OPTIMAL PLACEMENT AND SIZING OF DISTRIBUTED GENERATION UNITS IN ELECTRICAL POWER DISTRIBUTION NETWORKS

BY

MOSES IREKEFE AUGUSTINE

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DECLARATION

Student Declaration

This thesis entitled "Optimal Placement and Sizing of Distributed Generation Units in Electrical Power Distribution Network" is my original work and has not been presented for a degree in any other University. However, where other people's work has been used, it has been acknowledged and referenced accordingly. Therefore, no part of this thesis report may be reproduced without the prior written permission of the author and/or Moi University.

Signature: Date: 30th September, 2023

Moses Irekefe Augustine

ENG/MS/SEA/5658/22

Supervisors Declarations

We declare that this thesis has been submitted for examination with our approval as university supervisors.

Signature: Date: 30th September, 2023

Dr. Stephen Talai

Dept. of Mechanical, Production and Energy Engineering

Moi University, Eldoret, Kenya.

Signature: Date: 30th September, 2023

Dr. Lawrence Letting

Dept. of Electrical and Communication Engineering

Moi University, Eldoret, Kenya.

DEDICATION

This work is dedicated to the glory of the Almighty God who is the source of my inspiration and who enabled me by His grace to successfully complete my MSC studies.

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ABSTRACT

The attention of many researchers has recently been on the best ways to integrate Distributed Generation (DG) into conventional centralized electrical power distribution systems, particularly in the context of the smart grid idea. This is due to its reputation as a viable remedy for the lack of electric power supply. To optimize the environmental, financial, and technological advantages of the integration of DG units for distribution network operators, it is crucial to determine their ideal position and size. The main objective of this study was to develop and simulate an optimization system for the placement and sizing of distributed generation units in electrical power distribution networks for power loss reduction and voltage profile improvement. The specific objectives were to model and develop the load flow algorithm and codes; develop a meta-heuristic optimization algorithm and codes that selects the best location and size of the DG unit; simulate the nested load flow and optimization algorithms and codes on MATLAB and analyze the effectiveness of the developed algorithm via testing on the standard IEEE 33-bus radial electrical power distribution benchmark network. The Backward-Forward Sweep (BFS) technique was employed in the load flow modeling because it maximized the radial structure of distribution systems. The optimization algorithm was developed based on the Multi-objective Particle swamp optimization (PSO) meta-heuristic technique due to its effective global searching characteristic. The line and load data for the IEEE 33-bus test network, a cutting-edge benchmark for contemporary power distribution networks; were obtained from the Power Systems Test Case Archive- a secondary data source. For this network fed by a synchronous generator, the chosen base MVA (Mega Volt Amp) was 10 MVA and the base voltage was 12.66 kV. The total active and reactive power demands were 3.715 MW and 2.300 Mvar respectively. The simulation was done on the R2021a version of MATLAB/Simulink. The total real and reactive power losses obtained from base case simulation without the placement of any DG unit in the network were obtained as 201.893 kW and 134.641 kvar respectively while the per unit (p.u) average bus voltage was 0.9485 p.u. After the optimal allocation of one, two, three, and four DG units, the total real power loss (in kW) in the network was reduced by 140.89, 173.89, 189.89, and 195.89 respectively while the total reactive power loss (in kvar) reduced by 86.64, 114.64, 124.64 and 128.64 respectively. Likewise, the per unit average bus voltage improved by 0.0376p. u, 0.0458p.u, 0.0480p.u and 0.0498p.u respectively. Also, the decrease in the total real and reactive power losses and the improvement in bus voltage profiles varies proportionally with the number of DG units optimally placed. In conclusion, the results show that the total real power loss and the total reactive power loss of the network were significantly decreased; and the voltage profile of the system was drastically enhanced by incorporating DG units at predetermined buses. The developed algorithm is recommended for application in a real electrical power distribution network for more efficient integration of new distributed generation units in the current electrical power distribution networks.

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ABBREVIATIONS AND ACRONYMS (NOMENCLATURE)

ADN -	Active Distribution Network
DNOs -	Distribution Network Operators
DERs -	Distributed Energy Resources
PV -	Photovoltaic
SHP -	Small Hydro Power
DG -	Distributed generation
ESS -	Energy storage system
PQ -	Active and reactive power
OPF -	Optimal Power Flow
VSC -	Voltage source convertors
SVCM -	Static voltage characteristic model
PSO -	Particle swarm optimization
IEEE -	Institute of Electrical and Electronic Engineers
NSGA -	Non-denominated Sorting Generic Algorithm
MSA -	Moth–Swarm Algorithm
SFLA -	Modified shuffled frog leaping algorithm
MIDACO -	Mixed Integer Distributed Ant Colony Optimization
ANN -	Artificial Neutral Network
BO -	Butterfly Optimization
BFS -	Backward-Forward Sweep
Pi -	Net real power injection in bus ‘i’
Qi -	Net reactive power injection in bus ‘I’
R_{ij} -	The line resistance between bus ‘i’ and ‘j’
V_i -	The voltage at bus ‘i’

δ_i - The angle at bus ‘i’

$Loss_k$ - Distribution loss at section k

N_{SC} - The total number of sections PL = The real power loss in the system

P_{DGi} - The real power generation DG at bus i

P_{Di} - The power demand at bus i

CHAPTER ONE: INTRODUCTION

1.1 Background of the Study

The integration of Distributed Generation (DG) units within the electrical power grid has grown substantially over the past few decades. Distributed Generation has the potential to be a desirable energy source. They not only make the electricity system more secure and sustainable, but they also open the door to renewable energy sources like wind and solar. Distributed Generation (DG) according to Chiradeja & Ramakumar (2004) "refers to small-scale power generating (typically 1kW to 50MW) that generates electricity at a location closer to clients than central generation plants". DG has recently seen considerable growth in the power sector due to its capacity to utilize renewable energy resources as well as its ability to reduce power loss, improve dependability, and cost-effective investment. Installation of DG units in less-than-ideal sites may increase system losses, which would increase costs and have the reverse of the desired effect (Kroposki et al., 2013). Centralized generation to dispersed generation, with distributed energy resources utilizing renewable are the primary forces behind the current modern electricity grid. Hybridizing a number of the renewable energy sources (RESs) captures the best features of the sources (Barukcic et al., 2021). In centralized distribution system structure, voltage is compromised, equipment stretched beyond operating limit, high power loss and generation failure and hence, Decentralized/Distributed distribution structure for robust power management is required.

Due to its reputation as a viable remedy for the lack of electric power supply, DGs Technology has come to the attention of numerous researchers. Additionally, according to Azizivahed et al., (2019), "correct DG installation improves the voltage stability and profile of the system distribution system, releases line loading, and promotes system efficiency" (p.661). However, the optimal allocation of DGs, also known as finding the right locations and DG sizes, is what will most likely lead to improvements in the aforementioned technical characteristics. For instance, the outstanding placement of DGs in a system distribution must consider many restrictions, for instance power demand, limit of voltage, DG dimension, and ultimate power insert by DGs, etc. in order to reduce active power loss and enhance voltage profile (Georgilakis & Hatziargyriou, 2013).

While installing the DGs in the power network, the nodes of the system, buses, DGs sizes/powers should be chosen based on the best allocation during the planning phase of the project. Following the deployment of the DGs, the projects operational phase is when the best jurisdiction of the controllable DGs products is of concern. There are various methods for solving this optimization problem that take these two components either into account concurrently or separately (Acharya et al., 2006). In addition to this question, there is a problem of research relating to the resolution of the used data input in the optimization mechanism. In general, the problem is more computationally difficult due to the synchronous method and improved data input resolution. There are two methods employed in the research when it comes to modelling the apparatus in the issue of optimization. One method makes use of an analytical model (a set of equations) of the control network, whilst the other utilizes a simulation or replication tool to calculate the intention or objective and restriction functions of the optimization challenge. The analytical technique typically results in the system model having more approximations and ignoring, which reduces how realistically the system is represented. A simulation tool for analysing power system, on the other hand, ensures less neglect, leading to a more accurate modelling of the system (Hung et al., 2010).

To optimize the environmental, financial, and technological advantages of DG units for Distribution Network Operators (DNOs), it is crucial to determine their ideal position and size. The most difficult aspects of power loss reduction DG applications are choosing the right site, size, and operating plans. According to the studies of Atwa, et al., (2010), “in case DG units are sized incorrectly and inappropriately sited, the revert power flow from greater DG units might result in immoderate losses and overburden feeders” (p.360). It is paramount to note that the installation of DG, which prioritizes relationship over aggregation, is fundamentally irrational. Due to this, DG would not provide the system with the intended benefits, and even then, energy generated by centralized units might be a better replacement (Sansawatt et al., 2010). In order to allow for a significant DG penetration, this method should be transformed to active network management. Traditionally, the two basic methods for decreasing power losses are capacitor installation and reconfiguration (Atwa, et al., 2010). DG was presented as an alternate choice that is more desirable in every way for DNOs during the past ten years. Since the optimum DG allocation, reconfiguration, and capacitor placement are nonconvex problems, the presence of local optimum may hinder the convergence of the global optimum. A number of meta-heuristic techniques can effectively solve this issue.

A properly sized and located DG can have a variety of positive effects on the power system, including a decrease in overall power losses and an improvement in power quality characteristics including frequency, standard voltage wave, and voltage profile (Pandey, and Arora, 2016). The advantages depend on how well-installed the units of DG are in the distribution system. However, placing the units of DG in the wrong place and oversizing them might result in unanticipated problems with the power system, including harmonic distortion, power loss, fault current, voltage flicker, and voltage sags. Additional research on the distribution power network has revealed various effects of DG deployments on power systems. By installing the appropriate DG units, for example, overall power loss might be drastically cut and reduced to 13% (Sahib et al., 2017). According to (Sadeghian et al., 2017), “In order to prevent economic harm and voltage collapse, respectively, power loss reduction and improved voltage stability are crucial components of power system operation”. As a result, study is required to identify the best location and size of the units of DG in the distribution network (Khorasany & Aalami, 2016). Power flow calculations are also the foundation of optimal distribution generation integration. The calculation of power flows is a crucial component of optimization since all variables must be redone using the fresh parameters.

The main goals of the majority of methods used to identify the outstanding location and size for the units of DG have been voltage advancement and power loss deduction. One of the most effective and well-liked techniques is Particle swarm optimization (PSO) (AlRashidi and El-Hawary, 2009). In this research, The Backward-Forward Sweep (BFS) technique was used for the load flow calculation and a very flexible adaptive multi-objective Particle Swarm Optimization (PSO)-based optimization system which was able to select the best size and location for the placement of DG units has been developed. When simulated on MATLAB/Simulink and applied on a standard IEEE 33-bus radial electrical power distribution benchmark network, the developed optimization system was capable of decreasing the overall power losses while keeping each bus voltage in a predetermined scope. Also, the maximum positioning of single and multiple DG units was considered for performance comparison and the proposed algorithm could accommodate the placement of three distinct DG kinds discussed in the literature and also up to 4 DG units.

1.2 Problem Statement

The optimal integration of distributed generation units into the conventional electrical power systems (particularly in the context of smart grid idea) and the subsequent management of electricity from them; has been of concern to many researchers over the past few years. Due to its reputation as a viable remedy for the lack of electric power supply, DG Technology has come to the attention of numerous researchers. Additionally, the reduction of overall power in an Active Distribution Network depends on the size and location of DG units and correct installation of DG units improves the voltage profile and stability of the system distribution, releases line loading, and promotes system efficiency. However, the maximum allocation of DG units, also known as finding the right locations and DG sizes, is what will most likely lead to improvements in the aforementioned technical characteristics. To reduce active power loss and enhance voltage profiles, for example, an optimum allocation of DGs in an electrical power distribution system must take into account different limitations, including power demand, limit of voltage, DG size, maximum power injection by DGs, etc. Hence, the need to develop an adaptive optimization technique for the optimum placement and sizing of distributed generation units in the electrical power distribution network for power losses deduction and voltage profile advancement.

1.3 Research Main Objective

To develop and simulate a multi-objective optimization system for the sizing and placement of Distribution Generation (DG) units in electrical power distribution networks for power losses reduction and voltage Profile improvement.

1.4 Specific Objectives

To achieve the main aim of the study, these specific objectives were set:

i. Formulate the optimization objective functions and constraints for the total power losses and voltage profiles;

ii. Model and develop the load flow algorithm and coding based on the Backward-Forward Sweep (BFS) load flow strategy to identify the power flow and power losses;
iii. Develop an adaptive multi-objective meta-heuristic Particle Swarm Optimization (PSO) strategy to determine the optimal location (s) and size(s) of the DG(s);
iv. Apply and simulate (evaluate) the nested load flow and optimization algorithms in a standard IEEE 33-bus radial electrical power distribution benchmark network;
v. Examine the effectiveness of the developed optimization system in terms of aggregate power losses deduction and voltage profile advancement or improvement via performance analysis and comparison with the previous studies.

1.5 Justification of the Study

A properly sized and located DG can have a variety of positive effects on the power system, including a decrease in overall power losses and an improvement in power standard and quality characteristics including voltage profile, standard voltage wave, and frequency (Pandey, and Arora, 2016). The advantages depend on how well-installed the units of DG are in the distribution system. However, placing units of DG in the wrong place and oversizing them might result in unanticipated problems with the power system, including, voltage sags, power loss, fault current, voltage flicker, and harmonic distortion. Additional research on the distribution power network has revealed various effects of DG deployments on power systems. By installing the appropriate DG units, for example, overall power loss might be drastically cut and reduced to 13% (Sahib et al., 2017).

The main goals of the majority of methods used to identify the outstanding location and size for units of DG have been voltage advancement or improvement and power loss deduction. One of the most effective and well-liked techniques is Particle swarm optimization (PSO). Hence, the need them to formulate an adaptive PSO based optimization system capable of demonstrating the best DG position at the lowest possible cost and identifying the best DG units with the goal of decreasing overall power losses while keeping the voltage at each bus within a predetermined range.

1.6 Research Scope

The developed optimization system in this research is applicable only to the optimal placement of Distributed Generation such as hybrid solar Photovoltaic (PV), Small Hydro Power (SHP), fuel cells, micro turbines, gas turbines and geothermal generation coexisting with the Energy Storage System (ESS). It entails the development of a very flexible and robust adaptive multi-objective particle swamp optimization-based meta-heuristic technique for optimal allocation of the above-mentioned DG types in the conventional electrical power distribution system with a view of voltage improvement and power losses reduction. The overall implementation steps involved problem formulation and modelling, load flow modelling and optimization, MATLAB Codes development and Simulation and testing on standard IEEE 33-bus radial electrical power distribution system benchmark network for performance analysis. No hardware implementation and experiment are assumed to be present in the Active Distribution Network (ADN).

1.7 Thesis Outline

Chapter 1: Is an introduction that describes the background of the research, highlights the problem statement, lays out the goals and objectives, motivation for the research, scope and contribution to knowledge and outlines the thesis.

Chapter 2: This contains a comprehensive review of the theoretical frameworks of the research background and critical review of previously done related works. Some background information regarding various optimization techniques with regard to power systems in electrical power system networks is reviewed. The ideology of heuristic and non-heuristic algorithms was also covered. It also offers a summary of a few analytical tools employed by such algorithms.

Chapter 3: The system implementation which entails the problem formulation, load flow modelling, algorithm development steps and flow charts, coding, benchmark case network, data collection methodology is described in depth, including the simulation tool, the optimization method, and the load flow methodology employed.

Chapter 4: The nested load flow and optimization algorithms and codes were simulated and applied to a standard IEEE 33-bus radial electrical power distribution benchmark system network. The system's results were acquired, discussed and analyzed and the performance was examined and assessed in light of the best outcomes.

Chapter 5: This is the concluding chapter that presents the findings of the result analysis and discusses useful recommendations for prospective and forthcoming research.

CHAPTER TWO: LITERATURE REVIEW

2.1 Brief Definition of Active Distribution Network (ADN)

A local power source that is connected to the distribution network and used on a small scale is referred to as "Distributed Generator (DG)”. The concept of Distributed Energy Resources (DERs) refers to the connection of distributed generated electricity and controllable loads to power distribution networks (Injeti & Thunuguntla, 2020). The electrical Power distribution network has become active with the aggregation of Distributed Generation and hence is referred to as “Active Distribution Network (ADN)”.

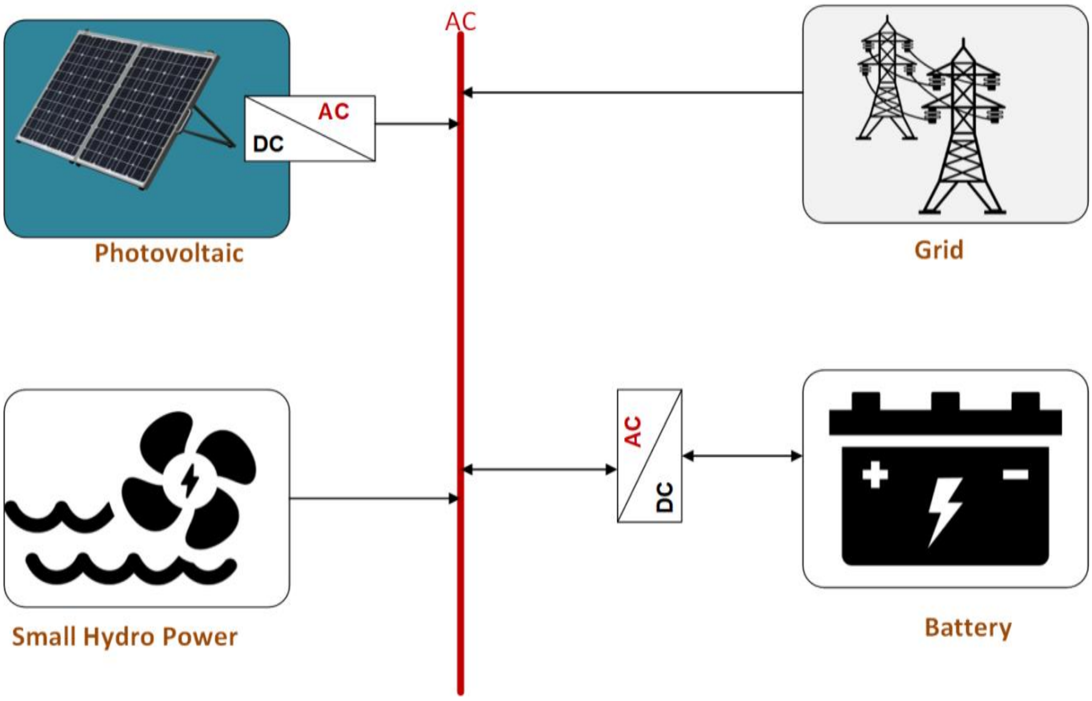

Figure 2.1: Active Distribution Network (ADN) with two Renewable Energy Sources (RES) and Storage Unit (Yang, 2019).

Table 2.1: Comparison between Centralized Generation and Distributed Generation (Shomefun et al., 2018).

S/N	Centralized Generation	Distributed Generation
1	Centrally located	It is not location bound-It is distributed
2	Specific site of installation	It can be installed anywhere in which energy source is present
3	Excellent economies of scale	Small-scale power generation technologies (in the range of 1 kW to 500 MW)
4	Transmits electricity over a long distance	Transmits electricity over a short distance
5	Negatively affects the environment	Environmentally friendly
6	It is part of the grid	It can be isolated or integrated into the grid
7	Basically, gas and hydro turbines	The technologies adopted in DG comprise small gas turbines, micro-turbines, fuel cells, wind and solar energy, biomass, small hydro-power etc.

2.2 Connection Schemes of Electrical Power Distribution System

A system with constant voltage distributes electrical energy throughout the entire system. The following distribution circuits are typically utilized in real life.

2.2.1 Radial System

In this system, different feeders supply the distributors only at one end and radiate from a single substation. In the single-line schematic of a radial system for Direct Current (DC) distribution depicted in Figure 2.2 (i), a feeder OC feeds a distributor AB at point A. The distributor is obviously fed solely from one end, in this example point A. A single-line diagram of the radial system for distributing Alternating Current (AC) is shown in Figure 2.2 (ii). The radial system is only utilized when low voltage power is generated and the substation is located in the middle of the load (Zhang and Wu, 2007).

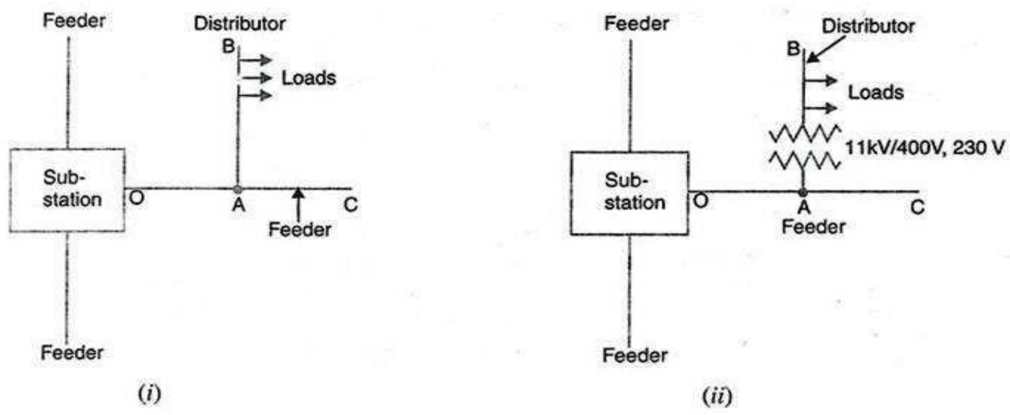

Figure 2.2: Radial Distribution System for DC (i) and AC (ii) (Zhang and Wu, 2007)

This is the least expensive distribution circuit and also the simplest. Hence, it has these shortcomings:

i. The distributor end that is closest to the feeding point will have a heavy load.

ii. All of the consumers are served by a single feeder and distributor. As a result, any issue with the feeder or distributor interrupts supply to the customers who are on the side of the fault that is opposite the substation.

iii. When the load on the distributor changes, the customers at the far end would experience significant voltage variations. This technique is only used for short distances as a result of these restrictions.

2.2.2 Ring Main System

In this arrangement, a loop is made by the primaries of the distribution transformers. The loop circuit departs from the bars of the substation bus, round the area of service, and then comes back to the substation. Figure 2.3 depicts the diagram of the single-line of the ac distribution ring main system that the substation feeds to the closed feeder LMNOPQRS. The distributors are tapped from various locations M, O, and Q of the feeder through distribution transformers (Zhang and Wu, 2007).

The advantages of the ring main system are:

i. Consumer terminal voltage instabilities are lessened.

ii. The system is exceptionally trustworthy due to the fact that each distributor is fed by two feeders. Even if a component of the feeder fails, the supply continues to flow. Consider, for instance, that a flaw appears at any point F along feeder section SLM. The feeder section SLM can then be turned off for maintenance while still giving all clients uninterrupted service via feeder SRQPONM.

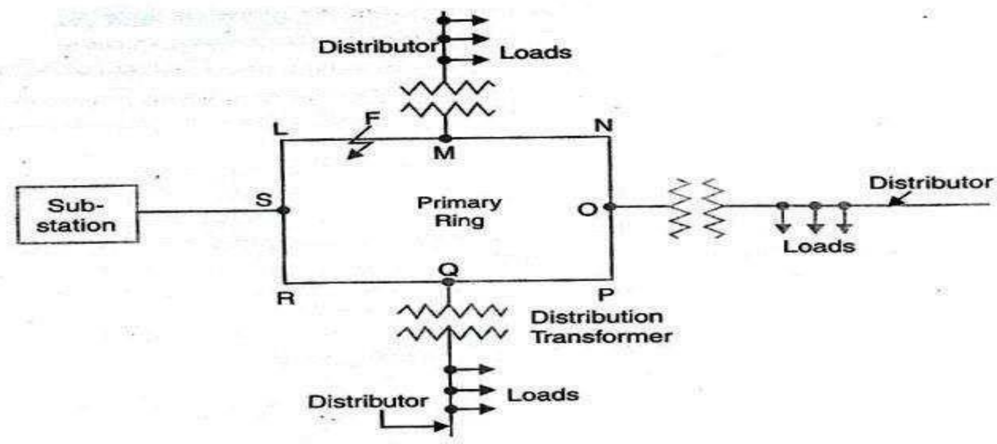

Figure 2.3: Ring Main System (Zhang and Wu, 2007)

2.2.3 Interconnected system

When the feeder ring is powered by two or more producing stations or substations, the system is said to be interconnected. Figure 2.4 depicts the single-line diagram of a networked system that has two substations, S1 and S2, located at locations D and C, respectively. Using this technique, the closed feeder ring ABCD is provided. The feeder ring points O, P, Q, and R are connected to distributors by distribution transformers (Zhang and Wu, 2007)

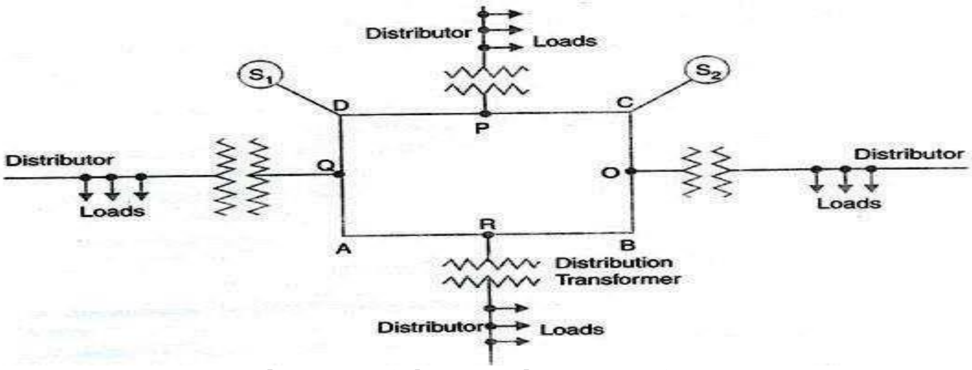

Figure 2.4: Interconnected System (Zhang and Wu, 2007)

The following are some advantages of interconnected system:

i. It enhances the dependability of the service.

ii. Any area served by one generating station during climax load hours may also be supplied by the second generating station. As a result, the reserve power capacity is reduced and the system efficiency is increased.

