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Optimal Placement of Distributed Generation in Distribution Networks Using Grey Wolf Optimization

by

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A THESIS

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The undersigned certify that they have read, and recommended to the Institute of Engineering for acceptance, a progress report of thesis entitled **“OPTIMAL PLACEMENT OF DISTRIBUTED GENERATION IN DISTRIBUTION NETWOK USING GREY WOLF OPTIMIZATION’’** submitted by **Mahendra Kumar Das,** in partial fulfillment of the requirements for the degree of Master of Science in Power System Engineering.

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ABSTRACT

This thesis presents a comprehensive study on the integration of Distributed Generation (DG) into power systems, with a focus on the optimal placement and sizing of DG units. The research aims to investigate the impact of DG on system stability and power loss reduction, as well as to propose a novel optimization algorithm for the optimal placement and sizing of DG units. The integration of distributed generation (DG) is expected to play an important role in the electric power system planning and market operations. As DG are integrated into the distribution system, it results in operating situations that hampers the conventional system without generation directly connected at the distribution level.

The Grey Wolf Optimization algorithm is applied to an IEEE 33 bus power system and practical 33 kV 59 Bus Galyang Feeder of Pyuthan District to determine the optimal placement and size of DG units, resulting in a significant reduction in power loss and improvement in voltage levels. The simulation results demonstrate that the proposed algorithm can effectively improve system stability and reduce power loss, making it a valuable tool for power system operators and planners. The thesis concludes with a discussion of the limitations of the proposed algorithm and suggestions for future research

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LIST OF ABBREVIATIONS

DG	: Distributed Generation
GA	: Genetic Algorithm
IEEE	: Institute of Electrical and Elelctronics Engineers
CIGRE	: International Council on Large Electric Systems
DC	: Direct Current
AC	: Alternating Current
DS	: Distribution System
RDS	: Radial Distribution System
GWO	: Grey Wolf Optimisation
PSO	:Particle Swam Optimisation

LIST OF NOTATIONS

V	: Voltage magnitude
V_{max}	: Maximum voltage
V_{min}	: Minimum voltage
P	: Active power
P_{max}	: Maximum value of active power flow
Q	: Reactive power
δ	: Phase angle
I	: Current magnitude
Y	: Admittance magnitude
θ	: Admittance angle
R	: Resistance
X	: Reactance

CHAPTER 1 : INTRODUCTION

1.1 Background

The contemporary electrical distribution network is perpetually faced with an incessantly burgeoning load demand. This escalating load imposition consequently leads to an augmented burden on the system and a commensurate reduction in voltage levels. The challenge of limited capital for power generation and transmission systems is a common issue for utilities in underdeveloped and developing nations, particularly as load growth outstrips resources. The performance of the transmission and distribution network has a considerable impact on the power system's efficiency, and high losses in these systems can significantly reduce overall efficiency. Financial losses for utilities are also a concern, as reducing power losses can lead to increased revenue. For utilities facing capital constraints, maximizing the efficiency of existing infrastructure through smart and efficient means can provide dual benefits. By delaying the need for costly reinforcement of the existing system, utilities can also generate additional revenue to put towards future upgrades.

In addition to the growing load demand, the power distribution system is also facing challenges related to deregulation and privatization. Lack of reactive power sources within system is one issue that frequently arises, which can be addressed by installing dedicated sources or utilizing the reactive energy produced by distributed generators. With the emergence of innovation in the smart grid and liberalized energy markets, the interconnection of resources for distributed generation, especially those utilizing sustainable energy sources like solar and wind, at the distribution level has become increasingly viable. Distribution companies aim to minimize real losses in order to increase profit and avoid penalties. As a result, there has been a significant amount of research dedicated to developing methods for reducing losses in systems. In contrast to transmission levels, distribution levels have a greater R/X ratio, which causes significant power losses and a decrease in voltage magnitude. Financial health and general efficiency of distribution utilities are directly impacted by the losses in distribution networks, which are substantially higher than those in transmission networks. Power utilities are attempting to reduce losses at the distribution level by a variety of methods, including the best placement of distributed generators, network reconfiguration, and the use of shunt capacitors for reactive power compensation, in order to boost overall effectiveness of power supply. The active power requirement is fulfilled partially by the dispersed generators, which lowers the current and MVA in the lines. Distributed generators can enhance the power factor, voltage profile and stability of the distribution network while also lowering energy and peak demand losses.

As the distance from the substation grows, the voltage at distribution network nodes normally falls. This characteristic makes it essential to manage load and strategically place distributed generation resources to maintain a stable and efficient distribution of electricity. Reactive power supply must be sufficient to keep the voltage profile within a suitable range is necessary. which enhances the system's stability and dependability. Adopting cutting-edge technology and making the best use of already-existing resources are crucial to meeting the rising load demand while maintaining electricity quality and cost effectiveness. An effective and viable approach in the power system is the efficient distribution of DG. In a power system consisting of distributed energy resources, small-scale modular energy conversion devices located in close proximity to the point of end use contribute relatively small amounts of energy. The distribution network has a direct relationship with both demand and generation, and storage systems, DG units, and regionally responsive needs can all be managed separately or in conjunction with the electrical grid. Inadequate placement of new distributed generators is a frequent reason why the electricity distribution system's voltage dips, and voltage collapse in places with significant critical loading might result from this. Thus, the optimal placement of DG is crucial to prevent voltage collapse and enhance the voltage profile.

1.2 Problem Statement

With the integration of renewable energy sources into the grid, the matter of placing and sizing distributed generation (DG) units in distribution systems has gained significant importance. DG unit integration can increase voltage stability and minimize losses, but it also presents fresh difficulties for system coordination and management. However, the best possible placement and sizing of DG units is crucial for achieving these benefits while avoiding negative impacts on the system. The traditional methods of DG placement and sizing are often time-consuming and computationally expensive. The (GWO) algorithm is an optimization technique inspired by the nature which is found to be used effectively in solving complex optimization problems. In this thesis, we propose to use the (GWO) algorithm to solve our Problem that is to search for the optimal placing and number and sizing of DG units in a distribution system. The goal of this research is to investigate the effectiveness of GWO in finding the number and location of Optimal DG and its unit placement and sizing and to compare its performance like computing time and accuracy to conventional approaches.

1.3 Objective and Scope of the Thesis

This thesis seeks to determine the ideal location of DG units inside a distribution system using the Grey Wolf Optimization (GWO) approach. Additionally, it makes an effort to assess how this location may affect voltage stability and system losses.

The scope of this thesis includes:

- A thorough examination of existing literature will be conducted, focusing on GWO, the utilization of the algorithm of GWO, the integration of DG units in networks, voltage profile and its stability.

- The GWO algorithm will be developed and implemented to achieve the optimal placement of DG units within the system.
- The simulation and analysis of the active and reactive power losses , voltage profile and increment of voltage of system of IEEE 33 Test bus and Galyang 33 kV Feeder of Pyuthan District with different scenarios.
- The GWO method's usefulness will be evaluated based on its performance and will be compared to that of other optimization algorithms frequently used for placement of DG for different scenario in distribution systems.
- The conclusion and recommendations for future research on the finding the Optimal place, size and number of DG units.

1.4 Limitation of the Thesis

- The scope of the thesis is restricted to using the GWO algorithm to position DG units in the best possible location and size, and may not take other optimization algorithms or techniques into account.
- The thesis is limited to simulating the distribution system using a specific software or platform, which may not accurately represent all types of distribution systems.
- The thesis may not consider the influence of additional elements, like as load demand or weather conditions.
- The influence of DG units on other network elements like wires and transformers may not be taken into account in the thesis.
- The thesis might not take into account how DG units affect the system's harmonics and power quality.

1.5 Outlines of Thesis

The thesis' remaining sections are structured as follows:

Chapter 2 presents a discusses the various challenges associated with integrating DG units in distribution systems, including voltage stability issues. Additionally, the literature review covers current methods and techniques for optimal DG placement and sizing, such as heuristic algorithms, optimization methods, and simulation-based approaches. The chapter concludes along with a summary of the research gaps and opportunities in the area of DG integration and optimal placement.

Chapter 3 focuses on the development of a methodology in distribution systems intended in improving to improve the voltage of the system and reduction of loss through the ideal positioning and sizing of DG units.

Chapter 4 describes simulation results of the overall system using load flow method, and result of GWO. The outputs are analyzed, and the main outcome of the study is discussed in this chapter.

Chapter 5 is the conclusive chapter, which summarizes and highlights the contribution of thesis work and gives potential areas of further work.

CHAPTER 2 : LITERATURE REVIEW

In addition to conducting an extensive literature analysis on distributed generation and the deployment of DG units, this chapter gives a summary of the state of the art at the moment.

2.1 Introduction to Power System

Electricity plays a pivotal role in facilitating daily routines and is vital for various aspects of human life. The absence of electricity can have far-reaching consequences, such as the shutdown of factories, disconnection of communication systems, and adverse effects on national infrastructure. Recognizing the significance of a reliable grid power system, extensive research efforts are dedicated to enhancing national grids. The power system comprises three essential components: generation, transmission, and distribution. Generation systems, commonly known as power plants, utilize thermodynamics to convert energy from one form to another, such as converting the energy from burning fuel into electrical energy. The task of transferring electric energy from power plants to the distribution system is carried out by transmission systems, which act as the link between generating and distribution systems. In turn, the distribution system makes sure that the produced energy is efficiently transferred to users, satisfying their demand and avoiding system outages. Maintaining an equilibrium between electricity supply and demand is crucial. Insufficient supply relative to demand can lead to power outages and disruptions. Therefore, ensuring an adequate and reliable supply of electricity is of paramount importance.

Electric utilities employ three main types of power distribution systems: radial, loop, and mesh network systems. Among these, the radial distribution system is widely adopted due to its cost-effectiveness and straightforwardness in terms of planning, design, and operation. In a system with radial distribution, power flows unidirectionally from the main substation to load. However, this configuration poses a risk of complete power loss if the flow is interrupted.

Each consumer feeder caters to a specific service area, and the loads on each feeder can vary based on the number of consumers it serves. As we know that the profile of voltage profile inside the network and losses of power are impacted by these load changes. As electric DS continue to expand and grow more complex, they face challenges such as increased system losses and inadequate voltage regulation. These issues stem from significant power loss, typically ranging from 10-13%, that occurs during transmission at the distribution level. Such losses lead to escalated energy costs and a suboptimal voltage profile along the distribution feeder.

To improve the distribution networks' capacity to reliably transmit power, it is crucial to address these issues and seek ways to minimize power loss while improving voltage regulation. Achieving a more efficient power system entails reducing power losses and maintaining a robust voltage profile at each feeder.

2.2 Distributed Generation

Even though it typically refers to generation units which are in small scale and situated in proximity to or at loads but the definition of distributed generation (DG) is inconsistent in the literature. However, depending on variables like voltage level, unit connection, prime-mover type, non-dispatchable generation, and maximum power rating, the definition may change. [2]. "The generation of electricity by facilities that are sufficiently smaller than central generating plants to allow interconnection at nearly any point in a power system," as stated by IEEE [3], is what is meant by distributed generation. The (CIGRE) [4] offer more detailed definitions of DG based on its type, size and location. The term "distributed generation" is used by CIGRE to refer to "all generation units with a maximum capacity of 50 MW to 100 MW, typically connected to the distribution network, and not centrally planned or dispatched." According to

CIRED, DG refers to "all generation units with a maximum capacity of 50 MW to 100 MW, usually connected to the distribution network." When defining distributed generation, Chambers [6] adopts an economic stance, defining it as "relatively small generation units of 30 MW or less situated at or near customer sites to meet specific customer needs, support economic operation of the distribution grid, or both." The term "distributed generation" is defined by Dondiet [7] "a small source of electric power generation or storage, typically ranging from less than a kW to tens of MW, that is not part of a large central power system and is located close to the load." The definition included here storage facilities in the DG. The term "distributed generation" is defined by Ackermann [2] as "an electric power generation source connected directly to the distribution network or on the customer side of the meter." Ackermann offers the most inclusive description, with no limitations on the DG's dimensions. The term also takes into account the location of DG.

2.3 Types of Distributed Generation Sources

Distribution systems typically use two main categories of DG sources: dispatchable and non-dispatchable. Figure 2.1 provides a visual representation of these types, and the following details will be covered in more detail:

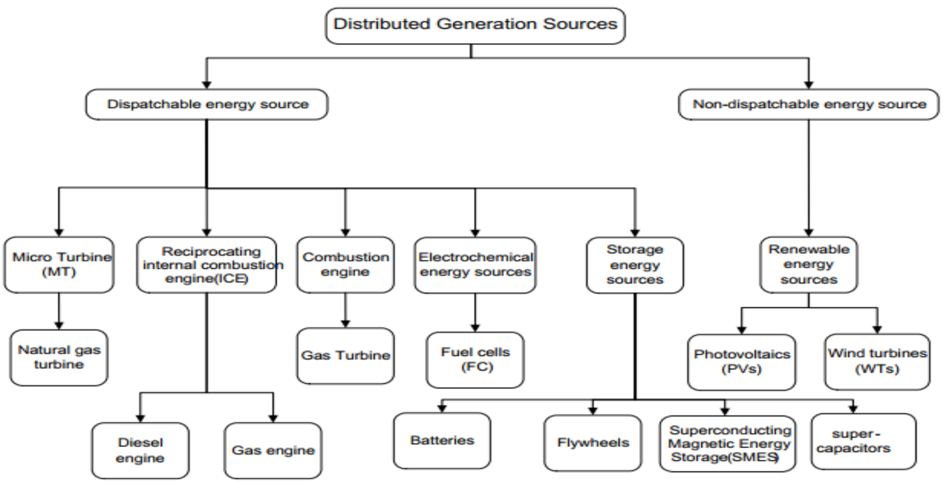

Figure 2-1: Sources for DG

2.3.1 Wind Turbines

One of the most used sources of DG worldwide is generally regarded as wind energy. The fundamental element in utilizing wind energy is a wind turbine, which changes the wind's kinetic energy into the mechanical energy and then mechanical energy is subsequently changed into the electrical energy by means of alternating current (AC) generators of the synchronous and induction types. The wind turbine frame incorporates these generators. The wind turbine is made up of a nacelle, shaft, a rotor and a coupling mechanism, and turbine blades. A collection of wind turbines that have placed in a specific location is known as wind farm. To maximize electric capacity, wind farms should be established in areas with ample wind resources. The rating of a power in wind turbine typically ranges from 0.3 to 7 MW, while its overall efficiency ranges from 20% to 40% [8]. In addition to being a clean energy source that is kind to the environment, wind energy also has a number of financial advantages over other renewable energy sources.

2.3.2 Photovoltaic

Solar cells, made of semiconductor materials like monocrystalline and polycrystalline silicon, are the primary building block of a photovoltaic system. These solar cells are comparable to other solid-state electrical components such integrated circuits, diodes, and transistors [10]. A solar cell assembly creates a panel or module, which normally has between 36 and 72 cells. Solar modules are interconnected in either a series or parallel configuration to form a solar array, which harnesses sunlight to generate power. Photovoltaic (PV) systems exhibit a wide power range, encompassing solar cells as small as 0.3 kW and large-scale systems with multiple megawatts of capacity [11].

Photovoltaic generation efficiency is still quite poor, often under 20%, when compared to wind turbine efficiency. On the other hand, the photovoltaic modules have a lengthy lifespan that frequently exceeds 25 years. It is crucial to remember that over time, the modules' efficiency may gradually decline and reach about 75–80% of the nominal value [12]. Maximum Power Point Tracking (MPPT) power electronic converters are used to connect solar DG units with the power grid [13].

2.3.3 Fuel Cells

With the use of electrochemical processes and without the use of combustion, fuel cells are a well-known distributed generation (DG) technology that can convert chemical energy into various forms of energy like electrical and thermal energy [15]. A conductive electrolyte called an ionophore separates the two electrodes in a fuel cell, just like in batteries. Fuel cells don't need to be recharged like batteries do because the reactant materials are constantly being fed into the cell. With typical efficiencies between 40% and 60%, fuel cells are remarkably effective at producing power. The overall efficiency can surpass 80% [12] when the electrical power and produced heat are combined in a combined heat and power (CHP) system. Depending on the use and whether the configuration is mobile or fixed, fuel cell capabilities can range from 1 kW to several MW. References [16, 17] include comprehensive details on the various fuel cell models and uses. Numerous advantages of fuel cells include their low physical footprint, quiet operation, and absence of toxic pollutants. Fuel cells have an energy density more than 10 times more than that of a standard battery [12].

2.3.4 Reciprocating Internal Combustion Engine (ICE)

One or more pistons are used in a reciprocating engine, sometimes referred to as a piston engine, which can transform pressure to rotating motion which is generally known as an internal combustion engine (ICE) and is regarded to be the most popular and cost-effective DG technology.[18]. Reciprocating engines may be linked to the grid without a power electronics interface, in contrast to other DG systems.

2.3.5 Micro-turbines

Micro-turbines are compact devices that pair a tiny generator with a tiny turbine. These generators can have capacities ranging from several kilowatts to megawatts [19] and are commonly powered by natural gas. Micro-turbines run at extremely high speeds, typically between 50,000 to 120,000 rpm [20], unlike traditional combustion turbines. They also operate at lower pressures than standard combustion turbines. Micro-turbines have a number of advantages, including their small size, which makes it possible to put them in limited spaces, as well as their low gas emissions and noise, high efficiency, and relatively low installation and maintenance costs. Micro-turbines produce electricity at a frequency that is substantially higher than the nominal power frequency (for example, 1500-4000 Hz as opposed to 50 Hz or 60 Hz) because to its fast rotation [20]. Power electronics converters, such as AC-DC-AC converters, are needed to link microturbines to the grid and to enable their operation in parallel with other types of DG sources.[19].

