OPTIMAL PLACEMENT OF SOLAR DISTRIBUTED GENERATION FOR RELIABILITY IMPROVEMENT IN DISTRIBUTION NETWORKS USING WHALE OPTIMIZATION ALGORITHM (CASE STUDY: BISHOFTU SUBSTATION 2)

A THESIS SUBMITTED

IN PARTIAL FULFILMENT OF THE REQUIREMENTS

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POWER SYSTEM AND ENERGY ENGINEERING

BY

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ADVISOR'S APPROVAL SHEET ONE

This is to certify that the thesis entitled "OPTIMAL PLACEMENT OF SOLAR DISTRIBUTED GENERATION FOR RELIABILITY IMPROVEMENT IN DISTRIBUTION NETWORKS USING WHALE OPTIMIZATION ALGORITHM: (A CASE STUDY AT BISHOFTU DISTRIBUTION SUBSTATION 2)'' submitted in partial fulfillment of the requirement for the degree of Masters of Science in Electrical Engineering with specialization in "POWER SYSTEM AND ENERGY ENGINEERING" is carried out by HIKMA NUREDIN. ID No GPPoSyR/0005/15, under my supervision. Therefore, I recommend that the student has fulfilled the requirements and hence thereby can submit the thesis to the department.

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Undersigned Board of examiners of the final open defense by HIKMA NUREDIN have read and evaluated her thesis entitled "Optimal placement of Solar Distributed Generation for reliability improvement in distribution networks using Whale Optimization Algorithm: (a Case Study at Bishoftu Distribution Substation 2)" and examined the candidate. Therefore, to certify that the thesis has been accepted in partial fulfillment of the requirement for the degree.

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DECLARATION

I declare that this thesis was prepared entirely by myself. All ideas, data collection plans, analysis methodologies and write up contained within this thesis are original work, unless otherwise acknowledged through appropriate citations. To the best of my knowledge, this thesis or substantial parts of it have not been previously submitted for any other qualification at this University or elsewhere.

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ABSTRACT

The power distribution system in Bishoftu, Ethiopia, is faced with significant reliability challenges, including frequent interruptions, overloading, and poor performance that fall below national standards. These issues are caused by increasing load demand and inefficient system management. To address these challenges, the integration of solar-based distributed generation (DG) was investigated as a solution to enhance the reliability of the Bishoftu Substation. The K9 feeder, which exhibits the most severe reliability issues, was selected for this study, with initial reliability indices of SAIFI = 363.5 interruptions/customer/year and SAIDI = 803.14 hours/customer/year, far exceeding the national standards of SAIFI = 20 and SAIDI = 25. The Whale Optimization Algorithm (WOA) was utilized in MATLAB to determine the optimal sizing and placement of DG units, with the aim of minimizing SAIFI and SAIDI. Solar energy was identified as the most viable DG option based on local solar irradiance data. Significant improvements were demonstrated through optimization, with SAIFI and SAIDI reduced by up to 86% and 87% respectively, achieving values of SAIFI = 50.89 interruptions/customer/year and SAIDI = 104.4 hours/customer/year. An economic analysis was also conducted to evaluate the initial investment and life cycle costs, ensuring the feasibility of the proposed solution. It was concluded that the integration of optimally sized and placed solar DG units can drastically improve system reliability, reduce interruptions.

Keywords: ***Distribution Network, Power System Reliability, Distributed Generation (DG) Optimization, Whale Optimization Algorithm (WOA).***

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ACRONYMS

ABC: Artificial Bee Colony

CBOM: Cuckoo Based Optimization Method

CPS: Conventional Power System

DG: Distributed Generation

DSM: Demand Side Manegment

DS: Distribution System

EENS: Expected Energy Not Supplied

GA: Genetic Algorithm

MOMSOS: Multi Objective Multi Strategy Optimization System

NSGA III: Non dominated Sorting Genetic Algorithm III

PDNR: Power Distribution Network Reconfiguration

PSO: Particle Swarm Optimization

PV: Photovoltaic

RES: Renewable Energy Sources

SAIDI: System Average Interruption Duration Index

SAIFI: System Average Interruption Frequency Index

SLD: Single Line Diagram

WT: Wind Turbine

WOA: Whale Optimization Algorithm

CHAPTER ONE

INTRODUCTION

1.1 Background

In the traditional method, the primary role of a conventional power system (CPS) is to supply electricity to customers while keeping operating costs low, ensuring a specific level of reliability and quality [1].

Today's power systems are under pressure because of growing energy needs, old infrastructure, and environmental issues. Power generation also adds to greenhouse gas emissions, making things worse. These problems affect how reliable our electricity supply is.

To solve these issues, it's important to check how reliable the power system is. For operators, this helps decide where to invest, reduce energy losses, plan maintenance, and follow rules. For customers, it means better service and understanding the benefits of system upgrades.

A power system has three main parts: generating power, transmitting it, and distributing it. The distribution part which includes things like transformers, power lines, and circuit breakers is the weakest link. When these parts fail, it directly affects customers, causing most of the reliability issues in the system [2].

The main goal of a power system is to give people reliable, uninterrupted, and affordable electricity. When the power goes out (voltage drops to zero), it's a problem for consumers and affects power quality. Reliability is part of power quality and focuses on preventing these outages.

Old ways of measuring reliability focused on whether the system could meet demand in a centralized setup. But now, with changes like renewable energy and decentralized systems, those old methods don't work as well. Modern power systems need to be reliable not just for consumers but also for private power producers (like solar or wind farms). The Cigre C1.27 working group has introduced new ways to define reliability, considering renewable energy, distributed generation, and storage systems, to make sure the system works well for everyone in this modern setup [3].

Today, everyone agrees that using renewable energy sources (RESs) as DG is key to meeting growing electricity needs and reducing carbon emissions. Adding DG to distribution systems is a smart way to improve reliability and power quality as demand rises. It also helps cut pollution and supports a more open electricity market.

However, how well DG works depends on the type, location, and size of the DG units. Choosing the right setup can maximize benefits like better performance and lower emissions, while avoiding problems like voltage fluctuations, higher energy losses, and increased costs [4].

Distribution systems face challenges because their load (demand) changes over time, making them harder to control. As demand keeps growing, the system runs closer to its limits, leading to problems like higher power losses, poor voltage regulation, and reduced reliability and security. To keep consumers happy, operators must provide both enough power (quantitative) and good-quality power (qualitative).

Two solutions to improve performance are PDNR (Power Distribution Network Reconfiguration) and DGs. PDNR involves changing the open/closed status of switches in the network to balance loads between feeders. This reduces power losses, improves voltage regulation, and boosts reliability. However, since the load keeps growing and is unpredictable, PDNR alone is not enough to fix all issues.

Adding DGs (like solar or wind power) to the system can help. DGs improve voltage levels, reduce strain on feeders, and provide uninterrupted power, making the system more reliable and efficient overall. [5].

In Bishoftu city, Ethiopia, the power distribution system faces significant challenges that result in poor service quality and frequent interruptions. One major issue is the aging infrastructure, which is outdated and characterized by weakened poles, sagging lines, and deteriorating equipment. During the summer rainy season, heavy storms and winds often cause poles to fall or lines to touch, leading to short circuits and outages. Furthermore, environmental disturbances such as lightning strikes exacerbate these issues, resulting in frequent and prolonged interruptions in power supply. Additionally, rapid industrial and residential growth has led to continuous load increases, pushing the distribution system to its loadability limits and resulting in frequent overloading, higher power losses, and reduced voltage stability. Voltage fluctuations are also common, contributing to poor power quality and customer dissatisfaction. Maintenance practices in Bishoftu are inadequate, with utilities facing shortages of spare parts, insufficient labor, and outdated routines, which prolong downtimes during outages. The absence of Supervisory Control and Data Acquisition (SCADA) systems further complicates matters by preventing real time fault detection, monitoring, and remote control, slowing down fault isolation and restoration during outages. These challenges underscore the urgent need for modernizing Bishoftu’s distribution system to ensure a more reliable and uninterrupted power supply.

1.2 Case Study: Bishoftu Distribution Substation 2

To effectively place DG units within the Bishoftu Distribution Substation 2, it is crucial to have a comprehensive understanding of the substation's unique features, layout, and load characteristics. This section describes the specific attributes of Bishoftu Substation 2, reflecting the typical structure of distribution substations in the region.

Bishoftu, strategically located near Ethiopia’s capital, Addis Ababa, with 8.777674°, 38.980865° as seen in Figure below has been designated by the government as a key industrial zone, capitalizing on its proximity to the lively city. Renowned for its stunning crater lakes, the city also serves as a vibrant resort destination, attracting both tourists and locals. In addition to its natural beauty, Bishoftu is home to several respected training and research institutions, including the Ethiopian Air Force and the Ethiopian Management Institute Conference Centre, fostering education and innovation.

Ethiopia Bishoftu

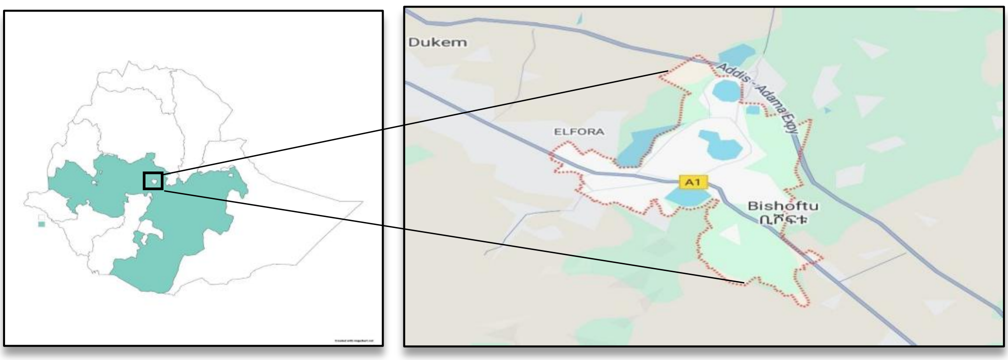


Figure 1. 1: Location map of Bishoftu town, Ethiopia.

The Bishoftu substation is powered by a 132 kV three phase transmission line from the Kality substation. With a total capacity of 88 MVA, the substation uses three transformers to lower the voltage from 132 kV to 15 kV for distribution. At the end user level, the voltage is further reduced to 400/220 volts to meet customer requirements.

It consists of 12 radial feeders each serving a distinct geographic region. This radial configuration means that each feeder operates independently, without redundancy, making reliability improvements through DG placement more critical.

The feeder service area includes both densely populated residential neighborhoods and semi urban areas, resulting in varied load demands. Additionally, certain feeders are in areas that experience frequent interruptions due to environmental factors like heavy rain or vegetation.

Each feeder has basic protection devices such as fuses and reclosers to isolate faults, but no remote monitoring or advanced control system is available. This setup relies on manual inspection and local maintenance crews to identify and address outages, which can lead to longer downtime in the event of faults.

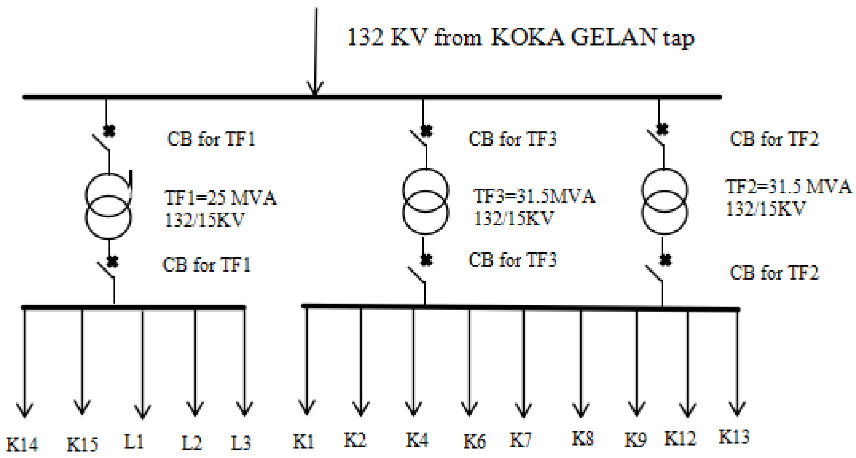


Figure 1. 2: Single line diagram of bishoftu substation 2

1.2 Statement of problem

The reliability of power distribution systems is a critical factor in ensuring uninterrupted electricity supply, which is essential for economic development, social well-being, and quality of life. However, the Bishoftu Distribution Substation, particularly its K9 feeder, faces severe reliability challenges, with a SAIFI of 363.5 interruptions per customer per year and a SAIDI of 803.14 hours per customer per year. These values significantly exceed the national standards of SAIFI 20 and SAIDI 25, indicating frequent and prolonged power outages that disrupt daily life, hinders industrial productivity, and impedes economic growth in the region.

These frequent and prolonged outages are driven by overloading of the distribution system, exacerbated by rapid urbanization and increasing electricity demand. The existing infrastructure, designed for lower loads, is unable to handle the current stress, leading to frequent failures. Additional contributing factors include aging infrastructure, high failure rates, and inadequate maintenance practices, which collectively strain the network and disrupt economic activities, social services, and quality of life in the region.

Despite the critical need for reliability improvement, existing literature and practices reveal significant gaps. Previous studies have explored the use of DG for reliability enhancement, but many rely on traditional optimization techniques, such as Genetic Algorithms (GA), which often yield suboptimal results due to their limitations in handling complex, non-linear problems. Moreover, the integration of renewable energy sources, such as solar PV systems, into distribution networks has not been thoroughly investigated in the context of reliability improvement, particularly in regions like Bishoftu, where grid instability and frequent outages are prevalent.

Policy frameworks also highlight the need for sustainable and reliable energy solutions. For instance, Ethiopia’s National Electrification Program (NEP) emphasizes the importance of improving grid reliability and integrating renewable energy sources to achieve universal electricity access. However, there is a lack of practical, cost-effective strategies for implementing these policies, especially in distribution networks with high failure rates and poor reliability indices.

From personal observation and experience, the frequent power interruptions in the K9 feeder have led to significant economic losses for businesses, disrupted educational activities, and created dissatisfaction among residential customers. These issues underscore the urgency of addressing the reliability challenges in the distribution network.

This research study is necessary to address these gaps by:

1. Investigating the optimal placement and sizing of DG units using advanced optimization techniques, specifically WOA, which has not been extensively applied to this problem in existing literature.

2. Comparing the performance of WOA with traditional methods, such as GA, to demonstrate its superiority in minimizing SAIFI and SAIDI.

3. Evaluating the economic feasibility of integrating solar PV systems, including inverters and battery storage, to provide a sustainable and cost-effective solution for reliability improvement.

By addressing these issues, this study aims to contribute to the existing body of knowledge, provide actionable insights for policymakers, and offer a practical framework for enhancing the reliability of distribution networks in Bishoftu and similar regions.

1.3 Objectives of the Study

1.3.1 General Objective

- To optimize the placement and sizing of DG for reliability improvement in the K9 feeder of Bishoftu Distribution Substation 2 using WOA.

1.3.2 Specific Objectives

The specific objectives of this study are:

- To conduct a reliability analysis of the K9 feeder by evaluating SAIFI and SAIDI.
- To develop and implement a MATLAB-based optimization model for DG placement and sizing.
- To determine the optimal DG placement and size based on feeder load distribution and reliability constraints.

- To compare the reliability of the K9 feeder before and after placement of DG.
- To design a solar-based DG system for the K9 feeder.
- To compare the performance of WOA with Genetic Algorithm (GA) for DG optimization.
- To perform a sensitivity analysis by varying key input parameters in the WOA optimization process.
- To conduct a cost-benefit analysis of the optimized DG placement for economic evaluation.

1.4 Significance of the Study

Localized Reliability Enhancement: By focusing on Bishoftu substation feeder 9, the study directly addresses the specific reliability challenges faced by this area. This can lead to more targeted and effective solutions, ensuring a more stable power supply for the local community.

Reduction in Power Outages: Bishoftu, like many areas in Ethiopia, experiences frequent power outages. Optimal placement of DG can help mitigate these outages, providing a more consistent power supply to residents and businesses in the area.

Economic Growth: Improved reliability and reduced outages can foster economic growth in Bishoftu. Businesses can operate more efficiently without the disruption of power cuts, and new enterprises may be attracted to the area due to the stable power supply.

Improved Voltage Profile: This study can help maintain voltage levels within acceptable limits for feeder 9, improving the quality of power delivered to consumers. This is particularly important for sensitive equipment and industrial operations in the area.

Environmental Benefits: By incorporating renewable energy sources as part of the DG, this study can contribute to reducing the carbon footprint of the Bishoftu substation. This aligns with global and local efforts to promote sustainable energy practices.

Scalability and Replicability: The methodologies and findings from this study can serve as a model for other substations in Ethiopia and similar regions. This can lead to broader improvements in the national power distribution network.

Community Impact: Reliable power supply is crucial for the wellbeing of the local community. Improved reliability can enhance the quality of life for residents, supporting essential services such as healthcare, education, and communication.

1.5 Scope of the Study

This study is focused on assessing the reliability of the power distribution system at Bishoftu Substation 2 on the optimal placement of Distributed Generation (DG) to enhance system reliability. The analysis involves collecting relevant data to evaluate the system's reliability performance, using interruption data from two years as the basis for the analysis.

1.6 Methodology

To achieve the above-mentioned objectives, power reliability problems in proposed distribution system feeders, the following Methodology procedures were conducted which is also shown in figure 1.1:

Literature review: A literature related to power system reliability and distribution generation system network, books; papers articles journals were reviewed.

Data collection: Relevant data was collected from Bishoftu substation 2. This data was gathered from recorded data.

Data Analysis: Based on the information gathered, the nature of Bishoftu substation 2 was investigated.

Modeling: DGs was modeled.

Simulation: The Simulation of distribution system with and without DG was carried out on MATLAB software.

Performance evaluation and cost analysis.

