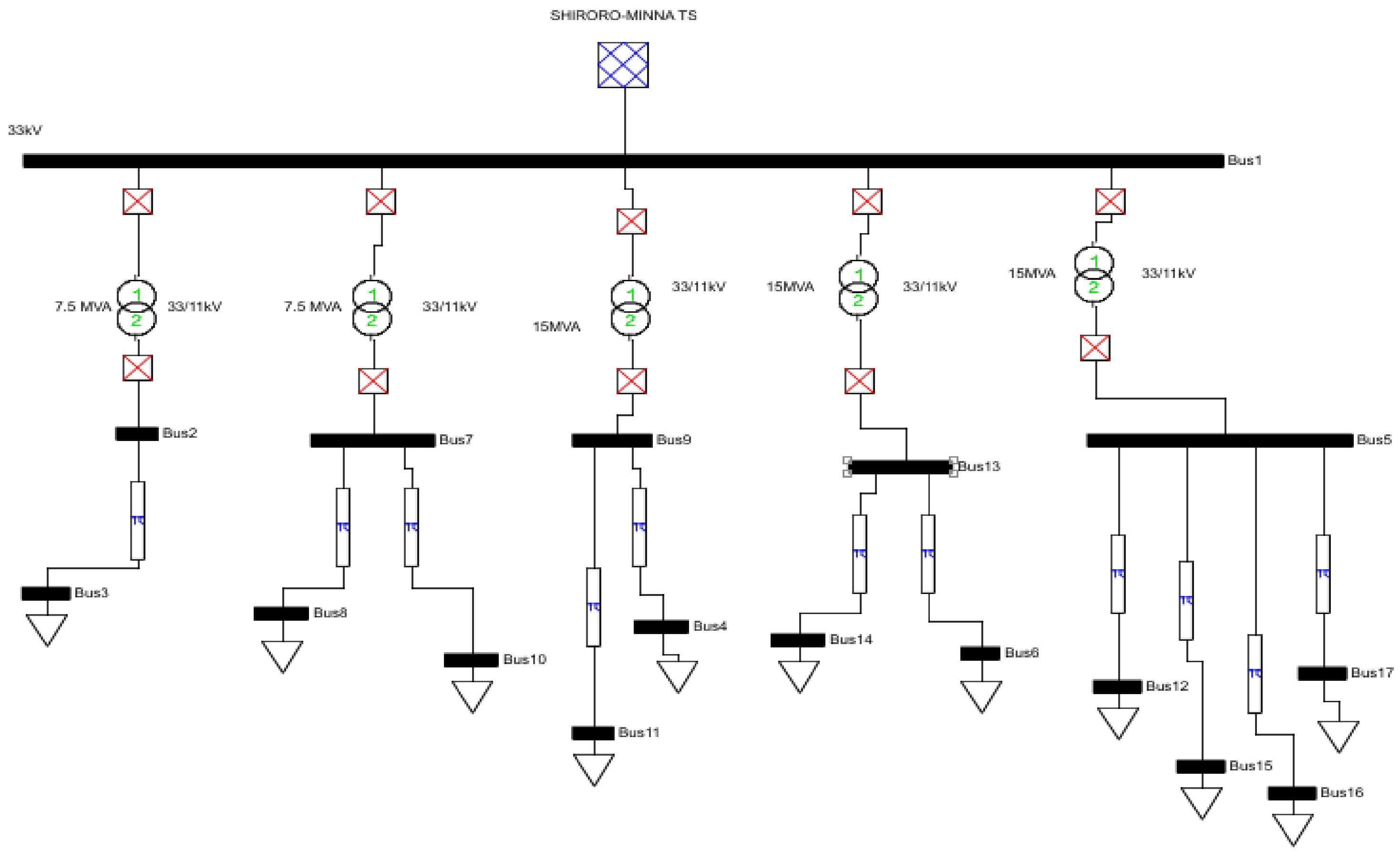

Figure 3.3: PSAT One-line diagram of 33/11kV Minna Injection Substation

Table 3.3 depicts the node data of the Minna Distribution Network (DN) using MATPOWER model.

Table 3.3: Node data of the case study (MATPOWER model)

Bus i	Bus type	Pd	Qd	Base kV	Vmax	Vmin
1	3	0	0	33	1.1	0.95
2	1	0	0	11	1.1	0.95
3	1	3.7	3.1	11	1.1	0.95
4	1	5.7	4.9	11	1.1	0.95
5	1	0	0	11	1.1	0.95
6	1	2.7	2.3	11	1.1	0.95
7	1	0	0	11	1.1	0.95
8	1	1.2	1	11	1.1	0.95
9	1	0	0	11	1.1	0.95
10	1	0.2	0.1	11	1.1	0.95
11	1	5.1	4.3	11	1.1	0.95
12	1	3.4	2.9	11	1.1	0.95
13	1	0	0	11	1.1	0.95
14	1	4.0	3.4	11	1.1	0.95
15	1	1.1	1.0	11	1.1	0.95
16	1	2.6	2.2	11	1.1	0.95
17	1	0.028	0.019	11	1.1	0.95

3.4 Optimization Techniques

Optimization technique can be defined as searching for the best element from available alternatives that follow specific criteria or objectives. The optimization problem can be linear, non-linear, or both, which includes single-objective or multi-objective problems. Besides, any optimization problem may be constrained or unconstrained. In this research, the objective of the optimization problem is to minimize the system power loss by satisfying the network power-flow equations and network voltage profile. Therefore, it is important to formulate a non-linear constraint optimization problem with both equality and inequality constraints. These constrained optimization problems are always challenging due to the existence of different types of constraints and variables, complex function properties, and the variability of feasible search space.

There are different widely used optimization techniques which include genetic algorithm (GA), scatter search (SS), particle swarm optimization (PSO), differential evolution (DE), etc. Particle swarm optimization has been chosen to solve this research's optimum DG capacity allocation problem. Both PSO and GA are population-based search techniques. Although PSO shares some common attributes with GA, they also have some significant differences. Some advantages of PSO over GA are discussed below (Premalatha and Natarajan, 2009):

i. PSO is easy to implement and has fewer parameters to adjust, which will help solve complex power system problems. However, it does not have genetic operators like crossover and mutation, and the optimization process is based on updating the velocity and position of each particle.
ii. It has a more effective memory capability than the GA.
iii. The information sharing mechanism of PSO is different from GA. In PSO, all particles tend to converge to the best solution quickly compared to GA (Casas *et*

al., 2018). This characteristic of PSO will help to use this technique in those power system applications where the determination of faster results is necessary.

iv. PSO is less sensitive to the nature of the objective function.

3.4.1 Particle swarm optimization

Doctor Kennedy and Eberhart proposed particle swarm optimization as a heuristic global optimization method in 1995. It is based on studies of flock movement behaviour in birds and fish (Ramírez-Ochoa *et al.*, 2022) and is derived from swarm intelligence. The fundamental PSO algorithm comprised "i" particles, with each particle's position representing a potential solution in D-space (dimensional space). According to the following three principles, the particles alter their state:

i. Maintain inertia
ii. Change the condition based on its most optimistic position
iii. Change the condition based on the swarm's most optimistic position.

The most optimist position influences the position of each particle in the swarm during its motion (individual experience) and the most optimist particle in its surroundings (near experience). The most optimist position of the surrounding is equivalent to one of the wholes of the most optimist particle when the whole particle swarm is surrounding the particle; this algorithm is known as the full PSO. Each and every particle moves to a newly updated position utilizing velocity according to its own experience, known as $Pbest$. $gbest$ is the best value that any particle in the population has obtained so far. The PSO is made up of velocity variations of each particle towards its $Pbest$ and $gbest$ over time. The distance between a particle's current location and $Pbest$, as well as the distance between a particle's current position and $gbest$ (Bai, 2010), causes each particle to try to change its current position and velocity. The particle's velocity and position are changed with respect to the following equality after discovering the best values.:

$$V_{id}^{k+1} = V_{id}^{k} + C_1 r_1^{k} (Pbest_{id}^{k} - x_{id}^{k}) + C_2 r_2^{k} (gbest_{id}^{k} - x_{id}^{k}) \tag{3.11}$$

$$x_{id}^{k+1} = x_{id}^{k} + V_{id}^{k+1} \tag{3.12}$$

In this position of equality, V_{id}^{k} and x_{id}^{k} denote the particle speed “i” at “k” times and the d-dimension quantity of its location, respectively; $Pbest_{id}^{k}$ denotes the d-dimension quantity of the individual “i” at its most optimist position at "k" times. The d-dimension quantity of the swarm in its most optimist position is $gbest_{id}^{k}$. The velocity figures C_1 and C_2 represent the length when flying to the most particle of the entire swarm and the most optimistic individual particle, respectively. r_1 and r_2 are random fiction, while 0-1 is a random number. Therefore, this technique is employed to solve optimal DG placement in this research.

3.4.2 Objective function

This research aimed at improving the voltage profile across the distribution feeder and reducing power loss. The overall power loss on the test network is represented by the objective function, which may be written in terms of branch resistance R_i, active and reactive Q_i Power and voltage V_i.

1. Power losses reduction:

$Losses_{with\ DG} \leq Losses_{without\ DG}$

$$P_{Loss} = \sum_{k=1}^{n} R_i \frac{P_i^2 + Q_i^2}{V_i^2} \tag{3.13}$$

$$F_i = P_{Loss} = \sum_{k=1}^{n} I_i^2 \cdot R_i \tag{3.14}$$

Where:

I_i is the current

P_i are the active power losses

Q_i are the reactive power losses

V_i is the voltage on the line

R_i represents the line resistance

$+\ n$ is the total number of nodes on the network.

F_i is the power loss minimization objective function.

Subjected to inequality constraints

$$V_i^{min} \leq V_i \leq V_i^{max} \tag{3.15}$$

$$I_i \leq I_i^{max} \tag{3.16}$$

$$V_{DG}^{min} \leq V_{DG} \leq V_{DG}^{max} \tag{3.17}$$

3.4.3 Constraints for distributed generator optimization

At a steady state operating condition, the active power supplies by DG to the network should be prevented from flowing back to the substation to avoid system instability and unnecessary faults in the system.

Power Injection Constraint:

$$\sum_{i=1}^{k} P_{DG} < P_{load} + P_{losses} \tag{3.18}$$

The Equality Constraints are:

$$\sum_{i=1}^{k} P_{DG} + P_{substation} = P_{losses} + P_{load} \tag{3.19}$$

Where:

$P_{DG} =$ Power supply by DG

$P_{substatiuon}$ = Power supply from substation

P_{losses} = Power delivered to the network connected loads

P_{load} = Power losses on the network

k = number of distributed generators connected

Voltage deviation is given by:

$$VD_i = |1 - V_i| \quad (3.20)$$

The sum of voltage deviations

$$SVD_i = \sum_{i=1}^{n} |1 - V_i| \quad (3.21)$$

Where: V_i is the voltage at the bus i, and n is the number of nodes.

Voltages at all nodes should be within the acceptable limits of $\pm 5\%$ $(0.95 \le V_i \le 1.05)$ the nominal voltage.

The conventional flowchart of Particle Swarm Optimization (PSO) techniques is shown in Figure 3.4. In the proposed framework, PSO was performed to update the velocity and position of each particle optimally.

