Voltage Sag Mitigation in the Distribution System by Optimal Allocation of Distributed Generation Units

Saman Kanzi

Submitted to the
Institute of Graduate Studies and Research
in partial fulfillment of the requirements for the degree of

Master of Science
in
Electrical and Electronic Engineering

Eastern Mediterranean University
February 2022
Gazimağusa, North Cyprus

Approval of the Institute of Graduate Studies and Research

Prof. Dr. Ali Hakan Ulusoy
Director

I certify that this thesis satisfies all the requirements as a thesis for the degree of Master of Science in Electrical and Electronic Engineering.

Assoc. Prof. Dr. Rasime Uyguroğlu
Chair, Department of Electrical and Electronic Engineering

We certify that we have read this thesis and that in our opinion it is fully adequate in scope and quality as a thesis for the degree of Master of Science in Electrical and Electronic Engineering.

Assoc. Prof. Dr. Reza Sirjani
Supervisor

Examining Committee

1. Prof. Dr. Osman Kükrer
2. Assoc. Prof. Dr. Reza Sirjani
3. Asst. Prof. Dr. Moein Jazayeri

ABSTRACT

In this thesis, a genetic algorithm (GA) based optimization is used to increase the voltage stability of a power network employing Distributed Generation (DG) Units. GA determines the best placements for DG Units in the power network. The number and sizes of DGs utilized are likewise calculated using the specified method.

First, the backward/forward sweep method has been tweaked to enable for analysis of the iterative process' convergence. Then, rectified the issue without the use of GA has been applied. The key rationale for adopting GA to tackle the problem is that, given the quantity and size of DGs, determining the ideal locations for them might be quite difficult and time intensive.

An index termed objective indices, which indicates the power flow and voltage deviation of the power network, is proposed to evaluate and compare the possible options. The bus voltages, and hence the network's VI, are determined using a Forward/Backward load flow. Moreover, by weight factors method (WF), because of the approach utilized, all WFs have an equal probability of influencing the output of the objective function, making them unified and dimensionless. As a result, by considering the number of buses affected by voltage sag has been considered to mitigate the voltage sag and enhancing voltage amplitudes in a radial distribution system.

The findings imply that using DGs enhances the voltage stability of the network. Furthermore, because GA is an optimization algorithm, it may discover the best

solution for the issue in terms of the number, size, and position of DGs after a given number of iterations. The thesis finishes with the best solution to the problem as well as the load flow data for the ideal condition.

Keywords: Distributed Generation, Genetic Algorithm, Particle Swarm Optimization, Objective Function, Weight Factor, Backward/Forward Power Flow, Voltage Indices, Active and Reactive Power Losses.

ÖZ

Bu tezde, Dağıtılmış Üretim (DG) Birimleri kullanan bir güç şebekesinin voltaj kararlılığı, genetik algoritma (GA) tabanlı bir optimizasyon kullanılarak geliştirildi. Güç ağındaki DG Birimleri için en uygun konumlar GA tarafından belirlenir. Önerilen yaklaşım ayrıca kullanılan GM'lerin sayısını ve boyutlarını da hesaplar.

İlk olarak, geri/ileri tarama yöntemi, yinelemeli sürecin yakınsamasının analizini mümkün kılmak için ince ayar yapılmıştır. Daha sonra sorun giderilerek GA kullanılmadan uygulandı. Sorunu çözmek için GA'yı benimsemenin temel mantığı, DG miktarı ve boyutu göz önüne alındığında, bunlar için ideal konumların belirlenmesinin oldukça zor ve zaman alıcı olabileceğidir.

Olası seçenekleri değerlendirmek ve karşılaştırmak için, güç şebekesinin güç akışını ve voltaj sapmasını gösteren, nesnel endeksler olarak adlandırılan bir endeks önerilmiştir. Bara voltajları ve dolayısıyla ağın VI'sı bir İleri/Geri yük akışı kullanılarak belirlenir. Ayrıca, ağırlık faktörleri yöntemine (WF) göre, kullanılan yaklaşım nedeniyle, tüm WF'ler, onları birleştirilmiş ve boyutsuz hale getirerek, amaç fonksiyonunun çıktısını etkileme konusunda eşit bir olasılığa sahiptir. Sonuç olarak, gerilim çökmesinden etkilenen bara sayısı dikkate alınarak, bir radyal dağıtım sisteminde gerilim çökmesini azalttığı ve gerilim genliklerini arttırdığı düşünülmüştür.

Sonuçlar, DG'lerin kullanılmasının ağın voltaj kararlılığını geliştirdiğini göstermektedir. Ayrıca, bir optimizasyon algoritması olan GA, belirli sayıda iterasyondan sonra DG'lerin sayısı, boyutu ve konumu açısından problem için en uygun çözümü belirleyebilir. Tez, problemin en iyi çözümü ve optimum durum için yük akışının bulguları ile sona ermektedir.

Anahtar Kelimeler: Dağıtılmış Nesil, Genetik Algoritma, Parçacık Sürü Optimizasyonu, Amaç Fonksiyonu, Ağırlık Faktörü, Geri/İleri Güç Akışı, Gerilim İndeksleri, Aktif ve Reaktif Güç Kayıpları.

ACKNOWLEDGMENT

I would want to thank Assoc. Prof. Dr. Reza SIRJANI for his supervision, assistance, and guidance from the very beginning of this thesis, as well as for providing me with incredible experiences throughout the process. Above all, and most importantly, he constantly encouraged and supported me in many ways. His thoughts, experiences, and ambitions have enriched and motivated my development as a student. I owe him far more than he realizes.

I would like to thank the members of my graduate committee, especially Prof. Dr. Osman KÜKRER and Asst. Prof. Dr. Moein JAZAYERI, for their advice and guidance. I am appreciative in every manner for all of their suggestions and encouragement.

I would also like to express my gratitude to my dear sister, Sara Kanzi and my girlfriend Pelin Karşili and also my friends and classmates Keyvan Khatibi, Arian Roshani Tabrizi, Yusuf Cohar, Davood Forghani, Danial Forghani, Mohammad Lotfi, Amir Molaei, Masoud Moradi, Javad Maleki, Atefe Ahamdniai, Mehmet Ali Sözgen and Canberk Balkır for their moral support, understanding and encouragement.

My appreciation would not be complete without giving credit to my dear parents Maryam and Mohammad.

To all who are not mentioned but in one way or another helped in completion of this study, thank you very much.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter 1

INTRODUCTION

1.1 Background

Although not everyone agrees with the term "power quality," everyone agrees that it has become an increasingly significant feature of power distribution, particularly in the second half of the 1990s [1]. There are several confusions about what the quality of power actually entails; it appears that everyone has their own version. The phrase "power quality" is used in a variety of contexts and has distinct meanings.[2], There is several terms for the quality of power; the most popular is power supply quality or voltage quality. All of these concepts are concerned with the interaction between the utility and the user, or the power system and the load in technical terms. This relationship's treatment isn't novel in and of itself. The objective of the power system has always been to provide consumers with reliable electrical energy; however, the focus on this relationship is new.

In fact, that electricity quality has only recently become a concern does not negate the fact that it has always been a concern. Utility companies all over the world have been investing in what is known as power quality for decades. In fact, the phrase has been in use for quite some time. In 1969, the phrase "power quality" was coined by the United States Navy in reply to regulations for the electricity supplied by electronic devices [1]. This research provides a comprehensive review of the power quality field, and including usage of monitoring devices and even the use of static transfer switches.

Soon after, a number of studies arose that used the phrase "power quality" in regard to aerial power systems. The high quality of power was identified as one of the purposes of industrial power system planning in 1970, along with safety, reliable service, and cheap startup and ongoing costs. Simultaneously, the word voltage quality was used in Scandinavia and the Soviet Union, particularly to describe gradual voltage magnitude changes [3].

Amongst the most hazardous areas of system reliability difficulties is voltage sag, which can cause serious damage to sensitive devices [3]. A short circuit, wind pollution on the insulating material, or the initiation of massive motors such as massive induction motors can all produce a sudden drop in RMS (Root Mean Square) voltage level. The sag phenomenon can last anywhere from 2 to 10 cycles (200 ms) and has a magnitude of 0.1 to 0.9. Apart from all forms of problems, induction motors account for 60% of total electric load and are regarded a prominent source of voltage sag [3]. Many techniques to alleviate voltage sag have been proposed, including the use of DVRs (Dynamic Voltage Restorers) in shunt and series configurations to inject reactive and active power to requite for voltage sag [1], [3]. Another option is to install DGs (Distributed Generations) in the electrical network, which has a number of advantages, including enhancing protection dependability [4] and voltage profile, lowering losses, and mitigating voltage sag, also the majority of them are ecologically benign[3].

1.2 Problem Statement

Voltage sag is a typical occurrence in electrical network, and it has a substantial impact on the quality of power system in causing harmful effects to most electronic equipment such as PCs, PLCs, and Variable Speed Drives [1], thus finding strategies to mitigate it is beneficial. To eliminate voltage sag, Distributed Generation (DG) is employed; however, the location of DG must be appropriately defined and improved using an optimization approach such as Genetic Algorithm [1], [3], such that DG improves rather than hinders the electrical network's performance. Furthermore, several types of distributed generators are extensively utilized nowadays for a variety of reasons, but each has its own features and responses in the electrical network [1], [3], [4]. As a result, it is critical to position each type in the proper area to avoid poor electrical network grid performance, which could result in catastrophic damage to the power system. For instance, if the number of buses experience voltage sag grows when DGs are placed into the power system grid, or if there is no appropriate DG site, many control systems would fail, and many processes controlled by sensitive devices will cease or be blocked. All of these problems lead to substantial financial losses. On buses subjected to voltage sag, malfunction and failure of sensitive equipment or process control result in considerable economic losses. When end users are looking for a way to describe voltage sag and estimate the expected number of production interruptions as accurately as feasible, a techno-economic analysis can be used to calculate the estimated financial loss [3]. Points 1 to 3 provide a quick description of the problem statement.

1. Voltage sag has a significant impact on the electrical network grid and can cause harm to sensitive devices, but it can be reduced by using dispersed generation. The selection of an electric network that accurately replicates the real distribution network is in great demand.
2. To mitigate voltage sag, distributed generation must be placed in the best feasible location. More sensitive loads and technological gadgets will be

destroyed if the number of buses suffering voltage sag continues to climb. Power quality issues like as voltage sag will occur if DGs are installed incorrectly in the distribution power system.

3. For grid performance and environmental purposes, various types of distributed generation are widely used, and each kind has its own set of features and consequences on the electrical grid [6]. As a result, being in the best possible location for voltage sag reduction is crucial.

1.3 Objectives of Research

In order to achieve the aim of minimizing system losses and enhancing voltage profile through optimal location and size of distributed generation (DG), the following concerns were addressed.

In order to reduce the search area of the algorithms, both reactive and active power flow, and other power loss sensitivity items, were used.

To create a multi-objective function that takes the real power loss reduction index (PLRI), the reactive power loss reduction index (QLRI), and the voltage profile improvement index into consideration (VPII). [7]

1.4 Thesis Organization

This thesis consists of five chapters and organized as follows:

- The evaluation of the literature of numerous distributed generation penetration objectives is covered in Chapter 2. Reviewing the methodologies used in prior studies to mitigate voltage sag, as well as the recommended optimization approaches used in these studies. An overview of the literature on the numerous DGs used to reduce voltage sag.

- The methodology of research is utilized to model and construct the genetic algorithm method to assign dispersed generation at the best site is presented in Chapter 3 along with a flow chart of the optimization operations.
- The results and analyses for a distribution system with 33-buses and installation DGs in the system by using two methods of optimization to reduce the losses and improving voltage profile, are discussed in Chapter 4.

Chapter 2

LITERATURE REVIEW

2.1 Introduction

The constant depletion of traditional power producing sources has resulted from exponentially increasing electricity consumption. Power generation of traditional are centralized and unsuitable for today's liberalized electrical market's environmental and cost concerns. The utilities' primary goal is to deliver electricity to its clients in a steady, acceptable, and economical manner. In this view, DGs may be able to assist in the resolution of these issues to some level. DGs are progressively becoming fundamental pieces of the electric distribution power since they need less space for installing, have lower unit sizes, and can be powered by both nonrenewable and renewable sources [5][6].

The DGs are tiny, ranging in power from a few kW to roughly 100 MW. DGs are also power generation sources that are connected directly to target consumers [8]. DG units that are strategically located reduce system losses and increase voltage profile, system dependability, the ability of load, the stability of voltage, the security of voltage, and the quality of power. Furthermore, DGs are capable of greatly reducing harmonics, voltage sags, and swells, as well as delaying transmission and distribution investment [7]. As a result, DG deployment in distribution systems benefits not just consumers but also utilities. Furthermore, the estimation of modular DGs necessitates a reduction in space, establishment time, and expenditure. As a result, DG has piqued the interest of a growing number of academics[8]–[11]. This has prompted the writers to provide a complete review on the subject. Apart from these benefits, DG technology has some drawbacks if it is not deployed in the best possible position [12], [13]. DG may cause issues with stability. Protection issues may arise as a result of bidirectional power flow. Furthermore, islanding challenges may be accompanied by frequency issues. As a result, the following significant issues and facts about DG installation and sizing must be studied [12].

i. The classes of DGs are a critical aspect in achieving optimal distribution of power system performance. The form of injected electricity from DG units is solely determined by the type of DG to be deployed to meet load requirements [5].

ii. To optimize the general performance and capability of the system, the DG sizing and location factors must be properly defined.

iii. For cost-effective operation, determine the rating (size) and quantity of DGs to be put in the electricity system. Due to their excessive size, DGs generate bidirectional power flow.

Table 2.1: DG generation at various levels [5]

Class	**Size**
DG on a micro scale	1 (W)– < 5 (Kw)
DG on a small scale	5 (kW) < 5 (MW)
DG on a medium scale	5 (MW) < 50 (MW)
DG on a large scale	50 (MW) – < 300 (MW)

iii. Analyze the safety components of the system for continuing duty and keep suitable indices (the index of the profile of voltage, power loss, the level of penetration, also the index of level's short-circuit) [12], [14].

As a result, the installation of the DG extremely important for dependable functioning and meeting consumer demand. Also, these factors must be carefully examined for optimal DG sizing and placement. The restrictions and addition of the current study could be summarized as follows based on the literature review.

In the future, the research could be expanded to include standalone and islanding challenges related with DG operation, as well as the influence on electric distribution networks.

The uncertainties constrained in (DG output, load model and electricity prices) may also be included for long term and expansion planning of existing distribution system. In addition, by combining two or more hybrid metaheuristic approaches.

2.2 Distributed Generation (DG)

In spite of the fact that the notion of distributed generation is not latest, it has recently gained popularity due to its several advantages over central power plants. The name for DG differs from country to country. It doesn't have a conventional definition or size, and it's known by a variety of names in different countries, including distributed generation, embedded generation, and decentralized generation. Several academics define DG as "an electric power source linked directly to the distribution network or on the client site of the meter." "All generating units that are normally connected to the distribution system and are not centrally planned or dispatched, with a maximum capacity ranging from a few kW to 100 MW," according to the definition. according to the International Council on Large Electricity Systems (CIGRE) [8][17]. Rather than connecting to the transmission network, electricity producing units are directly connected to the local distribution networks [15]. Table 1 [13], [15] illustrates the DG's electricity generation at various quantities based on generation capacity.