2.3 Distributed Generation Location and Size Problems

2.3.1 Technical Problems

Power loss is one of a power network most crucial feature. Figure 2.5 depicts a 3D plot of power loss versus position to show the importance of optimum size and placement. It demonstrates how the loss depends on where distributed generation (DG) is located. It is not advisable to install as much capacity as feasible within the network since, for a given bus, increasing DG capacity results in losses decreasing up to a point before climbing again and may be exceeding the original losses (Acharya et al., 2006).

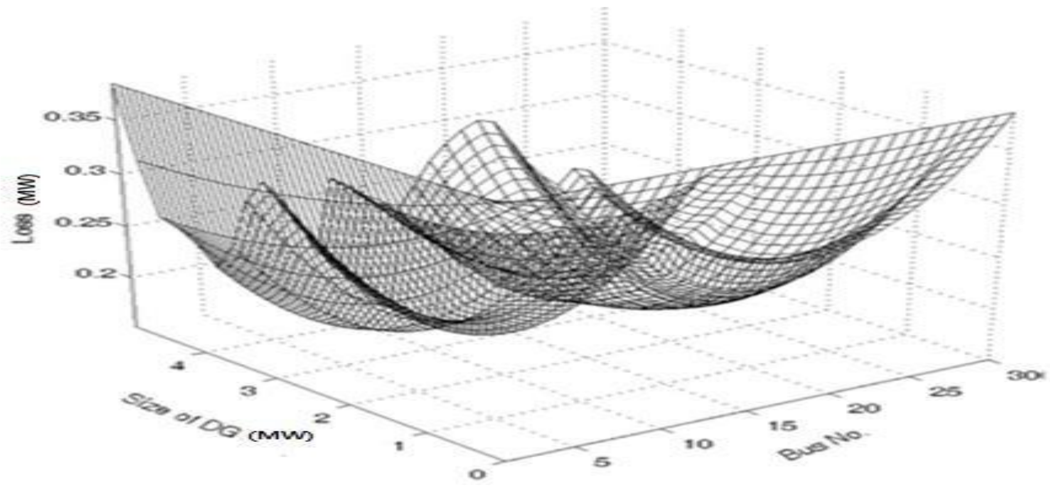

Figure 2.5: The influence of the DG's size and location on system loss (Acharya et al., 2006).

The aggregate amount of extra DG deployed to the network offers another problem in the optimization process because enhancing the DG penetration level or enhancing the DG capacity is the main goal of numerous developers and distribution network operators (DNO) (Harrison &Wallace, 2003). As a result, there could be an increase in voltage or a spike in the fault level. Because the installation of DG can change these elements, it is vital to make sure that the modification of the fault current amplitude, length, and direction has no impact on how well protective device function. (Celli & Pilo, 2001). Due to newly constructed infrastructure like substations, the network structure may alter during these years. Since it is extremely difficult to review all conceivable network configurations to identify the ideal point because of this dynamicity, the network structure is taken for granted that it will not change during the planning phase. The direction of electricity flow is another effect of distribution generation. DG will change the distribution system power flow, making it impossible to continue to think of it as a system with unidirectional power flow. As a result, it is no longer accurate to assume that power moves in a single direction (Borbely and Kreider, 2001; Jenkins et al., 2000). This will have an effect on how the power distribution system is managed and run. As a result, more research into how new DGs affect distribution networks should be taken into account.

2.3.2 Problems with Exhaustive Calculations

Any specific technical problem covered in Section 2.3.1 can be approached using heuristic strategies, such as voltage rise. These algorithms look for data in the area matching to the placements and capabilities of potential distribution network-connected DG plants. They are exhaustive in terms of computation. The computational burden of the exhaustive analysis is significantly increased when numerous connections and the irregularity of demand and generation are taken into account, even though computationally intensive extensive methods applied to a connection estimated for a particular demand and generation scenario are not always the case (Keane et al., 2013).

2.4 Non-linearity Issues with the Electrical Power System

Through the use of solution strategies, the DG maximum allocation problem is recognized as a mixed integer nonlinear optimization issue. Often, this entails maximizing system voltages or lowering cost and power loss. The criteria for each type of application are different. The algorithm must take into account more objectives and constraints, which necessitates the usage of more data and increases the difficulty of the non-linear implementation (Abu-Mouti & El-Hawary, 2011). Some optimization strategies, for instance, the loss sensitivity factor, where a portion of the buses is not taken into account, may miss the optimal position. Figure 2.6 provides an example of this concept.

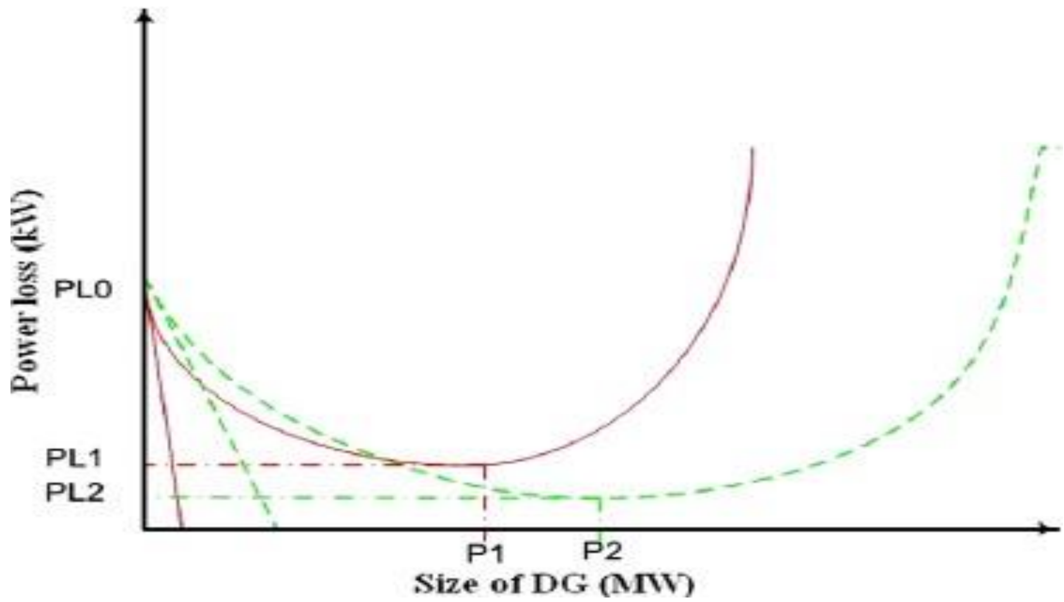

Figure 2.6: Non-linearity in loss curve (Acharya et al., 2006).

2.5 Distributed Generation (DG) Sizes

DGs can also be described in terms of their capability, claims (Ackermannet al., 2001). There is agreement that because to technical limitations, DG capacity cannot exceed 100–150 MW, hence they are split into four size types:

(i) Micro distributed generation ranges from 1 to 5 kW.

(ii) Low-power distributed generation: 5 kW and 5 MW

(iii) Medium distributed generation is from 5 to 50 MW.

(iv) Large distributed generation is from 50 MW to a maximum of 150 MW

Micro-turbines, for instance, fall within the category of small dispersed generating. Their scale has a volume of 0.4 to 1 cubic metre (El-Khattam and Salama, 2004).

2.6 The Effects of Distributed Generation (DG) on Power Losses and Voltage Profile

2.6.1 Voltage Profile

Since it has been shown that the penetration of DGs in the distribution system may result in over-voltages or under-voltages, the question of how far this assertion is valid is raised. DGs are meant to assist and enhance the system voltage. Additionally, some DG technologies, like photovoltaic and wind turbines, change their output power level gradually. Voltage fluctuations as a result lead to a decline in the quality of the electricity supplied to users (Vitaet al., 2015). The discordance of DGs with the current voltage control techniques has also been found to cause over-voltages and under-voltages in distribution networks incorporating DG. Voltage regulators, capacitors, and altering the tap on transformers are the main tools used to control distribution networks. These techniques, which were created for radial (unidirectional) power flow, have a history of being exceedingly dependable and effective. Thus, due to the meshed (bidirectional) power flow that DGs introduced to the networks, their installation in distribution networks has had a significant impact on the performance of voltage control methods today. On the other hand, because distribution networks support reactive compensation for voltage control, regulation of frequency, and serve as spinning reserves in the event of main system fault indices, the introduction of DG has had a favourable effect on them.

2.6.2 Power Losses

Due to their placement close to the load centres, DGs have proven to be able to reduce distribution networks' power losses (both real and reactive). Numerous studies, the majority of which were previously reported, showed that the location and size of a DG unit are crucial factors in the deduction of power losses (Nieto et al., 2016; Ceakiet al., 2017).

The capacitor allocation procedure, which aims to deduce power losses, and the DG allocation process are quite similar. The key distinction between the two processes is that, in contrast to capacitor banks, DG units have an impact on both actual and reactive power. It has been demonstrated that installing a relatively small DG unit and prudently connecting it to the network can significantly reduce power losses in networks with elevated power losses (Nieto et al., 2016; Ceakiet al., 2017).

2.7 Load and Generation Modelling

Modelling the generation of electricity load is crucial for managing electrical power systems. Either constant power or constant impedance can be used to model loads. In Ochoa et al. (2006) papers, load is modelled as a steady power and represents the highest and lowest load demand in two distinct scenarios. However, the load modelling does not take into account variations in load levels over time. Time variations load modelling approaches give the analysis of load (and also generation) hourly intervals for the horizon of a year or longer. It produces 8760 analysis intervals each year as a result (Ochoa et al., 2008). In order to overcome the load and generation uncertainty across an annual horizon, mathematical and analytical modelling is used. Deterministic load modelling and probabilistic load flow (PLF) are two commonly used methodologies in distribution generation operation and planning.

2.7.1 Deterministic Load Flow (DLF)

There are several literary works that make use of the static load condition. Numerous load situations, including peak load (Zou et al., 2012), could be taken into account because the load on the distribution system changes throughout the day. This load pattern scenarios each consider a single load point. The conditions on which the optimization is based on the work of (Khalesi et al., 2011) are light, average, and peak load levels. In order to address system security, a worst-case scenario is defined as a full capacity generation at the point of lowest load (Ackermann et al., 2001).

2.7.2 Probabilistic Load Flow (PLF)

Probabilistic Load Flow (PLF) was developed as an alternative to Deterministic Load Flow, which determines system states and power flows by using precise estimates of power generation and load demands from a selected network design. The notion was first created in the 1970s (Borkowska, 1974), and the uncertainties are considered as input random variables with probabilistic density functions (PDF) or cumulative density functions. (CDF). The output states are estimated as random variables when using PDFs or CDFs. In order to evaluate the effects of renewable energy sources, PLF is used to examine how the distribution network functions and makes plans in the face of unpredictability. Based on Cui and Franchetti (2013), branch flows are considered to be linearly coupled and active and reactive power to be independent of one another. Additionally, a normal distribution and a discrete distribution, respectively, are expected for the load and generation. In another way, variable generation is handled as a discrete random variable in traditional generation whereas dispatch and grid configurations are treated as continuous random variables (Williams & Crawford, 2013). The PLF can be worked out numerically, i.e., using a Monte Carlo (MC) methodology, analytically, i.e., applying a convolution method, or a combination of them in order to create PDFs of stochastic variables of system states and line flows (Chen et al., 2008). Analytical PLF is less precise than mathematical methods like MC because it makes linear assumptions

2.7.3 Distributed Generation (DG) Modelling

According to Tafreshi and Mashhour (2009), "depending on the kind of DG and type of interface to the network, the connection bus of the DG is either represented as a Photovoltaic (PV) bus, an Active and Reactive Power (PQ) bus, or a Static Voltage Characteristic Model (SVCM) in power flow studies". DGs can be directly connected to the grid using synchronous or asynchronous generators, power electronic connections, or both. The operating principle and kind of the DG unit determine the control strategy for the inverter and electrical machine. Variable reactive power and a different voltage value may be present in each repeat of the PV bus. In the power factor control mode, the PQ bus can inject a specific value of P and Q into the grid or separately change P and Q. The constant PQ model is often found to be sufficient for distribution system load flow analysis (Farag et al., 2011; Eminoglu and Hocaoglu, 2005). It should be mentioned that the IEEE standard 1547 advises against the DG units controlling the voltage at the installation bus. The simplest way to depict DG-units while they are operating in parallel with the system is by negative load modelling, which injects both active and reactive power regardless of the terminal voltage. DG is modelled as a negative load in this study.

2.8 Distributed Generation (DG) Types and DG Injection Model

In the power grid, distributed generation (DG) provides electricity. Some of its distinctive characteristics are small, compact, and clean electric power generating units that are placed at or near an electrical load (client) (Mistry and Roy, 2014). Some DGs, such compound heat and power (CHP), are not totally clean and are referred to as conventional DG in some publications. On the other hand, more contemporary DGs like solar or wind turbines, which are fully ecologically friendly, belong under the second group. Technically speaking, DGs are divided into various sorts based on their capacity or type of injection. Based on their terminal features in terms of their ability to deliver active and reactive power, DG may be divided into four major types (Hung et al.,2010):

Type 1: These are DG equipment that can only produce Real (or Active) Power (P), such as fuel cells, solar panels, and microturbines. Reactive power (Q) can be produced or consumed with real power generation by a fuel cell, microturbine, and PV array with a four-quadrant inverter, it should be noted.

Type 2: These are DG units that can only produce Q, like gas turbines. Since there is no need to produce any actual electricity, gas turbine generators behave as a synchronous condenser in this scenario.

Type 3: These are DG units that can generate both P and Q. Voltage Source Converters (VSC) and DG units based on synchronous machines are included in this group. Synchronous machines serve as the foundation for Type 3-DG units for small hydro, geothermal, and mixed cycles. The DG with the synchronous generators can be modelled using either continuous terminal voltage control (voltage control mode) or constant power factor control (power factor control). PQ nodes stand for power factor control mode DGs, while PV nodes stand for voltage control mode DGs.

Type 4: These are DG machines such as induction generators used in wind farms that have the ability to generate P but absorb Q.

2.9 Load Flow Methodologies in Electrical Power Distribution Networks

The computation of the voltages at each node and the currents at each branch is made possible through load flow analysis, which is a vital task in the regulation of power systems (Chiradeja and Ramakumar, 2004). The results of the load flow approach hold significant knowledge about the power system; without it, many analyses would not be possible. Utilizing load flow techniques lessens the requirement for extra power system investments in communication and sensor infrastructure. Several technologies that track, analyse, and manage the power system also provide load flow results. Numerous power system applications, including distributed generator and capacitor placements (Kroposki et al., 2013), economic dispatch, power quality enhancements, network reconfiguration and service restoration, power systems optimization, among others, use load flow analysis directly or indirectly (Zhenquan et al., 2018). For the analysis of power flow in both distribution networks and transmission networks, many load flow techniques have been developed. Backward/Forward Sweep (BFS) and Direct Load Flow (DLF) methods are two of the power flow analysis techniques frequently employed in distribution networks. In power transmission systems, the Newton Raphson method, Gauss method, and fast-decoupled method are frequently utilized (Yadav and Srivastava, 2015; Parizad et al., 2010; Injeti and Kumar, 2011). Due to the high resistance (R) to reactance (X) ratio in distribution networks, the load flow techniques utilised in a power transmission network might not function effectively there. The Newton-Raphson approach for distribution networks applications has been improved by a small number of researchers, but it still takes a long time to compute (Yadav and Srivastava, 2015). The backward/forward sweep suggested by is effective for power distribution systems, but when used in operations involving networks with dynamic topological structures (such as network reconfiguration challenges), it necessitates node or branch renumbering (Shaaban and Petinrin, 2013). Such methods, such as capacitor placement in a radial distribution network or optimal dispersed generation placement, are effective for static networks when the network topology remains constant (Acharya et al., 2006).

2.10 Voltage Stability in Electrical Power System

The distribution system steady-state and dynamics are brought about by DG integration. This effect was covered in Section 2.4.2. However, one of the most detrimental interruptions to the power system is a network voltage instability issue. Most DGs cannot create reactive electricity as of Section 2.8 As a result, they are unable to support voltage stability in a dynamic condition. As a result, voltage stability limits must be taken into account while developing and running distribution systems (Gareh, 2012). Modern power systems are run close to their security limits; therefore, voltage stability has become fairly crucial. Therefore, one of the most crucial factors to take into account when planning distributed generating is voltage stability. Voltage stability is the ability of the system to keep the voltage at a certain level while transferring both active and reactive power (Abdel-Akher et al., 2011).

Voltage stability comes in two different varieties. Short-term (transient) voltage stability is limited to a few seconds, while long-term (steady state) voltage stability lasts up to several minutes. The majority of optimization discussions centre on long-term voltage stability. The phrase "voltage collapse" describes a condition in which the system is unable to maintain the voltage and is valuable for warning of potential voltage collapses (Bollen and Fainan, 2011). When a deeper comprehension of voltage stability issues is needed, dynamic analysis becomes more important. In order to identify the buses in radial networks that are most susceptible to voltage collapse, a voltage-stability index was proposed in DG planning in (Chakravorty and Das, 2001). In order to account for the effects of aggregated DGs on the voltage security of a transmission grid, bus indices are developed in (Gil et al., 2009) based on the voltage stability margin (VSM), which is based on the P-V curve idea. The following Section 2.11.1 will cover the P- V idea. A technique based on voltage sensitivity is proposed to identify the best locations for DGs. The network nodes are ranked according to their readiness to receive new generations using the voltage sensitivity index (VSI). (Willis, 2004) anticipated that, “subject to security restrictions, generators can connect to any point in the network and are not geographically constrained by existing protection devices or generator controllers”.

2.10.1 P-V Analysis

In the analysis of voltage stability in power systems, PV analysis is a frequently used graphical technique. The active power (P) can either reflect the power flow via an interconnection between two regions or the overall active power demand in that area. The state variable (V) represents the voltage at a given bus. The P-V curve is created by increasing the load demand and addressing the new power flow. (Hedayati et al., 2008). Figure 2.7 depicts how a DG affects a bus voltage stability.

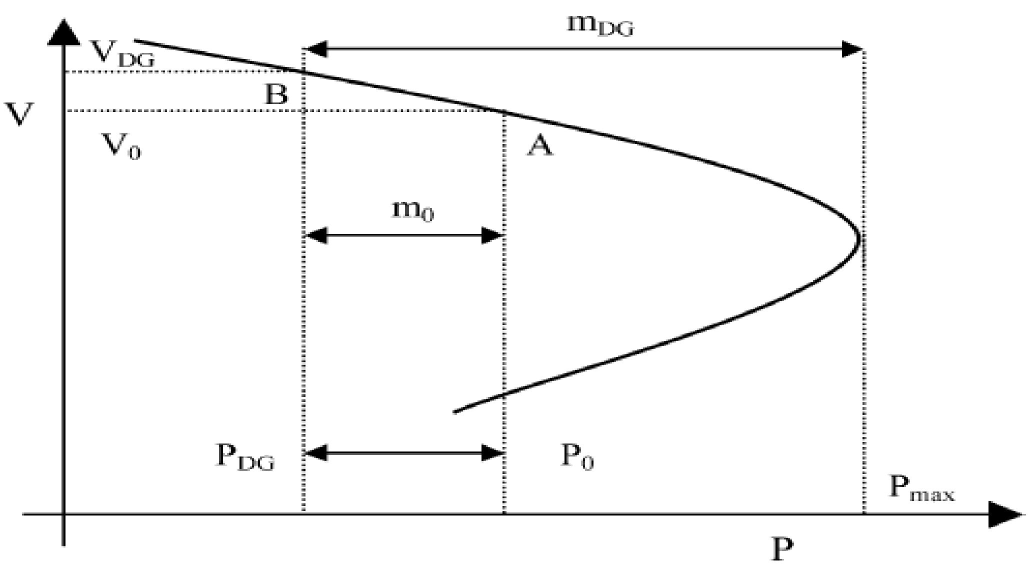

Figure 2.7: Enlargement of voltage stability margin on the P-V curve (Hedayati et al., 2008).

2.10.2 Continuation of Power Flow

The analysis of power-flow continuation is used in certain research to determine the best location for DG units in distribution networks (Cañizares, 1998). Following that, an objective function and iterative algorithm will be used to install the DG units with a specific capacity in these buses. The voltage collapse points or maximum loading in this procedure is determined using the continuing power-flow method. Obtaining voltage profiles of crucial buses in relation to their loading situations allows for the evaluation of voltage stability investigations. PV curves offer insightful data about how the system behaves under various loads. It has been utilized by the electric power sector to identify voltage stability margins and regions at risk of voltage collapse (Aly & Abdel-Akher, 2012).

2.10.3 Modal Analysis

Gao et al., (1992) proposed modal analysis. It can be used to determine the features of instability and to locate the ideal locations for load-shedding, reactive power compensation, and generator re-dispatch programs. The power flow Eigenvalues and Eigenvectors are calculated as part of the modal analysis. Jacobian These measurements are used to pinpoint voltage collapse-prone buses just before it occurs. It also includes information on the loads that caused the voltage breakdown. Contrary to the continuation of power flow, there is no need to subject the system to maximum stress when a modal analysis is used (Ajjarapu, 2006).

2.11 The Concept of Multi-Objectiveness in Optimization

Specific objective optimization produces optimal results for a single aspect, which the utilities may not find satisfactory (Nangia et al., 2005). As a result, multiple approaches must be used to fix the issue (Wadhwa and Jain, 1990). There are several benefits of using Multi-objective Optimization (MO) approaches. It enables the administration of many objectives and facilitates the decision-making process at the conclusion of the optimization or before to starting it (Berizzi et al., 2001). On the other hand, due to inherent conflicts between them, many objectives might not be optimized at once (Abou et al., 2007). There are typically three ways to approach multi-objectiveness when trying to solve this issue.

2.11.1 Programming using Priorities

This tactic is based on tried-and-true techniques for producing trade-off surfaces. Once the objectives are merged into a single parameterized objective function, trade-offs are generated based on the weighting factor values (Abou El-Ela et al., 2007). (Nangia et al., 1998) used the weighting approach to combine the cost of generation function and system transmission losses in order to investigate the relationship between each objective and its weight component in an optimal power flow problem. In the paper by (Yun et al., 2005), writers used a goal programming simplex extension of the simplex to solve a voltage control problem by prioritizing the control objectives. To improve the dependability and stability of a power system functioning, certain goals, such as altering the reactive power of generators, are taken into consideration. The authors of the article (Abou El-Ela et al., 2010) used weighting criteria to attain the overall maximal composite advantages of increasing DGs. Priority goal programming is a straightforward and efficient technique, however if prior weight assessment is to be applied, extensive sensitivity analysis is needed (Nangia et al., 1998).

2.11.2 Sequential Goal-Achieving Programming

The master objective function in this strategy is one single objective function. The most essential objective is typically this one, thus it is minimized first (Nangia et al., 2005). The additional constraints are applied to the other goal functions, which are regarded as slaves. Then, within a predetermined range, the master objective function is released to optimize a different slave objective function (Abou El-Ela et al., 2007). Until all of the objectives have been taken into account, the process is repeated. In their work (Nangia et al., 2005), the multi-objective optimal power flow (MOPF) problem (SGP) was solved using sequential goal programming. Based on the order or objective minimization, six various scenarios are taken into account, including generation, system transmission losses, and environmental contamination. Based on a regret analysis, the ultimate course of action is chosen.

2.11.3 Multi-Objective Pareto-based Algorithms

Since there is no single optimal solution for Pareto-based multi-objective programming that simultaneously maximizes all of the objective functions, it is also referred to as a non-deterministic technique (Haji et al., 2013). In these circumstances, the decision-makers search for the ideal course of action. Pareto optimality is used in place of optimality in this approach (Aghaei et al., 2012). In Pareto-based multi-objective algorithms, all objectives are optimized simultaneously, and solutions that are not dominated by another solution are chosen and shown in an n-dimensional space, where n is the total number of objectives. In other words, this method directly addresses the multi-objective problem by using different objective functions, producing an optimal set of points (Pareto frontier) (Shaaban and El-Saadany, 2014).

2.12 The Concept of Heuristic and Non-Heuristic Optimization Techniques

Numerous techniques have been used to integrate renewable energy sources optimally. Numerous formulations have been solved using a combination of search-based methods, calculus-based methods, and these two approaches alone. Non-heuristic methods include calculus-based ones like linear programming. While their locations are fixed, these optimization techniques regard the DG capacities as continuous variables (Jabr and Pal, 2009). A review of the various techniques used up until this point is presented in this section. Heuristic (conventional) and non-heuristic optimization fall under two broad groups. Conventional, classical, or derivate-based optimization are other names for non-heuristic optimization. To find the optimal solution, methods like gradient operators in a single path search are used in this class. Examples of non-heuristic algorithms include interior-point approaches, linear and non-linear programming, and quadratic programming. (Farhat and El-Hawary, 2009).