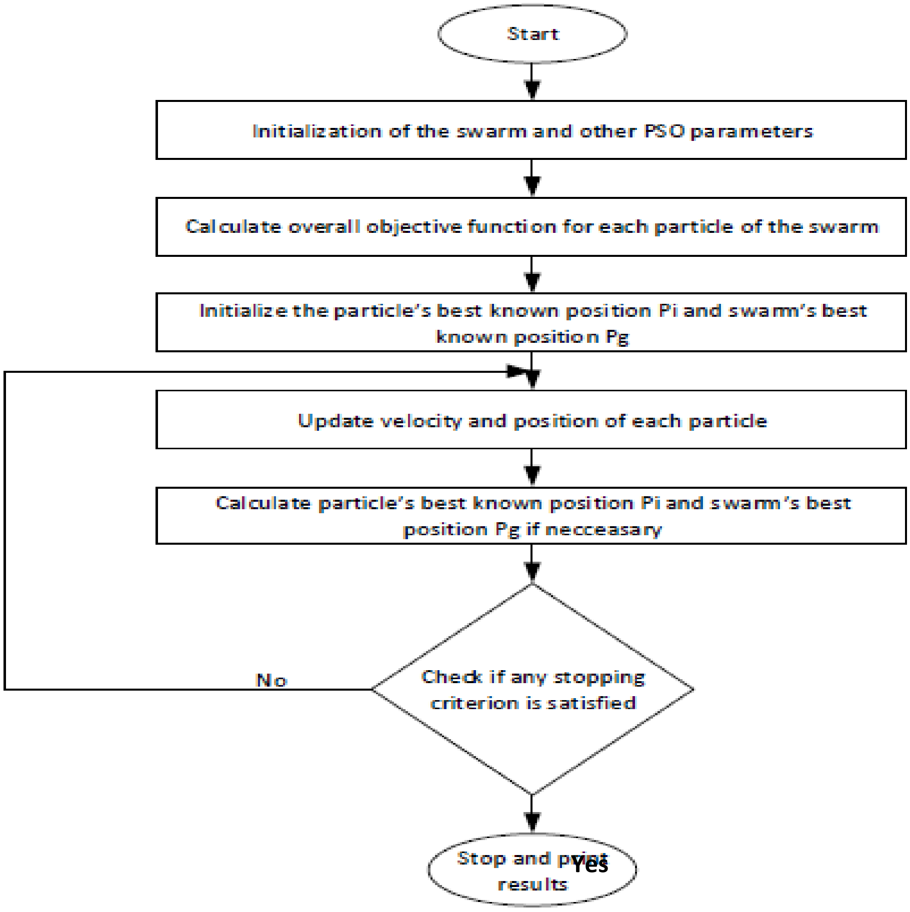

Figure 3.4: Flow chart of the conventional PSO (Umar *et al.*, 2015)

3.5 Voltage Profile Sensitivity Index

Generally, power system stability includes angle stability, frequency stability, and voltage stability. Voltage profile stability has been a subject of great interest in recent attempts to secure power system operations (Machowski *et al.*, 2020). It refers to the ability of a power system to maintain steady voltages at all buses when there is a progressive or uncontrollable drop in its voltage magnitude after a disturbance, increase in load demand, or change in operating conditions (Ingole and Gohokar, 2017). Voltage instability can lead to a voltage collapse which can be defined as a point in time at which the voltage becomes uncontrollable after a voltage instability (Adewuyi *et al.*, 2019). Two major symptoms of voltage collapse are a low voltage profile and inadequate reactive power support (Lee and Song, 2019). Generally, a distribution system is a low-voltage network that is prone to voltage collapse phenomena when it experiences an increase in its load demand or an inadequate reactive power supply. Although it has been thought that DG can improve the voltage profiles, considering its capacity, location of integration, and technology, precautions should be taken in selecting DG. If there is a lack of reactive power support, it is not wise to use an induction generator-based DG as it would consume more reactive Power, thereby affecting the voltage profiles. Sometimes, the excessive capacities of synchronous and solar-type DGs can create a voltage rise problem.

3.5.1 Voltage profiles with DG units

Traditionally, distribution networks have been modelled as passive networks for power delivery and consumption considering the voltage drop phenomena. The R/X ratio of a transmission system is very low, while the resistance of the conductors in a distribution system is very high; this leads to voltage drops along the distribution lines from the substation to load centres. To illustrate the effect of voltage, and drop, a per-phase equivalent circuit of a line segment serving unit load is shown in Figure 3.5. Here, the source voltage is V_S, and the load voltage is V_L. The line has resistance R and reactance X. After applying Kirchhoff's voltage law in that circuit, we obtain the voltage drop equation (Kersting, 2018):

$$\Delta V = V_S - V_L = (R + jX)I \cong re\left[ZI\right] \qquad (3.5)$$

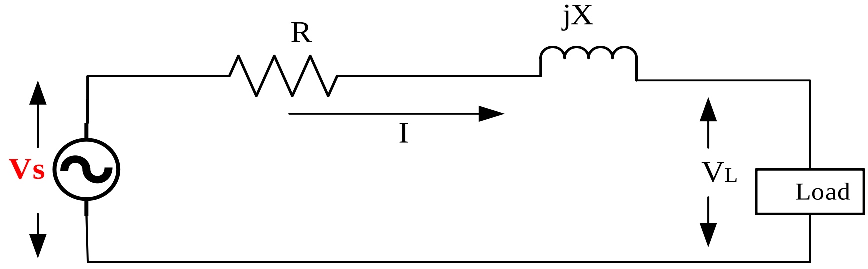

Figure 3.5: Equivalent circuit of radial line with a generator and a load

Now, to investigate the impact of an SPVG unit on the voltage profile, a generation unit with a capacity of 3MW and runs at a unity leading power factor is installed at a node. However, with the presence of SPVG, the characteristic of the network changes significantly.

3.6 Distribution Network (DN) Losses

Both transmission and distribution systems transfer power from one voltage level to another. However, energy losses occur throughout the energy travel from generation plants to the load centers due to transmission and distribution line resistances. Generally, a distribution system operates at a low voltage level and has a high resistance value, unlike a transmission system. Therefore, the current passing through this high-resistance material causes a significantly greater energy dissipation in a distribution network than in a transmission network. The loss is almost 7% of the total energy production, only around 30% is transmission loss, and the remaining 70% is in the distribution area.

This high distribution loss has some negative impacts on the system as it causes an increase in energy demand which can increase the cost of the production or purchase of energy and can increase load currents across the devices. As a result, reducing a utility's distribution losses is important to make its grid more energy efficient.

3.6.1 Optimum SPVG placement and power loss minimisation

Losses in a distribution network are mainly of two types, technical and non-technical. The latter include mainly electricity theft, losses due to poor equipment installation and operation, calculation and accounting mistakes, and damaged meters delivered and consumed but not charged (Chuwa and Wang, 2021). On the other hand, technical losses comprise variable and fixed losses. Fixed losses are often referred to as iron losses which occur mainly in the cores of transformers and motors, while variable losses are known as copper losses which occur mainly in power delivery equipment, such as lines and cables, and the copper parts of transformers. This loss varies depending on the amount of electricity delivered through that device. This variable loss is the most significant part among all technical losses, almost proportional to the square of the current. Real power losses in a distribution system depend on the resistances of power delivery elements (distribution lines), core losses of transformers and motors, and dielectric and rotational losses.

Real power loss is much larger than other losses. The real power loss of any element is associated with its series resistance and the current flowing along it. Therefore, total real power loss in a distribution system having an 'n' number of branches is given by:

$$P_L = \sum_{i=1}^{n} I_i^2 R_i \tag{3.6}$$

Where I_i is the current magnitude, and R_i is the resistance. Once I_i can be obtained from the power flow study, we can easily find out the real power loss of the total system.

Now, if we consider the simple three-phase balanced equivalent radial transmission line with generation shown in Figure 3.5, the line loss becomes

$$P_{Loss} = 3I_i^2 R \tag{3.7}$$

Where:

R is per phase resistance of the line, and I is current through the line, which is obtained using:

$$I = \frac{P_G}{\sqrt{3} V_G \cos\theta_G} \tag{3.8}$$

Where:

P_G = generated Power

V_G = magnitude of the generated voltage

$\cos\theta_G$ = power factor of the generator

Using the value of I, we get the power loss from (3.3) as:

$$P_{LOSS} = \frac{R}{|V_G|^2 COS^2\theta_G}(P_G)^2 \tag{3.9}$$

At any location in a distribution network, total system losses tend to reduce as the penetration level of DG (size of DG) increases and reaches a minimum value for some levels of penetration which is called its optimum DG size. Further increases in the penetration level tend to increase the system losses. The capacity of the DG unit for which the minimum power loss is observed is called the optimum DG capacity.

The structure of a distribution system is such that Power should flow from the substation to the consumer (Northcote *et al.*, 2017). When a DG is placed in a network, it is desirable that Power should be consumed within that distribution network, thereby reducing power losses. Any size of DG greater than the optimum size will create a reverse power flow toward the distribution substation. Therefore, excessive Power flows through small conductors toward the transmission area will increase power losses in a distribution network. So, power loss is highly dependent on the DG capacity. Maximum power output by DG units is limited to 75% of PQ_{Load} (Sadiq *et al.*, 2019). Equation (3.10) defines DG size operational constraints.

$$0 \le DG_{size} \le 0.75PQ_{Load} \tag{3.10}$$

The positive benefits of DG are also location-dependent (Viral and Khatod, 2015). To determine the optimal location of DG on the network under consideration, unit DG was placed on different nodes of the 17-node test system one at a time. Here a 3MVA unity power factor, synchronous Solar Photovoltaic Generator (SPVG) DG unit, was considered, and the total power loss on the network changed its pattern after adding a 3000 kW DG at different nodes. Particle Swarm Optimization (PSO) steps were archived using the flowchart shown in Figure 3.6.

