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Application of meta-heuristic algorithms to reconfigure radial distribution system for optimal cost and reliability

by:
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CERTIFICATE OF APPROVAL

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Abstract

This research focuses on the application of Metaheuristic algorithms in the field of power system optimization. The specific problem used to demonstrate that is the reconfiguration of the radial distribution system in terms of reliability and system loss. The primary goal of this work is to analyze the performance of multiple metaheuristic algorithms in reconfiguring radial distribution systems. While all algorithms offer the solution to the problem, different algorithms favor different kinds of optimization problems and can find solutions faster and slower than others. GA, PSO, CSO, and GWO are considered for comparison.

The problem formulated is to optimize the radial distribution system while maintaining strict radiality for maximum reliability and minimum system loss. For this, a new approach is suggested where reliability indices and network loss are converted to into monetary value. Minimization of this value is the primary optimization goal. Reliability indices are converted by considering losses arising to customers and utility due to faults.

IEEE 33 bus radial test system and Gothatar Feeder from Mulpani substation are taken as a test system. In both cases, reconfiguring the system for radiality shows significant improvement in the system's operational cost. For the IEEE 33 bus system, the operational cost was reduced from \$576096 to \$516871, a 10% reduction in yearly loss cost. For the Gothatar feeder, the cost was reduced to \$358206 from \$408641, again resulting in the reduction of loss cost by over 12%. Optimizing the 33 bus system for minimum cost using different algorithms while not maintaining strict radiality showed that GA was by far better at finding the solution. GA averaged 1.8 seconds per iteration while converging at 39.6 iterations. PSO, CSA, and GWO averaged similar iteration count but their time per iteration was way off from GA. Similarly, for the Gothatar feeder with strict radiality, GA provided results exceptionally faster than the rest of the algorithms.

Results show that GA is better suited for handling optimization problems related to power systems than other algorithms. While other algorithms like PSO and CSO also are capable of finding optimal solutions, GA's offspring computing mechanism is faster and immune to being trapped within a local minima. Results also show that optimizing existing radial feeders can be economically viable or even lucrative in some cases.

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LIST OF ABBREVIATIONS

CS	Cuckoo Search.
CSA	Cuckoo Search Algorithm.
GA	Genetic Algorithm.
GWO	Grey Wolf Optimization.
IEEE	Institute of Electrical and Electronics Engineers.
INPS	Integrated Nepal power System.
MOO	Multi Objective Optimization.
PSO	Particle Swarm Optimization.

CHAPTER ONE

Introduction

1.1 Background

The distribution system plays a critical role in the power system, as it is responsible for delivering electricity from the transmission system to end-users. The distribution system comprises a network of radial feeders that can be reconfigured to optimize the system's performance. Distribution system reconfiguration involves changing the topology of the network by closing and opening switches to minimize power losses, improve voltage stability, and enhance system reliability.

Traditional methods for reconfiguring distribution networks have focused on heuristic techniques including trial and error, rule-based approaches, and expert systems. These approaches take a lot of time and might not be the best for dealing with challenging optimization issues. Furthermore, they might not provide global optimality since the result might just be a local minimum.

There is a need for innovative and sophisticated optimization approaches that can effectively handle difficult optimization problems due to the growing complexity of distribution networks. A class of optimization algorithms known as meta-heuristic algorithms draws its inspiration from natural phenomena like evolution, swarm activity, and animal behavior. They can guarantee global optimality in particular situations and solve complex optimization problems by searching the whole solution space.

The Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Differential Evolution (DE), Grey Wolf Optimization (GWO), and Cuckoo Search (CS) are just a few of the meta-heuristic algorithms that have been presented in the literature. These algorithms are used to solve several optimization issues in power systems, including the best way to move electricity, how to allocate resources efficiently, and how to reconfigure distribution systems.

It is a difficult task to optimize the distribution system for both cost and dependability. The goal of cost optimization is to reduce the distribution system's overall cost, which includes investment, operation, and maintenance costs. On the other side, reliability optimization strives to ensure that the distribution system runs dependably, with as few disruptions to the supply of energy as possible.

Dependability indices like the System Average Interruption Frequency Index (SAIFI), System Average Interruption Duration Index (SAIDI), and Customer Average Interruption Duration Index (CAIDI) are frequently used to measure dependability in distribution systems. The frequency and length of supply disruptions are measured by these indicators, which are crucial for preserving customer happiness and the standing of the power company.

Creating approaches that can optimize the distribution system for cost and reliability has drawn more attention in recent years. These methods employ multi-objective optimization approaches to determine the best cost-reliability ratio. Multi-objective optimization includes simultaneously maximizing the number of competing goals to identify a set of solutions that best captures the trade-off between these goals.

Multi-objective optimization can be applied in the context of distribution system reconfiguration to maximize a number of different goals, such as minimizing power losses, maximizing voltage stability, and maximizing reliability indices. The use of weighting factors or other aggregation techniques can be used to aggregate these objectives into a single objective function.

As a result of the potential for large cost savings and increased system dependability, distribution system reconfiguration is a significant issue in power system engineering. Complex optimization problems cannot be solved using conventional distribution system reconfiguration methods. Therefore, there is a need for novel and sophisticated optimization methods that may effectively address challenging optimization issues. Promising optimization methods, meta-heuristic algorithms have demonstrated success in a range of power system optimization issues. We will discuss the problem statement and the study's goals in the section that follows.

1.2 Problem Statement

Reconfiguring the topology of the network by opening and closing switches is a critical step in power system engineering that reduces power losses, boosts voltage stability, and increases system reliability. The distribution system must be optimized for both cost and reliability, which is a difficult task that necessitates the application of sophisticated optimization methods.

To improve the distribution system for both cost and reliability, this research's goal is to create a methodology for reconfiguring the distribution system. The IEEE 33-bus test system and real-world radial distribution feeder of Gothatar, Mulpani substation, Kathmandu will be used as a case study in the project.

A multi-objective optimization problem, the distribution system reconfiguration problem comprises competing goals including decreasing power losses and maximizing system reliability. The goal functions' non-linearity, non-convexity, and the solution space's combinatorial nature make the issue even more challenging.

Optimal power flow, economical dispatch, and distribution system reconfiguration are only a few of the optimization issues in the power systems where meta-heuristic algorithms have demonstrated good performance. However, there is little research on the use of meta-heuristic algorithms for distribution system reconfiguration.

It is crucial to ensure that the distribution system is designed and operated in a way that can handle unexpected events, such as the loss of a transmission line, and that the reconfiguration process is executed properly to avoid errors or malfunctions. Proper training and procedures for system operators and maintenance personnel are also essential to prevent incidents related to distribution system reconfiguration.

1.3 Objective

The main objective is to apply multiple meta-heuristic algorithms to the IEEE 33-bus test system and radial distribution feeder of Gothatar and optimize the distribution system for both cost and reliability while comparing their performance.

This objective will guide the investigation into the use of meta-heuristic algorithms for optimizing the radial distribution system for both cost and reliability. The literature review will provide a comprehensive understanding of the state-of-the-art meta-heuristic algorithms and their applications in distribution system reconfiguration. The methodology development will provide a systematic approach for applying meta-heuristic algorithms to the distribution system reconfiguration problem. The comparison of different algorithms' performance on the IEEE 33-bus test system and a radial distribution feeder from a section of INPS will identify the most effective algorithms for the problem at hand.

1.4 Scope and Limitations

The scope of this research will be focused on the impact of network reconfiguration on the reliability of radial distribution systems. The study will consider different Meta-heuristic Optimization techniques and will analyze their computational efficiency. The study will be conducted using the programs developed in Python.

The research has the following limitations:

- The analysis will focus on the impact of network reconfiguration on the reliability indices of the system, but will not consider other factors that may impact power system stability.
- The results of this research may not be directly applicable to other types of distribution systems or other real-world scenarios.

1.5 Report Organization

The three main sections of this report are front matter, body, and rear matter. Cover pages, copyright, certificate of approval, acknowledgment, abstract, table of contents, a list of tables and figures, and a list of abbreviations are all included in the front matter. Introduction, Literature Review, Methodology, and Results and Discussion, Conclusions, and Recommendations are all included in the main body. Timelines and progress information are also included in this section. The back matter also includes an appendix and references.

CHAPTER TWO

Literature Review

2.1 Previous Studies

In [1], authors propose a method for estimating the reliability indices of distribution systems, considering factors such as interruption time, unsupplied energy, and network structure parameters, using radial single-feeder networks. The effectiveness of an automatic sectionalizer implementation on unsupplied energy is evaluated, and neural networks are used to train the data set obtained from extensive computational experimentation. In the study conducted by the author in [2], a new methodology is introduced for evaluating reliability in radial distribution networks using an ac optimization model based on mixed-integer nonlinear programming and the Pareto front technique. The model aims to reduce repair time and failure rates while minimizing costs such as power losses, optimal capacitor location and size, and non-supplied energy costs, and maximizing reliability. A fuzzy set approach is used to estimate outage parameters, and the methodology is illustrated through a case study involving a 33-bus distribution network. The work presented in research Paper [3], presents a technique for assessing the reliability of complex radial distribution systems, which uses a tree data structure and various algorithms to dynamically respond to network topology changes, determine affected areas after a failure, and evaluate network constraints after reconfiguration. In [4], the author introduces a model for assessing the reliability of radial distribution networks that includes voltage drop and feeder loading constraints. The model estimates nodal voltages using compensation techniques and a simplified version of the power summation load flow. It allows for the evaluation of post-restoration voltages without modifying the data structure used to evaluate reliability indices, and results from a large-scale distribution network demonstrate the model's effectiveness in assessing the impact of network constraints on reliability indices with an acceptable level of accuracy and computational cost.

Moving to optimization approaches, a study conducted by the author in [5], provides insights into optimization approaches used in science and technology, with a focus on metaheuristics for multi-objective optimization (MOO). It explores the application of evolutionary techniques and contemporary methods within the algorithmic domain, specifically emphasizing their relevance in non-conventional energy and distributed power generation systems. The evaluation of metaheuristic algorithms is conducted by considering factors such as computation time, resource utilization, response rate, and scheduling costs. The paper also includes a comprehensive analysis of metaheuristicc algorithms reported in the recent past, along with their pros and cons, to assist new researchers in the field of MOO.

In the research of [6], authors outline an approach for the optimal reconfiguration of radial distribution systems (RDS) to attain the desired performance, specifically emphasizing loadability maximization. Given that the solution space for this problem is discrete, the paper introduces a fuzzy adaptation of the evolutionary programming algorithm to address this aspect. The method put forward aims to maximize a fuzzy index created through the utilization of a maximum loadability index. Similarly, research in [7] uses GA as efficient approach to solving the problem of reconfiguration in an electrical power radial distribution network. The objective is to minimize the system active power loss and enhance the system voltage profile while satisfying operating constraints. The method uses an improved genetic algorithm to determine the optimal location of tie and sectionalizing switches to yield optimal performance for the network. The approach is tested on a typical distribution network and is found to be effective in reducing active power loss and total voltage deviation. Further contributions to the field of distribution system optimization are found in [8], which presents an algorithm designed for the reconfiguration and capacitor allocation in radial electrical networks, aiming to minimize energy losses while accounting for various load levels. The model proposed employs mixed-integer non-linear programming, incorporating a continuous function to address discrete variables. To tackle the optimization problem, the primal-dual interior point technique is applied. Additionally, a novel sensitivity index is assessed using Lagrange multipliers specifically for distribution system reconfiguration. The algorithm combines two sequential solution-based approaches to associate reconfiguration with capacitor allocation.

A modified plant growth simulation algorithm is introduced in [9] to solve the constrained non-linear optimization problem of network reconfiguration in the presence of distributed generation such as solar cells or wind turbines connected to the radial network. The algorithm aims to minimize real power loss while considering the bidirectional current flow caused by the integration of distributed generation, which may increase efficiency but reduce system stability. The modified algorithm does not require barrier factors or crossover rates and can handle changing objective functions and continuously varying power from distributed generation. In [10], author explores a feeder reconfiguration method to minimize reliability indices in a radial distribution system. The method uses Binary Particle Swarm Optimization to identify optimal tie switches that minimize interruptions in service. The paper also investigates the influence of various parameters in Binary Particle Swarm Optimization on the rate of convergence of the optimal solution. Similarly, authors in [11] also utilize a modified plant growth simulation algorithm to solve the network reconfiguration problem in electrical power systems with distributed generation. The algorithm is efficient and suitable for real-time applications, as it allows for continuous guiding search and changing objective functions to accommodate the continuously varying power output from distributed generation.