Only a few DG technologies are currently in the research stage. The key DGs technologies are listed in Table 2.2 [15], together with their electric power generating limits, benefits, and limitations.

Table 2.2 The merits and demerits of major DG technologies

No.	Technology of DG	Alternatives for Electric Power Generation	Merit(s)	Demerit(s)
1	Solar Tech. (SPV), (STPP), Solar Thermal	200 (W)–3000 (kW) 1 (MW)–80 (MW) 10–10 (MW)	- The simplest and most hygienic method - The cost of maintenance is quite low. - There is no need for fuel. - Overall, the product is environmentally beneficial.	- Large sun collectors are required. - Solar thermal systems are hazardous to one's health. - For storage, a battery bank is required. - The SPV module poses a disposal issue. - The initial investment is fairly high.
2	Combined Gas Turbine with Integrated Gasification	30 (kW)–3000 (kW)	- The efficiency of the system has improved. - Less emitted - Reliability is very important.	- Heat that was not used was released into the sky. - More upkeep is required - The initial investment is fairly high.
3	Turbine (Micro)	30 (kW)–1 (MW)	- The efficiency of the system has improved. Less emitted Reliability is more	- Emissions are lower - The initial investment is higher
4	Internal Combustion	5kW–10 MW	- Quick reaction - Less money is invested.	- Emissions are higher. - More maintenance is required
5	Hydro (Small)	5 (kW)–100 (MW)	- Source of energy that is both free and renewable - Installation costs are lower - Eco-friendly	- Generations are reliant on water. - During floods, the property is damaged. - The demand for load cannot be met. - The initial investment is higher
6	Hydro (Micro)	1 (kW)–1 (MW)	- Emission with low weight free Less noise	- The price is higher. - Working at a low temperature - Efficiency is reduced. - The initial investment is higher.
7	Wind Turbine	200 (W)–3 (MW)	- The cost of production is quite low. - There is no negative impact on the global environment. - There is no need for fuel. Land conservation	- Wind turbines are dangerous. - Pollution due to noise - The production is affected by the wind speed. - Wind speed has a big impact on variable power production.
8	Energy of Bio-Mass	100 (kW)–20 (MW)	- Source of renewable energy. - Reduce the amount of greenhouse gases (GHGs) released into the atmosphere. -Reduce your reliance on conventional fuel. - Desertification is halted.	- Biomass combustion pollutes the atmosphere. - There is a source limitation. - The cost of maintenance is high. - Erosion of the soil.
9	Geothermal Energy	5 (MW)–100 (MW)	- Stations require a little amount of area, therefore it's cost-effective. - There is no need for gasoline.	- Pollution of rivers due to waste water discharge. - Noise pollution is a serious problem.

			- Source of renewable energy - Its price does not increase with time.	- Gases are released into the atmosphere. - The removal of subsurface fluid on a large scale could cause harm to the surface structure.
10	The Energy of Tidal	0.1–1 (MW)	- It reduces GHG emissions. - There is no need for gasoline. - Energy consumption can be predicted.	- The positioning of machinery is proving to be a challenge. - It's possible that supply will only be accessible for a limited time. - Machines and related equipment are costly.
11	Fuel Cell (FC) Technology Alkaline FCs Phosphoric- Acid FCs Molten Carbonate FCs Solid Oxide FCs Proton Exchange FCs Battery Storage	1 (kW)–300 (kW) 100 (W)–50 (kW) 200 (kW)–2 (MW) 250 (kW)–2 (MW) 250 (kW)–5 (MW) 1–250 (kW) 0.5–5 (MW)	- Environmentally friendly and low-noise - The importance of efficiency is greater. - A variety of fuels are available. - They are able to work in conjunction with a waste water treatment plant.	- Overpriced - There is a need for fuel processing. - Less long-term sturdiness - The initial outlay is more.
12	System of Hydrogen Energy	40–400 (MW)	- Free of carbon - This is a non-traditional source of energy. - It's a form of energy storage device.	- Storage, packaging, and distribution are all difficult tasks. - It's difficult to pressurize. - The initial investment is higher.
13	The Energy of Ocean	100 (kW)–1000 (kW)	- This is a source of energy that is based on renewable resources. - Carbon free	- It's difficult to control. - Efficiency is extremely low. - The initial investment is substantial.

2.2.1 The Importance of Optimum Sizing and Placement

DG unit location and size in distribution networks is crucial and difficult, because they reduced losses of system, improved voltage profile of system, ability of load, reliability, stability, security of power, the regulation of voltage, the stability of voltage margin, quality of power, and voltage swell and sag, power factor of system, and other factors. Furthermore, bidirectional power flow has been recorded [7]. Furthermore, DG units allow for network development to be postponed in order to meet demand growth. While the placement of DG at random causes numerous issues, all of the above-mentioned qualities would be adversely affected. Furthermore, because the systems are built for unidirectional power flow, the protective system of the system is disrupted by bidirectional power flow, which may result in increased system losses [13], [16]. As a result, the optimal and suitable location and size of DG units in the distribution system is crucial in order to maximize their advantages to utilities and customers [7].

2.2.2 DG's Effects

The effects of DG can be divided into three groups, as shown below.

i. The Effects of DG Units on the Environment

ii. DG Units' Economic Impacts

iii. DG Units' Technical Effects.

2.2.2.1 DG's Effects on the Environment

The development of green energy has become necessary due to the rapid depletion of traditional resources and the effects of pollution and climate change. DGs are garnering the observation of researchers, academics, and conservationist in this regard. Because most DG systems are powered by renewable energy, they are a viable choice. According to published literature, fuel combustion is responsible for 80 percent of global pollution [16].

Many academics have argued that DG technologies can reduce carbon emissions, which are the primary cause of global warming [17]–[19]. According to a survey published in the United Kingdom in 1999, CHP-based DG technology can reduce carbon emissions by roughly 41% [13].

In terms of the environment, DG technology can bring ancillary service benefits to society. Greenhouse gases (GHG) similarly particulate matter, carbon monoxide, hydrocarbons, sulfur oxides, and nitrogen oxides are produced in enormous quantities by central power producing units. These pollutants play a significant role in global warming [17]–[19]. Many studies have found that using DG technologies on a broad scale reduces emissions significantly [17], [18]. As a result, the installation of DG might lead to decreased health-care expenses.

Eventually, DGs can aid a country's diversification of energy sources.[5] Solar photovoltaic, wind turbines, and hydroelectric turbines are examples of DG technologies that do not use fossil fuels. On the other side, natural gas is burned in microturbines, fuel cells, and several interior combustion engines. This growing diversification serves to protect the economy from rising costs, disturbance, and fuel scarcity [13], [20].

When compared to typical heating equipment and grid-supplied electricity, DG provides a 30% reduction in harmful carbon dioxide (CO_2) ejection. The micro turbine has a high efficacy of operation of more than 40% and releases very little harmful gases (NO_X < o7 ppm) [13], [17]–[19].

2.2.2.2 Impacts of DG on the Economy

The following are some of the primary benefits acquired by utilities and customers as a result of the shift to DG use.

The following are some of the additional elements that influence the economy of investors or utilities:

i. Facilities enrichment investments that have been postponed.

ii. Some DG technologies have lower operating and maintenance expenses.

iii. Increased efficiency.

iv. Health-care investments are reduced as a result of the improved environment.

v. Lower fuel costs as a result of better efficiency.

vi. Lower reserve needs and additional expenses.

vii. Lower operating costs as a result of peak shaving.

viii. Enhanced security for critical loads [5], [13], [21].

2.2.2.3 DG's Technical Effects

Integrating DG into a distribution system is never simple. The placement and size of DG techniques are crucial. The distribution power system may suffer technical challenges if the right sizing and position of DG is not designated appropriately, as explained in [19], [24], and [25]:

- ***Power Losses***

a. Active Power Losses

b. Reactive Power Losses

c. Active and Reactive Power Losses

- ***The Profile of Voltage***

a. The Excess of voltage

b. The Fluctuation of Voltage

- ***Reliability.***

Power Losses

Because of their proximity to load centers, the placement of DG units in distribution networks has a big impact on power losses. The DG units are placed so that system losses are kept at a minimum. DGs that are properly sized and positioned can considerably reduce electrical losses. It is normal to see 10–20 percent reductions in system losses [7], [8], [10], [17], [18], [22], [23].

- *Active power losses*

Solar photovoltaic, micro turbines, and fuel cells are examples of DG technologies that can produce active electricity [10]. DG units that are strategically positioned can greatly reduce system losses[11], [24]–[27] .

- *Reactive Power Losses*

A variety of DG technologies, including as the KVAR compensator and synchronous compensator [10], [26], are also incapable of generating reactive power. DG units with the right size and placement can dramatically reduce system losses. Furthermore, if DG is not situated and proportioned properly, the request and contribute of reactive power are disrupted [11].

- *Active and Reactive Power Losses*

Many DG systems, such as synchronous generators [23], [26], can produce both active and reactive electricity. DG units that are properly located and scaled can greatly reduce reactive and active power loss components [11], [28], [29].

The Profile of Voltage

The appropriate placement and size of DGs in distribution networks may greatly enhance the voltage profile of the system. The voltage profile is determined by the connected load and the kind of DG to be installed. As the voltage profile improves, so does the system performance [8].

The Excess of Voltage

Voltage increase, voltage fluctuation, harmonics and transients, and voltage regulation are all technical challenges that develop as a result of DG installation at random. The DG unit installation and system specifications, network strength, reactive and active power output from regional bus bars, also load type determine the voltage violation [15], [33].

The Fluctuation of Voltage

Because of a mismatch between the reactive power concern of the load and the reactive power given by the system, the placement of DG units into the distribution network generates voltage oscillations [15], [34], [35].

Reliability

Electric utilities are responsible for delivering electricity to their customers in a wise, efficient, and dependable (decent) method. It's worth emphasizing that the purpose is to keep power systems reliable because interruption costs and outages have a number of economic consequences both for utility and its customers. One of the main reasons for installing DGs in distribution systems is to improve the system's reliability. The DG can be used as a backup supply system or as the primary supply system. The DG can also be used to defer further charges during high load periods [7], [30], [31].

The reliability of a system could be evaluated using reliability indices. Some of the indices related to reliability are SAIFI, SAIDI, CAIFI, CAIDI, AENS, ENS, and EENS. In addition, a rise in SAIDI improves system dependability [8].

2.2.3 Problem Objectives

This research presents a wide approach and requirements for optimum size and positioning of DG units in distribution networks. After that, assemble the suitable collection of parameters in a logical sequence to produce an optimal solution with acceptable restrictions [7].

By taking into account appropriate parameters and composing the objective function, which can be as follows [37], define the problem objective, which can be multi-objective or single (single objective functions include minimizing system power losses, improving system voltage profiles, lowering costs, increasing system reliability, and so on; multi-objective functions are a combination of two or more single objective functions).

2.2.3.1. Objective Function

The goal function must first be decided whether it should be decreased or increased. After that, the objective function is optimized[21] by forming it while taking into account all of the parameters that go with it.

$$y = x_1 + x_2 + x_3 + \dots x_n = \sum_{k=1}^{n} x^k \tag{2.1}$$

where '*n*' is the number of parameters on which the objective function is based; in this case, four parameters must be taken into account.

(1) Power loss of system: it is calculated as follows:

$$x_1 = x(P_L) = P_L \tag{2.2}$$

where P_L is the total system loss, and final x_1 is the result of modifying the P_L by using the weight factor.

$$x_1 = \beta_j \frac{P_L\,(afterDG)}{P_L\,(beforeDG)} \tag{2.3}$$

where $'j'$ is the number of bus where DG will be put, and β is weight factor.

(2) *Profile Factor of Voltage:* Because profile of voltage is influenced by the voltage on bus, this could be represented as the voltage after installation of DG 1.0 p.u. and voltage before DG placement 1.0 p.u., respectively. The aim of the expression to improve voltage profile.

$$\chi_2 = \mu_j \, (V_{busj}^{afterDG})^2 \tag{2.4}$$

(3) *Current Factor of Short-Circuit:* This variable is concerned with security and can be defined as

$$SCLj = \frac{i_{sclj}^{afterDG} - i_{sclj}^{beforeDG}}{i_{slcj}^{afterDG}} \tag{2.5}$$

$$\chi_3 = \eta_j \, (SCL_j)^2 \tag{2.6}$$

(4) *Sizing (Capacity) Element:* The resources of DG can be exploited more efficiently; however, attaining this goal necessitates correct sizing; otherwise, over-sized DG can induce reverse power flow. If DG is assigned to the 'j^{th}' bus with the capacity 'CP,'

$$\chi_4 = \sum_{j=1}^{n} \lambda_j \frac{CP_j}{S_{base}} \tag{2.7}$$

As a result, the final objective function will be

$$y = x_1 + x_2 + x_3 + x_4 \tag{2.8}$$

Adding all of the values from Eqs. (3), (4), (6), and (7) together

$$y = \sum_{j=1}^{n} \beta_j \frac{P_L^{afterDG}}{P_L^{beforeDG}} + \sum_{j=1}^{n} \mu_j \left(V_{busj}^{afterDG}\right)^2 + \sum_{j=1}^{n} \eta_{j(SCL_j)}{}^2 + \sum_{j=1}^{n} \lambda_j \frac{CP_j}{S_{base}} \tag{2.9}$$

where element of system losses (the weight) is introduced by β, element of the profile of voltage (the weight) introduced by μ is, η is short-circuit (the weight), also λ is factor of sizing (the weight).

2.2.3.2 Constraints

Constraints are critical variables to consider. All constraints must be met by the goal function. If all of the limitations are not met, and there is any misalignment, the resulting sizing and placement will be ineffective and may cause the system to malfunction. The main limitations [6] are as follows:

(1) *Bus Voltage Constraint:* The bus voltage shall vary within a certain range.

$$V_{min} < V_{busj}^{afterDG} < V_{max} \quad (2.10)$$

V_{MIN} can go up to (0.95 pu) and V_{MAX} can go up to (0.95 pu) with this 75 percent tolerance of bus voltage (1.05 p.u)

(2) *Current Constraint of Short-Circuit:* Amount of short-circuit current could be kept within a safe range; if it exceeds this range, the system will be harmful; this factor serves as a safety net.

$i_{sclj}^{afterDG}$ < Installed safety devices for short circuit current levels

(3) *The Size of DG (Capacity):* The installed DG units' total active power should not exceed the system's full load demand.

$$\sum_{j=1}^{No.ofDG} CP_j \leq P_{load} \quad (2.11)$$

The bidirectional power flow is hampered by this limitation.

(4) *Constraints of Power Factor:* The installed DG's power factor must vary within a certain range.; utilities are also eager in running at higher power factors; this factor is mostly evaluated during the sizing process.

$0.8 \leq pf_{DGj} \leq 1$ *j = 1,2,... No. DG*

(5) *The Factor of Weight (WF)*: It must be obtained by the following equation, for example.

$$\beta + \mu + \eta + \lambda = 1 \tag{2.12}$$

The following formula can be used to compute the weight factors:

(5) *Weight β:* This can be determined using the formula:

$$\beta = \frac{P_L^{beforeDG}}{P_L^{afterDG}} \tag{2.13}$$

(6) *Weight μ:* this can be obtained as follows

$$\mu_j = \frac{1}{\left(V_{busj}^{afterDG} - 1\right)2} \tag{2.14}$$

(7) *Weight η*: this can be assessed as follows:

$$\eta = \left(\frac{I_{sclj}^{afterDG}}{I_{sclj}^{afterDG} - I_{sclj}^{beforeDG}}\right)^2 \tag{2.15}$$

(8) *Weight λ:* this can be calculated as follows:

$$\lambda = \frac{S_{base}}{CP_j} \tag{2.16}$$

After analyzing all of these weight factors, they must be normalized by multiplying them by a common component that is acceptable, such that their total equals one.