As the size of the power system network grows, mathematical models for optimization problems could become so complicated that other deterministic techniques and the traditional optimization methods might not be applicable to them. An alternative is to implement the answer using a new class of optimization methods called “heuristics” (Grenville et al., 1996). According to Grenville et al. (1996), the term "heuristic” refers to “algorithms that mimic particular natural characteristics, such the ant colony optimization algorithm or the genetic algorithms use of the notion of evolution through selection and mutation” (Grenville et al., 1996).

- **Characteristics of Heuristic Algorithms**

The overall optimal solution should be accurately (stochastic) estimated by a heuristic. A well-behaved heuristic can withstand changes in the problem characteristics. It implies that the entire class of problems, not just one particular problem, should be addressed. A heuristic may be stochastic despite its name and not contain subjective components, which is a key characteristic of such algorithms (Grenville et al., 1996)

Table 2.2: Classification of Heuristic Optimization Techniques (Irrisari et al., 1997).

Trajectory Heuristic	Population Based Heuristic
Simulated Annealing	Genetic Algorithm
Threshold Accepting	Differential Evolution
Tabu Search	Ant colony
Hill Climbing	Particle Swarm Optimization
Greedy randomized adaptive search Procedures	Scatter search
Variable neighborhood search	Path re-linking
Iterated local search	Artificial bee colony optimization

2.13 Particle Swarm Optimization (PSO) Technique

An optimization method called particle swarm optimization is based on how swarms move and function. PSO approaches problem-solving with the idea of social interaction. Russell Eberhart, an electrical engineer, and Kennedy, a social psychologist, created it in 1995 (Kennedy and Eberhart, 1995). The social structure or system model of a simple organism called a particle swarm causes a group to get together for a specific purpose, like seeking for food. Including the largest possible percentage of people in a group engaged in similar activities is crucial. The collective behavior of the species is demonstrated by bee swarms, fish schools, and flocks of birds, for example.

A smart algorithm based on biological evolution is called PSO. Every member of the population is referred to as a particle, which stands for a prospective answer to the optimization issue. And the placement of the food is thought to be the overall best choice. In the solution space, each individual searches for the global optimal solution, and each particle has a fitness function value and speed that it can use to change its own direction of motion. All atoms in the population have the ability to remember things, so while they are hunting for food, they may change their own position and the best position they have ever been in. In order to achieve the goal of locating food, each particle uses continual learning to determine both their personal optimal location and the optimal position for the entire population, leading to access to the food. In other words, particles are capable of social learning and self-perception (Prommee and Ongsakul, 2008).

A hunter who is a bird suspect to a particle is depicted in figure 2.8. All bird groups will fly in the same direction when hunting for victims, with the leader of each group being the bird closest to the victim with the lowest distance and best fitness. Fitness value consideration will make use of the particle swarm model. The particles stand for fitness-valued solutions. Additionally, a crucial characteristic in the pursuit of food by birds, for instance, is the utilization of each particle velocity to determine the direction of its motion. Following that, all of the flock particles would improve their directions in accordance with the best particle direction fitness. Thus, the outcome of this procedure aids in choosing the best course of action.

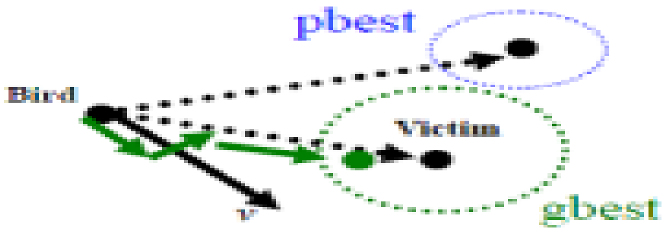

Figure 2.8: Bird searching for food with PSO (Prommee and Ongsakul, 2008).

PSO uses a swarm of particles to scan the search space in quest of the best solution. Each particle is represented by a velocity vector v that updates the current position and a vector s of length n that represents the particle position. As a result, each particle is able to modify its flight in response to its own and other particles flying experiences. The best result (fitness) that each particle has so far is related to the coordinates in the solution space that each particle has recorded. This value is best, often known as pbest. Another best value that the PSO monitors is the best value so far attained by any particle in the neighborhood of that particle. The name of this value is gbest. According to

Figure 2.9, the fundamental idea of PSO is to accelerate each particle randomly weighted toward its pbest and gbest positions at each time step. Each particle tries to change its position using the following data: current positions, current velocities, distances from the current position to the pbest and the current position to the gbest (AlRashidi and El-Hawary, 2009).

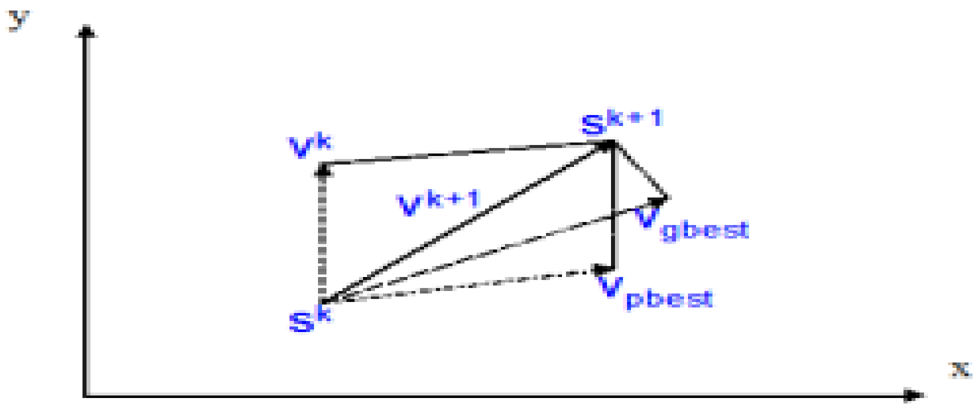

Figure 2.9: Concept of modification of a searching point by PSO (Kennedy and Eberhart, 1995)

Benefits of PSO: According to (AlRashidi and El-Hawary, 2009), the PSO technique has the following advantages over alternative optimization techniques:

i. It can handle objective functions with stochastic nature, such as in the case of representing one of the optimization variables as random, and it does not require the good initial solution to start its iteration process.

ii. With simple mathematical and logical procedures, it is easy to implement and program.

Disadvantages of PSO: PSO shortcomings are still present, and they are as follows (AlRashidi and El-Hawary, 2009):

i. To develop and adapt the competing method to suit various optimization situations, further parameter tuning is necessary, and programming abilities are required.

2.14 Distributed Generation (DG) Planning

In general, DG planning entails justification of energy resource and service allocation patterns, formulation of local policies pertaining to energy consumption, economic development, and energy structure, and analysis of interactions between economic cost, system reliability, and energy supply security (Irrisari et al., 1997). It entails a structured strategy to maximizing the placement, quantity, and size of distributed resources. Planning is divided into two categories in the literature: short-term planning and long-term planning.

2.14.1 Short-Term Planning

To make sure the system can continue to meet all needs and fulfill the existing consumer load, short-term planning is done. The short-term procedure culminates in a series of decisions regarding the distribution of dispersed generation in the lead phase. As an illustration, a four-year lead time would suggest that the decision is taken four years before it is put into action (Willis, 2004). Power system scheduling and control depend on short-term load projections (Taylor and McSharry, 2007). Figure 2.10 gives an illustration of this. For the network ancillary services or sources of active or reactive electricity, many projects are thus required. Additionally, a voltage regulator may need to be installed or the transformer's tap may need to be modified inside the network in order to account for voltage loss and maintain a smooth voltage profile.

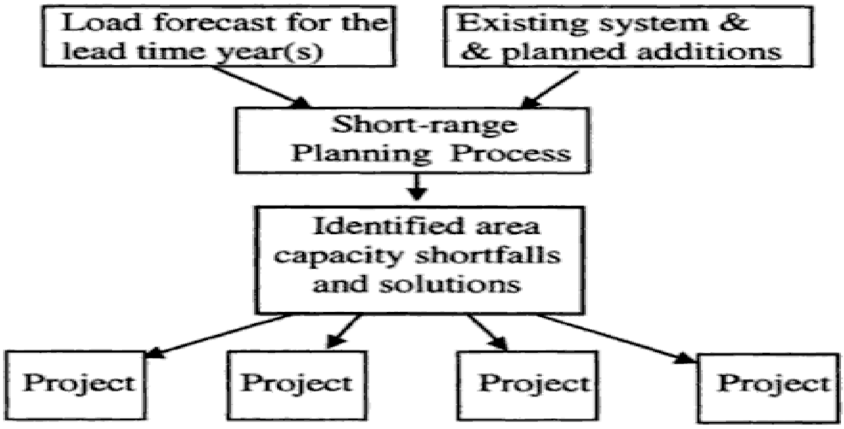

Figure 2.10: The Short-term planning process (Willis, 2004).

2.14.2 Long-Term Planning

Similar to short-term planning, long-term DG planning aims to identify the least expensive growth strategy that will guarantee a consistent supply of electricity to meet future demand. The availability of sufficient energy even in challenging circumstances is a reliability concern (Marzano et al., 2010). In contrast to short-term planning, long-term planning results in a long-term strategy rather than a choice (Willis, 2004). Major occurrences might have a lasting impact on the network of the electrical system, so it is important to take into account the current level of uncertainty. Not all of the potential projects will really be carried out. A multi-scenario ensures that short-term decisions match a variety of long-range situations, as seen in Figure 2.11.

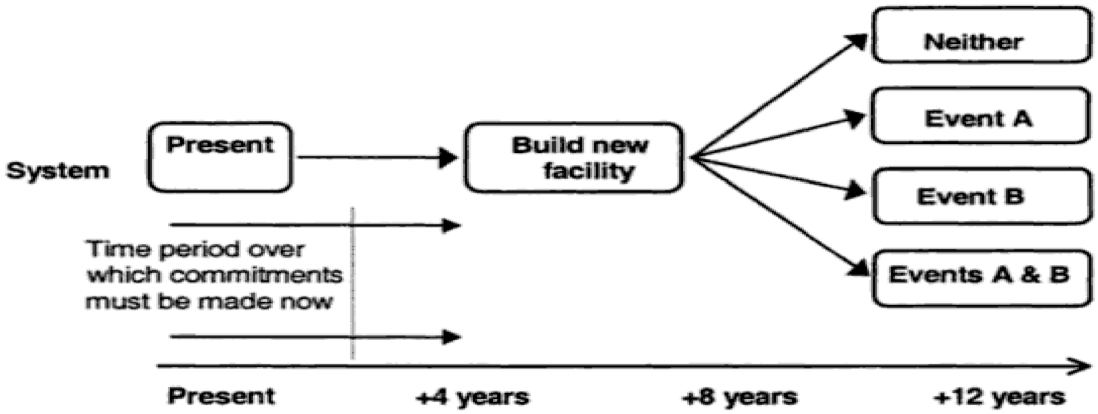

Figure 2.11: The Long-term planning process (Willis, 2004).

2.14.3 Load Duration Curve and Approximated Load Duration Curve

Electrical power systems are subject to a wide range of uncertainties. Uncertain fuel prices, rising demand, and equipment failures are the main drivers of uncertainty (Ryan et al., 2010). The load duration curve was first introduced in (Hagan and Suzanne, 1987) to address the load uncertainty. It is a straightforward model that gives the overall amount of time spent during a certain period. Figure 2.12 depicts the demand over a specific time period.

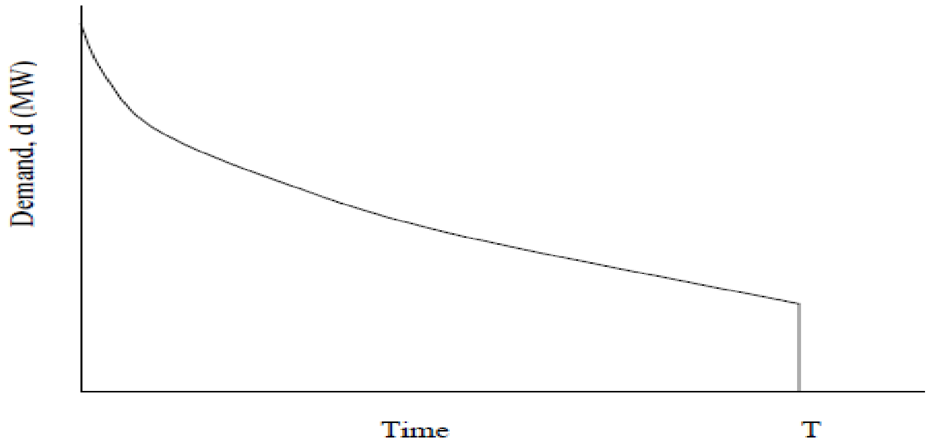

Figure 2.12: Load duration curve (Mc Calley, 2009)

A piecewise constant curve with k segments can be used to approximate the load duration curve, as shown in Figure 2.13. This model disadvantage is that it ignores technical constraints as well as stochastic fluctuations.

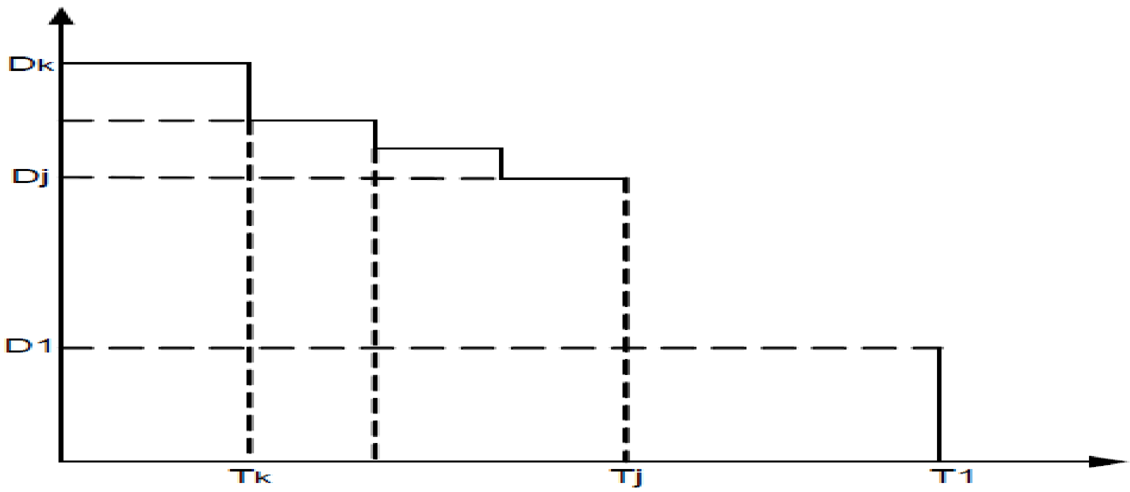

Figure 2.13: Approximated load duration curve (Mc Calley, 2009)

2.15 Order of Optimization

DG ideal location (Nara et al., 2001), optimal sizing (Vovos et al., 2005), and optimal capacity evaluation (Harrison and Wallace, 2005) problems are addressed by optimal integration of distributed energy resources. This integration is not only concerned with methodologies but also with how the optimization approach is used to accomplish the optimal placecement. Three categories of approaches could be made for the literature: Three methods: identifying the best places for a given DG capacity, finding the best DG capacity for a given location, and a combination method, have been proposed.

2.15.1 Pre-Specified Capacity

This method uses an optimization engine to locate the optimum locations for DGs with certain, discrete capacity. The works of (Nara et al., 2001), (Kim et al., 2002), and (Kuri et al., 2004) all adopted this strategy. A multiple of a certain capacity is assumed to be the ideal DG site and size in some publications (El-Khaltam et al., 2004). Pre-specifying capacity drawback is that it prevents some solutions from being chosen that do not meet the standard. It will make the system less efficient. In order to expand the search space exploration capability and prevent the issue, a wide range of capacities should be investigated (Harrison et al., 2007).

2.15.2 Pre-Specified Location

In the second strategy, the optimization engine looks for DG capacity at each place that has been given before executing it (Harrison et al., 2007). The techniques frequently employ continuous capacity functions that are resolved using the technique described in Section 2.12. The drawback of this strategy is that it may already have small DGs at the best locations determined by the optimization engine, indicating that a very small facility would not be profitable. The optimization to discover a workable solution would be disabled if a minimum capacity was pre-specified for each bus. The combination of r sites in a network of n buses indicated by $\binom{n}{r}$ adds a substantial load even in a modest distribution network when choosing the number of optimum locations out of the number of buses (Mardaneh and Gharehpetian, 2004).

2.15.3 Combined Approach

Calculus-based approaches, which regard the DG capacities as continuous variables while their locations stay constant, are no longer the only solutions available for the complicated electrical power system problem (Vovos et al., 2005). Instead, by applying search-based approaches in the optimization, the combined size and location optimization strategy was made achievable. The combined technique has been widely used in the literature (Celli and Pilo, 2001; Celli et al., 2005; Nara et al., 2001); typically, the same procedure is applied to a particular instance of a problem numerous times in order to discover the optimum answer. This approach enables the examination of a wide range of fascinating questions, but principally at the expense of predetermining the number of DG units (Harrison et al., 2007).

2.16 Critical Review of Related Works on Co-ordination of Optimization Techniques

Over the past two decades, the distribution networks have faced significant issues and obstacles as a result of the ill-advised and unregulated installation of Distributed Generations. In contrast to unidirectional power flow from higher to lower voltages, bidirectional power flow in modern distribution networks is a necessary issue, as are the crucial issues of voltage drop and power losses (Barukcic et al., 2021). In an effort to improve the voltage profiles and reduce or even completely eliminate power losses in contemporary distribution networks with DG, researchers from all over the world are researching the aforementioned issues. They have presented a variety of techniques and methodologies for choosing the ideal sitting and sizing of DGs and the summary of the most recent research critically reviewed are presented in table 2.3. In (Yadav and Srivastava, 2015), a genetic and particle swarm optimization methods have been used to determine where and how big a capacitor should be. The proposed methodology has been used to test the performance of these algorithms on a 12-bus radial distribution system. The outcomes demonstrated that the suggested methodology is more efficient and capable of producing superior outcomes than other analytical techniques. Then, using two distinct approaches, (Parizad et al., 2010) attempted to establish the best location and size of DG in terms of lowering losses and stabilizing voltage. The initial strategy sought to reduce actual power losses by creating an exact loss formula that identified the ideal site for DG installation. The second method involved using a voltage stability index to place the DG at the best possible spot. By employing the forward-backward sweep method, power flow was calculated. The study made use of two distribution systems: a 30-bus loop and a 33-bus radial system. The suggested solutions significantly improved voltage profiles and reduced power losses.

Fuzzy logic was used in (Injeti and Kumar, 2011) to determine the best location for a single DG unit, and a novel analytical expression for DG scaling used in radial networks was also suggested. The objectives of the study were to reduce actual and reactive power losses and enhance the voltage profile. To show that the suggested techniques may be used in radial distribution systems of various sizes and configurations, three distinct distribution systems (12-bus, 33-bus, and 69-bus) were used. The findings show that the proper installation of a DG unit has significantly reduced actual and reactive power losses and produced a notable voltage profile

Table 2.3: Critical Review of Recent Related Works on Co-ordination of Optimization Technique

Research (Author and Year)	**Title**	**Methodology**	**Research gap/Limitation**
(Barukcic et al., 2021)	Co-Simulation Framework for Optimal Allocation and Power Management of DG_S in Power Distribution Networks Based on Computational Intelligence Techniques	Optimization tools applying Mixed Integer Distributed Ant Colony Optimization (MIDACO) and Artificial Neutral Network (ANN) were used to solve optimization problem while OpenDSS was used for load calculation. The computational tools were implemented in Python programming environment.	ANN has several advantages which includes outperformance in discrete space search. However, it easily gets trapped in global optimum dimensional search space. Thus, has low convergence rate. An improved optimization technique is required to handle the issue of local minima and global optimum problems.
(Injeti and Thunuguntla, 2020)	Optimal Integration of DG_S into Radial Distribution Network in the Presence of Plug-in Electric Vehicles to Minimize Daily Active Power Losses and to Improve the Voltage Profile of the System using Bio-inspired Optimization Algorithms.	An efficient multi-objective function is proposed using Particle Swamp Optimization (PSO) and Butterfly Optimization (BO) as optimization techniques to minimize the objectives of the system. Load flow analysis was done using repetitive backward-forward sweep while the simulation was implemented using MATLAB software.	Two algorithms are combined in sequential form which favours optimal location but takes more time. Further modification is needed to improve time. Therefore, a robust improved optimization method that will combine the capabilities of both PSO and BO is required.
(Azizivahed et al., 2019)	Multi-Objective Energy Management Approach Considering Energy Storages in Distribution Networks with Respect to Voltage Security.	The proposed energy management problem with two objective functions to minimize the operation cost and voltage deviation was solved using modified shuffled frog leaping algorithm (SFLA). The microgrid consists of PV units, diesel generator units and ESS	Optimal DG size and placement on the network was not done. Hence, the need for an integrated optimization technique for optimal sizing and location of DG units.

(Saleh et al., 2019)	Impact of Optimum Allocation of Distributed Generations on Distribution Network Based on Multi-Objective Different Optimization Techniques.	Single and multi-objective functions were solved using PSO and MSA (Moth–Swarm Algorithm) and tested on IEEE 33-bus radial system	Two optimization techniques were used independently and the results compared. PSO is effective for power loss reduction and MSA is effective for voltage deviation. Hence the need improved algorithm that can handle more objective function at the same time
(Yang et al., 2019)	Coordination Control Strategy for Power Management of Active Distribution Network	Coordination of both active and reactive power (PQ) injection through the scheduling of adjustable PQ node	The network system model was not optimized to determine the optimal values. Therefore, there is need for optimization for optimal solutions of the objective functions
(Mohamed et al., 2017)	Power Management Strategy to Enhance the Operation of Active Distribution Networks.	Optimal power flow and particle swarm optimization	Optimal power flow shows ineffectiveness when hybrid renewable energy sources and large network are involved. PSO is subject to trapping at the local minimum in high-dimensional space and has low convergence rate in the iterative process.

(Di Silvestre et al., 2016) have given a very intriguing study. The goal of the author was to increase the effectiveness of electricity distribution by lowering energy losses in an island-based medium voltage distribution network. The installation of distributed photovoltaic (PV) generation units was one of the suggested actions. In order to determine the ideal location and size of the PV units, the Non-denominated Sorting Generic Algorithm-II (NSGA-II) multi-objective optimization technique was employed. The fact that economic issues like utility costs and customer subsidies were included makes this study significantly different from others in this field. The installation of PV generation units results in considerable improvements in terms of investment payback, voltage drop, and greenhouse gas emission reduction, as demonstrated by the application of the suggested approach on an existing medium voltage distribution network of Lampedusa Island.

2.17 Optimization Techniques

To guarantee that electrical energy of the necessary standard may be provided for the least amount of money/highest dependability, there is an increasing need for improved efficiency and effectiveness optimization techniques. Applications of various optimization strategies in the power system were discussed in Chapter two. Although the topic of optimization is so vast that it would take books to explain it, there are some fundamental components to any form of optimization that must be mentioned. The strong nonlinearity of power system issues has made optimization strategies a major topic in this field. For example, network loss, which was covered in Section 2.3.1 of chapter two on technical difficulties, is incredibly non-linear. Equation (2.1) below provides insight into the network real power loss nonlinearity.

$$P_L = \sum_{i=1}^{n} 1 \ \sum_{j=1}^{n} [Aij(PiPj + QiQj) + Bij(QiPj - PiQj)] \qquad (2.1)$$

Where;

$A_{ij} = \frac{Rij\cos(\delta i-\delta j)}{ViVj}$ and $B_{ij} = \frac{Rij\sin(\delta i-\delta j)}{ViVj}$

Every optimization has variables, objectives, and constraints that make up its components. Power system optimization problems involve a variety of variables, objectives, and constraints that must be considered for optimization.

2.17.1 Variables

The three main types of variables that could be present in any optimization are control variables, state variables, and constraint variables. Examples of control or independent variables that can be adjusted arbitrarily within their constraints to minimize or maximize the objective function are adjustments to transformer taps and generator outputs. Load bus voltage magnitudes and angles are examples of states or dependent variables that are established as a result of the controls yet need to be observed. Variables connected with constraints are known as constraint variables. The Lagrangian multiplier is a particular sort of constraint variable used in traditional optimization approaches (Cartina et al., 2007).

2.17.2 Objectives: Multiple-Objective and Single-Objective Strategies

Power system problems have been simplified over the years by using single-objective optimization techniques and fewer assumptions (Pindoriya et al., 2010). For many years, several optimization strategies have been put out to address the issues associated with the best possible integration of DGs in terms of operations and planning (Haji et al., 2013). In a larger sense, research suggests that these methods could be used in reactive power planning, var planning, economic/environmental dispatch, planning for the growth of the transmission and distribution networks, etc. Techniques like the weighted sum method, the ε-constraint approach, the goal programming method, etc.

are examples of single-objective optimizations (Pindoriya et al., 2010). All objectives are transformed into an aggregated scalar objective function problem in weighted sum. Given scalar weights, each goal that needs to be improved is integrated into a single function that can be solved using any single-objective optimization method. Some optimization techniques, particularly traditional ones, may have difficulty deciding how to balance several objectives because they call for a thorough understanding of the systems. The Epsilon constraint approach proposes treating all other objectives as constraints and maximizing a single-objective function. The foundation of the goal programming approach is reducing a sum of objectives deviations from user-specified targets.