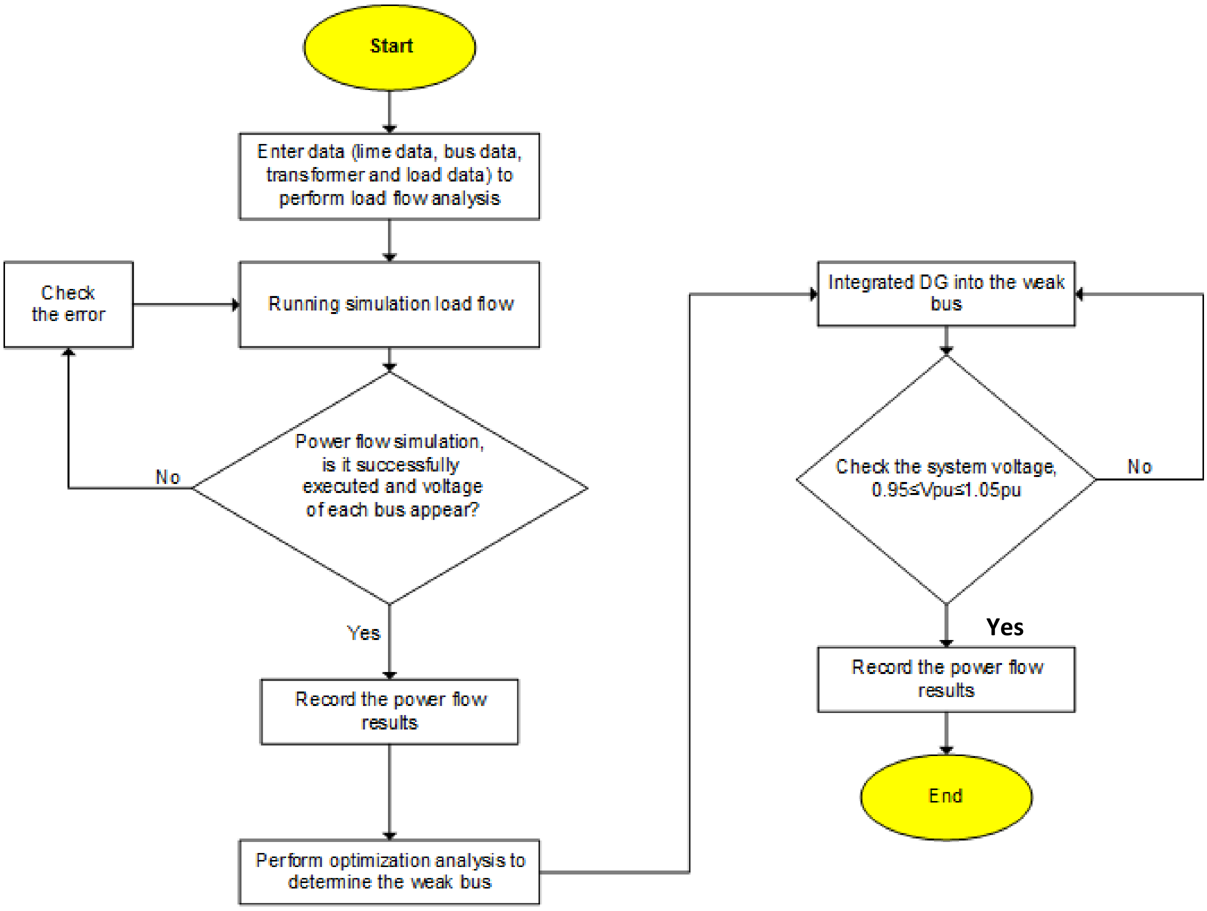

Figure 3.6: Flowchart implementation for DG-unit allocation

CHAPTER FOUR

4.0 RESULTS AND DISCUSSION

Power flow analysis remains a principal tool used in power system studies. The planning and operation of a power system require such computations to dissect the steady-state performance of the power system under different working conditions and to consider the impacts of changes in equipment configuration. Power flow solutions produced for these reasons were analysed utilizing computer programs. The fundamental aim of power flow performance is to generate the load power utilization at all buses of a known electric power system and Power (active and reactive) at every node. The importance of power flow analysis in electrical power engineering includes numerical investigation of a power system. Unlike conventional circuit analysis, power flow typically uses streamlined notation; for example, a one-line diagram and per unit system, focusing on different types of AC power parameters. The important data obtained from the power flow study are the magnitude and phase angle of the voltage at each node and the active and reactive power flowing in each line. This work used PSAT to simulate the 17-node test network utilizing the Newton-Raphson technique, as shown in Figure 4.1.

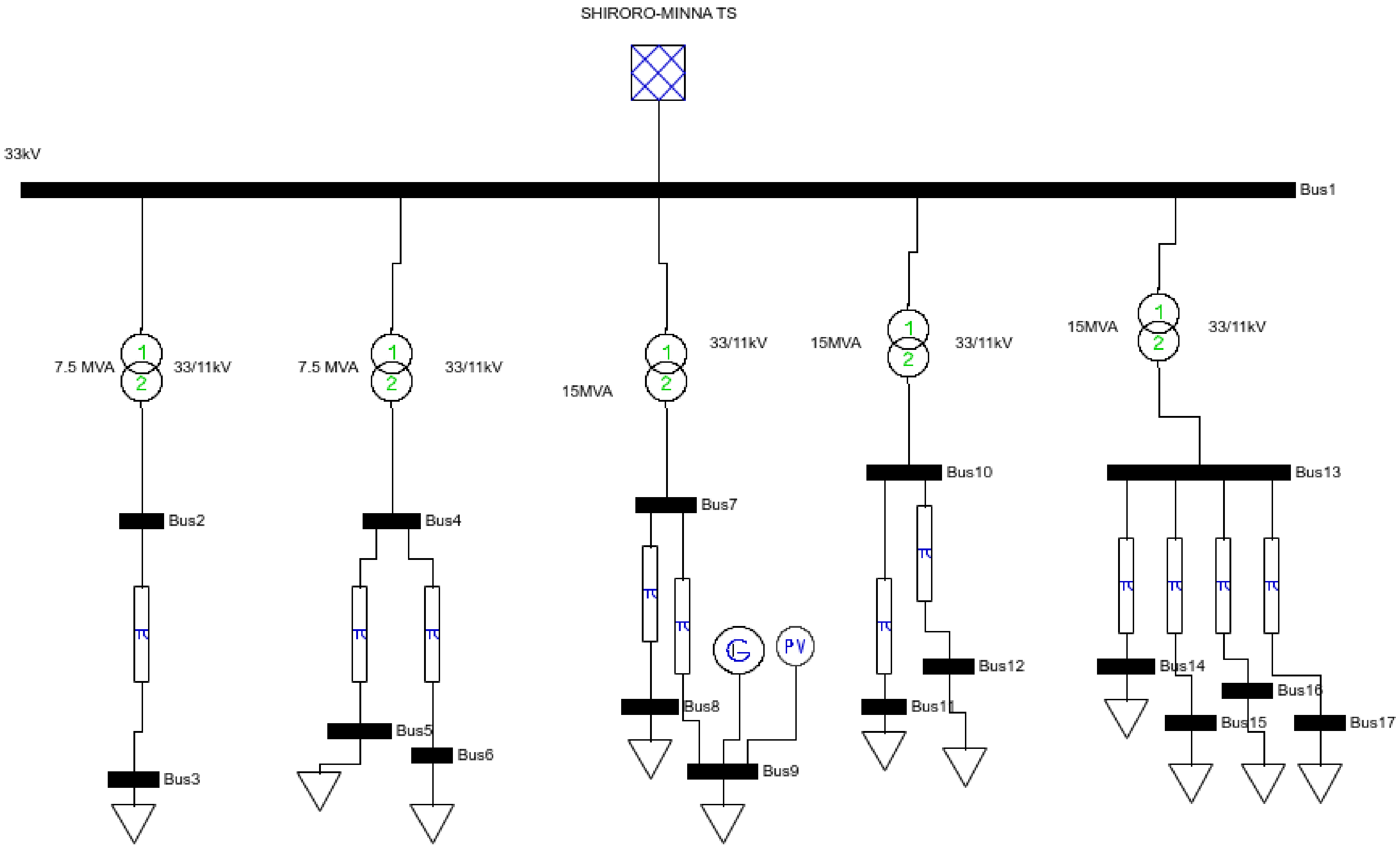

Figure 4.1: PSAT model of test network with SPVG

4.1 Impact of Distributed Generation (SPVG) on Test Network

In this study, solar based SPVG unit was considered. Here, a 17-node test network (Minna town injection substations) was used, which has a peak load demand of 29.720MW with a total generation of 30.920MW. However, according to the PSO optimization results, node 9 was the optimal location for SPVG deployment because it had the node with the least power loss on the simulated network, as illustrated in Figure 4.2.

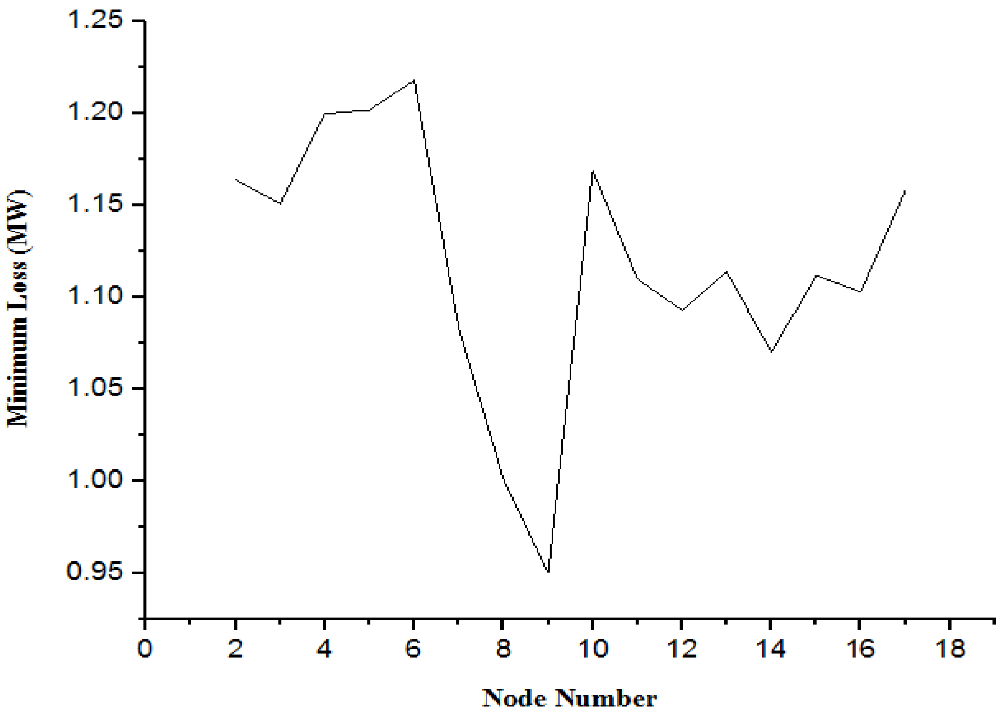

Figure 4.2: Minimum value of network losses with the installation of SPVG-unit at node 9.

The simulation converged in three iterations by power flow computation without a mismatch through the iterative procedure. Consequently, results were obtained on voltage profile, active power loss, and reactive power loss of the distribution network for the steady-state operation. Losses on the network are highly dependent on the location of DG, the network structure, DG technology, load demand, and generation and load variations. Therefore, a power flow study has been carried out on the 11 kV Abuja Electricity Distribution Company, AEDC Minna Region feeder emanating from Shiroro 33/11 kV

Transmission Station (TS) using PSAT and MATPOWER software. The following two cases have been considered in the power flow study. Case I: Optimization result of the base case study network using MATPOWER. Case II Optimization result of the base case study network using PSAT. The shunt capacitor was then used to validate the results.

Table 4.1 shows the total active and reactive power losses at the optimum location after placing SPVG on the test network.

Table 4.1: Total active and reactive power losses for SPVG placement on node 9

Method	Optimum Location	Optimum DG size (MW)	Active power loss (MW)	Reactive power loss (MW)
PSO	Node 9	3	0.95	0.47

The convergence characteristic of the applied method using artificial intelligence (particle swarm optimization techniques) for both loss reduction and voltage deviation was shown in Figure 4.3.