Natural gas is the fuel used by microturbines, which makes them a dispatchable source of energy. Due to this quality, intermittent generation issues with renewable energy sources are eliminated. In light of this, micro-turbines show potential as DG components that can be successfully included into microgrid systems.

2.3.6 Storage Devices

Storage devices in DG systems, such as flywheels, batteries, super-capacitors, and superconducting magnetic energy storage, are essential for improving system stability, power quality, and reliability. They enable fast load response, enhance system reliability, and smooth out generation profiles of non-dispatchable DG sources. Power electronics converters facilitate their integration with the power system network.

2.4 Benefit of DG

The relevance of DG in systems of the future is anticipated to increase, and its performance can be evaluated based on cost and benefits. The costs associated with DG include investment costs, maintenance costs, and operating costs. Investment costs include the cost of the DG unit, site preparation, SCADA system, and protection system. Maintenance costs include repair and scheduled maintenance, while operating costs include labor costs, taxes, and fuel costs.

Distributed generation (DG) offers a range of economic and operational benefits. From an economic standpoint, DG increases voltage profiles, which enhances system efficiency reducing losses, and minimizing the need for additional equipment, resulting in cost savings. It also presents a low-risk investment with shorter installation times, reducing upfront capital requirements. On the operational side, DG provides reliable, clean, and cost-effective energy with low emissions. By reducing load on feeders and optimizing network configuration, it enhances system reliability and minimizes the likelihood of faults. DG can be integrated with modern power electronics devices to meet power quality requirements and ensure a stable voltage profile.

Furthermore, DG can offer ancillary services such as bypassing congestion in transmission grids, deferring investments in infrastructure, and providing on-site production to reduce demand and transmission losses. It can also improve voltage support and supply quality in areas where it is challenging. Depending on its size and position within the system, DG offers various advantages. Notably, one of the key advantages is the reduction of line losses, making careful sizing and placement of DG crucial for maximizing its benefits.

2.5 Necessity of Separate Load Flow for Distribution System

The traditional approach for transmission system load flow involved employing the Gauss-Seidel iteration method with the nodal admittance method. However, advancements have been made by utilizing the nodal impedance matrix method to enhance this technique. But it still requires a large computation time as the number of buses increases. In distribution systems, which generally have a large number of buses, the Gauss-Seidel method is not suitable as it would require a longer computation time.

For the last three decades, the Newton-Raphson (NR) method and its variations have been widely used with sparse techniques and optimum ordering. However, the NR method converges only for low R/X ratio, which is not suitable for distribution systems as they generally have a large R/X ratio and poor convergence characteristics.

There have been many load flow algorithms developed and established for distribution systems, but most of these methods assume radial distribution feeders. Therefore for load flow analysis in radial distribution networks, the Backward/Forward (BW/FW) Sweep algorithm is widely recognized as the most commonly used approach. This method is illustrated in the methodology section of the study.

2.6 Distribution System Losses Reduction Techniques

Distribution system loss refers to the energy loss that occurs as electricity is transmitted and distributed from the transmission system to the end-use customer. This loss can be caused by a variety of factors, including resistance in transmission lines, transformers, and other equipment, as well as losses due to line charging and other factors. These losses can be significant and can result in increased costs for utilities and customers. Due to environmental concerns and rising construction costs, there has been a rise in demand for tolerating heavier loads and resolving delays in the construction of new generating plants. There are several ways to decrease system losses in distribution networks to address these issues. These methods can be broadly categorized into three basic approaches.

2.6.1 Reduce the equivalent resistance

One effective method for minimizing losses in distribution system is to reduce the equivalent resistance of the conductors. The square of the current and the conductor resistance determine how much power is lost in a conductor. By decreasing the resistance of the system, the power loss can be mitigated. This can be achieved by upgrading to larger conductors with a greater cross-sectional area since resistance is inversely proportional to the cross-sectional area. Alternatively, auxiliary conductors can be added to operate in parallel with the existing ones. However, it is important to consider the cost-effectiveness of this approach, as it may be applicable in situations with specific demand requirements or when the cost of conductors and installation is outweighed by the energy savings achieved.

2.6.2 The placement of compensating capacitors

Strategic placement of compensating capacitors at specific load nodes is another effective method. These capacitors inject reactive power into the system, offsetting the inductive load power and minimizing losses. By decreasing the reactive power flowing through the conductors, overall losses are reduced. This approach is especially beneficial for systems with low power factor, as the capacitors have a greater impact on loss reduction. Moreover, capacitors installation improves voltage levels and power factor. Determining the optimal size and location of capacitors involves considering cost savings, peak power loss reduction, and adherence to voltage limits. In recent years, the trend has shifted towards installing capacitors in primary distribution feeders instead of substations, taking advantage of pole-mounted equipment and the cost-effectiveness of closer placement to reactive loads.

2.6.3 Network reconfiguration

Network reconfiguration is an effective method to reduce losses in a distribution system (DS). This approach involves modifying the structure of the system and adjusting the states of switches, transitioning them from open to closed positions. By doing so, loads can be redistributed from heavily loaded feeders to lightly loaded ones, and from routes with higher resistance to those with lower resistance. These changes in network configuration help optimize the distribution of power and minimize losses within the system. This minimizes I^2R losses and improves the overall operating conditions. Reconfiguring the network improves the voltage profile throughout the feeders while also reducing losses. Ongoing studies and experiments in various utilities are focused on exploring the benefits of feeder reconfiguration for minimizing power losses and improving system performance.

2.6.4 DG Placement

The growth in electricity demand is increasing rapidly, and distributed generation (DG) emerges as a better alternative to meet this energy demand. Along from lowering energy losses, transmission congestion, improving voltage profile, and increasing dependability, DG also has reduced operational expenses. Its smaller size makes it shorter investment and installation periods, and more adaptable to setup compared to conventional generation units. DG helps address issues like load maturation, line overloading, supply timbre, and equipment maintenance intervals, leading to reduced line losses and improved power quality. By establishing power systems closer to consumers, High losses, low reliability, and poor power quality are issues that centralized power plants must deal with, and DG shows to be a viable option for overcoming problems faced to these issues. The modular and small size of DG also makes it suitable for decentralized environments with uncertain demand and supply, provided they are placed strategically and sized appropriately. Analysis tools are crucial for evaluating and optimizing DG implementation.

2.7 Literature review

The strategic placement of distributed generation (DG) in a distribution system is a valuable approach to enhance the overall performance of the network. When combined with other optimization strategies such as capacitor placement and network reconfiguration, it can yield significant benefits. However, it is essential to ensure that DG units are appropriately located and sized to avoid adverse effects. Inadequate placement and sizing of DG units can lead to suboptimal reduction of power losses and result in a voltage profile that falls below acceptable limits. Therefore, careful consideration of DG placement and sizing is crucial to maximize its advantages while maintaining a stable voltage profile in the distribution system.

Utilities can benefit from decreased system losses, greater voltage regulation, and increased supply reliability by effectively assigning DGs. In order to address problems including high power loss, low reliability, and poor power quality as well as satisfy the rising energy needs of loads, DG is a viable alternative. Achieving the optimal placement and assignment of DG units presents a notable challenge in system design, which can be addressed using various approaches aimed at maximizing effectiveness and efficiency. These methods are divided into the following four categories:

(a) Classical methods
(b) Analytical methods
(c) Meta-heuristic methods
(d) Other methods

These methods are discussed in brief as below-

(a) Classical methods:

In the literature, several methodologies have been proposed for the placement and sizing of distributed generators (DGs) within a distribution network. These methodologies offer diverse approaches and techniques to address this important aspect of DG integration. A strategy that tries to reduce losses, line loading, and the need for reactive power is based on generalized optimization techniques and is described in [22]. A loss function is utilized as the objective function in the problem formulation, while real and reactive power injections at the bus are subject to specific constraints. Lagrangian multipliers are used to solve the optimization issue using the generalized reduced gradient approach, often known as the second order method.

Another approach is outlined in [23] and is a straightforward way for placing and sizing generators optimally with the intention of effectively lowering costs and power loss. The weighting element, which balances the cost and loss aspects, is the main emphasis of this approach. Additionally, the load flow Newton-Raphson approach is utilized.

Both methodologies aim to strike a balance between costs and benefits when determining the optimal size and location of (DG) units. The overarching goal is to improve the voltage profile, minimize losses, and enhance supply reliability within the distribution network.

(b) Analytical method:

The analytical method presented in [26] aims to minimize power loss in the system by finding the optimal location to place distributed generators (DGs) in both radial and meshed systems. The method derives separate expressions for each type of system and proposes a complex procedure based on phasor current to solve the location problem. However, it is important to note that this method is only for optimal placement of DG with unity power factor in power system and considers fixed size of DG.

Additionally, the method is tested on IEEE 6-bus and 30-bus test systems and is not iterative, thus reducing the chances of convergence problems and providing quick results.

In [28], the proposed method is based on improved analytical expressions to calculate the optimal size of four different types of DG and a methodology to identify the best location for DG allocation is presented. A technique to obtain the optimal power factor is presented for DG capable of delivering real and reactive power. In order to achieve a high loss reduction in large-scale primary distribution networks, this article examines the deployment of several DG units.

(c) Meta-heuristics methods:

For the purpose of minimizing loss in power systems, several studies have put forth strategies for the ideal placement and sizing of distributed generators (DG). As an illustration, Deependra Singh et al. (reference [24]) suggested a method for testing 16-bus, 37-bus, and 75-bus test systems under various load situations. To determine the ideal position and size of DG, H. E. A. Talaat et al. (reference [25]) developed an approach utilizing genetic algorithms with three separate algorithms created. A technique using a genetic algorithm was put out by T. N. Shukla et al. (reference [26]) for allocating DG in a radial distribution system for the lowest possible losses on a 33-bus test system. On a 13-node and 37-node radial test feeder, I. Kumaraswamy et al. (reference [27]) proposed a method employing a genetic algorithm for assigning DG for loss reduction and voltage profile enhancement. A method for allocating multiple DGs in distribution networks using the load flow method was presented by G. Pavan Kumar (reference [28]) and tested on a 38-bus test system. On a 33-bus test system with power restrictions of 0-2MW and 0-3MW, Abdulhamid Musa et al. (reference [29]) proposed a solution using evolutionary algorithms for the best placement and sizing of numerous DGs. M. Dixit et al. (reference [30]) proposed a technique to optimize the solution for DG placement on 15-bus and 33-bus test systems utilizing the Artificial Bee Colony (ABC) algorithm and an Index Vector Method (IVM). To find the ideal position and DG size for loss minimization in power systems, all of these strategies have made use of various optimization algorithms.

(d) Other methods:

It is described in [31] how to numerically arrange distributed generation (DG) units in distribution networks. This method identifies the buses that are most vulnerable to voltage collapse and is based on the continuing power flow method. The bus that is most vulnerable has DG fitted. This approach is tested on a standard 34-bus test system. Additionally, while reducing power losses, it could be able to increase the maximum loading, the voltage stability margin, and the capacity for power transmission.

CHAPTER 3 : METHODOLOGY

The transition from passive to active distribution networks has been facilitated by the increased deployment of distributed generation (DG). When expanding the distribution system with DG, several factors must be considered, including DG unit capacity, optimal location selection, technology choices, network connection requirements, existing system capacity, and protection schemes. Various methodologies and tools have been developed for that such as analytical tools, optimization programs, and heuristic techniques. A mixed integer nonlinear optimization problem can be used to represent the optimal DG placement problem. To overcome this challenge, several algorithms and goals have been investigated. Over the past decade, tremendous effort has been made in this area.

3.1 Power Flow Analysis in Distribution System

A distribution feeder's power-flow analysis is comparable to that of a networked transmission system. A distribution feeder's power-flow analysis is comparable to that of a networked transmission system. However, due to certain distinctive characteristics, distribution networks are often categorized as ill-conditioned.

Radial or weakly meshed networks, characterized by high R/X ratios, multi-phase unbalanced operation, and unbalanced distributed load, pose unique challenges in the design and operation of distribution systems. Newton Raphson (N-R), Gauss Seidel (G-S), and other transmission system algorithms do not function well in distribution networks as a result of the aforementioned problems and due to the unique characteristics of radial distribution feeders. These iterative methods, which are often used in transmission network power-flow analyses, are not appropriate for distribution networks. To enable proper analysis and modeling of the distribution network, a special iterative method made for radial systems is used. The sweeping algorithm is an iterative methodology that gives advantages in terms of decreased computation effort and calculation time.

3.1.1 Backward / Forward Sweep Algorithm

In a radial distribution system (RDS), the backward/forward sweep algorithm takes advantage of the distinct route from any given bus back to the source. This essential characteristic is used by the sweep algorithm, which uses the backward sweep and the forward sweep as its two major steps. These steps are iteratively repeated until convergence is achieved. The algorithm follows a specific process, as outlined in Table 3.1, to compute the various parameters and variables in the distribution system.

The backward sweep sums current or power flows and updates voltage, while the forward sweep calculates voltage drops and updates current or power flows. In distribution systems, various methods, such as power summation, current summation, or admittance summation, are utilized during the sweeping process.

Table 3-1: Backward/Forward Sweep Algorithm

Backward/Forward Sweep Algorithm	
Initialize all bus voltages	
1	Backward Sweep: Sum currents or power flows (and possibly update voltage)
2	Forward Sweep: Calculate voltage drops (and possibly update current/power)
Repeat step 1 and 2 until convergence is achieved.	

Consider a branch with resistance R1 and inductive reactance X1 that connects nodes 1 and 2. From Figure 3.1, the current passing through Branch 1 is represented by,

$$I_1 = \frac{V_1\angle\delta_1 - V_2\angle\delta_2}{R_1 + jX_1} \tag{1}$$

$$I_1 = \frac{P_2 - jQ_2}{V_2\angle\delta_2} \tag{2}$$

where,

$V_1\angle\delta_1$, $V_2\angle\,\delta_2$ are the voltage and phase angles of node 1 and 2

P_2 is the sum of all active power loads and active power losses of all branch after node number 2 and active power load at node 2

Q_2 is the sum of all reactive power loads and reactive power losses of all branch after node number 2 and reactive power load at node 2

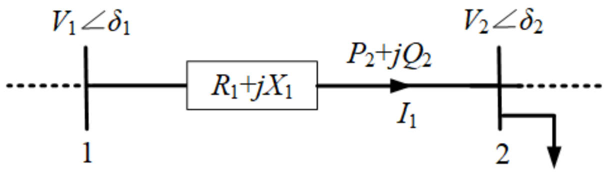

Figure 3-1: Electrical equivalent of a typical branch connected between two nodes.

Combining equation 1 and 2 we get

$$\frac{V_1\angle\delta_1 - V_2\angle\delta_2}{R_1 + jX_1} = \frac{P_2 - jQ_2}{V_2\angle\delta_2} \tag{3}$$

$$|V_1||V_2|[cos(\delta_1 - \delta_2) + jsin(\delta_1 - \delta_2)] - |V_2|^2 = (P_2 - jQ_2)(R_1 - jX_1) \tag{4}$$

Taking the above equation's real and imaginary components apart,

$$|V_1||V_2|cos(\delta_1 - \delta_2) = |V_2|^2 + P_2R_1 + Q_2X_1 \tag{5}$$

&

$$|V_1||V_2|sin(\delta_1 - \delta_2) = P_2X_1 - Q_2R_1 \tag{6}$$

Squaring and adding equations (5) and (6)

$$|V_2|^4 + 2|V_2|^2(P_2R_1 + Q_2X_1 - 0.5|V_2|^2) + (R_1^2 + X_1^2)(P_2^2 + Q_2^2) = 0 \tag{7}$$

Equation (7)'s straightforward solution and independence from the phase angle simplify the formulation of the problem. Consequently, from equation (7)

$$|V_2|^2 = \sqrt{\{(P_2R_1 + Q_2X_1 - 0.5|V_2|^2)^2 - (R_1^2 + X_1^2)(P_2^2 + Q_2^2)\}} - (P_2R_1 + Q_2X_1 - 0.5|V_2|^2) \tag{8}$$

$$|V_{i+1}|^2 = \sqrt{\left\{\left(P_{i+1}R_j + Q_{i+1}X_j - 0.5|V_i|^2\right)^2 - \left(R_j^2 + X_j^2\right)(P_{i+1}^2 + Q_{i+1}^2)\right\}} - \left(P_{i+1}R_j + Q_{i+1}X_j - 0.5|V_i|^2\right) \quad (9)$$

where,

Node, i =1,2,3....n ;

Branch, j = 1,2,3 ...n-1

n is the total number of nodes

In branch 'j', the real and reactive power losses is given by

$$P_{loss,j} = R_j \frac{P_{i+1}^2 + Q_{i+1}^2}{|V_{i+1}|^2} \quad (10)$$

$$Q_{loss,j} = X_j \frac{P_{i+1}^2 + Q_{i+1}^2}{|V_{i+1}|^2} \quad (11)$$

The total real and reactive power loss of the system is

$$TPL = \sum_{i=1}^{n-1} P_{loss,\mathrm{i}} \quad (12)$$

$$TQL = \sum_{i=1}^{n-1} Q_{loss,i} \quad (13)$$

Following the completion of those procedures, load flow is used to calculate the voltage, angle, active power losses, and reactive power losses of the system.