In the study conducted by the authors in [12], the importance of renewable energy resources, such as wind and solar, is discussed in addressing energy generation challenges and reducing greenhouse gas emissions. It focuses on reliability assessment in distribution systems with the integration of wind turbine generators, electric storage systems, and photovoltaic panels. The study employs a Markov model to analyze the stochastic behavior of these renewable components and their impact on the reliability of conventional distribution systems, demonstrating that their integration enhances system reliability. Work in[13], discusses the assessment of electric service reliability by quantifying customer costs associated with power interruptions. It highlights the use of customer surveys to estimate these interruption costs, particularly in Canadian electric utility customers across residential, commercial, and industrial sectors. The study, sponsored by multiple utilities and organizations, presents comprehensive survey results, with a focus on the monetary cost outcomes. Research in [14], addresses the assessment of reliability worth in power systems planning by considering two critical aspects. Firstly, it examines the impact of temporal variations in interruption costs across different sectors on the expected annual outage cost of the system. Secondly, it introduces a probability distribution approach to model interruption costs, highlighting its advantages over the conventional customer damage function method. Examinations of specific instances indicate that integrating fluctuating costs over time in the industrial sector leads to a notable decrease in outage expenses. This implies that the customer damage function method may potentially underestimate the value of reliability by a factor of three to four. In [15], the author demonstrates the application of fundamental power system reliability evaluation techniques to assess reliability worth. It establishes a link between estimations of customer interruption costs and anticipated reliability indices of the power system. The method is illustrated through practical applications across different domains, such as generation, composite generation and transmission, and distribution system assessment, utilizing a hypothetical test system. Study in [16], introduces a multi-dimensional customer segmentation model for assessing customer interruption costs in power system planning and operation. The model employs hierarchical clustering to group electricity customers based on similar cost characteristics, considering parameters such as economic size, economic activity, and energy consumption. Case studies in South Africa and Sweden are used to evaluate the model, comparing it to conventional customer segmentation approaches. The proposed model proves effective, reducing the variability of cost estimates and enabling the estimation of customer interruption costs from smaller survey samples.

Authors in [17] discuss the growing need for justifying new facilities and optimizing system cost and reliability in power supply. The paper presents two approaches for assessing customer interruption costs in intricate radial distribution systems: a comprehensive analytical method and a time-sequential Monte Carlo simulation technique. The research incorporates real-world distribution systems and contrasts outcomes obtained through the analytical approach, employing average restoration times, with those derived from the simulation method utilizing random restoration times. Furthermore, the study investigates the influence of alternative supply and protection devices on customer interruption cost indices. Research done by the authors in [18] introduces a time-sequential Monte Carlo simulation method for evaluating unreliability costs incurred by customers in distribution systems. It constructs yearly chronological load models specific to diverse customer sectors and integrates random load fluctuations to accommodate uncertainty in system load. The concept of time-varying cost weight factors is introduced and combined with the customer damage function to formulate time-varying cost models for each customer sector. These models are then employed to assess interruption costs for seven distinct customer sectors. The study highlights that different load and cost models yield varying interruption costs, which can impact planning and operational decisions.

2.2 Distribution System

A distribution system, sometimes referred to as an electrical distribution system, is a network of equipment and power lines that transports energy from a high-voltage transmission system to residences and commercial buildings at lower voltages. As they provide the final mile of the electrical supply chain and deliver power to end customers, distribution systems are a crucial component of the electrical power infrastructure. The primary distribution system and the secondary distribution system are the two main components of the distribution system. From the substation to the distribution transformer, which transforms the high voltage into low voltage suited for consumer use, high voltage power must be transported via the primary distribution system. This low-voltage power is distributed to specific users via the secondary distribution system.

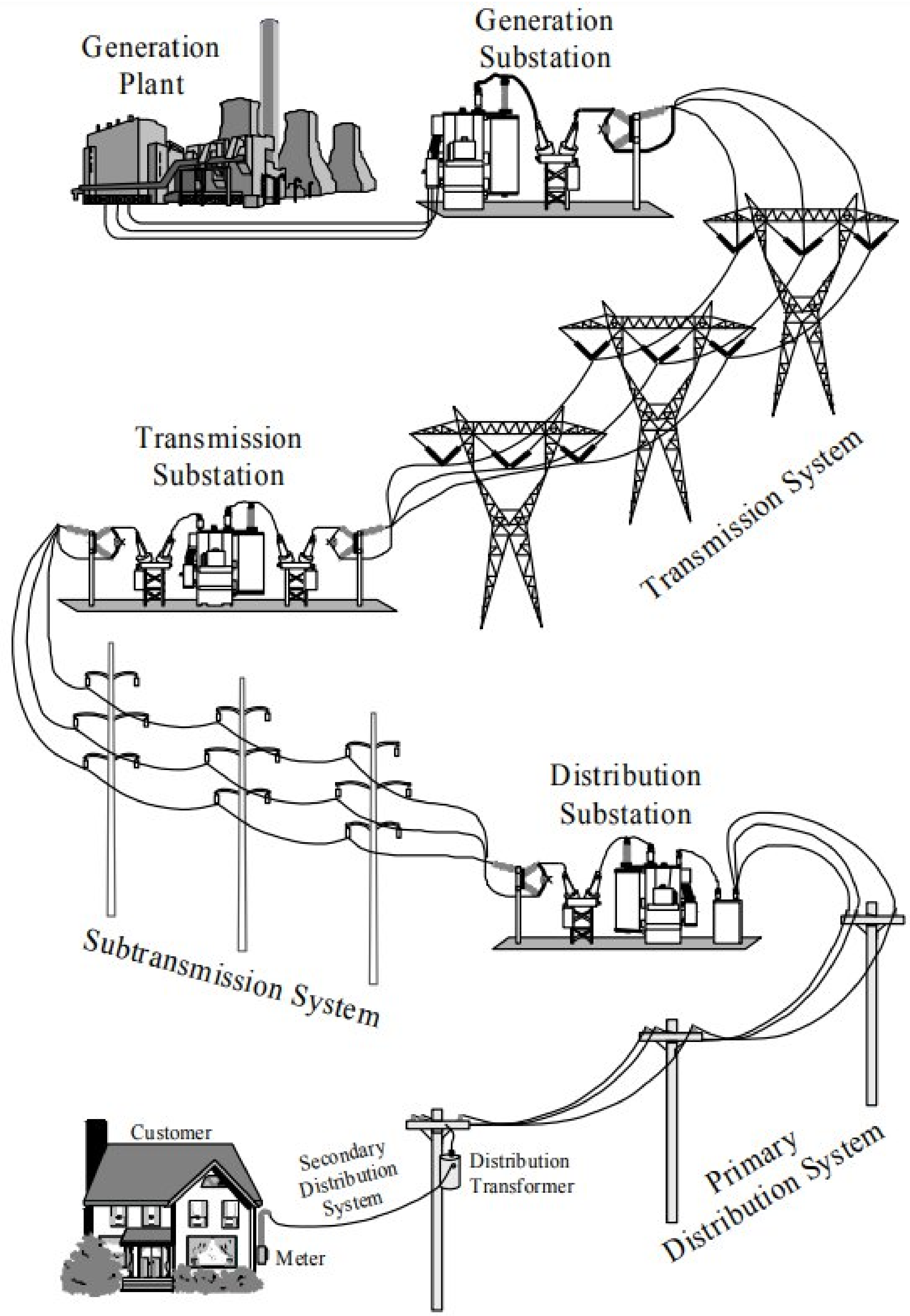

Figure 2.1: Different Parts of Electrical Power System [19].

Distribution systems are built with redundancies to assure supply continuity even in the event of equipment failure or a weather-related outage. These systems are designed to be extremely dependable and resilient. Multiple distribution circuits, transformers, and other safety equipment are used to achieve this. While the secondary distribution system runs at voltages of 240 V, the primary distribution system normally runs at voltages of 11/33 kV. Transformers and other equipment may be placed closer to residences and places of business since the secondary distribution system uses lower voltages, which allows for more exposure to the power lines.

The configuration of distribution systems might be radial or loop. Power moves linearly in a radial system from the substation to the distribution transformer and finally to each consumer. Although less expensive and simpler to build, this sort of system has less built-in redundancy, which might cause outages in the case of a problem or a piece of equipment failing. The distribution system is built with numerous channels for power to flow in a loop form, increasing redundancy and reliability. Although more difficult and expensive to build, this kind of technology offers better service continuity and resilience.

Fuse and circuit breakers are just two of the defensive tools the distribution system is equipped with to guard against overloading and to swiftly isolate faults when they do occur. These safeguards can manually or automatically disconnect the troubled area of the network, reducing the effects of an outage and assisting in ensuring worker and public safety. Numerous obstacles and dangers, like as weather-related outages, equipment malfunctions, and cyberattacks, can affect distribution systems. Utilities are looking at new technologies and strategies to increase the security, resilience, and dependability of their distribution systems as the demand for power rises.

The integration of dispersed energy resources, such as solar cells and wind turbines, is one of the main difficulties faced by distribution system operators. While these technologies have the potential to produce clean, renewable energy, maintaining a steady and reliable electrical grid can be difficult due to their intermittent nature and fluctuating output. To combine these resources and control their fluctuation, utilities are looking into novel strategies like microgrids and energy storage systems.

The requirement to update outdated infrastructure presents distribution system operators with additional difficulties. To maintain dependability and resilience, many distribution systems that were constructed decades ago need to be upgraded or replaced. Given the high cost and potential disruption to customer service during building, this can be a considerable challenge. Utilities are looking into a variety of cutting-edge techniques and technology to tackle these problems. One such strategy is the application of smart grid technologies, which integrate sensors, communication networks, and advanced analytics to raise the distribution system's dependability and effectiveness. Smart grid technologies, for instance, can speed up the usage of distributed energy resources and assist utilities in detecting and responding to outages as well as identify areas of the network that are at risk of failure.

Utilizing advanced distribution management systems (ADMS), which are software platforms that assist utilities in managing and improving the distribution system, is another strategy. Utility companies can increase the distribution system's resilience and dependability by using ADMS to optimize the use of distributed energy supplies, detect faults more rapidly, and predict equipment failures before they happen. To better control the fluctuation of distributed energy resources, utilities are also looking into the usage of energy storage devices. In addition to offering backup power in the event of an outage, energy storage devices can help reduce volatility in the generation of renewable energy.

The usage of microgrids, which are compact electrical grids that can run separately from or in tandem with the primary distribution system, is also being investigated by utilities. By functioning independently during periods of high demand or main grid failures or by providing backup power in the case of an outage, microgrids can assist in increasing the resilience and dependability of the distribution system.

Distribution systems, which are in charge of supplying electricity to residences and businesses, are an essential component of the electrical power infrastructure. The need to connect distributed energy resources, update outdated infrastructure, and boost resilience and reliability are only a few of the challenges and dangers that these systems must overcome despite their high level of reliability and resilience. To meet these difficulties, utilities are looking at a variety of new technologies and strategies, such as smart grid technologies, enhanced distribution management systems, energy storage systems, and microgrids. Utilizing these technologies, utilities may promote the move to a cleaner, more sustainable energy future while assisting in maintaining the distribution system's dependability and resilience.

- Radial distribution system: An electrical distribution system known as a radial distribution system transmits power linearly from a substation to the end consumers. In this system, the substation disperses power to a network of feeders, which branch out to several transformers, and ultimately to the loads. A single path that travels from the substation to the farthest point of the distribution network is formed by the interconnected distribution lines. Power only flows in one way, making it simple to anticipate the system's voltage drop and current flow. In comparison to other distribution systems, this makes the design of radial distribution systems very straightforward and affordable.

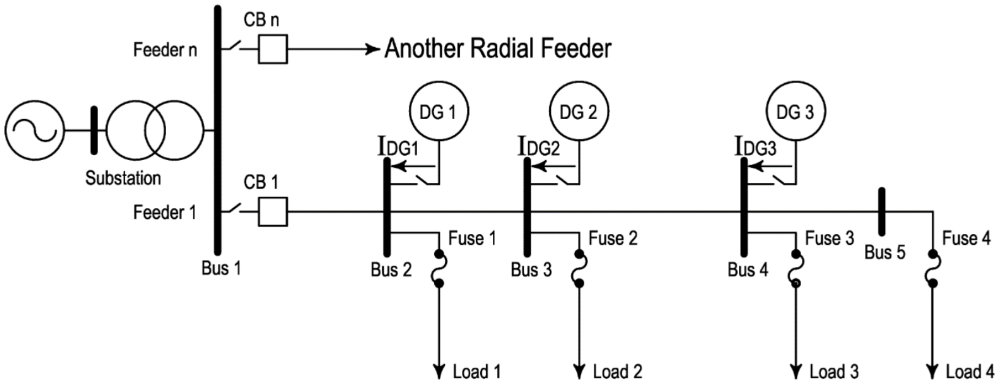

Figure 2.2: Radial Distribution System [20].

The radial distribution system's ease of use and upkeep is one of its main benefits. Because of the system's linear design, any errors or outages that happen in one area of the network have no impact on the remainder of the network. This minimizes downtime and guarantees a steady supply of electricity to the customers while making it simple to identify and resolve issues. Additionally, due to the design's simplicity, adding new feeders to the substation or adding new transformers along the existing feeders makes it simple to expand the network. This makes the radial distribution system an ideal choice for areas with low power demand and where the power supply is not critical, such as residential areas or small commercial centers.

- Loop system: In a loop system, power is dispersed through a network of interconnected secondary circuits after first flowing from the substation to the primary circuit. In contrast to a radial system, which only delivers one feed from the substation to each customer, a loop system offers many paths for electricity to flow, enhancing the system's dependability and flexibility.