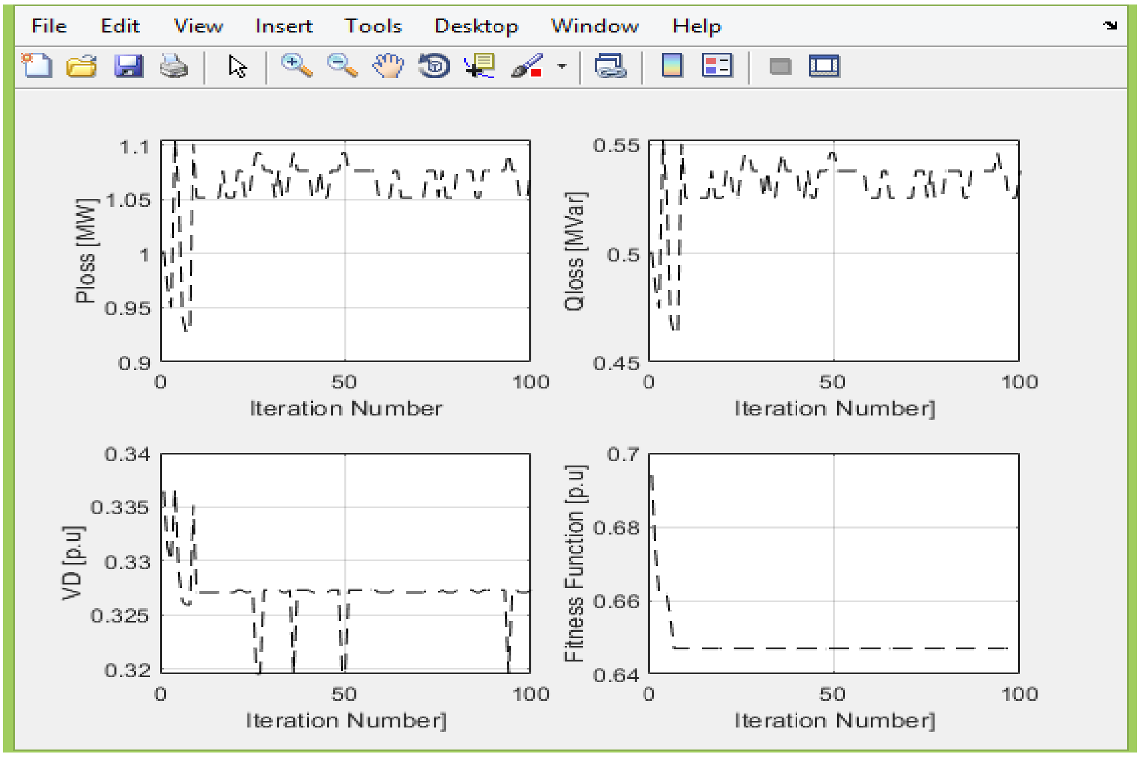

Figure 4.3: PSO convergence characteristic

4.1.1 Case I: MATPOWER optimization results

To investigate the impact of SPVG in mitigating the power losses in the system, the Newton-Raphson power flow program was run on the model network without and with SPVG for the steady state conditions of the system. The results of pre- and post-insertion of the SPVG are shown in Table 4.2. It was obvious from the table that both active and reactive power losses in the branches decreased considerably after SPVG was installed in the test network. In addition, the voltage profiles improved, and system stability was maintained after reducing the line losses.

Table 4.2: Summary of active and reactive power losses on the test system after optimization with SPVG

S/N	Branch	Losses			
		Before Optimization		After Optimization	
	ID	kW	kVar	kW	kVar
1	Line1	46.0	20.0	46.0	20.0
2	Line2	46.0	20.0	46.0	20.0
3	Line3	6.0	0.0	6.0	0.0
4	Line4	5.0	0.0	5.0	0.0
5	Line5	0.0	0.0	0.0	0.0
6	Line6	415.0	210.0	248.0	210.0
7	Line7	92.0	50.0	99.0	50.0
8	Line8	117.0	60.0	40.0	20.0
9	Line9	154.0	80.0	154.0	80.0
10	Line10	55.0	30.0	55.0	30.0
11	Line11	25.0	10.0	25.0	10.0
12	Line12	175.0	90.0	175.0	90.0
13	Line13	40.0	20.0	40.0	20.0
14	Line14	4.0	0.0	4.0	0.0
15	Line15	23.0	0.10	23.0	0.10
16	Line16	0.0	0.0	0.0	0.0
		1203	**600**	**966**	**560**

Figure 4.4 and 4.5 depicts real and reactive power loss before and after optimization on the base case study network. Power loss on the affected nodes was significantly reduced after optimization.

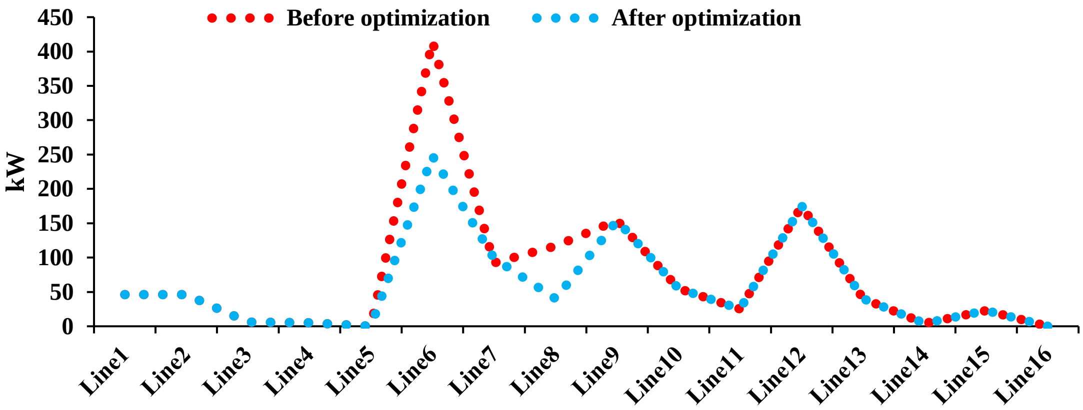

Figure 4.4: Real power losses with before and after optimization on a test system

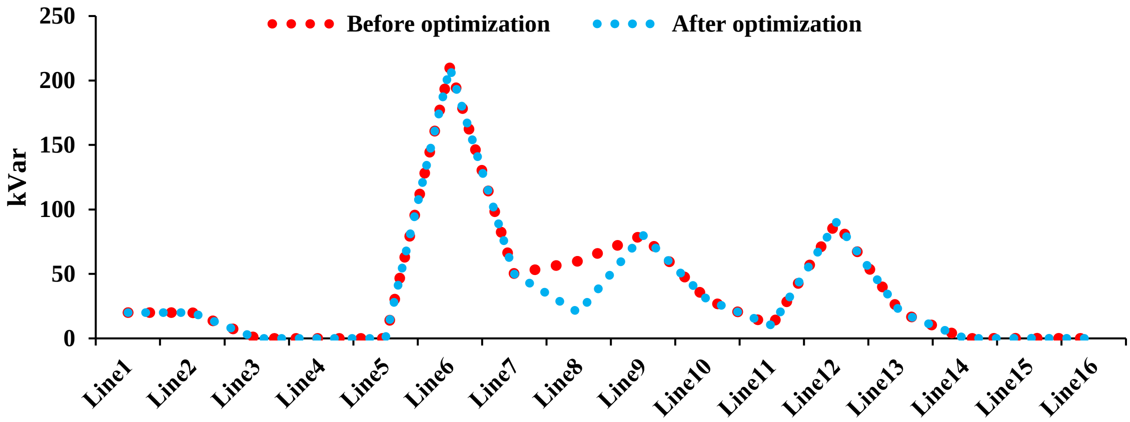

Figure 4.5: Reactive power losses before and after optimization on a test system

4.1.2 Voltage profile deviation on the test network

Table 4.3 depicts the summary of voltage deviation on the test network before and after optimization using MATPOWER.

Table 4.3: Summary of voltage deviation on test system before and after optimization

Node No.	VD (p.u) Before optimization	After Optimization
1	1.000	1.000
2	0.990	0.990
3	0.980	0.980
4	0.996	0.996
5	0.993	0.993
6	0.996	0.996
7	0.970	0.977
8	0.955	0.963
9	0.954	0.969
10	0.982	0.980
11	0.970	0.970
12	0.974	0.974
13	0.980	0.980
14	0.971	0.970
15	0.977	0.977
16	0.973	0.973
17	0.980	0.980

The affected nodes voltages were significantly improved. These are represented with curve on Figure 4.6.

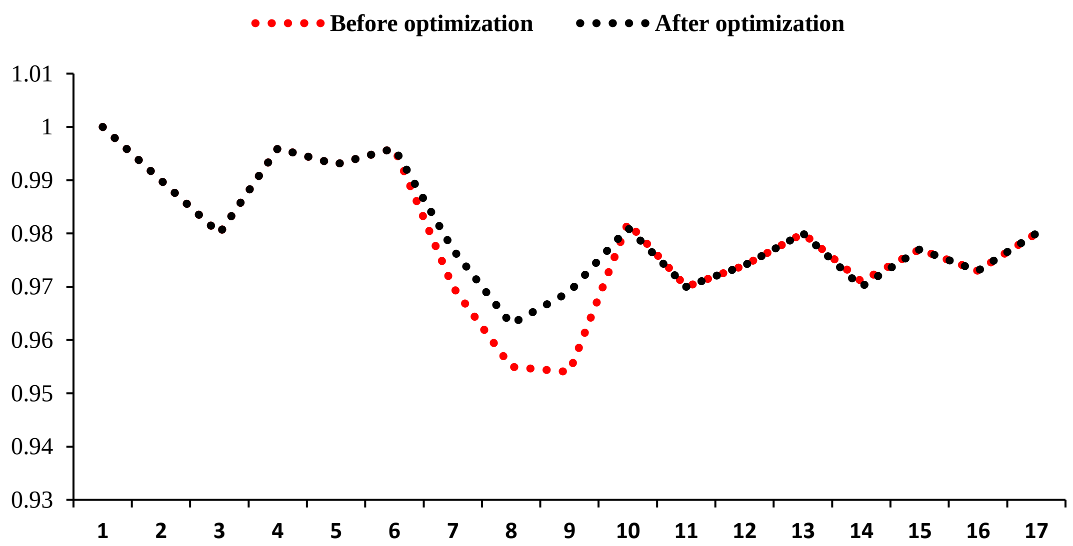

Figure 4.6: Voltage deviation before and after optimization on the test networks

4.2 Case II: PSAT Optimization Results

Table 4.4 shows the summary of active and reactive power losses before and after optimization on the base case study network.

Table 4.4: Summary of active and reactive power losses on the test system after optimization with SPVG

S/N	Branch ID	Losses			
		Before Optimization		After Optimization with SPVG	
		kW	kVar	kW	kVar
1	Line1	45.6	22.8	45.6	22.8
2	Line2	39.8	19.9	39.8	19.9
3	Line3	0.0	0.0	0	0
4	Line4	4.6	2.3	4.6	2.3
5	Line5	0.1	0.0	0.1	0
6	Line6	91.7	45.8	87.3	43.6
7	Line7	116.8	58.3	39.7	19.8
8	Line8	55.0	27.5	55	27.5
9	Line9	24.9	12.4	24.9	12.4
10	Line10	4.4	2.2	4.4	2.2
11	Line11	23.0	11.5	23	11.5
12	Line12	45.6	22.8	45.6	22.8
13	Line13	0.3	6.4	0.3	6.4
14	Line14	415.4	207.5	63.1	31.5
15	Line15	154.0	76.9	154	76.9
16	Line16	175.2	87.5	175.2	87.5
		1196.4	**603.9**	**762.6**	**387.1**

Reduction in active and reactive power loss before and after optimization were represented in Figures 4.7 and 4.8.