3.2 Problem Formulation

The focus of this section is the problem formulation for determining the optimal size and location of Distributed Generation (DG) while considering various constraints related to different standard operational limits.

3.2.1 Objective Function

The objective of this thesis work for DG placement problem is to minimize the power distribution losses in the network.

$$Min\ F = \sum P_{Loss} \tag{144}$$

3.2.2 Constraints

There are certain standard limits for the parameters defined for the proper operation of the power system

3.2.2.1 Constraints on bus Voltage Magnitude

$$V_{min} \leq V_i \leq V_{max} \tag{15}$$

Where, $V_i = Voltage\ magnitude\ at\ i^{th}\ bus,$

$V_{min} = Minimum\ Voltage\ limit,$

$V_{max} = Maximum\ Voltage\ limit,$

These voltage constraints are necessary to keep the voltage level within acceptable limits and avoid issues like over-voltage or under-voltage which may be arise due to the integration of distributed generation (DG). By enforcing these constraints, the distribution system's voltage can be regulated.

In this work, the allowable voltage limits are considered as ± 10%.

3.2.2.2 Constraints on Line current

The line loading constraint ensures that the current flowing through each line or branch in the distribution system does not exceed its thermal limit. Overcoming the temperature limit may result in overheating and line damage, jeopardizing the system's dependability and safety. By enforcing this constraint, the system can prevent overloading of lines due to the integration of distributed generation (DG), ensuring the system operates within safe operating conditions. The constraints on line loadings can be given as :

$$I_i \leq I_i^{Rated} \tag{16}$$

Where, $I_i = Current\ flow\ in\ i^{th}\ bus,$

$I_i^{Rated} = Current\ permissible\ for\ i^{th}\ bus,$

3.2.2.3 Constraints on power flow equation

The total active and reactive power injected into the distribution system (from the slack bus and DGs) must match the total active and reactive power used by the loads and lost in the lines. This is ensured by the power balance equation. For the distribution system to run steadily and dependably, this power balance must be maintained.

$$P_{SB} + \sum_{i=1}^{NDG} P_{DG}^{i} = \sum_{i=1}^{nb} P_{DLi}^{loss} + \sum_{i=2}^{nb} P_i^{load} \tag{17}$$

$$Q_{SB} + \sum_{i=1}^{NDG} Q_{DG}^{i} = \sum_{i=1}^{nb} Q_{DLi}^{loss} + \sum_{i=2}^{nb} Q_i^{load} \tag{18}$$

Where, P_{SB}, Q_{SB} = Active and reactive power of the slack or infinite bus respectively.

P_{DLi}^{loss} , Q_{DLi}^{loss}=Active and reactive losses of the i^{th} distribution lines respectively

P_{DG}^{i}, Q_{DG}^{i}= Real and reactive power supply of the i^{th} DG to the grid, respectively

P_i^{load}, Q_i^{load}= Systems active and reactive demand at i^{th} bus, respectively

N_{DG}= Number of total DG units

3.2.2.4 Constraints on DG penetration boundaries

The amount of installed distributed generation (DG) capacity in a power system in relation to the overall system capacity is known as the penetration level of DG. It is typically quantified as a percentage. A high penetration level of DG indicates that most portion of power are supplied by distributed generators, while a low penetration level indicates that the majority of the power is still being supplied by centralized power plants. The degree of DG penetration may have an impact on the distribution network's efficiency and cost-effectiveness, as well as the stability and dependability of the power system. There are many factors that may impact the degree of DG penetration such as the price and accessibility of DG technologies, regulations and policies of Government and the availably of incentives for the installation of DG.

$$\sum_{i=1}^{NDG} S_{DG}^{i} \leq penetration\ level * S_{Total} \tag{19}$$

Where, S_{DG}^{i} is the apparent power generated by ith DG.

S_{Total} is the total apparent power of the system.

The permissible amount of penetration in this research is set at 50%.

3.3 Optimization Techniques

Numerous approaches have been researched over time to address the issue of maximizing distributed generation (DG) in distribution system. These methods include traditional approaches and mathematical algorithms. Among them, artificial intelligence (AI) algorithms have gained popularity in recent years for distribution network reconfiguration. Some of the commonly used AI algorithms include artificial neural networks (ANN), genetic algorithms (GA), ant colony optimization (ACO), simulated annealing algorithms (SA), and particle swarm optimization (PSO). These algorithms offer different approaches to optimize the integration and placement of DG units aiming to enhance system efficiency and performance.

3.3.1 Analytical Method

The classical method of optimizing DG units in distribution systems focuses on a specific demand-generation snapshot scenario. It formulates an objective function, typically targeting real power losses, to determine the optimal capacity of the DG unit. However, this approach has limitations when applied to distribution networks with DG plants. It cannot consider factors such as energy losses, operational solutions like coordinated voltage control, or generation curtailment. Analytical approaches provide indicative results but are scenario-limited. Therefore, care must be taken when using these methods, as they may not capture the full range of considerations in DG unit siting and sizing.

3.3.2 Exhaustive Method

Exhaustive analyses of the search space for DG plant locations and sizes in a distribution network can address single or multiple technical issues and constraints. Using this technique, it is possible to add a wide range of indices or parameters that reflect various technical and non-technical factors in the objective function. However, conducting exhaustive analyses can be time-consuming due to the comprehensive exploration of the search space.

3.3.3 Linear Programming (LP) Method

Distribution networks have used linear programming (LP) for capacity allocation and energy optimization. Since in LP we linearize the power flow and the results of power flow, some approximation error is introduced. However, when discrete turbine sizes are taken into account, this inaccuracy is not substantial. The goal of an optimal power flow (OPF) problem, which may be created using LP, is to lower the annual cost of curtailing active generating. Different limitations, such as voltage, temperature, and short circuit restrictions, are characterized using the linearized sensitivity factors determined from AC power flow. LP has benefits including the ability for developing operational methods and powerful optimization abilities.

3.3.4 AC Optimal Power Flow (OPF) Method

The AC optimal power flow (OPF) is a nonlinear programming (NLP) problem widely used in the electric industry as a powerful optimization tool. Various solution methods are available for solving the AC OPF, including specialized techniques tailored to OPF. Depending on the requirements of the individual research, the AC OPF can be configured with various objectives and constraints. The AC OPF issue may be solved using a variety of strategies, such as branch and bound methods and linear programming methods. Commercial NLP problem solvers like CONOPT and KNITRO are frequently employed. Local optimal of a non-convex NLP can usually be determined, but obtaining the global optimum is rarely guaranteed in reality.

3.3.5 Genetic Algorithm

The Genetic Algorithm (GA), which mimics the process of natural selection in biological evolution, is a technique for solving optimization problems that are both limited and unconstrained. The GA operates through iterative adjustments to a population of individual solutions. In order to produce children for the following generation, parents are chosen from the present population in each iteration. Evolutionary progression is the process through which a population moves over successive generations toward an ideal solution.

The GA uses two primary categories of rules:

1. The process of determining which individuals, referred to as parents, contribute to the population of the next generation is governed by selection rules.

2. Reproduction involves genetic operators such as crossover (recombination) and mutation. In the process of generating offspring for the next generation, crossover combines genetic material from two parents, while mutation introduces random alterations to individual parents, resulting in the formation of children.

3.3.6 Metaheuristics Method

A metaheuristic approach is an iterative procedure that combines different concepts to guide a subordinate heuristic, allowing for effective searching and exploitation of the search space. The issue of the best distribution of distributed generation has been addressed using metaheuristic algorithms such as ant colony optimization (ACO), artificial bee colony optimization (ABC), tabu search (TS), particle swarm optimization (PSO), simulated annealing (SA), and genetic algorithms (GA) .

In the ACO algorithm, the artificial ants build solutions repeatedly by taking into account accumulated prior search experience, which is represented by pheromone trails and heuristic data. The search procedure is directed by this probabilistic heuristic structure.

The dynamics of social insect populations, in which interactions take place through chemical and/or physical cues, serve as the inspiration for the ACO and ABC algorithms. In order to address optimization issues, these algorithms imitate social insect colony behaviors including bee dance and ant pheromone emission. ABC algorithms have been used to determine the appropriate size, power factor, and positioning of DG units in order to minimise real power loss in the system.

3.3.6.1 Grey Wolf Optimization

The grey wolf, scientifically known as Canis lupus, is a member of the Canidae family. Grey wolves are recognized as apex predators, occupying the highest position in the food chain. They exhibit a strong inclination to live in packs, with an average group size ranging from 5 to 12 individuals. Notably, grey wolves adhere to a highly structured social hierarchy, characterized by strict dominance relationships among pack members, as depicted in Figure 3-2.

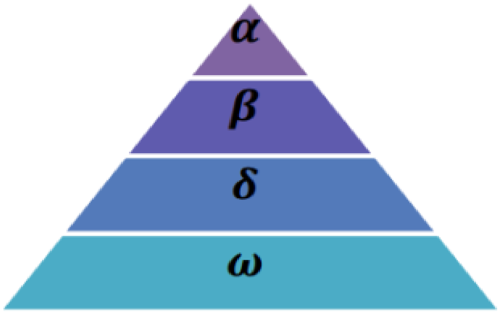

Figure 3-2: Grey wolf social structure (dominance decreases from top down).

The leaders of the grey wolf social structure, known as alphas, consist of a male and a female and represent the dominant individuals within the pack. The alpha bears the primary responsibility for decision-making regarding hunting, sleeping arrangements, wake-up timings, and other activities related to the pack. The alpha's judgments are communicated to the pack and generally followed by its members. While there are occasional instances of democratic behavior among the alphas, where they yield to the demands of other wolves in the pack, such behavior is infrequent. The pack collectively shows recognition of the alpha's authority by lowering their tails when gathered. The alpha wolf, also referred to as the dominating wolf, commands the pack, and only the alpha wolves are allowed to mate within the pack. It is important to note that the pack's leader does not necessarily have to be the strongest; instead, they excel as adept pack managers.

In the hierarchical structure of a wolf pack, the second tier is occupied by the beta wolves. These pack members, referred to as betas, play a supportive role in decision-making and engagement in various pack activities alongside the alpha. The beta wolf, which can be of either gender, is often seen as a potential successor to the alpha position in the event of the alpha wolves' absence or aging. The beta wolf not only oversees the subordinate wolves but also demonstrates deference to the alpha. They assist the alpha in decision-making processes and maintain order within the pack. The beta provides input to the alpha and communicates the alpha's directives to the rest of the pack.

The omega wolf is at the bottom of the food chain. Within the pack, Omegas serve as the scapegoats. They are the last wolves allowed to feed and are perpetually submissive to all dominant wolves. Even while the omega may seem less significant than the other members of the pack, its loss can cause internal strife and other issues for the whole pack. The omega serves as a vehicle for other wolves to vent aggression and resentment, aiding in the upkeep of the hierarchy. Omegas occasionally act as the pack's caregivers, taking on tasks like babysitting.

Within the wolf pack hierarchy, there exists a category known as subordinates or delta wolves, which includes individuals who are not alphas, betas, or omegas. While they are subordinate to the alpha and beta wolves, the delta wolves hold authority over the omega wolves. This group encompasses various roles such as scouts, sentinels, elders, hunters, and caretakers. Scouts are responsible for monitoring the borders of the territory and alerting the pack to potential threats. Sentinels ensure the pack's safety and act in its defense. Elders are experienced wolves who may have previously held alpha or beta positions. Hunters assist alphas and betas in capturing prey to provide sustenance for the pack. Caretakers are responsible for attending to the weak, sick, and injured members of the pack.

Muro et al. described the key stages of group hunting as a significant social characteristic of grey wolves, in addition to their social hierarchy.

- Tracing, pursuing, and closing in on the prey.

- Engaging in persistent pursuit, surrounding, and exerting pressure on the prey until it ceases movement.
- Initiating an assault on the targeted prey.

These stages, as elucidated by Muro et al., depict the fundamental progression of grey wolf group hunting as shown in Fig.3-3

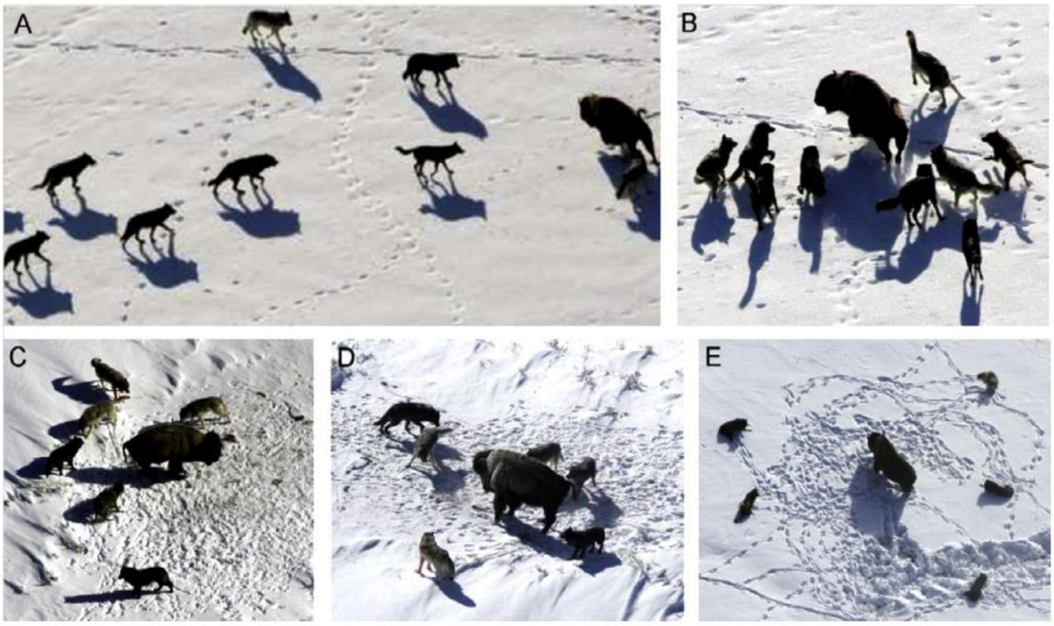

Figure 3-3: Hunting behavior of grey wolves: (A) chasing, approaching, and tracking prey (B–D) pursuiting, harassing, and encircling (E) stationary situation and attack

In this research, the study integrates mathematical modeling of hunting strategies and the observed social hierarchy in grey wolves to formulate the Grey Wolf Optimization (GWO) algorithm, primarily aimed at optimization purposes. The mathematical models developed encompass the representation of the social hierarchy, incorporating elements such as prey tracking, encircling, and attacking. Subsequently, the GWO algorithm is outlined, utilizing these mathematical models as a guide for the optimization process.

- Social hierarchy

The GWO algorithm incorporates the social structure of wolves into its framework. Within the GWO algorithm, the social order is quantitatively represented. The fittest solution, known as the alpha (α), holds the highest ranking, while the second fittest solutions are referred as the beta (β) and third fittest solution are referred as delta (δ) wolves occupy the subsequent positions. The remaining potential solutions are represented by the omega (ω) wolves. In the GWO algorithm, the α , β and δ wolves take charge of the hunting or optimization process, while the omega wolves follow their lead.

- Encircling prey

As previously discussed, grey wolves employ encircling tactics during their hunting behavior. To mathematically represent this encircling behavior, the following equations are proposed:

$$\vec{D} = \left|\vec{C} \cdot \overrightarrow{X_p}(t) - \vec{X}(t)\right| \tag{20}$$

$$\vec{X}(t+1) = \overrightarrow{X_p}(t) - \vec{A} \cdot \vec{D} \tag{21}$$

where t means current iteration number and $\overrightarrow{X_p}$ and $\overrightarrow{X}$ indicates the position vector of a prey and grey wolf respectively. The coefficient vectors $\vec{A}$ and $\vec{C}$ are calculated as follows:

$$\vec{A} = 2\,\vec{a} \cdot \overrightarrow{r_1} - \vec{a} \tag{22}$$

$$\vec{c} = 2\overrightarrow{r_2} \tag{23}$$

where $\vec{a}$ is the component which values linearly decreased from 2 to 0 across several iterations and r_1, r_2 are random vectors between [0, 1].

- Hunting:

Grey wolves possess the ability to detect and encircle their prey. During the hunting process, the alpha wolf assumes primary responsibility, occasionally receiving assistance from the beta and delta wolves. However, in an abstract search space, the precise location of the optimal prey remains uncertain. To emulate the hunting behavior of grey wolves mathematically, the best candidate solution, as well as the beta and delta wolves, are considered to possess superior information regarding the potential prey's location. Consequently, the first three best solutions encountered thus far are retained, while the other search agents, including the omegas, are compelled to adjust their positions based on the best search agent's location. To facilitate this process, the following formulas are proposed.

$$\overrightarrow{D_\alpha} = \left|\overrightarrow{C_1} \cdot \overrightarrow{X_\alpha} - \vec{X}\right|, \overrightarrow{D_\beta} = \left|\overrightarrow{C_2} \cdot \overrightarrow{X_\beta} - \vec{X}\right|, \overrightarrow{D_\delta} = \left|\overrightarrow{C_3} \cdot \overrightarrow{X_\delta} - \vec{X}\right| \tag{24}$$

$$\overrightarrow{X_1} = \overrightarrow{X_\alpha} - \vec{A}_1 \cdot \overrightarrow{D_\alpha}, \overrightarrow{X_2} = \overrightarrow{X_\beta} - \vec{A}_2 \cdot \overrightarrow{D_\beta}, \overrightarrow{X_3} = \overrightarrow{X_\delta} - \vec{A}_3 \cdot \overrightarrow{D_\delta}, \tag{25}$$

$$\overrightarrow{X_{(t+1)}} = \frac{\overrightarrow{X_1} + \overrightarrow{X_2} + \overrightarrow{X_3}}{3} \tag{26}$$

Figure 3-4 illustrates the process by which a search agent adjusts its position in a 2D search space based on the influence of the alpha, beta, and delta wolves. In the GWO algorithm, the positions of the alpha, beta, and delta wolves create a circle within the search space. This circle represents the potential location of the prey. The final positions of the wolves in the algorithm are determined within this circle. The remaining wolves in the pack then adjust their positions randomly around this presumed prey location, following the guidance of the alpha, beta, and delta wolves.