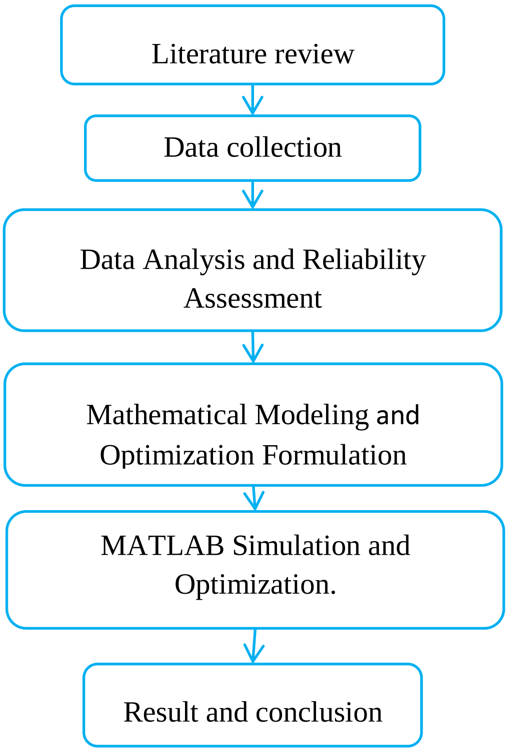


Figure 1. 3: Methodology block diagram

1.7 Thesis Layout

The thesis is structured into five chapters, each outlined as follows:

Chapter One introduces the study, including its background, objectives, problem statements, scope, significance, and methodology. It also provides an overview of the entire thesis.

Chapter Two explores the theoretical frameworks related to reliability and distributed generation, along with a review of existing literature on power reliability and distribution systems.

Chapter Three analyzes the electrical data from the Bishoftu substation 2, including information on the number of customers, distribution transformers, and interruption duration and frequencies. This chapter presents a numerical analysis of the collected data and calculates key reliability indices.

Chapter Four focuses on simulation studies and system modeling, examining various mitigation alternatives. The results are presented with clear explanations.

Chapter Five concludes the thesis by discussing the findings, offering recommendations, and suggesting directions for future research

CHAPTER TWO

THEORETICAL BACKGROUND AND LITERATURE REVIEW

2.1 Introduction

This chapter aims to provide a clear understanding of the concepts related to DG and its impact on the reliability of power systems. It will define key terms to ensure a solid foundation for the discussions that follow. The chapter will review existing research to identify important methods, findings, and gaps in knowledge about how DG is integrated into power systems and how it affects reliability. Special attention will be given to examining the different reliability measures used to assess the performance of power systems, especially when DG is included.

The theoretical background and literature review are essential for several reasons. A strong theoretical framework helps explain the complexities of DG and its effects on reliability, allowing for a deeper analysis of the topic. By reviewing past research, this chapter will guide the choice of methods used in the study, ensuring that the research builds on established approaches and adds to the ongoing discussion in the field.

2.2 Distributed Generation (DG)

DG is becoming very important in modern power systems. As energy demand grows, fossil fuels are running out, and there's a bigger focus on clean energy, DGs are gaining more attention and value [6].

2.2.1 Definition and Types of DG

There's no single definition of DG, but it generally refers to small, decentralized power units located close to where energy is used. Examples include solar panels, wind turbines, fuel cells, and biomass systems. These can work alone or connect to the grid. The U.S. Department of Energy defines DG as small energy units near load centers, while IEEE describes it as power sources under 10 MW that can connect to the grid almost anywhere [7].

DGs can be categorized based on the type of energy they use, primarily into renewable and non-renewable sources.

Renewable DGs use naturally available and sustainable energy sources, making them environmentally friendly and increasingly popular. One of the most common types is solar power, which converts sunlight into electricity using photovoltaic (PV) panels. Solar DGs are widely used in residential, commercial, and industrial applications due to their ease of installation and low operational costs. Another significant renewable DG is wind power, which generates electricity through wind turbines. Wind energy is highly effective in areas with strong and consistent wind speeds, and it is commonly used in both onshore and offshore wind farms. Hydropower, though traditionally associated with large dams, also exists in smaller forms known as micro-hydro systems, which generate electricity from the flow of water in rivers or streams. Biomass power is another renewable DG type that produces electricity by burning organic materials such as agricultural waste, wood, or biogas. Biomass generation is useful in rural areas where agricultural residues are readily available, providing both energy and waste management solutions.

On the other hand, non-renewable DGs rely on fossil fuels such as diesel, natural gas, and coal, making them more traditional but less sustainable. Diesel and gas generators are widely used for backup power and in remote areas where grid electricity is unreliable. They are effective for emergency situations but contribute to greenhouse gas emissions and fuel dependency. Microturbines, which are small combustion turbines, operate on natural gas or liquid fuels and provide efficient, low-emission power for commercial and industrial applications. Another advanced type of DG is fuel cells, which generate electricity through electrochemical reactions, typically using hydrogen or natural gas. Fuel cells are known for their high efficiency and low emissions, making them a promising alternative to traditional generators.

Each type of DG has its own advantages and limitations. Renewable DGs are gaining widespread adoption due to their sustainability and lower environmental impact, while non-renewable DGs continue to be used where fuel availability and high-power reliability are required. The choice of DG type depends on factors such as energy needs, cost, resource availability, and environmental considerations. With the increasing focus on clean energy, the shift toward renewable DGs is expected to grow, contributing to a more sustainable and resilient power system.

2.2.2 Advantages of DG

DG has been added to power systems, especially at the Low Voltage (LV) level, to make them more reliable, secure, and efficient [13].

The rise in renewable energy (RE) use is driven by factors like improving reliability, security, better technology, regulations, and reducing emissions. Additionally, competition in the electricity market, outdated grid equipment, and capacity limits have pushed the adoption of DG technologies to solve these challenges in modern power systems [7].

Different aspect of using DG in electrical systems can be discussed from environmental, economic and technical viewpoints. The merits of using DG must first be considered to better understand their economic advantages. The merits of utilizing DG in electrical distribution systems can be briefly stated as follows:

- Improved efficiency of the system.
- Reduced operating cost due to peak load shaving.
- Reduced care investment due to the improved environment.
- Reduced maintenance cost.
- Reduced investment in the system expansion.
- Enhanced protection for significant loads.
- Reduced requirements and the associated costs.
- Reduced fuel costs.

A. Economic Benefits

Putting DG units closer to where electricity is used has many economic benefits. It avoids the need for costly new power lines, upgrades to existing systems, and expanding transmission and distribution networks. Because DGs are small and quick to build, they are flexible and adapt easily to economic changes. They also help suppliers meet market needs and offer customized electricity services. Overall, DG is a cheaper way to handle growing energy demands while cutting down on investment costs [42].

Key economic benefits of DG include:

- Rapid installation at any location with modular designs, enabling capacity adjustments by adding or removing modules.

- Cost savings through the elimination of long-distance high voltage transmission and promotion of competitive markets.
- Peak shaving, which stabilizes electricity prices during high demand periods and offers flexibility in price evaluation.
- Provision of ancillary services and reduction of peak demand on central power stations, lowering operational costs for remote applications.
- Incremental capacity adjustments to meet increasing load demands.
- Reduced reliance on central plants, leading to lower wholesale power prices by supplementing grid power.
- Low capital costs and short-term investment opportunities, minimizing installation times and investment risks.
- Enhanced economic benefits by reducing power losses, feeder loads, and maintenance costs for electric equipment.
- Consistent running costs when renewable energy sources are utilized.

B. Technical Benefits

Adding DG helps both power companies and consumers. It makes the power system more reliable, reduces outages, and avoids the need to extend power lines to remote areas. DG also helps with issues like thermal overloads, reduces energy losses, and improves voltage support. The specific benefits depend on where the DG is placed and what type of technology is used [43].

Key technical benefits include:

- Improved power supply reliability through backup generation.
- Voltage regulation and power loss reduction.
- Enhanced system security by diversifying energy sources and addressing power quality issues, such as voltage sags, by raising network voltage levels.
- Reduced power flow in transmission networks, alleviating constraints and improving voltage profiles.
- Support for peak load shaving, mitigating issues like load shedding and transmission congestion.
- Provision of ancillary services and additional self-generation options for consumers.

C. Environmental Benefits

Centralized power plants produce a lot of harmful emissions like carbon dioxide, sulfur oxides, and nitrogen oxides, which harm the environment and contribute to climate change. DG is a cleaner option it reduces greenhouse gases, noise pollution, and protects nature. Modern DG technologies, often using renewable energy, support sustainable electricity generation and help companies use energy more efficiently by meeting both heat and power needs [44].

Environmental benefits of DG include:

- Reduced carbon emissions and air pollution.
- Minimization of noise pollution and conservation of ecological resources.
- Decreased need for new transmission circuits and large networks, preserving land resources.

2.3 Reliability in Power Systems

Reliability in power systems measures how well the grid can keep delivering electricity to consumers, even with issues like faults, maintenance, or changes in demand. It’s assessed using two key factors: adequacy and security [41].

Adequacy refers to the power system’s ability to meet the electricity demand under normal operating conditions. It ensures that the system has enough generation capacity, transmission lines, and distribution networks to supply power reliably without any shortages. Adequacy involves careful planning and operational strategies to make sure that sufficient resources are available to handle peak loads and other predictable demands. This includes maintaining reserve capacity and ensuring that all parts of the system generation, transmission, and distribution are properly sized and coordinated to meet consumer needs consistently.

Security, on the other hand, focuses on the system’s ability to withstand and recover from sudden disturbances, such as equipment failures, natural disasters, or faults. A secure power system is designed to maintain stable operations even during unexpected or adverse conditions. This is achieved through the use of protective devices, redundancy in critical components, and well-prepared contingency plans. Security measures help the system quickly adapt to disruptions, minimize the impact on consumers, and restore normal operations as efficiently as possible.

Together, adequacy and security ensure that the power system is both capable of meeting demand and resilient enough to handle unexpected challenges, providing reliable electricity to consumers.

2.3.1 Types of Power Interruption

Power interruptions in distribution systems can vary in terms of duration, frequency, and impact. Understanding these different types is essential for evaluating system reliability and planning improvements. Key types include:

Momentary Interruptions: Short duration outages, typically lasting less than a minute, often due to transient faults such as lightning strikes or tree contacts. Protective devices like reclosers or fuses usually clear these faults quickly, restoring power without requiring extensive repair.

Temporary Interruptions: Similar to momentary interruptions but slightly longer in duration, often lasting from a few seconds to a few minutes. Temporary interruptions can result from temporary conditions that require brief interruption and automatic reclosure of power.

Sustained Interruptions: These interruptions last longer, typically over a minute, and are caused by faults that cannot be cleared automatically. Sustained interruptions require manual intervention or repair work, such as fixing damaged equipment after severe weather or equipment failure.

Planned Interruptions: Scheduled outages for necessary maintenance, system upgrades, or inspections, with customers notified in advance. These interruptions are controlled by the utility to improve or maintain system reliability.

Unplanned Interruptions: Unexpected outages due to unforeseen events such as storms, equipment malfunctions, or accidents. Unplanned interruptions typically require longer restoration times and can disrupt service reliability.

Each type of interruption affects customers differently, and understanding their causes and impacts helps utilities implement strategies to minimize outages and improve reliability.

2.3.2 Distribution System Reliability Indices

Reliability indices are quantitative measures that evaluate the reliability of a distribution system, often used by utilities to assess performance and identify areas for improvement. Reliability indices in distribution systems can be divided into two categories: customer-oriented indices and energy-oriented indices. These indices provide utilities with insights into how interruptions affect customers and the energy supply, helping guide improvements in service reliability.

A. Customer Oriented Indices

These indices focus on the frequency and duration of interruptions experienced by individual customers, highlighting the direct impact of outages on end users.

SAIFI (System Average Interruption Frequency Index): This measures how often the average customer experiences a power outage [37]. Mathematically, this is given in Eq. (2.1).

$$\text{SAIFI} = \frac{\text{Total Number of Customer Interruptions}}{\text{Total Number of Customers Served}} \tag{2.1}$$

SAIDI (System Average Interruption Duration Index): This measures the average time a customer experiences power outages over a period.

It is commonly measured in minutes or hours of interruption. Mathematically, this is given in Eq. (2.2).

$$\text{SAIDI} = \frac{\text{Total Duration of Customer Interruptions}}{\text{Total Number of Customers Served}} \tag{2.2}$$

CAIDI (Customer Average Interruption Duration Index): This measures the average time it takes to restore power after an outage [35]. Mathematically, this is given in Eq. (2.3).

$$\text{CAIDI} = \frac{\text{Total Duration of Sustained Interruptions}}{\text{Total Number of Sustained Interruptions}} \tag{2.3}$$

MAIFI (Momentary Average Interruption Frequency Index): This measures how often customers experience short, momentary outages (typically less than 5 minutes) [38]. Mathematically, this is given in Eq. (2.4).

$$\text{MAIFI} = \frac{\text{Total Number of Momentary Interruptions}}{\text{Total Number of Customers Served}} \tag{2.4}$$

B. Energy Oriented Indices

These indices focus on the total energy not supplied due to interruptions, assessing the overall impact on energy delivery rather than individual customer experiences.

ENS (Energy Not Supplied): This measures the total amount of energy (in kWh or MWh) that was not delivered to customers due to outages. It reflects the impact of outages on energy supply [41]. Mathematically, this is given in Eq. (2.5).

$$\text{ENS} = \sum_{i=1}^{N}(Pi * Ui) \tag{2.5}$$

Where, Pi = Load (kW) interrupted during the outage.

Ui = Duration (hours) of the outage for i^{th} event.

N = Total number of outages.

AENS (Average Energy Not Supplied): This measures the average energy not supplied per customer due to outages [36]. Mathematically, this is given in Eq. (2.6).

$$\text{AENS} = \frac{\text{Total Energy Not Supplied (kWh)}}{\text{Total Number of Customers}} \tag{2.6}$$

These indices, when used together, provide a comprehensive view of reliability, enabling utilities to assess both customer impact and energy delivery performance.

2.4 Optimization Techniques for DG Placement

DG should be placed in locations that minimize power losses while considering system constraints. If DG is placed in non-optimal locations, it can increase power losses, cause over voltage or under voltage issues, and exceed line capacity limits.

Another critical issue is the DG penetration limit, which refers to how much power can be safely injected into the distribution system. Injecting too much power can harm the system, leading to problems like high node voltages, increased fault currents, and instability in the grid. Researchers focus on finding the right balance to ensure the system remains healthy and stable [12].

2.4.1 Overview of Optimization Techniques

Many optimization techniques have been used to find the best location and size for DG. Early methods relied on classical mathematical programming, but these struggled with complex, non-differentiable problems and constraints. Today's DG placement issues are not simple convex problems, making those older methods less effective.

Now, metaheuristic optimization algorithms are becoming popular because they:

1. Are simple and easy to use,
2. Don't need gradient information,
3. Avoid getting stuck in local optima, and
4. Can be applied to a wide range of problems across different fields.

These algorithms are better suited for solving the complex challenges of modern DG placement [10].

Metaheuristic algorithms are powerful tools for solving complex NP-hard problems quickly and efficiently. They work by optimizing (minimizing or maximizing) an objective function. These algorithms are grouped into three main types:

1. Evolutionary algorithms,
2. Physics-based algorithms, and
3. Swarm intelligence algorithms.

There are also other categories, but these three are the most common. Metaheuristics are widely used because they handle tough problems effectively and deliver good solutions in a reasonable time.

Evolution-based methods are inspired by natural evolution. They start with a randomly generated population, which improves over time through generations. The key strength of these methods is that the best individuals are combined to create the next generation, allowing the population to become more optimized over time.

The most popular evolution-based technique is Genetic Algorithms (GA), which mimics Darwin's theory of evolution. Other well-known algorithms include Evolution Strategy (ES), Probability Based Incremental Learning (PBIL), Genetic Programming

(GP), and Biogeography Based Optimizer (BBO). These methods are effective for solving complex optimization problems [8].

Physics-based methods are inspired by the physical laws of the universe. These algorithms simulate natural phenomena, such as gravitational forces, chemical reactions, or cosmic events, to solve optimization problems. They are designed to explore and exploit search spaces efficiently, often mimicking processes like annealing, gravitational attraction, or the expansion and contraction of the universe. These methods are known for their ability to handle complex, non-linear problems and provide robust solutions.

Swarm-based methods, on the other hand, mimic the social behavior of animal groups, such as bird flocks or ant colonies. These algorithms focus on collective intelligence, where individuals in a group work together to find optimal solutions. For example, Particle Swarm Optimization (PSO) is inspired by how birds flock and search for food, while Ant Colony Optimization (ACO) is based on how ants find the shortest path to food sources. Swarm-based techniques are popular for their simplicity, adaptability, and effectiveness in solving a wide range of optimization problems.

2.4.2 Whale Optimization Algorithm (WOA)

A new optimization algorithm called the Whale Optimization Algorithm (WOA) was introduced by Mirjalili and Lewis [9]. It is inspired by the hunting behavior of humpback whales, which are known for their intelligence and unique movement. Humpback whales hunt by creating spiral-shaped bubbles to trap groups of krill or small fish near the water's surface. They dive down and then swim up in a spiral pattern, using bubbles to surround and capture their prey.

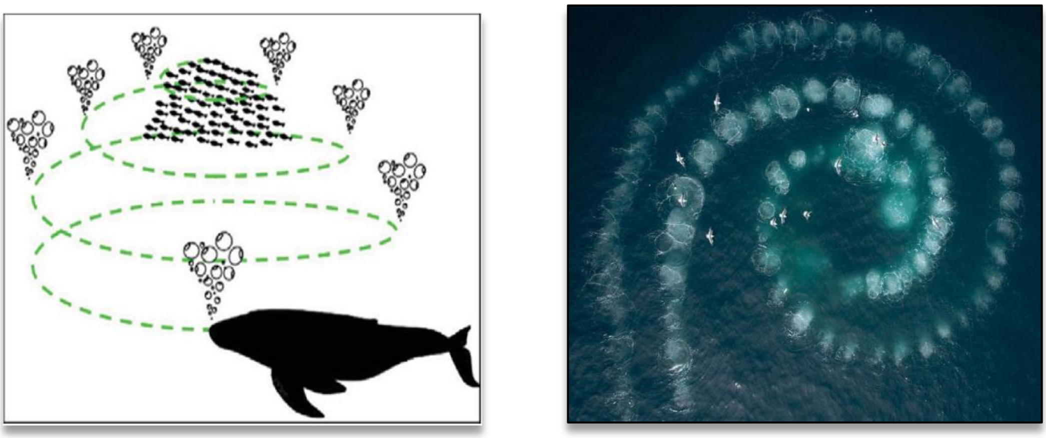
The WOA mimics this behavior through three main strategies [10]:

1. Encircling the prey (focusing on a target),

2. Searching for prey (exploring the search space), and

3. Spiral bubble-net attacking (exploiting the best solutions).

These strategies make WOA an effective metaheuristic algorithm for solving optimization problems.