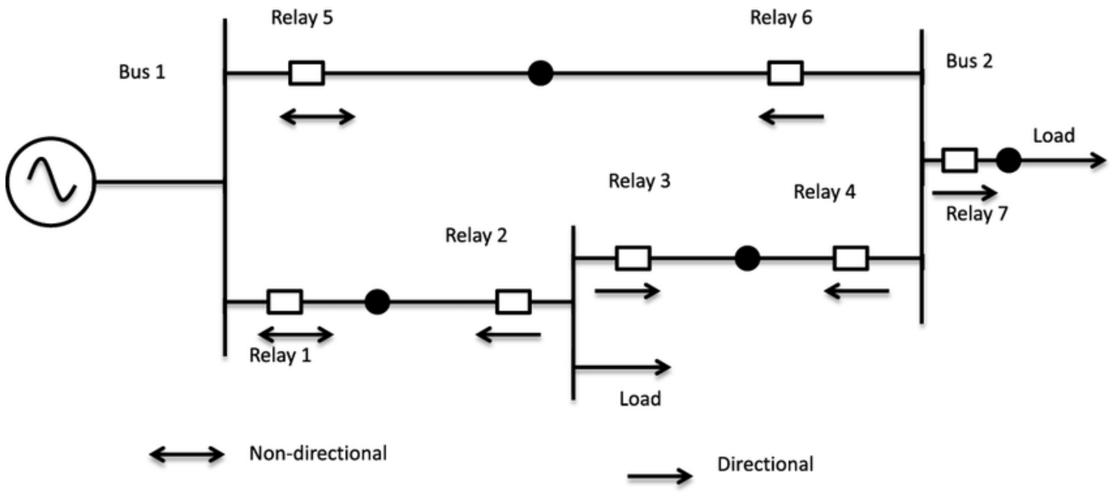

Figure 2.3: Loop Distribution System [21].

Each circuit in a loop system has two power sources and can switch between them in the event of a power failure. This enables quicker restoration times and more client satisfaction. A mesh or grid-like arrangement of the loops is usual, and there are numerous connections among the various circuits. With this architecture, single-point failures are less likely to occur and the system's stress can be distributed more evenly. The loop system's greater complexity, meanwhile, can also result in higher operating and maintenance expenses. In comparison to the radial system, the loop system is generally more durable and dependable, especially in places with high population density and heavy loads, like hospitals and emergency services.

- Meshed distribution system: A mesh or loop is created in a network distribution system by the connections between the distribution lines. Multiple pathways are available for the flow of electricity in this system, increasing reliability and lowering the possibility of power outages. Power can be rerouted along alternative pathways if a failure develops in one area of the network to maintain supply.

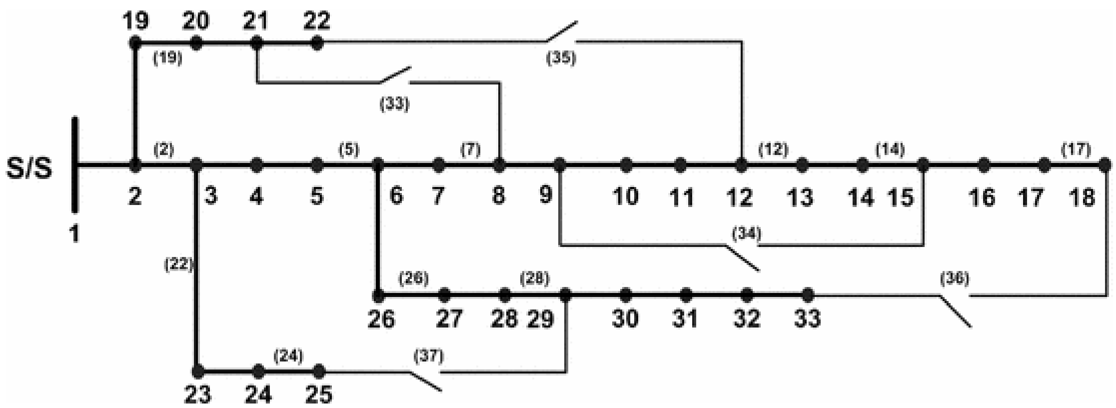

Figure 2.4: Meshed Distribution System [22].

When there is a significant energy demand and there are a lot of connections, network distribution systems are frequently utilized in urban and suburban areas. They require more equipment, including as switches, circuit breakers, and safety devices, than radial systems, thus they are also more expensive to install and maintain. However, they may be a more appealing option for locations with high demand or urgent power demands due to their greater reliability and flexibility.

2.3 Reliability

To guarantee a steady and reliable supply of electricity to users, power system reliability is a crucial component of electrical engineering and energy management. It includes a variety of methods, plans, and evaluations for preserving the reliability and standard of electrical service. For many industries, including residential, commercial, industrial, and critical infrastructure, a power system's dependability is essential.

The dependability of specific parts, such as circuit breakers, transformers, and generators, can have an impact on the reliability of a power system. The importance of routine maintenance and prompt replacement of these parts cannot be overstated. The impact of equipment failures or outages can also be reduced by adding redundant equipment and pathways to the power system. Faults are quickly detected and isolated by sophisticated protection mechanisms and relays, preventing them from cascading over the network. Planning for peak demand and effective resource allocation depend on accurate load forecasts. Reliability is increased via maintenance procedures like planned maintenance and condition-based equipment monitoring. To further reduce service interruptions, quick response to unforeseen circumstances like storms or equipment breakdowns is essential.

The final step in the delivery of power, maintaining a steady flow of electricity from substations to end consumers, is the emphasis on distribution system reliability. It is the final link in the supply chain for power and directly affects the level of service that customers receive.

Several important indices are used to express distribution system reliability:

- **SAIFI (System Average Interruption Frequency Index)** measures the average number of interruptions that a typical customer experiences over a specific period, often per year. It reflects the frequency of outages and is expressed as interruptions per customer.

- **SAIDI (System Average Interruption Duration Index)** represents the average duration of interruptions experienced by a typical customer over a specific period, often per year. It quantifies the duration of outages and is expressed in minutes.

- **CAIDI (Customer Average Interruption Duration Index)** measures the average time it takes to restore power to a customer after an interruption. It's calculated by dividing SAIDI by SAIFI and is expressed in minutes per interruption.

- **CAIFI (Customer Average Interruption Frequency Index)** indicates the average number of interruptions experienced by a customer before service is restored. It's calculated by dividing SAIFI by SAIDI.

- **MAIFI (Momentary Average Interruption Frequency Index)** measures the frequency of very brief interruptions (often less than 5 minutes) and provides insight into the quality of power supply, especially for sensitive equipment.

- **MAIDI (Momentary Average Interruption Duration Index)** represents the average duration of momentary interruptions and helps evaluate the impact of short disruptions on customer operations.

- **ENS (Energy Not Supplied)** and **AENS (Average Energy Not Supplied)** reflect the total energy not supplied during interruptions and the average energy not supplied per customer over a specified period, respectively.

These indices provide valuable information for utilities, regulators, and consumers, helping ensure that electrical service remains dependable and meets the needs of modern society. They assist in performance evaluation, planning and investment, regulatory compliance, consumer satisfaction, risk management, and enhancing distribution system resilience.

2.4 Backward/Forward Sweep Algorithm

The Forward and Backward Sweep Load Flow Algorithm is a computational method used to analyze power flow and voltage profiles in electrical distribution systems. It involves iteratively solving the power flow equations for each bus in the system. The algorithm starts by assigning initial values to the voltage magnitude and phase angle at the slack bus, which is typically a bus with a fixed voltage magnitude and phase angle. Then, the algorithm proceeds with the following steps:

Forward Sweep:

- For each bus in the system, starting from the slack bus and moving downstream, calculate the complex power injections at each bus based on the known voltage magnitudes and phase angles.

- Update the voltage magnitude and phase angle at each bus based on the power injections and the line impedance.

Backward Sweep:

- For each bus in the system, starting from the last bus and moving upstream towards the slack bus, calculate the complex power flows on each line based on the known voltage magnitudes and phase angles.
- Update the voltage magnitude and phase angle at each bus based on the power flows and the line impedance.

These forward and backward sweeps are repeated iteratively until the convergence criteria are met. The convergence criteria are typically based on the maximum difference between the voltage magnitudes and phase angles at consecutive iterations. The governing equations are shown below:

$$P_i = \sum_{k=1}^{n} V_i V_k (G_{ik} \cos(\theta_i - \theta_k) + B_{ik} \sin(\theta_i - \theta_k)) \tag{2.1}$$

$$Q_i = \sum_{k=1}^{n} V_i V_k (G_{ik} \sin(\theta_i - \theta_k) - B_{ik} \cos(\theta_i - \theta_k)) \tag{2.2}$$

Backward Sweep:

$$P_{ik} = V_i V_k (G_{ik} \cos(\theta_i - \theta_k) + B_{ik} \sin(\theta_i - \theta_k)) \tag{2.3}$$

$$Q_{ik} = V_i V_k (G_{ik} \sin(\theta_i - \theta_k) - B_{ik} \cos(\theta_i - \theta_k)) \tag{2.4}$$

where:

P_i and Q_i are the real and reactive power injections at bus i,
P_{ik} and Q_{ik} are the real and reactive power flows on the line between buses i and k,
V_i and V_k are the voltage magnitudes at buses i and k,
θ_i and θ_k are the phase angles at buses i and k,
G_{ik} and B_{ik} are the conductance and susceptance of the line between buses i and k.

The total system loss (P_{loss}) can be calculated using the following equation:

$$P_{\text{loss}} = \sum_{i=1}^{n} P_i \tag{2.5}$$

where n is the total number of buses in the system.

2.5 Metaheuristic Techniques

Power system engineering is one of several disciplines where complicated optimization problems are frequently encountered. Metaheuristic techniques have become effective tools for resolving these issues. Due to the complexity and non-linearity of the issues, these strategies offer a flexible and effective tool for locating optimal or nearly optimal solutions in situations where standard methods can struggle. To solve issues with generation, transmission, distribution, and even integrated energy systems, metaheuristic techniques have been widely used in the field of power systems.

Metaheuristic techniques are kinds of optimization that are not constrained by particular mathematical frameworks or problem structures. They are better suitable for complicated and multi-dimensional optimization problems since they are made to explore and exploit the solution space in more diverse ways.

Numerous metaheuristic approaches have garnered recognition for their efficiency in addressing diverse optimization challenges. Among the frequently employed methods are:

1. **Genetic Algorithm (GA):** Inspired by the process of natural evolution, GA involves generating a population of potential solutions (individuals), evolving them over multiple generations through selection, crossover, and mutation operations to find the optimal solution.

2. **Particle Swarm Optimization (PSO):** PSO simulates the social behavior of bird flocks or fish schools. Individuals (particles) move through the solution space, adjusting their velocity based on their own best solution and the best solution found by the group.

3. **Ant Colony Optimization (ACO):** ACO draws inspiration from the foraging patterns exhibited by ants. It involves simulating artificial ants that deposit pheromones on paths and adjust their choices based on pheromone levels, enabling the discovery of optimal paths in complex networks.

4. **Simulated Annealing (SA):** SA mimics the annealing process in metallurgy. It starts with an initial solution and explores the solution space by accepting worse solutions with a decreasing probability, which allows it to escape local optima.

5. **Differential Evolution (DE):** DE optimizes a population of candidate solutions by applying mutation and crossover operators. It is effective for optimization problems with continuous and discrete variables.

6. **Harmony Search (HS):** Inspired by musicians' improvisation process, HS generates new solutions by considering both the current solutions and memory of

best solutions, creating harmony among different components.

7. **Grey Wolf Optimization (GWO):** GWO is inspired by the social hierarchy and hunting behavior of grey wolves. It mimics the leadership hierarchy of alpha, beta, and delta wolves to optimize solutions in a search space.

8. **Cuckoo Search Optimization (CSO):** CSO is inspired by the brood parasitism of some cuckoo species. It employs a combination of Levy flights and random walk strategies for exploring the solution space.

Metaheuristic techniques have found numerous applications in power system engineering. Some examples include:

- **Unit Commitment and Economic Dispatch:** GA, PSO, and DE have been extensively used to optimize the scheduling and operation of power generation units to meet demand while minimizing costs and maintaining system stability.

- **Optimal Power Flow:** Metaheuristic techniques like GA, PSO, DE, GWO, and CSO have been applied to solve the optimal power flow problem, determining the optimal settings for generation and load in a power system while respecting constraints.

- **Distribution System Reconfiguration:** Techniques such as PSO, GWO, and CSO help find optimal configurations of distribution networks to minimize power losses, improve voltage profiles, and enhance overall system reliability.

- **Transmission Network Expansion Planning:** ACO, GWO, and hybrid metaheuristics have been used to determine the most cost-effective expansion plans for transmission networks to accommodate growing demand and improve system reliability.

- **Renewable Energy Integration:** Metaheuristic methods play a crucial role in identifying the most effective locations and sizes for incorporating renewable energy sources into a power system. This ensures their optimal utilization, striking a balance between maximizing their contribution and minimizing associated costs.