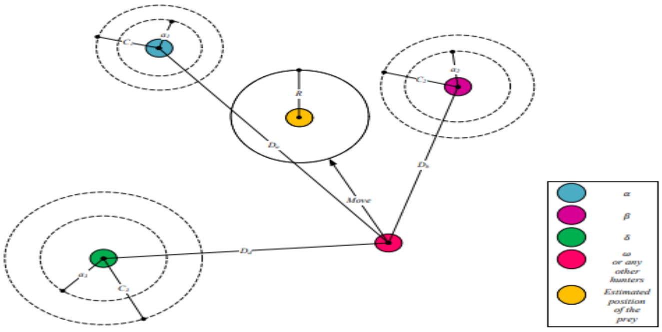

Figure 3-4: Position updating in GWO

Pseudocode for GWO

Step 1: Initialize the population of grey wolves Xi (i = 1, 2, ..., n).

Step 2: Set the initial values for variables a, A, and C.

Step 3: Calculate the fitness of each search agent.

Step 4: Identify the best search agent as $\boldsymbol{X}_{\alpha}$.

Step 5: Identify the second-best search agent as $\boldsymbol{X}_{\beta}$.

Step 6: Identify the third best search agent as $\boldsymbol{X}_{\boldsymbol{\delta}}$.

Step 7: Execute the following loop until reaching the maximum number of iterations:

- For each search agent:
- Update the position of the current search agent using the equations mentioned above.
- Update the values of a, A, and C.
- Recalculate the fitness of all search agents.
- Update $\boldsymbol{X}_{\alpha}$, $\boldsymbol{X}_{\beta}$, and $\boldsymbol{X}_{\boldsymbol{\delta}}$ based on the new fitness values.
- Increment the iteration counter.

Step 8: Return $\boldsymbol{X}_{\alpha}$ as the final solution.

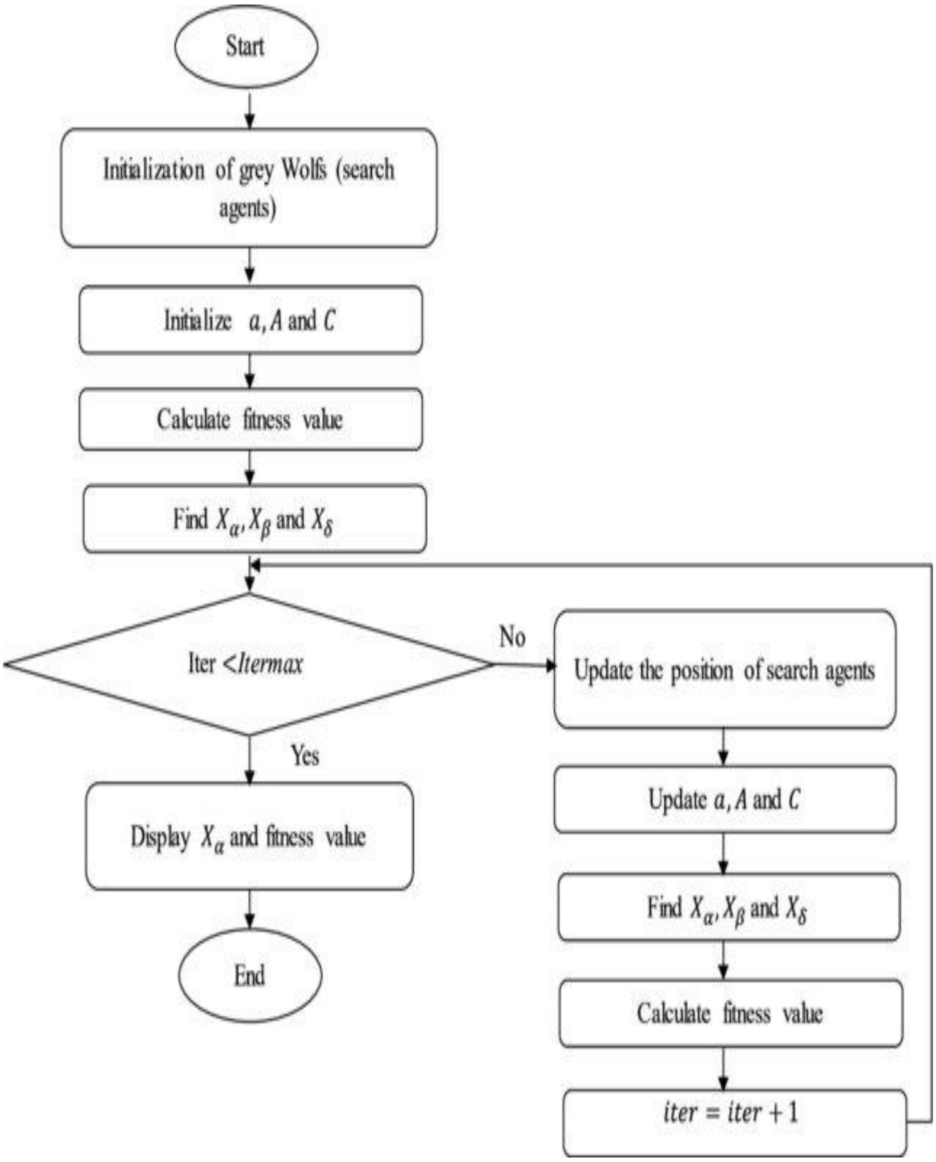

Figure 3-5: Flowchart of GWO

3.4 Implementation Steps of GWO

The GWO algorithm incorporates three fundamental steps, inspired by the hunting behavior of grey wolves: searching for prey, encircling the prey, and attacking the prey.

These steps are crucial in achieving efficient optimization. Through the mathematical modeling of the social hierarchy and integration of the hunting behavior observed in grey wolves, the GWO algorithm showcases its capability to tackle various optimization tasks effectively.

In the GWO algorithm, the terms "alphas," "betas," and "deltas" play crucial roles in the optimization process. In a real scenario, they represent potential solutions within the decision space. The beta and delta wolves indicate the second and third best answers, respectively, while the alpha wolf corresponds to the best solution thus far. These wolves embody promising configurations or parameters that show strong performance in solving the problem.

GWO's implementation phases start with the algorithm establishing the number of iterations, which establishes how long the optimization process lasts. Then, initializing a population of wolves at random, the problem's alternative solutions are represented. The issue being addressed determines the precise properties of these wolves, such as the size of the decision space (DG), their number, and their initial locations.

Next, load flow calculations are performed for each wolf's position in the decision space. In this step, the objective function and fitness value of each wolf are evaluated, serving as a measure of their performance in solving the problem. The wolves' fitness values determine the quality of their solutions. The α, β and δ wolves are identified based on their fitness values, representing the best solutions found thus far in the optimization process.

To improve the solutions, the positions of the wolves are updated using a predefined equation. This equation guides the wolves' movements towards better solutions, taking into account the positions of the α, β and δ wolves. The updated positions are then subjected to load flow calculations again to re-evaluate the fitness of each wolf.

The alpha (α), beta (β), and delta (δ) wolves undergo updates based on their new fitness values. If a wolf exhibits a superior fitness value compared to the current alpha wolf, it replaces the alpha wolf and becomes the new alpha. Similarly, the second-best wolf takes the position of the beta wolf, and the third-best wolf becomes the delta wolf. This iterative process allows for the refinement of the overall solution quality, as the best-performing wolves are continually identified and updated in the optimization process.

After each iteration, the iteration counter is incremented, and the GWO algorithm checks whether the stopping criteria have been met. If the stopping criteria are satisfied, the algorithm terminates, and the alpha wolf represents the optimal solution obtained by the GWO algorithm. On the other hand, if the stopping criteria are not met, the algorithm continues to repeat the process. In each iteration, the positions of the wolves are updated iteratively to further enhance and improve the solutions.

In summary, the alphas, betas, and deltas in the GWO algorithm represent the best-performing wolves, which correspond to potential solutions in a real scenario. The implementation involves initializing the population, evaluating their fitness through load flow calculations, updating their positions based on the α, β and δ wolves, and iteratively improving the solutions until the stopping criteria are met. Ultimately, the alpha wolf represents the optimal solution obtained by the GWO algorithm. Figure 4-3shows the flowchart of GWO.

The following stages provide as an illustration of the GWO technique:

Step 1: Determine the number of iterations, denoted as 't'.

Step 2: Generate an initial population of hunting wolves randomly, initializing positions for the alpha (α), beta (β), and delta (δ) wolves. Set parameters for the design space size, maximum iterations, and population count. Perform load flow calculations for each population to compute the objective function.

Step 3: Conduct a load flow analysis to evaluate the objective function and calculate the fitness value for each wolf.

Step 4: Identify the best alpha wolf, the second-best beta wolf, and the third-best delta wolf using equations (4-5) to (4-10).

Step 5: Update the positions of the wolves using equation (4-11).

Step 6: Repeat the load flow analysis and calculate the fitness value for each wolf.

Step 7: Adjust the positions of the alpha, beta, and delta wolves.

Step 8: Increment the iteration counter, 't'.

Step 9: If the stopping criteria are met, proceed to step 10; otherwise, go back to step 5.

Step 10: Terminate the algorithm. The alpha wolf represents the optimal solution achieved by the GWO optimizer

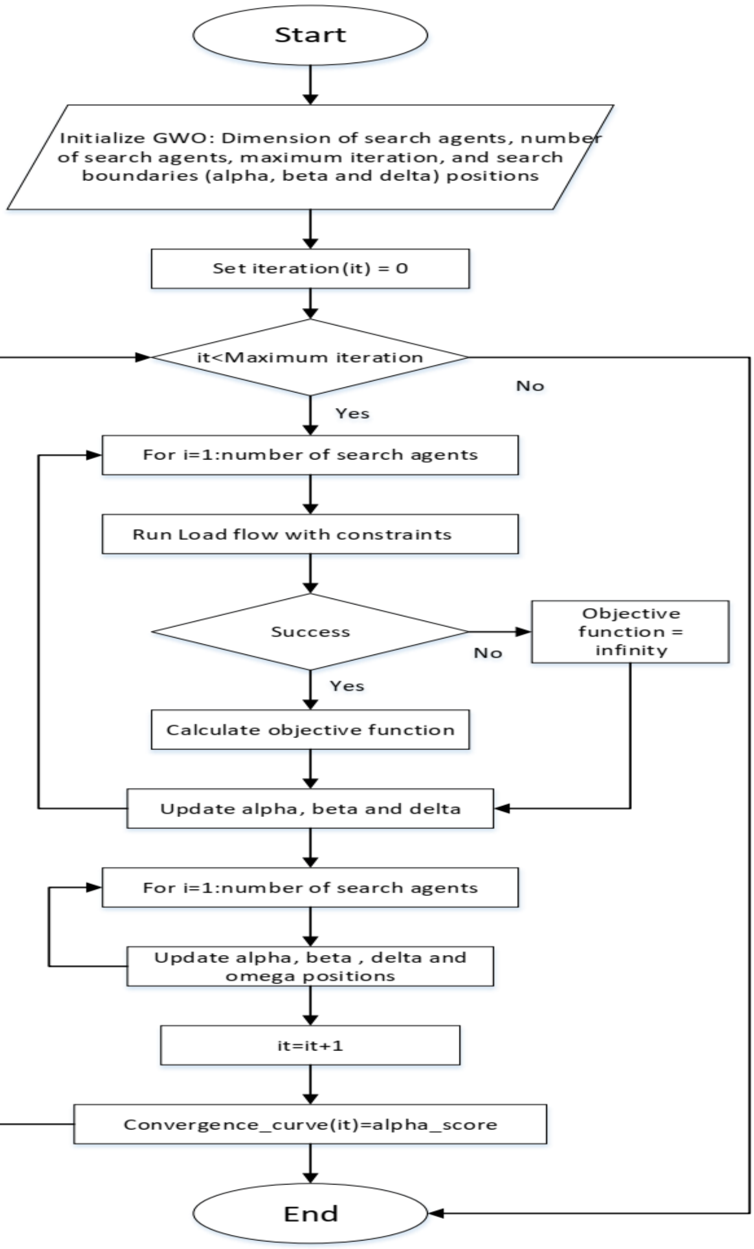

Figure 3-6: Flowchart of GWO for optimal placement of DG

3.5 DG Technologies

Based on their capacity to inject active and/or reactive power to the power system, DG technologies are classed. DG technologies are categorized into the following classes as a result:

- Type 1 DG

Type 1 DG is referred to as DG that can inject both active and reactive power. Synchronous machines used in small hydro, geothermal, and combined cycle applications make up the Type 1 category of DG units. Both constant terminal voltage control and constant power factor control can be used to represent these DG units.

DG units can be categorized into two modes of operation based on their control strategy. When DG units operate in power factor control mode, they are referred to as PQ (constant power factor) nodes. On the other hand, when DG units operate in voltage control mode, they are known as PV (constant voltage) nodes [61]. In the specific study mentioned, the DG units are modeled as PQ nodes and employ power factor control mode with a power factor of 0.8.

- Type 2 DG

Type 2 DG is referred to as DG that can inject active power (P) only. Photovoltaic (PV) systems, fuel cells and micro turbines are examples of DG technologies that fall under the Type 2 category and are connected to the primary grid via converters or inverters [62, 63]. DG units in the Type 2 category do not use or supply reactive power to the system. They have a unity power factor, which means they only transmit or absorb actual power.

- Type 3 DG

DG that are capable of injecting reactive power (Q) only are referred as TYPE 3 category.DG units equipped with a synchronous compensator are classified as Type 3 category.

- Type 4: DG capable of injecting active power (P), but consuming reactive power (Q)

It is crucial to recognize that the selection of DG technology has a significant influence on the performance of the distribution network. The paper under consideration utilizes Type 1, Type 2, and Type 3 DGs for analysis purposes.

3.6 Evaluation Indices

In assessing the effects of DG units on power system performance, several indices are used, as shown in Table 3.2. These indices provide measures of the effectiveness of DG installations.

ALR (Active Loss Reduction) and RLR (Reactive Loss Reduction) represent the reduction in active and reactive power losses, respectively, after the installation of DG units. These indices quantify the improvement in loss reduction achieved by DGs, with higher values indicating greater loss reduction. The VI (Voltage Index) is an indicator of the deviation from the desired bus voltage targets. It compares the actual bus voltage (Vi,1) when DG is present in the network to the desired voltage (Vi,0), both expressed in pu. A lower VI value shows that DG units are doing better at keeping the voltage within the specified range. These indices offer valuable information about how well DG units operate in terms of loss reduction and voltage regulation within the power system.

Table 3-2: Performance Indices

Index	Formula
Active Loss Reduction	$ALR = \frac{\mathrm{Re}\{losses_0\} - \mathrm{Re}\{losses_i\}}{\mathrm{Re}\{losses_0\}} \times 100\%$

Reactive Loss Reduction	$RLR = \frac{\mathrm{Im}\{losses_0\} - \mathrm{Im}\{losses_i\}}{\mathrm{Im}\{losses_0\}} \times 100\%$
Voltage Index	$VI = \sum_{i=1}^{n} \left(V_{i,0} - V_{i,1}\right)^2$
Minimum Voltage	Vmin= min(Voltage of all bus)

CHAPTER 4 : RESULTS AND DISCUSSIONS

4.1 Study System

4.1.1 IEEE 33 BUS

The methodology described above has been successfully implemented on the IEEE 33 bus power system. The analysis focuses on a radial distribution system comprising 33 buses operating at a voltage level of 12.66 kV. The IEEE 33 bus system is set up with branches that are linked to buses 2, 3, and 6. Bus 2 is specifically related to buses 19, 20, 21, and 22. Three buses—23, 24, and 25—are connected to bus number 3. Bus 6 has eight connections, from 26 to 33. The system's overall load is 2300 kVAr of reactive power and 3715 kW of active power. Buses 24 and 25 have the highest active load of 420 kW, and bus 30 has the highest load of 600 kVAr reactive. In contrast, bus 11 has a minimum active load of 45 kW, while bus 15 has a minimum reactive load of 10 kVAr. Bus 1 serves as the system's reference bus, having no load and a bus voltage of one per unit (pu). Please see Annex A for the complete line data and load data for the IEEE 33 bus system.