2.2.3.3 Required Indices

The indices play an important role in determining the system's efficiency. The indices shown here provide information on parameter deviation. They can also tell whether the parameters are within acceptable limits [5].

(1) *Power Loss Index:* This index can be used to evaluate the amount of the difference between reactive and active power losses owing to the location of DGs.

$$PL_I = \left(1 - \frac{Re\{LossesafterDG\}}{Re\{LossesbeforeDG\}}\right) \times 100 \tag{2.17}$$

$$QL_I = \left(1 - \frac{Im\{LossesafterDG\}}{Im\{LossesbeforeDG\}}\right) \times 100 \tag{2.18}$$

Here PL_I and QL_I are the %age fluctuation of active and reactive power losses respectively. Re (Losses after and before DG) and Im (Losses after and before DG) represent active and reactive power losses after and before installation, respectively.

(2) *Improvement of Voltage Profile (VPII):* this calculates the deviation of voltage after installing the DG units in the distribution network, and can be represented as

$$VP_{II} = \gamma \,.\left(\frac{VP_{afterDG}}{VP_{beforeDG}}\right) - 1 \times 100 \tag{2.19}$$

where $VP_{beforeDG}$ would be as

$$VP_{beforeDG} = \sum_{K=1}^{N} V_k \tag{2.20}$$

And

$$\gamma = \begin{cases} 1 & 0.95 < V_k < 1.05 \\ 0 & V_k < 0.95 \ or \ V_k > 1.05 \end{cases} \qquad K = 1,2,\ldots \tag{2.21}$$

The highest value of *VPII*, shows a suitable refinement in profile of voltage.

(3) *Short Circuit Current Level Index:* this can be calculated using the following formula:

$$I_{scI} = \rho \,.\left(\frac{I_{scl}^{afterDG}}{I_{scl}^{beforeDG}} - 1\right) \times 100\% \tag{2.22}$$

where I_{scl} short-circuit current level index and

$$I_{scl} = \sum_{K=1}^{N} I_{SCI}^{K} \tag{2.23}$$

To determine if a short-circuit current level exceeds the circuit breakers' (CBs) permissible magnitude or not, this must be determined by ρ, and ρ can be introduced as

$$\rho = \begin{cases} 1, & I^K < I_{Switch}^K \\ 0, & I^K > I_{Switch}^K \end{cases} \qquad K = 1,2,\ldots \tag{2.24}$$

Assuming that short-circuit current level of each buses in allowable range of the circuit breakers, then ρ would be 1 otherwise 0.

(4) *The Level of Penetration:* The degree of DG component penetration in the electricity system could be determined using the penetration's average of DG units in the system [7].

$$\sum_{j=1}^{N} \sum_{t=1}^{m} x_4 . P_{DGt.j} \leq r \; . \; \sum_{j=1}^{N} P_{Dj} \tag{2.25}$$

Where, N is the total number of buses, M defined (DG units that will be installed in total), x_4 is defined as the factor of capacity, $P_{DGt.j}$ is the rated power of the t^{th} DG, also 'r' is the greatest penetration level s percent of peak load and P_{Dj} (peak active load) at bus 'j'.

Differentiation from the above-mentioned way of operation may result in unexpected system losses, a lower profile of voltage, and poor system reliability, efficiency, and overall performance, among other things.

2.3 Generalized Algorithm for DG Siting and Sizing

It is vital to address optimal DG siting and sizing in the distribution network in order to optimize the advantages of DG. It leads to a decrease in system losses, costs, and distribution company investments, and improving in voltage profile system, system dependability, and the stability of voltage. Researchers in the past have used the approaches listed below to achieve their goals effectively.

The most common strategies and methods for siting and sizing DG can be classified as follows [5].

i. Analytical Techniques

ii. Classical Optimization Techniques

iii. Artificial Intelligent (Meta-heuristic) Techniques

iv. Miscellaneous Techniques

v. Other Techniques for Future Use.

2.3.1 Analytical Techniques

Analytical approaches use a mathematical model to represent the system and determine its direct numerical solution. These strategies produce very precise results with a shorter computing time. Such strategies are appropriate for tiny and simple systems with a small number of state variables. The use of these strategies has been documented in [5]. Analytic techniques, on the other hand, perform poorly in terms of computational efficiency for big and complicated systems.

Eigen-Value Based Analysis (EVA)

EVA offers unique properties that can be used to study the power system's stability. When the load does not remain static, as described by [15], stability becomes a critical requirement for the successful behavior of power system elements.

Index Method (IMA)

The index approach is based on the idea that the real value of any parameter might change. Furthermore, indices are expressed as a change or relative deviation. Index-based assessment has been frequently utilized for evaluating dependability, as presented by [6].

Sensitivity Based Method (SBM)

Changes in one or more variables will have an influence on the target variable, according to the approach. The method's main purpose is to mitigate the size of the search space. [18], [38] highlight the multiple loss sensitivity factor-based methodologies often utilized for designing and installing DG units and capacitors in distribution networks.

Point Estimation Method (PEM)

The approach is particularly effective for determining the appropriate size and placement of non-dispatchable DG for an uncertain power result. This technique is the most successful and generates acceptable results when dealing with ambiguity. Appropriate probability density functions are also required by the PEM for input parameters that are frequently confusing, as described by [8].

2.3.2 Classical Optimization Technology

These approaches are used to reduce the created formulation in accordance with the requirements, within the constraints of the constraints. After that, use an appropriate optimization approach to get the best value for the goal functions. These techniques are categorized as.

Linear Programming (LP)

The method is useful for the purpose of function optimization with linear objective functions as well as their restrictions. The approach's convergence property is great. The LP's restriction can only handle the objective functions of linear and the limitations specified in [6].

Mixed non-linear Programming (MINLP)

The approach is a hybrid of (LP), and (NLP), and combined integer programming (MIP). The method works with both discrete and continuous variables, as well as nonlinear functions. Due to the nonlinear character of power flow formulae. Furthermore, [5], [32] implemented a MINLP-based method that may provide exact, well planned, and genuine solutions for multi-objective formulations.

Dynamic Programming (DP)

DP is a multi-stage sequential optimization technique capable of dealing with real-time and complex issues in a reliable and efficient method. In these applications in a specific order, the approach will be applied in multiple temporal domains to solve a problem by breaking it down into smaller parts. [33] proposes that the procedure requires relatively little time to provide the best possible result.

Sequential Quadratic Programming (SQP)

The algorithm is constant in nature and is best suited to dealing with non-linear formulations with inequality restrictions. Because load flow equations contain various non-linear formulations and inequality requirements, the approach is capable of efficiently handling DG unit sizing. Furthermore, in reactive power optimization, the algorithm is based on area investigation [5].

Ordinal Optimization (OO)

The approach is a tool that may be used to speed up the process of solving simulation-based optimization challenges. This technique comes with a well-organized linear programming since the compute ground is so strong. As a result, the method may be used to determine the optimal size and position of DG in power distribution system in order to fulfill objectives like reducing system losses and cost, or the recommended trade-off between loss reduction and DG capacity [8].

Optimal Power Flow (OPF)

In the context of future power system expansion initiatives, the OPF solver method is critical for determining the best performance of current power systems. Also, as described by [39], assist in obtaining information in reaction to the quantity of voltage of bus and the flowing reactive power, as well as the phase angle of each line. A forward–backward sweep is utilized to determine load flow and a binary group search optimization (BGSO) technique is considered to solve the rearrange problem [34]. For addressing ill-conditioned power systems, [5] proposed a Newton-like technique. Their method showed voltage convergence, but it was ineffective for calculating optimal power flow.

In solving such systems, the Newton Raphson (NR) and also fast decoupled load flow (FDLF) approaches are inefficient. Even if various advances in Newton-Raphson Methods have improved the program's robustness, the processing time is still too long [27]. Finding all of the node voltages is the initial step in the distribution power flow. Current, power fluxes, system losses, and other steady-state metrics may all be calculated simply from these voltages. Some applications, particularly in the distribution optimization and automation areas (for example, VAR planning, network optimization, state estimation, and so on), need frequent quick load flow solutions [1]. The station sends out a radial network that traverses the network region but has no typical linkages to other sources. The Forward-Backward Sweep Method (FBSM) is explained, which is simple to program and performs quickly. The method is intended to solve the differential algebraic system defined by the Maximum Principle [6], which is used to determine the solution.

The Newton-Raphson technique and its variations were designed specifically for transmission networks with a mesh topology, parallel lines, and several redundant connections between generating and load locations. A distribution system often starts at a substation, where electric power is transferred from a high-voltage transmission system to a lower-voltage power system before being distributed to customers [40]. For radial distribution systems, [35] suggested an enhanced Backward/Forward sweep load flow method that comprises the backward sweep, also the deconstructed forward sweep. KVL and KCL are used in a backward sweep to ascertain the voltage at each demanding bus.

[21], [40] describe the characteristics of the back/forward sweep approach with various line X/R ratios, as well as the convergence criterion. [42] explains the convergence theorem for a basic sort of optimal control issue.

According to method described by [36] suggested three distinct methods for solving radial distribution networks. He suggested load-flow distribution techniques that were decoupled, fast decoupled, and extremely fast decoupled. Chiang [36] proposed decoupled and rapid decoupled distribution load-flow algorithms that were comparable to those proposed by Baran and Wu [12], [36]. A direct technique for solving radial distribution networks was provided by [5]. Their design issue is that no node in the network may have more than three branches, i.e. one incoming and two outgoing. A novel load-flow approach for getting the solution of radial distribution networks was proposed by [8], [42]. To characterize actual power, reactive power, and voltage magnitude, they used the three key equations derived in. The Newton-Raphael approach and its variations account for the bulk of power flow algorithms used in industry, as they were built specifically for transmission networks with a meshed architecture, parallel lines, also several unneeded paths from the generation locations to the load points. Large power systems have also been shown to be unsuccessful when using the Gauss-Seidel power flow method. [42].

Continuous Power Flow (CPF)

The CPF is a mathematically sound approach for solving nonlinear equations systems. The approach is based on using the Jacobian matrix of load flow equations to identify voltage collapse scenarios. When the matrix value becomes zero, the voltage sag is illustrated by the singular matrix. Then, as [14] advises, select the bus with the highest sensitivity to narrow the search field.

2.3.3 Artificial Intelligence

Intelligent procedures are strategies capable of obtaining efficient, accurate, and optimal solutions in a smart manner. The idea is based on the most recent and adorable meta-heuristic search strategies, which are derived from artificial intelligence. These strategies are ideal for resolving complex issues in a variety of fields. (GA), (PSO), (FL), (HBMO), (SA), GA-II (NSGA-II), (ANN), (BIA), (ACO), and (ABC) are several of the methods that have been used in the meta-heuristic methods.

Fuzzy Logic (FL)

Lotfi A. Zadeh first proposed this strategy in 1965, Rather than using exact valued functions, approximate language variables are used.[37] has highlighted the degree of membership function in addition to the linguistic variables.

Genetic Algorithm (GA)

GA is a method of adaptive optimization based on natural selection and genetics. Natural evolutionary concepts including selection, mutation, heredity, and crossover affected the algorithm. The genetic algorithm is basic and straightforward to comprehend, and it does not need a thorough understanding of complex mathematics. Because there are so many factors, the algorithm takes longer to compute. According to [35], [37], GA starts its search with a population picked at random.

In Ref.[38], the capacity of GA to solve optimum DGA was examined. In Ref.[39], they compared their suggested Improved Herefoord Ranch Algorithm (IHRA) to three previous algorithms: Simple GA (SGA), Herefoord Ranch Algorithm (HRA), and Improved GA (IGA). Through a single goal function, all of these strategies were used to reduce active power losses. GA can handle both single objective functions [40] and multi objective (MO) models[41], with the MO model being subjected to the -constraint approach in Ref. [42]The influence of DG and DGA on dependability with GA integration was investigated by the authors in Ref.[43]. In DGA, a combination of optimum power flow and GA has been used. According to one study, combining GA with OPF can result in the optimal connection spots for a given number of DG units[44].

Ref. [45]provide an unique framework based on GA and Monte Carlo (MC) simulation to address the shortcomings of their own suggested analytic technique. They also considered weather conditions, switching, and load increase when determining the best location and size for hybrid wind, solar, and CHP DGs in the standard IEEE 34 bus radial network. To optimize the position and size of a single DG, the results are given as a trade-off optimum front among four objective values. The authors of Ref. [45]used GA to optimize the position and size of DGs in the network, despite the fact that DG sites were assigned to multiple candidate buses, in order to maximize cost savings, energy loss, and interruption.

Many studies have been conducted to determine the best site for dispersed generation. In [46], a fuzzy method and a (GA) are utilized to determine the best locations and sizes for DG units[47].

Particle Swarm Optimization (PSO)

Optimization of Particle Swarms (PSO) The PSO was founded in mid-1995 by Kennedy and Eberhart, who were inspired by the capacity of birds to flock and schools of fish in pursuit of food. Also, in PSO, a collection of randomly generated solutions passes over the design area, with the optimum solution prevailing over the number of iterations, according to[47].

Non-dominated Sorting GA-II (NSGA-II)

Any multi-objective optimization formulation can be solved using this method to find global optimal solutions. In addition, compared to previous optimizing approaches suggested by [5], it has a higher level of accuracy.

Plant Growth Simulation Algorithm (PGSA)

The method is a straightforward and rapid optimization approach that does not require parameter changes. This technique may be used to address a variety of optimal problems in various systems, such as DG and capacitor sizing and placement in a radial distribution system. Furthermore, the method is capable of addressing the modeling issues posed by the proposed radial distribution scheme [5].

Ant Colony Search Algorithm (ACS)

The method is based on real ants' foraging activity in order to find the quickest paths from their nest to the food source. Each ant uses pheromone trails to converse and make decisions. The strength of the pheromone trail deposited on the ground is measured by the characteristics of the solution (protein source) incorporated by [8].

Artificial Bee Colony Algorithm (ABC)

Bees are divided into three categories using the ABC method: employees, spectators, and scouts. The food source exemplifies a possible solution to the complexity of problem, and the genus amount of a food source is similar to an element of the solution achieved by [20].

2.3.4 Miscellaneous Techniques

There are various different types of procedures that have been identified in the literature and are listed below under miscellaneous techniques.

Bellman-Zadeh Algorithm (BZA)

BZA is based on a multi-objective and fuzzy functions strategy for introducing DG in the distribution system in the appropriate feeder, according to [3].

Encoded Markov Cut Set Algorithm (EMCS)A (EMCS) is a set with the fewest number of items in which each element's failure causes a system outage. The method is particularly useful for assessing system reliability [5].

Monte Carlo Simulation (MCS)

MCS is an iterative method based on the use of random numbers that produces better results as the number of iterations grows in a shorter processing time. Based on the deportment and consequence of accidental processes described by , the MCS is divided into two types: probabilistic and deterministic. [48]

Clustering-based Method

The method works by grouping patterns with comparable activity patterns. In this technique, each node is meant to function as an independent cluster. As a result, the shortest distance from a certain cluster is represented by a handful of nodes. Until the number of clusters reaches the user-specified value, the heap process continues to integrate the two clusters with the shortest distance. The method, according to [46], reduces calculation load and convergence rate.