(a) (b)

Figure 2. 1: Schematic of the spiral bubble net attacking strategy (a) and whales moving in a spiral pattern (b).

The WOA has several advantages, including a simple structure, strong stability, excellent optimization ability, and easy implementation. In WOA, each whale represents a search agent, and the humpback whale updates its position to hunt prey, mimicking its natural hunting behavior. This makes WOA an efficient and effective tool for solving optimization problems [11].

Shrinkage Encircling

The WOA uses the foraging behavior of humpback whales to perform a targeted search, which helps in updating positions and finding the best solution. In WOA, the humpback whale follows a '9' shaped path to locate and capture its prey, as shown in Figure 3(b). This path uses echolocation to efficiently communicate positions and conduct a global search.

In the algorithm, the target prey's position represents the best solution to the optimization problem. Once the ideal position is identified, the other whales quickly move closer and encircle the prey. Their positions are updated based on this behavior, helping the algorithm converge toward the optimal solution. This is expressed as:

$$\boldsymbol{D}=|C\cdot\boldsymbol{X}^*_{(t)}-\boldsymbol{X}_{(t} \tag{2.7}$$

$$\boldsymbol{X}_{(t+1)}=\boldsymbol{X}^*_{(t)}-A\cdot\boldsymbol{D}\mathrm{X}_{(t+1)} \tag{2.8}$$

where t denotes the iteration, $\boldsymbol{X}*$ denotes the optimal prey's position and $\boldsymbol{X}$ denotes the prey's position. A and C are two adjustable parameters, and they are expressed as:

$$A=2a \cdot r-a \tag{2.9}$$

$$C=2 \cdot r \tag{2.10}$$

$$a=2-2t/T\text{a} \tag{2.11}$$

where r denotes a stochastic value in [0,1], a is decremented from 2 to 0 and T denotes the maximum iteration.

Bubble Net Attacking

The bubble-net attack in WOA as shown in Figure 3(a) combines two key mechanisms: the rocking surrounding the predator-prey mechanism and the logarithmic spiral bubble-net predator-prey mechanism. The rocking mechanism is controlled by a variable A, which depends on a. The value of A is randomly chosen between $-a$ and a, where a decreases from 2 to 0 over time. When A is within the range [−1, 1], the whale dynamically adjusts its position to move closer to the prey.

The logarithmic spiral mechanism helps estimate the distance to the prey. The whale then swims rapidly toward the surface, creating a spiral-shaped bubble net to trap the prey. This behavior is mathematically modeled to update the whale's position, allowing the algorithm to efficiently converge toward the optimal solution. The position is expressed as:

$$\boldsymbol{D}'=|\text{C}^{\cdot}\boldsymbol{X}^{*}{}_{(t)}-\boldsymbol{X}_{(t)}| \tag{2.12}$$

$$\boldsymbol{X}_{(t+1)}=\boldsymbol{D}' \cdot e^{bl} \cdot \cos(2\pi l)+\boldsymbol{X}^{*}{}_{(t)} \tag{2.13}$$

where $\boldsymbol{D}'$ denotes the distance, l denotes a stochastic value in [−1,1] and b denotes a logarithmic spiral number.

In WOA, the rocking surrounding the predator-prey mechanism allows the whale to shrink, encircle, and engulf the prey. Meanwhile, the logarithmic spiral bubble-net predator-prey mechanism enables the whale to create bubbles, move in a spiral pattern, and calculate the distance to effectively hunt the prey. Both mechanisms have an equal chance of being selected, with a 50% probability for each, ensuring a balanced approach between exploration and exploitation in the optimization process.

The position is expressed as:

$$\boldsymbol{X}_{(t+1)} = \begin{cases} D' \cdot e^{bl} \cdot \cos(2\pi l) + X^*_{(t)} & \text{if } p \geq 0.5 \\ X^*_{(t)} - A \cdot D & \text{if } p < 0.5 \end{cases} \tag{2.14}$$

where p denotes a stochastic value in [0,1].

Random Searching

If $|A| > 1$, the whale moves outside the shrinking, encircling circle of the bubble net and does not focus on the target prey to update its position. Instead, it randomly searches for prey based on shared positional information among other whales. This behavior helps WOA expand the search area, improve its optimization ability, and avoid getting stuck in local solutions, ensuring a more effective and robust search process. This is expressed as:

$$\boldsymbol{D} = |C \cdot \boldsymbol{X}_{rand(t)} - \boldsymbol{X}_{(t)}| \tag{2.15}$$

$$\boldsymbol{X}_{(t+1)} = \boldsymbol{X}_{rand(t)} - A \cdot \boldsymbol{D} \tag{2.16}$$

where $\boldsymbol{X}_{rand}$ denotes the random position vector of a humpback whale.

WOA offers several advantages that make it highly suitable for optimizing the placement and sizing of DG units in distribution systems. These benefits are critical for improving the efficiency, reliability, and performance of power distribution networks. Below are the key advantages of WOA, supported by relevant literature:

1. Effective Global Search

WOA mimics the hunting behavior of humpback whales, enabling it to explore the solution space thoroughly and avoid getting stuck in local minima. This capability is essential for identifying optimal DG placements that minimize power losses and improve voltage profiles in distribution systems [1].

2. Multi-Objective Optimization

WOA is well-suited for multi-objective optimization, allowing it to balance various factors such as cost, reliability, and environmental impact when determining the optimal locations and sizes of DG units. This is particularly important in modern power systems where multiple objectives must be considered simultaneously [30].

3. Robustness and Adaptability

WOA is robust against variations in system parameters, making it effective in dynamic environments typical of distribution systems. Its adaptability allows it to be applied to different types of DG technologies, including renewable sources like solar and wind, which can vary significantly in output [31].

4. Simplicity and Ease of Implementation

The algorithm's straightforward mathematical formulation makes it easy to implement without requiring extensive parameter tuning. This simplicity is advantageous for practitioners and researchers applying WOA in real-world scenarios [32].

5. Improved Voltage Profiles and Reduced Losses

Studies have shown that using WOA for optimal DG placement can lead to significant improvements in voltage profiles and reductions in power losses within distribution systems. This is critical for enhancing the reliability and efficiency of power delivery to consumers [33].

6. Fewer Parameters to Adjust

Compared to other optimization algorithms, WOA requires fewer control parameters, simplifying the optimization process. This feature reduces the complexity involved in tuning the algorithm for specific applications in DG placement [8].

7. Hybridization Potential

WOA can be effectively combined with other optimization techniques, such as Genetic Algorithms or Particle Swarm Optimization, to create hybrid models that leverage the strengths of multiple approaches. This versatility can lead to improved performance in optimizing DG placement [34].

8. Proven Effectiveness in Power Systems

Numerous studies have validated the effectiveness of WOA in various power system applications, particularly in optimizing the placement and sizing of DG units. These studies demonstrate WOA’s capability to address real-world challenges in energy distribution [32].

This paper utilizes WOA as a primary tool for optimizing the placement and sizing of DG units in distribution systems. By leveraging WOA’s effective global search capabilities, the study aims to identify optimal configurations that minimize power losses and enhance voltage stability across the network. The algorithm’s strength in multi-objective optimization allows for a balanced consideration of cost, reliability, and environmental impact, which is increasingly important in today’s energy landscape.

2.5 Literature Review on DG Placement and Reliability Enhancement

In [14], researchers examined the optimal placement for a DG by focusing on performance metrics linked to reliability and the total cost of electricity consumed. However, their analysis was restricted to three reliability factors: energy not supplied, overall cost, and market price of electricity. This limited scope does not provide a comprehensive understanding of the network's reliability. In contrast, the most widely recognized parameters for such analyses around the world are SAIDI, SAIFI, and EENS.

In [15], authors explored how the installation of DG impacts power losses and voltage drops within a DS at various locations. Using the IEEE 37 bus radial distribution system as a model, the study found that placing DG at the most critical bus specifically, the one farthest from the feeder significantly decreased both power losses and voltage drop in the system.

In [16, 17], a case study was conducted using ETAP software to analyze the impact of Distributed Generators (both synchronous and induction generators on the voltage profile and power losses in an 11kV distribution feeder. The findings indicated that optimally placing and sizing the synchronous generator resulted in a more favorable voltage profile and reduced power losses compared to the induction generator. In contrast, the induction generator was associated with higher power losses than the system without any DG, primarily due to its absorption of reactive power from the grid.

In [18] authors used multi objective method whale optimization (MOWOA) technique to position optimally sized DGs in optimal locations. To prove its effectiveness, the suggested method was tested on different test systems for radial distribution, including the bus systems IEEE 33 bus& IEEE 69. However, conducting additional research in economic analysis is necessary to determine the optimal time frame for linking profits gained from minimizing technical losses with the expenses associated with the installation, operation, and maintenance of distributed generation units, while considering different demand scenarios.

In [19] authors implemented the CBOM method for solving the optimal placement, sizing, and PF of DG problem in Distribution Networks. Although using the method presented in this paper to find the optimal location, size, and PF of DG in this case study, power loss has decreased by 93.87%, the voltage of all buses is within the allowable limit, in order to improve the performance of the CBOM method, the authors suggested it can be combined with other optimization methods such as the GA, or to avoid falling into the local optimum, it can be combined with different learning methods such as cube chaos mapping.

In [20] authors used GA, a heuristic approach to determine the best location for DG placement. Load flow and GA were tested on 33 bus and 69 bus radial distribution system. The test results showed the best location for the DG to be placed. However, to enhance the proposed genetic algorithm adding an adaptive archive and testing it under more environments and parameters is needed.

Table 2. 1: A summary of some of the literature on the optimal placement and sizing of DG in distribution systems.

Ref	DG type	Objective function	Optimization algorithm	Strengths	Drawbacks
[21]	WT and PV	-Active Power Losses -Voltage Profile Fluctuation -Voltage Stability	NSGA III	-Multi-objective optimization -Handles complex systems	-Computationally intensive -Requires fine-tuning
[22]	WT, PV and Biomass	-Cost -Active Power Losses -Voltage Profile Fluctuation	MOMSOS	-Handles multiple DG types. -Cost effective.	-Limited to specific test systems.
[23]	PV	-Reactive Power Losses -Active Power Losses -Voltage Profile Fluctuation	GA + PSO	-Combines GA and PSO for better performance.	- Complex implementation. -High computational cost.
[24]	WT and PV	-Cost -Active Power Losses	ABC	-Simple and effective for cost minimization.	-Limited to small-scale systems.
[25]	PV	-Reactive Power Losses -Active Power Losses	Analytical method	-Simple and straight forward.	-Limited to theoretical analysis. -Lacks practical validation.

[26]	WT and PV	-Active Power Losses -Distribution reliability -Enable load sharing	PSO	-Effective load sharing with the substation. -Handles uncertainties in DG performance.	-Limited to theoretical analysis. -Lacks practical validation. -Does not consider economic analysis.
[27]	General DG	-Distribution reliability	ANN	-Unique approach using AI for DG placement. -ANN reduces human error and computational time.	-Limited to static distribution networks. -Lacks practical validation. -Does not consider economic analysis.
[28]	WT and PV	-Cost -Voltage Profile Fluctuation	AHA	-Considers uncertainties in load & DG output power. -Significantly reduces costs, emissions and voltage deviation.	-Implementation is complex due to scenario generation and multi-objective optimization. -Does not explicitly address reliability indices.
[29]	General DG	-Cost -Active Power Losses -Voltage Profile Fluctuation	MMOD	-Introduces memory based approach to pareto optimal solutions -Effectively reduces power loss, improves voltage profile and minimizes investment cost	-Does not explicitly address reliability indices. -Limited to theoretical analysis. -Lacks practical validation. - Does not consider uncertainties in load & DG output power.

The literature on DG placement and its impact on reliability enhancement provides valuable insights into various optimization techniques and their outcomes. The studies reviewed highlight the importance of considering multiple factors, such as power losses, voltage profiles, and reliability indices, in the optimal placement of DG units. While early studies focused on basic reliability metrics, more recent approaches have expanded to incorporate advanced methodologies like Whale Optimization, Genetic Algorithms, and multi objective strategies.

A common theme across the reviewed studies is the critical role of DG placement in reducing power losses and improving voltage stability, particularly when placed at strategic locations within the distribution network.

CHAPTER THREE

DATA COLLECTION AND ANALYSIS

This chapter is structured to guide through the research methodology employed in this study. It begins with a detailed case study of the Bishoftu Distribution Substation 2, highlighting its network description, specific features, and the challenges associated with DG placement. Following this, the chapter addresses data collection and processing, discussing various data sources and the methods used to prepare the data for analysis. A reliability analysis of the existing network is conducted next, focusing on baseline reliability indices, which sets the foundation for the formulation of the optimization problem for DG placement, including objectives and constraints. The WOA setup is then detailed, outlining its customization and relevant parameters. The chapter continues with an overview of the MATLAB simulation setup and implementation, emphasizing the integration of reliability and optimization models. Evaluation metrics and assessment criteria are presented to measure the effectiveness of the WOA and the improvements in reliability.

To provide a clear understanding of the network under study, Table 3.1 presents the detailed configuration of the Bishoftu Distribution Substation 2, including its feeders, associated customers, total lengths, and conductor sizes. This data serves as the foundation for the subsequent reliability analysis and optimization framework discussed in this chapter.

The table provides a detailed overview of the feeders in the Bishoftu Distribution Substation 2, listing each feeder (e.g., k1, k2, k6), the customers they serve (e.g., Steely, Bishoftu Town, Abyssinia), the total length of each feeder in kilometers (ranging from 2.3 km to 54 km), and the conductor sizes used (AAC50 or AAC95). This data highlights the network's structure and variability, with some feeders serving industrial customers like Steely and Bishoftu Automotive, while others cater to residential areas such as Bishoftu Town and Dire Town. The table serves as a critical input for modeling the network's electrical characteristics and conducting reliability analysis.

Table 3. 1: Distribution's Feeder Specification.

Feeder	Customer	Total length of feeder (km)	Conductor Size (mm)
k1	Steely	2.3	AAC95
k2	Steely	2.3	AAC95
k6	Steely and partial Bishoftu Town	34	AAC95
k7	Bishoftu Automotive and partial Bishoftu Town	19	AAC50
k8	Bishoftu Town	14.5	AAC95
k9	Air Force & and partial Bishoftu Town	4.9	AAC95
k12	Abyssinia	3.5	AAC95
k13	Abyssinia	3.5	AAC50
k14	Abyssinia &Dire Town	54	AAC95
k15	Abyssinia, Steely and partial Bishoftu Town	24	AAC50
L1	C & E	3.5	AAC95
L2	Sheba	5.8	AAC95

3.1 Motivations for DG Placement Within This Case Study

The integration of DG in Bishoftu Distribution Substation 2, particularly for Feeder K9, is driven by the need to address specific challenges and improve the overall performance of the distribution network. The key motivations are:

1. Improving Reliability

Feeder K9 has very poor reliability, with frequent and long power outages (SAIFI: 363.5, SAIDI: 803.14). DG units, especially solar PV systems, can provide local power generation, reducing dependency on the main grid and minimizing outages.

2. Using Solar Energy Potential

Bishoftu has high solar energy potential, which is discussed more in section 3.8, making it ideal for solar DG. Using solar power diversifies the energy mix, reducing reliance on hydropower, which can be affected by droughts and seasonal variations.

3. Reducing Costs

DG can lower transmission losses and delay expensive upgrades to the grid. For Feeder K9, where overloading is a major issue, DG offers a cost-effective way to meet growing electricity demand.

4. Supporting National Goals

DG aligns with Ethiopia’s plans for energy security and sustainability. It helps diversify the energy mix, improve energy independence, and gain community support for renewable energy.

In general, DG placement in Bishoftu Substation 2 is motivated by the need to improve reliability, use local solar energy, save costs, and support national energy goals. This makes DG a practical solution for Feeder K9’s challenges.

3.2 Data Collection

A variety of data, software, and methodologies were utilized during the course of this thesis. Numerous books, manuals, standards, and research studies some of which are detailed in the literature review were consulted for reference. Additionally, data was collected from Ethiopian Electric Power (EEP) and Ethiopian Electric Utility (EEU) regarding substation interruptions and specific information about substation equipment.

From the collected data on the distribution network, this study presents an overview of the customer distribution across various feeders. The data categorizes customers into commercial, industrial, and residential sectors, offering insights into how each sector is served by different feeders. This information is crucial for understanding the load demands on each feeder and can help in assessing the operational characteristics of the network.

The following table provides a detailed breakdown of the number of customers served by each feeder. By analyzing this distribution, we can gain a better understanding of the feeder network's structure and the potential impacts of faults and interruptions on different customer categories. This analysis forms the foundation for evaluating system performance and planning future maintenance and upgrades.

Table 3. 2: Customer Distribution Across Feeders.

Feeder	Commercial	Industrial	Residential	Total
k1	-	1	-	1
k2	-	1	-	1
k6	152	1	3300	3362
k7	-	7	-	7
k8	9	7	69	85
k9	11	12	5128	5151
k12	-	1	-	1
k13	-	1	-	1
k14	27	6	1452	1485
k15	643	74	3250	3967
L1	-	1	-	1
L2	-	8	-	8
System	906	125	13998	15025

The above table provides an overview of the number of customers across various feeders categorized by commercial, industrial, and residential sectors. The system total shows that there are 15,025 customers in total, with 906 commercial, 125 industrial, and 13,998 residential customers.