- **Load Shedding and Restoration:** These techniques play a role in developing strategies for load shedding and restoration in emergency situations, ensuring that power distribution is balanced during disruptions.

Metaheuristic techniques have revolutionized the field of power system optimization. Their ability to navigate complex, high-dimensional solution spaces makes them valuable tools for solving intricate problems in power generation, distribution, and transmission. As technology advances and power systems become more intricate, the application of metaheuristics is expected to continue playing an important role in ensuring the reliability, efficiency, and sustainability of modern energy systems.

CHAPTER THREE

Methodology

3.1 Overall Flow Chart

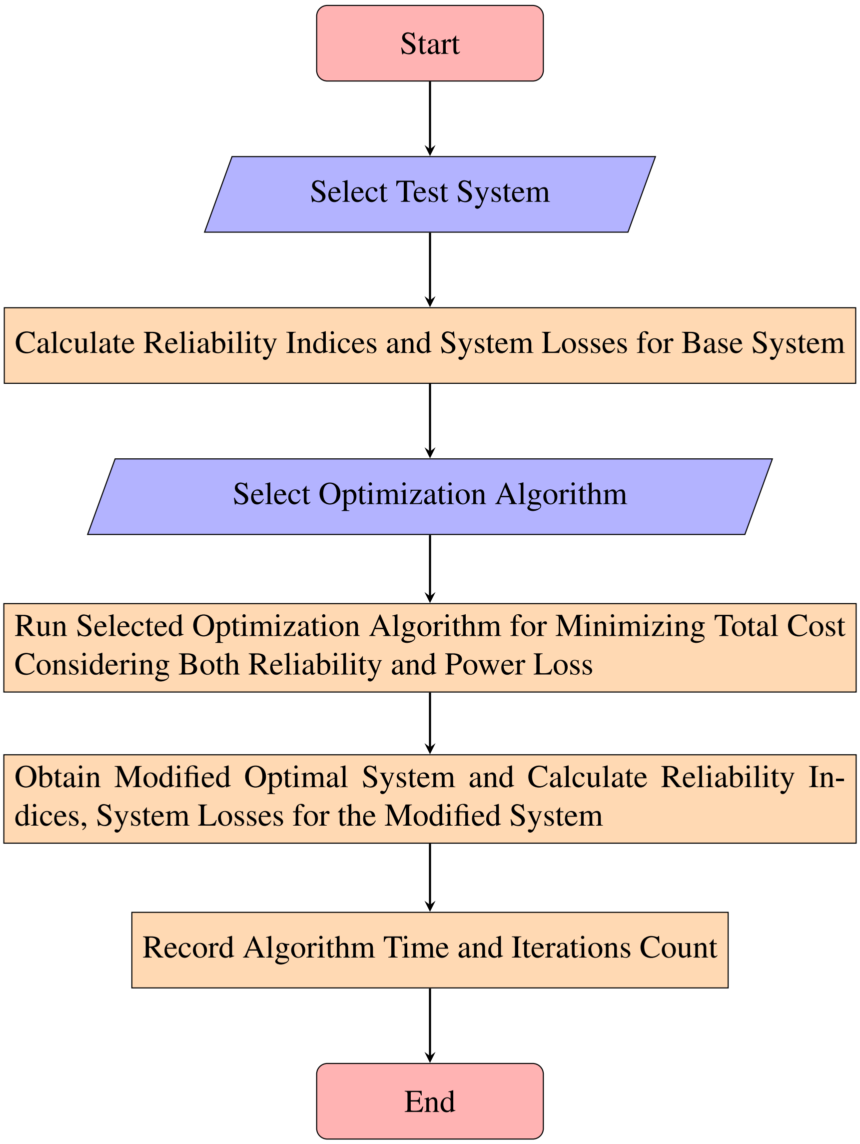

Figure 3.1: Process Flow Chart

3.2 Test System

The research work is carried out in two sets of test systems. IEEE 33 bus standard test system and a radial distribution feeder from a section of INPS are used.

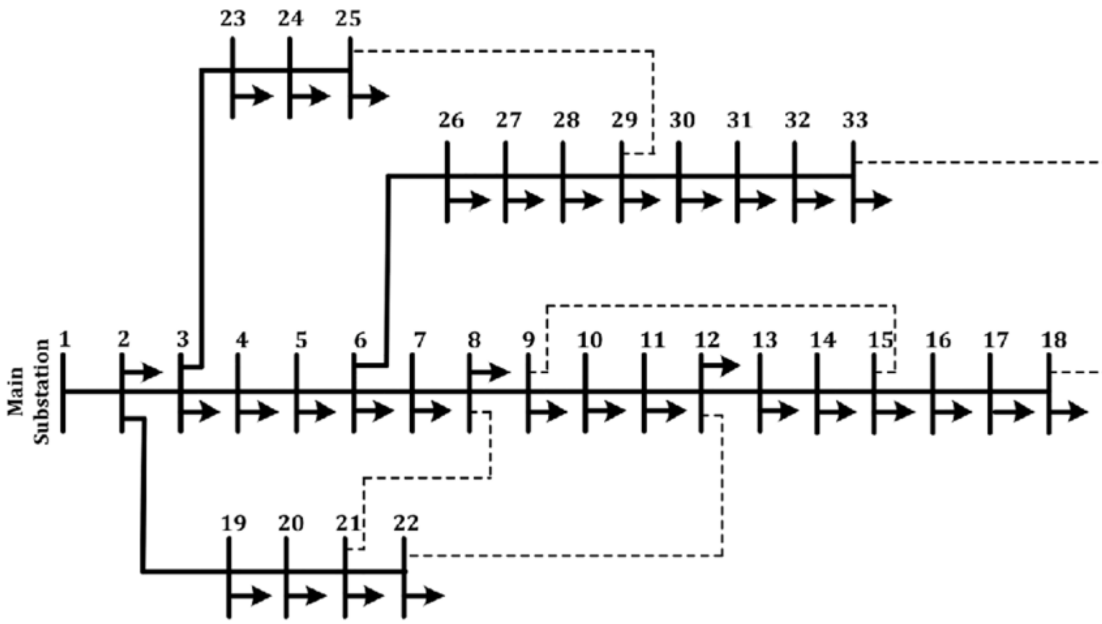

Figure 3.2: IEEE 33 bus test system with tie lines [23]

The test system will be a real-world radial distribution feeder of the Gothatar, Kathmandu substation. The feeder contains 68 branches and up to 5 switching lines will be added for study. For reliability study data of faults clearing time of six months period between Shrawan 2077 to Poush 2077 are taken. Some salient features are

Table 3.1: Main features of Gothatar feeder.

No of Bus	69
Total Load	4.99 MW
No of Branches	68
Faults Per year	130
Shutdown time per year	46 hr 52 minutes

3.3 Tools and Software

Python along side pypower library will be used for this research. All optimization algorithms will be written in python. Pypower provides necessary algorithms for performing loadflow, computing network matrices, network losses etc for electrical power and distribution system.

3.3.1 Genetic Algorithm

Genetic Algorithm (GA) is a metaheuristic optimization algorithm that is inspired by the process of natural selection and genetics. It is commonly used for solving optimization problems, including those related to power system engineering.

The GA operates by generating a population of candidate solutions, called chromosomes, that are represented as binary strings or arrays. Each chromosome represents a potential solution to the problem being solved, and the goal of the GA is to evolve the population of chromosomes over successive generations to obtain better and better solutions.

The key operators of GA are crossover, mutation, and selection. Crossover involves combining two chromosomes from the current population to create a new chromosome that inherits some traits from both parents. Mutation involves randomly altering some bits or elements of a chromosome to introduce new variations into the population. Selection involves choosing the fittest chromosomes from the current population to form the basis of the next generation.

The fitness function is a crucial component of GA, as it determines how well a chromosome solves the problem being solved. The fitness function assigns a fitness score to each chromosome based on how well it performs relative to other chromosomes in the population.

This process can be illustrated by the flowchart shown in figure 3.3.

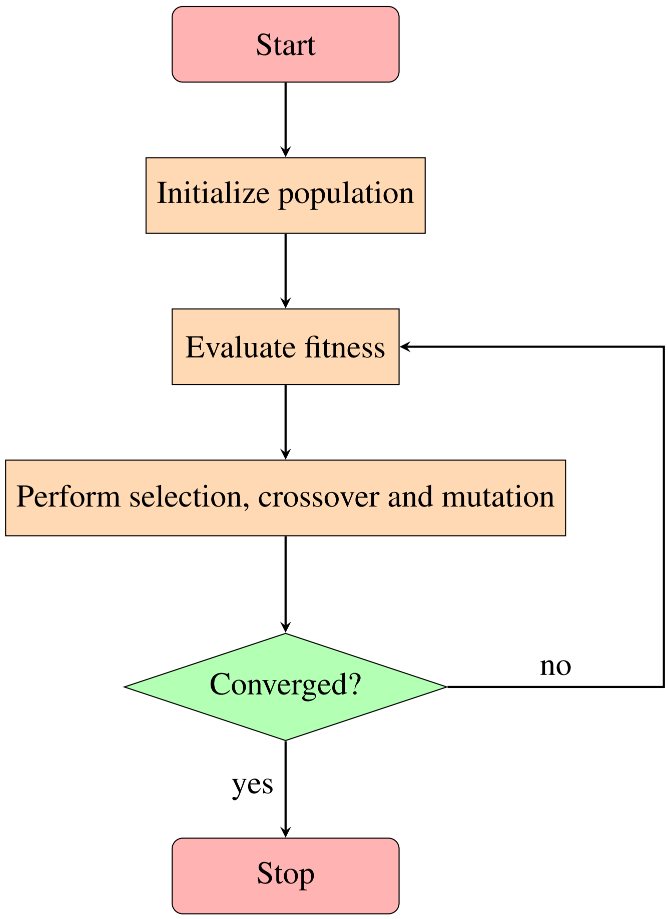

Figure 3.3: Genetic Algorithm Process Flowchart

3.3.2 Particle Swarm Optimization

Particle Swarm Optimization (PSO) stands as a metaheuristic optimization technique influenced by the collective behaviors observed in bird flocking or fish schooling. It finds frequent application in addressing challenges associated with optimizing continuous non-linear functions.

In PSO, a population of particles is initialized with random positions and velocities in the search space. Each particle in the population represents a potential solution to the problem. The fitness value of each particle is evaluated using the objective function. The particle updates its position and velocity based on its own previous best solution and the global best solution found by the swarm. This process continues until a stopping criterion is met.

The PSO algorithm can be summarized in the following steps:

1. Initialize the swarm with a set of particles randomly distributed in the search space, with velocities and positions randomly assigned.

2. Evaluate the fitness of each particle.

3. Set the particle's best known position and fitness value.

4. Set the swarm's best known position and fitness value.

5. Update the particle's velocity and position based on its own best known position and the swarm's best known position.

6. Evaluate the fitness of each particle in the new position.

7. Update the particle's best known position and the swarm's best known position if the fitness value of the new position is better than the current best.

8. Repeat steps 5-7 until a stopping criterion is met (e.g., a maximum number of iterations or a target fitness value is reached).

3.3.3 Cuckoo Search Algorithm

Cuckoo Search (CS) is a nature-inspired optimization algorithm that is based on the breeding strategy of cuckoo birds. It was first proposed by Xin-She Yang and Suash Deb in 2009. From global optimization to parameter estimation and feature selection, CS has proven its effectiveness.

The core concept driving CS is inspired by the behavior of cuckoo birds, wherein they deposit their eggs in the nests of other birds, relying on them to nurture the cuckoo chicks as their own. This is an evolutionary strategy that allows cuckoos to distribute their eggs more widely and increase the chances of their offspring surviving.

The CS algorithm starts by randomly generating a population of potential solutions, which are represented as cuckoo eggs. These eggs are then laid in the nests of other birds, which represent the search space for the optimization problem. The quality of each egg is evaluated using a fitness function, which measures how well the solution satisfies the objective of the optimization problem.

The algorithm then proceeds through a number of iterations, during which each cuckoo egg is either replaced with a new egg or left unchanged. The replacement of an egg is called a ”discovery event” and is based on the idea that the cuckoo bird that laid the egg may have been discovered by the other bird and the egg destroyed. The probability of a discovery event is determined by a parameter called the ”discovery rate”, which controls the intensity of the search.

The algorithm also includes a ”levy flight” mechanism, which simulates the random movement of birds in search of food. This allows the algorithm to escape from local optima and explore new regions of the search space.

Algorithm 1 Cuckoo Search Algorithm

```
Initialize population of cuckoo eggs randomly
Evaluate the fitness of each cuckoo egg
while stopping criteria not met do
    Select a cuckoo egg based on its fitness
    Generate a new cuckoo egg using Levy flights
    Evaluate the fitness of the new cuckoo egg
    if the new cuckoo egg is better than the selected cuckoo egg then
        Replace the selected cuckoo egg with the new cuckoo egg
    else
        Abandon the new cuckoo egg
    end if
    Perform a random walk to discover a new nest
    Evaluate the fitness of the cuckoo egg in the new nest
    if the new cuckoo egg is better than the cuckoo egg in the new nest then
        Replace the cuckoo egg in the new nest with the new cuckoo egg
    end if
end while
```

3.3.4 Grey wolf Optimization

Grey Wolf Optimization (GWO) is a meta-heuristic algorithm that is inspired by the hunting behavior of grey wolves. The algorithm has been successfully applied to solve optimization problems in various fields such as engineering, economics, and computer science.