Tabu-Search Algorithm (TS)

[47] presented Tabu Search as a heuristic technique in 1986. The usage of adaptable memory in the algorithm is a key aspect since it allows for the most flexible search

behavior. It works in a sequential fashion, with the search beginning at one point and the algorithm selecting a new place in the search space to go on to the next current point.

Bat Algorithm (BA)

The echolocation properties of microbats with different vibration speeds and loudness were used to create this approach. This approach produces an objective function that may be combined with the function to be improved to create a new optimization function. This approach outperforms the other method regarding accuracy and efficiency [8].

Big Bang Big Crunch Optimization Algorithm (BB-BC)

BB-BC is a method for optimizing that is inspired by nature. In 2006, it was initially introduced. It has great convergence properties and takes less time to compute. Candidate explanations are dispersed across the entire investigating area at random during this process. The BB-BC makes random point in an orderly manner before condensing them into a point (single). The concurrency operator has multiple inputs but only one output in the Big Crunch phase, which is the total mass indicated by[8], [25].

Brute Force Algorithm (BF)

The BF method is a straightforward problem-solving method. The method entails calculating all possible solution candidates in a systematic manner and determining if each option fulfills the problem statement. We can handle tiny difficulties completely with the BF. Finally, examining how far the other algorithms deviate from the absolute answer obtained by the BF algorithm advocated by [49] can help us evaluate their performance.

Backtracking Search Optimization Algorithm (BSOA)

A new development algorithm, the BSOA, has been developed. It is used to find solutions to numerical optimization functions that are real-valued, non-linear, non-differential, and intricate. It is suggested because it is easier to use, more effective, and quicker, and it can be used to a wide range of numerical optimization methods. [49]

Modified Teaching Learning Based Optimization Algorithm (MTLBO)

The MTLBO algorithm is advanced method for global optimization that is both decent and reliable. The algorithm is capable of addressing complicated problems with high dimensions. The algorithm increased the search space's disruption potential. In respect of concurrence accuracy, speed, and stability, the algorithm outperforms other algorithms developed by [50].

2.3.5 Other Promising Techniques for Future Use

There may be a variety of innovative optimization strategies that can accommodate the complicated difficulties of DG sizing and location, which can be categorized as follows.

Shuffled Frog Leaping Algorithm (SFLA)

This method is a heuristic optimization strategy that is based on the tendency of a bunch of frogs to seek out sites with more food. Meme evolution improves the quality of an individual's memes and improves the frog's performance toward the objective.

With global search capability executed by [51], the technique is extremely efficient and effective in terms of computation.

Imperialist Competitive Algorithm (ICA)

This method is an iterative method that separates a country's population into two colonies, imperialists, and empires, starting with its population. A vector including sociopolitical qualities such as culture, language, and religion is used to represent every country. [52] implemented various ways for stage-based calculation, but our method is more competent and efficient.

Simulated Annealing (SA) algorithm

The process of expanding the dimension of a material's particles and reducing flaws by heating and restrained cooling it. These are both material qualities that are dependent on free thermal energy. The free heat energy is affected by material heating and cooling. As a result, the sluggish rate is causing massive shrinkage. As a result of the modest cooling integrated in the SA algorithm, the probability of selecting the worst solution slowly decreases as it searches the solution space swiftly as indicated by[53].

Bacterial Foraging Optimization Algorithm (BFOA)

The approach is based on the capacity to forage [54]. Bacteria, according to this hypothesis, look for food in a method that gives them the greatest energy per unit of time. The individual bacterium can also send out signals to connect with others. After examining the two preceding factors, the bacterium makes a decision to look for food in this process. Chemotaxis is a type of movement in which a bacterium moves by taking little steps while looking for nutrition. In the issue exploration arena, the core principle of BFOA is to emulate the chemotactic movement of virtual bacteria, as recommended by [54].

Intelligent Water Drop Algorithm (IWDA)

It's a population-based optimization technique that's affected by nature. Because of the way rivers find their way, the approach is known as the water drop technique. The river's flow always seeks to choose the best path from source to destination out of a plethora of options. Many artificial water drops aid in the alteration of their environment, allowing the optimal path to emerge. [55].

Cuckoo Search (CS) method

The idea is inspired by the cuckoo, a unique bird that lays its eggs in the nest of a host bird and employs a duplication process to do so (a crow or other bird species). During this phase, certain hosts birds may engage in direct fight with cuckoos. Cuckoos are generally quite proficient at imitating the colors and shape of a few specific hosts' eggs. [56] describes the cuckoo search as an adaptive approach for engineering issue optimization.

Invasive Weed Optimization Algorithm (IWO)

It is established on a mathematical approach for stochastic optimization. The strategy is prompted by the presence of invasive weeds in natural settings and is based on weed biology and ecology. Dispersal is used to infiltrate agricultural systems with weeds. Every secure weed consumes the field's unused resources, grows into a flowering weed, and produces additional weeds on its own [55].

Table 2.3: The Merits and Demerits of various DG sizing and siting techniques

Objectives	Techniques	Merits	Demerit	References
As a single goal, lowering system losses is essential.	(GA) with fuzzy-clustering	Improve clustering accuracy in noisy conditions.	When high quality findings are desired, the convergence time is longer and there is a loss of accuracy.	[23], [31], [56]
	An analytical based technique	More efficient and accurate, significantly reduction of losses	For a sophisticated system, additional time was required.	[5], [11]
	A new analytical technique based on the Power Stability Index (PSI) was used.	Efficiency and accuracy improved	Problem formulation is difficult for large and complex systems, and computation time increases.	[50]
	Using Rank Evolutionary Particle Swarm Optimization to hybridize with EP in the PSO method (REPSO).	Capable of quickly locating the most ideal and next-best candidates based on a ranking system.	The method is inefficient for a large number of functions.	[23], [47]
	Modified Teaching Learning Based Optimization (MTLBO) algorithm	For worldwide optimization, dependable, accurate, robust, and superior performance are required.	For worldwide optimization, dependable, accurate, robust, and superior performance are required.	[9]
	(ABC) based optimization method	Multi-variable and Multi-modal outcomes are great for global optimization.	Low efficiency, which is highly dependent on the algorithm's control parameters.	[3], [57]
	An enhanced analytical technique for various DG installations has been established thanks to a loss sensitivity item and an comprehensive load flow.	Simple method for computing real-time changes in all network variables while narrowing the search space and reducing uncertainty.	This time-consuming approach fails to produce results at the crucial point of transference limit due to the singularity of power flow.	[15], [36]
	For the objectives, an analytical model was used, also a new PSO algorithm.	When there are fewer function evaluations, accuracy and computational efficiency are key.	For a large number of function evaluations, the method is inefficient.	[50], [58]
	A method for determining how dispersed generating affects the distribution network.	System losses and branch congestion are being reduced.	The voltage profiles have remained the same.	[16]
	A probabilistic model using the beta and Rayleigh probability density functions.	Utilizing renewable DG resources to their full potential	We were unable to collect all of the information related to wind and solar uncertainties.	[19]
	Sensitivity analysis-based technique	Reduces the amount of time it takes to find something, as well as the amount of time it takes to lose something.	There isn't enough data to use as an input for a probability distribution.	[35]
	Adoption of an improved analytical (IA) approach	With minimal computation time, it's possible to accommodate ideal DG sizing and location.	IA's total system losses are slightly higher than they are in reality.	[8]
	Mixed Integer Non-linear Programming (MINLP) based technique	The freedom to install any type and number of DG, as well as a smaller search area and strong convergence characteristics, are all benefits.	First, a Siting Planning Model (SPM) was required, followed by a Capacity Planning Model (CPM) (CPM)	[8]
	Monte Carlo algorithm	Simulation time is independent on the number of generation units.	As a result of the large number of runs required, more computer time is required.	[19], [48]
	(KFA)	Complexity is minimal.	It only gives valid results for Gaussian linear models.	[5]
	A supervised BBBC strategy is the BBBC technique.	With a faster convergence time and the capacity to handle networks of any scale, it is applicable to both unbalanced and balanced distribution systems.	The computational time for a huge system is longer.	[59]
	For DG scale and siting, the Distribution Network Planning (DSP) model is used to optimize variable for binary decision making.	More precise	Adjusting the balance between grid power purchases and DG generation	[28]
	(SLP), (GRG), and LINGO software tools	For the formulation of linear models, it is quite efficient.	Provide a rough solution.	[51]
	A method combining GA with (CCP) and (MCS).	The higher the capacity to withstand generation and load uncertainty, the shorter the time convergence.	Complicated, nonlinear, many uncertainty inputs and multiple probability limited outputs are not possible to solve.	[75]
Losses are minimized, and the	GA & (PSO)	More capable of identifying optimal solutions and mastering the art of locating the best ones	Process that takes a long time	[7,58]

voltage profile is improved.	PSO is compared to Algorithm (PGSA), a multi-objective MINLP- approach.	Crossover and mutation rate are not necessary as external barriers and control factors.	Solutions that are inferior in terms of quality	[32]
	A practical method based on the notion of continuous power flow (CPF).	With the capacity to manage a wide range of DG numbers and penetration levels, it is extremely efficient, durable, and effective.	Due to the great complexity of power systems and the lack of knowledge on voltage stability limits,	[55]
	(PFDE)	Capable of tackling issues involving multi-objective optimization	Convergence necessitates several repetitions.	[64]
	Heuristic technique based on sensitivity analysis	The search space is being reduced, the voltage profile is being improved, and system losses are being dramatically reduced.	There is no information about the placement of several DG and capacitors.	[67]
	For DG allocation, use the Algorithm (BSOA).	For a optimization solution, this is the perfect property.	The researchers utilized a non-uniform crossover technique, which is a random mutation procedure with just one potential outcome for each target.	[68]
	(PSO)	A high level of precision and a short convergence time	Because of this, its direction and velocity are not maintained, making it ineffective for large scale and complicated networks.	[51,70,74]
	(BA)	The precision and efficiency of other algorithms fade in contrast.	The adjustment parameters have a significant impact on the convergence rate.	[72]
	An approach based on visual optimization	In terms of applications, it's quite simple, efficient, adaptable, and practical.	Proper weight factor selection is critical for accuracy and efficiency.	[78]
	For optimization GA and OPF algorithms, a sensitivity analysis-based technique is used, as well as OPF algorithms.	Easier reactive and active power dispatch, great transmission loss reduction, and efficiency for complex and large situations necessitated less calculation time	The formulation requires complex mathematics to solve, and it cannot control issues with discontinuities or non-convexity, nor can it handle multiple minima.	[82]
	BFOA	GA and PSO provide higher convergence, durability, and accuracy.	Global convergence is a difficult task.	[95,100]
As a single goal, we want to improve the voltage profile.	Harmony search algorithm	Capable of handling both continuous and discontinuous functions, disparity-free, GA conquered, and good global search	The rate of local convergence is sluggish.	[54]
	New algorithm	It's an excellent technique to figure out which bus is the best option for distributing DG for larger systems without having to make any adjustments.	Only type-IV DG was studied with this method.	[56]
	Weibull and beta probability distribution functions, as well as MINLP	Capable of solving both nonlinear and linear problems.	Its capacity to find and provide round off results is solely dependent on its speed and dependability.	[73]
Cost and system losses are being reduced.	(BF) algorithm and MINLP	Decrease the space of search, and the time it takes to find the best solution will be reduced.	Effectiveness was harmed, and optimization was not feasible.	[21]
	Successive Elimination	The calculation time was significantly lowered.	To determine the required investment, a multi-stage planning process was required.	[49]
	Meta heuristic (SFLA) Algorithm	Computing performance that is both efficient and good, as well as a worldwide search capacity	Have an uneven starting population, slow seeking pace, and a penchant for catching local maxima.	[35]
	Method (PEM), Algorithm II (NSGA-II), and (MO) optimization	shorter time for convergence and the capacity to retain better findings for a range of data types, as well as the ability to handle load, power price, and generation uncertainty more effectively.	The precision of the PEM approach must be compromised, and it necessitates complex computing.	[43,61,86]
	For load flow analysis, a traditional iterative search methodology and the Newton Raphson method are used.	Excellent convergent and dependable properties	When some adversities are experienced, it fails.	[76]
System losses, costs, voltage profile, and system load ability are all reduced.	MCS-based technique and improved particle swarm optimization (IPSO)	When compared to other ways, it had a higher degree of precision and net savings, and it was capable of handling all types of loads as the DG penetration level increased.	Selecting the inertia weight was difficult.	[19,25]
	To deal with the uncertainties, the PSO	The computational work is reduced, and real numbers rather	For big and complicated systems, it becomes inefficient	[10]

	and the Weibull probability function were used.	than binary numbers are used as particles.	and provides multiple-optimal solutions.	
System dependability, cost and loss minimization, load growth, and voltage profile improvement	Method based on multi-objective evolutionary GA	Ability to work quickly and precisely in real-life scenarios for all conceivable combinations	Different non-inferior options are combined in a compromise.	[18]
	The Sensitivity of Loss, index vector, also the sensitivity index of voltage approaches are combined.	Deferring larger kVA requirements for the same size while reducing search space	Enhanced performance	[26]
	(DP) for time-dependent load	The DP permits sub-solutions to a complicated issue to be discovered.	offer a portion of the answers	[27]
	GA based technique employed	Capable of tackling multidimensional, non-differential, unbalanced, complicated, discrete, and continuous problems. In addition, instead of a single answer, a set of variables is offered.	When a high-quality answer is sought, time-consuming processes and accuracy suffer, and GA may be poor estimates of adequate search regions due to population size restrictions.	[34]
	For optimization, an integrated methodology-based technique was employed, as well as an MPSO-based strategy.	Convergence performance is superior to PSO.	A approach based on integers will be used for site selection.	[51]
	(MTS)	Ability to remember things in a flexible way, resulting in the most adaptable conduct	The ability to have an adaptive memory, which leads to the most flexible behavior.	[60]
Cost, emission, and system losses are reduced, and the voltage profile is improved.	Improved honey bee mating optimization (HBMO) algorithm	Has strong computing capacity and produces better and more accurate results in less time.	When the number of iterations is increased, the process becomes slower and inefficient.	[17]
	PEM was used to tackle uncertainty connected with DG, generation, and load demand using a combined (ACO) and (ABC) based algorithm.	In comparison to previous methods, it is more effective, easier to apply, and has the capability of being extended to multi-objective problems.	ABC is a multi-objective algorithm that generates a set of nondominated solutions.	[16]
	(MIP)	Random variables related to load and generation can be used.		[62]
	HMSFLA Method	When compared to other algorithms, such as GA, performance improved.	It's crucial to choose the value using a new search acceleration factor, C.	[40,46]
Power reliability and quality are improving.	A multi-objective method based on the BZ algorithm was used to determine the optimal placement of DG in the distribution system.	Give suggestions for maximizing and use of renewable DG supplies.	We were unable to obtain all of the wind and solar uncertainty data.	[63]
The location of the fault in the distribution system is being investigated.	In the presence of DG in the distribution system, a general method for locating faults has been developed.	Provide information on the DG level's projected penetration in the distribution system at any time in the future.	Only greater DG penetration levels yield good outcomes.	[59]
	L R fuzzy load points idea is used with a pseudo dynamic based technique to handle uncertainty.	The algorithm is transparent and may be applied to extremely complicated systems.	When an expert rule-based system is not set up properly, it is costly, imprecise, and does not produce satisfying results.	[71]
	(ACOPF)	capable of solving nonlinear multi-objective formulations and delivering a global optimization solution	The strategy becomes unsuccessful when the network is crowded.	[65,66]
To locate vulnerable nodes and assess their influence on the distribution system and stability of voltage.	Approach GA optimization based	Capable of solving non-differential, imbalanced, and difficult problems with several faces.	More convergence time is required.	[81]
	(CPF)	dependable and efficient	The power system's high dimensionality restricts what can be done.	[52]
The sensitivity of the power flow equations was found.	GA	Capable of resolving multifaceted, non-differential, unbalanced, and challenging situations.	There is a need for more convergence time.	[79]
	For optimization of the Monte Carlo (MC) technique, a new index method was developed.	Dimension has a direct relationship with accuracy.	For a large and complicated system, it is complex and computationally expensive, resulting in poor efficiency.	[50]

	An technique based on clustering was used.	Converging time is very short in order to lessen calculating burdens.	convergent delay	[83]
Extensive examination of DG optimum placement strategies	Optimal power flow, artificial optimization algorithms, and hybrid intelligence techniques are examples of analytical methodologies.	Optimization strategy that is systematic and precise	Method that takes a long time and is difficult to understand.	[13,14,69]
DG integrated cost analysis was used to look into the comparison.	Also, sensitivity to determine the optimal option for DG placement using a heuristic technique (LRIC).	able to assess the DG's economic potential	More iterations are required, and the global optimal solution is not guaranteed.	[9]

Chapter 3

RESEARCH METHODOLOGY

3.1 Power Flow

Power flow studies have been carried out to assess how a power system operates at steady state, or at the design level. Load flow analysis is used to determine distribution system goals such as voltage magnitudes, losses, voltage profile, and so on. Researchers have been examining the load flow of distribution networks in recent years (radial, ring, interconnected). These methods can be Newton Raphson, Gauss-Seidel, or backward forward (b/f) sweep methods because to their unique characteristics. The following are the primary characteristics:

i. scheme of connection
ii. high ratio between R and X (R/X ratio)
iii. unbalanced operation or multiphase
iv. unbalancing in load distribution
v. DG units.