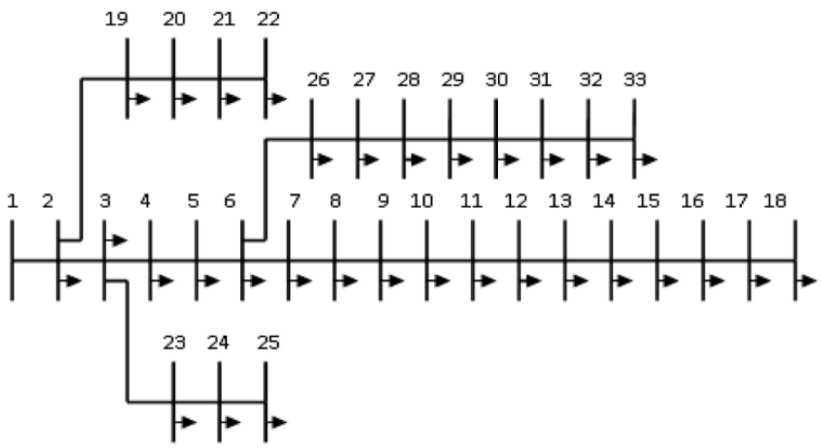

Figure 4-1: IEEE 33 test bus System

4.1.2 GALYANG 33kV FEEDER

After demonstrating the effectiveness of the suggested algorithm, the methodology was applied to a practical distribution system, Galyang feeder, of Pyuthan, Nepal. Galyang feeder originates from Jhimrukh substation situated in Pyuthan. The feeder is under the control of Pyuthan Distribution Center, Nepal Electricity Authority. Required branch data, and load data was collected for the feeder and plotted in QGIS. Bus numbers and branch numbers were assigned. Later, the data was entered in MS-Excel. Initially, nbr number of branch data was supplied in nbr number of rows. Branch data included branch resistance and branch reactance. Bus data for nbus number of buses was also fed to the computer program. Bus data included bus number, real and reactive power load at the bus. It is to be noted that nbus = (nbr + 1) in a radial network.

Figure 12 shows the GIS plot, and Table 3 has the system data for Galyang feeder.

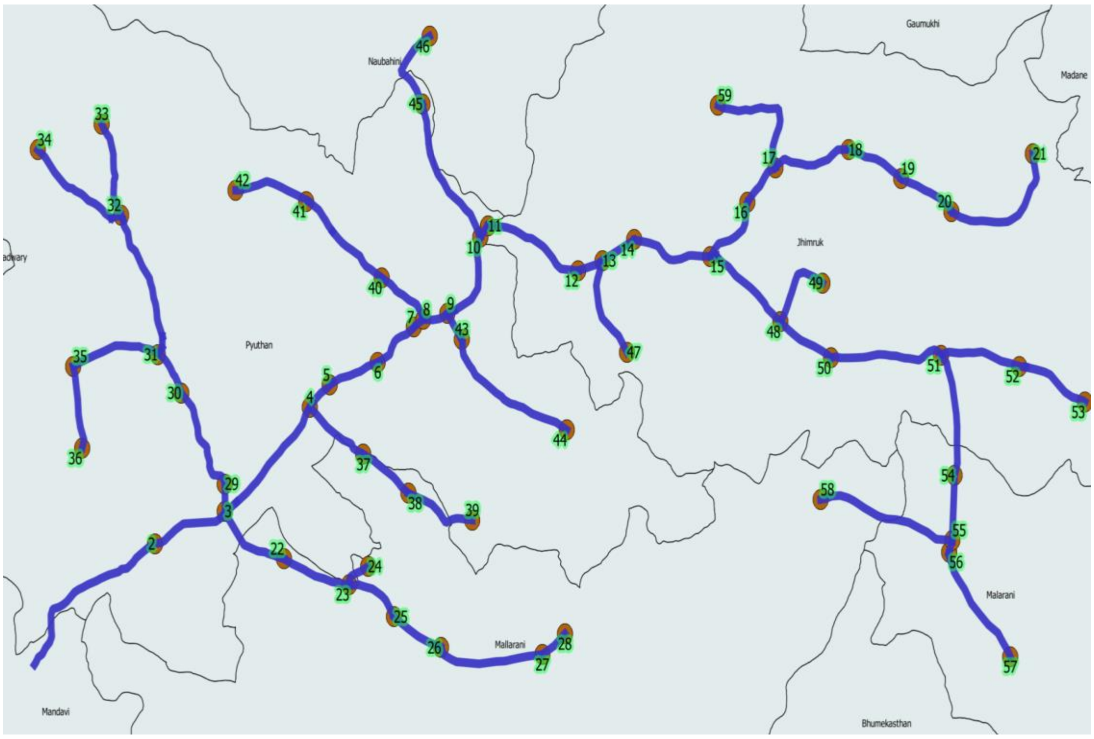

Figure 4-2: GIS Plot of Galyang Feeder

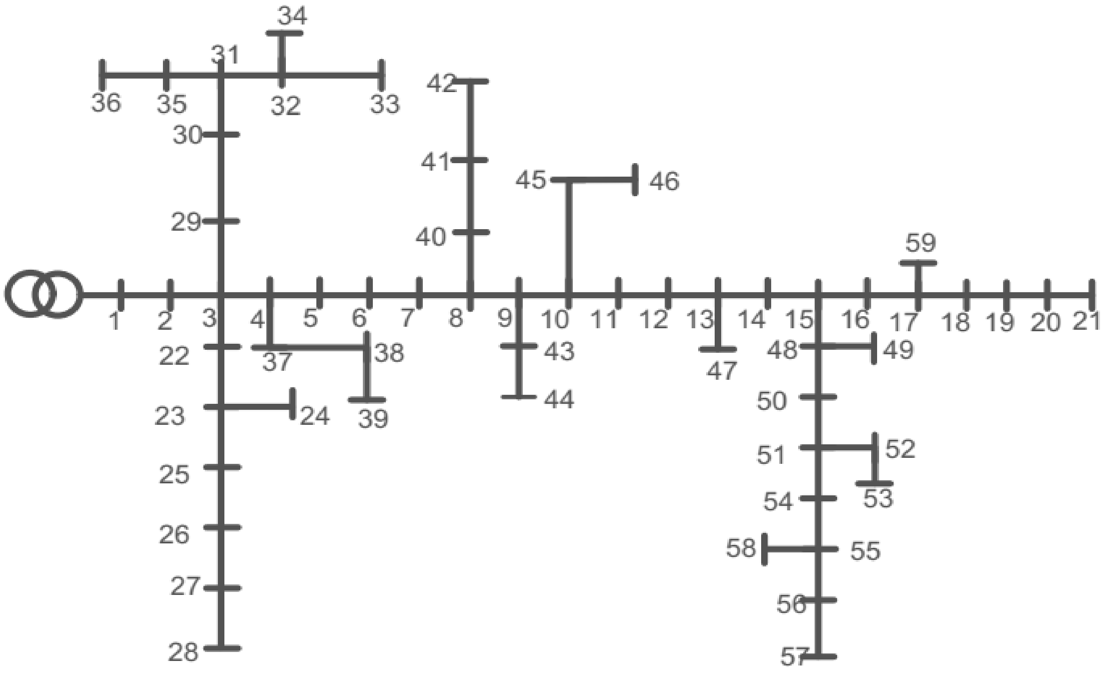

Figure 4-3: Single Line Diagram of Galyang Feeder

Table 4-1: Branch Data of Galyang Feeder

Branch No.	Sending Bus	Receiving Bus	Length (Km)	Resistance (Ohm)	Reactance (Ohm)
1	1	2	2.04281	1.11313	0.68434
2	2	3	0.95976	0.52297	0.32152
3	3	4	1.5374	0.37666	0.48428
4	4	5	0.32625	0.07993	0.10277
5	5	6	0.62115	0.56624	0.2143
6	6	7	0.59875	0.54582	0.20657
7	7	8	0.14002	0.12764	0.04831
8	8	9	0.41376	0.37718	0.14275
9	9	10	0.88211	0.80413	0.30433
10	10	11	0.15097	0.13762	0.05208
11	11	12	1.27746	1.16453	0.44072
12	12	13	0.32274	0.29421	0.11135
13	13	14	0.45025	0.24534	0.15083

14	14	15	1.0329	0.94159	0.35635
15	15	16	0.77867	0.70983	0.26864
16	16	17	0.49797	0.45395	0.1718
17	17	18	1.00706	0.91804	0.34744
18	18	19	0.7322	0.66747	0.25261
19	19	20	0.72633	0.66212	0.25058
20	20	21	1.55795	1.42023	0.53749
21	3	22	0.91261	0.49728	0.30572
22	22	23	0.87903	0.47898	0.29447
23	23	24	0.3308	0.08105	0.1042
24	23	25	0.6865	0.37407	0.22998
25	25	26	0.67227	0.36632	0.22521
26	26	27	1.34672	0.73383	0.45115
27	27	28	0.35231	0.32116	0.12155
28	3	29	0.34965	0.19052	0.11713
29	29	30	1.13751	0.61983	0.38106
30	30	31	0.492	0.4485	0.16974
31	31	32	1.45056	1.32233	0.50044
32	32	33	0.95942	0.87461	0.331
33	32	34	1.29661	1.18199	0.44733
34	31	35	1.12601	1.02647	0.38847
35	35	36	0.81578	0.74367	0.28144
36	4	37	0.83355	0.75986	0.28757
37	37	38	0.68857	0.6277	0.23756
38	38	39	0.91462	0.83376	0.31554
39	8	40	0.6687	0.60958	0.2307
40	40	41	1.2087	1.10185	0.417
41	41	42	0.96373	0.87854	0.33249
42	9	43	0.3093	0.28196	0.10671
43	43	44	1.69266	1.54302	0.58397
44	10	45	1.54667	1.40994	0.5336
45	45	46	0.94109	0.85789	0.32467
46	13	47	1.04896	0.95623	0.36189
47	15	48	1.1143	1.01579	0.38443
48	48	49	0.85422	0.7787	0.2947
49	48	50	0.73588	0.67082	0.25388

50	50	51	1.45103	1.32276	0.50061
51	51	52	1.10826	1.01029	0.38235
52	52	53	0.84446	0.76981	0.29134
53	51	54	1.21947	1.11167	0.42072
54	54	55	0.64195	0.5852	0.22147
55	55	56	0.13183	0.07183	0.04416
56	56	57	1.30912	1.19339	0.45165
57	55	58	1.76071	1.60506	0.60744
58	17	59	1.38285	1.2606	0.47708

Table 4-2: Bus Data for Galyang Feeder

Bus Number	Power Demand	
	P (KW)	Q (KVAR)
1	0	0
2	90	44
3	113	54
4	23	10
5	45	22
6	45	22
7	45	22
8	23	10
9	45	22
10	45	22
11	23	10
12	45	22
13	23	10
14	23	10
15	45	22
16	23	10
17	45	22
18	23	10
19	45	22
20	23	10
21	23	10

22	45	22
23	45	22
24	45	22
25	23	10
26	45	22
27	45	22
28	23	10
29	45	22
30	45	22
31	45	22
32	45	22
33	23	10
34	23	10
35	45	22
36	45	22
37	45	22
38	23	10
39	45	22
40	45	22
41	45	22
42	45	22
43	45	22
44	45	22
45	45	22
46	45	22
47	45	22
48	45	22
49	45	22
50	45	22
51	45	22
52	45	22
53	45	22
54	45	22
55	23	10
56	45	22
57	23	10
58	45	22
59	23	10
Total	2349	1126

4.2 IEEE 33 TEST System :

4.2.1 Base Case Simulation for IEEE 33 TEST System :

Figure 4.2 shows the test system's base case voltage profile, which was produced from load flow modeling. The reference bus (bus 1) has the highest calculated voltage value of one pu, whereas bus 18 has the lowest calculated voltage value of 0.9038 pu. In the radial distribution system (RDS), the voltage gradually decreases from bus 1 to bus 18 cause of the radial nature of the distribution system, where power flows from the source (bus 1) towards the farthest end (bus 18). Additionally, the voltage continues to decrease gradually from bus 19 to bus 33. It is important to note that bus 18 has the lowest voltage of all the system's buses.

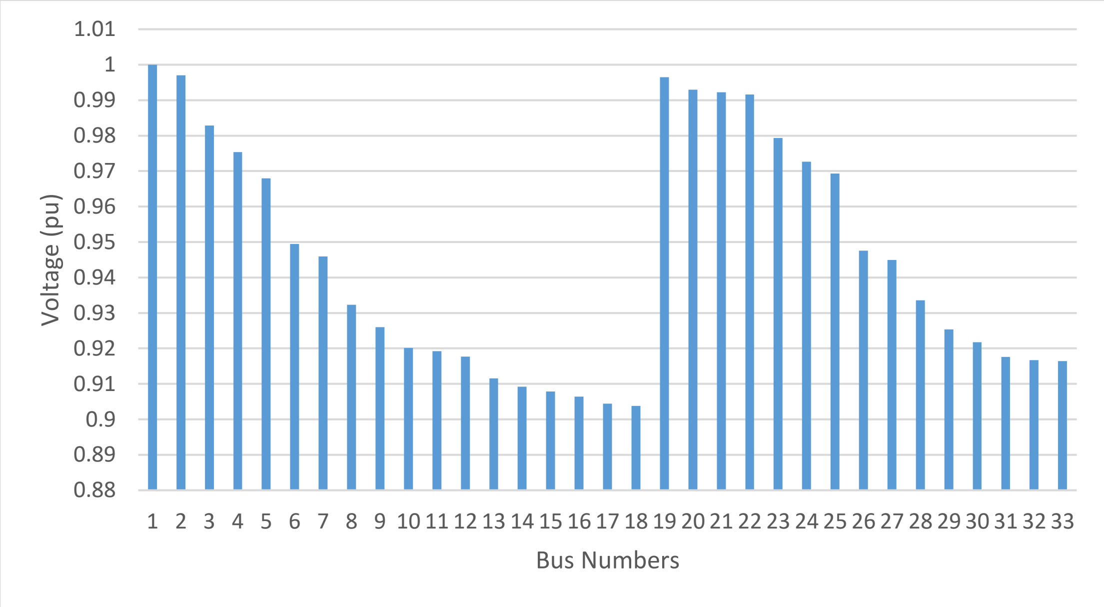

Figure 4-4 : Voltage profile of IEEE 33 bus Base Case Test System

For approximately half of the buses in the system, the voltage regulation limit is not met, highlighting the necessity for voltage control actions. After performing the load flow analysis of the radial distribution system (RDS), it was determined that the total real power loss is 211 kW and the total reactive power loss is 143 kVAr.

The detailed information regarding the real and reactive power losses in the branches for the base case load flow can be found in Annex B.

4.2.2 Optimal Placement of Type 2 DGs :

As outlined in our methodology, we utilized Type 2 Distributed Generators (DGs) that are capable of injecting real power only. The penetration level and type of DG were fixed, and an optimal solution for a single DG was determined. Subsequently, the number of DGs was increased, and power loss and minimum voltage were recorded for various DG locations and sizes obtained through Grey Wolf Optimization. The optimal location and sizing of the DGs are presented in the table below

Table 4-3: Simulation result for Optimal Placement of Type 2 DG in IEEE 33 Test Bus 1

No of DG	1	2	3	4	5
DG installed Bus	8	14,30	8, 15, 31	10, 16, 29, 32	10,14,17, 30,31
DG size(KVA)	1791.1	759.1, 1037.8	535.4, 508.8, 752.6	353.4, 411.5, 483.1, 323.9	336.9,191.8, 210.7,188.7, 523.9
Active Power Loss (kw)	118.1	88.3	84.9	88.6	92.4
Reactive Power Loss (kVAR)	82.9	60.2	57.01	58.8	61.3
Loss Reduction(%)	44.02 %	58.15%	59.76 %	58.00%	56.20%
Minimum Voltage	0.9432	0.9634	0.9629	0.9591	0.9560

Simulation results obtained through the implementation of the Grey Wolf Optimization (GWO) algorithm on the IEEE 33 bus power system indicate that strategically sizing and placing distributed generation (DG) units can effectively minimize power loss and improve voltage levels within the system.

When considering the case of a single DG unit, the algorithm found that the optimal placement was at bus 8, with an optimal size of 1791.1 kVA. This led to a minimum voltage of 0.9432 pu and a reduction in power loss of 44.02% compared to the base case.

As the number of DG units was increased to two, the algorithm found that the optimal placement for these units was at bus 14 and bus 30, with optimal sizes of 759.1 kVA and 1037.8 kVA respectively. This configuration resulted in a minimum voltage of 0.9634 pu and reduction in power loss of 58.15% when compared to the base case.

As soon as the number of DG units was raised to three, the algorithm identified bus 8, bus 15 and bus 31 as the optimal placement for these units, with optimal sizes of 535.4 kVA, 508.8 kVA and 752.6 kVA respectively. This configuration led to a minimum voltage of 0.9629 pu and a reduction in power loss of 59.76% when compared to the base case.

When the number of DG unit was increased to four DG units, the algorithm found that bus 10, bus 16, bus 29 and bus 32 were the optimal placement for these units, with optimal sizes of 353.4 kVA, 411.5 kVA, 483.1 kVA and 323.9 kVA respectively. This configuration resulted in a minimum voltage of 0.9591 pu and a 58.00% decrease in power loss from the base case

With a total of five DG units installed, they were placed at buses 10, 14, 17, 30, and 31. The sizes of the DG units were 336.9 kVA, 191.8 kVA, 210.7 kVA, 188.7 kVA, and 523.9 kVA, respectively. This configuration led to a significant reduction in active power loss by 56.20%, equivalent to 92.4 kW, and a reduction in reactive power loss by 61.3 kVAR. The minimum voltage achieved in the system was 0.956 pu.