The GWO algorithm is based on a population of wolves that are divided into four levels of hierarchy, alpha, beta, delta, and omega. The alpha wolf is the best solution found so far, while the omega wolf is the worst solution. The algorithm starts with an initial population of randomly generated solutions, and then iteratively updates the population using three operators: encircling, attacking, and following.

In the encircling operator, the alpha wolf leads the other wolves to surround the prey, which represents the global optimum solution. In the attacking operator, the beta and delta wolves try to attack the prey from different angles. In the following operator, the omega wolf follows the other wolves to explore new areas of the search space.

$$x_i^{t+1} = \begin{cases} \frac{1}{2}(x_{\alpha,i}^t + x_{\beta,i}^t) - a_{1,i} \cdot D_{\alpha\beta}^t & \text{if}; r_1 < 0.5 \\ \frac{(x_{\alpha,i}^t + x_{\beta,i}^t)}{2} + a_{1,i} \cdot D_{\alpha\beta}^t & \text{otherwise} \\ \frac{(x_{\alpha,i}^t + x_{\beta,i}^t)}{2} - a_{2,i} \cdot D_{\alpha\beta}^t & \text{if}; r_2 < 0.5 \\ \frac{(x_{\alpha,i}^t + x_{\beta,i}^t)}{2} + a_{2,i} \cdot D_{\alpha\beta}^t & \text{otherwise} \\ x_{\delta,i}^t - D_i \cdot r_3 & \text{otherwise} \end{cases} \tag{3.1}$$

$$x_i^{t+1} = \begin{cases} u_{\max,i} & \text{if } x_i^{t+1} > u_{\max,i} \\ u_{\min,i} & \text{if } x_i^{t+1} < u_{\min,i} \\ x_i^{t+1} & \text{otherwise} \end{cases} \tag{3.2}$$

$$a_i = 2 - l \cdot \frac{iter}{max_i ter} \tag{3.3}$$

$$A = 2a \cdot r - a \tag{3.4}$$

$$C = 2r \tag{3.5}$$

$$l = 2 \cdot rand \tag{3.6}$$

Where,

D: Dimension of the problem

N: Number of wolves in the pack

x_i: Position vector of the ith wolf

$f(x_i)$: Objective function value of the ith wolf

X_1, X_2, X_3: Position vectors of the alpha, beta, and delta wolves, respectively

a, A, C, l: Parameters used to update the positions of the wolves

l (iteration): Current iteration number

Algorithm 2 Grey Wolf Optimization

Initialize the wolf pack with random solutions
Initialize the parameters a, A, C, and l
while the stopping criterion is not met **do**
  for each wolf in the pack **do**
    Update the position of the wolf using Eq. (3.1)
    if the position of the wolf is outside the search space **then**
      Bring the wolf back inside the search space using Eq. (3.2)
    end if
    Evaluate the fitness of the wolf
    if the fitness of the wolf is better than that of the alpha wolf **then**
      Update the alpha wolf's position
    else if the fitness of the wolf is better than that of the beta wolf **then**
      Update the beta wolf's position
    else if the fitness of the wolf is better than that of the delta wolf **then**
      Update the delta wolf's position
    end if
  end for
  Update the values of a, A, C, and l using Eq. (3.3), (3.4), (3.5), and (3.6)
end while

In this algorithm, Eq. (3.1) updates the position of each wolf based on the positions of the alpha, beta, and delta wolves, and Eq. (3.2) brings the wolf back inside the search space if its position is outside the search space. Eqs. (3.3), (3.4), (3.5), and (3.6) update the values of the parameters a, A, C, and l based on their current values and the iteration number.

3.4 Problem Formulation

3.4.1 Reliability Parameters

The System Average Interruption Frequency Index (SAIFI) is given by:

$$SAIFI = \frac{\sum_{i=1}^{n} \lambda_i N_i}{\sum_{i=1}^{n} N_i} \tag{3.7}$$

where λ_i is the failure rate per year for i-th load point and n is the total number of load points. N_i is the no of customers at load point i.

The System Average Interruption Duration Index (SAIDI) is given by:

$$SAIDI = \frac{\sum_{i=1}^{n} U_i N_i}{\sum_{i=1}^{n} N_i} \tag{3.8}$$

where U_i is the annual duration of outage per year at load point i.

Energy Not Supplied (ENS) represents the average energy not supplied per customer and is typically expressed in units such as kilowatt-hours (kWh) or megawatt-hours (MWh). The ENS is calculated as:

$$ENS = \sum_{i=1}^{n} L_{avg(i)} * U_i \tag{3.9}$$

3.4.2 Power Loss Calculation

One of objective is to minimize total system loss of distribution system. The distribution system real power loss is expressed as 3.10:

$$P_{loss} = \sum_{i=1}^{N} R_i \cdot \frac{\left(P_i^2 + Q_i^2\right)}{V_i^2} \tag{3.10}$$

subject to the following constraints:

$$I_i \leq I_{\max}$$
$$V_{\min} \leq V_i \leq V_{\max}$$
$$g_i(I,k) = 0, \quad g_v(V,k) = 0$$

Where:

R_i is the resistance of the i-th branch

V_i, I_i, P_i, and Q_i are voltage, current magnitude, real power, and reactive power at the sending end of the branch, respectively
$I_{\max}$ is the maximum current
$V_{\min}$ and $V_{\max}$ are the minimum and maximum voltages, respectively
$g_v(V,k)$ and $g_i(I,k)$ represent Kirchhoff's current and voltage laws, respectively

Equation 3.10 is used as the main objective to find system reconfiguration that provides minimum loss in this approach.

3.4.3 Optimization Objective

A new equation is proposed by research [24] to combine reliability indices and network losses using their monetary value. This is main minimization objective

$$Minimize\ TC = TLC + UIC + CIC_{kWh} + CIC_t + RC \tag{3.11}$$

with the following constraints:

$$I_i \leq I_{\max}$$
$$V_{\min} \leq V_i \leq V_{\max}$$
$$g_i(I,k) = 0, \quad g_v(V,k) = 0$$

Where,
TC is the Total cost of the distribution system.
TLC is the total loss cost of the distribution system and is defined as equation 3.12:

$$TLC = C_P \cdot \sum_{d=1}^{365} \sum_{h=1}^{24} P_{loss} \tag{3.12}$$

C_P is the price of electricity per kWh.
UIC is defined as Utility Interruption cost. It represents economic value of lost electricity due to interruption and is given by equation 3.13:

$$UIC = C_P \cdot ENS \tag{3.13}$$

CIC_{kWh} is defined as Customer Interruption Cost as per kWh and signifies opportunity cost associated with loss of energy to the customer. Energy loss will result in end revenue loss for customers, which is much higher than electricity price. It is given by

3.14:

$$CIC_{kWh} = ENS * IEAR \tag{3.14}$$

Where IEAR (Interrupted Energy Assessment Rate) is the energy cost for the consumer considering their loss in the outage.
CIC_t is the customer interruption cost per time and signifies the opportunity cost associated with outage frequency to the customer. It is given by 3.15

$$CIC_t = SAIFI * ICPE \tag{3.15}$$

Where ICPE is the Interruption cost per event.
RC is the reconfiguration cost representing the cost of opening and switching tie lines.

CHAPTER FOUR

Results and Discussion

4.1 Results

In this section, the detailed results of optimization experiments using Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Cuckoo Search Algorithm (CSA), and Grey Wolf Optimization (GWO) are presented. Two sets of experiments: one allowing meshed or looped configurations during reconfiguration and the other maintaining strict radiality were conducted. For each case, each algorithm was run 10 times and recorded with various performance metrics, including execution time, number of iterations, and convergence behavior.

4.1.1 IEEE 33 bus system

At first, the IEEE 33 bus system was taken as a test system. It has 33 buses, 32 branches, and 5 switchable tie lines. The following parameters were used for computation.
Energy cost=0.1$ per kWh
Interruption Cost per Event = 100$ per event [6]
Customer Interrupted energy assessment rate = 1-3$ per kWh [25]
Tielines Cost =5000$ [26]

Though the original Customer Interrupted energy assessment on [25] is 5$, we've reduced this lower as the current feeder under study supplies very few commercial consumers and no industrial consumers. The rate is higher for industrial consumers than for corporate and residential consumers. Reliability data are taken from [27]. The proposed tie lines are

Table 4.1: Tie lines of IEEE 33 bus System

SN	From Bus	To Bus
1	21	8
2	9	15
3	12	22
4	18	33
5	25	29

4.1.1.1 Analysis of the Base System

As an initial step, the base system without any modification was analyzed. A load flow was performed, reliability costs were calculated, and based on that total operating costs of the system were calculated. The following results were obtained.

Table 4.2: IEEE 33 bus system base parameters

Parameter	Value
Active power Loss	202.6 kW
Reactive Power Loss	135.14 kVAR
SAIFI	1.43
SAIDI	5.164
CAIDI	3.6
ASAI	0.999
ENS	41938.87 kWh
AENS	5.97 kWh

Based on the above parameters of 4.2 total operation cost of the base system was calculated.

Table 4.3: Cost analysis of IEEE 33 bus base system

Parameter	Value
Loss Cost	177545$
Utility Energy Interruption cost	4193$
Customer Energy Interruption Cost	83877$
Interruption event Cost	310480$
Total Cost	576096$

The voltage profile and branch losses of the initial system are shown in figure 4.1 and 4.2 respectively.

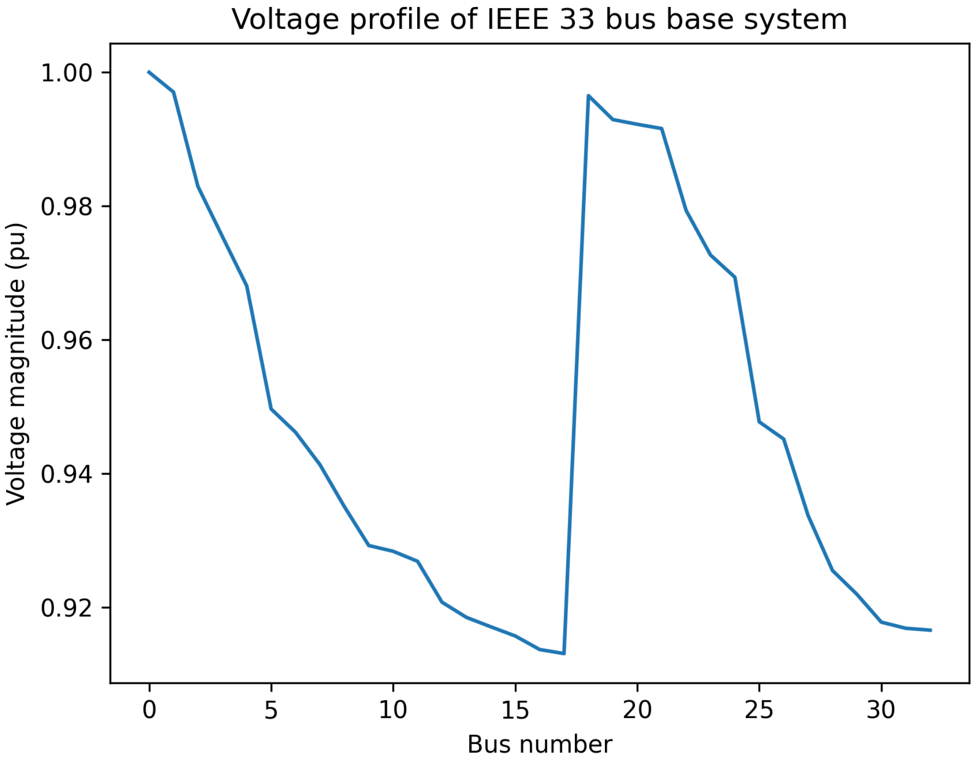

Figure 4.1: IEEE 33 bus base system voltage profile

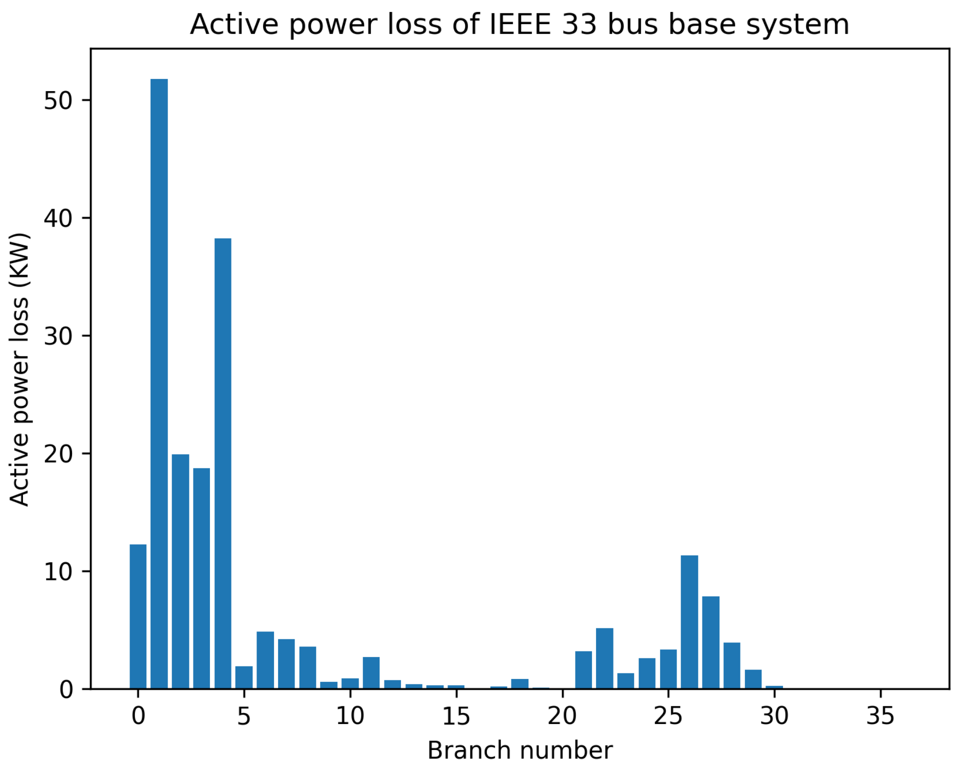

Figure 4.2: Active power loss of IEEE 33 bus base system

4.1.1.2 Reconfiguration solution (Radiability not maintained)

Upon running the optimization algorithm without strict radiability constraint, the following solutions in table 4.4 were reached. The result here shows four of five proposed tie lines are deemed feasible to switch on.