2.17.3 Constraints

Under specific operational constraints, distributed generation integration works well. Various restrictions have been taken into account in literature when developing distribution generating. There are two kinds of constraints: equality constraints and inequality constraints. Limits on power conservation result from the equality restrictions. The optimization procedure must satisfy these power flow equations, which regulate the flow of power across a network (AlRashidi and AlHajri, 2011). Examples of inequality limitations include the heat limit for branches or the voltage limit for bus bars. The constraints used in distribution generating proper planning are discussed in the sections that follow (Payasi et al., 2011).

2.17.3.1 Equality constraints

Total load demand (P_{DT} and Q_{DT}) and total active and reactive power loss (P_{LT} and Q_{LT}) must be equaled by the traditional generation overall active and reactive power generation (P_{GT} and Q_{GT}) and DG units (P_{DGT} and Q_{DGT}).

$P_{GT} + P_{DGT} - P_{DT} - P_{LT} = 0$……………… (2.2)

$Q_{GT} + Q_{DGT} - Q_{DT} - Q_{LT} = 0$…………… ……… (2.3)

2.17.3.2 Inequality Constraints

The inequality constraints highlight the physical device restrictions in the power system as well as the limits designed to guarantee system maintenance within the designated security margin.

i. Voltage Profile Limit

Bus voltage magnitudes must be maintained within acceptable ranges in order to meet stability criteria. These limitations can be expressed mathematically as follows:

$V^{min} | \leq |V_i| \leq |V^{max}| \quad \forall\, i \in \{number\ of\ buses\}$ .... (2.4)

ii. Line Thermal Limit

The loading at thermal equilibrium which corresponds to the highest permissible conductor temperature is known as the line thermal rating. In simple words, line thermal rating is the maximum amount of current that a power line can safely carry without overheating (AlRashidi and AlHajri, 2001). The maximum thermal capacity (S^{max}) of the lines must be well within the MVA limits (S_k) across any branch, which are used to represent the power carrying capability of feeders (Payasi et al., 2011).

$S^{max} \leq S_k \;\forall\, i \in \{number\ of$ branches$\}$ .... (2.5)

iii. Phase Angle Limit

The maximum and lower limits of the bus voltage angle δ_i at bus i serve as restrictions for all buses

$\delta_i^{min} \leq \delta \leq \delta_i^{max} \;\forall\, i \in \{number\ of$ buses$\}$ ………………………. …. (2.6)

iv. Active and Reactive power Generation Limit

The lower and upper limitations of P_{gen} and Q_{gen} must be used to limit the generated power from both installed DGs and conventional generators.

$(P_{gen})^{min} \leq P_{gen} \leq (P_{gen})^{max}$ ………………………………… …………… (2.7)

$(Q_{gen})^{min} \leq Q_{gen} \leq (Q_{gen})^{max}$ ………………………………………………… (2.8)

v. Substation Transformer Capacity Limit

The total power delivered by the substation transformer (S_{load}^{total}) must be less than the transformer capacity limit (S_{sst}^{max}) for the substation. Power exporting outside the substation (reverse flow of power through distribution substation) will result in extremely significant losses, which is another justification for limiting power in substations (Acharya et al., 2006). As a result, the substation power transfer ought to be restricted.

$(S_{load})^{total} \leq (S_{sst})^{max}$……………………………… ………………… …. (2.9)

vi. Number of DG Limit

To restrict the overall number of DGs that can be deployed in a distribution network, a maximum number of DGs $(N_{DG})^{max}$ must be employed.

$N_{DG} \leq (N_{DG})^{max}$ …………………………………… ……. …… …… (2.10)

vii. Short Circuit Level/Ratio Limit

To make sure that the fault current with DG $(SCL)_{rated}$ won't raise the rated fault current of the existing installed protective devices, a short circuit calculation is taken into account.

$(SCL)_{WDG} \leq (SCL)_{rated}$ …………………………………………………… (2.11)

The short circuit ratio limit could also be considered in transient research. The generator power (PDG) to short circuit level $(SCL)_{BUS}$ ratio at each bus is known as the short circuit ratio. According to European standard EN50160, 1994, “the system will remain stable if the short circuit ratio stays below 10%” (Payasi et al., 2011).

$$\left(\frac{PDGi}{SCLi.Cos\,(\emptyset)}\right) X\ 100\ \leq 10\%\ \ \forall\ i\ \ \in \mathrm{N} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(2.12)}$$

viii. Power Factor Limit

Distributed generators are thought to operate in power factor control mode. Therefore, a power factor restriction is required.

$$\mathrm{Cos}\ (\emptyset_{DG}) = \frac{P}{\sqrt{[(\mathrm{PDG})^2 + (QDG)^{\wedge}2]}} = Constant\ \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(2.13)}$$

where P_{DG} denotes the real power output of the device, Q_{DG} denotes the reactive power output, and $\emptyset_{DG}$ denotes the constant power factor angle of the device

2.17.3.3 Curtailment Constraints

Curtailment is the temporary reduction or redirection of certain DG power to a dump load. The amount of power that can be exported without pushing the local network voltage over its limit is capped at that amount. This changes depending on the season and time of day (Gill et al., 2011).

2.18 Overview of Distributed Generation (DG) Allocation Methodologies

The placement and sizing of DGs have been optimized using a variety of methodologies, including analytical-based methods, heuristic algorithms, genetic algorithms, and tabu search. The best active power compensation can be used to model the ideal DG allocation. Contrary to capacitor allocation studies, which have been researched for a long time, DG allocation studies are relatively recent (Prommee and Ongsakul, 2008). To reduce system power loss, (Abu-Jasser and Husam, 2011) presented an analytical method for placing DG in both radial and meshed systems. This approach separates the expressions for the radial and network systems, and a sophisticated solution based on the current phase was presented to address the location issue. The size of the DG is treated as fixed and only the location is optimized.

The majority of traditional optimization techniques are derivative-based approaches that can address continuous or differentiable issues. These techniques, however, cannot ensure that the result is a global optimum. The main limitations of such techniques are the potential for getting stuck in local optimal, inability to handle non-differentiable or non-continuous situations, and unnecessary calculations. Heuristic and meta-heuristic optimization techniques were developed to address these shortcomings. One of these techniques is particle swarm optimization (PSO), which was widely used (Prommee & Ongsakul, 2008; Peng et al., 2012; Nikzad et al., 2011; Abu-Jasser & Husam, 2011). The social behavior of swarms served as the inspiration for the stochastic population-based meta-heuristic optimization method known as PSO. It excels at handling power systems optimization issues like Optimal Power Flow (OPF), reconfiguration, capacitor placement, unit commitment, and economic dispatch as well as other single- and multi-objective constrained problems in many different domains. An extremely large-scale problem with a wide searching space, continuous variables, and discrete variables is the placement and sizing of DGs. Such issues can be handled using this algorithm. It contains less adjustable parameters and clear specifications when compared to other clever algorithms (such as Simulated Annealing-SA, Independent Component Analysis-ICA, and Generic Algorithm-GA). The application of this method to the DG allocation problem is made easier by its straightforward structure, good convergence characteristics, and great global searching capabilities.

2.19 The Per Unit System

The power system industry frequently employs the per-unit approach to describe values for voltages, currents, powers, and impedances of various pieces of power machinery. Typically, transformers and AC equipment utilize it. The per-unit value for a given quantity (such as voltage, current, power, impedance, torque, etc.) is the value pertaining to a base quantity.

Usually, one of the two base values from the list below is used:

i. The base power is equal to the equipment nominal power.
ii. The base voltage is equal to the equipment nominal voltage.

These two base values serve as the foundation for all other base quantities. The natural rules of electrical circuits govern the base current and base impedance after the base power and base voltage have been selected.

Base current = $\frac{\textbf{\textit{base power}}}{\textbf{\textit{base voltage}}}$ …………………………………… (2.14)

Base impedance = $\frac{\textbf{\textit{base voltage}}}{\textbf{\textit{base current}}}$ ………………………………… (2.15)

A per-unit system is a statement of system quantities as fractions of a predetermined base unit quantity in the field of electrical engineering known as power systems analysis. Quantities stated as per-unit do not change when they are referred from one side of a transformer to the other, simplifying calculations. In power system analysis, where there may be a lot of transformers, this might be a significant advantage. The per-unit approach is utilized in studies on motor starting, power flow, and short circuit evaluation. A per unit system principal goal is to incorporate significant changes in absolute values into basic relationships. As a result, representations of system elements having per unit values take on a more consistent appearance.

Units for electrical power, voltage, current, impedance, and admittance are provided through a per-unit system. Any two independent units, with the exclusion of impedance and admittance, can be chosen as the base values; commonly, power and voltage are used. The units of measurement are all multiples of the chosen base values. For instance, the base power might be a transformer's rated power or a randomly chosen power that makes the system's power amounts more practical. The bus nominal voltage could be the base voltage. The same symbol (p.u) is used to denote various types of quantities; it should be obvious whether a given amount is a voltage, current, or another type of measurement.

- Reasons for Using the Per-Unit System

i. Irrespective of their overall size, similar equipment (generators, transformers, and lines) would have similar per-unit impedances and losses expressed on their individual ratings. As a result, per-unit data may be quickly examined for obvious mistakes. A per unit figure outside of the expected range merits investigation for possible mistakes.

ii. Manufacturers often provide per unit values for the impedance of the device.

iii. Three-phase calculations use the constant less frequently.

iv. Per-unit amounts, regardless of voltage level, are the same on each side of a transformer.

v. Calculations performed manually or automatically are made simpler by normalizing variables to a common base.

vi. It makes automatic calculation techniques numerical stability better.

vii. Information concerning relative magnitudes is necessary when representing data as per unit.

2.20 The Backward-Forward Sweep (BFS) Load Flow Technique

Load flow is one of the most crucial variables in planning and operation studies of power systems. For load flow analysis at the transmission level, either Gauss-Seidel or Newton-Raphson or their variants are used. Due to the distribution network unique characteristics, such as its radial construction, high Resistance/Reactance (R/X) ratio, and unbalanced loads, the aforementioned approaches have been weak and have a very poor convergence characteristic. Branch-based and node-based procedures can be used to classify load flow techniques proposed for distribution networks (Farag et al., 2011). In node-based techniques, the power or current of the node is utilized as a state variable to solve the power flow problem, whereas in branch-based approaches, the power or current of the branch is employed (Farag et al., 2011). Due to their low memory needs, high computing efficiency, and strong convergence properties, forward/backward sweep-based approaches have been the most extensively adopted techniques for distribution system load flow analysis. Each iteration of the BFS core operating principle requires two calculation operations. Calculating node voltage from the sending end to the receiving end makes up the forward sweep. The branch current and/or total power from the receiving end to the sending end are calculated by the backward sweep. The voltage is maintained constant throughout the backward sweep, and the current or power value is maintained constant during the forward sweep. The convergence of the power flow is evaluated after each iteration (Eminoglu and Hocaoglu, 2005).

- Summary of the Benefits of BFS Load Flow Technique

i. Compared to traditional methods, it is an effective iterative method for the quick convergence tendency in radial distribution networks.

ii. This strategy is still relatively simple to implement in a distribution management system.

iii. There is no need to sequentially number the branches which makes it considerably simpler in terms of computation. But in order to compute current and power, a branch identification method must be used to count the number of connected nodes and subsequent linked branches.

iv. This approach maximizes the radial structure of distribution systems, resulting in high speed, reliable convergence, and little memory usage.

CHAPTER THREE: METHODOLOGY

3.1 Methodological Framework and Research Design

Quantitative method was used throughout the research process and the techniques that have been employed include modelling and simulation. The overall implementation steps involved problem formulation and modelling, load flow and optimization algorithms and MATLAB Codes development, Simulation and testing on standard IEEE 33-bus radial electrical power distribution system benchmark network for performance analysis. The three main parts of the overall optimization system are:

i. The Backward-Forward Sweep (BFS) Load flow part one (Without DG placement/Base Case Calculation) algorithm and codes

ii. The Backward-Forward Sweep (BFS) Load flow part two algorithm and codes

iii. The main (overall) nested multi-Objective Particle Swamp Optimization (PSO)-based algorithms and codes incorporating the algorithms and codes stated in (i) and (ii) above for the optimal placement and sizing of the DG units.

3.2 Research Population, Sample Size, Software and Data Collection

The overall research population which is the case network where the optimization system is targeted for application is- radial electrical power distribution networks such as the 14-bus, 15-bus 30-bus, 31-bus, 33-bus, 69-bus, 85-bus system etc., in any country in Africa or outside Africa with increased penetration of grid integration of renewable energy sources. The benchmark network which constitutes the research sample size where the developed optimization algorithms has been tested is the standard IEEE 33-bus radial electrical power distribution network- being a cutting-edge benchmark for contemporary power distribution networks. The simulation software used was the

R2021a version of MATLAB. For the IEEE 33-bus radial distribution system load flow modelling, analysis and simulation, the line data and load data were obtained from the Power Systems Test Case Archive- a secondary data source (Power Systems Test Case Archive, 2022)

3.3 Problem Formulation and Modelling: Objective Functions and Constraints

The active power loss minimization and voltage stability enhancement objectives are taken into account while formulating the DG location and sizing problem as a multi-objective problem while observing system and unit limits. Power loss reduction and index enhancement for voltage stability are the two primary objective functions that are optimized. The analysis also takes into account the minimum and maximum voltage magnitudes as well as the power balance as constraints of the problem.

3.3.1 Optimization First objective function: Power losses reduction

According to (Hung et al., 2010), it is true that the electrical power distribution system has power losses of roughly 13% of the total power generated. Therefore, the first objective function of the optimization is to cut down on power losses. The diffident electrical parameters are computed using a backward-forward power flow (Atwa et al., 2010). Figure 3.1 below illustrates how each receiving bus in radial electrical power distribution networks is served by a single transmitting bus.

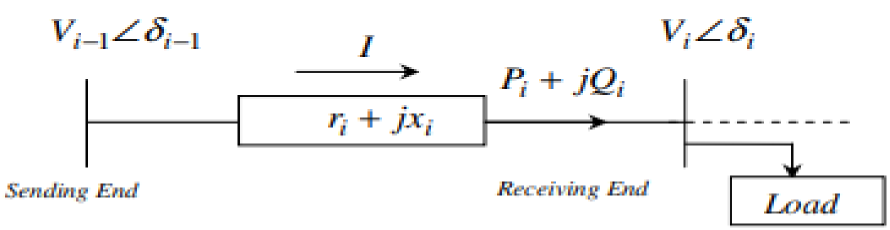

Figure 3.1: One line diagram of a two-bus system (Atwa et al., 2010).

From figure 3.1, the line losses between the receiving and sending end buses P_{loss} (i), can be calculated using equation 1 below:

$$P_{loss}(i) = r_i \frac{Pi^2 + Qi^2}{Vi^2} \quad (3.1)$$

According to Kothari (2006), given the operational conditions of the system, equation (3.2) below can be used to calculate the value of the active and reactive power losses in an electrical power distribution network. It should be noted that the precise formula for calculating power losses can be simply derived from the fundamental relation.

$$P_L = \sum_{i=1}^{n} 1 \ \sum_{j=1}^{n} [Aij(PiPj + QiQj) + Bij(QiPj - PiQj)] \quad (3.2)$$

Where;

$$A_{ij} = \frac{Rijcos(\delta i - \delta j)}{ViVj}$$

$$B_{ij} = \frac{Rijsin(\delta i - \delta j)}{ViVj}$$

Where;

P_i & Q_i = Net real and reactive power injections at bus ‘i’

R_{ij} = The line resistance between bus ‘i’ and ‘j’

V_i & δ_i = The voltage and angle at bus ‘i’

(r_i+jx_i) = The impedance of the line connecting buses i−1 and i

The first objective of the DG placement technique is to minimize the total power losses. Mathematically, this objective function can be written as:

$$f_1 = \text{Minimize } P_L = \sum_{i=1}^{Nbus} [Ploss(i)] \quad (3.3)$$

Subject to the power balance constraints:

$$\sum_{i=1}^{N} (PDGi) = \sum_{i=1}^{N} (PDi + PL) \quad (3.4)$$

Each DG unit must produce active and reactive power that is less than the system combined active and reactive loads. This restriction is defined mathematically as follows:

$P_{DG} \leq \sum Pload$ …………………………………………………………………………… (3.5)

$Q_{DG} \leq \sum Qload$ …………………………………………………………………………… (3.6)

Voltage constraints:

$|V_i|^{min} \leq |V_i| \leq |V_i|^{max}$ ……………………………………………………. …………………… (3.7)

Current limits:

$|I_{ij}| \leq |I_{ij}|^{max}$ ………………………………………………………………… (3.8)

Where;

$P_{loss}(i)$ = Distribution power loss between the receiving and sending end buses 'i'

N_{bus} = Total number of buses

P_L = The real power loss in the system

P_{DGi} = The real power generation DG at bus 'i'

P_{Di} = The power demand at bus 'i'

3.3.2 Optimization Second objective function: Voltage profile improvement

The IEEE Power System Engineering Committee definition of voltage stability is as follows (Atwa et al., 2010): "Voltage stability is the ability of a system to maintain voltage such that load power will rise as load admittance increases and such that both power and voltage are regulated". As the goal for improving voltage stability, fast indicator of voltage stability (SI Index) proposed by (Chakravorty & Das (2001) is chosen.

From figure 3.1,

$V_{i-1} < \delta_{i-1} - V_i < \delta_i = I.(r_i + jx_i)$ ……………………………………………… (3.9)

$(V_i < \delta_i)^*. I = P_i - jQ_i$ …………………………………………………… (3.10) where "I" denotes the complex conjugate operator and "*" stands for the current amplitude.

From equation (3.22) and (3.23), we get:

$$Vi^2 - Vi.Vi - 1 + [(Pi^2 + Qi^2).(\mathrm{ri}^2 + \mathrm{xi}^2)]^{\frac{1}{2}} = 0 \ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3.11)}$$

Roots of Equation (3.11) are real if:

$$V(i-1)^2 - 4.[(Pi^2 + Qi^2).(\mathrm{ri}^2 + \mathrm{xi}^2)]^{\frac{1}{2}} \geq 0 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3.12)}$$

From this, the voltage stability index for bus i (SI_i) is derived as:

$$\mathrm{SIi} = \mathrm{V(i-1)}^4 - 4.(Pixi - Qiri)^2 - 4.(Piri + Qixi)^2.V(i-1)^2 \geq 0 .. \text{(3.13)}$$

The value of SI should be greater than zero for all buses during stable operation, i.e., SIi (i=2, 3...N_{bus}) >0. All buses grow more stable as the SI value approaches one. The bus that has the lowest SI value is the one that is most vulnerable to voltage collapse. Each bus in the network network is given a SI value according to the proposed algorithm. Consequently, the following is the second objective function:

$$f_2 = \frac{I}{I + SImin} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots .. \text{(3.14)}$$

where SI_{min} is the minimum SI value of all the buses.

3.4 Design Variables

From equations (3.1) through (3.8), it is clear that the decision variables include both the capacities and locations of the DGs to be installed at the candidate buses, which can be denoted as [P_{DG1}, P_{DG2}…., P_{DGNbus}], and that the state variables include the voltage, active power, and reactive power at each bus, all of which can be obtained by power flow computation. P_{DGi}=0 (i=2, 3, ...N_{bus}) indicates that bus i cannot accommodate a DG unit. The decision variable for determining the optimal capacity of the DG at a predetermined location is one dimension, whereas the decision variable for determining the best location of the DG at a predetermined capacity is two-dimensional. It should be noted that the **per unit system** was employed in the load flow analysis coding.

3.5 BFS Load Flow Problem Formulation and Modelling

Calculating actual and reactive power losses that occur in the network is the goal. Hence, to determine the power flow:

$$P_{n+1} = P_n - P_{loss,n} - P_{Ln+1} \quad (3.15)$$

$$Q_{n+1} = Q_n - Q_{loss,n} - Q_{Ln+1} \quad (3.16)$$

Where:

P_n = *Real power flow out of bus*,

Q_n = *Reactive power out of bus*,

P_{Ln+1} = *power loss at* $n+1$ *bus*,

Q_{Ln+1} = *reactive power loss at* $n+1$,

For the real and reactive power losses between n and n+1 bus:

$$P_{loss}(n, n+1) = R_n \left(\frac{Pn^2 + Qn^{\wedge}2}{Vn^{\wedge}2}\right) \quad (3.17)$$

$$Q_{loss}(n, n+1) = X_n \left(\frac{Pn^2 + Qn^{\wedge}2}{Vn^{\wedge}2}\right) \quad (3.18)$$

Where:

$P_{loss}(n, n+1)$ is the *real power loss between n and* $(n+1)$ buses and,

$Q_{loss}(n, n+1)$ is the *reactive power loss between n and* $(n+1)$ buses

Therefore, the overall power loss will be:

$$P_{loss}(n, n+1) = \sum_{n=1}^{t} [\text{Ploss}(n, n+1)] \quad (3.19)$$

$$Q_{loss}(n, n+1) = \sum_{n=1}^{t} [\text{Qloss}(n, n+1)] \quad (3.20)$$

3.6 Algorithms for the BFS Load Flow Implementation

- Assumptions:

i. The initial voltage is 1 p.u

ii. The initial real and reactive power losses are both zero.

iii. A single line diagram can be used to depict the Radial Distribution Network (RDN) because it is a balanced system.

- To determine various network matrices:

1. Start
2. Convert the voltages, power, resistance, and reactance into per unit form.
3. Calculate matrix [A]: (Matrix of Branch-Node Incidence):

$A_{i,j}$ = {−1 if j = $sending\ node$ and

$A_{i,j}$ = {+1 if j = $receving\ node$

4. Determine the number of end nodes in order to determine the number of possible pathways.
5. Determine how many nodes are along each potential path. The bus matrix [B] will have dimensions (l x m) if the lateral has as many as 'm' branches at most.
6. Create a next-linked node matrix [C] to determine linked branches that exist beyond a branch.

- **For the Load Flow**:

1. Consider a flat voltage start:

$V_i = 1 + 0j$, for i = 1 to n, $Pl_j = 0$, and $Ql_j = 0$, for j = 1 to b

Where, n = total nodes, m = total branches, Pl_j and Ql_j = actual and reactive power losses, respectively.

2. Set the iteration count (IT) = 1 to IT_{MAX} as the maximum.

3. Determine the current from every branch:

$I_j = \{\frac{Si+1}{Vi+1}\}*$ for i = 1 to b and,

S_{j+1} here equals (P_{i+1} + jQ_{i+1}).

4. **Backward Sweep**: Update current going backwards from the end nodes:

$I_k = \sum_j I_j$ for $k = 1$ to b and $where$ j ∈ C_j

Here, C_j is the collection of linked nodes after the k branch, IT = iteration count

5. **Forward sweep**: starting at the source node, update the nodal voltages using branch currents:

$V_{k+1} = V_k - (I_k * Z_k)$ for $k = 1$ to n

6. Determine the Real and Reactive Power Losses:

$Pl_j = Il_j * R_j$ and

$Ql_j = Il_j * X_j$

Total real power loss = $\sum_{j=1}^{b}(Plj)$

Total reactive power loss = $\sum_{j=1}^{b}(Qlj)$

7. Examine the deviation between the real and reactive power losses data from the current and previous iterations.

If

Deviation is minimal (∈), move on to step.

Else

Move on to step 3.