Because of the aforementioned concerns, with distribution networks, Newton Raphson and other transmission system algorithms have been unsatisfactory. The back/forward sweeping technique is used to investigate the distribution system. Unlike NR approaches, this technique does not require a Jacobian matrix. Nevertheless, for modern active distribution networks, the traditional backward forward sweep strategy is ineffective.

Finding all of the node voltages is the initial step in the distribution power flow. It is feasible to determine current, system losses, power flows, and other steady-state parameters directly from these voltages.

To address the radial distribution system, a forward backward sweeping method is proposed in this study. 33bus radial distribution systems are used to test the suggested technique. The backward forward sweeping method is used to solve a recursive relationship of voltage values. The load flow will be simulated in MATLAB to answer the equations. The recommended load flow approach's mathematical formulation is described in the next section [12].

The first phase entails determining the system's known and unknown variables. PV nodes, PQ nodes, and slack nodes are the three types of nodes in a power system. The node type is critical for power flow analysis since it provides us with the system's most important known variable:

1. PQ nodes: in this kind of buses reactive and active power are known, but the phase angle and the voltage of the bus are unknown and must be determined by iterations. PQ nodes are usually substation nodes; additionally, if a DG is linked to the system with a fixed active and reactive power, the node connecting the DG to the network can also be called a PQ node.

2. PV nodes: voltage magnitude and active power are known variables that are given in the analysis for PV nodes; bus angle and reactive power Q are unknown variables. In order to maintain the node voltage constant, PV nodes must generally incorporate some type of reactive power management; thus,

buses with capacitor banks are commonly used as PV nodes. Furthermore, if the generation unit is capable of enough reactive power compensation to manage the power, power plants or DG buses might be called PV nodes.

3. Slack node: sometimes referred to as the slack bus, it is the reference node. In a power flow study, the power system should only have one slack bus indicated. The voltage and phase of the slack bus are both constant, with V=1p.u and a zero-phase angle. Because the effective generation at this node is crucial for loss compensation in the network, the reactive and active power is the variable to be addressed in a slack bus. Because the size of the losses in the system cannot be computed unless all currents are calculated, one bus must have zero reactive and active power limitations to feed the losses in the system.

As previously stated, power system load flow analysis is an analytical issue that can be solved for active power, reactive power, voltage, or phase. Equations of complex voltages are used to represent complex power. Iterative or nonlinear approaches are used to solve the unknown variables after receiving the set of equations. The admittance between the buses represents transmission lines, and the admittance between the buses represents the system admittance in a matrix known as the admittance matrix. [34]

The equivalent entry Y_{ij} in the admittance matrix is simply set to 0 if there is no transmission line between the i^{th} and j^{th} bus. The following is the relationship between the admittance matrix, bus current, and voltages:

$$I_{bus} = Y_{bus} V_{bus} \tag{3.1}$$

$$Y_{bus} = \begin{bmatrix} Y_{11} & \cdots & Y_{1n} \\ \vdots & \ddots & \vdots \\ Y_{n1} & \cdots & Y_{nn} \end{bmatrix} \tag{3.2}$$

The elements of the Y matrix are designated as:

$$Y_{ii} = |Y_{ii}| \angle \theta_{ii} = |Y_{ii}|(\cos\theta_{ii} + j\sin\theta_{ii}) = G_{ii} + jB_{ii} \tag{3.3}$$

$$Y_{ij} = |Y_{ij}| \angle \theta_{ij} = |Y_{ij}|(\cos\theta_{ij} + j\sin\theta_{ij}) = G_{ij} + jB_{ij} \tag{3.4}$$

We can define the voltages, current injections, real and reactive power created or consumed by the bus, which is directly related to the complex voltages on the buses, as follows:

$$V_i = |V_i| \angle \delta_i = |V_i|(\cos\delta_i + j\sin\delta_i) \tag{3.5}$$

$$I_i = Y_{i1}V_1 + Y_{i2}V_2 + \cdots + Y_{in}V_n = \sum_{k=1}^{n} V_{ik}\, V_k \tag{3.6}$$

The complex power at bus-i is given by: Assuming that the current introduced into the bus is positive and that the current consumed by the bus is negative.

$$P_i - jQ_i = V_i^* I_i = V_i^* \sum_{k=1}^{n} V_i\, V_k \tag{3.7}$$

$$= \sum_{k=1}^{n} |Y_{ik}\, V_i\, V_k|(\cos\delta_i - j\sin\delta_i)(\cos\theta_{ik} + j\sin\theta_{ik})(\cos\delta_k + j\sin\delta_k) \tag{3.8}$$

Therefore, the reactive and active power can be expressed as follows:

$$P_i = \sum_{K=1}^{n} |Y_{ik}\, V_i\, V_k|\, cos(\theta_{ik} + \delta_k - \delta_i) \tag{3.9}$$

$$Q_i = -\sum_{K=1}^{n} |Y_{ik}\, V_i\, V_k|\, sin(\theta_{ik} + \delta_k - \delta_i) \tag{3.10}$$

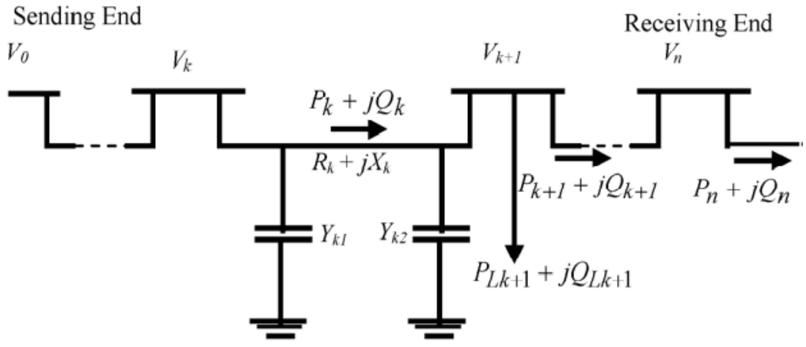

Figure 3.1: Single Line Diagram

3.1.1 The Problem's Formulation

Use the simplified recursive equations obtained from the single-line model in Fig. 3.1 to compute power flows in a distribution system. The voltage magnitude and power losses of the 33 bus system may be assessed using the power flow analysis. The goal of the function is to locate the power flow. [55]

$$P_{k+1} = P_k - P_{Loss,k} - P_{Lk+1} \tag{3.11}$$

$$Q_{k+1} = Q_k - Q_{Loss,k} - Q_{Lk+1} \tag{3.12}$$

Where;

P_k Active power emitted from the bus.;

P_Q Reactive energy emitted from the bus.;

$P_{Loss,k}$ Real power Loss in the line section connecting buses *k*

$Q_{Loss,k}$ Reactive power Loss in the line section connecting buses *k*

P_{Lk+1} Active load power in bus *k+1*;

Q_{Lk+1} Reactive load power in bus *k+1*

The following formula can be used to compute the power loss in the line segment linking buses *k* and *k+1*:

$$P_{loss}\,(k, k+1) = R_k \frac{P_k^2 + Q_k^2}{V_k^2} \tag{3.13}$$

$$Q_{loss}\,(k, k+1) = X_k \frac{P_k^2 + Q_k^2}{V_k^2} \tag{3.14}$$

Where;

P_{loss} *(k,k+1)* Real power Loss in the line section connecting buses *k* and *k+1*

Q_{loss} *(k,k+1)* Reactive power Loss in the line section connecting buses *k* and *k+1*

After then, the feeder's overall power loss, P, is computed by summing the losses of all feeder line sections, which is expressed as

$$P_{T,loss}\,(k, k+1) = \sum_{k=1}^{n} P_{loss}\,(k, k+1) \tag{3.15}$$

$$Q_{T,loss}\,(k,k+1) = \sum_{k=1}^{n} Q_{loss}\,(k,k+1) \tag{3.16}$$

Where;

$P_{T,loss}$ *(k,k+1)* Total Active Power Loss in the line section;

$Q_{T,loss}$ *(k,k+1)* Total Reactive Power Loss in the line section

The backward/forward sweep approach has been modified to allow for the examination of the iterative process' convergence. Consider Figure 3.1, where a branch connects the nodes 'k' and 'k+1'. Backwards from the last node, the active power (P_K) and reactive (Q_K) powers of flowing via branch from node 'k' to node 'k+1' may be calculated and are given as

$$P_k = P'_{k+1} + r_k \frac{(P_{k+1}^2 + Q_{K+1}^2)}{V_{k+1}^2} \tag{3.17}$$

$$Q_k = Q'_{k+1} + X_k \frac{(P_{k+1}^2 + Q_{K+1}^2)}{V_{k+1}^2} \tag{3.18}$$

Where;

$$P'_{k+1} = P_{k+1} + P_{Lk+1} \tag{3.19}$$

$$Q'_{k+1} = Q_{k+1} + Q_{Lk+1} \tag{3.20}$$

P_{LK+1} and Q_{LK+1} are loads that are connected at node 'k+1',

P_{K+1} and Q_{K+1} are the effective real and reactive power flows from node 'k+1'.

The voltage magnitude and angle at each node are calculated in forward direction.

$$I_k = \frac{V_k < \delta_k - V_{k+1} < \delta_{k+1}}{r_k + jx_k} \tag{3.21}$$

To find the angle and voltage of all nodes in a distribution system, iteratively employ the magnitude and phase angle equations in a forward manner.

All nodes are assumed to have a flat voltage profile at initially, i.e., 1.0 pu. The branch powers are computed repeatedly using the updated voltages at each node. In the suggested load flow technique, power summing is done in the backward walk, while voltages are obtained in the forward walk. [40] The detailed procedure of the power flow computation utilizing the back/forward sweeping technique is depicted in Figure 3.2. On the IEEE 33–bus network, the proposed backward Forward sweep technique is used.

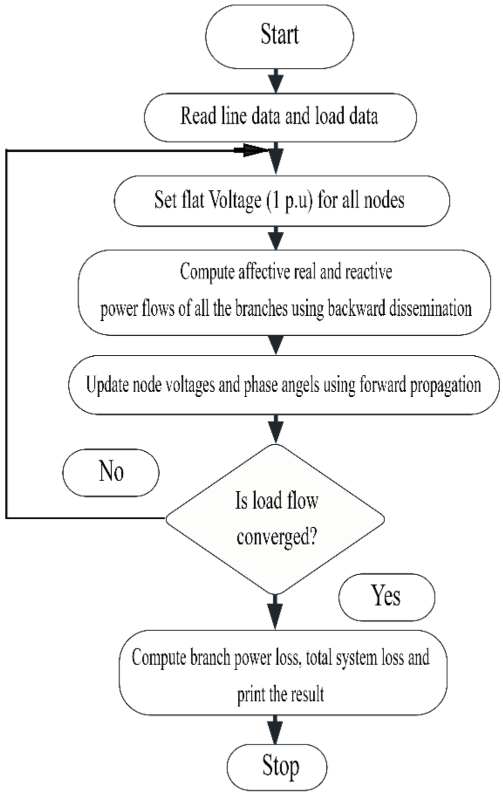

Figure 3.2: Flow cart for backward / forward sweep method [34]

3.1.2 Volatge Deviation

Voltage deviation is required for the objective function computation to examine the DGs' influence on the system. The voltage of the slack bus is believed to be constant at all times, hence it is not taken into account while computing voltage deviation. To calculate the voltage deviation, multiply the entire, the whole difference in bus voltages (excluding slack bus) by one less than the total number of buses (p.u).

(dropping slack bus out). [7] Using this approach, The ultimate voltage deviation value will be roughly independent of network size:

$$V_{dev} = \frac{\sum_{i=2}^{Bus\ No}|1 - V_i|}{BusNo - 1} \tag{3.22}$$

where: V_{dev} introduces the totall deviation of voltage in the system buses.

3.2 Optimization

DG Allocation Strategy Using GA

The task of selecting the installation of optimal DG is framed as a multi-objective constrained problem. In this study, the suggested genetic algorithm (GA) and particle swarm optimization (PSO) methods were applied. The generated findings were compared to the PSO method's outcomes. The results are also compared to those obtained using the genetic method and particle swarm optimization[6].

3.2.1 Genetic Algorithm (GA)

In this thesis, the genetic approach was used as the optimization strategy (GA). This method is straightforward to implement, computationally simple, and consistently produces excellent results. The initial population, or collection of probable solutions obtained at random in a search space and stated in an appropriate coding, is the starting point of GA. Each solution is a distinct entity that functions similarly to a chromosome. Chromosomes in GA are made up of a string of genes, each of which is represented by the value of binary (0s and 1s). GA is used to reduce a specific objective function, (J_{obj}), so that given a specified (J_{obj}), each person goes through a fitness evaluation, (J_i), which is a measure of each individual's performance. [21]

After each individual's fitness has been allocated, the population is subjected to three basic operators: selection, mutation, and crossover.

The operator in charge of deciding on convergence is selection, and if you use the appropriate selection technique, you may avoid premature convergence to a load optimum. There are several methods for determining someone is fit to reproduce depending on their fitness evaluation. Tournament selection, fitness proportional selection, roulette wheel selection, scaling selection, ranking selection, and elitist selection are all examples of different types of selection.