From the data, can be seen that certain feeder, such as k6 and k9, serve a large number of residential customers, with k6 providing electricity to 3,300 residential customers and k9 serving 5,128. On the other hand, feeders like k1, k2, k7, k12, and k13 have very few or no residential customers, indicating they may serve smaller, more specific customer bases, possibly for industrial or commercial purposes.

Feeders such as k15 serve a significant portion of commercial (643) and industrial (74) customers, as well as a large number of residential customers (3,250), making it one of the more critical feeders in the network. Smaller feeders like k8 and k14 also provide service to a balanced mix of customers, with k14 having a notable number of residential customers (1,452).

Overall, this distribution highlights the variation in customer bases across different feeders, which is important for understanding the potential impacts of faults, interruptions, and system reliability across different customer categories.

From the collected substation interruption data, it is evident that faults in the distribution system can be broadly categorized into unplanned faults and planned interruptions, each presenting unique challenges to system reliability.

Unplanned faults occur unexpectedly and are often caused by external factors or system failures. Permanent Earth Faults (DPEF) arise when a conductor makes direct contact with the ground, typically due to fallen tree branches, insulation degradation, or animal interference, leading to prolonged outages that require manual intervention. Similarly, Permanent Short Circuit Faults (DPSC) result from direct contact between conductors, commonly caused by equipment malfunctions, extreme weather events like lightning, or human errors during maintenance, which can generate high fault currents and cause significant equipment damage.

On the other hand, temporary faults often clear automatically. Temporary Earth Faults (DTEF) occur due to brief connections between a conductor and the ground, triggered by events such as lightning strikes or transient contact with vegetation. Likewise, Temporary Short Circuit Faults (DTSC) involve momentary contact between conductors, often caused by high winds, debris, or animal interference, leading to short lived outages that self-resolve without manual intervention.

Planned interruptions, categorized as Distribution Operational Faults (DOP), are intentional outages scheduled for system maintenance, testing, or upgrades. Unlike unplanned faults, these interruptions are carefully planned to enhance system reliability and efficiency. While they cause temporary outages, their proactive nature ensures the long-term stability and performance of the distribution system.

This classification, based on the comprehensive interruption data collected, provides valuable insights into the nature and frequency of faults. It highlights the need for effective strategies to mitigate unplanned faults and optimize maintenance schedules to ensure the reliable operation of the distribution network.

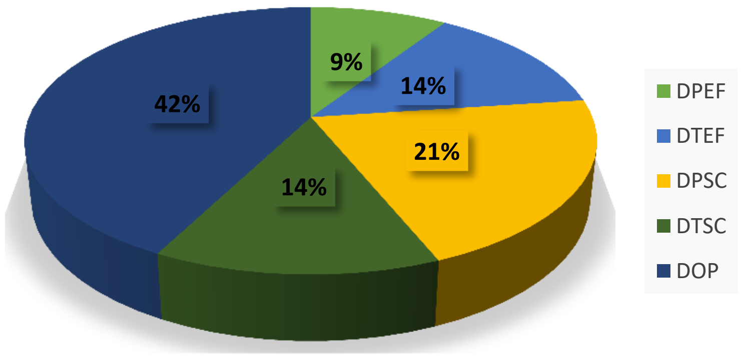


Figure 3. 1: Distribution of Fault Types in the Entire Distribution System.

The above chart illustrates the distribution of fault types in the analyzed distribution system. The faults are categorized into unplanned and planned interruptions. Among the unplanned faults, DPEF and DTSC each account for 14% of the total interruptions, while DPSC contributes 21%, and DTEF represents the smallest share at 9%. The planned interruptions, categorized as DOP, dominate the distribution, making up 42%. This analysis highlights the prevalence of planned interruptions over unplanned faults and underscores the need for strategies to mitigate unplanned faults to improve system reliability

In addition to understanding the customer distribution across feeders, it is essential to analyze the frequency of interruptions that occur on each feeder. This data provides insights into the operational performance of the distribution system and highlights areas with higher disruption rates. By examining the frequency of interruptions, we can assess the reliability of each feeder and identify patterns that may require attention.

The following pie chart illustrates the frequency of interruptions across various feeders in the system, offering a visual representation of how often each feeder experiences disruptions.

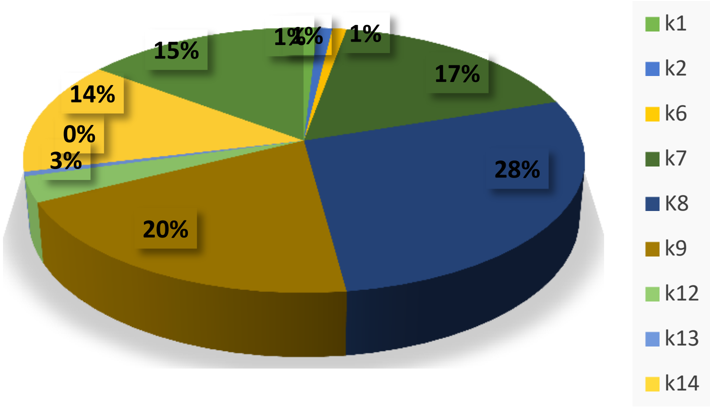


Figure 3. 2: Distribution of Interruptions by Feeder.

The above pie chart provides a detailed breakdown of the frequency of interruptions across different feeders in the system. The data reveals that feeder k15 experiences the highest level of interruptions, accounting for 28% of the total. This is followed by feeder k1, which contributes 20% of the interruptions. Feeders k2 and k7 also stand out, comprising 17% and 15% of the interruptions respectively. The chart highlights a significant disparity in interruption frequency between the top offenders and the remaining feeders, which each contribute less than 5% individually.

3.3 Reliability Analysis of the Existing Network

This section evaluates the reliability of the existing network by analyzing key performance indices, including SAIFI, SAIDI, and ENS. It provides an overview of the network's current performance, highlighting areas of inefficiency and identifying opportunities for improvement to enhance reliability.

Table 3. 3: Frequency and Duration of Interruption for year 2022

Feeder	Frequency of Interruption (Int/yr.)			Duration of Interruption (Hrs. /yr.)		
	Planned	Unplanned	Total	Planned	Unplanned	Total
k1	5	8	13	60.2	15.92	76.12
k2	6	8	14	57.04	16.58	73.62
k6	6	7	13	128.54	8.84	137.38
k7	170	95	265	58.1	163.36	221.46
k8	143	107	250	224.7	335.24	559.94
k9	201	210	411	161.98	568.23	730.21
k12	15	22	37	14.1	33.7	47.8
k13	1	12	13	3.1	1.98	5.08
k14	34	43	77	157.96	493.02	650.98
k15	88	150	238	191.9	354.86	546.76
L1	11	4	15	56.6	75.39	131.99
L2	12	17	29	40.2	106.27	146.47
System	772	803	1375	1154.42	3373.39	3327.81

Table 3. 4: Frequency and Duration of Interruption for year 2023

Feeder	Frequency of Interruption (Int/yr.)			Duration of Interruption (Hrs. /yr.)		
	Planned	Unplanned	Total	Planned	Unplanned	Total
k1	14	5	19	7.28	22.67	29.95
k2	14	5	19	7.28	22.8	30.08
k6	3	15	18	24.11	28.47	52.58
k7	243	55	298	173.55	572.15	745.7
k8	309	161	270	246.73	309.21	555.94
k9	238	78	316	224.24	651.83	876.07
k12	8	57	65	21	96.07	117.07
k13	2	3	5	7.45	0.08	7.53
k14	216	84	300	15.06	90.56	105.62
k15	128	121	249	223.65	146.48	370.13
L1	14	11	25	8.07	53.84	61.91
L2	14	6	20	16.02	47.16	63.18
System	1243	632	1604	974.44	2041.32	3015.76

The feeder interruption data for 2022 and 2023, as presented in these tables, provides valuable insights into the reliability performance of the system over two consecutive years. The data includes both the frequency and duration of planned and unplanned interruptions for each feeder, as well as for the entire system. By analyzing these metrics, a clear picture emerges regarding the reliability challenges and trends for the feeders.

Frequency of Interruptions

The total frequency of interruptions across the system increased from 1575 interruptions/year in 2022 to 1875 interruptions/year in 2023, reflecting a notable rise in reliability challenges. Feeder k8 recorded the highest total interruptions for both years, with 450 interruptions in 2022 and an even higher 470 interruptions in 2023. This increase was driven by a mix of planned and unplanned events, highlighting its susceptibility to outages. Similarly, feeders k9 and k7 experienced significant numbers of interruptions, maintaining high totals of 411 and 265 interruptions in 2022, and increasing to 306 and 298 interruptions in 2023, respectively.

On the other hand, feeders like k1, k2, and k13 showed consistently lower total interruptions, with frequencies below 20 interruptions/year for both years. This indicates relatively stable performance for these feeders, although some fluctuations in planned and unplanned interruptions were observed.

Duration of Interruptions

The duration of interruptions shows a more complex trend. In 2022, the system recorded a total downtime of 4527.81 hours/year, which significantly reduced to 3015.76 hours/year in 2023. This overall reduction is a positive sign, likely reflecting efforts to improve maintenance practices and address reliability issues.

Feeders k7 and k8 stood out with the longest interruption durations in both years. Feeder k7 experienced 1221.46 hours of total downtime in 2022, which slightly reduced to 825.38 hours in 2023, though it still represents a significant reliability concern. Similarly, k8 recorded 759.94 hours of downtime in 2022 and remained high at 818.88 hours in 2023, showing a slight increase despite efforts to mitigate unplanned interruptions.

In contrast, feeders such as k1 and k2 consistently reported lower total downtime, staying below 80 hours/year in both years. Feeder k13 had the lowest interruption durations, with just 5.08 hours in 2022 and 7.53 hours in 2023, indicating minimal impact on service reliability.

Table 3. 5: Reliability indices for the year 2022

Feeder	SAIFI (Int./Year/Customer)	SAIDI (Hr./Year/Customer)	CAIDI(Hr.)
k1	13	76.12	5.86
k2	14	73.62	5.26
k6	13	137.38	10.57
k7	265	221.46	4.61
k8	250	559.94	1.69
k9	411	730.21	1.78
k12	37	47.8	1.29
k13	13	5.08	0.39
k14	77	650.98	8.45
k15	238	546.76	2.3
L1	15	131.99	8.8
L2	29	146.47	5.05

Table 3. 6: Reliability indices for the year 2023

Feeder	SAIFI (Int./Year/Customer)	SAIDI (Hr./Year/Customer)	CAIDI(Hr.)
k1	19	29.95	1.58
k2	19	30.08	1.58
k6	18	52.58	2.92
k7	298	745.7	2.77
k8	270	555.94	1.74
k9	316	876.07	1.74
k12	65	117.07	1.8
k13	5	7.53	1.51
k14	300	105.62	0.28
k15	249	370.13	1.49
L1	25	61.91	2.48
L2	20	63.18	3.16

Table 3. 7: Average Reliability indices for the two years

Feeder	SAIFI (Int./Year/Customer)	SAIDI (Hr./Year/Customer)	CAIDI(Hr.)
k1	14	53.04	3.72
k2	14	51.85	3.42
k6	3	94.83	6.75
k7	281.8	483.58	3.69
k8	260	557.94	1.72
k9	363.5	803.14	1.76
k12	8	82.44	1.56
k13	2	6.31	0.95
k14	188.5	378.3	4.37
k15	243.5	458.45	1.9
L1	14	96.95	5.64
L2	14	104.89	4.1

Based on the analysis of reliability indices (SAIFI, SAIDI, CAIDI) as seen in the three figures above and customer distribution on table 3, Feeder k9 was identified as the most appropriate candidate for DG placement, with Feeder k15 being a strong alternative.

Feeder k9 serves the largest number of customers in the network, with a total of 5151 customers, predominantly residential (5128), complemented by a small number of commercial and industrial customers. It exhibits a high frequency of interruptions (SAIFI = 363.5) and significant downtime (SAIDI = 803.14 hours), indicating poor reliability. These characteristics make Feeder k9 a priority for reliability enhancement through DG integration, as the benefits of improving this feeder's performance will have the most widespread impact on customers. Additionally, residential feeders are ideal candidates for DG placement, especially renewable energy sources like solar PV, due to their variable load profiles and potential for load support.

Feeder k15 emerges as a strong alternative, given its balanced mix of customer types, serving 3967 customers distributed across residential, commercial, and industrial sectors. With moderately high interruption frequency (SAIFI = 243.5) and downtime (SAIDI = 458.445 hours), Feeder k15 offers a unique opportunity to address reliability issues across diverse customer types, potentially enhancing the overall system performance. This feeder's load diversity makes it particularly suitable for DG placement, as it can serve multiple sectors with varying energy demands.

The remaining feeders, while important, do not exhibit the same urgency for DG integration based on reliability metrics and customer impact. For instance, feeders such as k8 and k7 show high SAIFI and SAIDI values; however, their relatively smaller customer bases (85 and 7, respectively) limit the scope of their improvement's impact. Feeder k6, with its predominantly residential customer base (3300 customers) and low SAIFI (15.5), already exhibits better reliability compared to others, making it a lower priority for intervention. Similarly, feeders such as k1, k2, k12, k13, L1, and L2 have minimal customer bases, predominantly serving single industrial or commercial entities. While these feeders might benefit from DG placement for specific load support, their overall contribution to system wide reliability improvement is limited.

In conclusion, Feeder k9 is recommended as the primary focus of this thesis for optimal DG placement due to its large customer base, high interruption frequency, and significant downtime. Feeder k15 is suggested as a strong alternative due to its diverse load distribution and potential to enhance reliability across multiple customer sectors. By focusing on these feeders, the study aims to maximize the reliability benefits of DG integration while addressing key reliability concerns in the distribution network.

3.4 WOA Setup

A. Customization of the WOA for Optimal DG Placement in the Bishoftu Network

The WOA was customized and implemented to determine the optimal placement of DGs in the Bishoftu distribution network. This section describes the specific adaptations made to the WOA for the DG placement problem, the parameter selection process, and the steps followed to achieve the study's objectives.

The standard WOA was tailored to address the unique requirements of DG placement in a distribution network. The algorithm was adapted to handle:

Multi objective optimization: Minimizing reliability indices (e.g., SAIFI, SAIDI) while adhering to system constraints such as voltage limits and power balance.

Feeder topology: Incorporating the specific structure and parameters of the Bishoftu feeder to ensure realistic and feasible DG placements.

Search space constraints: Limiting candidate locations for DG placement to buses where installation is technically and economically viable.

This customization ensured that the WOA's search process effectively explored feasible solutions and converged toward optimal results.

B. WOA Parameters and Their Selection

The following WOA parameters were chosen based on the specific requirements of the DG placement problem:

1. Population Size:

A population size of 30 whales was selected to balance computational efficiency and the diversity of solutions explored.

2. Maximum Iterations:

The algorithm was set to run for 100 iterations, sufficient for convergence in preliminary testing while avoiding excessive computation time.

2. Convergence Control Parameters:

a: Linearly decreased from 2 to 0 during iterations to balance exploration and exploitation.

b: Used in the spiral updating equation to simulate the encircling behavior of whales.

3. Fitness Function:

The fitness function was designed to evaluate DG placement based on the improvement in reliability indices, penalizing solutions that violated system constraints. These parameters were fine-tuned through trial simulations to ensure optimal performance.

C. WOA Steps Adapted to the Study

A customized WOA framework enabled the study to efficiently identify optimal DG placements, meeting the reliability improvement objectives for the Bishoftu feeder, as summarized in the flowchart below, which outlines the WOA steps applied in this study.

WOA flowchart

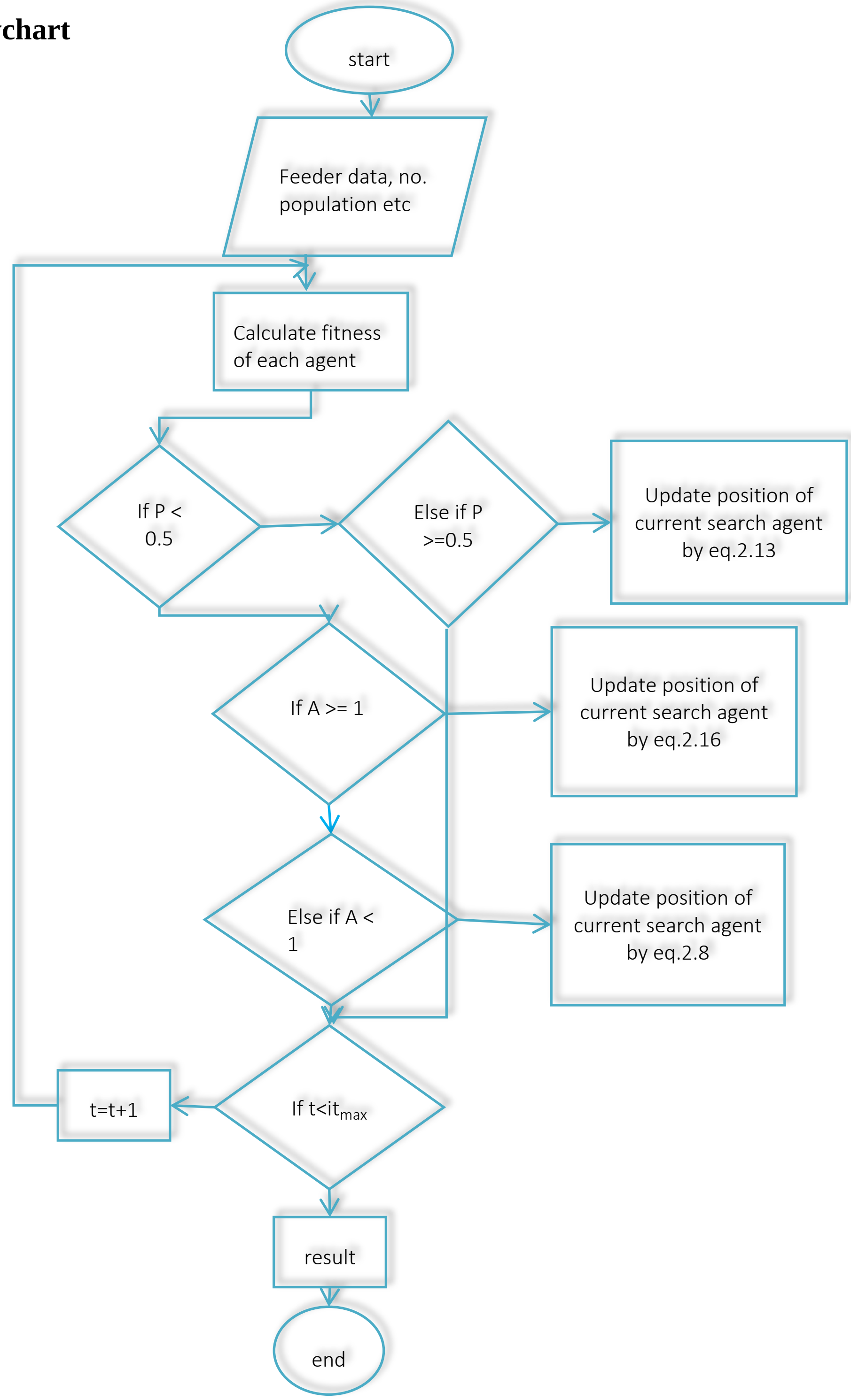


Figure 3. 3: WOA flowchart

3.5 MATLAB Simulation Setup and Implementation

This section details the MATLAB simulation setup and implementation process for optimal distributed generation (DG) placement aimed at improving the reliability of the Bishoftu Distribution Substation 2 feeder. The simulation combines network modeling, reliability analysis, and optimization techniques to achieve the objectives of the study.