8. Until $IT=IT_{MAX}$, $IT=IT+1$

9. Return the total real and reactive power losses as well as Pl_j, Ql_j, and IT.

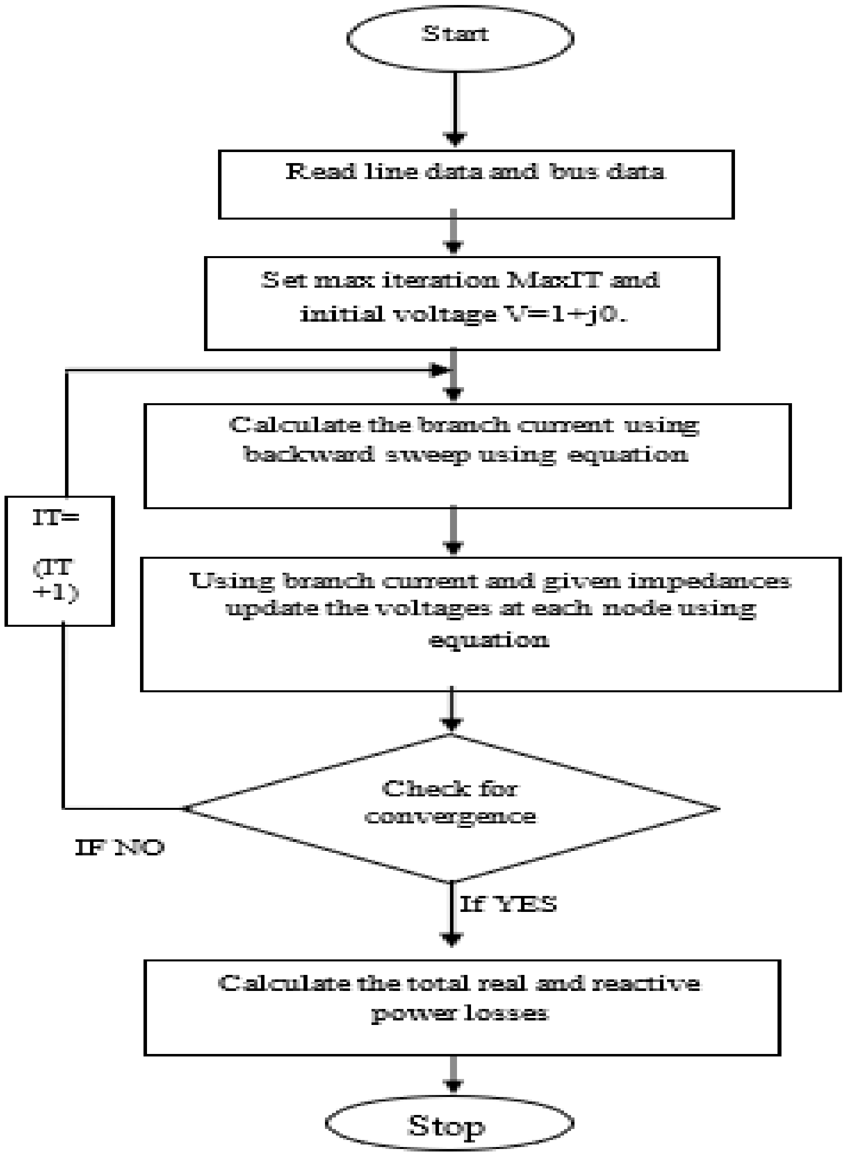

Figure 3.2: BFS Load Flow Implementation Algorithm Flow Chart

- BFS Load Flow Algorithms Implementation MATLAB/Simulink codes

The written detailed MATLAB live codes for the implementation of the BFS load flow algorithms which are made up of two parts nested in MATLAB M-File application have been included in appendices 1 and 2 at the end of this report. The first part handles the base case (without DG placement) calculation by loading/calling in the modelled line data and the load data and it is also nested within the second part that perform the full load flow calculation which gives the bus voltage profiles and line power losses.

3.7 The Adaptive Multi-Objective Particle Swamp Optimization (PSO) Algorithm

The MPSO algorithm and codes start by initializing a collection of random particles, which can then iteratively discover the best solution. According to its own experience and the experience of the particles in its immediate vicinity, each particle modifies its position. The best location for each is denoted by the letters Pbest and Gbest, respectively.

Equations (3.21) and (3.22) below can be used to explain how the particle location changes (AlRashidi and El-Hawary, 2009):

$$v_i^{k+1} = wv_i^k + c_1r_1 (Pbest_i - s_i^k) + c_2r_2 (Gbest - s_i^k) \quad \ldots\ldots (3.21)$$

$$s_i^{k+1} = s_i^k + v_i^{k+1} \quad \ldots\ldots (3.22)$$

Where;

c_1, c_2 = The weighting factor

r_1, r_2 = The random numbers between 0 and 1

w = The weighting function

v_i^k = The current velocity of particle i at iteration k

v_i^{k+1} = The modified velocity of particle i

s_i^k = The current position of particle i at iteration k

s_i^{k+1} = The modified position of particle i

$Pbest_i$ = The personal best of particle i

Gbest = The global best of the group

Equation (3.21) represents the speed function, which is used in the iterative process to update each particle speed in accordance with the Pbest and Gbest optimal solutions.

Equation (3.22) is the location function, which indicates that after a certain number of iterations, particles update their positions to find the best solution.

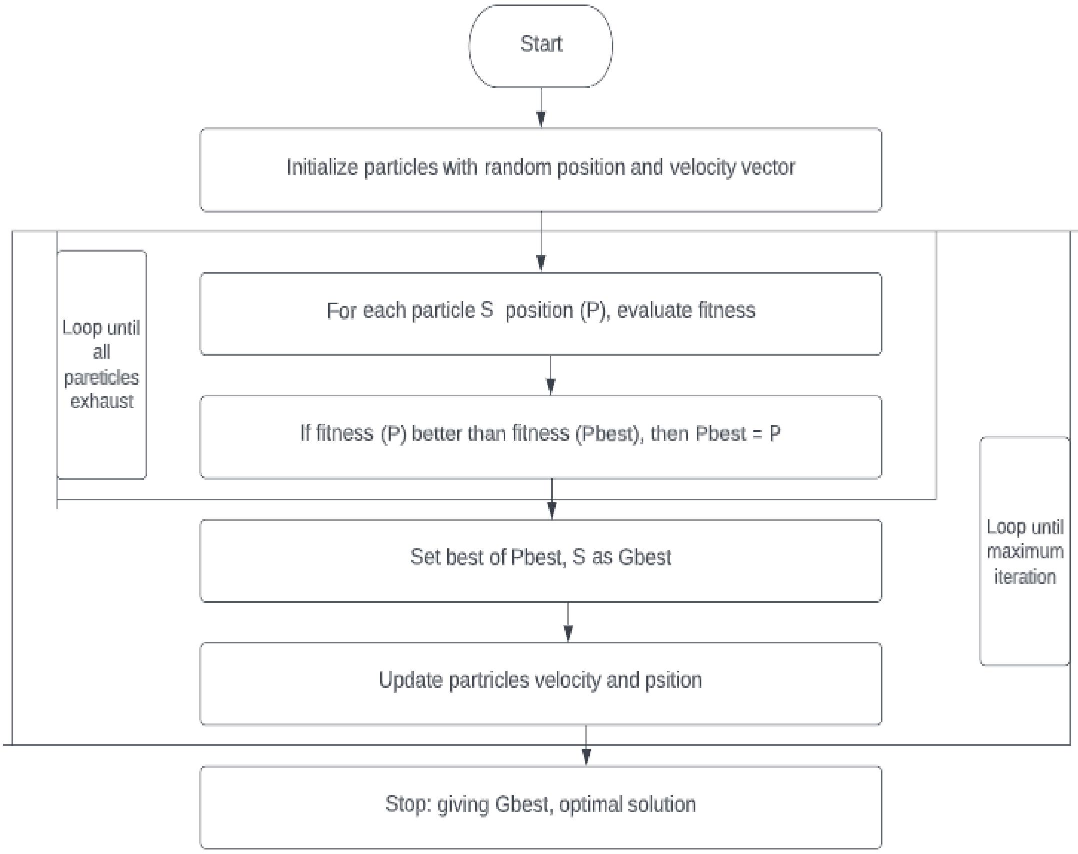

Figure 3.3: Algorithm Flowchart for the Particle Swamp Optimization (PSO) Implementation

3.8 Overall Multi-Objective PSO-Based Optimal Placement and Sizing of DG Optimization System Algorithm, Coding and Implementation

The reduction of power losses, as given in equation (3.3), serves as the optimization first objective function. The optimization core problem was established by the nested BFS load flow and MPSO algorithms and codes. The MATLAB M-File application was used to program these procedures. Figure 3.4 shows the overall flowchart of the optimization system. The following implementation steps were taken in order to put the overall algorithms for solving the problem of dispersed generation placement that minimizes power losses and improve voltage profile into practice:

Step 1: Input line and bus data and bus voltage limits.

Step 2: Utilizing a distribution load flow based on Backward-Forward Sweep (BFS), calculate the loss.

Step 3: The third step involves creating an initial population (array) of particles in the solution space at random, with random locations and velocities. Put k, the iteration counter, at 0.

Step 4: Determine the total loss for each particle using equation (3.2) if the bus voltage is within the acceptable range. If not, that particle is impossible.

Step 5: Compare each particle objective value to its best individual value. Set the objective value as the current P_{best} and note the related particle position if it is less than P_{best}.

Step 6: Pick the particle that has the lowest individual best P_{best} value among all particles, and make that value the current global best G_{best}.

Step 7: Using equations (3.21) and (3.22), update the particle velocity and position.

Step 8: Proceed to Step 9 if the iteration count exceeds the allowed number. Otherwise, return to Step 4 and set iteration index k = k + 1.

Step 9: Print the ideal optimal response (optimal solution) to the target issue. The best position combines the ideal (optimal) DG sizes and positions (location) with the appropriate fitness value, which represents the minimum amount of power loss.

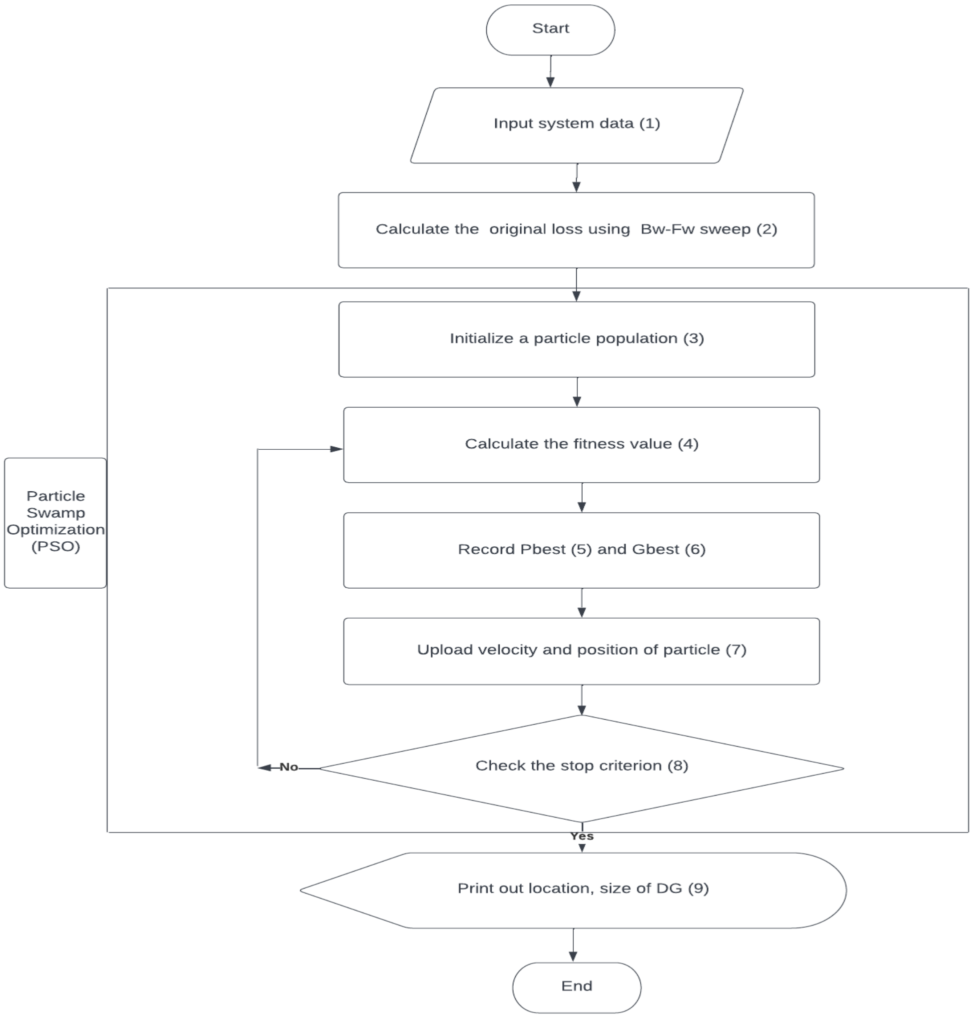

Figure 3.4: Overall flowchart for the multi-objective PSO-based optimal placement and sizing of DG optimization system

- The written detailed overall nested MATLAB live codes for the implementation of the multi-objective PSO-based optimization system incorporating the BFS load flow algorithms and codes have been clearly outlined in appendix three at the end of this report.

CHAPTER FOUR: RESULTS AND DISCUSSION

4.1 Results and Analysis

As anticipated, the overall nested multi-objective Particle Swamp Optimization (PSO)-based codes for the best positioning and sizing of Distributed Generation (DG) units in electrical power distribution networks were able to arrive at a good solution by performing finite steps of execution steps on a finite set of potential solutions when run on the MATLAB R2021a version. For the PSO parameters, population size is equal to 100 and maximum generation (k_{max}) is equal to 50. For a given DG penetration, the algorithm would take the real and reactive power and calculate the real and reactive power losses (P_{Loss} in kW and Q_{Loss} in kvar) which would then be compared with the original power losses. The location of the bus for DG placement will not be fixed initially but the algorithm will finally print the best location (bus number) and the optimum DG size for the placement. The size of the DG implies the amount of the real power and the reactive power. The simulated optimization system has the following salient features:

i. Flexibility to changes
ii. High convergence rate-reaches the optimum solution in just a matter of few seconds in less than 100 iterations and has a maximum iteration limit of 100
iii. Ability to accommodate three different types of DGs (Types 1-that generates real power only, Type 2-that generates reactive power only and Type 3-that generates both real and reactive powers) discussed in the literature. An embedded prompt command in the nested codes asks for the types of DG placement at the start of the simulation

iv. Ability to place up to four DG units in the IEEE 33-bus radial electrical power distribution network. An embedded prompt command in the nested codes asks for the number of DG units to be placed at the start of the simulation.

4.1.1 IEEE 33-Bus Radial Electrical Power Distribution System

Figure 4.1 below depicts the single line diagram of the IEEE 33-bus radial electrical power distribution system benchmark network where the nested overall algorithm was tested. There are thirty-three buses and thirty-two lines in it (branches). The base MVA is 10 MVA and the base kV is 12.66 kV (voltage level across all buses). For all buses, the maximum and lowest voltage limitations were taken into consideration at ±5%. A synchronous generator supplies electricity to the distribution network. The network is loaded with 3.715 MW (real power) which is the total active power demand and 2.300 Mvar (reactive power) which is the total reactive power demand, coupled to 32 branches with various power factors (Power Systems Test Case Archive, 2022). The 33-bus system has 32 lines with the original (base configuration) total real and reactive power losses equal to 201.893 kW (5.44% of the total real power demand) and 134.641 kvar (5.85% of the total reactive power demand) respectively. The upper bound size of DG is 3000 kW. Tables 4.1 and 4.2 present the line data and load data of the system, obtained from the Power Systems Test Case Archive, a secondary data source (Power Systems Test Case Archive, 2022)

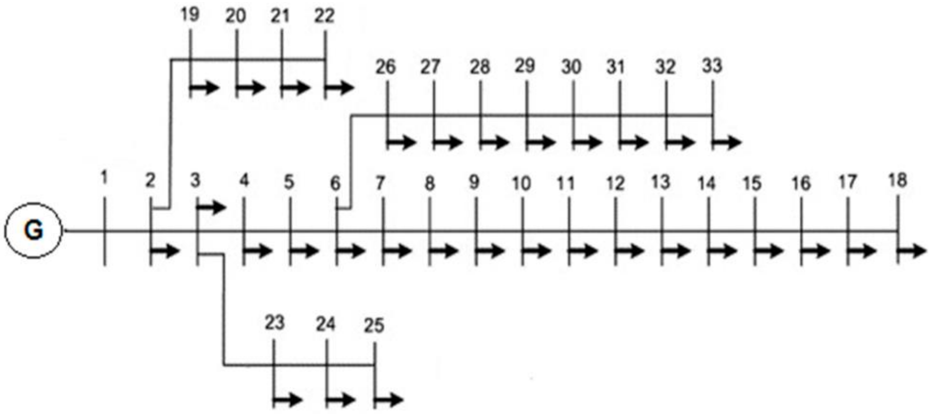

Figure 4.1: Single line diagram of the IEEE 33-bus radial electrical power distribution system (AlRashidi and El-Hawary, 2009).

Table 4.1: Line data of the IEEE 33-bus radial electrical power distribution system (Power Systems Test Case Archive, 2022).

Line Name	From Bus	To Bus	Length (km)	Resistance (Ohm/km)	Reactance (Ohm/km)
BRANCH-1	1	2	1	0.0922	0.047
BRANCH-2	2	3	1	0.493	0.2511
BRANCH-3	3	4	1	0.366	0.1864
BRANCH-4	4	5	1	0.3811	0.1941
BRANCH-5	5	6	1	0.819	0.707
BRANCH-6	6	7	1	0.1872	0.6188
BRANCH-7	7	8	1	1.7114	1.2351
BRANCH-8	8	9	1	1.03	0.74
BRANCH-9	9	10	1	1.044	0.74
BRANCH-10	10	11	1	0.1966	0.065
BRANCH-11	11	12	1	0.3744	0.1238
BRANCH-12	12	13	1	1.468	1.155
BRANCH-13	13	14	1	0.5416	0.7129
BRANCH-14	14	15	1	0.591	0.526
BRANCH-15	15	16	1	0.7463	0.545
BRANCH-16	16	17	1	1.289	1.721
BRANCH-17	17	18	1	0.732	0.574
BRANCH-18	2	19	1	0.164	0.1565
BRANCH-19	19	20	1	1.5042	1.3554
BRANCH-20	20	21	1	0.4095	0.4784
BRANCH-21	21	22	1	0.7089	0.9373
BRANCH-22	3	23	1	0.4512	0.3083
BRANCH-23	23	24	1	0.898	0.7091
BRANCH-24	24	25	1	0.896	0.7011
BRANCH-25	6	26	1	0.203	0.1034
BRANCH-26	26	27	1	0.2842	0.1447
BRANCH-27	27	28	1	1.059	0.9337
BRANCH-28	28	29	1	0.8042	0.7006
BRANCH-29	29	30	1	0.5075	0.2585
BRANCH-30	30	31	1	0.9744	0.963
BRANCH-31	31	32	1	0.3105	0.3619
BRANCH-32	32	33	1	0.341	0.5302

Table **4.2:** Load data of the IEEE 33-bus radial electrical power distribution system (Power Systems Test Case Archive, 2022).

Load	Location (Bus Bar)	Real Load (kW)	Reactive Load (kvar)
L2	2	100	60
L3	3	90	40
L4	4	120	80
L5	5	60	30
L6	6	60	20
L7	7	200	100
L8	8	200	100
L9	9	60	20
L10	10	60	20
L11	11	45	30
L12	12	60	35
L13	13	60	35
L14	14	120	80
L15	15	60	10
L16	16	60	20
L17	17	60	20
L18	18	90	40
L19	19	90	40
L20	20	90	40
L21	21	90	40
L22	22	90	40
L23	23	90	50
L24	24	420	200
L25	25	420	200
L26	26	60	25
L27	27	60	25
L28	28	60	20
L29	29	120	70
L30	30	200	600
L31	31	150	70
L32	32	210	100
L33	33	60	40
Total load		3715	2300

4.1.2 Base Case Load Flow Simulation Results and Analysis

The loads of all buses were maintained constant (with the assumption that the effects of dynamic loads are negligible) in all simulations with values that were equal to those shown in Table 4.2 above. Without attaching any DG to the network, the BFS load flow algorithm was implemented on the investigated distribution system, yielding the results for the base case power loss in each branch (line) of the system and the voltage profile for each bus as shown in table 4.3.

Table 4.3: Bus voltages and line losses without DG placement (Base Case)

Bus No	Voltage (Pu)	Line No	Ploss (kW)
1	1.0000	1	12.1927
2	0.9970	2	51.5711
3	0.9830	3	19.7934
4	0.9755	4	18.5931
5	0.9682	5	38.0256
6	0.9498	6	1.9131
7	0.9463	7	4.8342
8	0.9415	8	4.1773
9	0.9352	9	3.5575
10	0.9294	10	0.5531
11	0.9286	11	0.8802
12	0.9271	12	2.6638
13	0.9210	13	0.7286
14	0.9187	14	0.3569
15	0.9173	15	0.2813
16	0.9160	16	0.2515
17	0.9140	17	0.0531
18	0.9134	18	0.1610
19	0.9965	19	0.8322
20	0.9929	20	0.1008
21	0.9922	21	0.0436
22	0.9916	22	3.1812
23	0.9794	23	5.1432
24	0.9727	24	1.2873
25	0.9694	25	2.5940
26	0.9479	26	3.3211
27	0.9453	27	11.2766
28	0.9339	28	7.8180
29	0.9257	29	3.8881
30	0.9222	30	1.5928
31	0.9180	31	0.2131
32	0.9171	32	0.0132
33	0.9168	Total power Losses	201.8925
Average bus voltage	0.948594		

4.1.3 Simulation Results and Analysis after the Placement of DG Units

Starting from the placement of one to four DG units, the voltage profiles and power losses before and after the optimal siting and sizing of the DG units in the standard IEEE 33-bus test system were compared and the results obtained are presented in both tabular and graphical forms in the following sections. Although, the developed algorithm is so robust and flexible that it can accommodate type 1-DGs, type 2-DGs and type 3-DGs, only type 3-DGs based on synchronous machines such as Small Hydro, Geothermal were considered in all the placement cases (1 to 4 DG units) in order to achieve the highest value of power loss reduction and superior voltage profiles than the other variants. This is because it has the capacity to produce real power (P) and reactive power (Q) simultaneously, which reduces the amount of current flowing through the branch and, as a result, lowers voltage drops.

4.1.3.1 Placement of One DG Unit (Results from MATLAB)

Table 4.4a: Bus voltage profiles after the optimal installation of one DG unit in a standard IEEE 33-bus system

|Bus| No.	|V| |Pu|
1	1.000
2	0.999
3	0.996
4	0.997
5	0.999
6	1.002
7	0.999
8	0.994
9	0.988
10	0.983
11	0.982
12	0.981
13	0.975
14	0.973
15	0.971
16	0.970
17	0.968
18	0.968
19	0.999
20	0.995
21	0.994
22	0.994
23	0.993
24	0.986
25	0.983
26	1.000
27	0.998
28	0.987
29	0.979
30	0.976
31	0.972
32	0.971
33	0.971

Average bus voltage level= 0.9862

Minimum bus voltage level = 0.9700

Table 4.4b: Line power losses and power flow after the optimal installation of one DG unit in a standard IEEE 33-bus system

|Line| No.	|Ploss| |kW|	|Pflow| |kW|
1	1.003	1192.300
2	2.010	730.188
3	0.262	-304.579
4	0.553	-425.093
5	1.544	-486.186
6	1.711	1076.774
7	4.319	951.023
8	3.728	726.707
9	3.174	672.574
10	0.493	613.689
11	0.785	561.209
12	2.375	492.563
13	0.649	426.590
14	0.318	284.248
15	0.251	224.417
16	0.224	161.132
17	0.047	97.682
18	0.160	379.588
19	0.829	272.807
20	0.100	186.107
21	0.043	93.638
22	3.094	986.031
23	5.003	862.263
24	1.252	443.585
25	2.317	1067.322
26	2.965	799.313
27	10.066	687.593
28	6.978	541.343
29	3.470	364.115
30	1.420	311.301
31	0.190	213.875
32	0.012	45.883