The simulation results indicate that the placement of three DG units at bus 8, bus 15, and bus 31 and their corresponding optimal sizes of 535.4 kVA, 508.8 kVA, and 752.6

kVA respectively, relative to the base scenario, this had the system's lowest power loss at 59.76%. The minimum voltage observed in the system was 0.9629 pu. This confirms that the optimal placement of three Type 2 DG units at bus 8, bus 15, and bus 31 and their optimal sizes is the most efficient configuration for reducing power loss in the system.

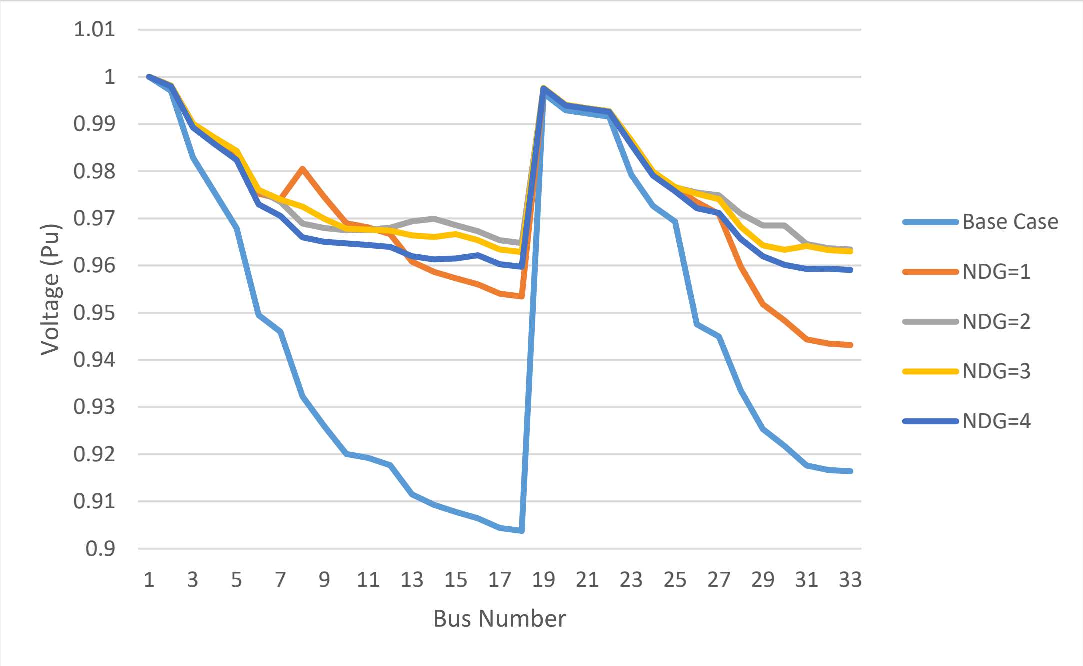

Figure 4-5: Voltage Profile with respect to Number of DGs(Type-2)

The voltage profile, as shown in figures 4.5 and 4.6, demonstrates the improvement in the voltage level throughout the system with the placement of DG units. The results indicate that the voltage profile has been significantly improved and the overall system voltage level has been increased as a result of the optimal placement of DG units. The figures clearly show the positive impact of DG units on the voltage profile of the system and support the conclusion that the optimal placement and sizing of DG units results in improved voltage stability.

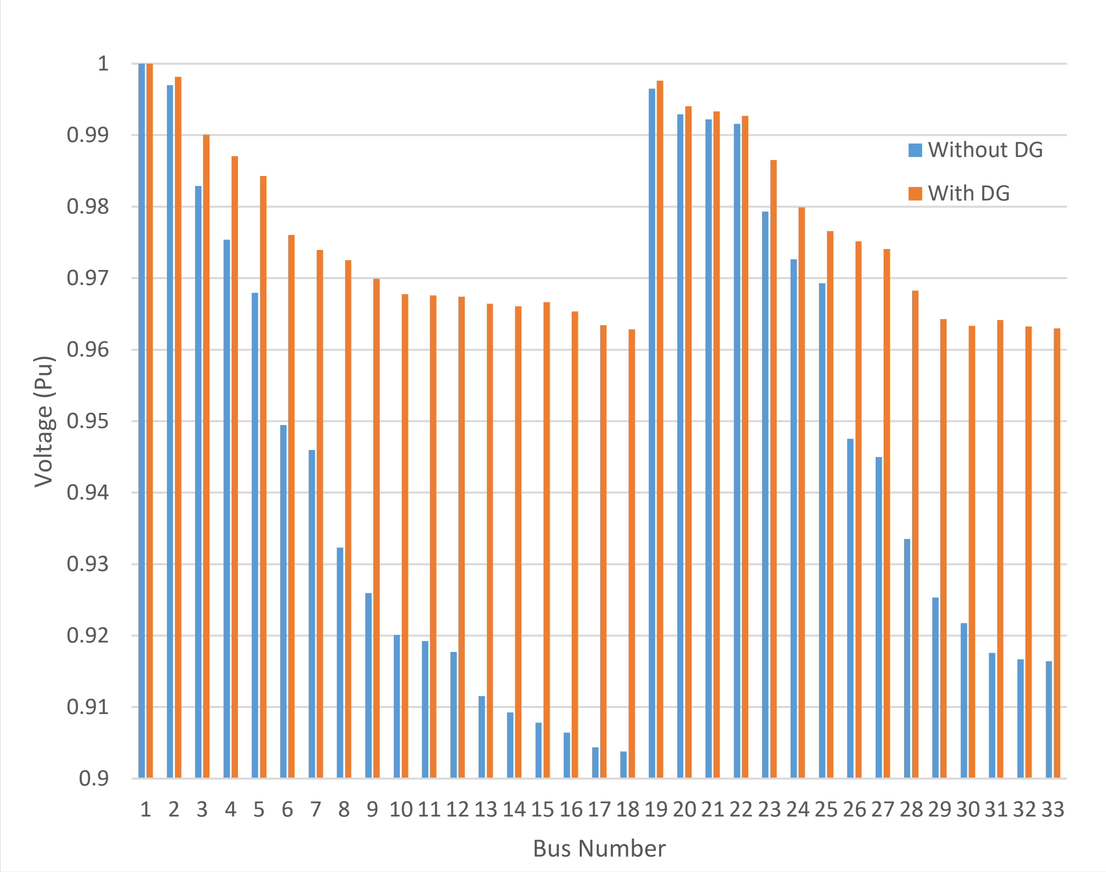

Figure 4-6 Voltage Profile before and after addition of DGs(Type-2) in IEEE 33 Test bus

4.2.3 Optimal Placement of Type 3 DGs :

As outlined in our methodology, we utilized Type 3 Distributed Generators (DGs) that are capable of injecting reactive power only. The penetration level and type of DG were fixed, and an optimal solution for a single DG was determined. Subsequently, the number of DGs was increased, and power loss and minimum voltage were recorded for various DG locations and sizes obtained through Grey Wolf Optimization. The optimal location and sizing of the DGs are presented in the table below

Table 4-4: Simulation result for Optimal Placement of Type 3 DG in IEEE 33 Test Bus

No of DG	1	2	3	4	5

DG installed Bus	30	12,30	13,24,30	7,14,24,30	7,8,14,24,30
DG size(KVA)	1258	465.1, 1063.4	387.8, 544.4, 1037.1	430.1, 301.3, 481.7, 903.1	277.8, 169.6, 256.9, 442.3, 901.3
Active Power Loss (kw)	151.4	141.8	138.3	136.8	136.6
Reactive Power Loss (kVAR)	103.8	96.4	94.2	93.30	93.00
Loss Reduction(%)	28.24%	32.79%	34.45%	35.16 %	35.26%
Minimum Voltage	0.9165	0.9303	0.9317	0.9341	0.9336

The simulation outcomes achieved through the implementation of the Grey Wolf Optimization (GWO) algorithm on the IEEE 33 bus power system illustrate the considerable benefits of optimizing the placement and sizing of distributed generation (DG) units.

In the case of a single DG unit, the algorithm determined that the most favorable location was at bus 30, with an optimal size of 1258 kVA. This resulted in a minimum voltage of 0.9165 pu and a substantial reduction in power loss by 28.24% compared to the base case. With an increase in the number of DG units to two, the algorithm identified bus 12 and bus 30 as the optimal locations for these units, with optimal sizes of 465.1 kVA and 1063.4 kVA, respectively. This configuration led to a minimum voltage of 0.9303 pu and a remarkable decrease in power loss by 32.79% compared to the base case.

In addition, when there were three DG, the algorithm identified bus 13, bus 24 and bus 30 as the optimal placement for these units, with optimal sizes of 387.8 kVA, 544.4 kVA and 1037.1 kVA respectively. This configuration led to a minimum voltage of 0.9317 pu and a 34.45% decrease in power loss from the base case.

When there were four DG units instead of three, the algorithm identified bus 7, bus 14, bus 24 and bus 30 as the optimal placement for these units, with optimal sizes of 430.1

kVA, 301.3 kVA, 481.7 kVA and 903.1 kVA respectively. This configuration led to a minimum voltage of 0.9341 pu and a 35.16% decrease in power loss as compared to the base case.

Finally, with five DG units, the algorithm found that bus 7, bus 8, bus 14, bus 24 and bus 30 were the optimal placement for these units, with optimal sizes of 277.8 kVA, 169.6 kVA, 256.9 kVA, 442.3 kVA and 901.3 kVA respectively. This configuration resulted in a minimum voltage of 0.9336 pu and a 35.26% decrease in power loss when compared to the base case.

The algorithm determined new ideal locations and sizes for each DG unit as the number of units rose, improving voltage levels and further reducing power loss. The most optimal configuration was found to be with three DG units, placed at bus 13, bus 24 and bus 30, with optimal sizes of 387.8 kVA, 544.4 kVA and 1037.1 kVA respectively. This configuration led to a minimum voltage of 0.9317 pu and a power loss reduction of 34.45% compared to the base case.

Type 2 DG units demonstrated substantial improvements in reducing power losses and enhancing voltage compared to Type 3 DG units. This distinction is important to consider when assessing the advantages of different DG types in optimizing power system performance.

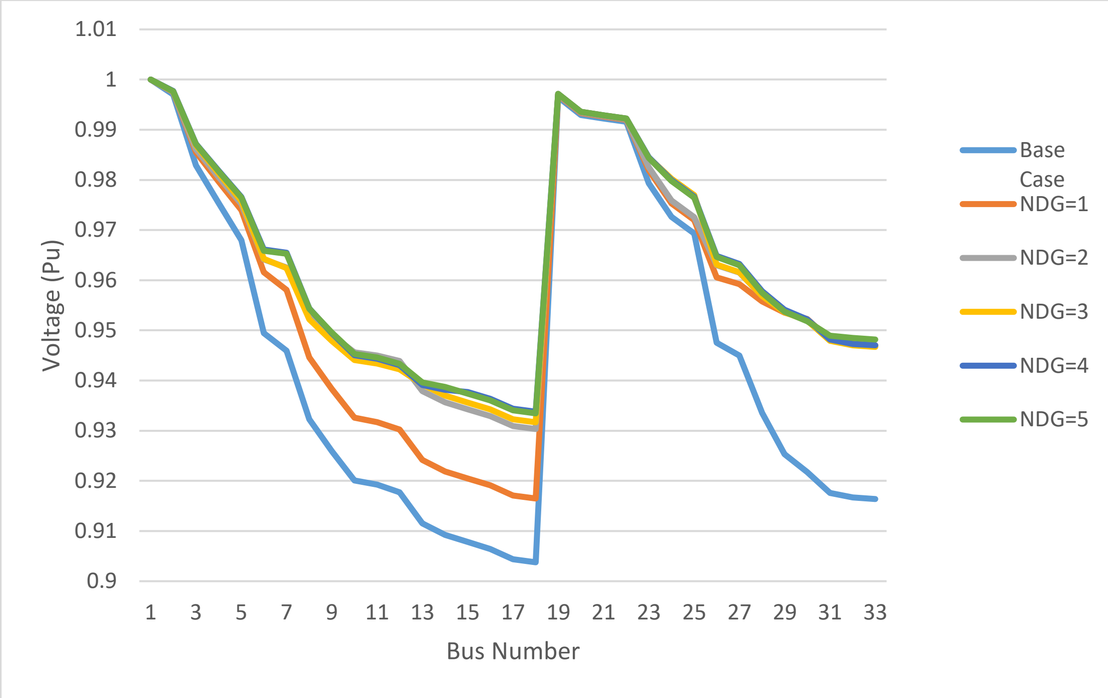

Figure 4-7: Voltage Profile of Voltage Profile with respect to Number of DGs(Type-3)

The simulation results obtained through the implementation of the Grey Wolf Optimization algorithm on the IEEE 33 bus power system illustrate that the optimal placement and sizing of distributed generation (DG) units can yield substantial improvements in voltage stability and power loss reduction. The enhancements in the voltage profile across the system resulting from the integration of DG units are presented in figures 4.5 and 4.6. It is evident that the strategic placement of DG units has significantly enhanced the voltage profile and increased the overall voltage level of the system. Although some bus voltages occasionally fall below the acceptable limit, the overall voltage profile has demonstrated improvement. These findings clearly demonstrate the positive impact of DG units on the system's voltage profile, highlighting the importance of appropriate DG unit location and sizing for achieving enhanced voltage stability.

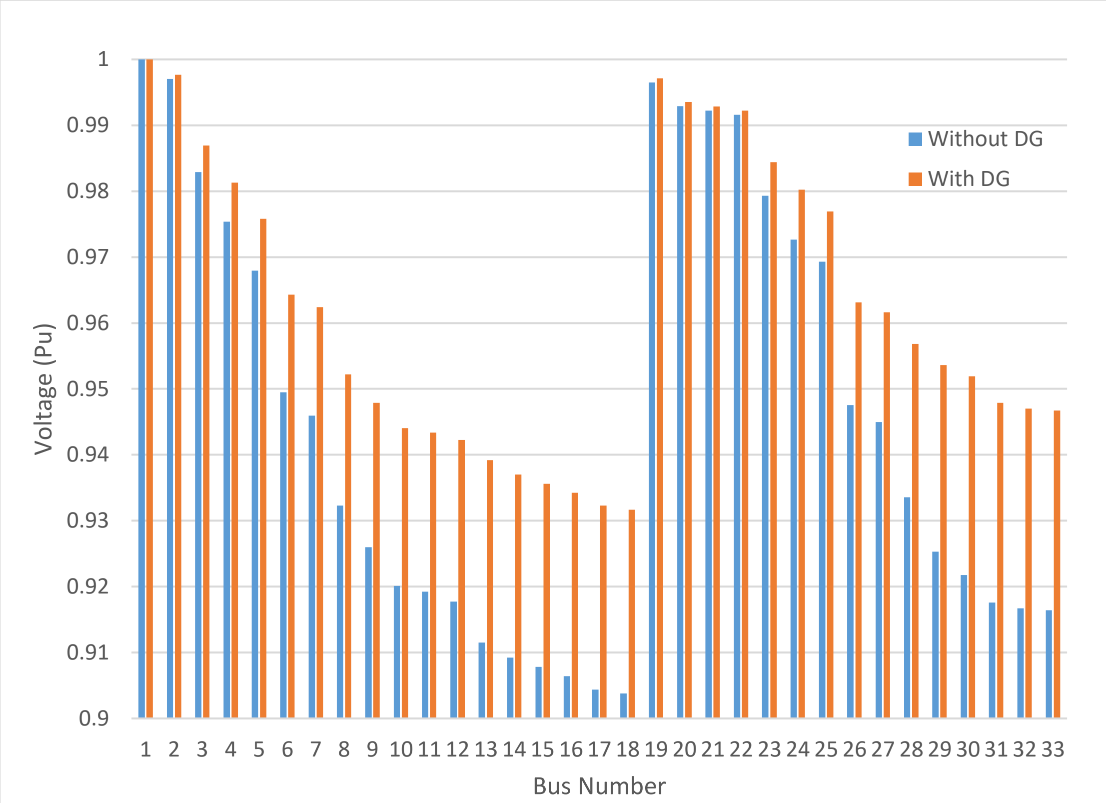

Figure 4-8 Voltage Profile before and after addition of DGs(Type-3) in IEEE 33 Test bus

4.2.4 Optimal Placement of Type 1 DGs :

In this study, we employed the Grey Wolf Optimization algorithm to determine the optimal placement and sizing of Type 1 distributed generation (DG) units in an IEEE 33 bus power system. These DGs were capable of injecting both real and reactive power, and the penetration level, power factor, and type of DG were fixed. By increasing the number of DGs, we recorded the power loss and minimum voltage for various DG locations and sizes obtained through the optimization algorithm. The results showed that the optimal placement and sizing of DGs can significantly reduce power loss and improve voltage levels in the system, as outlined in the table below.