During the selection procedure, two individuals selected to reproduce, and new progeny are created by crossover and mutation. Low performers are culled at this time, and as a result, progress happens. As illustrated in Figure 3.3, in the situation of a crossover with a crossing site, a cross point *k* is picked at random from the interval[50], where *l* is the individual's string length.

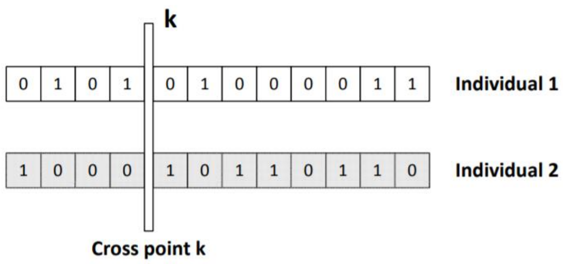

Figure 3.3: Representation of two individuals and the cross-position *k*.

As shown in Figure 3.4, two new strings are generated by exchanging all characters between *k + 1* and l.

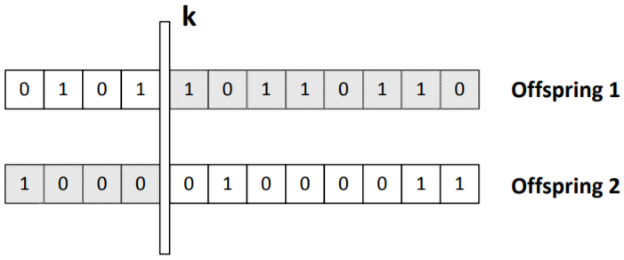

Figure 3.4: Representation of two individuals after mating the progenitors.

The constituents of both parents' strings are swapped from the first to the second place of crossover. As a result, to ensure genetic variety, the mutation operator is registered to every member of the present offspring with a probability, (p_{mut}). Depending on the situation, the best probability value varies. Any of the individuals' genes can be altered, and binary genes can be mutated by changing a 0 to 1 or a 1 to 0, as shown in Figure 3.6.

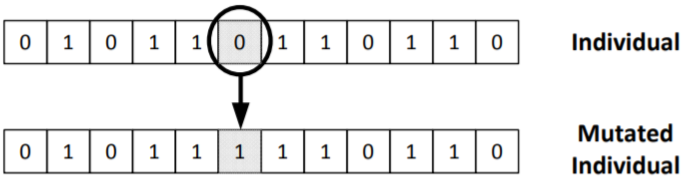

Figure 3.5: Representation of the mutation of a gene in an individual (GA)

Using the three operators results in the creation of a new population. The original population as well as the next generation are assessed for finding the best person. If the progenitor fitness function value is higher than the offspring fitness function value, an individual from the first generation is replaced by an individual from the second generation. The created population goes through the identical assessment, selection, and mutation processes as the previous one once the first generation is completed. The highest generation or a defined value of the objective function evaluation might be used as a stop condition. Figure 3.4 shows a generic method for implementing the Genetic Algorithm.

3.2.2 Particle Swarm Optimization

As an optimization tool, the PSO employs a population-based selection mechanism, in which particles alter their position (state) over time. Particles move about in a multidimensional search space in a PSO system. During flight, each particle adjusts its position based on its own (Pbest) and adjacent particle's (Gbest) experiences, utilizing the best position that it and its neighbor have encountered (Figure 3.6).

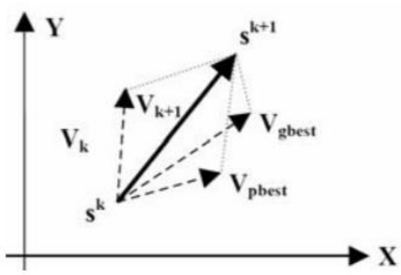

Figure 3.6: Representation of the mutation of a gene in an individual (PSO)

The concept of velocity can be used to illustrate this change. The following equation can be used to change the velocity of each agent:

$$v_{id}^{k+1} = \omega v_{id}^{k} + C_1 rand \times \left(pbest_{id} - s_{id}^{k}\right) + C_2 rand \times \left(gbest_d - S_{id}^{k}\right) \quad (3.23)$$

3.3 Objective Function

The multi-objective index for evaluating distribution performance of the system for DG size and location planning with load models incorporates the indices listed below (equation 3.26) for DG size and location planning with load models by providing a weight to each index. [61]

Recall the objective function's generalized form.

$$\text{Minimize } f(x) = \{f_1(x), f_2(x), \dots, f_k(x)\} \quad (3.24)$$

Where,

$f_1(x)$, $f_2(x)$…………..$f_k(x)$ are available in the objective function

Subject to

Equality Constraints $g(x) = g_i(x), g_2(x), \dots \dots \dots g_k(x) = 0$ (3.25)

Inequality Constraints $h(x) = h_i(x), h_2(x), \dots \dots \dots h_k(x) \geq 0$ (3.26)

Formulation of Operational Constraints

To satisfy the distribution network's electrical requirements, the above-mentioned multi-objective function is reduced under many operational constraints.

Operational restrictions are divided into two categories.

Equality of Constraints $g_i(x) = 0$ (3.27)

Equality of Constraints $h_i(x) \geq 0$ (3.28)

where *k* is the number of objective functions and *x* denotes the control variable vector

3.3.1 Active Power Loss Reduction Index

The reduction of the power system's system power loss is a common strategy for DG sizing and installation. The active power loss minimization factor index each bus is defined as the percentage decrease in actual power loss from the base scenario when a DG is installed at bus I. [6] The PLRI (Real Power Loss Reduction Index) is calculated as follows:

$$f_1 = PLRI = \frac{P_{L(base)} - P_{L(DG)}}{P_{L(base)}} \quad (3.29)$$

Where,

$P_{L(base)}$ denotes the real power loss before installation of a DG.

$P_{L(DG)}$ denotes the real power loss in the system after DG installation.

3.3.2 Reactive Power Loss Reduction Index

The Reactive Power Loss Reduction Element Index is included in the objective function to assess the impact of DG on reactive power losses. When a DG is assigned to bus I, the percentage decrease in reactive power loss is compared to the base scenario.

$$f_2 = QLRI = \frac{Q_{L(base)} - Q_{L(DG)}}{Q_{L(base)}} \tag{3.30}$$

Where,

$Q_{L(base)}$ denotes the reactive power loss before installation of a DG.

$Q_{L(DG)}$ denotes the reactive power loss in the system after DG installation.

3.3.3 Voltage Profile Improvement

The voltage at each bus, as well as the line flow, should be within acceptable limits in a power network. These constraints are necessary to guarantee that adding DG to the system does not increase the cost of voltage control or line replacements. The Voltage Profile Improvement Index aids in determining which size-location pair is responsible for higher voltage deviations from the base voltage. The VPII (Voltage Profile Improvement Index) is defined as follows:

$$f_3 = VPII = \frac{1}{\frac{|V_{nom}| - |V_{DGi}|}{|V_{nom}|}} \tag{3.31}$$

Where,

$V_{(DG)}$ $is\ the\ voltage\ once\ the\ DG\ has\ been\ installed.$

3.4 Objective indices

The objective indices are calculated from the voltage deviation and power flow. IQ_L and IP_L indicate the reactive and active power losses indexes, respectively. IV_{dev} also displays the voltage deviation index. [6] The following equations determine the initial network load flow results, which are used to compute these indexes:

$$IP_{L_n} = P_{L_n} / P_{L_o} \tag{3.32}$$

$$IQ_{L_n} = Q_{L_n} / Q_{L_o} \tag{3.33}$$

$$IV_{dev_n} = V_{dev_n} / V_{dev_0} \tag{3.34}$$

The reactive and active power losses, and deviation of voltage, for installing DG on the network's nth distribution bus are represented by QL_n , PL_n, and V_{devn}

3.5 Calculation of Weight Factors (WFs)

The (WFs) are determined according to the approach described in Reference[60]. The (WFs) are obtained using the objective indices collected in the previous section. These weight factors are inversely proportional to the mean value of the indices they are associated to. The strategy used gives all (WFs) an equal chance to influence the objective function outcome, making them merged and immeasurable. As a result, the lowest objective value is linked to the largest weight factor in order to ensure that it has the same chance of influencing the OF as the larger one. The weight factors are computed as follows:

$$W_p = 1 / \sum_{Dist\ Bus} IP_{L_i} \quad W_q = 1/\sum_{Dist\ Bus} IQ_{L_i} \quad W_v = 1 / \sum_{Dist\ Bus} IV_{devi} \tag{3.35}$$

where Dist Bus is a list of all buses in distribution system, and

The total sum (W) computed by dividing the sumation of the final result weight factors for each aim from (3.32) by the total sum (W) calculated by (3.33). The calculated values must also satisfy the equation (3.34)

$$W = w_p + w_q + w_v \quad , \quad w_p = \frac{w_p}{w}, w_Q = \frac{w_q}{w}, w_v = \frac{w_v}{W} \tag{3.36}$$

3.6 Objective function (OF) Calculation

Calculation of objective function by using objective indices and weight components as follows:

$$OF = w_p \times IP_L + w_Q \times IQ_L + w_V \times IV_{dev} \tag{3.37}$$

where:

The reactive and active power losses, also deviation indices of voltage, are represented by, IQ_L, IP_L and IV_{dev}.

The (WFs) between 0 - 1 resulting from equation are $W_P, W_Q, and\ W_V$. (3.36)

3.7 Voltage Sag Mitigation

The proposed method addresses the magnitude of voltage sag propagation. This factor considers the number of buses affected by voltage sag. (3.38) Demonstrates the proposed function for reducing voltage sag and enhancing voltage magnitudes in a radial distribution system [15].

$$V_{sp} = \omega_1 V_l + \omega_2 V_m + \omega_3 V_h \quad (3.38)$$

V_l represents the number of buses with a voltage value decrease below 0.1 p.u, V_m represents the number of buses with a voltage value between 0.4 p.u and 0.7 p.u, and V_h represents the number of buses with a voltage value between 0.7 p.u and 0.9 p.u when there is a voltage sag. To amplify voltage support in more acrimonious buses, weighting coefficients are introduced as ω_1=0.1, ω_2=0.3, and ω_3=0.6.

Chapter 4

CASE STUDY AND RESULTS

4.1 System Data

This is a way for finding the best sitting and sizing for DG. There are two aspects to the problem. The first is the best place for DG, while the second is the best size. The first part's result is a number, which is either a bus number or a suggestion for installing DGs. The proposed method for multi-distributed generation optimization has been applied in MATLAB and tested in a power system. The optimization was done using the GA approach, which is intended to mimic optimal DG siting and size in any radial distribution system. The parameters of the GA technique that was used to tackle the difficulties in this study are listed in the tables. As a result, in this thesis, the Particle Swarm Optimization (PSO) approach is employed as a comparison.

As indicated in Figure 1, buses are stationed at each branch. At each bus, the active and reactive powers are provided. The last bus in each branch is usually the poorest of the others. As a result, the last bus can be regarded the greatest site for Distributed Generation, but we must keep in mind that due to the distribution of loads on the buses, one of the buses in the middle of each branch may also be the weakest bus.

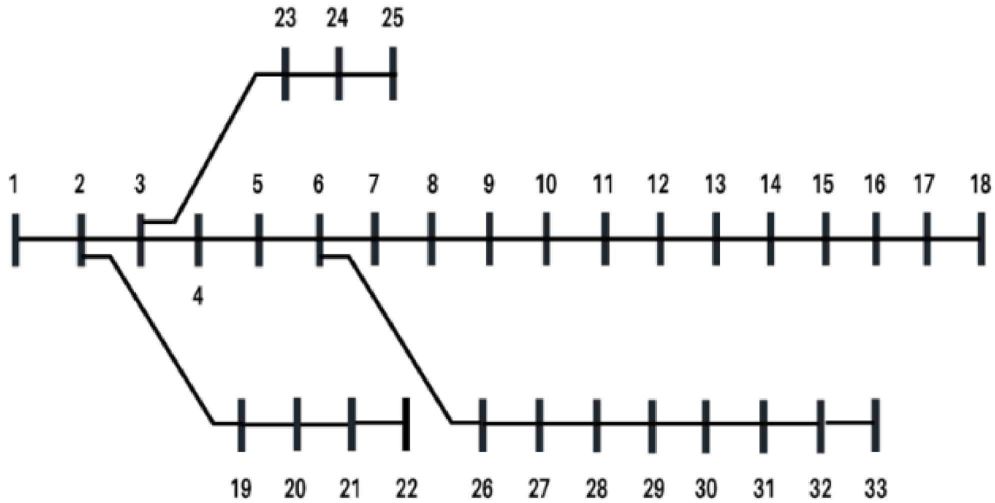

Figure 4.1: Single Line Diagram with 33-Bus

Table 4.1: Line Data

Line No.	**In Bus**	**Out Bus**	**Resistance (Ω)**	**Reactance (Ω)**
1	1	2	0.0922	0.0470
2	2	3	0.4930	0.2511
3	3	4	0.3660	0.1864
4	4	5	0.3811	0.1941
5	5	6	0.8190	0.7070
6	6	7	0.1872	0.6188
7	7	8	0.7114	0.2351
8	8	9	1.0300	0.7400
9	9	10	1.0440	0.7400
10	10	11	0.1966	0.0650
11	11	12	0.3744	0.1238
12	12	13	1.4680	1.1550
13	13	14	0.5416	0.7129
14	14	15	0.5910	0.5260
15	15	16	0.7463	0.5450
16	16	17	1.2890	1.7290
17	17	18	0.7320	0.5740
18	2	19	0.1640	0.1565
19	19	20	1.5042	1.3554
20	20	21	0.4095	0.4784
21	21	22	0.7089	0.9373
22	3	23	0.4512	0.3083
23	23	24	0.8980	0.7091
24	24	25	0.8960	0.7011
25	6	26	0.2030	0.1034
26	26	27	0.2842	0.1447
27	27	28	1.0590	0.9337
28	28	29	0.8042	0.7006
29	29	30	0.5075	0.2585
30	30	31	0.9744	0.9630
31	31	32	0.3105	0.3619
32	32	33	0.3410	0.5302

Table 4.2: Bus Data

Bus No.	$P_{D\ (KW)}$	$Q_{D\ (KVar)}$	Bus No.	$P_{D\ (KW)}$	$Q_{D\ (KVar)}$
1	0	0	**18**	90	40
2	100	60	**19**	90	40
3	90	40	**20**	90	40
4	120	80	**21**	90	40
5	60	30	**22**	90	40
6	60	20	**23**	90	50
7	200	100	**24**	420	200
8	200	100	**25**	420	200
9	60	20	**26**	60	25
10	60	20	**27**	60	25
11	45	30	**28**	60	20
12	60	35	**29**	120	70
13	60	35	**30**	200	600
14	120	80	**31**	150	70
15	60	10	**32**	210	100
16	60	20	**33**	60	40
17	60	20			

Table 4.1 and Table 4.2 illustrate respectivly, line data and bus data in power system (case study).

4.2 DG Allocation

Table 3 summarizes the results for optimal siting and scaling difficulties in distributed generation based on the pre-installation values of the goal functions for DG. PSO method is considered to compare with GA algorithm results, as well as the position, DG size. The goal function in the first column, for example, is P_{loss}, which has been reduced to get the best outcomes.