Table 4.4c: Optimal DG size and location and total power losses before and after the optimal installation of one DG unit in a standard IEEE 33-bus system

```
---------------------------------------------
        Optimal Size & Location
---------------------------------------------
Power-Loss Before DG (kW):          201.89
Power-Loss Before DG (kvar):        134.64
Power-Loss After DG (kW):            61
Power-Loss After DG (kVAR):          48
Optimal Location DG (Num Bus):        6
Optimal Size Power-DG (kW):          2583
Optimal Size Power-DG (kvar):        1770
Total Active Power Demand (kW):      3715
Total Reactive Power Demand (kvar):  2300
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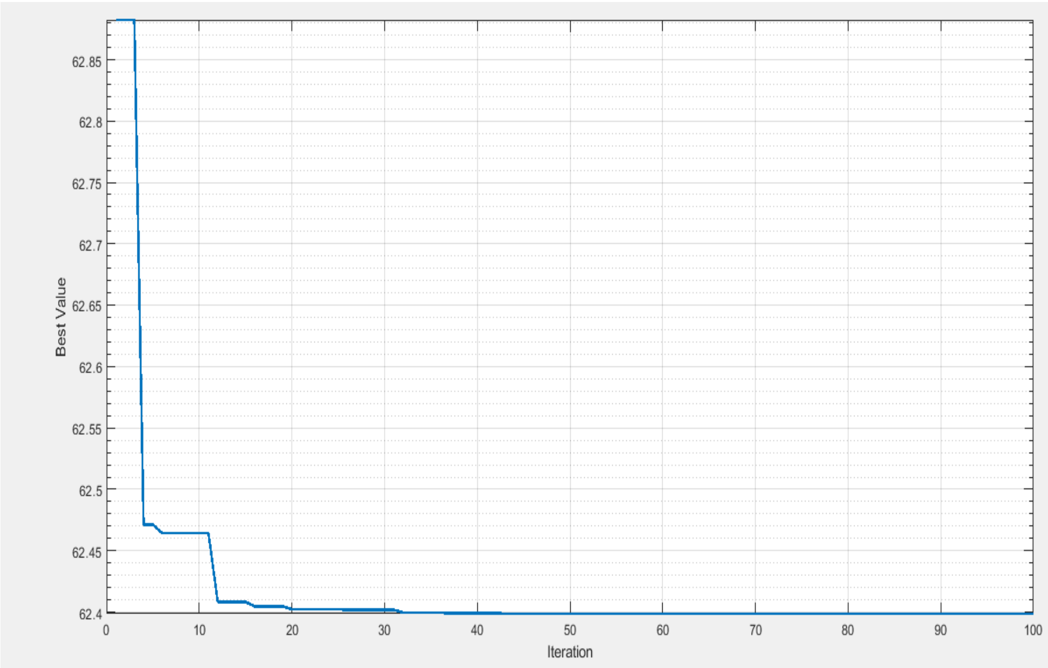

Figure 4.2: Best iteration values for the optimal placement of one DG unit

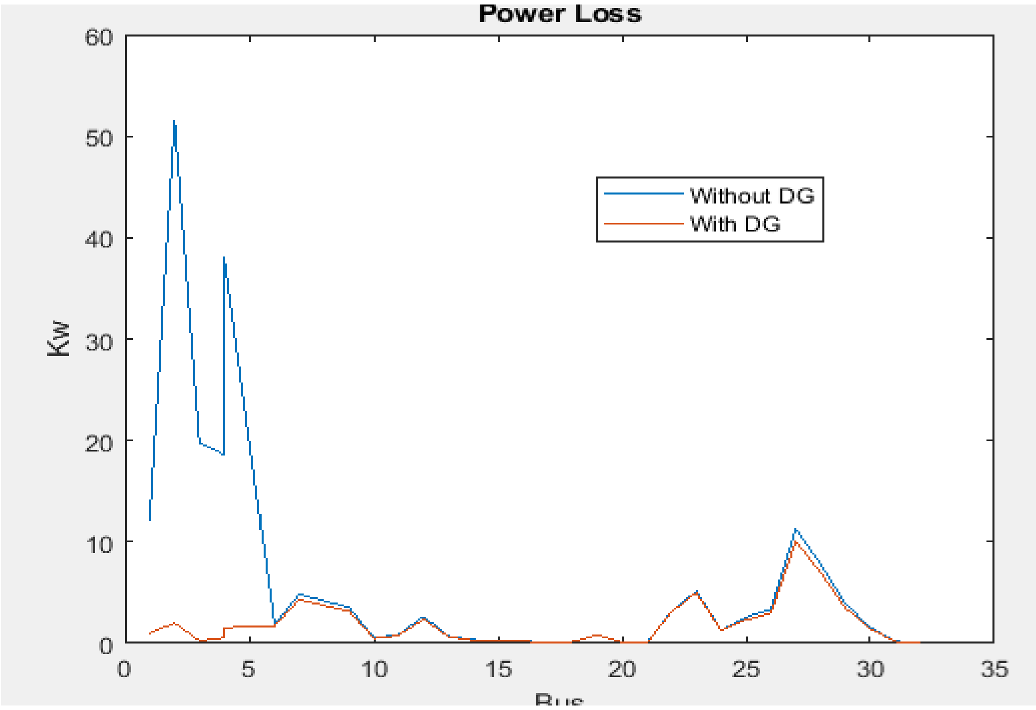

Figure 4.3: Power loss before and after the optimal placement of one DG unit in a standard IEEE 33-bus system

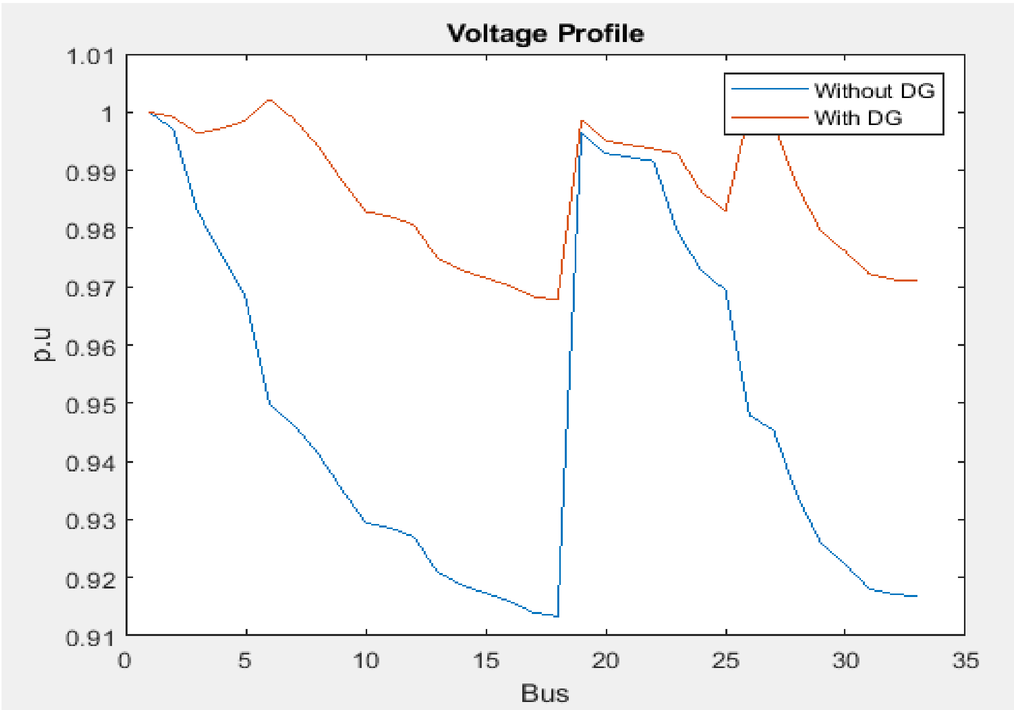

Figure 4.4: Bus voltage profiles before and after the optimal placement of one DG unit in a standard IEEE 33-bus system

When compared with the old system without DG units, the optimal installation of 1 DG unit results in better average bus voltage levels of 0.9862 per unit as against 0.9486 per unit. Additionally, the lowest voltage level in the system without DG units is 0.9168 per unit whereas the minimum bus voltage level after one type 3-DG unit is installed, giving is 0.9700. Likewise, the optimal installation of the one DG unit brought about a reduction of 140.89 kW amounting to 69.79% and 86.64 kvar amounting to 64.35% in the overall real and reactive power losses respectively.

4.1.3.2 Placement of Two DG units (Results from MATLAB)

Table 4.5a: Bus voltage profiles after the optimal installation of two DG units in a standard IEEE 33-bus system

|Bus| No.	|V| |Pu|
1	1.000
2	0.999
3	0.994
4	0.993
5	0.993
6	0.992
7	0.991
8	0.991
9	0.993
10	0.995
11	0.995
12	0.996
13	1.001
14	0.999
15	0.998
16	0.996
17	0.994
18	0.994
19	0.998
20	0.995
21	0.994
22	0.993
23	0.990
24	0.984
25	0.980
26	0.993
27	0.993
28	0.996
29	0.999
30	1.001
31	0.997
32	0.997
33	0.996

Average bus voltage level = 0.9944

Minimum bus voltage level = 0.9800

Table 4.5b: Line power losses and power flow after the optimal installation of two DG units in a standard IEEE 33-bus system

|Line| No.	|Ploss| |kW|	|Pflow| |kW|
1	2.191	1757.747
2	6.375	1294.959
3	0.191	256.995
4	0.051	136.208
5	0.032	75.987
6	0.082	238.284
7	0.007	36.354
8	0.225	-170.040
9	0.407	-230.370
10	0.120	-289.518
11	0.315	-335.962
12	1.745	-398.599
13	0.616	388.678
14	0.302	275.132
15	0.238	216.488
16	0.212	155.707
17	0.045	95.492
18	0.160	381.962
19	0.829	272.837
20	0.100	186.128
21	0.043	93.648
22	3.111	988.374
23	5.029	862.924
24	1.259	443.909
25	0.079	-233.302
26	0.176	-283.182
27	0.955	-343.862
28	0.986	-395.709
29	1.072	-501.135
30	1.349	403.867
31	0.180	269.197
32	0.011	60.499

Table 4.5c: Optimal DG size and location and total power losses before and after the optimal installation of two DG units in a standard IEEE 33-bus system

----

Optimal Size & Location

Power-Loss Before DG (kW):	201.89
Power-Loss Before DG (kvar):	134.64
Power-Loss After DG (kW):	28
Power-Loss After DG (kvar):	20
Optimal Location DG (Num Bus):	30 13
Optimal Size Power-DG (kW):	1146 845
Optimal Size Power-DG (kvar):	1065 396
Total Active Power Demand (kW):	3715
Total Reactive Power Demand (kvar):	2300

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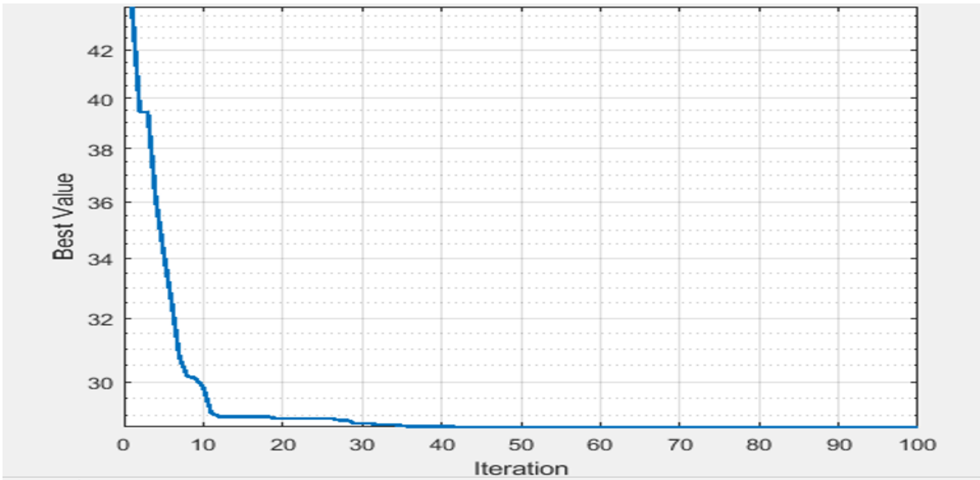

Figure 4.5: Best iteration values for the optimal placement of two DG units

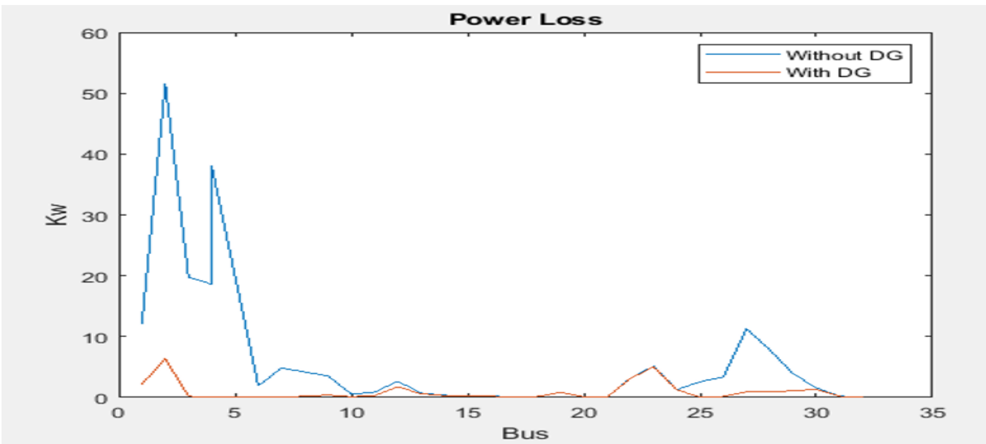

Figure 4.6: Power loss before and after the optimal placement of two DG units in a standard IEEE 33-bus system

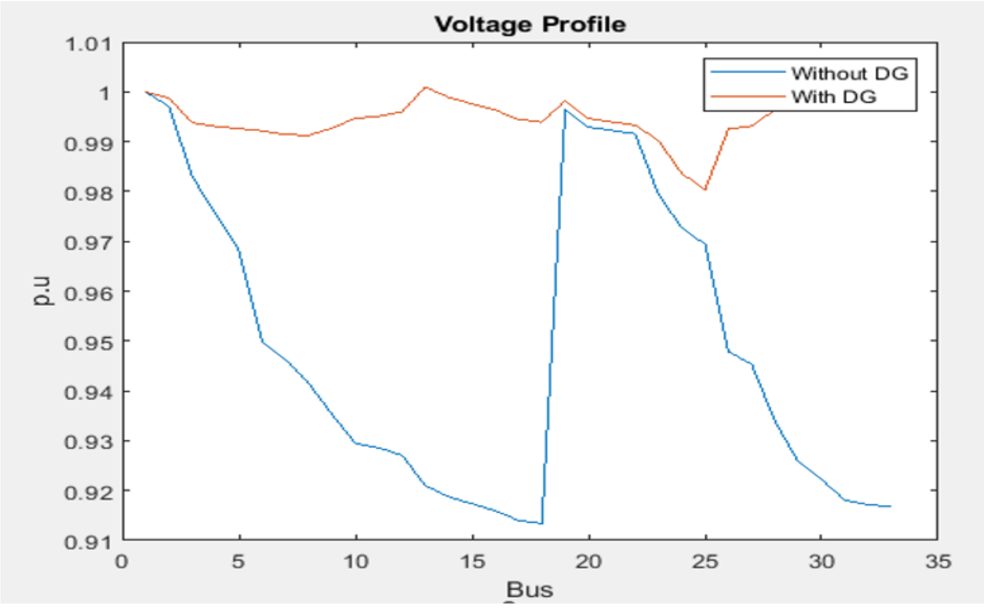

Figure 4.7: Bus voltage profiles before and after the optimal placement of two DG unit in a standard IEEE 33-bus system

By comparison with the old system without DG units, the optimal installation of two type 3-DG unit results in better average bus voltage levels of 0.9944 per unit as against 0.9486 per unit. Also, the lowest voltage level in the system was increased from 0.9168 per unit to 0.9800 per unit. Similarly, the optimal installation of the two DG units brought about a reduction of 173.89 kW representing 86.13% and 114.64 kvar representing 85.15% in the overall real and reactive power losses respectively.

4.1.3.3 Placement of Three DG units (Results from MATLAB)

Table 4.6a: Bus voltage profiles after the optimal installation of three DG units in a standard IEEE 33-bus system

|Bus| No.	|V| |Pu|
1	1.000
2	0.999
3	0.998
4	0.997
5	0.996
6	0.994
7	0.993
8	0.992
9	0.993
10	0.994
11	0.994
12	0.995
13	0.999
14	1.001
15	1.000
16	0.998
17	0.996
18	0.996
19	0.999
20	0.995
21	0.995
22	0.994
23	0.998
24	1.000
25	0.997
26	0.994
27	0.995
28	0.997
29	0.999
30	1.001
31	0.997
32	0.996
33	0.996

Average bus voltage level = 0.9966

Minimum bus voltage level = 0.9920

Table 4.6b: Line power losses and power flow after the optimal installation of three DG units in a standard IEEE 33-bus system

|Line| No.	|Ploss| |kW|	|Pflow| |kW|
1	0.507	844.856
2	0.562	382.916
3	0.555	440.501
4	0.291	319.890
5	0.408	259.868
6	0.157	333.391
7	0.088	132.249
8	0.046	-76.972
9	0.142	-138.489
10	0.055	-199.441
11	0.163	-246.888
12	1.022	-310.233
13	0.550	-366.629
14	0.300	269.266
15	0.237	211.695
16	0.212	152.291
17	0.045	93.580
18	0.160	375.117
19	0.828	272.728
20	0.100	186.061
21	0.043	93.616
22	0.076	-154.610
23	0.400	-237.599
24	1.217	416.288
25	0.027	-130.147
26	0.080	-192.259
27	0.509	-253.287
28	0.582	-309.542
29	0.727	-422.150
30	1.350	413.909
31	0.181	275.076
32	0.011	62.140

Table 4.6c: Optimal DG size and location and total power losses before and after the optimal installation of three DG units in a standard IEEE 33-bus system

Optimal Size & Location			
Power-Loss Before DG (kW):	201.89		
Power-Loss Before DG (kvar):	134.64		
Power-Loss After DG (kW):	12		
Power-Loss After DG (kvar):	10		
Optimal Location DG (Num Bus):	24	14	30
Optimal Size Power-DG (kW):	1080	752	1053
Optimal Size Power-DG (kvar):	521	351	1021
Total Active Power Demand (kW):	3715		
Total Reactive Power Demand (kvar):	2300		

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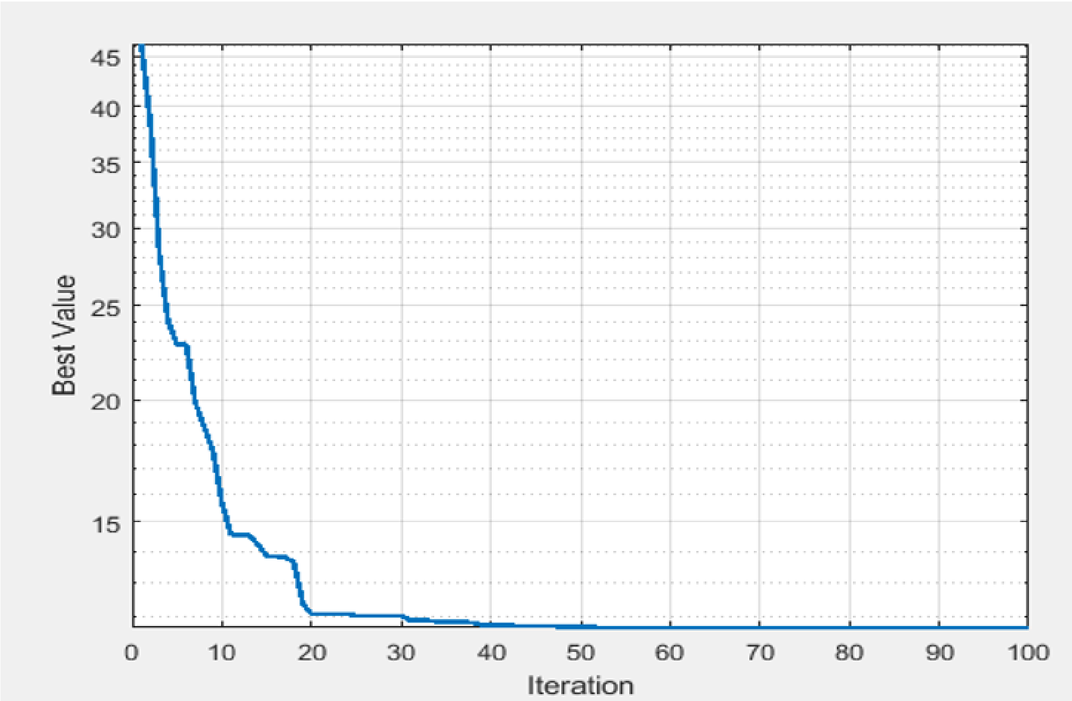

Figure 4.8: Best iteration values for the optimal placement of three DG units

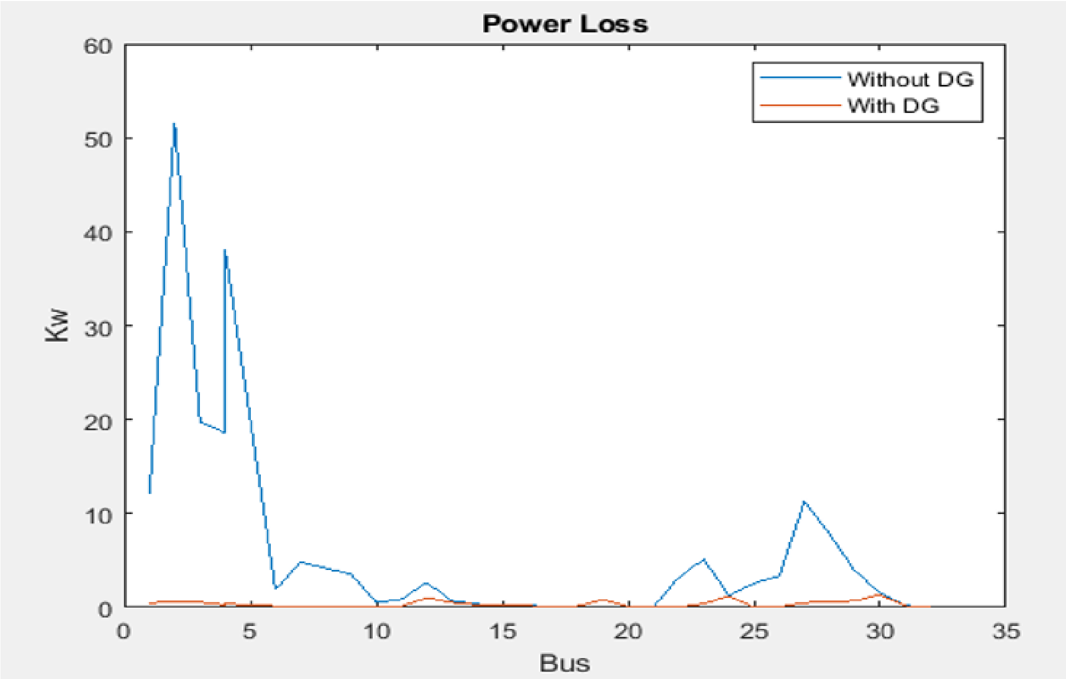

Figure 4.9: Power loss before and after the optimal placement of three DG units in a standard IEEE 33-bus system

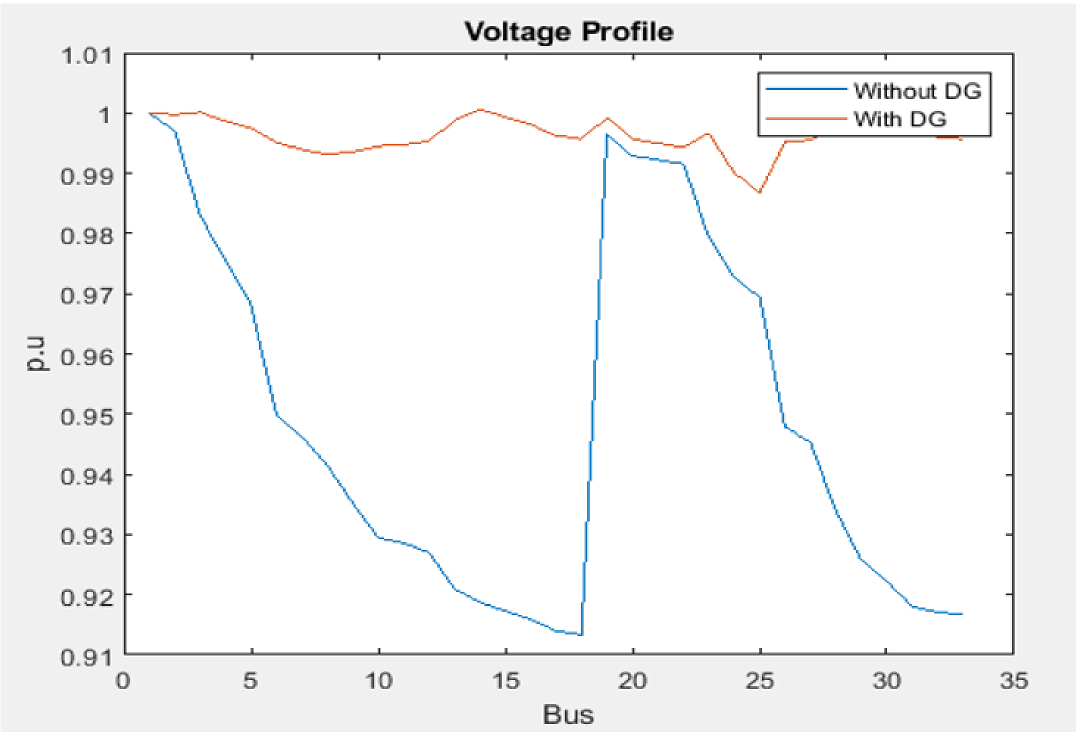

Figure 4.10: Bus voltage profiles before and after the optimal placement of three DG units in a standard IEEE 33-bus system

The optimal installation of three type 3-DG units produces better average bus voltage levels 0.9966 per unit as opposed to 0.9486 per unit, and also raises the lowest voltage level in the system from 0.9168 per unit to 0.9920 per unit. Likewise, in comparison with the old system without DG units. Similar to this, the three DG units optimal installation resulted in reductions in the overall real and reactive power losses of 189.89 kW, or 94.06%, and 124.64 kvar, or 92.57.15%. respectively.

4.1.3.4 Placement of Four DG units (Results from MATLAB)

Table 4.7a: Bus voltage profiles after the optimal installation of four DG units in a standard IEEE 33-bus system

|Bus| No.	|V| |Pu|
1	1.000
2	1.000
3	0.999
4	0.999
5	0.999
6	1.000
7	1.001
8	0.999
9	0.998
10	0.998
11	0.998
12	0.998
13	1.000
14	1.001
15	1.000
16	0.999
17	0.997
18	0.996
19	0.999
20	0.995
21	0.995
22	0.994
23	0.999
24	1.000
25	0.997
26	1.000
27	0.999
28	0.999
29	1.000
30	1.000
31	0.996
32	0.996
33	0.995

Average bus voltage level = 0.9984
Minimum bus voltage level = 0.9940

Table 4.7b: Line power losses and power flow after the optimal installation of four DG units in a standard IEEE 33-bus system

|Line| No.	|Ploss| |kW|	|Pflow| |kW|
1	0.251	592.516
2	0.068	130.732
3	0.017	73.975
4	0.008	-45.966
5	0.078	-106.012
6	0.127	-297.265
7	0.458	280.332
8	0.061	86.510
9	0.008	28.362
10	0.001	-30.161
11	0.016	-73.046
12	0.210	-130.652
13	0.164	-186.020
14	0.300	258.689
15	0.237	203.119
16	0.211	146.165
17	0.045	90.084
18	0.160	361.754
19	0.828	272.687
20	0.100	186.036
21	0.043	93.604
22	0.004	-34.794
23	0.110	-123.254
24	1.217	419.073
25	0.026	133.541
26	0.011	72.083
27	0.001	12.269
28	0.013	-47.621
29	0.112	-166.613
30	1.352	419.422
31	0.181	278.274
32	0.011	63.045

Table 4.7c: Optimal DG size and location and total power losses before and after the optimal installation of four DG units in a standard IEEE 33-bus system

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Optimal Size & Location

Power-Loss Before DG (kW):	201.89
Power-Loss Before DG (kvar):	134.64
Power-Loss After DG (kW):	6
Power-Loss After DG (kvar):	6
Optimal Location DG (Num Bus):	14 30 24 7
Optimal Size Power-DG (kW):	587 790 965 789
Optimal Size Power-DG (kvar):	272 895 466 377
Total Active Power Demand (kW):	3715
Total Reactive Power Demand (kvar):	2300

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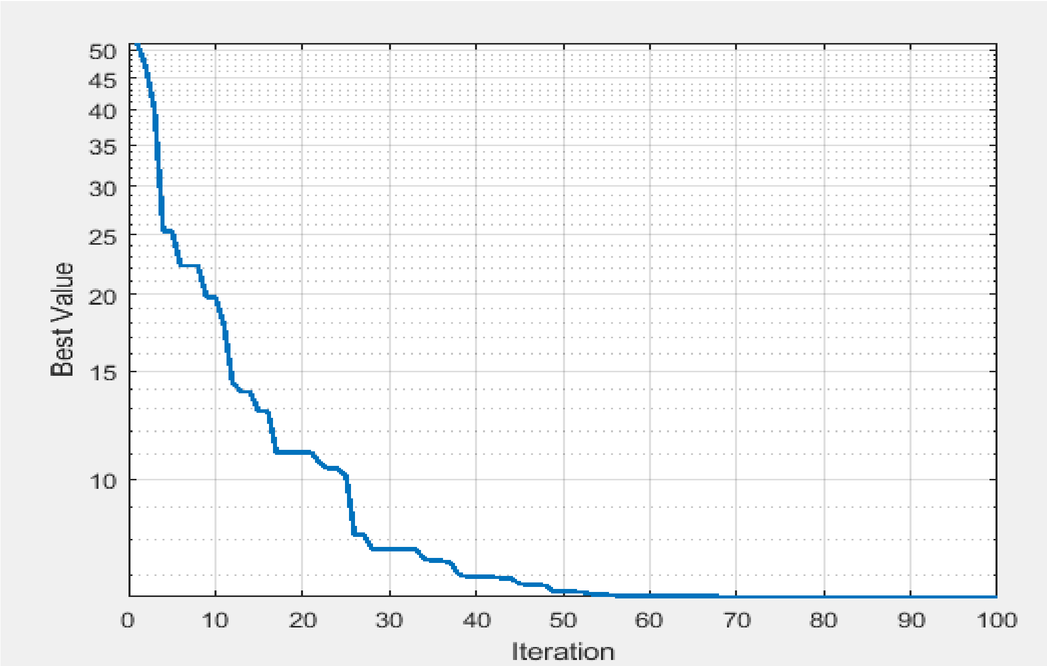

Figure 4.11: Best iteration values for the optimal placement of four DG units

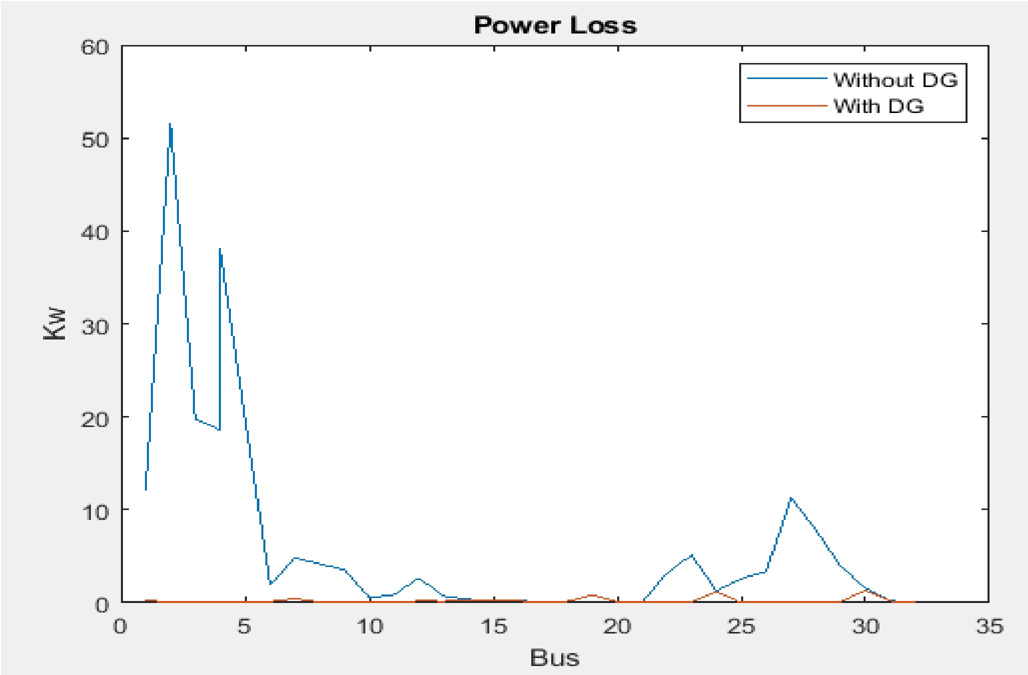

Figure 4.12: Power loss before and after the optimal placement of four DG units in a standard IEEE 33-bus system

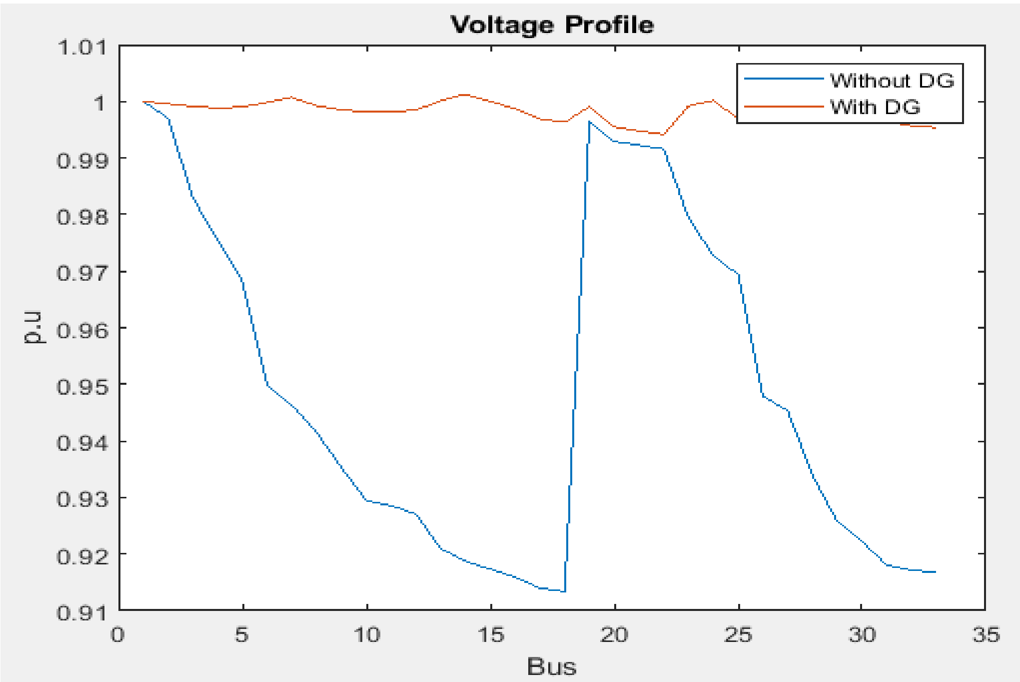

Figure 4.13: Bus voltage profiles before and after the optimal placement of four DG units in a standard IEEE 33-bus system

In comparison to the old system without DG units, the optimal installation of four type 3-DG units results in better average bus voltage levels (0.998364 per unit) as opposed to (0.948594 per unit), and also raises the lowest voltage level in the system from 0.9168 per unit to 0.994 per unit. Similar to this, the optimal integration of four DG units reduced actual and reactive power losses overall by 195.89 kW, or 97.03%, and 128.64 kvar, or 95.54%, respectively.

4.1.4 Overall Comparison of Voltage Profiles and Power Losses Before and After the Four Cases of DG Units Placement

Having obtained the simulation results for the four different cases of DG units placement, the overall comparison of the bus voltage profiles and power losses before and after the DG placements was done and the results of the analysis including graphical plots using excel are presented in the following sections.

4.1.4.1 Overall Voltage Improvement comparison and Calculations

The overall comparison of the bus voltage profiles before and after the DG units placements was done and the overall % average improvement in the bus voltage profiles in all the four cases of DG units optimal placements were calculated in excel using the values obtained from the simulations and equations 4.1-4.3. The results of the analysis are presented in table 4.8. The bus voltage profiles for all the scenarios in a single plot and the % average improvement in bus voltage profiles versus no of DG units for the four cases of DG units optimal placements were also plotted in excel as shown in figure 4.14 and figure 4.15 respectively.

Average bus voltage levels = $\frac{\boldsymbol{sum\ of\ voltages\ in\ all\ the\ 33\ buses}}{\mathbf{33}}$ …………………. (4.1)

Average improvement in bus voltage levels after DG placement = **(**Average bus voltage after DG placement **—** Average bus voltage without DG) ……………… (4.2)

% Average improvement in bus voltage levels after DG placement =

$$\left(\frac{\textit{Average improvement in voltage level after DG placement}}{\textit{Average bus voltage without DG}}\right) * \mathbf{100} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots..(4.3)$$

Table 4.8: Overall bus voltage profiles comparison of without DG and after the four cases of DG unit's optimal placement and bus voltage profiles improvement calculations

Bus No	No DG V (Pu)	1 DG V (Pu)	2 DGs V (Pu)	3 DGs V(Pu)	4 DGs V(Pu)
1	1	1	1	1	1
2	0.997	0.999	0.999	0.999	1
3	0.983	0.996	0.994	0.998	0.999
4	0.9755	0.997	0.993	0.997	0.999
5	0.9682	0.999	0.993	0.996	0.999
6	0.9498	1.002	0.992	0.994	1
7	0.9463	0.999	0.991	0.993	1.001
8	0.9415	0.994	0.991	0.992	0.999
9	0.9352	0.988	0.993	0.993	0.998
10	0.9294	0.983	0.995	0.994	0.998
11	0.9286	0.982	0.995	0.994	0.998
12	0.9271	0.981	0.996	0.995	0.998
13	0.921	0.975	1.001	0.999	1
14	0.9187	0.973	0.999	1.001	1.001
15	0.9173	0.971	0.998	1	1
16	0.916	0.97	0.996	0.998	0.999
17	0.914	0.968	0.994	0.996	0.997
18	0.9134	0.968	0.994	0.996	0.996
19	0.9965	0.999	0.998	0.999	0.999
20	0.9929	0.995	0.995	0.995	0.995
21	0.9922	0.994	0.994	0.995	0.995
22	0.9916	0.994	0.993	0.994	0.994
23	0.9794	0.993	0.99	0.998	0.999
24	0.9727	0.986	0.984	1	1
25	0.9694	0.983	0.98	0.997	0.997
26	0.9479	1	0.993	0.994	1
27	0.9453	0.998	0.993	0.995	0.999
28	0.9339	0.987	0.996	0.997	0.999
29	0.9257	0.979	0.999	0.999	1
30	0.9222	0.976	1.001	1.001	1
31	0.918	0.972	0.997	0.997	0.996