Table 4-5: Simulation result for Optimal Placement of Type 1 DG in IEEE 33 Test Bus

No of DG	1	2	3	4	5
DG installed Bus	30	14,30	14,30,32	14,17,30,32	14,17,30, 31,32
DG size(KVA)	1643.8	668.8, 974.9	669.5, 524.6, 449.6	431.8, 212.8, 489.2, 420.5	451.9,164.4, 398.1,158.9, 282.9
Active Power Loss (kw)	81.1	51	49.3	52.4	54.9
Reactive Power Loss (kVAR)	59.6	34.2	32.5	34.3	35.8
Loss Reduction(%)	61.564%	75.82%	76.63%	75.16%	73.98%
Minimum Voltage	0.9336	0.9690	0.9714	0.9702	0.9681

When considering the case of a single DG unit, the algorithm found that the optimal placement was at bus 30, with an optimal size of 1643.8 kVA. This led to a minimum voltage of 0.9336 pu and a 61.564% decrease in active power loss relative to the base case.

As the number of DG units was increased to two, the algorithm found that the optimal placement for these units was at bus 14 and bus 30, with optimal sizes of 668.8 kVA and 974.9 kVA respectively. This configuration resulted in a minimum voltage of 0.9690 pu and a 75.82% decrease in active power loss compared to the baseline.

Increasing the number of DG units to three allowed the algorithm to identify bus 14, bus 17 and bus 30 as the optimal placement for these units, with optimal sizes of 669.5 kVA, 524.6 kVA, and 449.6 kVA respectively. This configuration led to a minimum voltage of 0.9714 pu and a 76.63% decrease in active power loss against the standard case.

When there were four DG units instead of three, the algorithm identified bus 14, bus 17, bus 30, and bus 32 as the optimal placement for these units, with optimal sizes of 431.8 kVA, 212.8 kVA, 489.2 kVA, and 420.5 kVA respectively. This configuration led to a minimum voltage of 0.9702 pu and a 75.16% decrease in active power loss from the base case.

With a total of five DG units installed, they were placed at buses 14, 17, 30, 31, and 32. The sizes of the DG units were 451.9 kVA, 164.4 kVA, 398.1 kVA, 158.9 kVA, and 282.9 kVA, respectively. This configuration resulted in a significant reduction in active power loss by 73.98%, equivalent to 54.9 kW, and a reduction in reactive power loss by 35.8 kVAR. The minimum voltage achieved in the system was 0.9681 pu.

The algorithm took into account the reduction of reactive power loss in addition to active power loss, and both were reduced simultaneously. The summarized results in the table highlight the optimal placement and sizing of DG units, along with the corresponding reductions in active and reactive power loss. Additionally, the table presents the minimum voltage level achieved by applying the Grey Wolf Optimization algorithm to the IEEE 33 bus power system.

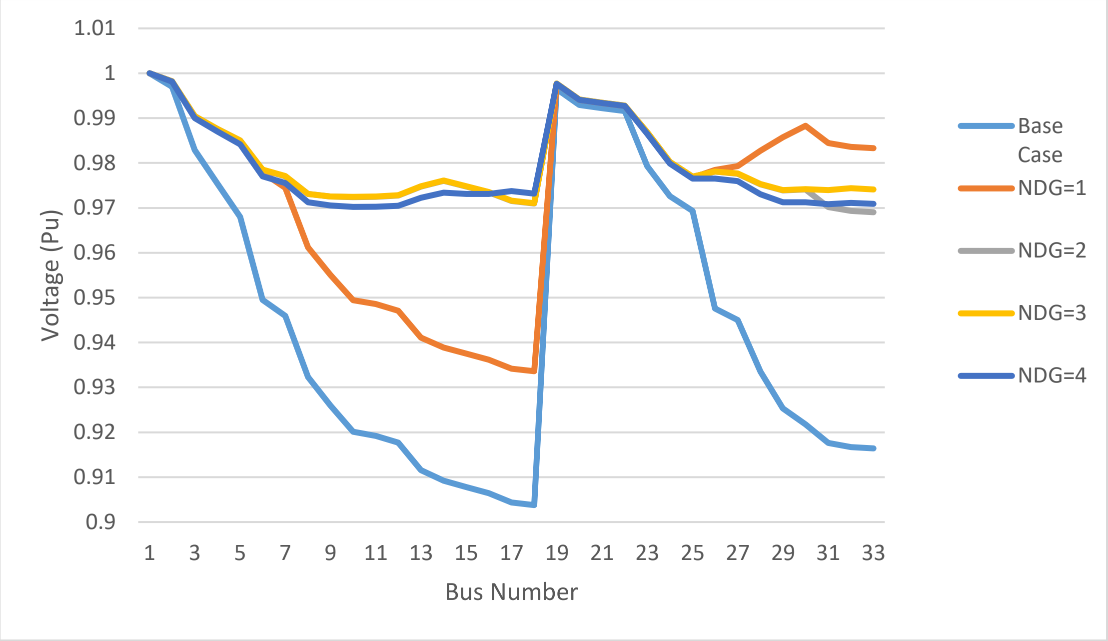

Figure 4-9: Voltage Profile with respect to Number of DGs(Type-1)

Additionally, the voltage regulation limit is met by all of the system's buses, as can be shown. The voltage profile, as shown in figures 4.5 and 4.6, demonstrates the improvement in the voltage level throughout the system with the placement of DG units. The results indicate that the voltage profile has been significantly improved and the overall system voltage level has been increased as a result of the optimal placement of DG units. The figures clearly show the positive impact of DG units on the voltage profile of the system and support the conclusion that the optimal placement and sizing of DG units results in improved voltage stability.

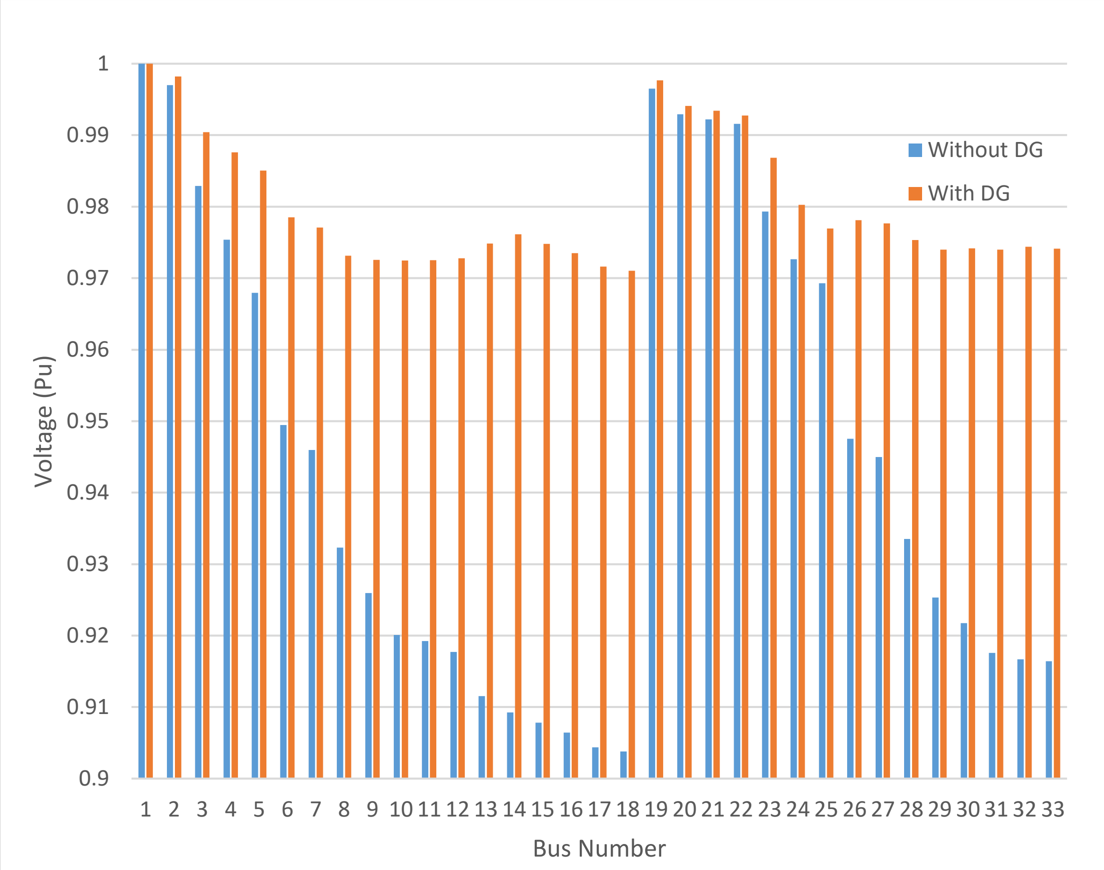

Figure 4-10 Voltage Profile before and after addition of DGs(Type1) in IEEE 33 Test bus

4.3 OPTIMAL PLACEMENT ON GALYANG FEEDER:

Due to the radial layout of the distribution system, the voltage profile for the 59-bus Galyang Feeder follows a decreasing order from bus 1 to bus 22, and then again from bus 24 to bus 58. Bus number 58 has the lowest voltage of all the buses. The fact that a sizable portion of the system's buses fall short of the voltage regulation limit shows the necessity for voltage control methods and optimization techniques to raise the voltage profile across the board. The overall active power loss is determined to be 140.3 kW after running the load flow simulation, and the total reactive power loss is determined to be 80.4 kVAr. Overall, the Galyang Feeder's base case study reveals voltage problems and power losses that must be fixed for the system to function within set performance parameters.

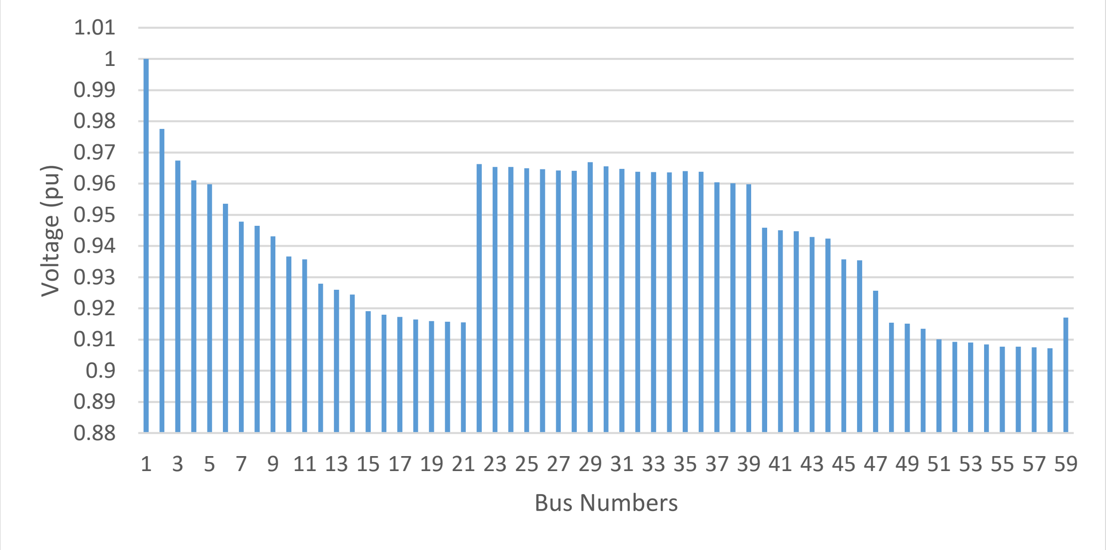

Figure 4-11 : Voltage profile of Base Case for Galyang Feeder

The active and reactive power losses in branches for base case load flow is tabulated in Annex B.

Table 4-6: Simulation result for Optimal Placement of DG in Galyang Feeder

No of DG	1	2	3	4	5
DG installed Bus	48	15,54	11,16,54	17,45,52,55	9,16,20,51,54
DG size(KVA)	976.9	618.5, 358.3	297, 408.5, 410.9	372, 169, 159.6, 275.6	389.5, 344.2, 150.1, 248.2, 218.1
Active Power Loss (kw)	38.2	34.8	27.9	34.1	38.1
Reactive Power Loss (kVAR)	22.7	21.4	17.2	24.1	22.6
Loss Reduction(%)	72.77 %	75.20%	80.11%	75.69%	71.07%
Minimum Voltage	0.9692	0.9703	0.9734	0.9698	0.9738

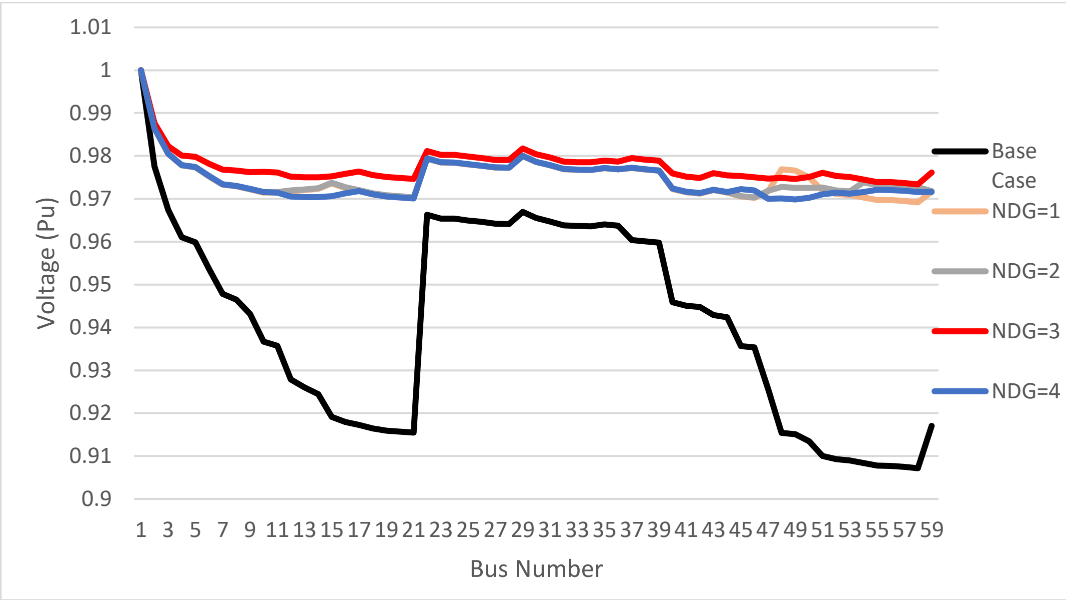

Figure 4-12: Voltage Profile with respect to Number of DGs in Galyang Feeder

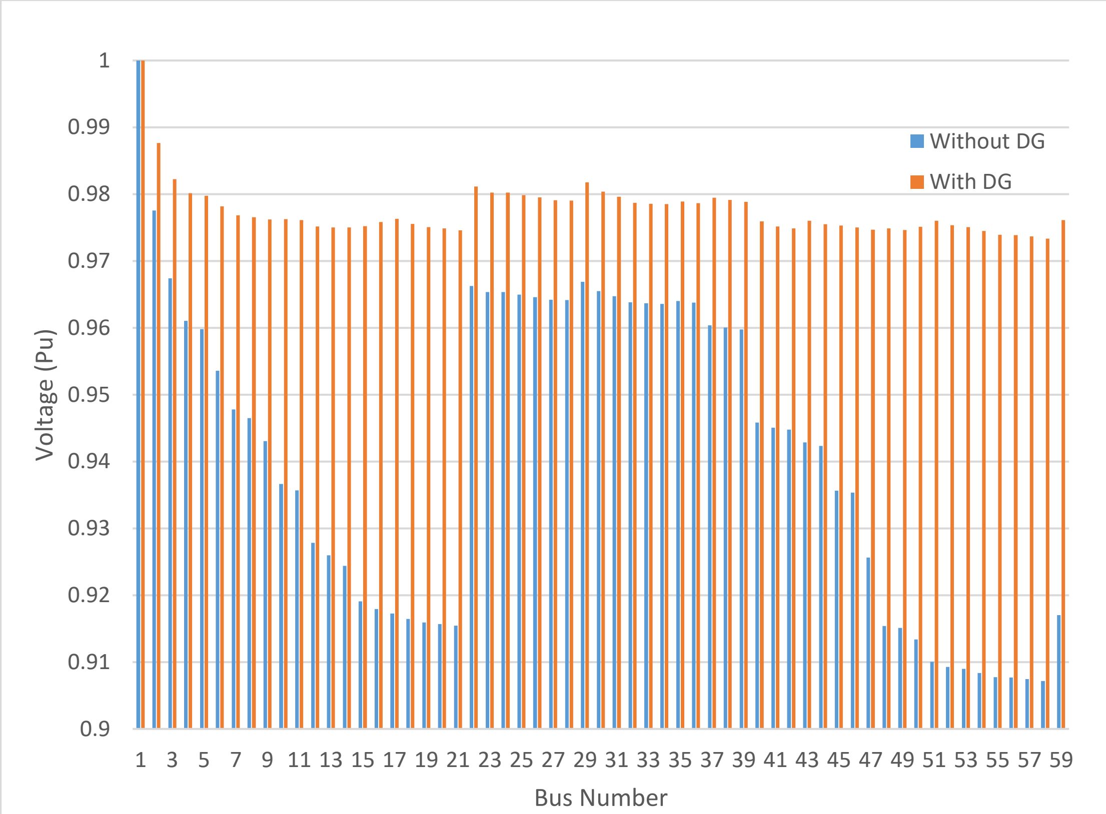

Figure 4-13 Voltage Profile before and after addition of DGs in Galyang Feeder

The simulation results obtained from the application of the Grey Wolf Optimization algorithm on the Galyang Feeder indicate that the optimal placement and sizing of distributed generation (DG) units can significantly reduce power loss and improve voltage levels in the system. The table summarizes the results, showing the optimal placement of DG units, their sizes and the reduction in active and reactive power loss as well as the minimum voltage level obtained by applying the Grey Wolf Optimization algorithm on the Galyang Feeder.