Tbale 4.3: Size and Loccation of DGs

Optimization Method	**DG location**		**DG Size (kW)**	
GA	30	5	1051.66	2802.63
PSO	30	6	1224.072	2516.12

4.2.1 Volatge Profile Improvment

The voltage profile of per bus in a 33-bus distribution is depicted in Figure 4.1. The data indicate various voltage levels before and after DG installation. The level of voltage on bus 18 was low prior to the installation of DG. After the installation, the voltage was increased. The optimization was carried out using the GA, with the PSO as a comparison approach. The GA is designed to simulate optimal DG seating and sizing in any radial distribution system, while the PSO is designed to simulate optimal DG seating and sizing in any radial distribution system. The GA and PSO parameters that were utilized to solve the problems.

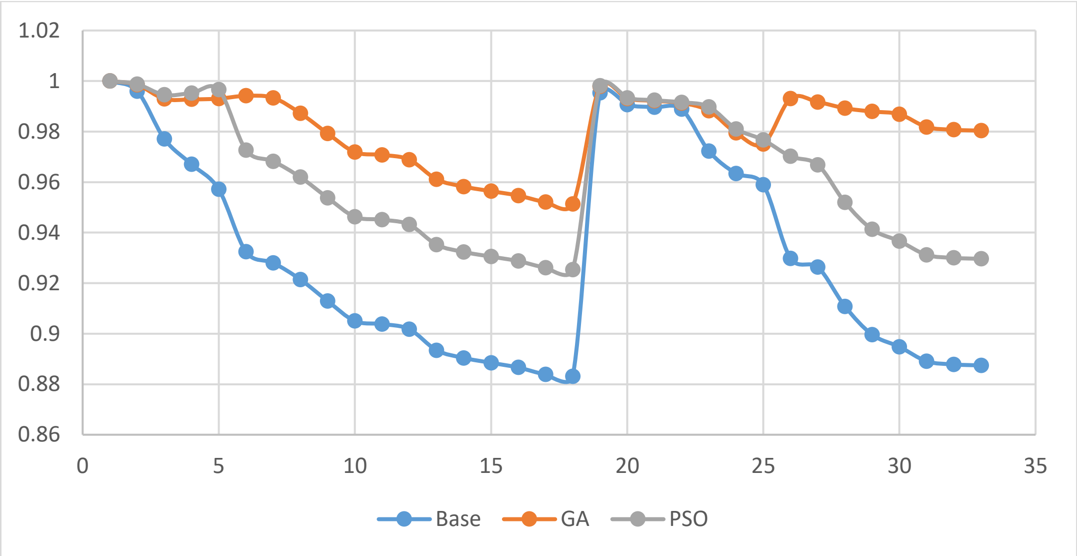

Figure 4.2: Voltage profile in a 33-bus radial distribution system

The impacts of DG installation on reactive losses, active losses, and voltage variation are depicted in figure 4.2, which shows the effects of DG installation on various distribution buses of the examined network. The derived indices from (3.32), (3.33) and (3.34) in the three aforementioned categories are used to evaluate these effects. For all test networks, the findings for the optimal installation bus using the lowest objective function. The influence of the final configuration on the profile of voltage is seen in Figure 4.2. In comparison to these numbers, the generated combinations boost the profile of voltage of two techniques. The proposed GA method, on the other hand, outperforms PSO significantly.

4.2.2 Reactive and Active Power Losses

Figures 4.2 and 4.3 show how the GA and PSO algorithms compare in terms of reducing actual and reactive power losses in the system.

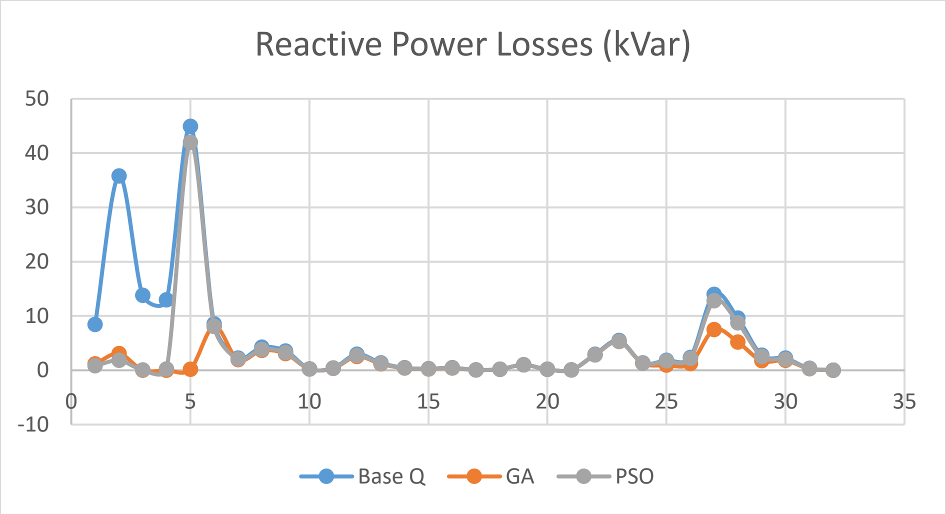

Figure 4.3: Reactive Power Losses in a 33-bus radial distribution system

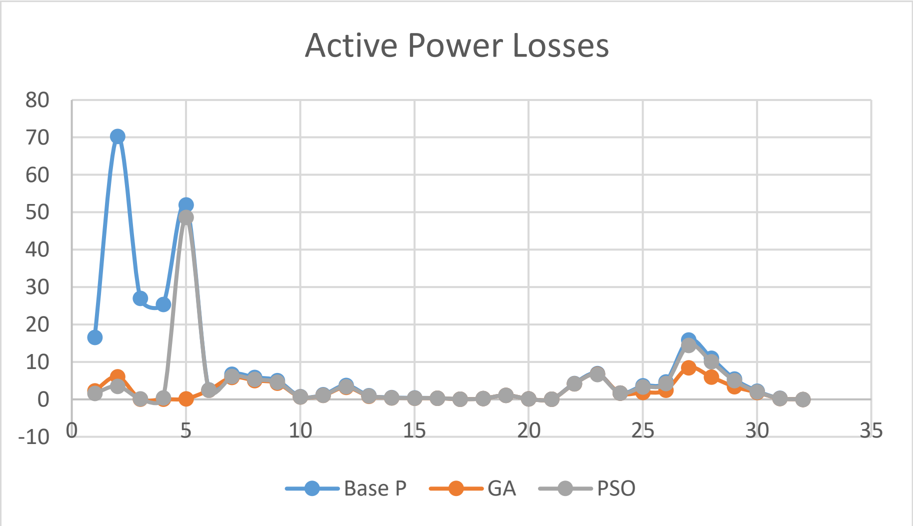

Figure 4.4: Active Power Losses in a 33-bus radial distribution system

The GA method results are compared with the results using PSO algorithm the real power losses and reactive power losses. The goal function in the first row, for example, is Ploss, which has been reduced to get the best outcomes. Table 4.3 shows the outcomes of the comparison.

Table 4.4: Real and reactive power losses before and after the installation of a DG

	Total Load	**Before Installation**	**After Installation (GA)**	**After Installation (PSO)**
Active Power Loss (kW)	3715	277.5517257	71.75426629	133.8365037
Reactive power loss (kVar)	2300	185.1595413	56.27141486	108.9959145

Table 4.4 illustrates, the overall real power loss of the system is decreased from 277.5517257 KW to 71.075426629 kW and 133.836537 kW due to the installation of the two DGs by using GA and PSO optimization methods respectively. Moreover, there is a huge difference between two methods to reduce the reactive power losses, according to the optimization results the overall reactive power losses is decreased from 185.1595413 kVar to 56.27141486 kVar in GA method and 108.9959145 by using PSO method.

4.2.3 Objective Function Calculation

The objective function for each network is calculated by combining the objective values with the weight factors provided in Table 4.4. The chart also identifies the best multi-DG configuration using two distinct techniques. The results of objective function in both methods, using GA algorithm, the best solution with the minimum objective function is obtained.

Table 4.5: Objectives indices results [6]

Number of DGs	**Opt. Method**	**Weight Factors**			**Objective Indices**			**Obj. Function**
		W_P	W_Q	W_V	IP_L	IQ_L	IV_L	
Multi DG	GA	0.3854	0.3278	0.2867	0.2585	0.3039	0.3474	0.2989
Multi DG	PSO	0.3981	0.3261	0.2756	0.4822	0.5886	0.6964	0.5759

Table 4.5 displays the results for all test networks for the optimum installation bus using the lowest objective function. According to the data, Bus 33 is the optimal place for the 33-bus system.

4.3 Voltage Deviation

Figure 4.5 illustrates the standard deviation values of two algorithms application on a selected networks. GA performs better on the network than PSO, as shown in the. Figure 4.5 represents a comparison voltage deviation before and after installing a multi DGs by using optimization methods.

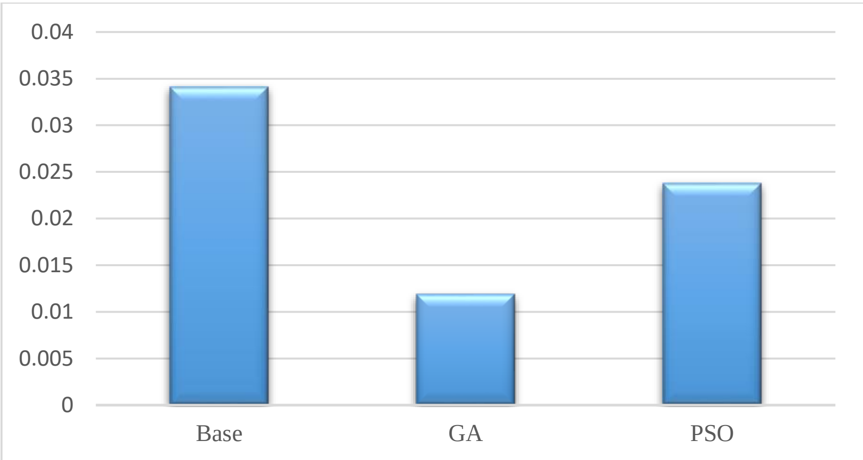

Figure 4.5: Standard Deviation of Final Results

4.4 Discussion

To see how well the proposed optimization strategy performs on DGs, the GA and PSO are applied to a 33-bus radial network, with Tables 4.4 and 4.3 reporting the findings. The GA is considered to observe the optimum solution with the smallest objective function. The 5 and 30 buses are the best locations for DG allocation.

Chapter 5

CONCLUSION AND FUTURE STUDY

Using weight factors and stated parameter indices, this work presents a unique multi-objective optimization technique for simultaneous optimum allocation of a single DG. Furthermore, by allocating a generating share to each network bus, the size of DG is reduced. Active power losses, reactive power losses, and bus voltage fluctuation were all evaluated in the networks. To handle the radial distribution system, this study develops a forward backward sweeping mechanism. Due to the aforementioned problems, Newton Raphson (NR) and other algorithms have unhappy with distribution networks, so the back/forward sweeping strategy is developed.

In this study, the technical factors of DG allocation are taken into account for optimization. However, given the quantity of available DG units on the market, the suggested algorithm can be simply applied to real-world network conditions. The sensitivity index method was used to find the best nodes for DG placement. The goals discussed are to reduce real power loss, keep voltage magnitude within defined minimum and maximum limits, avoid branch current constraint violations, and increase network voltage stability. The results show a considerable decrease in power loss as well as a better voltage profile. The ability of the suggested approach to decrease voltage sag in sensitive buses was also evaluated, and it was determined to be within acceptable limits.

It is possible to conclude that introducing DG to a network improves network parameters in the desired manner. Furthermore, a growth in DG capacity can enhance a part of the objective values in terms of the powerful parameters on the building of the objective function. When many DGs are employed in the right order, the goals are greatly increased. The defined index of objective values created multi-objective comparisons simple. Furthermore, using the suggested weight factor computation enhanced the indices' resolution when computing the objective function. By comparing the results to the exhaustive search method utilized in the current work, the correctness of the suggested technique may be validated.

The following are some of the potential future works of this thesis:

- We focused on DG unit placement and location, losses, enhancing voltage profile, and voltage sag reduction in the distribution network in this study. It is feasible to study these issues further based on other benefits of DG, such as improved economic benefits, system dependability, and environmental concerns.
- Furthermore, we employed GA as an optimization approach to address the problem in this thesis and PSO is considered is a method to compare with the case study. To overcome the problem, we recommend adopting various optimization techniques, particularly hieratic approaches such as PSO/GA, Ant Colony, and so on.
- Future research will examine using a hybrid optimization algorithm that combines the speed of PSO algorithm with the precision of a GA method to produce the best results.

REFRENCES

[1] A. S. N. Huda and R. Živanović, "Large-scale integration of distributed generation into distribution networks: Study objectives, review of models and computational tools," *Renewable and Sustainable Energy Reviews*, vol. 76. Elsevier Ltd, pp. 974–988, 2017, doi: 10.1016/j.rser.2017.03.069.

[2] C. Yammani, S. Maheswarapu, and M. S. Kumari, "Optimal Placement and Sizing of DER's with Load Variations Using Bat Algorithm," *Arab. J. Sci. Eng.*, vol. 39, no. 6, pp. 4891–4899, 2014, doi: 10.1007/s13369-014-1174-8.

[3] K. S. Ramudu, M. P. Lalitha, and P. S. Babu, "Siting and Sizing of DG for Loss Reduction and Voltage Sag Mitigation in RDS Using ABC Algorithm," *Int. J. Electr. Comput. Eng.*, vol. 3, no. 6, 2013, doi: 10.11591/ijece.v3i6.4399.

[4] M. Raoofat and A. R. Malekpour, "Optimal allocation of distributed generations and remote controllable switches to improve the network performance considering operation strategy of distributed generations," *Electr. Power Components Syst.*, vol. 39, no. 16, pp. 1809–1827, 2011, doi: 10.1080/15325008.2011.615799.

[5] P. Prakash and D. K. Khatod, "Optimal sizing and siting techniques for distributed generation in distribution systems: A review," *Renewable and Sustainable Energy Reviews*, vol. 57. Elsevier Ltd, pp. 111–130, May 01, 2016, doi: 10.1016/j.rser.2015.12.099.

[6] M. Pesaran H.A., M. Nazari-Heris, B. Mohammadi-Ivatloo, and H. Seyedi, "A hybrid genetic particle swarm optimization for distributed generation allocation in power distribution networks," *Energy*, vol. 209, p. 118218, 2020, doi: 10.1016/j.energy.2020.118218.

[7] M. M. Aman, G. B. Jasmon, A. H. A. Bakar, and H. Mokhlis, "A new approach for optimum simultaneous multi-DG distributed generation Units placement and sizing based on maximization of system loadability using HPSO (hybrid particle swarm optimization) algorithm," *Energy*, vol. 66, pp. 202–215, 2014, doi: 10.1016/j.energy.2013.12.037.

[8] S. Kaur, G. Kumbhar, and J. Sharma, "A MINLP technique for optimal placement of multiple DG units in distribution systems," *Int. J. Electr. Power Energy Syst.*, vol. 63, pp. 609–617, 2014, doi: 10.1016/j.ijepes.2014.06.023.

[9] J. A. Martín García and A. J. Gil Mena, "Optimal distributed generation location and size using a modified teaching-learning based optimization algorithm," *Int. J. Electr. Power Energy Syst.*, vol. 50, no. 1, pp. 65–75, 2013, doi: 10.1016/j.ijepes.2013.02.023.