32	0.9171	0.971	0.997	0.996	0.996
33	0.9168	0.971	0.996	0.996	0.995
Average level	0.9486	0.9862	0.9944	0.9966	0.9984
Average Improvement		0.0376	0.0458	0.0480	0.0498
% Average Improvement		3.9593	4.8262	5.0614	5.2467

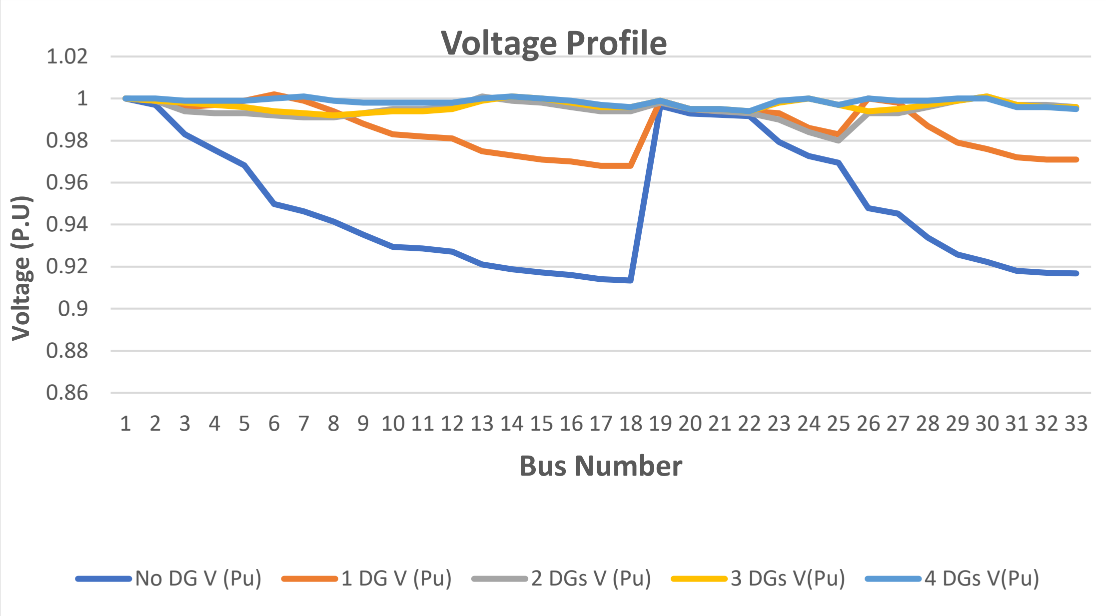

Figure 4.14: Bus Voltage profiles before and after the four cases of the optimal installation of DG units in a standard IEEE 33-bus test system.

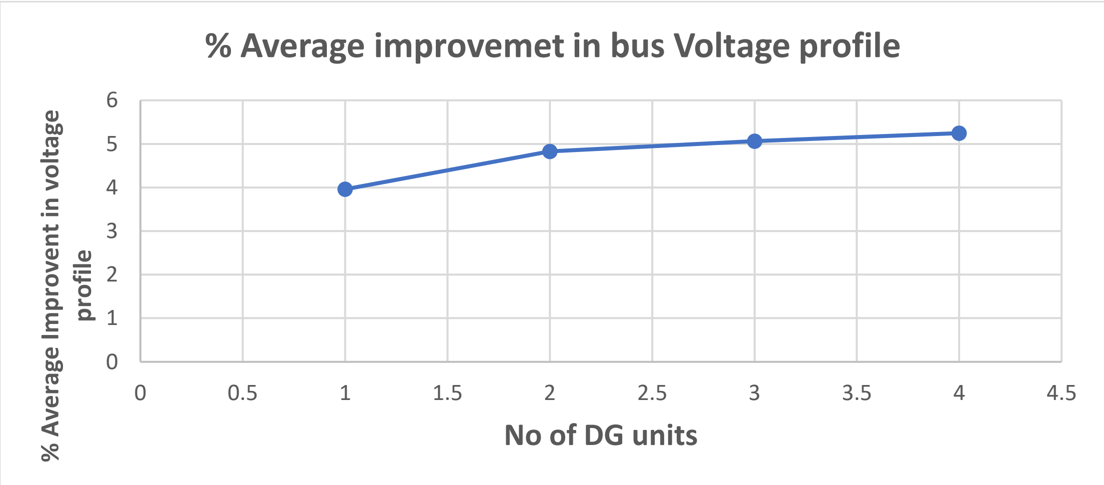

Figure 4.15: Plot of % average improvement in bus voltage profiles versus no of DG units in all the four cases of DG units optimal placement

4.1.4.2 Overall Power Losses Reduction Comparison and Calculations

The overall comparison of the power losses before and after the DG units placements was done and the % reduction in total real and reactive power losses in all the four cases of DG units optimal placements were calculated using the values obtained from the simulations and equations 4.4-4.7. The results of the analysis are presented in table 4.9 and the % reduction in the total real and reactive power losses for the four scenarios of optimal placements of DG units are also plotted in a single plot in excel as shown in figure 4.16

Reduction in total Real Power Losses (Ploss) after DG placement = **(**Total Ploss after DG placement − Total Ploss without DG) ………………….…………… (4.4)

Reduction in total Reactive Power Losses (Qloss) after DG placement = (Total Qloss after DG placement − Total Qloss without DG) ………………………… (4.5)

% Reduction in Total Ploss after DG placement =

$$\frac{\textbf{Reduction in Total Ploss after DG placement}}{\textbf{\textit{Total Ploss without DG}}}) * \mathbf{100} \ldots\ldots\ldots\ldots\ldots\ldots \quad (4.6)$$

% Reduction in Total Qloss after DG placement =

$$\frac{\textbf{Reduction in Total Qloss after DG placement}}{\textbf{\textit{Total Qloss without DG}}}) * \mathbf{100} \ldots\ldots\ldots\ldots\ldots\ldots \quad (4.7)$$

Table 4.9: Comparison of total power losses without DG and after the four cases of optimal placement of DG units and % reduction in total power losses calculations

Scenario	Total Ploss (kW)	Total Qloss (kvar)	Reduction in Total Ploss (kW)	Reduction in Total Qloss (kvar)	% Reduction in Total Ploss	% Reduction in Total Qloss
Without DG	201.89	134.64	-	-	-	-
1 DG	61	48	140.89	86.64	69.79	64.35
2 DGs	28	20	173.89	114.64	86.13	85.15
3 DGs	12	10	189.89	124.64	94.06	92.57
4 DGs	6	6	195.89	128.64	97.03	95.54

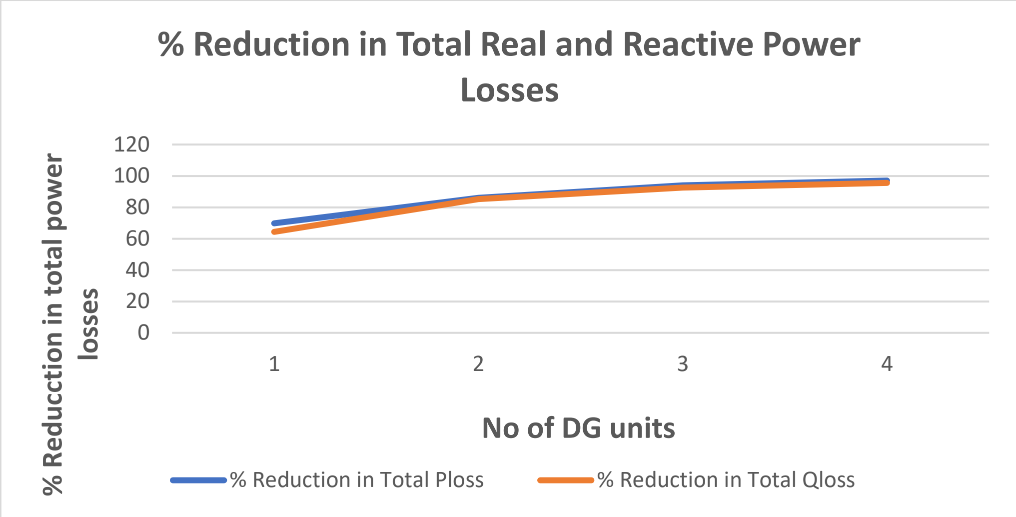

Figure 4.16: Plot of % reduction in total real and reactive power losses in all the four cases of DG units optimal placement

4.1.4.3 Overall Comparison of Optimal DG Locations and DG sizes with the Corresponding Bus Voltage Profiles

Table 4.10 below presents a summary of the optimal DG sizes (in terms of real and reactive power), the optimal DG locations (bus numbers) and the corresponding bus voltage levels for all the four cases of DG units optimal placements based on the simulation results earlier presented.

Table 4.10: Optimal DG locations and DG sizes comparison with the corresponding bus voltage profiles

Parameter	1 DG	2 DGs		3 DGs			4 DGs			
Optimal DG location bus no	6	30	13	24	14	30	14	30	2	7
Bus Voltage (Pu)	1.002	1.001	1.001	1.000	1.001	1.001	1.001	1.000	1.000	1.001
Optimal DG size (kW)	2583	1146	845	1080	752	1053	587	790	965	789
Optimal DG size (kvar)	1770	1065	396	521	351	1021	272	895	466	377

It is observed that the optimal locations of the DG units correspond to the buses with the highest values of voltage levels in all the four cases of the optimal placements of the DG units. In other words, the optimal location and size of the DG units simultaneously determines the improvement in the voltage profile as it also does determine the decrease in the total power losses.

4.1.5 Comparison of Produced Results with Those of Earlier Studies

The results of other approaches that were also tested on the IEEE 33-bus radial distribution system with one type 3-DG unit optimal placement and were given in (Injeti and Kumar, 2011; Peyman et al., 2016; Vijay and Singh, 2016) are presented in table 4.11 along with the outcomes of the obtained results. The comparison has shown that the developed technique in this study has proven to be comparable with; and even achieved a higher reduction in the total power losses than those of previous studies for an approximately the same size of DG (2.5 MW) optimally placed in bus 6 of the standard IEEE 33-bus radial electrical power distribution network.

Table 4.11: Comparison of existing methods and proposed method with type 3-DG optimal placement for 33-bus radial distribution system

Author	**Methodology/Optimization Technique Employed**	**Optimal DG location bus**	**DG type**	**DG size (MW)**	**% Reduction in Total Real power losses**	**% Reduction in Total Reactive Power losses**
Current work	Multi-Objective PSO	6	Type 3	2.583	69.79%	64.35%
(Injeti and Kumar, 2011)	Fuzzy Logic	6	Type 3	2.590	52.6%	36.9%
(Peyman et al., 2016)	Mixed PSO	6	Type 3	2.550	67.83%	61.66%
(Vijay and Singh, 2016)	General Algebraic Modelling Systems (GAMS)/Non-Linear Programming (NLP)	6	Type 3	2.533	67.86%	-

4.2 Discussion

The result analysis illustrated in figure 4.14 clearly shows the significant improvements in the bus voltage profiles starting from the optimal placement of one type 3-DG to four type 3-DG units in the network. Also, from table 4.8, it is observed that the improvement in the voltage profiles increases progressively as the number of DG units increases and the highest % average improvement (being 5.2467%) in bus voltage profiles was attained when four type 3-DG units were optimally placed in the network. Figure 4.15 further clearly confirmed how these improvements in bus voltage profiles vary proportionally with the number of DG units optimally placed in the system. Similarly, the result analysis presented in table 4.9 clearly demonstrated the effectiveness of the optimal placement of the DG units in the network in reducing the total active and reactive power losses whereby significant reduction was achieved in each of the case of DG unit placement. It is also observed that the reduction in total active and reactive power losses increases progressively as more DG units are being optimally placed in the system attaining the highest % reduction of 97.03% and 95.54% in total active and reactive power losses when four type 3-DG units were optimally placed in the network. Figure 4.16 further clearly demonstrated this correlation between the reduction in total power losses and the number of DG units and also, the reduction in the total active power losses is slightly more than the reduction in the total reactive power losses in each scenario of DG unit optimal placement

The obtained results demonstrate that the voltage profiles of the buses and the total power losses are significantly impacted by both the optimal locations and sizes of the DG units. In all the four cases of the type 3-DG units optimal placements, the bus voltage levels have been significantly improved and the total power losses have been remarkably reduced; with this improvement in voltage profiles and reduction in the total power losses proportional to the number of and hence, the capacity of the DG units optimally installed in the network. Furthermore, it has been noted throughout the simulations that the connection position of DG units is crucial for the entire network because it can lead to drastically different performance for different types of DG units.

As far as the overall network power losses go, the findings indicate that the linked DG size, independent of the DG type, plays a significant role because it has been found that the larger the DG, the greater the impact on the overall network power losses of the system. Furthermore, the location in which a DG unit (of any kind) is located is crucial because it has a completely different impact on the network overall power losses (both actual and reactive). Although, a set DG unit size cannot ensure the system will operate optimally (from the perspective of minimizing power losses) given the variability in system demands during the day, month, or year; for Distribution Network Operators (DNOs), this set ideal position is crucial for their planning since it enables them to integrate dispatchable DG units with a variety of power production sources and ensure the system will operate at its best.

Results from earlier techniques for the same distribution system have been contrasted with those from the developed algorithm in this study, which was generated for the IEEE 33-bus radial distribution system. The comparison has demonstrated that the suggested method is effective and can offer solid options for the best DG unit size and placement in electrical power distribution networks.

It should be noted that the annual load variability (effects of dynamic loads) and the cost implications of installing DG units are other factors that have not been considered in the current work. Distribution network loads vary significantly over the course of days, weeks, and months, which causes power losses and voltage profiles to vary significantly as well. The cost of different DG types also varies, with the initial installation cost per kW of DGs often being higher than that of big centralized plants.

On the other hand, the majority of DGs are pollution-free and have low operating costs, but even so, significant differences between the various DG types should be taken into consideration when evaluating their advantages. In an effort to promote the installation of DG units in electrical distribution networks, numerous national and European assistance mechanisms have been developed. The most well-known of them is the feed-in tariff, in which the owners of DGs are rewarded at a rate that enables them to quickly recoup the cost of their investment. The aforementioned parameters should be researched and taken into consideration in upcoming research aimed at improving the suggested algorithm. They should also be used to analyze an existing electrical power distribution network.

CHAPTER FIVE: CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

In this research work, a decision-making algorithm based on multi-objective Particle Swamp Optimization (PSO) technique for identifying the optimal sizes and positions of Distributed Generation (DG) unit placement in radial electrical power distribution networks has been developed and simulated. The developed algorithm was evaluated on the industry-standard IEEE 33-bus radial electrical power distribution system, and the test results were compared with those of previous research, demonstrating that the algorithm is well-functioning and has a tolerable level of accuracy. The validation test of the developed algorithm conducted on a standard IEEE 33-bus radial electrical power distribution benchmark network shows that the total real power loss satisfying the line limits and constraints and the total reactive power loss of the system, were significantly decreased; and the voltage profile of the system was drastically enhanced by incorporating DG units at predetermined places. As clearly shown from the analysis of simulation results, the decrease in the total real and reactive power losses and the improvement in bus voltage profiles is a function of the optimal location and size of the DG unit placement and these also increases as the number of DG units increases for the type 3-DGs. The highest % reduction in total real and reactive power losses (which are 97.03% and 95.54% respectively) were obtained when four type 3-DG units were placed in the network and this scenario also gives the maximum % average improvement (which is 5.2467%) in bus voltage profiles obtained.

The adopted optimization technique is quick and precise and this approach can be used to solve mixed integer nonlinear optimization issues in electrical power systems. This method parameters can be easily adjusted, and it has a very good convergence characteristic. The application of the developed algorithm in a real electrical power distribution network can assist engineers, electric utilities, and distribution network operators in the more efficient integration of new Distributed Generation (DG) units in the current electrical power distribution networks.

5.2 Recommendations

The proposed algorithm should be improved in further work while taking the following factors into account:

1. Yearly load fluctuations
2. Financial implications of installing Distributed Generation (DG) and the associated installation expenses.
3. Environmental effects brought on by the use of DG technologies
4. The application of the algorithm in a real electrical power distribution network.

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APPENDICES

Appendix A: Backward-Forward Sweep (BFS) Load Flow Implementation

MATLAB Live Codes Part 1 (Load Flow Calculation Before DG Placement)