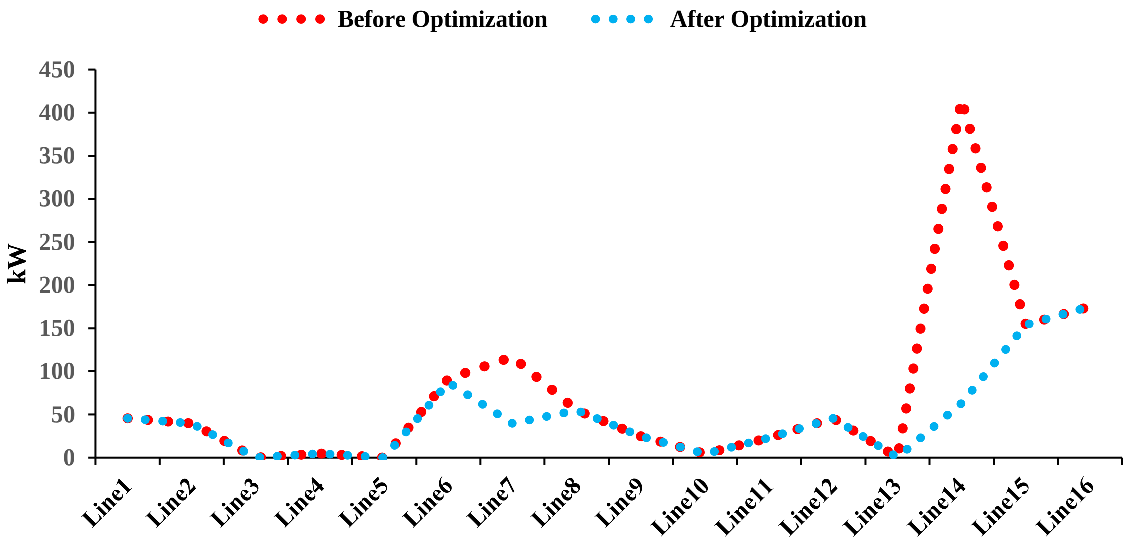

Figure 4.7: Active power losses before and after optimization on a test system

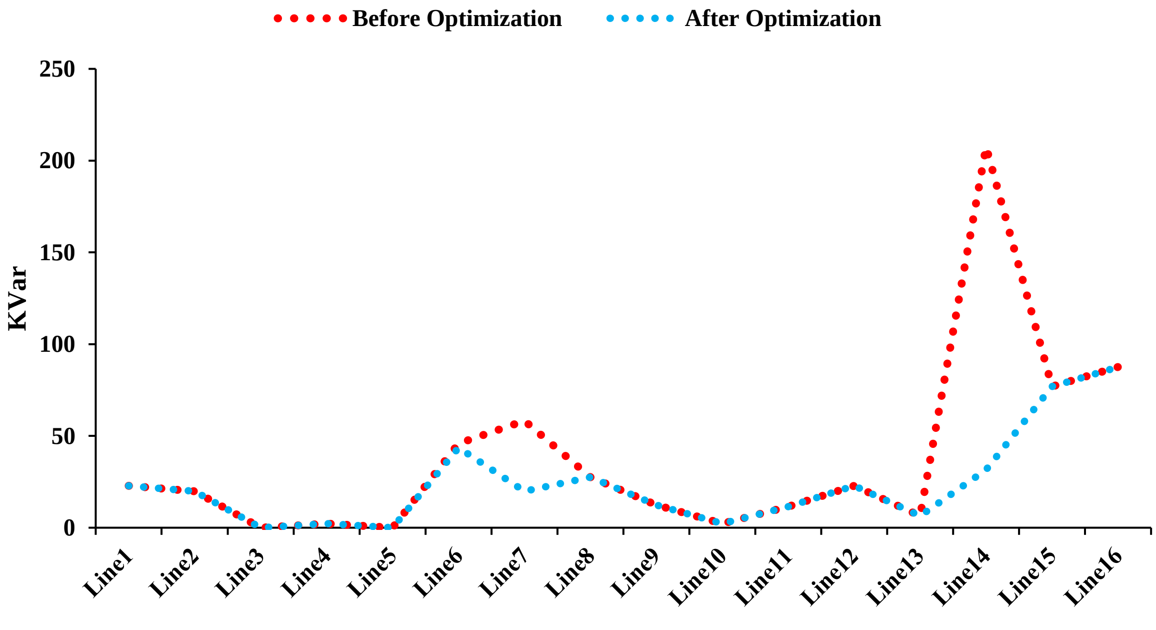

Figure 4.8: Reactive power losses before and after optimization on a test system

4.2.1 Voltage profile deviation on the test network (PSAT)

Table 4.5 depicts the summary of voltage deviation on the test network before and after optimization using PSAT.

Table 4.5: Summary of voltage deviation on test system before and after optimization

Node No.	VD (p.u) Before optimization	SPVG unit
1	1.000	1.000
2	0.989	0.989
3	0.979	0.979
4	0.997	0.997
5	0.994	0.994
6	0.997	0.997
7	0.969	0.993
8	0.955	0.979
9	0.953	1.000
10	0.981	0.981
11	0.970	0.970
12	0.974	0.974
13	0.980	0.980
14	0.970	0.970
15	0.977	0.977
16	0.973	0.973
17	0.980	0.980

Figure 4.9 illustrates voltage deviation before and after optimization on the base case study network.

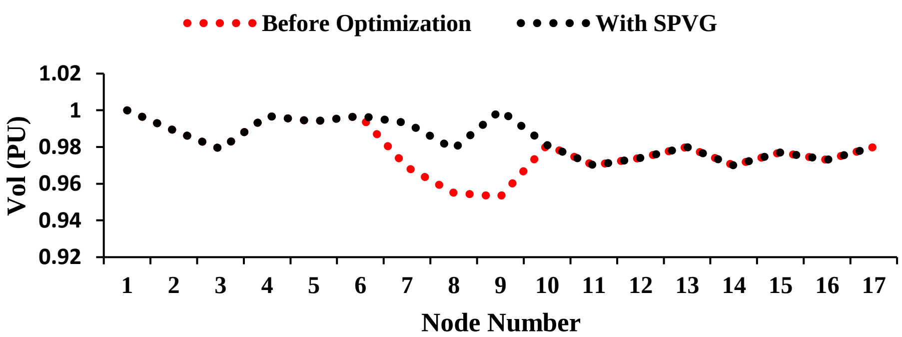

Figure 4.9: Voltage deviation before and after optimization on the test networks

Table 4.6 illustrates the active and reactive power losses obtained with MATPOWER and PSAT.

Table 4.6: Active and reactive line losses obtained with MATPOWER and PSAT optimization

Losses	Case I	Case II
kW	966	762.6
kVar	560	387.1

4.3 Validation of Total Losses Obtained by SPVG and Fixed Capacitor (FC) Bank

The suitability of SPVG in mitigating active and reactive power losses of the system is validated by the simulation results. The power losses incurred with FC been placed on the test network was higher compared to SPVG on the same optimal location. Therefore, the optimal placement and size of the SPVG unit were considered to achieve the objective function. Table 4.7 shows the active and reactive power losses before and after optimization with SPVG and FC on the test network.

Table 4.7: Total power losses and voltage drop after optimization with fixed capacitor (FC) and SPVG Unit

Network	Active power loss (kW)	Reactive power loss (kVAr)	%Voltage deviation
With shunt capacitor	1005.2	508.1	3.6
With SPVG	762.6	387.1	2.7

. The following lines before SPVG unit placement (line 7 between node1 and node2, line 14 between node13 and node14, line 15 between node13 and node15, and line16 between node13 and node 17) experienced heavy power losses due to high power flow beyond the capacity of the lines. After placement, the SPVG injected more inductive reactance into those lines to dampen power flow and avoid forming a loop flow since Power flows more where there is less load. Therefore, both real and reactive power losses were minimized. These are illustrated on the curves on Figure 4.10 and 4.11

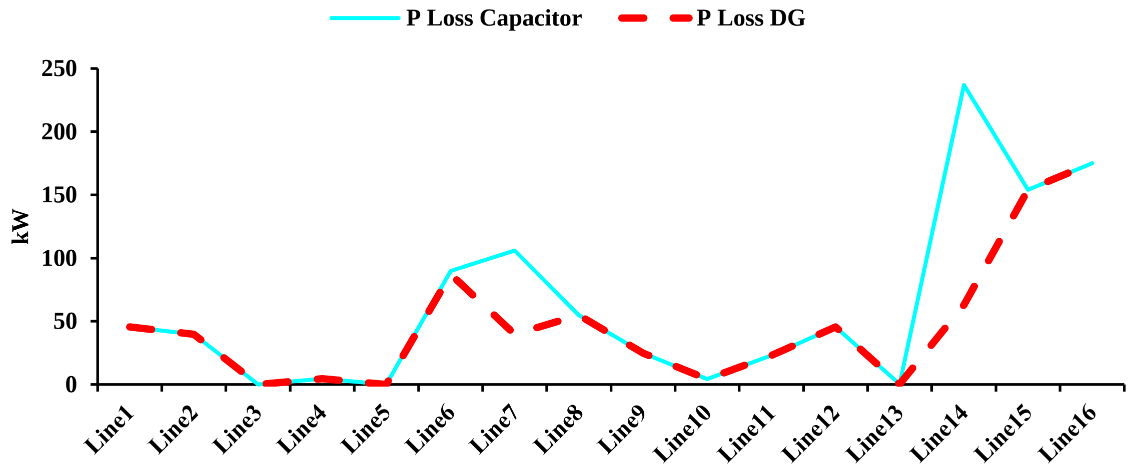

Figure 4.10: Real line losses with a capacitor bank and SPVG on a test system

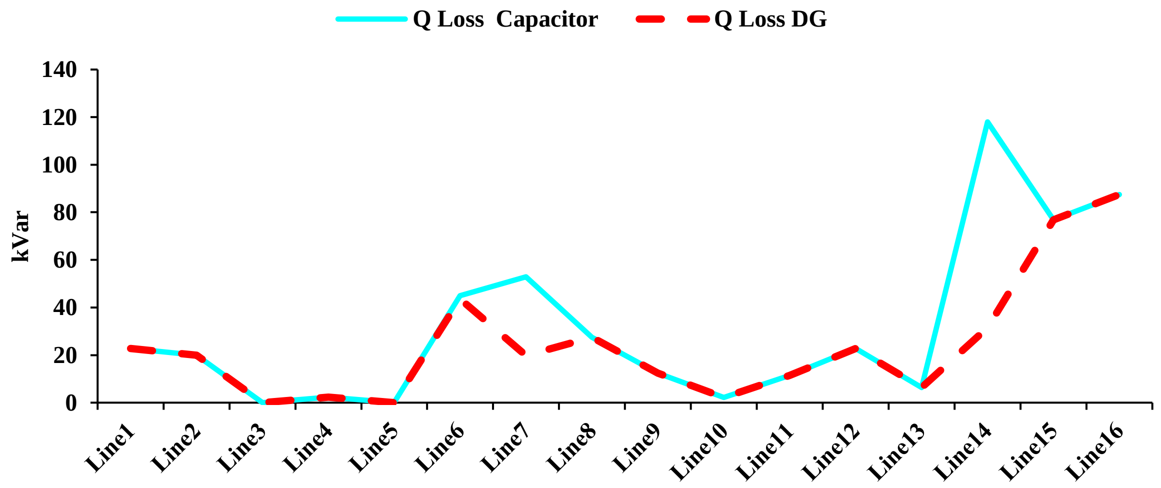

Figure 4.11: Reactive line losses with Capacitor bank and SPVG on the test network