Table 4.4: Reconfigured Tie lines of IEEE 33 bus System

SN	From Bus	To Bus	Status
1	21	8	Closed
2	9	15	Closed
3	12	22	Closed
4	18	33	Open
5	25	29	Closed

Parameters used of optimization algorithm was:
Population Size: 10
Maximum Iteration: 50
Stall Generations: 10
For Genetic algorithm following additional parameters were used:
Mutatiion Probability: 0.1
Cross over probability: 0.5
Parents Portion: 0.3
For Particle swarm optimization, following coefficients were used
C1:0.5, C2:0.3 and W:0.9
For Cucko Search algorithm, following parameters were taken
Assigned Probability: 0.25
Levy Parameter: 1.5

Upon simulating the system with these additional tie lines switched on, the following system parameters (table 4.5) are observed. Upon immediate observation, huge improvement in system operational parameters. Active power loss saw a 38% decrease. SAIFI, SAIDI, ENS, and AENS also improved quite significantly. CAIDI on the other hand has gotten worse.

Table 4.5: IEEE 33 bus system reconfigured parameters (non-radial)

Parameter	Base System	Reconfigured System
Active power Loss	202.6 kW	124.57 kW
Reactive Power Loss	135.14 kVAR	88.12 kVAR
SAIFI	1.43	0.29
SAIDI	5.16	1.75
CAIDI	3.6	5.95
ASAI	0.99	0.99
ENS	41938.88 kWh	13594.88
AENS	5.97 kWh	1.94

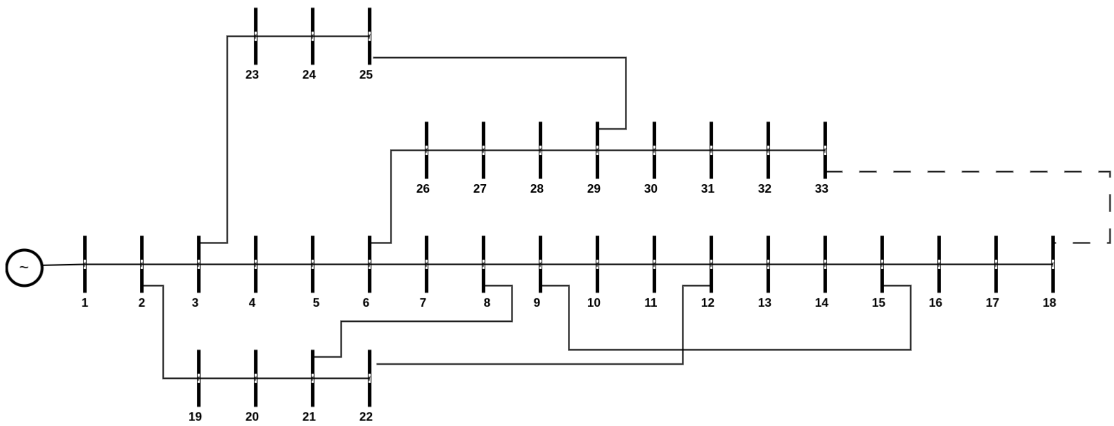

Figure 4.3: Restructured 33 Bus System (non-radial)

Having an additional path for electricity flow in the event of a fault reduced, the number of customers experiencing faults and hence reduction in SAIFI occurred. Again, less outage in the system is responsible for SAIDI. For CAIDI situation is different, only customers that are inside a loop are experiencing reduced outages, but on part of the system where there is still a radial feeder, these interruptions are not reduced much. So, a small portion experiences more outage resulting in higher CAIDI. ASAI also has improved but is insignificant. A reduced no of critical system failures has resulted in significant improvement in ENS and AENS

Based on the above parameters of 4.5 total operation cost of the reconfigured system was calculated. It's shown in table 4.6.

Table 4.6: Cost analysis of IEEE 33 bus reconfigured system (non-radial)

Parameter	Base System	Reconfigured System
Loss Cost	177545$	109130$
Utility Energy Interruption cost	4193$	1359 $
Customer Energy Interruption Cost	83877$	27189 $
Interruption event Cost	310480$	310640
Tieline Cost		20000 $
Total Cost	576096$	468319$

Here, on cost comparison, we can see that a significant chunk of the cost is Loss cost, where again we get to see above 37% reduction after reconfiguration. All other costs except the Interruption event cost and Tieline cost have decreased. Since customers are not experiencing power outages, utility energy interruption cost and customer energy interruption cost both have decreased. But, having to operate and maintain extra lines has added to Tieline's cost. And, the fact that the actual no of faults has further increased in the system due to the addition of 3 more lines has increased interruption event cost.

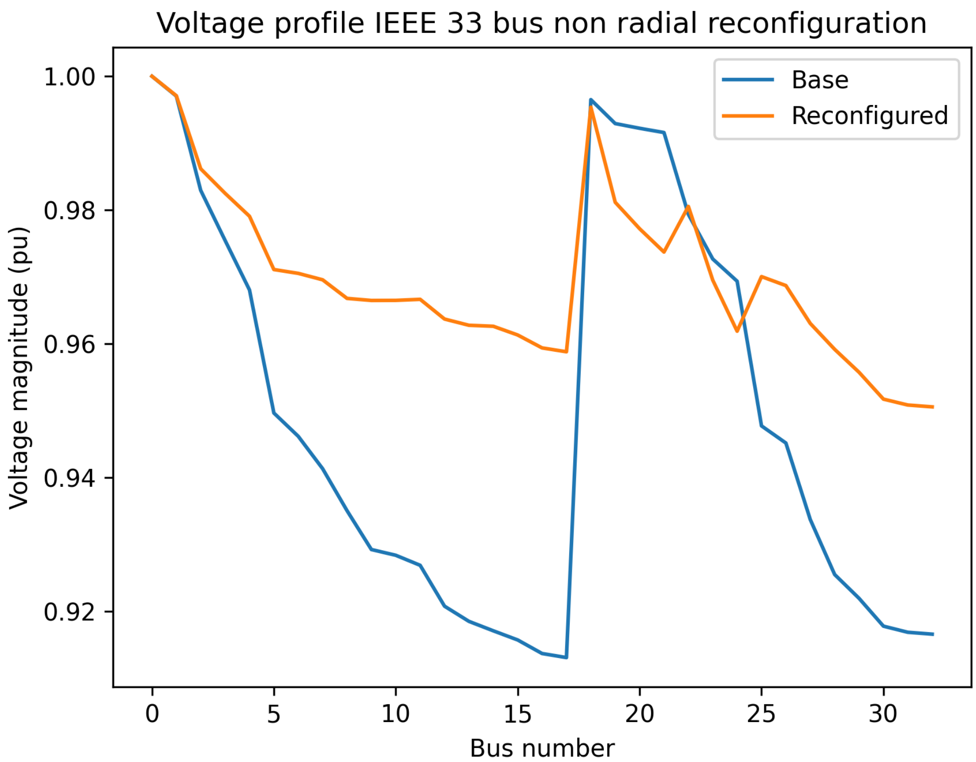

Figure 4.4: IEEE 33 bus reconfigured system voltage profile (non-radial)

In figure 4.4, It can be noticed that the voltage profile of the system has increased significantly. The change is more visible in the end bus of radial feeders. Similarly, in figure 4.5 we can see power loss in most branches especially starting branches of radial feeder have decreased significantly. But for some branches loss has increased as they now have to supply power to the additional bus due to the loop.

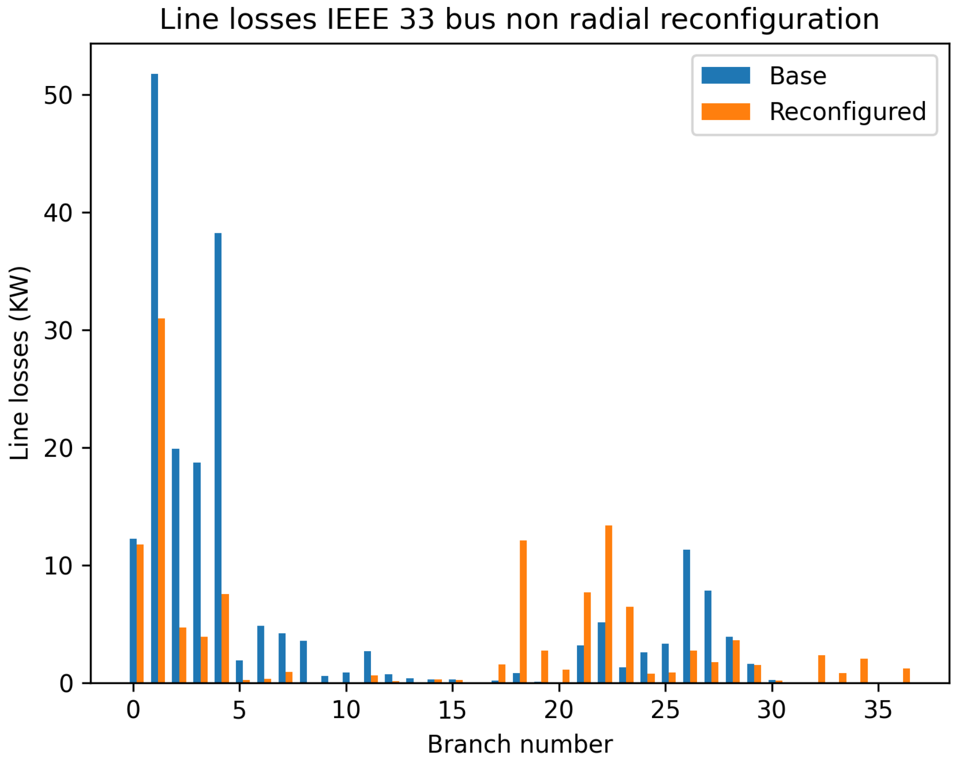

Figure 4.5: Active power loss of IEEE 33 bus reconfigured system (non-radial)

Since the four algorithms gave the same tielines reconfiguration, their comparison is done based on the time required for running these algorithms. The same metaheuristic algorithm can solve at different times for the same problem while running multiple times. This is due to a random selection of the starting population each time. Sometimes starting population may contain a point near to required solution or may even contain the solution itself. In these cases solution is reached quickly, and in cases where the starting population is very far from optimum, it may take more iteration and might not even find the solution.

This introduces a challenge in comparing different algorithms for the same problem. As even multiple runs of the same algorithms can be better or worse than before, we need a new way to compare algorithms. Here we've run all four algorithm 10 times each and recorded their time and iteration count for solution. Their average iteration per solution and average time per iteration is taken as a comparative factor.