```
function Fit=Load_Flow(DG,Num_DG,Type_DG)
format short;
% m=load('loaddata33bus.m');
% l=load('linedata33bus.m');

Pg=zeros(33,1);
Qg=zeros(33,1);
switch Type_DG
    case 1
        for n=1:Num_DG
        Ps=DG(n);
        Pg(round(DG(n+Num_DG),0))=Pg(round(DG(n+Num_DG),0))+Ps;
        end
    case 2
        for n=1:Num_DG
        Qs=DG(n);
        Qg(round(DG(n+Num_DG),0))=Qg(round(DG(n+Num_DG),0))+Qs;
        end
    case 3
         for n=1:Num_DG
        Ps=DG(n);
        Pg(round(DG(n+2*Num_DG),0))=Pg(round(DG(n+2*Num_DG),0))+Ps;
        Qs=DG(n+Num_DG);
        Qg(round(DG(n+2*Num_DG),0))=Qg(round(DG(n+2*Num_DG),0))+Qs;
         end
end
 m=load('loaddata33bus.m');
l=load('linedata33bus.m');

br=length(l);
no=length(m);
f=0;
d=0;
MVAb=100;
KVb=12.66;
Zb=(KVb^2)/MVAb;
% Per unit Values
for i=1:br
    R(i,1)=(l(i,4))/Zb;
    X(i,1)=(l(i,5))/Zb;
end
for i=1:no
    P(i,1)=((m(i,2)-Pg(i))/(1000*MVAb));
    Q(i,1)=((m(i,3)-Qg(i))/(1000*MVAb));
end
R;
X;
P;
Q;
C=zeros(br,no);
for i=1:br
    a=l(i,2);
    b=l(i,3);
```

```
    for j=1:no
        if a==j
            C(i,j)=-1;
        end
        if b==j
            C(i,j)=1;
        end
    end
end
C;
e=1;
for i=1:no
    d=0;
    for j=1:br
        if C(j,i)==-1
            d=1;
        end
    end
    if d==0
        endnode(e,1)=i;
        e=e+1;
    end
end
endnode;
h=length(endnode);
for j=1:h
    e=2;

    f=endnode(j,1);
   % while (f~=1)
   for s=1:no
     if (f~=1)
       k=1;
       for i=1:br
           if ((C(i,f)==1)&&(k==1))
                f=i;
                k=2;
           end
       end
       k=1;
       for i=1:no
           if ((C(f,i)==-1)&&(k==1));
                f=i;
                g(j,e)=i;
                e=e+1;
                k=3;
           end
       end
     end
   end
end
for i=1:h
    g(i,1)=endnode(i,1);
end
g;
w=length(g(1,:));
for i=1:h
    j=1;
    for k=1:no
        for t=1:w
            if g(i,t)==k
```

```
                g(i,t)=g(i,j);
                g(i,j)=k;
                j=j+1;
             end
         end
    end
end
g;
for k=1:br
    e=1;
    for i=1:h
        for j=1:w-1
            if (g(i,j)==k)
                if g(i,j+1)~=0
                    adjb(k,e)=g(i,j+1);
                    e=e+1;
                else
                    adjb(k,1)=0;
                end
             end
        end
    end
end
adjb;
for i=1:br-1
    for j=h:-1:1
        for k=j:-1:2
            if adjb(i,j)==adjb(i,k-1)
                adjb(i,j)=0;
            end
        end
    end
end
adjb;
x=length(adjb(:,1));
ab=length(adjb(1,:));
for i=1:x
    for j=1:ab
        if adjb(i,j)==0 && j~=ab
            if adjb(i,j+1)~=0
                adjb(i,j)=adjb(i,j+1);
                adjb(i,j+1)=0;
            end
        end
        if adjb(i,j)~=0
            adjb(i,j)=adjb(i,j)-1;
        end
    end
end
adjb;
for i=1:x-1
    for j=1:ab
        adjcb(i,j)=adjb(i+1,j);
    end
end
b=length(adjcb);

% voltage current program

for i=1:no
    vb(i,1)=1;
```

```
end
for s=1:10
for i=1:no
    nlc(i,1)=conj(complex(P(i,1),Q(i,1)))/(vb(i,1));
end
nlc;
for i=1:br
    Ibr(i,1)=nlc(i+1,1);
end
Ibr;
xy=length(adjcb(1,:));
for i=br-1:-1:1
    for k=1:xy
        if adjcb(i,k)~=0
            u=adjcb(i,k);
            %Ibr(i,1)=nlc(i+1,1)+Ibr(k,1);
            Ibr(i,1)=Ibr(i,1)+Ibr(u,1);
        end
    end
end
Ibr;
for i=2:no
      g=0;
      for a=1:b
          if xy>1
            if adjcb(a,2)==i-1
                u=adjcb(a,1);
                vb(i,1)=((vb(u,1))-((Ibr(i-1,1))*(complex((R(i-
1,1)),X(i-1,1)))));
                g=1;
            end
            if adjcb(a,3)==i-1
                u=adjcb(a,1);
                vb(i,1)=((vb(u,1))-((Ibr(i-1,1))*(complex((R(i-
1,1)),X(i-1,1)))));
                g=1;
            end
          end
        end
        if g==0
            vb(i,1)=((vb(i-1,1))-((Ibr(i-1,1))*(complex((R(i-
1,1)),X(i-1,1)))));
        end
end
s=s+1;
end
nlc;
Ibr;
vb;
vbp=[abs(vb) angle(vb)*180/pi];

for i=1:no
vbp(i,1)=abs(vb(i));
vbp(i,2)=angle(vb(i))*(180/pi);
end

for i=1:no
    va(i,2:3)=vbp(i,1:2);
end
for i=1:no
    va(i,1)=i;
```

```
end
va;

Ibrp=[abs(Ibr) angle(Ibr)*180/pi];
PL(1,1)=0;
QL(1,1)=0;

% losses
for f=1:br
    Pl(f,1)=(Ibrp(f,1)^2)*R(f,1);
    Ql(f,1)=X(f,1)*(Ibrp(f,1)^2);
    PL(1,1)=PL(1,1)+Pl(f,1);
    QL(1,1)=QL(1,1)+Ql(f,1);
end

Plosskw=(Pl)*100000;
Qlosskw=(Ql)*100000;
PL=(PL)*100000;
QL=(QL)*100000;


voltage = vbp(:,1);
%angle = vbp(:,2)*(pi/180);
 % hold on

% Plosskw
sum(Plosskw );
sum(Qlosskw);

Plosskw(33,1)=PL;
Qlosskw(33,1)=QL;

VD=sum((1-voltage).^2)*100;
Fit=PL+VD;
 %% EXCEL FOR DG
% %EXCEL
% T =table(Sr,Plosskw,Qlosskw,angle,voltage);
% T(:,1:5);
% excel_file = 'NO_DG_IEEE33.xlsx';
% writetable(T, excel_file,'Sheet',1,'Range','H1');
```

Appendix B: Backward-Forward Sweep (BFS) Load Flow Implementation

MATLAB Live Codes Part 2 (Load Flow Calculation after DG placement)

```
function [PL,QL,Vb]=Load_Flow2(DG,Num_DG,Type_DG)

format short;
tic
% m=load('loaddata33bus.m');
% l=load('linedata33bus.m');
Pg=zeros(33,1);
Qg=zeros(33,1);
switch Type_DG
    case 1
        for n=1:Num_DG
        Ps=DG(n);
        Pg(round(DG(n+Num_DG),0))=Pg(round(DG(n+Num_DG),0))+Ps;
        end
    case 2
        for n=1:Num_DG
        Qs=DG(n);
        Qg(round(DG(n+Num_DG),0))=Qg(round(DG(n+Num_DG),0))+Qs;
        end
    case 3
         for n=1:Num_DG
        Ps=DG(n);
        Pg(round(DG(n+2*Num_DG),0))=Pg(round(DG(n+2*Num_DG),0))+Ps;
        Qs=DG(n+Num_DG);
        Qg(round(DG(n+2*Num_DG),0))=Qg(round(DG(n+2*Num_DG),0))+Qs;
         end
end
m=load('loaddata33bus.m');
l=load('linedata33bus.m');

br=length(l);
no=length(m);
f=0;
d=0;
MVAb=100;
KVb=12.66;
Zb=(KVb^2)/MVAb;
% Per unit Values
for i=1:br
    R(i,1)=(l(i,4))/Zb;
    X(i,1)=(l(i,5))/Zb;
end
for i=1:no
    P(i,1)=((m(i,2)-Pg(i))/(1000*MVAb));
    Q(i,1)=((m(i,3)-Qg(i))/(1000*MVAb));
end
R;
X;
P;
Q;
C=zeros(br,no);
for i=1:br
    a=l(i,2);
    b=l(i,3);
    for j=1:no
        if a==j
```

```
            C(i,j)=-1;
        end
        if b==j
            C(i,j)=1;
        end
    end
end
C;
e=1;
for i=1:no
    d=0;
    for j=1:br
        if C(j,i)==-1
            d=1;
        end
    end
    if d==0
        endnode(e,1)=i;
        e=e+1;
    end
end
endnode;
h=length(endnode);
for j=1:h
    e=2;

    f=endnode(j,1);
   % while (f~=1)
   for s=1:no
     if (f~=1)
       k=1;
       for i=1:br
           if ((C(i,f)==1)&&(k==1))
                f=i;
                k=2;
           end
       end
       k=1;
       for i=1:no
           if ((C(f,i)==-1)&&(k==1));
                f=i;
                g(j,e)=i;
                e=e+1;
                k=3;
           end
       end
     end
   end
end
for i=1:h
    g(i,1)=endnode(i,1);
end
g;
w=length(g(1,:));
for i=1:h
    j=1;
    for k=1:no
        for t=1:w
            if g(i,t)==k
                g(i,t)=g(i,j);
                g(i,j)=k;
```

```
                j=j+1;
             end
         end
    end
end
g;
for k=1:br
    e=1;
    for i=1:h
        for j=1:w-1
            if (g(i,j)==k)
                if g(i,j+1)~=0
                    adjb(k,e)=g(i,j+1);
                    e=e+1;
                else
                    adjb(k,1)=0;
                end
             end
        end
    end
end
adjb;
for i=1:br-1
    for j=h:-1:1
        for k=j:-1:2
            if adjb(i,j)==adjb(i,k-1)
                adjb(i,j)=0;
            end
        end
    end
end
adjb;
x=length(adjb(:,1));
ab=length(adjb(1,:));
for i=1:x
    for j=1:ab
        if adjb(i,j)==0 && j~=ab
            if adjb(i,j+1)~=0
                adjb(i,j)=adjb(i,j+1);
                adjb(i,j+1)=0;
            end
        end
        if adjb(i,j)~=0
            adjb(i,j)=adjb(i,j)-1;
        end
    end
end
adjb;
for i=1:x-1
    for j=1:ab
        adjcb(i,j)=adjb(i+1,j);
    end
end
b=length(adjcb);

% voltage current program

for i=1:no
    vb(i,1)=1;
end
for s=1:10
```

```
for i=1:no
    nlc(i,1)=conj(complex(P(i,1),Q(i,1)))/(vb(i,1));
end
nlc;
for i=1:br
    Ibr(i,1)=nlc(i+1,1);
end
Ibr;
xy=length(adjcb(1,:));
for i=br-1:-1:1
    for k=1:xy
        if adjcb(i,k)~=0
            u=adjcb(i,k);
            %Ibr(i,1)=nlc(i+1,1)+Ibr(k,1);
            Ibr(i,1)=Ibr(i,1)+Ibr(u,1);
        end
    end
end
Ibr;
for i=2:no
      g=0;
      for a=1:b
          if xy>1
            if adjcb(a,2)==i-1
                u=adjcb(a,1);
                vb(i,1)=((vb(u,1))-((Ibr(i-1,1))*(complex((R(i-
1,1)),X(i-1,1)))));
                g=1;
            end
            if adjcb(a,3)==i-1
                u=adjcb(a,1);
                vb(i,1)=((vb(u,1))-((Ibr(i-1,1))*(complex((R(i-
1,1)),X(i-1,1)))));
                g=1;
            end
          end
        end
        if g==0
            vb(i,1)=((vb(i-1,1))-((Ibr(i-1,1))*(complex((R(i-
1,1)),X(i-1,1)))));
        end
end
s=s+1;
end
nlc;
Ibr;
vb;
vbp=[abs(vb) angle(vb)*180/pi];

for i=1:no
vbp(i,1)=abs(vb(i));
vbp(i,2)=angle(vb(i))*(180/pi);
end
toc;
for i=1:no
    va(i,2:3)=vbp(i,1:2);
end
for i=1:no
    va(i,1)=i;
end
va;
```

```
Ibrp=[abs(Ibr) angle(Ibr)*180/pi];
PL(1,1)=0;
QL(1,1)=0;
% losses
for f=1:br
    Pl(f,1)=(Ibrp(f,1)^2)*R(f,1);
    Ql(f,1)=X(f,1)*(Ibrp(f,1)^2);
    PL(1,1)=PL(1,1)+Pl(f,1);
    QL(1,1)=QL(1,1)+Ql(f,1);
    Pf(f,1)=Ibrp(f,1)*vbp(f,1)*cos(vbp(f,2)-Ibrp(f,2)/180*pi)*100000;
end

Plosskw=(Pl)*100000;
Qlosskw=(Ql)*100000;
PL=(PL)*100000;
QL=(QL)*100000;

voltage = vbp(:,1);
Vb=abs(voltage);
%angle = vbp(:,2)*(pi/180);
figure
plot(m(:,1),abs(voltage));
% hold on
% Plosskw
sum(Plosskw );
sum(Qlosskw);

Plosskw1(33,1)=PL;
Qlosskw2(33,1)=QL;
disp('---------------')
disp('  |Bus|  |V| ')
disp('   No.   |Pu|')
disp('---------------')
for n=1:33
 fprintf('\n%5g %8.3f',n,voltage(n))
end
disp('                           ')
disp('---------------------------')
disp('  |Line|  |Ploss|  |Pflow| ')
disp('   No.     |Kw|      |Kw|  ')
disp('---------------------------')
for n=1:32
 fprintf('\n%5g %8.3f  %10.3f',n,Plosskw(n),Pf(n))
end
%sprintf('Power-Loss=%d KW, Power-Loss=%d KVAr' ,PL,QL')
Sr=(1:33)';
Wo_DG=load('Without_DG.m');
V_nDG=Wo_DG(:,1);
Pl_nDG=Wo_DG(1:end-1,2);
plot(m(:,1),V_nDG)
hold on
plot(m(:,1),abs(voltage))
hold off
xlabel('Bus'),ylabel('p.u'),title('Voltage Profile')
legend('Without DG','With DG')
figure
plot(l(:,1),Pl_nDG)
hold on
plot(l(:,1),Plosskw)
```

```
hold off
xlabel('Bus'),ylabel('Kw'),title('Power Loss')
legend('Without DG','With DG')

 %% EXCEL FOR DG
% %EXCEL
% T =table(Sr,Plosskw,Qlosskw,angle,voltage);
% T(:,1:5);
% excel_file = 'NO_DG_IEEE33.xlsx';
% writetable(T,excel_file,'Sheet',1,'Range','H1');
```

Appendix C: Multi-Objective PSO-based Optimal Location and Sizing of DG Optimization System Implementation Overall Nested MATLAB Live Codes

```
% Final MSc Thesis project at Moi University
% MSc in sustainable Energy and Energy Access
% Course Code: SEA 899
% Project Title: Optimal placement and sizing of DG units in
electrical power distribution networks using adaptive Particle Swarm
Optimization in MATLAB/Simulink
% Grid integration of Distributed Generation Units
% Active distribution network simulation
% Student Name: Irekefe Moses A.
% Project Supervisors: Dr Lawrence Letting and Dr Stephen Talai
% Contact Info: mosesirekefe@gmail.com
%
clc;
clear;
close all;
Num_DG=input('Please Enter Number of DG [1 to 4]:  ');
Type_DG=input('Please Enter Type of DG 1:Real Power only, 2:Reactive
Power Only 3:Real & Reactive Power:  ');
%% Problem Definition
switch Type_DG
    case 1
     nVar=2*Num_DG;              % Number of Decision Variables
   for n=1:Num_DG
   VarMin(n)=0;                  % Decision Variables Lower Bound Size
of DG
   VarMin(n+Num_DG)=1;           % Decision Variables Lower Bound
Location of DG
   VarMax(n)= 3000;              % Decision Variables Upper Bound Size
of DG
   VarMax(n+Num_DG)=33;    % Decision Variables Upper Bound Location
of DG
   end
    case 2
      nVar=2*Num_DG;              % Number of Decision Variables
   for n=1:Num_DG
   VarMin(n)=0;                  % Decision Variables Lower Bound Size
of DG
   VarMin(n+Num_DG)=1;           % Decision Variables Lower Bound
Location of DG
   VarMax(n)= 3000;              % Decision Variables Upper Bound Size
of DG
   VarMax(n+Num_DG)=33;    % Decision Variables Upper Bound Location
of DG
   end
    case 3
           nVar=3*Num_DG;              % Number of Decision Variables
   for n=1:Num_DG
   VarMin(n)=0;                  % Decision Variables Lower Bound Size
of DG
   VarMin(n+Num_DG)=0;           % Decision Variables Lower Bound
Location of DG
   VarMin(n+2*Num_DG)=1;           % Decision Variables Lower Bound
Location of DG
   VarMax(n)= 3000;              % Decision Variables Upper Bound Size
of DG
```

```
    VarMax(n+Num_DG)=3000;    % Decision Variables Upper Bound Location
of DG
    VarMax(n+2*Num_DG)=33;    % Decision Variables Upper Bound Location
of DG
    end
end
VarSize=[1 nVar];

 %% PSO Parameters

MaxIt=100;      % Maximum Number of Iterations

nPop=Num_DG*40;         % Population Size (Swarm Size)

% PSO Parameters
w=1;            % Inertia Weight
wdamp=0.99;     % Inertia Weight Damping Ratio
c1=1.5;         % Personal Learning Coefficient
c2=2.0;         % Global Learning Coefficient

% If you would like to use Constriction Coefficients for PSO,
% % Constriction Coefficients
% phi1=2.05;
% phi2=2.05;
% phi=phi1+phi2;
% chi=2/(phi-2+sqrt(phi^2-4*phi));
% w=chi;          % Inertia Weight
% wdamp=1;        % Inertia Weight Damping Ratio
% c1=chi*phi1;    % Personal Learning Coefficient
% c2=chi*phi2;    % Global Learning Coefficient

% Velocity Limits
VelMax=0.1*(VarMax-VarMin);
VelMin=-VelMax;

%% Initialization

empty_particle.Position=[];
empty_particle.Cost=[];
empty_particle.Velocity=[];
empty_particle.Best.Position=[];
empty_particle.Best.Cost=[];

particle=repmat(empty_particle,nPop,1);

GlobalBest.Cost=inf;

for i=1:nPop

    % Initialize Position
    particle(i).Position=unifrnd(VarMin,VarMax,VarSize);

    % Initialize Velocity
    particle(i).Velocity=zeros(VarSize);

    % Evaluation
    particle(i).Cost=Load_Flow(particle(i).Position,Num_DG,Type_DG);
```

```
    % Update Personal Best
    particle(i).Best.Position=particle(i).Position;
    particle(i).Best.Cost=particle(i).Cost;
% Update Global Best
    if particle(i).Best.Cost<GlobalBest.Cost

        GlobalBest=particle(i).Best;

    end

end

BestCost=zeros(MaxIt,1);

%% PSO Main Loop

for it=1:MaxIt

    for i=1:nPop

        % Update Velocity
        particle(i).Velocity = w*particle(i).Velocity ...
            +c1*rand(VarSize).*(particle(i).Best.Position-
particle(i).Position) ...
            +c2*rand(VarSize).*(GlobalBest.Position-
particle(i).Position);

        % Apply Velocity Limits
        particle(i).Velocity = max(particle(i).Velocity,VelMin);
        particle(i).Velocity = min(particle(i).Velocity,VelMax);

        % Update Position
        particle(i).Position = particle(i).Position +
particle(i).Velocity;

        % Velocity Mirror Effect
        IsOutside=(particle(i).Position<VarMin |
particle(i).Position>VarMax);
        particle(i).Velocity(IsOutside)=-
particle(i).Velocity(IsOutside);

        % Apply Position Limits
        particle(i).Position = max(particle(i).Position,VarMin);
        particle(i).Position = min(particle(i).Position,VarMax);


 % Evaluation
        particle(i).Cost =
Load_Flow(particle(i).Position,Num_DG,Type_DG);

        % Update Personal Best
        if particle(i).Cost<particle(i).Best.Cost

            particle(i).Best.Position=particle(i).Position;
            particle(i).Best.Cost=particle(i).Cost;

            % Update Global Best
            if particle(i).Best.Cost<GlobalBest.Cost
```

```
                GlobalBest=particle(i).Best;

            end

        end

    end

    BestCost(it)=GlobalBest.Cost;

    disp(['Iteration ' num2str(it) ': Best Value = '
num2str(BestCost(it))]);

    w=w*wdamp;

end

BestSol = GlobalBest;

%% Results

figure;
%plot(BestCost,'LineWidth',2);
semilogy(BestCost,'LineWidth',2);
xlabel('Iteration');
ylabel('Best Value');
grid on;
[PL,QL,Vb]=Load_Flow2(round(GlobalBest.Position,0),Num_DG,Type_DG);
VD=sum((1-Vb).^2)*100;
VD1=11.64;
disp('                            ')
disp('----------------------------------------------')
disp('            Optimal Size & Location           ')
disp('----------------------------------------------')
disp(['Power-Loss Before DG (KW):                  '
num2str(201.89)]);
disp(['Power-Loss Before DG (KVar):                '
num2str(134.64)]);
disp(['Power-Loss After DG (KW):                   '
num2str(round(PL,0))]);
disp(['Power-Loss After DG (KVar):                 '
num2str(round(QL,0))]);
switch Type_DG
    case 1
disp(['Optimal Location DG (Num_Bus):              '
num2str(round(GlobalBest.Position(Num_DG+1:end),0))]);
disp(['Optimal Size Power-DG (KW):                 '
num2str(round(GlobalBest.Position(1:Num_DG),0))]);
case 2
disp(['Optimal Location DG (Num_Bus):              '
num2str(round(GlobalBest.Position(Num_DG+1:end),0))]);
disp(['Optimal Size Power-DG (KVar):                '
num2str(round(GlobalBest.Position(1:Num_DG),0))]);
case 3
disp(['Optimal Location DG (Num_Bus):              '
num2str(round(GlobalBest.Position(2*Num_DG+1:end),0))]);
```

```
disp(['Optimal Size Power-DG (KW):                    '
num2str(round(GlobalBest.Position(1:Num_DG),0))]);
disp(['Optimal Size Power-DG (KVar):                   '
num2str(round(GlobalBest.Position(Num_DG+1:2*Num_DG),0))]);
end
disp(['Total Active Power Demand  (Kw):           ' num2str(3715)]);
disp(['Total Reactive Power Demand  (Kvar):       ' num2str(2300)]);
disp('-----------------------------------------------');
```