The results show that as increasing the number of DG units, the optimal placement of these units and their sizes also change. For example, when considering the case of a single DG unit, the algorithm found that the optimal placement was at bus 48, with an optimal size of 976.9 kVA. This led to a minimum voltage of 0.9692 pu and a reduction in active power loss of 72.77%. As the number of DG units was increased to two, the algorithm found that the optimal placement for these units was at bus 15 and bus 54, with optimal sizes of 618.5 kVA and 358.3 kVA respectively. This configuration resulted in a minimum voltage of 0.9703 pu and a reduction in active power loss of 75.20%.

In addition, when the number of DG units was increased to three, the algorithm identified bus 11, bus 16, and bus 54 as the optimal placement for these units, with optimal sizes of 297 kVA, 408.5 kVA, and 410.9 kVA respectively. This configuration led to a minimum voltage of 0.9734 pu and a reduction in active power loss of 80.11%.

When there were four DG units instead of three, the algorithm identified bus 17, bus 45, bus 52, and bus 55 as the optimal placement for these units, with optimal sizes of 372 kVA, 169 kVA, 159.6 kVA, and 275.6 kVA respectively. This configuration led to a minimum voltage of 0.9698 pu and a reduction in active power loss of 75.69%.

With a total of five DG units installed, they were placed at buses 9, 16, 20, 51, and 54. The sizes of the DG units were 389.5 kVA, 344.2 kVA, 150.1 kVA, 248.2 kVA, and 218.1 kVA, respectively. This configuration resulted in an active power loss reduction of 71.07%, equivalent to 38.1 kW, and a reactive power loss reduction of 22.6 kVAR. The minimum voltage achieved in the system was 0.9738 pu.

It is important to note that the algorithm also considered the reduction of reactive power loss, which was also reduced at the same rate as the active power loss. This highlights the efficiency of the Grey Wolf Optimization algorithm in determining the ideal positioning and DG unit size for the specified system, leading to appreciable decreases in power loss and enhancements in voltage levels.

CHAPTER 5 : CONCLUSIONS AND FUTURE SCOPE

5.1 Conclusions

The findings of this study suggest that the GWO method is a useful optimization tool for determining where DG should be distributed most effectively. The voltage profile of the system can be improved and power loss can be greatly reduced by placing and sizing DG in the ideal location. Future research on the integration of DG in distribution networks can use the findings from this study as a guide.

5.2 Future Scope

In this thesis, work that needs to be performed in order to evaluate the feasibility of the proposed DG placement method. This will include evaluating the costs and benefits of the proposed DG placement, including any potential savings on transmission and distribution losses, as well as any potential impacts on the power system's reliability and efficiency. Ultimately, the results of this economic analysis will be used to determine the overall economic viability of the proposed DG placement method and its potential for implementation in real-world systems.

PUBLICATION

Paper I

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ANNEX A: Bus Data, Line Data of IEEE 33 Bus Test System

Table: Bus Data of IEEE 33 Bus Test System

Base MVA=100

Bus	Bus Type	Voltage Magnitude (pu)	Voltage Angle	P Gen (MW)	Q Gen (MVAr)	P Load (MW)	Q Load (MVAr)
1	1	1	0	4	2.5	0	0
2	3	1	0	0	0	0.1	0.06
3	3	1	0	0	0	0.09	0.04
4	3	1	0	0	0	0.12	0.08
5	3	1	0	0	0	0.06	0.03
6	3	1	0	0	0	0.06	0.02
7	3	1	0	0	0	0.2	0.1
8	3	1	0	0	0	0.2	0.1
9	3	1	0	0	0	0.06	0.02
10	3	1	0	0	0	0.06	0.02
11	3	1	0	0	0	0.045	0.03
12	3	1	0	0	0	0.06	0.035
13	3	1	0	0	0	0.06	0.035
14	3	1	0	0	0	0.12	0.08
15	3	1	0	0	0	0.06	0.01
16	3	1	0	0	0	0.06	0.02
17	3	1	0	0	0	0.06	0.02
18	3	1	0	0	0	0.09	0.04
19	3	1	0	0	0	0.09	0.04
20	3	1	0	0	0	0.09	0.04
21	3	1	0	0	0	0.09	0.04
22	3	1	0	0	0	0.09	0.04
23	3	1	0	0	0	0.09	0.05
24	3	1	0	0	0	0.42	0.2
25	3	1	0	0	0	0.42	0.2
26	3	1	0	0	0	0.06	0.025
27	3	1	0	0	0	0.06	0.025
28	3	1	0	0	0	0.06	0.02
29	3	1	0	0	0	0.12	0.07

30	3	1	0	0	0	0.2	0.6
31	3	1	0	0	0	0.15	0.07
32	3	1	0	0	0	0.21	0.1
33	3	1	0	0	0	0.06	0.04

Table: Line Data of IEEE 33 Bus Test Systems

From Bus	To Bus	R (p.u.)	X (p.u.)
1	2	0.0922	0.0477
2	3	0.493	0.2511
3	4	0.366	0.1864
4	5	0.3811	0.1941
5	6	0.819	0.707
6	7	0.1872	0.6188
7	8	0.7114	0.2351
8	9	1.03	0.74
9	10	1.04	0.74
10	11	0.1966	0.065
11	12	0.3744	0.1298
12	13	1.468	1.155
13	14	0.5416	0.7129
14	15	0.591	0.526
15	16	0.7463	0.545
16	17	1.289	1.721
17	18	0.732	0.574
2	19	0.164	0.1565
19	20	1.5042	1.3554
20	21	0.4095	0.4784
21	22	0.7089	0.9373
3	23	0.4512	0.3083
23	24	0.898	0.7091
24	25	0.896	0.7011
6	26	0.203	0.1034
26	27	0.2842	0.1447
27	28	1.059	0.9337
28	29	0.8042	0.7006

29	30	0.5075	0.2585
30	31	0.9744	0.963
31	32	0.3105	0.3619
32	33	0.341	0.5302

ANNEX B : Voltage after DG Placement

Table: Voltage of IEEE 33 bus Test system after addition of Type 2 DG

BUS Number	Base Case	N_{DG}=1	N_{DG} =2	N_{DG} =3	N_{DG} =4
1	1	1	1	1	1
2	0.997025	0.998127	0.998154	0.998157	0.998024
3	0.982893	0.989892	0.990065	0.990083	0.98924
4	0.975383	0.98675	0.98703	0.987059	0.985689
5	0.967957	0.983876	0.984267	0.984308	0.982389
6	0.949479	0.975305	0.975977	0.976049	0.972936
7	0.945954	0.97404	0.973546	0.973968	0.970513
8	0.932299	0.980516	0.968919	0.972505	0.965968
9	0.925966	0.974509	0.967954	0.969904	0.965057
10	0.920092	0.968937	0.967502	0.967787	0.964662
11	0.919223	0.968113	0.967642	0.967613	0.964364
12	0.917708	0.966676	0.968043	0.967414	0.963929
13	0.911532	0.96082	0.969405	0.966424	0.962013
14	0.909242	0.958649	0.969902	0.96605	0.961296
15	0.907816	0.957297	0.968565	0.966651	0.961528
16	0.906434	0.955987	0.967271	0.965354	0.962217
17	0.904385	0.954045	0.965352	0.963431	0.960288
18	0.903772	0.953464	0.964777	0.962855	0.959711
19	0.996497	0.997599	0.997626	0.997629	0.997496
20	0.992919	0.994025	0.994053	0.994056	0.993922
21	0.992215	0.993322	0.993349	0.993352	0.993219
22	0.991577	0.992685	0.992712	0.992715	0.992582
23	0.979307	0.986332	0.986505	0.986524	0.985678
24	0.972636	0.979709	0.979883	0.979902	0.97905

25	0.969311	0.976408	0.976583	0.976602	0.975747
26	0.94755	0.97343	0.97547	0.975175	0.972131
27	0.944985	0.970937	0.974896	0.974086	0.97114
28	0.933543	0.959818	0.97098	0.968241	0.965658
29	0.925324	0.951829	0.968496	0.964277	0.961974
30	0.921766	0.948372	0.968499	0.963347	0.960156
31	0.917604	0.944328	0.96454	0.964127	0.959237
32	0.916688	0.943438	0.963669	0.963256	0.959337
33	0.916404	0.943162	0.963399	0.962986	0.959066

Table: Voltage of IEEE 33 bus Test system after addition of Type 3 DG

BUS Number	Base Case	N_{DG}=1	N_{DG} =2	N_{DG} =3	N_{DG} =4	N_{DG} =5
1	1	1	1	1	1	1
2	0.997025	0.99744	0.997527	0.997659	0.997699	0.997688
3	0.982893	0.985526	0.986081	0.986925	0.987181	0.987107
4	0.975383	0.979657	0.980561	0.981289	0.981805	0.98171
5	0.967957	0.97394	0.97521	0.975816	0.976604	0.976486
6	0.949479	0.961567	0.964153	0.964297	0.966085	0.965883
7	0.945954	0.95809	0.96257	0.962406	0.965501	0.965272
8	0.932299	0.944619	0.952975	0.952192	0.954341	0.954324
9	0.925966	0.938373	0.949061	0.947902	0.949472	0.949584
10	0.920092	0.932579	0.945612	0.944073	0.945059	0.945299
11	0.919223	0.931722	0.944966	0.943394	0.944329	0.944581
12	0.917708	0.930228	0.943875	0.942238	0.943074	0.943348
13	0.911532	0.924138	0.937874	0.939208	0.939114	0.939592
14	0.909242	0.921879	0.935649	0.936986	0.938153	0.938756
15	0.907816	0.920472	0.934263	0.935602	0.937701	0.937375
16	0.906434	0.919109	0.93292	0.934262	0.936363	0.936037
17	0.904385	0.91709	0.930931	0.932275	0.934381	0.934054
18	0.903772	0.916485	0.930335	0.93168	0.933787	0.93346
19	0.996497	0.996912	0.996999	0.997131	0.997171	0.99716
20	0.992919	0.993336	0.993423	0.993556	0.993596	0.993584
21	0.992215	0.992631	0.992719	0.992852	0.992892	0.99288
22	0.991577	0.991994	0.992082	0.992215	0.992255	0.992243
23	0.979307	0.98195	0.982507	0.984424	0.98452	0.984403
24	0.972636	0.975296	0.975857	0.980251	0.979975	0.97976

25	0.969311	0.97198	0.972543	0.976952	0.976675	0.97646
26	0.94755	0.960533	0.962995	0.963121	0.96484	0.96463
27	0.944985	0.959221	0.961508	0.961611	0.96323	0.963009
28	0.933543	0.955755	0.956882	0.956827	0.957791	0.957498
29	0.925324	0.953546	0.953791	0.953615	0.954082	0.953734
30	0.921766	0.952231	0.952148	0.951928	0.952209	0.951842
31	0.917604	0.948204	0.94812	0.947899	0.948181	0.948932
32	0.916688	0.947318	0.947234	0.947013	0.947295	0.948466
33	0.916404	0.947043	0.946959	0.946738	0.947021	0.948192

Table: Voltage of IEEE 33 bus Test system after addition of Type 1 DG

BUS Number	Base Case	N_{DG}=1	N_{DG} =2	N_{DG} =3	N_{DG} =4
1	1	1	1	1	1
2	0.997025	0.998186	0.99821	0.998212	0.998152
3	0.982893	0.990255	0.990412	0.990421	0.99004
4	0.975383	0.987327	0.987581	0.987596	0.986978
5	0.967957	0.984666	0.985022	0.985043	0.984179
6	0.949479	0.977871	0.97849	0.978527	0.97706
7	0.945954	0.974456	0.977049	0.977088	0.975552
8	0.932299	0.961226	0.973088	0.973137	0.971276
9	0.925966	0.955092	0.972502	0.972557	0.970504
10	0.920092	0.949404	0.972406	0.972467	0.970222
11	0.919223	0.948562	0.972472	0.972534	0.970257
12	0.917708	0.947095	0.972729	0.972793	0.970457
13	0.911532	0.941116	0.974778	0.97485	0.972242
14	0.909242	0.938899	0.976059	0.976135	0.973408
15	0.907816	0.937517	0.974731	0.974807	0.973119
16	0.906434	0.936179	0.973444	0.97352	0.973075
17	0.904385	0.934197	0.971538	0.971614	0.973778
18	0.903772	0.933603	0.970967	0.971043	0.973209
19	0.996497	0.997658	0.997683	0.997684	0.997624

20	0.992919	0.994084	0.994109	0.994111	0.99405
21	0.992215	0.993381	0.993406	0.993407	0.993347
22	0.991577	0.992744	0.992769	0.99277	0.99271
23	0.979307	0.986696	0.986854	0.986863	0.986481
24	0.972636	0.980076	0.980234	0.980243	0.979859
25	0.969311	0.976776	0.976935	0.976944	0.976558
26	0.94755	0.97842	0.978078	0.978117	0.976555
27	0.944985	0.979323	0.977634	0.977676	0.975981
28	0.933543	0.98271	0.975272	0.975328	0.973066
29	0.925324	0.985708	0.973912	0.973979	0.971287
30	0.921766	0.988299	0.974102	0.974174	0.971247
31	0.917604	0.98442	0.970166	0.973991	0.970821
32	0.916688	0.983567	0.9693	0.974388	0.971138
33	0.916404	0.983303	0.969032	0.974121	0.97087

Table: Voltage of Galyang Feeder after addition of DG

BUS Number	Base Case	N_{DG}=1	N_{DG} =2	N_{DG} =3	N_{DG} =4
1	1	1	1	1	1
2	0.977565	0.986441	0.98647	0.987668	0.986476
3	0.967416	0.980458	0.980502	0.982261	0.980511
4	0.961051	0.977806	0.97786	0.980121	0.977872
5	0.959815	0.977354	0.977412	0.979779	0.977424
6	0.953601	0.9752	0.975271	0.978185	0.975286
7	0.947802	0.973309	0.973393	0.976835	0.973411
8	0.94649	0.97291	0.972998	0.976563	0.973016
9	0.94308	0.972185	0.972281	0.976208	0.972302
10	0.936662	0.971465	0.97158	0.976276	0.971604
11	0.93571	0.971483	0.971601	0.976139	0.971467

12	0.927866	0.971837	0.971983	0.975177	0.970509
13	0.925989	0.972027	0.97218	0.975034	0.970367
14	0.924421	0.972342	0.972501	0.975043	0.970379
15	0.919095	0.973597	0.973778	0.975231	0.970574
16	0.917932	0.9725	0.972682	0.975852	0.971285
17	0.917272	0.971876	0.972058	0.976328	0.971818
18	0.916436	0.971087	0.971269	0.975542	0.971029
19	0.915949	0.970629	0.970811	0.975086	0.97057
20	0.915708	0.970401	0.970583	0.974859	0.970342
21	0.915448	0.970156	0.970338	0.974615	0.970098
22	0.966288	0.979345	0.979388	0.98115	0.979397
23	0.965382	0.978452	0.978495	0.980258	0.978504
24	0.965344	0.978414	0.978457	0.98022	0.978466
25	0.964958	0.978033	0.978076	0.97984	0.978085
26	0.964611	0.977691	0.977734	0.979499	0.977743
27	0.964195	0.97728	0.977324	0.979089	0.977333
28	0.964139	0.977226	0.977269	0.979034	0.977278
29	0.966912	0.979961	0.980004	0.981764	0.980013
30	0.965504	0.978572	0.978615	0.980378	0.978624
31	0.964729	0.977808	0.977851	0.979615	0.97786
32	0.963814	0.976905	0.976948	0.978714	0.976957
33	0.963663	0.976755	0.976798	0.978565	0.976808
34	0.963609	0.976703	0.976746	0.978512	0.976755
35	0.964021	0.977109	0.977152	0.978917	0.977161
36	0.963764	0.976855	0.976899	0.978665	0.976908
37	0.960392	0.977158	0.977213	0.979475	0.977224
38	0.960065	0.976837	0.976892	0.979155	0.976903
39	0.959776	0.976553	0.976608	0.978871	0.976619
40	0.945847	0.972284	0.972372	0.975939	0.97239

41	0.945071	0.971529	0.971617	0.975187	0.971635
42	0.944761	0.971229	0.971316	0.974887	0.971334
43	0.942881	0.971992	0.972088	0.976016	0.972109
44	0.942336	0.971464	0.97156	0.97549	0.97158
45	0.935659	0.970498	0.970613	0.975314	0.972267
46	0.935354	0.970204	0.970319	0.975021	0.971974
47	0.925646	0.9717	0.971853	0.974707	0.970039
48	0.91538	0.976868	0.972786	0.97489	0.970114
49	0.915097	0.976603	0.972519	0.974624	0.969847
50	0.913415	0.975028	0.972589	0.975123	0.970271
51	0.910021	0.971851	0.972654	0.976034	0.971034
52	0.909282	0.971159	0.971962	0.975345	0.971445
53	0.909	0.970895	0.971699	0.975082	0.971181
54	0.90839	0.970324	0.97385	0.974513	0.971604
55	0.907745	0.96972	0.973249	0.973912	0.972104
56	0.907702	0.96968	0.973208	0.973872	0.972064
57	0.907482	0.969474	0.973003	0.973667	0.971858
58	0.907156	0.969169	0.9727	0.973364	0.971554
59	0.917042	0.97166	0.971841	0.976112	0.971601

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By MAHENDRA KUMAR DAS

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