MATLAB was chosen for its comprehensive tools for technical computing and power system analysis. Its flexibility allowed for seamless integration of the network model, reliability calculations, and the WOA. MATLAB's ability to handle large datasets and perform complex iterative calculations made it ideal for modeling the feeder's network and optimizing DG placement.

To model the existing distribution line of Bishoftu city and to analyze the current reliability status of the distribution network, several assumptions and data inputs were considered. These inputs served as the foundation for developing a reliability model in MATLAB 2017b and performing the associated analysis. Each input is vital to ensuring that the modeled network reflects the actual operating conditions of the distribution system. The key considerations are as follows:

1. City Line Data

The topology of the city's distribution network was analyzed, including feeder layouts, substation connectivity, and branch points. The feeder specific information allowed for a detailed study of interruptions at both the individual feeder and system levels.

2. Cable Length

The length of the distribution lines across the network was factored in as a critical parameter. Cable length directly influences the probability of interruptions and failure rates due to increased exposure to environmental factors, mechanical stress, and aging. Feeder lengths were measured and incorporated to estimate the likelihood of faults and calculate the energy not served (ENS) during interruptions.

3. Number of Customers

The number of customers connected to each feeder was used to calculate the reliability indices such as SAIFI, SAIDI, and CAIDI. These indices are customer weighted, meaning that the number of interruptions and their duration have a more significant impact on feeders with larger customer bases. The data was disaggregated into residential, commercial, and industrial customers to better reflect consumption patterns and interruption sensitivities.

4. Connected Load

The connected load data was utilized to determine the load demand for each feeder and its contribution to the overall system. Understanding the connected load is essential for evaluating the feeder's performance under both normal and fault conditions. It also influenced the placement and sizing of DG units to optimize reliability and ensure load demands are adequately met.

5. Failure Rate

The failure rate (λ) for each feeder, expressed in failures per year, was calculated based on historical interruption data. This metric measures the frequency of component failures and was a vital input for determining the baseline reliability of the distribution network. Feeders with higher failure rates were prioritized for improvement through optimal DG placement.

6. Duration of Interruption in Hours

The total downtime experienced by each feeder was assessed to determine the duration of interruptions (in hours per year). This data was critical for calculating SAIDI and CAIDI, which quantify the average downtime experienced by customers and the average restoration time for each interruption, respectively.

7. Frequency of Interruption

The annual frequency of interruptions per feeder, encompassing both planned and unplanned outages, was included as a key reliability parameter. This frequency, in conjunction with the duration of interruptions, allowed for a comprehensive assessment of the feeder's reliability status and its impact on the overall system.

By incorporating these inputs into MATLAB 2017b, a realistic model of the Bishoftu city distribution network was developed. The analysis enabled the identification of reliability challenges and informed the optimization process for distributed generation placement. These inputs ensured that the study reflected actual conditions, providing a solid foundation for achieving the thesis objectives of improving distribution network reliability.

Data Loading and Network Modeling

Daily interruption data for 2022 and 2023 was processed and imported into MATLAB to calculate reliability indices such as SAIFI and SAIDI. The single line diagram (SLD) of the feeder was developed using MATLAB's simulation environment, accurately representing the network's buses, lines and loads.

This model served as the foundation for evaluating the impacts of DG placement on reliability metrics.

Integration of Reliability and Optimization Models

The reliability model was integrated with the WOA to evaluate and optimize DG placement. The model calculated the reliability indices based on the loaded interruption data, while the WOA iteratively searched for DG locations that minimized these indices. The integration ensured that the optimization process was guided by practical reliability improvements and adhered to system constraints, such as voltage and load balancing.

Implementation Details

1. Initialization of the WOA

The WOA was initialized with carefully selected parameters, including the population size, number of iterations, and convergence criteria. These parameters were tuned to balance computational efficiency and the accuracy of the optimization results. The search space was defined to include all potential DG placement locations within the network.

2. Simulating DG Placement and Calculating Reliability Impacts

The WOA algorithm iteratively placed DG units in candidate locations, and the resulting reliability indices were recalculated for each placement. MATLAB scripts automated the process, integrating the optimization logic with the SLD model and reliability calculations. The simulations ensured that each proposed DG placement met technical and operational constraints.

3.6 Distributed Generation Sizing and Placement

Reliability is a critical concern in the operation of modern power distribution systems.

Frequent and prolonged interruptions can adversely affect consumers and utility performance. Optimal placement and sizing of DG units in distribution networks offer a promising solution to enhance the reliability of power supply. The integration of DG at optimal locations can minimize interruption frequency, reduce downtime, and improve overall system reliability indices such as SAIFI and SAIDI.

The enhancement of reliability is achieved by reducing the dependency on a single central source of generation and providing local support to loads during faults or contingencies. In this work, the WOA is employed to identify the optimal size and location of DG units with the objective of minimizing reliability indices while considering technical constraints.

3.6.1 Problem Formulation

The reliability improvement due to DG placement is assessed using reliability indices such as:

SAIFI: Measures the average number of interruptions per consumer per year.

SAIDI: Measures the total duration of interruptions per consumer per year.

The objective function for this optimization is formulated as:

$$\text{Minimize: } F = \alpha \cdot SAIFI + \beta \cdot SAIDI \quad (3.1)$$

Where:

F is the objective function to be minimized.

α and β are weight factors representing the relative importance of the SAIFI and SAIDI respectively.

SAIFI and SAIDI are the reliability indices that the optimization aims to reduce in the system.

3.6.2 Constraints

To ensure practical and feasible solutions, the following constraints are applied:

1. Voltage Limits

The voltage at all buses must remain within the specified range:

$$V_{min} \leq V_i \leq V_{max} \tag{3.2}$$

2. DG Capacity Constraint

The total active power generated by DG must not exceed the system's load demand plus total power losses:

$$P_{DG} \leq P_{load} + P_{loss} \tag{3.3}$$

3. Power Factor Constraint

The DG must operate at a minimum power factor of 0.95:

4. Reliability Constraint

The reliability indices after DG placement must improve compared to the base case:

$$\text{SAIFI with DG} \leq \text{SAIFI base} \tag{3.4}$$

$$\text{SAIDI with DG} \leq \text{SAIDI base} \tag{3.5}$$

3.6.3 Power Flow Analysis

Power flow analysis is a fundamental tool in power system studies used to determine the steady-state operating conditions of the network. It provides critical information on bus voltages, real and reactive power flows, line losses, and loading levels of system components. In the context of this thesis, power flow analysis is essential for DG placement on voltage profiles and verifying whether voltage constraints are maintained within acceptable limits after integration.

Given that the system under study is a radial distribution network, the Backward/Forward Sweep (BFS) algorithm is employed for the power flow analysis. The BFS method is particularly well-suited for radial and weakly meshed distribution systems due to its simplicity, computational efficiency, and ability to handle unbalanced loads. The algorithm operates in two main steps: a backward sweep, where branch currents are calculated from the load buses towards the substation, followed by a forward sweep, where bus voltages are updated from the substation towards the end nodes using the previously calculated currents.

This approach is iterated until bus voltages converge within a specified tolerance, ensuring an accurate representation of the voltage profile across the feeder. By applying this method before and after DG integration, it is possible to assess whether the installed DG helps maintain bus voltages within standard operational limits thereby supporting reliability objectives.

3.6.4 Identification of Optimal DG Placement

The optimal DG location and size are determined using MATLAB based code that integrates the WOA. The steps include:

1. Read system data (feeder parameters, load profiles, interruption data).

2. Perform base case reliability analysis to calculate SAIFI and SAIDI.

3. Apply the WOA to determine DG placement and size for minimizing reliability indices.

4. Evaluate all technical constraints for each candidate solution.

5. Select the solution with minimum SAIFI and SAIDI as the optimal DG placement.

The procedure is presented in the flow chart below.

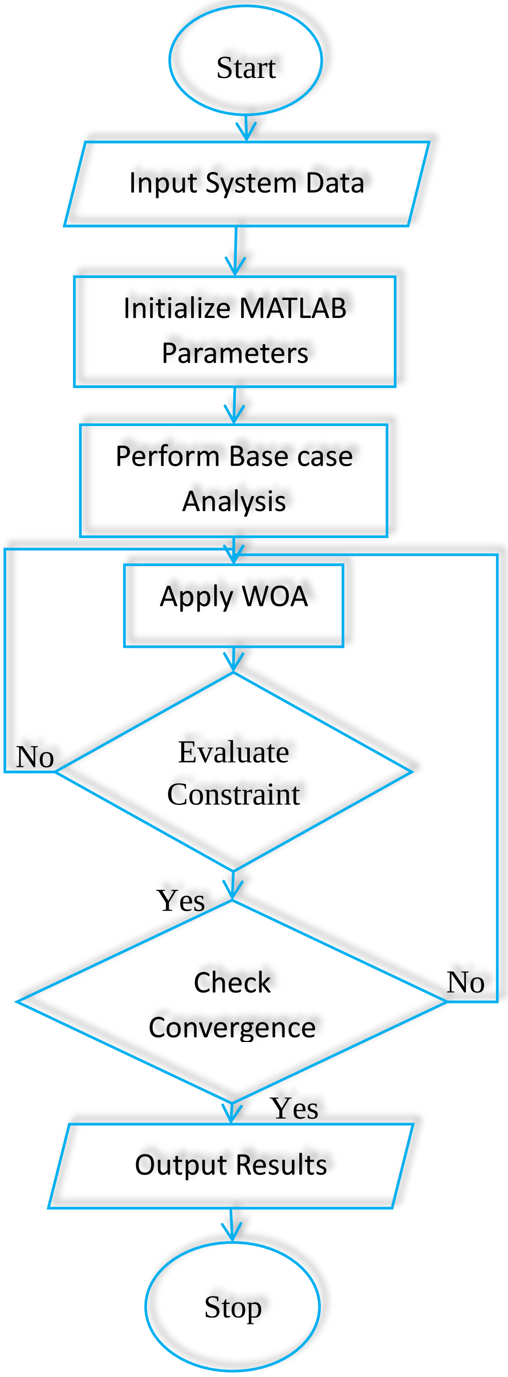


Figure 3. 4: The flowchart of optimal DG sizing and placement

3.7 Solar as the Optimal DG Selection for Bishoftu Substation

The assessment of renewable energy resources is crucial for determining the most viable DG technologies for enhancing reliability in the Bishoftu Distribution

Substation 2 network. To this end, the evaluation of renewable energy resources was carried out using 22-year climatological data (2000–2022) from NASA's POWER database. This comprehensive dataset highlights the case study area's favorable conditions for solar energy, making it strong candidates for DG implementation.

Wind resource data analyzed at heights of 10m and 50m indicate annual average wind speeds of 3.45 m/s and 4.95 m/s, respectively as seen in the table below.

Table 3. 8: Wind speed of Bishoftu city at 10m and 50m

Parameters	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Avg
Wind speed at 10m(m/s)	3.98	4.17	3.93	3.66	3.20	2.64	2.89	2.75	2.36	2.89	4.09	3.98	3.45
Wind speed at 50m(m/s)	5.55	5.92	5.51	5.10	4.43	3.74	4.23	4.04	3.41	5.79	6.00	5.76	4.95

The wind speeds as seen in the above table range from a low of 2.64 m/s in June to a high of 4.17 m/s in February at 10 meters, with the average annual wind speed recorded at 3.45 m/s. For wind speeds at 50 meters, the highest reading is 6.00 m/s in November, and the lowest is 3.41 m/s in September, with an average annual wind speed of 4.95 m/s.

International standards, such as those from the International Renewable Energy Agency (IRENA), suggest that for effective wind turbine operation, the average annual wind speed should ideally be 5 m/s or higher. With an average wind speed of 3.45 m/s at 10 meters and 4.95 m/s at 50 meters, Bishoftu's wind resources fall slightly below the threshold for optimal wind turbine efficiency, particularly at lower heights where wind speed is typically lower. While wind energy may still be viable at higher altitudes (such as 50 meters), it does not offer the same level of consistent potential as solar power for this specific location.

The following table shows the monthly solar irradiance data for Bishoftu. Solar irradiance levels range from 4.70 kWh/m²/day in July to 6.71 kWh/m²/day in January, with an annual average of 5.89 kWh/m²/day. These values indicate a relatively high level of solar energy potential throughout the year, especially during the peak months of January to March, where the irradiance levels are consistently above 6 kWh/m²/day.

Table 3. 9: Solar irradiance data of Bishoftu city

Parameters	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Avg
Solar irradiance (KWh/m^2/day)	6.71	6.66	6.68	6.28	6.18	5.60	4.70	4.79	5.46	6.23	6.16	6.03	5.89

International standards, such as those provided by IRENA, suggest that locations with an average daily solar irradiance of 4-5 kWh/m²/day are suitable for solar power generation. With an average of 5.89 kWh/m²/day, Bishoftu exceeds this threshold, making solar energy the most effective and reliable DG option in this region.

3.8 Solar Energy System Design

The load demand on feeder K9, based on collected data, is 3.2 MW. To meet this demand, the daily energy requirement is derived by considering the load over a 24-hour period. Additionally, system inefficiencies such as panel mismatch, inverter losses, and battery inefficiencies are accounted for by applying a correction factor of 1.25. This results in a corrected daily energy requirement of 92.16 MWh/day. The correction factor and assumptions are supported by established references [55, 59], which provide empirical data and guidelines for addressing real-world inefficiencies in solar PV systems.

Selection of DC System Voltage

The selection of the DC system voltage is guided by the total energy requirements and standard practices. According to established guidelines, a 12V system is typically used for energy requirements up to 1 kWh, 24V for up to 4 kWh, and 48V for requirements beyond 4 kWh [55, 59]. In this case, since the energy requirement significantly exceeds 4 kWh, a 240V DC system voltage is selected. This choice is supported by studies demonstrating that higher system voltages minimize energy losses, improve overall efficiency, and reduce current levels, which in turn lowers resistive losses and cable costs, as highlighted in the literature [56, 57]. By adopting a 240V DC system, the design aligns with best practices for large-scale energy systems, ensuring both efficiency and cost-effectiveness.

Calculation of Total Ampere Hours

The total ampere hour (Ah) requirement of the system is calculated as:

$$\text{Total Ah/day} = \frac{\text{Daily Energy Requirement}}{\text{System Voltage}} \tag{3.6}$$

$$= \frac{92.16\ \text{MWh/day}}{240\ \text{V}}$$

$$= 384000\ \text{Ah/day}$$

Sizing of the PV Array

The peak sun hours for the selected location are 5.89 hours/day. The total current required by the PV array is obtained by dividing the daily ampere hour requirement by the peak sun hours:

$$\text{Total solar array amps} = \frac{384000\ \text{Ah/day}}{5.89\ \text{hours/day}}$$

$$= 65{,}195\ \text{A.}$$

The number of modules connected in parallel is calculated as:

$$\text{Modules in Parallel} = \frac{\text{Total PV Array Current}}{\text{Module Operating Current} \times \text{Derating Factor}} \quad (3.7)$$

$$= \frac{65195\ \text{A}}{17.33\text{A} \times 0.9} \quad \approx 4179 \text{ modules.}$$

The number of modules connected in series is determined using:

$$\text{Modules in Series} = \frac{\text{System Voltage}}{\text{Module Voltage}} \quad (3.8)$$

$$= \frac{240\text{V}}{38.08\text{V}} \quad \approx 7 \text{ modules.}$$

Thus, the PV array design requires 1774 modules in parallel and 7 in series to meet the energy demands [58,60].

Battery Sizing

The battery system was designed to provide energy for 1.5 days without sunlight. The design and calculations were done independently, but references to existing studies were used to support the assumptions and choices made during the process.

Lead acid batteries were chosen because they are cost-effective, reliable, and widely available for solar applications, as mentioned in [57, 64]. Lithium-ion batteries, while efficient, were not selected due to their high cost and the need for a more economical solution for this project. Additionally, lead acid batteries are easier to maintain and recycle in many regions, making them a more practical choice for this application.

The depth of discharge (DOD) was set at 70%, and the battery efficiency was assumed to be 80%. These values are commonly recommended for solar storage systems, as shown in [63, 65].

Using these values, the total battery capacity was calculated with the following formula:

$$\text{Battery Capacity} = \frac{\text{Total Ah/day} \times \text{Autonomy Days}}{\text{DOD} \times \text{Efficiency}} \quad (3.9)$$

$$= \frac{384000 \text{ Ah/day} \times 1.5}{0.7 \times 0.8} \approx 102857 \text{ Ah.}$$

Lead acid batteries with a rated capacity of 2900 Ah and 48V are selected as the requirement and based on [57, 65].