Simulation details for different algorithms is presented below

Table 4.7: Comparison of Optimization Algorithm (non-radial)

SN	GA			PSO			CSA			GWO		
	iteration	time(s)	time per iteration	iteration	time(s)	time per iteration	iteration	time(s)	time per iteration	iteration	time(s)	time per iteration
1	38	64.6	1.7	48	513.6	10.7	40	1600	40	39	405.6	10.4
2	26	49.4	1.9	44	431.2	9.8	44	1672	38	50	525	10.5
3	43	81.7	1.9	50	490	9.8	44	1584	36	50	505	10.1
4	50	95	1.9	39	413.4	10.6	44	1584	36	39	440.7	11.3
5	50	85	1.7	41	434.6	10.6	44	1716	39	47	531.1	11.3
6	50	80	1.6	50	490	9.8	40	1640	41	28	282.8	10.1
7	38	64.6	1.7	22	160.6	7.3	40	1640	41	50	535	10.7
8	38	72.2	1.9	42	411.6	9.8	44	1760	40	43	447.2	10.4
9	34	64.6	1.9	39	413.4	10.6	44	1760	40	39	409.5	10.5
10	29	52.2	1.8	50	490	9.8	44	1804	41	37	373.7	10.1
Average	39.6	70.93	1.8	42.5	424.84	9.88	42.8	1676	39.2	42.2	445.56	10.54

The performance of algorithms was recorded on the computer with 12th Gen Intel® Core™ i7-12700H CPU and 16GB DDR5 Memory.

Upon closely observing data presented in table 4.17, It becomes clear that not all algorithms can search at the same pace and in the same iterations. GA was slightly better than its competitors for the average no of iterations required to find the solution (GA:40, Rest: 43). But in terms of computational time used, it left others in the dust. GA was able to converge in solution with an average time of 71 Seconds while PSO and GWO took more than 400 seconds. CSA on the other hand averaged above 1600 seconds for a solution.

Since the same fitness function was used across all algorithms and all algorithms shared the same number of particles per generation, the difference in time came only from how an algorithm generated a new population from the previous generation. GA's algorithm seemed superior for creating offspring as it was able to evaluate and find new generations every 1.8 seconds. PSO and GWO position updating algorithms seemed more resource-hungry at 9.88 and 10.54 seconds per generation, almost 5 times that of GA. The CSA's nesting algorithm was a highly taxing computation averaging above 400 seconds for a single generation.

The above algorithm was also run on the varying scenario of Customer Interruption Cost rate of \$1 to \$3 per kWh on steps increment of 0.5. Results are presented in table 4.8

Table 4.8: Tie Line status while varying CIC rate

Tie Lines	\$1/kWh	\$1.5/kWh	\$2/kWh	\$2.5/kWh	\$3/kWh
21–8	closed	closed	closed	closed	closed
9–15	open	closed	closed	closed	closed
12–22	closed	closed	closed	closed	closed
18–33	open	open	open	open	closed
25–29	closed	closed	closed	closed	closed

Results in table 4.8 show that tie line status is highly impacted by the CIC rate. Though we have taken the CIC rate the same for the whole feeder, in practice this rate is different for different types of customers. Usually, for residential customers, this cost is almost the same as energy cost, for Agricultural and Corporate consumers it's higher than energy cost and a lot higher for industrial consumers. This variation arises because the same interruption impacts different customers differently. The same blackout might have no to very little impact on residential customers but will have a high impact on industrial consumers as production of goods will halt, and machines will have to be restarted. In extreme cases, raw materials might be damaged and useless.

4.1.1.3 Reconfiguration solution with strict radiality

For obtaining strict radiality, all critical lines are first identified. Critical lines are those lines that don't have an alternate path and if opened will cause an outage in one or more buses. For the 33 bus system, only line 1 is critical. The open/close state of all remaining branches as well as tie switches are then initialized randomly. Any solution where one or more buses don't have a path or solutions where a loop is formed is discarded for further evaluation.

Upon running the optimization algorithm with the additional non-linear constraint of strict radiality, the following results were obtained as presented in table 4.9

Table 4.9: Branch Status in Reconfigured System (Radial)

SN	From Bus	To Bus	Status
1	1	2	Closed
2	2	3	Closed
3	3	4	Closed
4	4	5	Closed
5	5	6	Closed
6	6	7	Closed
7	7	8	Open
8	8	9	Closed
9	9	10	Open
10	10	11	Closed
11	11	12	Closed
12	12	13	Closed
13	13	14	Closed
14	14	15	Open
15	15	16	Closed
16	16	17	Closed
17	17	18	Closed
18	2	19	Closed
19	19	20	Closed
20	20	21	Closed
21	21	22	Closed
22	3	23	Closed
23	23	24	Closed
24	24	25	Closed
25	6	26	Closed
26	26	27	Closed
27	27	28	Closed
28	28	29	Closed
29	29	30	Closed
30	30	31	Closed
31	31	32	Closed
32	32	33	Open
33	21	8	Closed
34	9	15	Closed
35	12	22	Closed
36	18	33	Closed
37	25	29	Open

The new configuration of the line looks like figure 4.6

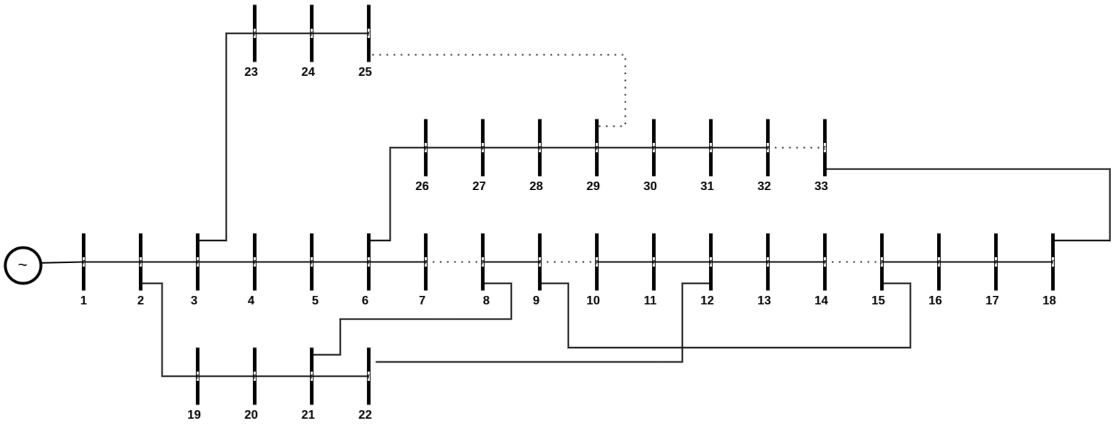

Figure 4.6: Reconfigured 33 bus system (Strictly Radial)

Upon simulating the system with these line configurations, the following system parameters (table 4.10) are observed. Upon immediate observation, a huge improvement in system operational parameters is noticed. Active power loss saw only a 30% decrease instead of a 38% decrease in non-radial solution. SAIFI, SAIDI, ENS, and AENS also improved quite significantly compared to the base system but not as much as the non-radial solution. CAIDI on the other hand has gotten better than non-radial solution.

Table 4.10: IEEE 33 bus system reconfigured parameters (Radial)

Parameter	Base System	Reconfigured System (non-radial)	Reconfigured System (Radial)
Active power Loss	202.6 kW	124.5 kW	139.55 kW
Reactive Power Loss	135.14 kVAR	88.12 kVAR	102.3 kVAR
SAIFI	1.43	0.29	0.88
SAIDI	5.16	1.75	3.52
CAIDI	3.6	5.95	3.98
ASAI	0.99	0.99	0.99
ENS	41938.88 kWh	13594.88 kWh	30544.88 kWh
AENS	5.97 kWh	1.93 kWh	4.35 kWh

As parameters are shown before, the system operating cost is also better than the base system but not as much as the non-radial solution. The full cost comparison is shown in table 4.11

Table 4.11: Cost analysis of IEEE 33 bus reconfigured system (Radial)

Parameter	Base System	Reconfigured System (non-radial)	Reconfigured System (Radial)
Loss Cost	177545$	109130$	122246$
Utility Energy Interruption cost	4193$	1359 $	3054$
Customer Energy Interruption Cost	83877$	27189 $	61089$
Interruption event Cost	310480$	310640$	310480$
Tieline Cost	20000	20000 $	
Total Cost	576096$	468319$	516871$

A Reconfigured System with radiality is not as good as a non-radial system because of the lack of loops. Loops allowed a non-radial system to serve most customers in case of a branch fault upstream. But in radial solution that is not possible. All downstream consumers will be affected by an upstream fault. Similarly, network loss is also less due to multiple parallel paths for power flow in the looped system.

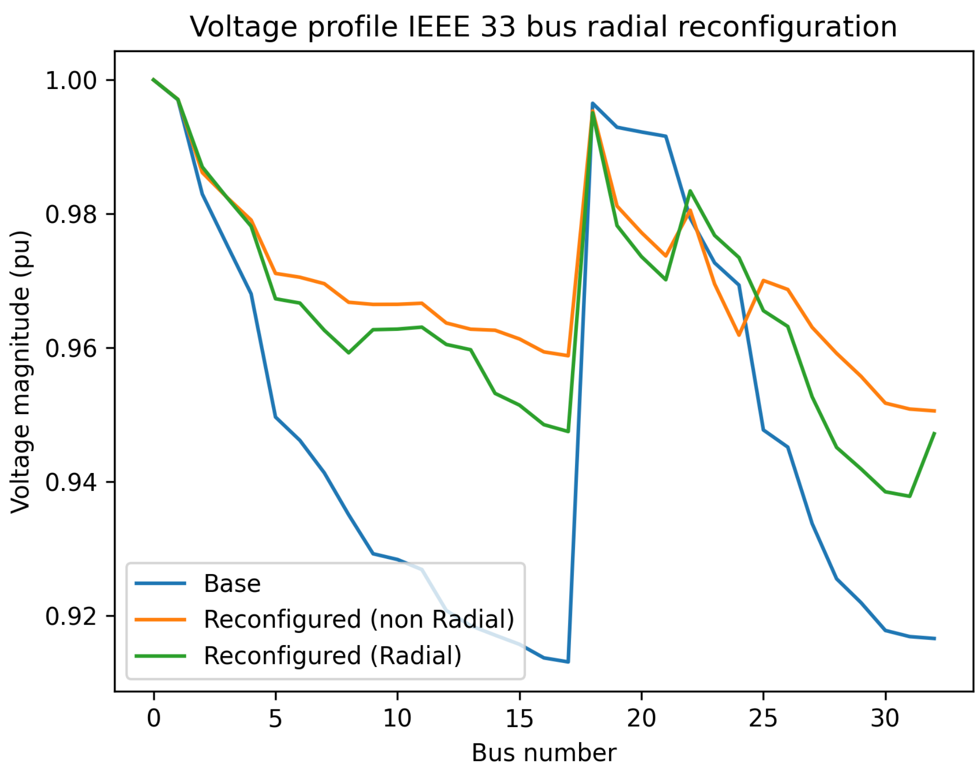

Figure 4.7: IEEE 33 bus reconfigured system voltage profile (Radial)

As expected, the radial reconfigured system has a better voltage profile than the base system but not as much better as the looped system as shown in figure 4.7. The same is the case for branch loss of the system shown in figure 4.8.

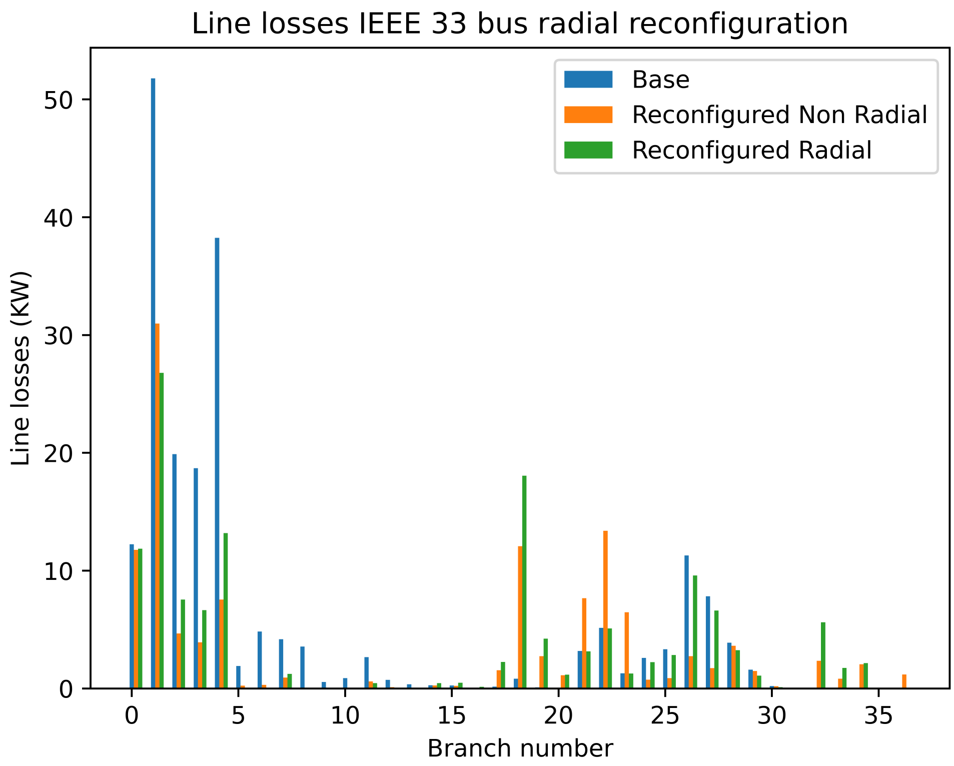

Figure 4.8: Active power loss of IEEE 33 bus reconfigured system (Radial)

4.1.2 Gothatar Feeder

For the next part of the work, a real-world feeder of Gothatar, Kathmandu was taken. The feeder is radial having 69 busses and serving 4096 customers in total. For the initial system, load flow was done and calculation for the base parameter was carried out. The results are presented in table 4.12.