The radial distribution feeder considered for the case study has a total of 29,720 kW, and the total losses incurred for the active and reactive power were 1197.4 kW and 603.7kVAr respectively, before the placement of SPVG at the optimal location. After SPVG integration in the network at the optimal node, the active and reactive power losses were reduced to 762.6kW and 387.1kVAr, respectively. Thus, the loss saving by SPVG is given as:

The Power saved by SPVG = power loss before SPVG - power loss after SPVG

= 1196.4 – 762.6

= 433.8 kW

In inclusion, the comparison of using the SPVG and shunt capacitor bank shows that in case of feeder loss reduction of the network, the choice of giving priority to SPVG than shunt capacitor bank in usage is made. It was observed from the results obtained after the simulation that there was a significant improvement in the voltage profiles and power transfer on the branch with SPVG. 63.74% of feeder loss reduction was achieved at the placement of SPVG, which is far better than 84.02% recorded with FC. Therefore, the SPVG unit alone can inject active and reactive power needed by the network to minimize feeder losses compared to the shunt capacitor. Figure 4.12 shows pictorial representation of these losses.

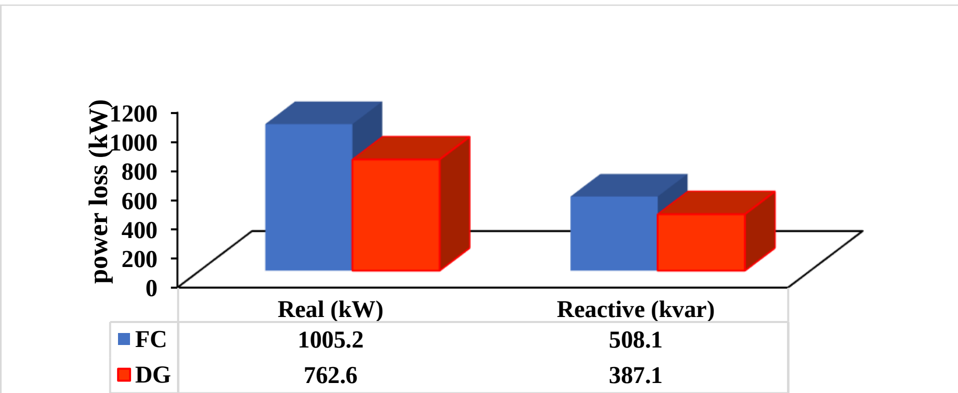

Figure 4.12: Comparison of total active and reactive power losses after optimization with SPVG and FC

4.4 Validation of Voltage Deviations on the Test Network with SPVG and FC

A solar photovoltaic generation (SPVG) in the distribution feeder, besides minimization of feeder loss, will also improve the voltage profile of the system. It is usually suitable to discuss the distribution voltage profiles of the feeder because the voltages are everywhere different on the feeder. One of the reasons that determine the quality of the power supply is maintaining the sender and receiver voltage as closely as possible. In order to achieve this, losses associated with the distribution network must reduce to the minimum acceptable limit. Table 4.8 shows voltage deviation before and after optimization with SPVG.

Table 4.8: Summary of voltage deviation on test system before and after optimization with FC and SPVG

Node No.	VD (p.u) Before optimization	VD (p.u) After optimization	
		Capacitor bank	SPVG unit
1	1.000	1.000	1.000
2	0.989	0.989	0.989
3	0.979	0.979	0.979
4	0.997	0.997	0.997
5	0.994	0.994	0.994
6	0.997	0.997	0.997
7	0.969	0.978	0.993
8	0.955	0.964	0.979
9	0.953	0.972	1.000
10	0.981	0.981	0.981
11	0.970	0.970	0.970
12	0.974	0.974	0.974
13	0.980	0.980	0.980
14	0.970	0.970	0.970
15	0.977	0.977	0.977
16	0.973	0.973	0.973
17	0.980	0.980	0.980

SPVG improves all the affected node voltages on the test network thereby stabilizing the system voltage with in the acceptable limit. Figure 4.13 represent the voltage deviation on the test network.

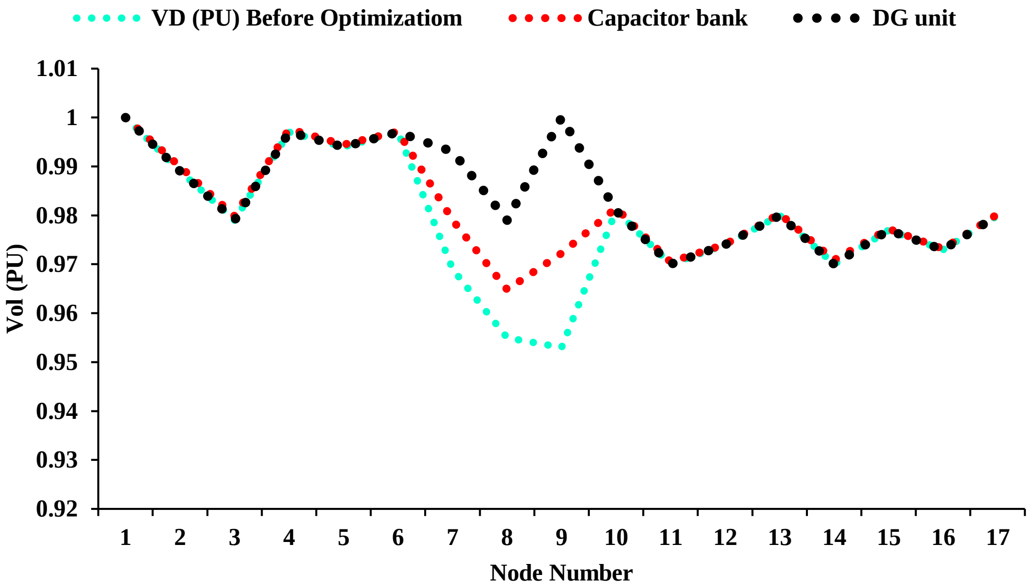

Figure 4.13: Voltage deviation before and after optimization with a capacitor bank and DG unit on the test networks.

The improvement in the voltage profile can be measured based on the reduction in the total voltage deviation (TVD) of a given network. Consider a distribution network in which the TVD is reduced from a value TVD_0 to TVD_i; the percentage improvement in voltage profile (%VI) can be represented using Equation (4.2). If the node voltages are in per-unit (PU), the TVD can be expressed using Equation (4.1)

$$TVD = \sum_{k=1}^{n} (1 - V_k) \tag{4.1}$$

$$\%VI = \frac{TVD_0 - TVD_i}{TVD_0} \times 100 \tag{4.2}$$

Where:

V_k is the voltage magnitude at *the* k^{th} node

n is the number of nodes in a network.

From the simulation, the total voltage drops at the weakest node before and after SPVG were obtained as 0.953pu and 1.0pu respectively. The percentage voltage profile improvement on the test network can be computed using Equation (4.3)

$$VI = \frac{1.0 - 0.953}{1.0} \times 100 = 4.7\% \tag{4.3}$$

Percentage voltage profile improvement at the weakest node before and after shunt capacitor placement on the base case study network compared to SPVG.

$$VI = \frac{0.972 - 0.953}{0.972} \times 100 = 2.0\%$$

CHAPTER FIVE

5.0 CONCLUSION AND RECOMMENDATION

5.1 Conclusion

This research work aimed to deploy Particle Swarm Optimization (PSO) effectively to determine the optimal size and location of Solar Photovoltaic Generation (SPVG) in the Minna Distribution Network to minimize power losses and improve the voltage profile on the feeder.

As seen from the results of two scenarios under chapter four, the power losses had been significantly reduced, and voltage profile improvement was achieved. Therefore, it could be deduced that the deployment of Solar Photovoltaic Generation on the distribution network characteristic can be used to minimize power losses on the distribution feeder. The voltage profile improvement recorded at the end of SPVG placement on the test network showed the possibility of voltage drop minimization within the acceptable limit.

5.2 Recommendations

With the present energy crises in Nigeria, integration of Renewable Energy Source (RES) technology into an existing distribution network has a paramount effect on the development of the country's socioeconomic and technological advancement with an attendant impact on sustainable energy and a clean environment for all. However, as observed from the result, SPVG has an effect on voltage profile improvement and power loss minimization in the distribution system, so SPVG is an important and essential technology that should be explored by utility and service providers to deliver reliable and quality power to consumers. Therefore, future work on SPVG should consider the performance analysis of the technology under different fault conditions. And hybrid model based on RES for a continuous electricity supply, as power generated from SPVG is fluctuating (intermittent) in nature.

5.3 Contribution to Knowledge

This thesis has contributed to the knowledge in the aspect of determination of the optimum deployment of SPVG on the Distribution Network using Artificial Intelligence techniques (Particles Swarm Optimization), Simulation and power flow of the Minna Town Injection Substation using PSAT and MATPOWER, Evaluating the impact of SPVG on the power loss and voltage profile of Minna Town Injection Substation using PSAT and MATPOWER and determination of the viability of SPVG to residential loads via the existing distribution network infrastructure.

REFERENCES

Abdelaziz, A., Osama, R. A., El-Khodary, S. J. (2012). Reconfiguration of distribution systems for loss reduction using the hyper-cube ant colony optimisation algorithm. *International Journal of Electronic and Electrical Engineering,* 6(2), 176-187.

Abdulkareem, A., Ogbe, D., & Somefun, T. (2020). Review of different methods for optimal placement of phasor measurement unit on the power system network. *Advance Science Technology Engineering System Journal,* 5(6), 1071-1081.

Abu-Mouti, F. S., & El-Hawary. (2011). Optimal distributed generation allocation and sizing in distribution systems via artificial bee colony algorithm. *IEEE Transactions on Power Delivery,* 26(4), 2090-2101.

Adeoye, O., & Ekejuiba, C. (2014). Assessment of line losses and methods of reduction on selected power transmission lines in Nigeria. *International Journal of Novel Research in Engineering Applied Science,* 3(2), 54-63.

Adewuyi, O. B., Shigenobu, R., Ooya, K., Senjyu, T., & Howlader, A. M. (2019). Static voltage stability improvement with battery energy storage considering optimal control of active and reactive power injection. *Electric Power Systems Research, 172*, 303-312.