Inverter Sizing

The inverter size is determined based on the total load demand, with an additional 20% margin incorporated to accommodate peak loads and ensure system reliability. To ensure compatibility with a wide range of appliances and achieve higher efficiency, a pure sine wave inverter is selected. The sizing of the inverter considers the total load demand along with the safety margin, ensuring that the system can handle variations in load without compromising performance. This approach aligns with established design practices and recommendations from the literature [66], which emphasize the importance of oversizing inverters to enhance reliability and efficiency in renewable energy systems.

Inverter Size =DG Size *1.2 = 3200 Kw*1.2 = 3840 kW.

This design ensures optimal energy generation and storage while minimizing system losses. The choice of a 48V system, lead-acid batteries, and a pure sine wave inverter is based on established best practices for designing reliable and cost-effective solar PV systems. These components are widely recommended in the literature [55–68] for their proven performance, efficiency, and ability to meet the demands of renewable energy systems. By adhering to these standards, the design achieves a balance between reliability, cost-effectiveness, and operational efficiency.

CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.1 Introduction

This chapter presents the results of the study, focusing on the reliability improvements achieved through the optimal placement and sizing of DG in the distribution network under investigation. The analysis begins with an overview of the initial reliability indices, which serve as the baseline for evaluating the network's performance. These indices include SAIFI, SAIDI, and ENS, highlighting the feeder’s existing operational challenges.

The chapter then details the optimized results obtained using the WOA, identifying the best DG size and location. The impact of these optimizations on the reliability indices is analyzed, demonstrating significant improvements compared to the initial state.

Additionally, the financial benefits of DG optimization are explored, focusing on cost savings achieved through reduced ENS and power losses. These findings emphasize the practical advantages of the proposed methodology for improving network reliability while lowering operational expenses.

Overall, this chapter provides a comprehensive analysis of the results, showcasing the effectiveness of DG placement in enhancing the reliability and efficiency of the distribution network.

4.2 Initial Reliability Indices

This section presents the initial reliability indices of the feeder, which serve as the baseline for evaluating the impact of DG optimization. These indices highlight the feeder's existing challenges in providing reliable service to customers.

The initial reliability indices are as follows:

SAIFI: 363.5 interruptions per customer per year.

SAIDI: 803.14 hours per customer per year.

ENS: 2021856.00 kWh/year reflecting significant energy interruptions due to frequent and prolonged outages.

These metrics demonstrate the feeder's current limitations, including frequent interruptions, prolonged downtimes, and significant energy and financial losses. They underscore the need for optimization to enhance reliability and reduce the negative impacts on customers and utility operations.

This baseline data provides the foundation for comparing the results after implementing the optimal DG placement and sizing, which are presented in subsequent sections.

Table 4. 1: International comparison for reliability indices [45],[46],[47],[48]

Countries	SAIFI (Int./Year/Customer)	SAIDI (Hr./Year/Customer)
United states	1.5	4
Canada	3.4	6.9
United Kingdom	0.8	1.5
Australia	0.9	1.2
Ethiopia	20	25
Bishoftu substation 2(Feeder K9)	363.5	803.14

The initial reliability indices of Bishoftu Substation 2 (Feeder K9) reveal significant disparities when compared to the standard values of various countries, as provided in the above table. This comparison underscores the feeder's severe performance challenges and highlights the pressing need for optimization in the local distribution network.

Developed countries, such as the United States, United Kingdom, and Australia, demonstrate relatively low SAIFI and SAIDI values, reflecting advanced infrastructure, efficient maintenance practices, and robust reliability standards. For instance, the United Kingdom reports the lowest SAIFI and SAIDI values, with customers experiencing fewer than one interruption annually and minimal downtime.

Within Ethiopia, the national averages of 20 interruptions per year per customer (SAIFI) and 25 hours per year per customer (SAIDI) are significantly higher than the global standards, reflecting broader challenges in the country's power distribution network. However, Bishoftu Substation 2 (Feeder K9) shows reliability indices that are substantially worse than both the national and international averages, with a SAIFI of 363.5 and a SAIDI of 803.14. These figures indicate nearly daily interruptions and prolonged outages, highlighting the severity of the reliability issues specific to this feeder.

4.3 Optimized Results

The optimization process for Bishoftu Substation 2 (Feeder K9) relies heavily on several input parameters that were critical for the simulation and analysis in MATLAB. These parameters include the number of buses, line length, failure rate, repair rate, total feeder load, and customer count. They provide the foundation for implementing the WOA to identify the optimal size and location for a DG unit that would improve the reliability of the feeder.

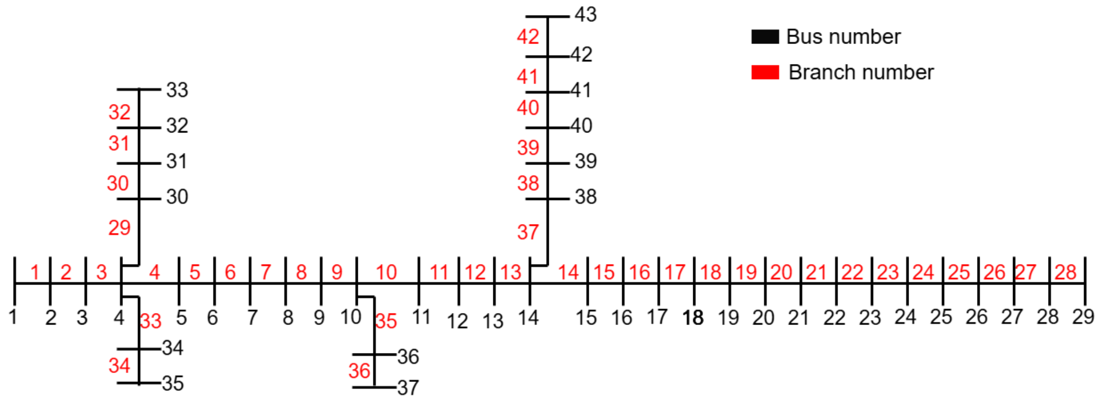


Figure 4. 1 Single line diagram of feeder K9

The selected distribution feeder is a 15 kV radial system consisting of 43 buses as shown in the above figure, accurately modeled based on the actual single line diagram(SLD). The feeder includes a main trunk line with 29 buses and 14 additional lateral buses, each connected to distribution transformers serving various load points.

The feeder supplies a total load of 3200 kW, which is distributed across the 43 buses.Transformer sizes along the feeder range from 25 kVA to 800 kVA, including common ratings such as 25, 50, 100, 200, 315, 400, 500, 630, and 800 kVA. These variations indicate a mix of small residential, commercial, and medium industrial loads throughout the network.

The failure rate for each bus is based on the total failure rate divided by the number of buses. This simplification assumes uniform failure rates across the network, which is a standard approach when detailed data is not available. In reality, these rates can vary based on factors such as bus location, environmental conditions, and maintenance practices.

The failure rate (λ) shows how often failures happen in the system. It is measured in failures per kilometer per year and is usually found using past data from the equipment or network [49][50].

$$\lambda = \frac{\text{Number of Failures}}{\text{Length of Line (km) per Year}} \tag{4.1}$$

The repair rate (μ) shows how fast repairs are done to restore service. It is measured in repairs per hour and is the opposite of repair time, helping to estimate how quickly faults are fixed [51][52].

$$\mu = \frac{1}{\text{Repair Time (hours)}} \tag{4.2}$$

The average repair time (Tr) is the usual time taken to fix a fault and bring back service. It is found by taking the opposite of the repair rate (μ) [53].

$$\text{Tr} = \frac{1}{\mu} \tag{4.3}$$

The repair rate was set to 0.529 repairs per hour, and the corresponding repair time was calculated to be 1.89 hours. This reflects the average time it takes to repair an interruption on the feeder.

This repair time, combined with the failure rate and feeder specific data, allowed for the calculation of key reliability indices.

With these parameters in place, the WOA was used to find the optimal size and location of the DG. The algorithm evaluates different configurations of DG size and placement to minimize the reliability indices, specifically the SAIFI and SAIDI, which are key metrics of distribution network reliability.

By running the optimization process, the optimal DG size and location were determined, and the results were used to compare the improvements in SAIFI, SAIDI, and other metrics such as ENS. These results demonstrate the potential impact of optimizing the DG placement and highlight the significant improvements in reliability that can be achieved through this process.

The Matlab inputs are presented in the following table.

Table 4. 2: Matlab input parameters

Parameter	Number of Buses	Line Length (km)	Failure Rate (failures/km/year)	Repair Rate (repairs/hour)	Total Customers	Total Load (kW)	Initial SAIFI (interruptions/year/customer)	Initial SAIDI (hours/year/customer)	Initial ENS (kWh/year)	X (Reactance, Ω)	R (Resistance, Ω)
Value	43	4.9	73.16	0.529	5141	3200	363.5	803.14	2,021,856	0.5	0.1

4.3.1 Optimized DG Placement and Sizing

The optimization of the DG size and placement for Bishoftu Substation 2 (Feeder K9) was performed using the WOA. This algorithm, known for its efficiency in solving complex optimization problems, was applied to determine the best DG size and location, aiming to minimize the system's reliability indices and maximize performance.

By following the WOA flowchart presented in Figure 3.3, the flowchart for optimal sizing and placement of DG in Figure 3.4, and the MATLAB input parameters outlined in Table 4.2, the following optimal results were obtained:

Optimal DG Size: 1.32 MW

Optimal DG Location: Bus 22

These results indicate that a DG unit with a capacity of 1.32 MW should be installed at Bus 22. This configuration was determined to be the most effective in improving the overall reliability of the feeder, as evidenced by the significant reductions in the SAIFI, SAIDI, and ENS.

The choice of Bus 22 as the optimal location is based on the load distribution across the buses and the operational characteristics of the network. This placement ensures compatibility with the network's load distribution while adhering to operational constraints, such as voltage levels and line capacity.

The optimal sizing of the DG unit is a critical factor in balancing the generation capacity with the feeder's demand. The selected size of 1.32 MW aligns well with the system's needs, providing sufficient generation capacity to improve reliability without overloading the system or introducing excessive operational costs.

Thus, the optimization process not only identified the ideal size and location for the DG unit but also ensured that these parameters contribute to enhanced system reliability, efficiency, and sustainability in the long term.

4.3.2 Optimized Reliability Indices

Following the implementation of the optimal Distributed Generation (DG) placement and sizing, there were notable improvements in the reliability indices of Bishoftu Substation 2 (Feeder K9). These enhancements highlight the positive impact of integrating a properly sized DG unit at the optimal location on the feeder's overall reliability performance.

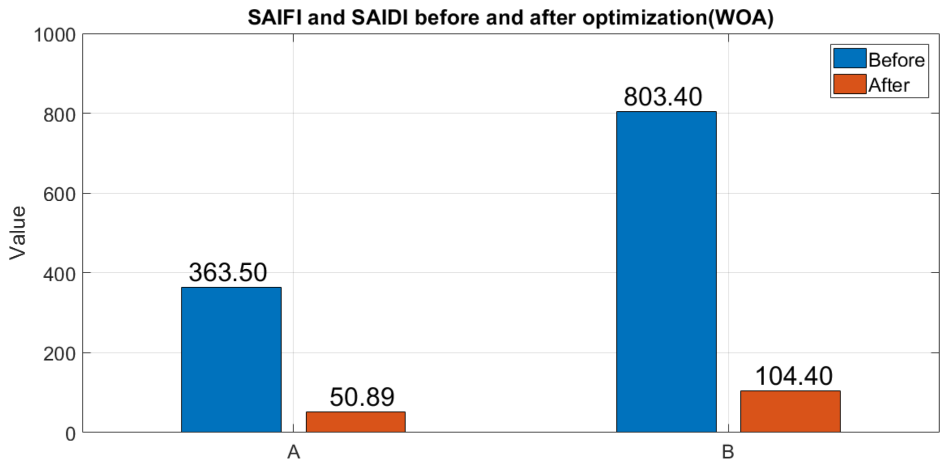


Figure 4.2: reliability indices comparison before and after WOA optimization

The graph above highlights the significant improvement in the reliability indices, SAIFI and SAIDI, for the K9 feeder after the optimal placement of DG using the WOA. These indices are critical in assessing the reliability of power distribution networks, and their reduction indicates a more dependable and efficient system.

Initially, the K9 feeder experienced frequent and prolonged power interruptions, as evident from the high SAIFI and SAIDI values. The pre-optimization SAIFI, standing at 363.5 interruptions per year per customer, reflects the excessive frequency of outages in the feeder. Similarly, the initial SAIDI value of 803.14 hours per year per customer underscores the extended duration of these outages, highlighting the challenges faced by customers relying on this distribution system. These values indicate a pressing need for intervention to enhance reliability.

Following the optimization of DG placement, the reliability indices saw remarkable improvement. The SAIFI value was reduced to 50.89 interruptions per year per customer, representing a 86% improvement. This substantial decline indicates a significant reduction in the number of outages, providing customers with a more stable power supply. Similarly, the SAIDI value dropped to 104.40 hours per year per customer, a 87% reduction in the average outage duration. These results demonstrate the effectiveness of DG in mitigating both the frequency and duration of interruptions.

The graph clearly illustrates the stark contrast between the initial and optimized values of SAIFI and SAIDI. The towering bars for initial values emphasize the magnitude of the reliability issues before optimization, while the substantially shorter bars for the optimized values highlight the dramatic improvements achieved. This visual representation underscores the importance of advanced optimization techniques such as WOA in addressing reliability challenges.

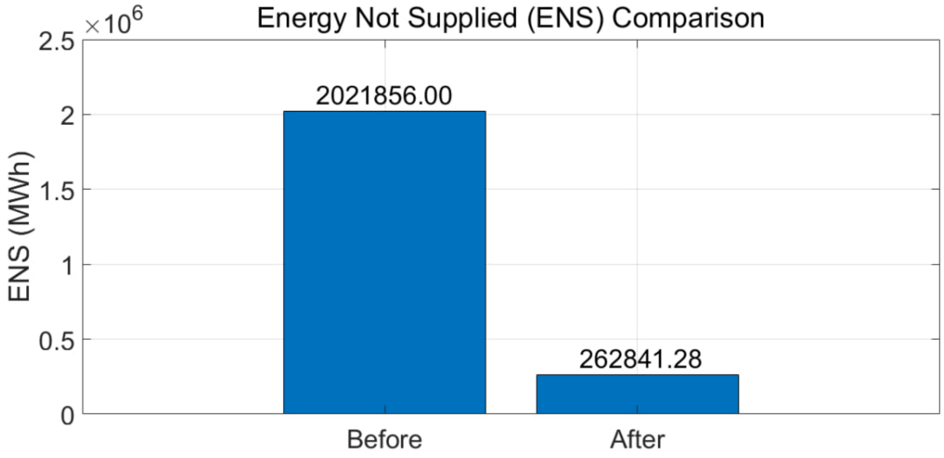


Figure 4.3: ENS comparison before and after WOA optimization

The bar chart above illustrates a comparison of ENS values, measured in kWh/year, for the initial and optimized scenarios of the network. The dramatic reduction in ENS after optimization highlights the effectiveness of the implemented measures in enhancing the network's reliability.

In the initial state, ENS is approximately 2,021,856 kWh/year, reflecting significant energy losses due to frequent outages and inadequate network performance. This high value underscores the need for urgent interventions to improve the distribution network and minimize energy wastage.

After optimization, ENS drops substantially to approximately 262,841.28 kWh/year, representing a reduction of over 87%. This improvement is primarily attributed to the optimal placement and sizing of DG, which enhances energy availability and reduces the frequency and duration of outages. Such a significant reduction in ENS not only benefits consumers through improved service reliability but also supports the utility by increasing energy sales and operational efficiency.

Table 4. 3: Percentage improvement of reliability indices.

Condition	SAIFI (Int./Year/Customer)	SAIDI (Hr./Year/Customer)	ENS (KWh/year)	SAIFI_Improvement(%)	SAIDI_Improvement(%)	ENS_Improvement (%)
Initial values	363.5	803.14	2021856	0	0	0
Optimized values	50.89	104.40	262841.28	86	87	87

The above table compares the initial and optimized values of key reliability indices—SAIFI, SAIDI, and ENS—showing the significant impact of system optimization. Initially, the SAIFI value was 363.5 interruptions per customer per year, which dropped by 86% to 50.89 after optimization, indicating fewer interruptions. The SAIDI, initially 803.14 hours per customer per year, reduced by 87% to 104.40 hours, reflecting shorter durations of interruptions. Similarly, the ENS decreased by 87%, from 2,021,856 kWh to 262841.28 kWh, signifying less energy lost during interruptions. Overall, the optimization, likely involving Distributed Generation placement, dramatically improved the system's reliability, efficiency, and energy conservation.

4.4 Reliability Improvement Comparison of WOA with GA

The effectiveness of the WOA is compared to that of the GA in improving the reliability indices of the K9 feeder. Both algorithms were employed to determine the optimal placement of DG, but significant differences were observed in their impacts on reliability measures specifically SAIFI and SAIDI. The results will be examined to highlight the advantages of the WOA approach in mitigating power interruptions and enhancing system reliability.

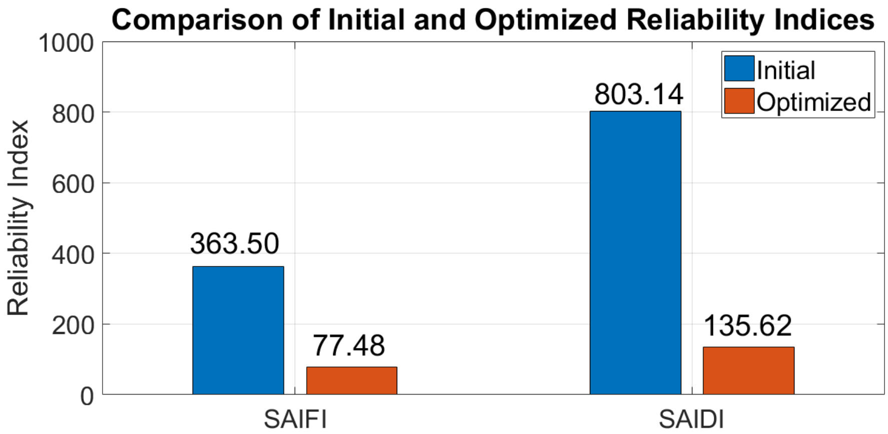


Figure 4.4: reliability indices comparison before and after GA optimization

The above graph illustrates the improvements in the reliability indices, SAIFI and SAIDI, for the K9 feeder following the optimal placement DG using GA. Initially, the K9 feeder faced significant challenges, as indicated by a high pre-optimization SAIFI value of 363.50 interruptions per year per customer and an initial SAIDI value of 803.14 hours per year per customer. These figures reflect frequent and prolonged power interruptions, underscoring the need for intervention to enhance system reliability.