[10] S. Kansal, B. B. R. Sai, B. Tyagi, and V. Kumar, "Optimal placement of wind-based generation in distribution networks," *IET Conf. Publ.*, vol. 2011, no. 579 CP, p. 104, 2011, doi: 10.1049/cp.2011.0141.

[11] D. Q. Hung, N. Mithulananthan, and K. Y. Lee, "Optimal placement of

dispatchable and nondispatchable renewable DG units in distribution networks for minimizing energy loss," *Int. J. Electr. Power Energy Syst.*, vol. 55, pp. 179–186, 2014, doi: 10.1016/j.ijepes.2013.09.007.

[12] A. El-Fergany, "Optimal allocation of multi-type distributed generators using backtracking search optimization algorithm," *Int. J. Electr. Power Energy Syst.*, vol. 64, pp. 1197–1205, 2015, doi: 10.1016/j.ijepes.2014.09.020.

[13] R. Viral and D. K. Khatod, "Optimal planning of distributed generation systems in distribution system: A review," *Renew. Sustain. Energy Rev.*, vol. 16, no. 7, pp. 5146–5165, 2012, doi: 10.1016/j.rser.2012.05.020.

[14] P. Dehghanian, S. H. Hosseini, M. Moeini-Aghtaie, and A. Arabali, "Optimal siting of DG units in power systems from a probabilistic multi-objective optimization perspective," *Int. J. Electr. Power Energy Syst.*, vol. 51, pp. 14–26, 2013, doi: 10.1016/j.ijepes.2013.02.014.

[15] B. Singh, V. Mukherjee, and P. Tiwari, "A survey on impact assessment of DG and FACTS controllers in power systems," *Renew. Sustain. Energy Rev.*, vol. 42, pp. 846–882, 2015, doi: 10.1016/j.rser.2014.10.057.

[16] M. Delfanti, D. Falabretti, and M. Merlo, "Dispersed generation impact on distribution network losses," *Electr. Power Syst. Res.*, vol. 97, pp. 10–18, 2013, doi: 10.1016/j.epsr.2012.11.018.

[17] M. Kefayat, A. Lashkar Ara, and S. A. Nabavi Niaki, “A hybrid of ant colony optimization and artificial bee colony algorithm for probabilistic optimal placement and sizing of distributed energy resources,” *Energy Convers. Manag.*, vol. 92, pp. 149–161, 2015, doi: 10.1016/j.enconman.2014.12.037.

[18] T. Niknam, S. I. Taheri, J. Aghaei, S. Tabatabaei, and M. Nayeripour, “A modified honey bee mating optimization algorithm for multiobjective placement of renewable energy resources,” *Appl. Energy*, vol. 88, no. 12, pp. 4817–4830, 2011, doi: 10.1016/j.apenergy.2011.06.023.

[19] M. Gomez-Gonzalez, F. J. Ruiz-Rodriguez, and F. Jurado, “Probabilistic optimal allocation of biomass fueled gas engine in unbalanced radial systems with metaheuristic techniques,” *Electr. Power Syst. Res.*, vol. 108, pp. 35–42, 2014, doi: 10.1016/j.epsr.2013.10.018.

[20] D. Rama Prabha, T. Jayabarathi, R. Umamageswari, and S. Saranya, “Optimal location and sizing of distributed generation unit using intelligent water drop algorithm,” *Sustain. Energy Technol. Assessments*, vol. 11, pp. 106–113, 2015, doi: 10.1016/j.seta.2015.07.003.

[21] M. A. Saad, H. A. A. El-Ghany, and A. M. Azmy, “Optimal DG deployment to improve voltage stability margin considering load variation,” *2017 19th Int. Middle-East Power Syst. Conf. MEPCON 2017 - Proc.*, vol. 2018-Febru, no. December, pp. 765–771, 2018, doi: 10.1109/MEPCON.2017.8301267.

[22] M. M. Aman, G. B. Jasmon, H. Mokhlis, and A. H. A. Bakar, “Optimal placement and sizing of a DG based on a new power stability index and line losses,” *Int. J. Electr. Power Energy Syst.*, vol. 43, no. 1, pp. 1296–1304, 2012, doi: 10.1016/j.ijepes.2012.05.053.

[23] S. Kansal, V. Kumar, and B. Tyagi, “Optimal placement of different type of DG sources in distribution networks,” *Int. J. Electr. Power Energy Syst.*, vol. 53, no. 1, pp. 752–760, 2013, doi: 10.1016/j.ijepes.2013.05.040.

[24] A. J. G. Mena and J. A. Martín García, “An efficient approach for the siting and sizing problem of distributed generation,” *Int. J. Electr. Power Energy Syst.*, vol. 69, pp. 167–172, 2015, doi: 10.1016/j.ijepes.2015.01.011.

[25] C. Yammani, S. Maheswarapu, and S. Matam, “Multiobjective optimization for optimal placement and size of DG using shuffled frog leaping algorithm,” *Energy Procedia*, vol. 14, pp. 990–995, 2012, doi: 10.1016/j.egypro.2011.12.1044.

[26] D. Q. Hung, N. Mithulananthan, and R. C. Bansal, “Analytical strategies for renewable distributed generation integration considering energy loss minimization,” *Appl. Energy*, vol. 105, pp. 75–85, 2013, doi: 10.1016/j.apenergy.2012.12.023.

[27] R. Viral and D. K. Khatod, “An analytical approach for sizing and siting of DGs in balanced radial distribution networks for loss minimization,” *Int. J. Electr. Power Energy Syst.*, vol. 67, pp. 191–201, 2015, doi:

10.1016/j.ijepes.2014.11.017.

[28] M. Esmaili, "Placement of minimum distributed generation units observing power losses and voltage stability with network constraints," *IET Gener. Transm. Distrib.*, vol. 7, no. 8, pp. 813–821, 2013, doi: 10.1049/iet-gtd.2013.0140.

[29] P. Karimyan, G. B. Gharehpetian, M. Abedi, and A. Gavili, "Long term scheduling for optimal allocation and sizing of DG unit considering load variations and DG type," *Int. J. Electr. Power Energy Syst.*, vol. 54, pp. 277–287, 2014, doi: 10.1016/j.ijepes.2013.07.016.

[30] W. S. Tan, M. Y. Hassan, M. S. Majid, and H. Abdul Rahman, "Optimal distributed renewable generation planning: A review of different approaches," *Renew. Sustain. Energy Rev.*, vol. 18, pp. 626–645, 2013, doi: 10.1016/j.rser.2012.10.039.

[31] Z. Wang, B. Chen, J. Wang, J. Kim, and M. M. Begovic, "Robust optimization based optimal DG placement in microgrids," *IEEE Trans. Smart Grid*, vol. 5, no. 5, pp. 2173–2182, 2014, doi: 10.1109/TSG.2014.2321748.

[32] Y. Cao, X. Wang, Y. Li, Y. Tan, J. Xing, and R. Fan, "A comprehensive study on low-carbon impact of distributed generations on regional power grids: A case of Jiangxi provincial power grid in China," *Renew. Sustain. Energy Rev.*, vol. 53, pp. 766–778, 2016, doi: 10.1016/j.rser.2015.09.008.

[33] M. Pesaran H.A, P. D. Huy, and V. K. Ramachandaramurthy, "A review of the optimal allocation of distributed generation: Objectives, constraints, methods, and algorithms," *Renew. Sustain. Energy Rev.*, vol. 75, no. September 2015, pp. 293–312, 2017, doi: 10.1016/j.rser.2016.10.071.

[34] S. Ouali and A. Cherkaoui, "An Improved Backward/Forward Sweep Power Flow Method Based on a New Network Information Organization for Radial Distribution Systems," *J. Electr. Comput. Eng.*, vol. 2020, 2020, doi: 10.1155/2020/5643410.

[35] S. Gopiya Naik, D. K. Khatod, and M. P. Sharma, "Optimal allocation of combined DG and capacitor for real power loss minimization in distribution networks," *Int. J. Electr. Power Energy Syst.*, vol. 53, pp. 967–973, 2013, doi: 10.1016/j.ijepes.2013.06.008.

[36] J. A. M. Rupa and S. Ganesh, "Backward-Forward_Sweep_Rupa_Ganesh," vol. 8, no. 10, pp. 1628–1632, 2014.

[37] Sujata Huddar, "Optimal Location and Sizing of DG using Fuzzy logic," *Ijmer*, vol. 4, no. 6, pp. 59–64, 2014, [Online]. Available: http://www.ijmer.com/papers/Vol4_Issue6/Version-6/IJMER-46065964.pdf.

[38] R. K. Singh and S. K. Goswami, "Optimum siting and sizing of distributed generations in radial and networked systems," *Electr. Power Components Syst.*, vol. 37, no. 2, pp. 127–145, 2009, doi: 10.1080/15325000802388633.

[39] S. Biswas, S. K. Goswami, and A. Chatterjee, “Optimum distributed generation placement with voltage sag effect minimization,” *Energy Convers. Manag.*, vol. 53, no. 1, pp. 163–174, 2012, doi: 10.1016/j.enconman.2011.08.020.

[40] D. H. Popović, J. A. Greatbanks, M. Begović, and A. Pregelj, “Placement of distributed generators and reclosers for distribution network security and reliability,” *Int. J. Electr. Power Energy Syst.*, vol. 27, no. 5–6, pp. 398–408, 2005, doi: 10.1016/j.ijepes.2005.02.002.

[41] A. A. Abou El-Ela, S. M. Allam, and M. M. Shatla, “Maximal optimal benefits of distributed generation using genetic algorithms,” *Electr. Power Syst. Res.*, vol. 80, no. 7, pp. 869–877, 2010, doi: 10.1016/j.epsr.2009.12.021.

[42] A. A. Abdelsalam and E. F. El-Saadany, “Probabilistic approach for optimal planning of distributed generators with controlling harmonic distortions,” *IET Gener. Transm. Distrib.*, vol. 7, no. 10, pp. 1105–1115, 2013, doi: 10.1049/iet-gtd.2012.0769.

[43] C. L. T. Borges and D. M. Falcão, “Optimal distributed generation allocation for reliability, losses, and voltage improvement,” *Int. J. Electr. Power Energy Syst.*, vol. 28, no. 6, pp. 413–420, 2006, doi: 10.1016/j.ijepes.2006.02.003.

[44] G. P. Harrison, A. Piccolo, P. Siano, and A. R. Wallace, “Hybrid GA and OPF evaluation of network capacity for distributed generation connections,” *Electr.*

Power Syst. Res., vol. 78, no. 3, pp. 392–398, 2008, doi: 10.1016/j.epsr.2007.03.008.

[45] M. F. Shaaban, Y. M. Atwa, and E. F. El-Saadany, "DG allocation for benefit maximization in distribution networks," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 639–649, 2013, doi: 10.1109/TPWRS.2012.2213309.

[46] K. Y. Liu, W. Sheng, Y. Liu, X. Meng, and Y. Liu, "Optimal sitting and sizing of DGs in distribution system considering time sequence characteristics of loads and DGs," *Int. J. Electr. Power Energy Syst.*, vol. 69, pp. 430–440, 2015, doi: 10.1016/j.ijepes.2015.01.033.

[47] S. Sharma, S. Bhattacharjee, and A. Bhattacharya, "Quasi-Oppositional Swine Influenza Model Based Optimization with Quarantine for optimal allocation of DG in radial distribution network," *Int. J. Electr. Power Energy Syst.*, vol. 74, pp. 348–373, 2016, doi: 10.1016/j.ijepes.2015.07.034.

[48] L. D. L. Pereira *et al.*, "Optimal allocation of distributed generation and capacitor banks using probabilistic generation models with correlations," *Appl. Energy*, vol. 307, pp. 1–40, 2022, doi: 10.1016/j.apenergy.2021.118097.

[49] M. A. Abdelkader, M. A. Elshahed, and Z. H. Osman, "An analytical formula for multiple DGs allocations to reduce distribution system losses," *Alexandria Eng. J.*, vol. 58, no. 4, pp. 1265–1280, 2019, doi: 10.1016/j.aej.2019.10.009.

[50] B. Mohanty and S. Tripathy, “A teaching learning based optimization technique for optimal location and size of DG in distribution network,” *J. Electr. Syst. Inf. Technol.*, vol. 3, no. 1, pp. 33–44, 2016, doi: 10.1016/j.jesit.2015.11.007.

[51] M. Heidari, M. Banejad, and A. Hajizadeh, “Using the modified shuffled frog leaping algorithm for optimal sizing and location of distributed generation resources for reliability improvement,” *J. AI Data Min.*, vol. 1, no. 2, pp. 103–110, 2013.

[52] M. Sedighizadeh and A. Eisapour-Moarref, “The Imperialist Competitive Algorithm for Optimal Multi-Objective Location and Sizing of DSTATCOM in Distribution Systems Considering Loads Uncertainty,” *Ina. Lett.*, vol. 2, no. 3, pp. 83–95, 2017, doi: 10.1007/s41403-017-0027-7.

[53] S. Chakraborty, S. Verma, A. Salgotra, R. M. Elavarasan, D. Elangovan, and L. Mihet-Popa, “Solar-based dg allocation using harris hawks optimization while considering practical aspects,” *Energies*, vol. 14, no. 16, 2021, doi: 10.3390/en14165206.

[54] K. R. Devabalaji and K. Ravi, “Optimal size and siting of multiple DG and DSTATCOM in radial distribution system using Bacterial Foraging Optimization Algorithm,” *Ain Shams Eng. J.*, vol. 7, no. 3, pp. 959–971, 2016, doi: 10.1016/j.asej.2015.07.002.

[55] D. S. Rani, N. Subrahmanyam, and M. Sydulu, “An Invasive Weed Optimization

for loss reduction in distribution systems," *Proceeding IEEE Int. Conf. Green Comput. Commun. Electr. Eng. ICGCCEE 2014*, no. October, 2014, doi: 10.1109/ICGCCEE.2014.6922311.

[56] M. Saric, J. Hivziefendic, T. Konjic, and A. Ktena, "Distributed generation allocation considering uncertainties," *Int. Trans. Electr. Energy Syst.*, vol. 28, no. 9, pp. 597–604, 2018, doi: 10.1002/etep.2585.

[57] N. Mohandas, R. Balamurugan, and L. Lakshminarasimman, "Optimal location and sizing of real power DG units to improve the voltage stability in the distribution system using ABC algorithm united with chaos," *Int. J. Electr. Power Energy Syst.*, vol. 66, pp. 41–52, 2015, doi: 10.1016/j.ijepes.2014.10.033.

[58] M. M. Aman, G. B. Jasmon, A. H. A. Bakar, and H. Mokhlis, "A new approach for optimum DG placement and sizing based on voltage stability maximization and minimization of power losses," *Energy Convers. Manag.*, vol. 70, pp. 202–210, 2013, doi: 10.1016/j.enconman.2013.02.015.

[59] P. Raja, M. P. Selvan, and N. Kumaresan, "Enhancement of voltage stability margin in radial distribution system with squirrel cage induction generator based distributed generators," *IET Gener. Transm. Distrib.*, vol. 7, no. 8, pp. 898–906, 2013, doi: 10.1049/iet-gtd.2012.0579.

[60] P. Mehta, P. Bhatt, and V. Pandya, "Optimal selection of distributed generating units and its placement for voltage stability enhancement and energy loss

minimization," *Ain Shams Eng. J.*, vol. 9, no. 2, pp. 187–201, 2018, doi: 10.1016/j.asej.2015.10.009.