Akram, U., Nadarajah, M., Shah, R., Milano, F. J. (2020). A review on rapid responsive energy storage technologies for frequency regulation in modern power systems. *International Journal of Electronic and Electrical Engineering,* 120, 109-626.

Al-Ammar, E. A., Farzana, K., Waqar, A., Aamir, M., Haq, A. U., Zahid, M., & Batool, M. (2021). ABC algorithm based optimal sizing and placement of DGs in distribution networks considering multiple objectives. *Ain Shams Engineering Journal,* 12(1), 697-708.

Amesi, C. I., Bala, T. K., & Ibe, A. O. (2017). Impact of Network Reconfiguration: Case Study of Port-Harcourt Town 132/33kV Sub-transmission Substation and Its 33/11kV Injection Substation Distribution Networks. *European Journal of Electrical Engineering Computer Science,* 1(1), 21-37.

Anderson, K., Li, X., Dalvi, S., Ericson, S., Barrows, C., Murphy, C., & Hotchkiss, E. (2020). Integrating the value of electricity resilience in energy planning and operations decisions. *IEEE Systems Journal,* 15(1), 204-214.

Anwar, A., & Pota, H. (2011). *Loss reduction of power distribution network using optimum size and location of distributed generation.* Paper presented at the AUPEC 5(3), 16-35.

Anwar, A., & Pota, H. (2012). *Optimum allocation and sizing of DG unit for efficiency enhancement of distribution system.* Paper presented at the 2012 IEEE International Power Engineering and Optimization Conference Melaka, Malaysia, 6(1), 201-221.

Asif, R. M., Rehman, A. U., Alsharabi, N., Rabbani, S., Shakir, M., Malik, N., Khan, A. A. (2022). Optimal Locating and Sizing of DG in Radial Distribution System Using Modified Shuffled Frog Leaping Algorithm. *IETE Journal of Research,* 4, 1-18.

Awasarmol, A., Malkhede, D., Mane, S., & Kahandole, K. (2020). Faulted pole indicator for utility grid *International Journal of Electronic and Electrical Engineering,* 1(1) 24-36.

Ayamolowo, O. J., Buraimoh, E., Salau, A. O., & Dada, J. O. (2019). *Nigeria electricity power supply system: The past, present and the future.* Paper presented at the 2019 IEEE PES/IAS PowerAfrica, 3, 34-54.

Bai, Q. J. (2010). Analysis of particle swarm optimization algorithm. *3*(1), 180. *Computer and Information Science Conference, International Journal of Electronic and Electrical Engineering,* 3(1), 180-197.

Berrada, A., Ameur, A., El Maakoul, A., & El Mrabet, R. (2021). Optimization modeling of hybrid DG systems. In *Hybrid Energy System Models,* 45-73.

Casas, S., Portalés, C., Morillo, P., & Fernández, M. (2018). A particle swarm approach for tuning washout algorithms in vehicle simulators. *International Journal of Electronic and Electrical Engineering,* 68, 125-135.

Chuwa, M. G., & Wang, F. (2021). A review of non-technical loss attack models and detection methods in the smart grid. *Electric Power Systems Research,* 199, 107-115.

Dembra, A., Sharma, A. J. (2014). Improvement in voltage profile and loss minimization using high voltage distribution system. *International Journal of Electronic and Electrical Engineering,* 3, 11-20.

Dugan, R. C., & Mcdermott, T. E. (2002). Distributed generation. *IEEE industry applications magazine,* 8(2), 19-25.

Eajal, A. A., & El-Hawary, M. J. (2010). Optimal capacitor placement and sizing in unbalanced distribution systems with harmonics consideration using particle swarm optimization. *International Journal of Electronic and Electrical Engineering, 25*(3), 1734-1741.

Eaton I. (2014). Power Outage Annual Report: Blackout Tracker. In. *International Journal of Electronic and Electrical Engineering, 5*(1), 21-39.

Ebrahimi M, M., Falaghi, H., & Farhadi, M. (2020). A Novel method of optimal capacitor placement in the presence of harmonics for power distribution Network using NSGA-II Multi-objective genetic optimization algorithm. *Mathematical Computational Applications,* 25(1), 17.

Hassan, A. S., Sun, Y., & Wang, Z. (2022). Water, Energy and Food Algorithm with Optimal Allocation and Sizing of Renewable Distributed Generation for Power

Loss Minimization in Distribution Systems (WEF). *International Journal of Electronic and Electrical Engineering,* 15(6), 2242.

Idoniboyeobu, Bala, T., & Blue-Jack, K. (2017). Performance Evaluation of the 132KV Sub-Transmission Lines in the Nigeria Power Network: A Case Study of Port Harcourt Sub-Region, Rivers State. *International Journal of Research in Engineering and Science (IJRES),* 5(12), 28-40.

Ingole, D., & Gohokar, V. (2017). Voltage stability improvement in multi-bus system using static synchronous series compensator. *Energy Procedia Journal of Electrical Engineering,* 117, 999-1006.

Jabr, R. A., Singh, R., & Pal, B. C. (2012). Minimum loss network reconfiguration using mixed-integer convex programming. *IEEE Transactions on Power systems,* 27(2), 1106-1115.

Jafar-Nowdeh, A., Babanezhad, M., Arabi-Nowdeh, S., Naderipour, A., Kamyab, H., Abdul-Malek, Z., & Ramachandaramurthy, V. K. (2020). Meta-heuristic matrix moth–flame algorithm for optimal reconfiguration of distribution networks and placement of solar and wind renewable sources considering reliability. *Environmental Technology Innovation,* 20, 101-118.

Jain, S., Kalambe, S., Agnihotri, G., Mishra, A. J. (2017). Distributed generation deployment: State-of-the-art of distribution system planning in sustainable era. *International Journal of Electronic and Electrical Engineering,* 77, 363-385.

Jayaprakash, J., Angelin, P., Jothi, L., & Juanola, P. (2016). Planning and coordination of relay in distribution system using Etap. *Pakistan. Journal of Biotechnol,* 13, 252-256.

Joseph, I., & Olorunkanmi, O. (2014). Issues and challenges in the Privatized Power Sector in Nigeria. *Journal of Sustainable Development Studies,* 6(1) 51-67.

Kersting, W. H. (2018). *Distribution system modeling and analysis*: CRC press *International Journal of Electronic and Electrical Engineering,* 2, 23-37.

Khasanov, M., Kamel, S., Halim Houssein, E., Rahmann, C., & Hashim, F. A. (2023). Optimal allocation strategy of photovoltaic-and wind turbine-based distributed generation units in radial distribution networks considering uncertainty. *Neural Computing Applications,* 35(3), 2883-2908.

Kifle, Y., Khan, B., & Singh, P. J. (2018). Assessment and enhancement of distribution system reliability by renewable energy sources and energy storage. *International Journal of Electronic and Electrical Engineering,8*(3), 219-262.

Klug, T. W., Beyene, A. D., Meles, T. H., Toman, M. A., Hassen, S., Hou, M., Jeuland, M. (2022). A review of impacts of electricity tariff reform in Africa. *Energy Policy,* 170, 113-226.

Kumar, M., Samuel, C., Jaiswal, A. J. (2015). An overview of distributed generation in power sector. *International Journal of* Technology & Management. 4(1), 3239-3326.

Kwon, N., Song, K., Ahn, Y., Park, M., & Jang, Y. (2020). Maintenance cost prediction for aging residential buildings based on case-based reasoning and genetic algorithm. *Journal of Building Engineering,* 28, 101-119.

Landeros, A., Koziel, S., & Abdel-Fattah, M. F. (2019). Distribution network reconfiguration using feasibility-preserving evolutionary optimization. *Journal of Modern Power Systems Clean Energy,* 7(3), 589-598.

Lee, Y., & Song, H. (2019). A reactive power compensation strategy for voltage stability challenges in the Korean power system with dynamic loads. *International Journal of Energy Sustainability,* 11(2), 326.

Lotfi, H. (2022). Optimal sizing of distributed generation units and shunt capacitors in the distribution system considering uncertainty resources by the modified evolutionary algorithm. *Journal of Ambient Intelligence Humanized Computing,* 13(10), 4739-4758.

Machowski, J., Lubosny, Z., Bialek, J. W., & Bumby, J. R. (2020). *Power system dynamics: stability and control*: John Wiley & Sons.1-5.

Malik, M. Z., Kumar, M., Soomro, A. M., Baloch, M. H., Farhan, M., Gul, M., & Kaloi, G. S. (2020). Strategic planning of renewable distributed generation in radial distribution system using advanced MOPSO method. *Energy Reports Journal,* 6, 2872-2886.

Mishra, D. K., Ghadi, M. J., Azizivahed, A., & Zhang, J. (2021). A review on resilience studies in active distribution systems. *Renewable Sustainable Energy Reviews,* 135, 110-201.

Mokhtarzadeh, M., Tavakkoli-Moghaddam, R., Triki, C., & Rahimi, Y. (2021). A hybrid of clustering and meta-heuristic algorithms to solve a p-mobile hub location–allocation problem with the depreciation cost of hub facilities. *Engineering Applications of Artificial Intelligence,* 98, 104-121.

Molla, A. (2020). *Power flow control in radial distribution system using static var compensator (svc): Case study on debre markos town distribution system. International Journal of Electronic and Electrical Engineering* 1(1), 27-43.

Northcote, G., James, I., & Wilson, R. (2017). *Control and automation of electrical power distribution systems*: CRC press *International Journal of Energy Sustainability,* 11(2), 326-341.

Okereafor, F., Idoniboyeobu, D., & Bala, T. (2017). Analysis of 33/11KV RSU Injection Substation for Improved Performance with Distributed Generation (DG) Units. *American Journal of Engineering Research . e-ISSN,* 2320-0847.

Okorie, N., Idoniboyeobu, D., & Braide, S. (2021). Optimization of Energy Efficiency for Electric Power Distribution System Losses. *International Journal for Research in Applied Science Engineering Technology,* 9, 12-21.

Oladimeji, J., Elutunji B, & Salau, A. O. (2019). *Nigeria Electricity Power Supply System: The Past, Present and the Future*. Paper presented at the IEEE PES/IAS PowerAfrica.6(1), 21-3E.

Otobo, J. C. (2022). Sustainability and Resilience in the Nigerian Power Sector. *Proceedings of the 5th European International Conference on Industrial Engineering and Operations Management Rome*, 75 - 86.

Petinrin, J., & Shaaban, M. (2019). Multiperiod coordination of local voltage controllers and energy storage for voltage regulation in distribution feeder-connected renewable energy sources. *Iranian Journal of Science Technology, Transactions of Electrical Engineering,* 43, 531-544.

Premalatha, K., & Natarajan, A. M. (2009). Hybrid PSO and GA for global maximization. *J Int. J. Open Problems Compt. Math,* 2(4), 597-608.

Prommee, W., & Ongsakul, W. (2011). Optimal multiple distributed generation placement in microgrid system by improved reinitialized social structures particle swarm optimization. *European Transactions on Electrical Power,* 21(1), 489-504.

Ramírez-Ochoa, D. D., Pérez-Domínguez, L. A., Martínez-Gómez, E.-A., & Luviano-Cruz, D. J. (2022). PSO, a swarm intelligence-based evolutionary algorithm as a decision-making strategy: *International Journal of Energy Sustainability, 11*(2), 117-128.