After optimization, the reliability indices showed substantial improvements, with an optimal DG size of 1500.00 kW located at Bus 18. The final SAIFI value was recorded at 77.48 interruptions per year per customer, reflecting a significant improvement of 78.68%. Similarly, the final SAIDI value improved to 135.62 hours per year per customer, indicating an improvement of 83.11%. These enhancements suggest that the optimization process effectively addressed the reliability issues faced by the K9 feeder.

Table 4. 4: Percentage improvement of reliability indices.

Algorithms	Optimal DG size (KW)	Optimal DG location	Final SAIFI (Int./Year/Customer)	Final SAIDI (Hr./Year/Customer)	SAIFI_ Improvement (%)	SAIDI_ Improvement (%)
GA	1500	Bus 18	77.48	135.62	78.68	83.11
WOA	3200	Bus 22	50.98	104.40	86	87

The comparison between WOA and GA reveals significant differences in their effectiveness in improving the reliability indices of the K9 feeder. As shown in Table 4.4, the WOA approach resulted in a final SAIFI value of 50.89 interruptions per year per customer, reflecting a 86% improvement from the initial value. In contrast, the GA approach achieved a final SAIFI value of 77.48 interruptions per year per customer, representing a 78.68% improvement. Similarly, the final SAIDI value with WOA was 104.40 hours per year per customer, marking a 87% reduction, compared to 135.62 hours per year per customer with GA, which is an 83.11% improvement. These results clearly demonstrate that WOA is more effective than GA in mitigating both the frequency and duration of power interruptions, thereby enhancing the reliability of the K9 feeder.

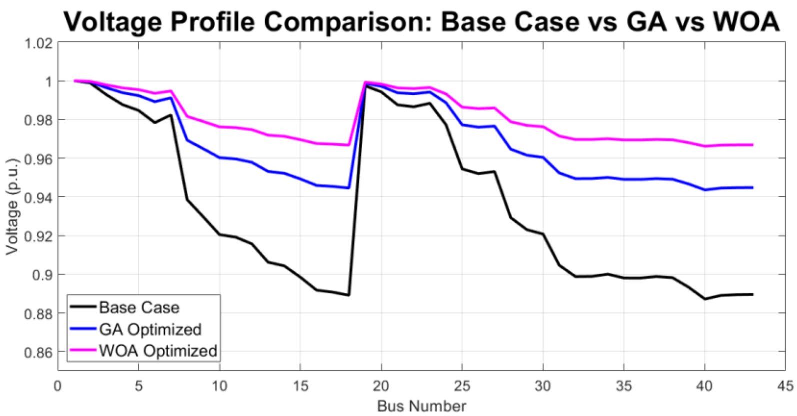


Figure 4. 5 Voltage profile comparison in base case and optimal DG location.

The figure illustrates the voltage profile comparison across the 43-bus radial feeder under three different scenarios: the base case without DG, DG placement optimized using GA, and DG placement optimized using WOA. The voltage magnitude at each bus is plotted in per-unit (p.u.), with the standard acceptable range to ensure proper operation of electrical equipment and maintain power quality.

In the base case scenario, represented by the black curve, the voltage progressively declines as the distance from the substation increases. This is a result of cumulative voltage drops due to line impedance and increasing load along the feeder. The voltage levels at several buses fall significantly below the lower limit of 0.95 p.u., with some dropping close to 0.86 p.u. This results in voltage levels falling below the acceptable threshold, thereby violating standard voltage constraints and indicating that the feeder, in its base case configuration, fails to maintain adequate voltage regulation throughout the system.

When DG is integrated based on GA, as shown by the blue curve, the voltage profile improves considerably. The presence of the DG helps support the voltage, especially at buses further from the substation. Despite the noticeable improvement, a few bus voltages still remain slightly below 0.95 p.u., which means that the GA-optimized DG placement does not fully ensure voltage constraint compliance across all buses.

In contrast, the WOA optimized DG placement, depicted by the magenta curve, shows the most favorable voltage profile. The voltage levels across the feeder are significantly elevated and consistently remain within the acceptable range. This indicates that the WOA based optimization effectively identifies the optimal size and location of DG to provide maximum voltage support, ensuring that all buses comply with standard voltage regulation constraints.

Overall, the power flow results demonstrate that the base case feeder configuration without DG leads to voltage constraint violations. Optimization algorithms, particularly WOA, substantially enhance voltage profiles, ensuring compliance with acceptable limits and improving system stability, efficiency, and reliability.

4.6 Cost Benefit Analysis

The cost benefit analysis of optimal DG placement and sizing demonstrates significant advantages for both consumers and the EEU. With the upcoming incremental electricity tariff changes, set to begin on September 11, 2024, under the International Monetary Fund (IMF) program, the benefits of these improvements become even more critical [54].

The integration of DG systems in Bishoftu city has led to substantial improvements in power supply reliability, with significant benefits for both consumers and the utility. The optimized placement of DG units has resulted in a remarkable 87% reduction in ENS, which translates to 1,759,014.72 kWh annually.

Payback Time Calculation

The payback time was calculated to determine the economic viability of installing a solar PV based DG system for improving the reliability of the distribution feeder. This calculation considers the savings achieved due to the reduction in ENS and the incremental tariff rates for electricity over time. The following steps outline the calculation process:

Assumptions

1. ENS Reduction:

The ENS reduction, which represents the difference between the initial and the improved ENS due to DG installation, is 1,759,014.72 kWh annually.

2. Electricity Tariff Rates:

Based on the quarterly tariff increments in Ethiopia, the tariff rates are assumed to increase as follows:

Year 1: 2.57 Birr/kWh

Year 2: 3.72 Birr/kWh

Year 3: 4.76 Birr/kWh

Year 4 and beyond: 5.81 Birr/kWh

4. Total System Cost:

The cost estimates for the solar PV system components were obtained through direct consultations with Green Scene Energy, a reputable local solar product supplier, as well as other local markets specializing in solar energy systems. The following breakdown provides a detailed cost analysis:

- Solar PV system including wiring and combiner box: 98,000 Birr.
- A single three phase 25kW inverter charger including is 20,000$ this system needs 40 pieces, so the total is 100,800,000 Birr.
- The cost for 2900Ah 2V @C10 LA Gel Battery including wiring and battery rack is 179,505 Birr.

The total cost of the solar PV system, including PV panels, inverters, batteries, installation, and other components, is 101,077,505 Birr.

4. Constant ENS Reduction:

The ENS reduction is assumed to remain constant over the system's lifetime.

5. System Lifespan:

The system is expected to have a lifespan of 25 years, as per the specifications of the PV modules and inverters.

Step 1: Calculate Annual Savings

The annual savings are calculated as the product of the ENS reduction and the corresponding electricity tariff for each year.

For years with incremental tariffs:

$$\text{Annual Savings (Year i)} = \text{ENS Reduction (kWh)} \times \text{Tariff Rate (Birr/kWh)} \quad (4.4)$$

Annual Savings (Year i) = ENS Reduction (kWh) × Tariff Rate (Birr/kWh)

Year 1:

Savings = 1,759,014.72 kWh × 2.57 Birr/kWh= 4,837,291 Birr.

Year 2:

Savings= 1,759,014.72 kWh × 3.72 Birr/kWh = 6,543,535 Birr.

Year 3:

Savings = 1,759,014.72 kWh × 4.76 Birr/kWh = 8,372,910 Birr.

Year 4 and beyond:

Savings = 1,759,014.72 kWh × 5.81 Birr/kWh = 10,219,876 Birr.

Step 2: Total Savings Over 25 Years

To calculate the total savings over the system's lifetime, the annual savings for each year are summed up.

$$\text{Total Savings} = \sum_{i=1}^{25} \text{Annual Savings (Year i)} \qquad (4.5)$$

For the first three years, the savings are calculated individually based on the incremental tariff rates, while for the remaining 22 years, the savings are constant at the Year 4 rate.

Total Savings = Savings (Year 1) + Savings (Year 2) + Savings (Year 3) + 22 × Savings (Year 4).

Substituting the values:

Total Savings = 4,997,144.47 + 7,233,784.75 + 9,252,574.24 + (22 × 11,294,760.37).

= 269,968,231.6 Birr.

Step 3: Calculate Payback Time

The payback time is determined by dividing the total system cost by the annual savings in the year where the breakeven point is reached.

$$\text{Payback Time} = \frac{\text{Total System Cost}}{\text{Annual Savings in the Payback Year}} \qquad (4.6)$$

Using the system cost of 101,077,505 Birr:

For Year 1: Cumulative savings = 4,837,291 Birr.

For Year 2: Cumulative savings = 4,837,291 + 6,543,535 = 11,380,826 Birr.

For Year 3: Cumulative savings = 11,380,826 + 8,372,910 = 19,753,736 Birr.

For Year 4: Cumulative savings = 19,753,736 + 10,219,876 = 29,973,612 Birr, and so on.

The year in which the cumulative savings exceed the total system cost is the payback year.

The payback time provides a clear indication of the system's economic feasibility. In this case, it will take approximately 10 years for the savings from ENS reduction to cover the investment cost. Any additional savings beyond this point contribute to the financial benefits of the system.

A 10-year payback period is widely recognized as favorable for solar energy investments, as evidenced by studies in [65, 66, 67, 68], confirming the financial feasibility of the proposed project.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATIONS

5.1. Conclusion

This study has successfully addressed the reliability challenges faced by Bishoftu Substation 2 of Feeder K9 by applying optimization techniques to improve the feeder's performance. Through the implementation of the WOA, the research has identified the optimal placement and sizing of DG units, resulting in significant improvements in key reliability indices.

The K9 feeder initially faced severe reliability challenges, with a SAIFI of 363.5 and a SAIDI of 803.14, far exceeding Ethiopia's standards of 20 and 25, respectively. By integrating optimally placed DG units, SAIFI was reduced by 86% to 50.89, and SAIDI by 87% to 104.40. ENS also decreased by 87%, significantly improving energy reliability and availability for customers.

The optimal DG size was determined to be 1.32 MW, with the most effective location identified as Bus 22. This configuration not only enhances the reliability of the feeder but also ensures compatibility with the network's load distribution and operational constraints.

The findings from this study underscore the potential of DG units in improving the performance of distribution networks, particularly in regions where reliability issues are prevalent. The results highlight the importance of employing optimization algorithms like WOA to address the challenges of power distribution in Ethiopia and similar developing regions, ensuring more reliable, efficient, and sustainable energy systems.

In conclusion, this research provides valuable insights into the effectiveness of DG placement and sizing for reliability improvement, offering a practical approach for optimizing the performance of power distribution systems in Ethiopia. Further research in this area will help refine the optimization methods and integrate additional technologies to enhance the overall reliability and sustainability of the national grid.

5.2 Recommendations

First and foremost, it is important to express sincere appreciation for the efforts and dedication of the EEP and Ethiopian Electric Utility EEU staff in their continuous work to improve the reliability and efficiency of the country's power distribution systems. Their commitment to advancing the infrastructure and enhancing the customer experience is commendable.

Based on the findings from this study, several recommendations are made to further optimize the performance of Bishoftu Substation 2 of Feeder K9 and similar distribution networks:

1. Upgrade Aging Infrastructure and Improve Maintenance Practices

The aging infrastructure of the K9 feeder is a major contributor to its poor reliability. It is recommended that EEU invest in upgrading outdated equipment, such as transformers, distribution lines, and switchgear, to reduce failure rates and improve system performance. Regular maintenance schedules should also be implemented to prevent prolonged downtime and ensure the longevity of the infrastructure.

2. Implement Load-Side Management Solutions

Overloading due to rapid urbanization and increasing electricity demand is a critical issue affecting the K9 feeder. The EEU should implement load-side management strategies, such as demand-side management (DSM) programs, to balance supply and demand. This could include incentivizing customers to shift their energy usage during peak hours or promoting energy-efficient appliances to reduce overall load stress on the network.

By implementing these recommendations, the reliability of the distribution network can be further improved, supporting the objectives of this thesis to create a resilient and efficient power system.

5.3. Future Works

This study has optimized the reliability of Bishoftu Substation 2 of Feeder K9, but future research could enhance its scope and sustainability. Key areas include integrating energy storage and automated fault detection for improved reliability, assessing renewable energy's impact on stability and hydro dependency, and conducting long term evaluations of system performance. Expanding the methodology to other feeders and substations, comparing optimization algorithms, and assessing the environmental benefits of DG units could further advance power distribution systems. These efforts aim to improve reliability and deliver sustainable energy solutions for Ethiopia and similar regions.

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APPENDIX A

Average monthly interruption duration and frequency of each feeder

Month	Outage in number	Feeder Name											
		K1	K2	K6	K7	K8	K9	K12	K13	K14	K15	L1	L2
Jan	Freq	0	0	3	20	56	24	2	0	0	24	0	1
	Dur(Hr)	0	0	25.75	42.36	47.61	12.66	1.4	0	0	39.58	0	0.5
Feb	Freq	2	2	2	26	55	83	5	1	0	33	1	2
	Dur(Hr)	0.5	0.5	0.7	59.8	90.27	134	24.2	0.43	0	25.19	0.38	25.78
Mar	Freq	17	17	7	43	59	33	1	0	61	44	5	4
	Dur(Hr)	56.4	56.4	51.81	165.96	97.5	80.32	7.42	0	102.77	63.49	23.03	15.05
Apr	Freq	0	0	3	46	51	21	0	0	66	36	3	1
	Dur(Hr)	0	0	29.38	106.03	65.82	71.75	0	0	69.83	59.45	2.32	1.45
May	Freq	3	2	1	19	28	12	2	2	30	9	0	1
	Dur(Hr)	6.77	4.1	3	353.14	55.55	63.21	1.52	1.52	117.8	56.41	0	6.05
Jun	Freq	1	1	0	35	61	23	1	0	53	32	5	5
	Dur(Hr)	11.63	11.63	0	173.98	114.3	130.92	1.17	0	92.83	59.2	40.5	31.87
Jul	Freq	1	1	1	35	47	24	2	3	56	32	1	2
	Dur(Hr)	0.62	0.62	0.62	82.33	76.14	66.18	5.48	3.13	106.89	74.69	3	6.2
Aug	Freq	3	3	1	29	59	63	5	2	0	39	1	1
	Dur(Hr)	12.93	12.93	0.92	68.53	135.74	73.6	39.84	1.45	0	107.21	0.1	6.92
Sep	Freq	0	1	0	42	53	90	1	0	0	24	1	0

	Dur(Hr)	0	1.18	0	73.13	111.2	71.9	1.63	0	0	13.94	0.65	0
Oct	Freq	1	1	1	33	49	51	2	1	0	24	0	1
	Dur(Hr)	0.57	0.57	0.57	60.81	92.87	40.03	7.57	0.57	0	15.72	0	8.3
Nov	Freq	0	0	3	20	56	24	2	0	0	24	0	1
	Dur(Hr)	0	0	25.75	42.36	47.61	12.66	1.4	0	0	39	0	0.5
Dec	Freq	2	2	3	27	35	37	4	3	0	21	1	1
	Dur(Hr)	3.46	3.46	3.78	39.08	38.43	8.71	4.45	0.78	0	13.23	0.38	0.38
Tot	Freq	30	30	25	375	609	485	27	12	266	342	18	20
	Dur(Hr)	92.88	91.39	142.28	1267.51	973	765.94	96.08	7.88	490.12	567.11	70.36	103

APPENDIX B

Average Frequency of Different Types of Faults.