Rathor, S. K., & Saxena, D. (2020). Energy management system for smart grid: An overview and key issues. *International Journal of Energy Research,* 44(6), 4067-4109.

Rini A, Jayakumar j, Prabaharan N, Palanisamy K, Umashankar S, & Thirumoorthy A. (2017). Frequency Control of a Stand Alone Hybrid Wind and Solar Based Distributed Generation System through an Optimized Energy Storage. *Advanced Engineering Research and Applications Journal,* 5, 270 - 285.

Rodriguez-Diaz, E., Chen, F., Vasquez, J. C., Guerrero, J. M., Burgos, R., & Boroyevich, D. J. I. E. M. (2016). Voltage-level selection of future two-level LVdc distribution grids: A compromise between grid compatibiliy, safety, and efficiency. 4(2), 20-28.

Sadiq, A. A., Adamu, S. S., & Buhari, M. (2019). Optimal distributed generation planning in distribution networks: A comparison of transmission network models with FACTS. *Engineering Science and Technology, an International Journal,* 22, 33-46. doi:10.1016/j.jestch.2018.09.013

Saleh, A. A., Mohamed, A. A., Hemeida, A., & Ibrahim, A. A. (2019). *Multi-objective whale optimization algorithm for optimal allocation of distributed generation and* *capacitor bank.* Paper presented at the 2019 International Conference on Innovative Trends in Computer Engineering (ITCE) 6, 209-235.

Sambaiah, K. S., & Jayabarathi, T. (2020). Loss minimization techniques for optimal operation and planning of distribution systems: A review of different methodologies. *International Transactions on Electrical Energy Systems,* 30(2), 122-1230.

Sayed, A. R., Wang, C., & Bi, T. (2019). Resilient operational strategies for power systems considering the interactions with natural gas systems. *Applied Energy Journal,* 24, 548-566.

Shaheen, A. M., Elsayed, A. M., El-Sehiemy, R. A., & Abdelaziz, A. Y. (2021). Equilibrium optimization algorithm for network reconfiguration and distributed generation allocation in power systems. *Applied Soft Computing Journal,* 98, 106-867.

Sule, A. (2010). Major factors affecting electricity generation, transmission and distribution in Nigeria. *J International Journal of Engineering Mathematical Intelligence,* 1(1), 159-164.

Taiwo, O. P., Tiako, R., & Davidson, I. E. (2017). *Investigation of voltage unbalance in low voltage electric power distribution network under steady state mode.* Paper presented at the 2017 IEEE 3rd International Conference on Electro-Technology for National Development (NIGERCON), 3, 114-119.

Ugwu, J., Odo, K., Oluka, L., & Salami, K. (2022). A Systematic Review on Renewable Energy Development, Challenges and Policies in Nigeria with an International Perspective and Public Opinions. *Intertional Journal Renew Energy Development,* 111, 287-308.

Umar, R., Mohammed, F., Deriche, M., & Sheikh, A. U. (2015). Hybrid cooperative energy detection techniques in cognitive radio networks. In *Handbook of research on software-defined and cognitive radio technologies for dynamic spectrum management,* 1-37.

Viral, R., & Khatod, D. K. (2015). An analytical approach for sizing and siting of DGs in balanced radial distribution networks for loss minimization. *International Journal of Energy Systems,* 67, 191-201.

Wang, L. (2016). *The fault causes of overhead lines in distribution network.* Paper presented at the MATEC Web of Conferences, *International Journal of Energy Sustainability,* 18(2), 126-139.

Wimalaratna, Y. P., Afrouzi, H. N., Mehranzamir, K., Siddique, M. B. M., Liew, S. C., & Ahmed, J. (2022). Analysing wind power penetration in hybrid energy systems based on techno-economic assessments. *Sustainable Energy Technologies Assessments,* 53, 102-538.

Zain ul Abideen, M., Ellabban, O., & Al-Fagih, L. J. E. (2020). A review of the tools and methods for distribution networks' hosting capacity calculation. *13*(11), 2758 *International Journal of Electronic and Electrical Engineering*,8(3), 219-262.

APPENDIX

APPENDIX: MATLAB PROGRAMMING CODE FOR DG PLACEMENT

- DG Parameter and penetration levels
- Initialization
- Velocity Constraints%%%%%%%%%

```
% Particle swarm optimization -PSO
% Haupt & Haupt
% 2021
clear

%ff = 'testfunction'; % Objective Function
% Initializing variables
popsize = 20; % Size of the swarm
npar = 3; % Dimension of the Problem
maxit = 100; % Maximum number of iterations
c1 = 1; % cognitive parameter
c2 = 4-c1; % social parameter
C = 0.1; % constriction factor
```

DG Parameter and penetration levels

```
Node_min = 2; % Least node to place DG
Node_max = 17; % Max nodes to place DG
DGP_min = 1; %minimum size of DG = 1 MW
DGP_max = 3; %maximum size of DG = 3 MW
DGQ_min = 0; %minimum size of DG = 0 MVAR
DGQ_max = 2; %maximum size of DG = 2 MVAR
```

Initialization

```
 Par_DG = particle_pos(popsize,npar);

 vel = rand(popsize,npar); % random velocities

% Evaluate initial population
%cost=feval(ff,par);  % calculates population cost using
Cost_all = ObjFun_DG_Placement(m_case17_radial, Par_DG,
popsize,npar);
cost = Cost_all(:,4);
                     % ff
minc (1) = min(cost);   % min cost
meanc(1)= mean(cost); % mean cost
globalmin=minc(1);   % initialze global minimum

% initialize local minimum for each particle
localpar = Par_DG;   % location of local minima
localcost = cost; % cost of local minima

% Finding best particle in initial population
```

```
[globalcost,indx] = min(cost);
globalpar=Par_DG(indx, :);
[indx_int1, indx_int2] = find(Cost_all == globalcost);
Init_cost_globe = Cost_all(indx_int1, :);
%end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Start iterations
iter = 0;  % counter

% Keep track of Global cost
Cost_all_Globe = zeros(maxit,4);
while iter < maxit
    iter = iter + 1;

% update velocity = vel
   w=(maxit-iter)/maxit; %inertial weiindxht
   r1 = rand(popsize,npar);  % random numbers
   r2 = rand (popsize,npar); % random numbers
   vel = C*(w*vel + c1 *r1.*(localpar) +
c2*r2.*(ones(popsize,1)*globalpar-Par_DG));
```

Velocity Constraints%%%%%%%%%

```
   %Loc limitations...not allowing part to jump over nodes
   [node_idx, node] = find(vel(:,1) > 0.5);
   if ~isempty(node_idx)
       vel(node_idx) = 1;
   end
%    %PDG_Size limitations...
%    [P_size_idx, P_size] = find(vel(:,2) > 0.5);
%    if ~isempty(P_size_idx)
%        vel(node_idx) = 1;
%    end
   % update particle positions
      Par_DG = Par_DG + vel;  % update particle position

      %%%%impose limits of nodes, and DG sizes%%%%%
      %impose limits of nodes,
      [Upp, idx_upp] = find(round(abs(Par_DG(:, 1)))>
Node_max);
      [Lww, idx_lww] = find(round(abs(Par_DG(:, 1)))<
Node_min);
      %impose limits of real power injection
      [UP_Pdg, idx_Ppdg] = find(Par_DG(:, 2)> DGP_max);
      [LW_Pdg, idx_PLdg] = find(Par_DG(:, 2)< DGP_min);
      %impose limits of reative power injection
      [UQ_Qdg, idx_Qpdg] = find(Par_DG(:, 3)> DGQ_max);
      [LW_Qdg, idx_QLdg] = find(Par_DG(:, 3)< DGQ_min);
      if Upp
          Par_DG(Upp, 1) = Node_max;
```

```
        end
        if Lww
            Par_DG(Lww, 1)= Node_min;
        end

        if UP_Pdg
            Par_DG(UP_Pdg, 2) = DGP_max;
        end
        if LW_Pdg
            Par_DG(LW_Pdg, 2)= DGP_min;
        end

        if UQ_Qdg
            Par_DG(UQ_Qdg, 3) = DGQ_max;
        end
        if LW_Qdg
            Par_DG(LW_Qdg, 3)= DGQ_min;
        end

    % Evaluate the new swarm
        %cost = feval(ff,par);    % evaluates cost of swarm
        Cost_all = ObjFun_DG_Placement(m_case17_radial,
Par_DG, popsize,npar);
        cost = Cost_all(:,4);

    % Updating the best local position for each particle
         bettercost = cost < localcost;
         localcost = localcost.*not(bettercost) +
cost.*bettercost;
         localpar(bettercost,:) = Par_DG(bettercost,:);

    % Updating index g
        [temp, t] = min(localcost);
    if temp<globalcost
            globalpar=Par_DG(t,:);
            indx=t;
            globalcost=temp;
    end
          [iter globalpar globalcost]    %#ok<NOPTS> % print
output each
                                           % iteration
         minc(iter+1)=min(cost);          %#ok<SAGROW> % min
for this
                                           % iteration
         globalmin(iter+1)=globalcost;    % best min so far
         meanc(iter+1)=mean(cost);        %#ok<SAGROW> % avg.
cost for this iteration
         Cost_all_Globe(iter, 1) = Cost_all(t,1);
         Cost_all_Globe(iter, 2) = Cost_all(t,2);
         Cost_all_Globe(iter, 3) = Cost_all(t,3);
         Cost_all_Globe(iter, 4) = globalcost;
```

```
end% while


     clf
     subplot(2,2,1)
     plot(Cost_all_Globe(:,1),'--');
     hold on;
     xlabel('Iteration Number');
     ylabel('Ploss [MW]');
     grid on;

     subplot(2,2,2)
     plot(Cost_all_Globe(:,2),'--');
     hold on;
     xlabel('Iteration Number]');
     ylabel('Qloss [MVar]');
     grid on;

     subplot(2,2,3)
     plot(Cost_all_Globe(:,3),':');
     hold on;
     xlabel('Iteration Number]');
     ylabel('VD [p.u]');
     grid on;

     subplot(2,2,4)
     plot(Cost_all_Globe(:,4),':');
     hold on;
     xlabel('Iteration Number]');
     ylabel('Fitness Function [p.u]');
     grid on;

     hold off;
```

```
MATPOWER Version 7.0, 20-Jun-2019 -- AC Power Flow (Newton)

Newton's method power flow (power balance, polar) converged
in 3 iterations.
```

```
function [PlossT, VD] = ObjFun_DG_Placement1(mpcb1, Par_DG,
i)
clc
define_constants
Loc_DG = Par_DG(i,1);
Size_DGP = Par_DG(i,2);
Size_DGQ = Par_DG(i,3);
mpopt = mpoption('pf.alg', 'NR');
mpcb = mpcb1;
DG_New = [Loc_DG    Size_DGP     Size_DGQ     3      -3
      1.0    100    1      999    0      0      0      0      0
      0      0      0      0      0      0      0];
```

```
mpcb.gen = [mpcb.gen; DG_New];
generator = mpcb.gen;
r = runpf(mpcb, mpopt);
Ploss = get_losses(r);
PlossT = sum(Ploss);
Bus_voltage = r.bus(:,VM);
VD = sum(1 - Bus_voltage);

end
```