No	Fault / Feeder	DPEF		DTEF		DPSC		DTSC		DOP	
		Aveg. Freq	Aveg. Freq %	Aveg .Freq	Aveg. Freq %	Aveg .Freq	Aveg. Freq %	Aveg .Freq	Aveg. Freq %	Aveg. Freq	Aveg. Freq %
1	k1	2	13.33	4.5	30	1	6.67	1	6.67	6.5	43.33
2	k2	3	18.75	4.5	28.12	1	6.25	1.5	9.38	6	37.5
3	k6	0.5	3.23	1.5	9.68	2	12.9	0.5	3.23	11	70.97
4	k7	30.5	10.83	45	15.99	83.5	29.66	47.5	16.87	75	26.64
5	k8	47	10.22	70	15.22	95.5	20.76	53.5	11.63	194	42.17
6	k9	37	11.4	59.5	18.34	44.5	13.71	44.5	13.71	139	42.84
7	k12	2.5	4.9	0.5	0.98	5	9.8	3.5	6.86	39.5	77.45
8	k13	1	11.11	0	0	0	0	0.5	5.56	7.5	83.33
9	k14	17	7.42	26	11.35	62	27.07	40	17.47	84	36.68
10	k15	13	5.34	16.5	6.78	42.5	17.45	36	14.78	135.5	55.65
11	L1	1	11.11	1	11.11	4	44.44	0.5	5.56	2.5	27.78
12	L2	0	0	0.5	2.04	10.5	42.86	2	8.16	11.5	46.94
13	System	154.5	9.2	229.5	13.67	351.5	20.94	231	13.76	712	42.42

APPENDIX C

ሰንጠረዥ ሀ1. የፀደቀ የቀረበ የችርቻሮ ኢነርጂ ታሪፍ እና አተገባበር

ተ.ቁ	ኢነርጂ ታሪፍ	መለኪያ	በስራ ላይ ያለው ታሪፍ	2024/25				2025/26				2026/27				2027/28			
				ሩብ አመት				ሩብ አመት				ሩብ አመት				ሩብ አመት			
				1ኛ (3ኛ ወር)	2ኛ	3ኛ	4ኛ	1ኛ	2ኛ	3ኛ	4ኛ	1ኛ	2ኛ	3ኛ	4ኛ	1ኛ	2ኛ	3ኛ	4ኛ
1	የመኖሪያ ቤት																		
1.1	0 — 50 ኪ.ዋ.ሰ	ብር /ኪ.ዋ.ሰ	0.27	0.35	0.43	0.52	0.60	0.68	0.76	0.84	0.92	1.00	1.08	1.16	1.24	1.32	1.40	1.48	1.56
1.2	51 — 100 ኪ.ዋ.ሰ	ብር /ኪ.ዋ.ሰ	0.77	0.95	1.13	1.31	1.49	1.67	1.85	2.03	2.21	2.39	2.57	2.76	2.94	3.12	3.30	3.48	3.66
1.3	101 — 200 ኪ.ዋ.ሰ	ብር /ኪ.ዋ.ሰ	1.63	1.89	2.15	2.41	2.67	2.93	3.19	3.45	3.72	3.98	4.24	4.50	4.76	5.02	5.28	5.55	5.81
1.4	201 — 300 ኪ.ዋ.ሰ	ብር /ኪ.ዋ.ሰ	2.00	2.46	2.92	3.38	3.84	4.30	4.76	5.22	5.68	6.14	6.60	7.06	7.52	7.98	8.44	8.89	9.35
1.5	301 — 400 ኪ.ዋ.ሰ	ብር /ኪ.ዋ.ሰ	2.20	2.66	3.12	3.57	4.03	4.49	4.95	5.41	5.86	6.32	6.78	7.24	7.70	8.15	8.61	9.07	9.53
1.6	401 — 500 ኪ.ዋ.ሰ	ብር /ኪ.ዋ.ሰ	2.41	2.85	3.29	3.73	4.17	4.62	5.06	5.50	5.94	6.39	6.83	7.27	7.71	8.16	8.60	9.04	9.48
1.7	ከ500 ኪ.ዋ.ሰ በላይ	ብር /ኪ.ዋ.ሰ	2.48	2.92	3.35	3.79	4.23	4.66	5.10	5.54	5.97	6.41	6.84	7.28	7.72	8.15	8.59	9.03	9.46
2	የንግድ (አጠቃላይ)	ብር /ኪ.ዋ.ሰ	2.12	2.61	3.09	3.57	4.05	4.53	5.01	5.50	5.98	6.46	6.94	7.42	7.90	8.39	8.87	9.35	9.83

3	አነስተኛ ኢንደስትሪ	ብር /ኪ.ዋ.ሰ	1.53	1.76	2.02	2.29	2.56	2.82	3.09	3.36	3.62	3.88	4.15	4.41	4.68	4.93	5.20	5.46	5.73
4	መካከለኛ ኢንደስትሪ	ብር /ኪ.ዋ.ሰ	1.19	1.39	1.61	1.83	2.05	2.27	2.49	2.71	2.94	3.16	3.38	3.60	3.82	4.04	4.26	4.48	4.70
5	የመንገድ መብራት	ብር /ኪ.ዋ.ሰ	2.12	0.35	0.43	0.52	0.60	0.68	0.76	0.84	0.92	1.00	1.08	1.16	1.24	1.32	1.40	1.48	1.56

ሰንጠረዥ ሀ2. እንዲጸድቅ የቀረበ የቻርቻር_የአገልግሎት ታሪፍ

ተ.ቁ	አገልግሎት ታሪፍ	መለኪያ	በስራ ላይ ያለው ታሪፍ	2024/25				2025/26				2026/27				2027/28			
				ሩብ አመት				ሩብ አመት				ሩብ አመት				ሩብ አመት			
				1ኛ (3ኛ ወር)	2ኛ	3ኛ	4ኛ	1ኛ (3ኛ ወር)	2ኛ	3ኛ	4ኛ	1ኛ (3ኛ ወር)	2ኛ	3ኛ	4ኛ	1ኛ (3ኛ ወር)	2ኛ	3ኛ	4ኛ
9	የመኖሪያ ቤት	ብር /#																	
9.1	ድህረ ክፍያ	ብር /#																	
9.1.1	እስከ 50 ኪ.ዋሰ	ብር /#	10.00	10.24	10.47	10.71	10.95	11.19	11.42	11.66	11.90	12.14	12.37	12.61	12.85	13.08	13.32	13.56	13.80
9.1.2	ከ 50 ኪ.ዋሰ በላይ	ብር /#	42.00	42.95	43.90	44.85	45.80	46.75	47.70	48.65	49.60	50.55	51.50	52.45	53.40	54.35	55.30	56.25	57.20
9.2	ቅድመ ክፍያ	ብር /#	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
9.2.1	እስከ 50 ኪ.ዋሰ	ብር /#	3.50	3.67	3.84	4.01	4.18	4.36	4.53	4.70	4.87	5.04	5.21	5.38	5.55	5.72	5.89	6.07	6.24
9.2.2	ከ 50 ኪ.ዋሰ በላይ	ብር /#	14.70	15.02													19.13	19.45	19.77
					15.33	15.65	15.97	16.28	16.60	16.92	17.23	17.55	17.87	18.18	18.50	18.82			
10	የንግድ (አጠቃላይ)	ብር /#	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
10.1	ድህረ ክፍያ	ብር /#	54.00	55.19	56.38	57.57	58.75	59.94	61.13	62.32	63.51	64.70	65.89	67.07	68.26	69.45	70.64	71.83	73.02
10.2	ቅድመ ክፍያ	ብር /#	18.90	19.31	19.71	20.12	20.53	20.94	21.34	21.75	22.16	22.57	22.97	23.38	23.79	24.19	24.60	25.01	25.42
11	አነስተኛ ኢንደስትሪ	ብር /#	54.00	55.19	56.38	57.57	58.75	59.94	61.13	62.32	63.51	64.70	65.89	67.07	68.26	69.45	70.64	71.83	73.02
12	መካከለኛ ኢንደስትሪ	ብር /#	54.00	55.19	56.38	57.57	58.75	59.94	61.13	62.32	63.51	64.70	65.89	67.07	68.26	69.45	70.64	71.83	73.02
13	የመንገድ መብራት	ብር /#	54.00	55.19	56.38	57.57	58.75	59.94	61.13	62.32	63.51	64.70	65.89	67.07	68.26	69.45	70.64	71.83	73.02

Figure 15: EEU tariff

APPENDIX D

Matlab code for optimal DG sizing and placement using WOA

```
% Read Line Data From Excel

filename= 'line_data.xlsx'% Excel data containing line data

line_data = readmatrix(filename)% Load data from excel

load_demand = [152.38, 304.76, 457.14, 609.52, 761.90, 914.28]; % Load at each bus in kW

total_customers = 5141; % Total number of customers on the feeder

% System Parameters

base_voltage = 15; % Base voltage in kV

line_impedance = line_data(:, 3) + 1j * line_data(:, 4); % R + jX

num_buses = size(line_data, 1) + 1;

% WOA Parameters

num_whales = 30; % Population size

max_iterations = 100;

dim = 2; % [DG size, DG location]

lb = [365, 2]; % Lower bounds: min DG size, min bus location

ub = [1095, num_buses]; % Upper bounds: max DG size, max bus location

% Objective Function

objective = @(x) objective_function(x, line_data, load_demand, total_customers, base_voltage,
line_impedance);

% Run WOA

[best_solution, best_score, convergence_curve] = whale_optimization(objective, num_whales,
max_iterations, lb, ub);


% Display Results

fprintf('        Initial Reliability Indices        \n');

[initial_SAIFI, initial_SAIDI, initial_ENS, initial_losses] = calculate_reliability(line_data,
load_demand, total_customers, base_voltage, line_impedance, 0, 0);
```

```
fprintf('SAIFI: %.4f, SAIDI: %.4f, ENS: %.4f, Losses: %.4f kW\n', initial_SAIFI, initial_SAIDI,
initial_ENS, initial_losses);

fprintf('\n        Optimized Results        \n');

[optimized_SAIFI, optimized_SAIDI, optimized_ENS, optimized_losses] =
calculate_reliability(line_data, load_demand, total_customers, base_voltage, line_impedance,
best_solution(1), round(best_solution(2)));

fprintf('Best DG Size: %.2f kW\n', best_solution(1));

fprintf('Best DG Location: Bus %.0f\n', round(best_solution(2)));

fprintf('SAIFI: %.4f, SAIDI: %.4f, ENS: %.4f, Losses: %.4f kW\n', optimized_SAIFI,
optimized_SAIDI, optimized_ENS, optimized_losses);

% Plot Convergence Curve

figure;

plot(convergence_curve, ' o');

xlabel('Iterations');

ylabel('Objective Value');

title('WOA Convergence Curve');

grid on;

% Reliability Function

function [SAIFI, SAIDI, ENS, total_losses] = calculate_reliability(line_data, load_demand,
total_customers, base_voltage, line_impedance, DG_size, DG_location)

    SAIFI = 0; SAIDI = 0; ENS = 0; total_losses = 0;

    bus_voltage = ones(size(load_demand)); % Initialize voltage profile

    for i = 1:size(line_data, 1)

        lambda = line_data(i, 6); % Failure rate

        repair_time = line_data(i, 7); % Repair time

        bus = line_data(i, 2); % To Bus

        load = load_demand(bus); % Load at this bus

        % DG Contribution

        if bus == DG_location

            fraction_supplied = min(1, DG_size / load); % DG Supply Ratio

        else
```

```
            fraction_supplied = 0;
        end
        % Adjust failure rate based on DG contribution
        lambda_adjusted = lambda * (1    fraction_supplied);
        % Update reliability indices
        SAIFI = SAIFI + lambda_adjusted / total_customers;
        SAIDI = SAIDI + (lambda_adjusted * repair_time) / total_customers;
        ENS = ENS + lambda_adjusted * repair_time * load;
        % Compute power losses and voltage profile
        current = load / base_voltage;
        total_losses = total_losses + abs(current)^2 * real(line_impedance(i));
        bus_voltage(bus) = bus_voltage(bus    1)    abs(current) * abs(line_impedance(i));
    end
end
% Objective Function Definition
function obj = objective_function(x, line_data, load_demand, total_customers, base_voltage,
line_impedance)
    DG_size = x(1);
    DG_location = round(x(2)); % Ensure DG location is an integer
    [SAIFI, SAIDI, ENS, total_losses] = calculate_reliability(line_data, load_demand,
total_customers, base_voltage, line_impedance, DG_size, DG_location);
    obj = SAIFI + SAIDI + ENS + 0.01 * total_losses; % Adjust weights as necessary
end
% Whale Optimization Algorithm (WOA)
function [best_solution, best_score, convergence_curve] = whale_optimization(obj, num_whales,
max_iterations, lb, ub)
    dim = length(lb); % Number of dimensions
    whales = rand(num_whales, dim) .* (ub    lb) + lb; % Initialize population
    fitness = arrayfun(@(idx) obj(whales(idx, :)), 1:num_whales); % Evaluate fitness for all whales
    [best_score, best_idx] = min(fitness); % Identify best solution
```

```
best_solution = whales(best_idx, :);
convergence_curve = zeros(1, max_iterations); % Track convergence
convergence_curve(1) = best_score;
% Main WOA loop
for t = 2:max_iterations
    a = 2    t * (2 / max_iterations); % Linearly decrease a from 2 to 0
    for i = 1:num_whales
        r = rand(); % Random number [0,1]
        p = rand(); % Probability to choose exploration or exploitation
        if p < 0.5
            % Exploitation phase
            A = 2 * a * r    a; % Compute A
            C = 2 * r; % Compute C
            D = abs(C * best_solution    whales(i, :)); % Distance to prey
            whales(i, :) = best_solution    A * D; % Update position
        else
            % Exploration phase
            rand_whale = whales(randi(num_whales), :); % Random whale position
            D = abs(rand_whale    whales(i, :)); % Distance to random whale
            whales(i, :) = rand_whale    a * D; % Update position
        end
        % Enforce boundary constraints
        whales(i, :) = max(lb, min(whales(i, :), ub));
    end
    % Update fitness and best solution
    fitness = arrayfun(@(idx) obj(whales(idx, :)), 1:num_whales); % Recalculate fitness
    [current_best_score, current_best_idx] = min(fitness);
    if current_best_score < best_score
        best_score = current_best_score;
```

```
        best_solution = whales(current_best_idx, :);
    end
    convergence_curve(t) = best_score; % Track convergence
  end
End
```

APPENDIX E

Matlab code for optimal DG sizing and placement using GA

```
%% Importing data from Excel file
filename = 'line_data.xlsx';    % My input file
data = readtable(filename);
% Extract system parameters
num_buses = data.num_buses(1);
line_length = data.line_length(1); % km
failure_rate = data.failure_rate(1); % failures/km/year
repair_rate = data.repair_rate(1); % repairs/hour
total_customers = data.total_customers(1);
total_load = data.total_load(1); % kW
initial_SAIFI = data.initial_SAIFI(1); % interruptions/year/customer
initial_SAIDI = data.initial_SAIDI(1); % hours/year/customer
% Load demand per bus
load_demand = data.load_demand'; % Read as column vector
% DG constraints from Excel
DG_min = data.DG_min(1);
DG_max = data.DG_max(1);
bus_min = data.bus_min(1);
bus_max = num_buses;
%% Defining optimization variables
lb = [DG_min, bus_min];
ub = [DG_max, bus_max];
% Initial guess
x0 = [(DG_min + DG_max) / 2, (bus_min + bus_max) / 2];
%% Defining the objective function
objective_function = @(x) SAIDI_SAIFI_Sum(x(1), round(x(2)), load_demand, initial_SAIFI,
initial_SAIDI);
% Optimization options
options = optimoptions('fmincon', 'Display', 'iter', 'Algorithm', 'sqp');
%% Running the optimization
```

```
[optimal_solution, ~] = fmincon(objective_function, x0, [], [], [], [], lb, ub, [], options);

% Extracting optimal DG size and location

optimal_DG_size = optimal_solution(1);

optimal_bus_location = round(optimal_solution(2));

%% Computing final SAIFI and SAIDI after DG placement

[final_SAIFI, final_SAIDI] = compute_SAIDI_SAIFI(optimal_DG_size, optimal_bus_location,
load_demand, initial_SAIFI, initial_SAIDI);

% Calculating percentage improvement

SAIFI_improvement = ((initial_SAIFI     final_SAIFI) / initial_SAIFI) * 100;

SAIDI_improvement = ((initial_SAIDI     final_SAIDI) / initial_SAIDI) * 100;

%% Displaying results

fprintf('Optimal DG Size: %.2f kW\n', optimal_DG_size);

fprintf('Optimal DG Location: Bus %d\n', optimal_bus_location);

fprintf('Final SAIFI: %.2f interruptions/year/customer\n', final_SAIFI);

fprintf('Final SAIDI: %.2f hours/year/customer\n', final_SAIDI);

fprintf('SAIFI Improvement: %.2f%%\n', SAIFI_improvement);

fprintf('SAIDI Improvement: %.2f%%\n', SAIDI_improvement);

%% Plotting comparison of SAIFI and SAIDI

figure;

bar([initial_SAIFI, final_SAIFI; initial_SAIDI, final_SAIDI]);

set(gca, 'XTickLabel', {'SAIFI', 'SAIDI'});

ylabel('Reliability Index');

legend('Initial', 'Optimized');

title('Comparison of Initial and Optimized Reliability Indices');

grid on;

%% Function to compute SAIFI and SAIDI

function [new_SAIFI, new_SAIDI] = compute_SAIDI_SAIFI(DG_size, bus_location, load_demand,
SAIFI, SAIDI)

    % Calculate DG contribution based on its size and location

    DG_contribution = DG_size / load_demand(bus_location);
```

```
    % SAIFI and SAIDI have different improvement factors
    new_SAIFI = SAIFI / (1 + DG_contribution * 0.85);
    new_SAIDI = SAIDI / (1 + DG_contribution * 0.87);
end
%% Objective function: minimize the combined index of SAIFI and SAIDI
function index = SAIDI_SAIFI_Sum(DG_size, bus_location, load_demand, SAIFI, SAIDI)
    [new_SAIFI, new_SAIDI] = compute_SAIDI_SAIFI(DG_size, bus_location, load_demand,
SAIFI, SAIDI);
    index = new_SAIFI + new_SAIDI;    % Goal is to minimize their sum
end
```

APPENDIX F

Code snippet for sensitivity analysis.

```
% Define system parameters
buses = [4, 6, 8]; % Buses to test
failure_rates = [60, 73.16, 85]; % Failure rates
repair_rates = [0.4, 0.529, 0.7]; % Repair rates
% Store results
results = [];
% Loop through parameter variations
for i = 1:length(buses)
    for j = 1:length(failure_rates)
        for k = 1:length(repair_rates)
            % Set current parameters
            bus = buses(i);
            lambda = failure_rates(j);
            mu = repair_rates(k);
            % Call the WOA based optimization function
            [optimalBus, optimalDGSize, newSAIFI, newSAIDI] =
WOA_DG_Optimization(bus, lambda, mu);
            % Store the results
            results = [results; bus, lambda, mu, optimalBus, optimalDGSize, newSAIFI,
newSAIDI];
            % Debugging: Print iteration results to check updates
            fprintf('Bus: %d | Failure Rate: %.2f | Repair Rate: %.3f | Optimal Bus: %d |
DG Size: %.3f MW | SAIFI: %.3f | SAIDI: %.3f\n', ...
                bus, lambda, mu, optimalBus, optimalDGSize, newSAIFI, newSAIDI);
        end
```

```
    end
end
% Display results in table format
fprintf('\nSensitivity Analysis Results:\n');
fprintf(' Buses | Failure Rate | Repair Rate | Optimal Bus | DG Size (MW) | New SAIFI | New SAIDI\n');
disp(results);
```

APPENDIX G

Feeder k9 MATLAB Simulink model for power flow analysis