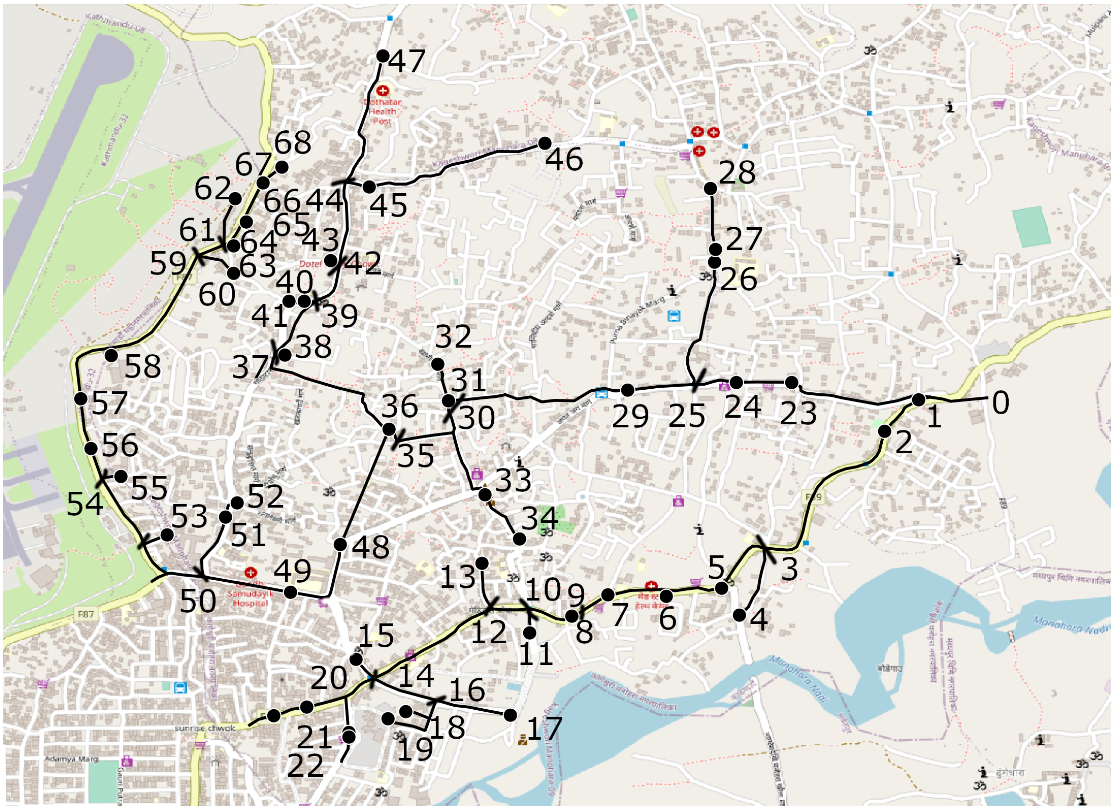

Figure 4.9: Gothatar Feeder Layout

Table 4.12: Gothatar System base parameters

Parameter	Value
Active Power Loss	134.81kW
Reactive Power Loss	63.15 kVAR
SAIFI	0.621
SAIDI	3.46
CAIDI	5.57
ASAI	0.99
ENS	17209 kW
AENS	3.44 kW

Based on the above parameters of table 4.12 total operation cost of the base system was calculated.

Table 4.13: Gothatar Feeder Initial operating cost

Parameter	Value
Loss Cost	118091.72 $
Utility Energy Interruption Cost	1720.99 8 $
Customer Energy Interruption Cost	34419.90 $
Interruption Event Cost	254408.57 $
Total Cost	408641.18 $

The initial voltage profile of the system and line loss of branches are shown in figure 4.10 and figure 4.11 respectively.

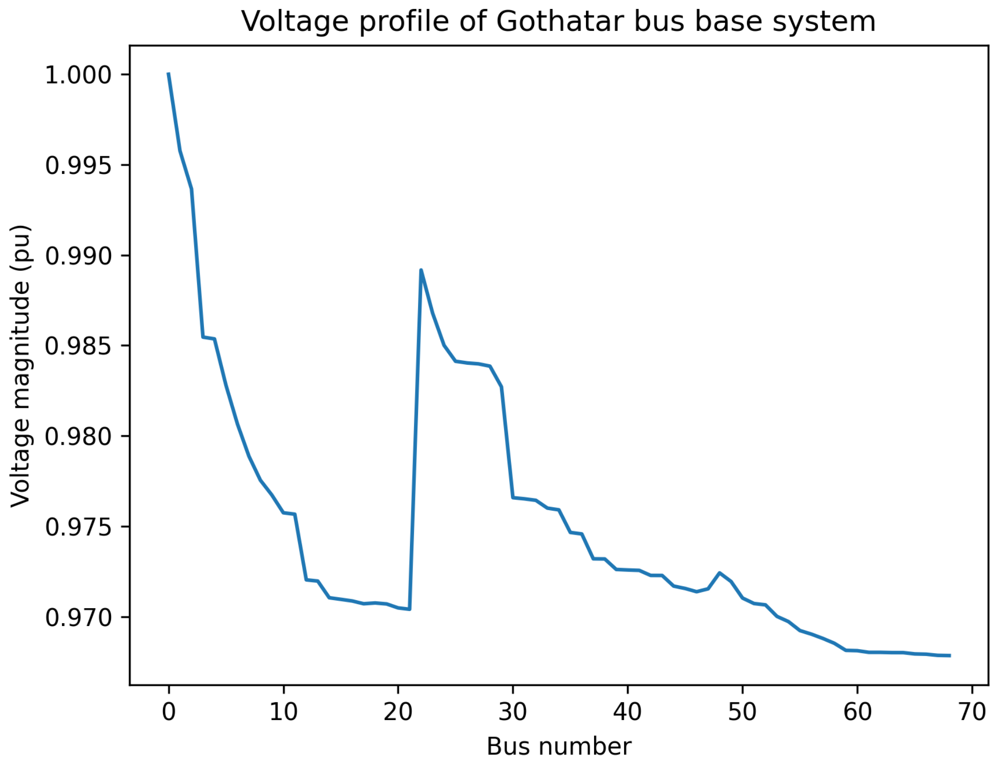

Figure 4.10: Voltage profile of Gothatar System

For the next part, five tie lines location was proposed for reconfiguring the feeder. Tie line location is based on the relative position of the bus in different lateral lines to minimize tie line length. The proposed system looks like figure 4.12.

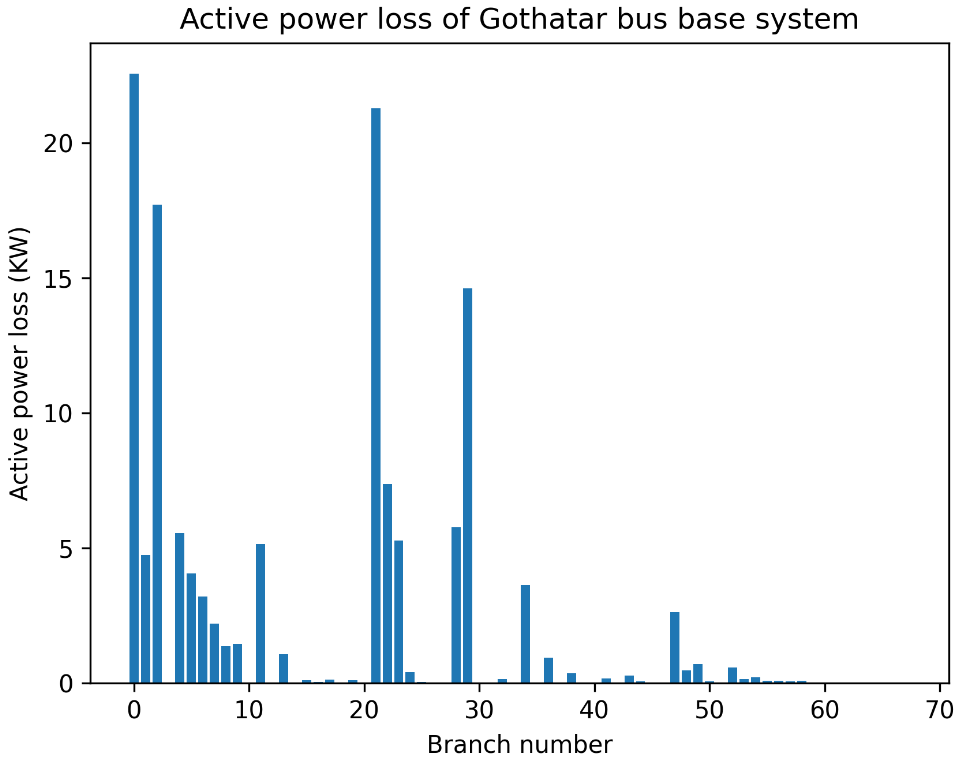

Figure 4.11: Line loss of Gothatar System

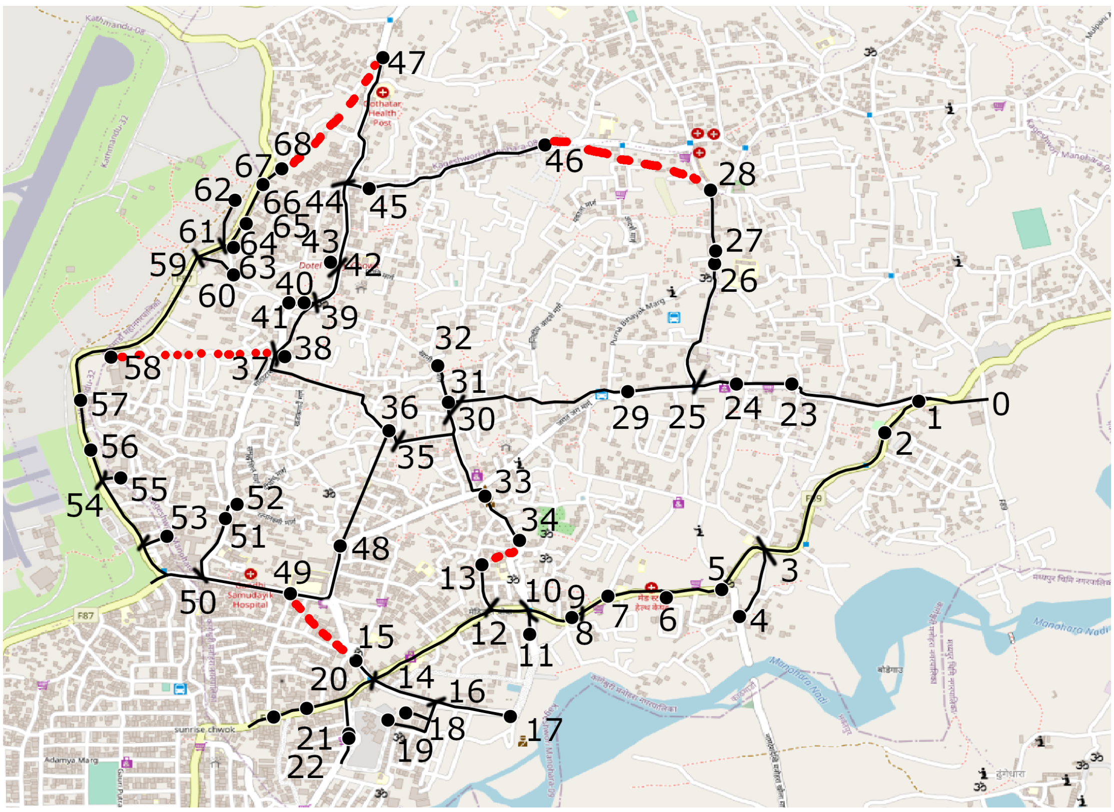

Figure 4.12: Proposed tie line location for Gothatar feeder (red dotted)

4.1.2.1 Reconfiguration with strict radiality

Next, the Gothatar feeder is reconfigured for minimum loss and reliability costs while maintaining strict radiality. For maintaining strict radiality, additional non-linear constraints are introduced in the system that stop forming loops. Affected lines in resulting solutions are presented in table 4.14 .Operating conditions calculated with the above

Table 4.14: Optimized Solution for Strict Radial Reconfiguration of Gothatar feeder

SN	From Bus	To Bus	Previous State	Current State
1	28	46	Open	Closed
2	37	58	Open	Closed
3	13	34	Open	Closed
4	39	42	Closed	Open
5	57	58	Closed	Open
6	30	33	Closed	Open

system are presented in table 4.15 and corresponding costs in 4.16.

Table 4.15: Reconfigured Gothatar System parameters

Parameter	Base Value	Reconfigured value
Active Power Loss	134.81kW	130.15 kW
Reactive Power Loss	63.15 kVAR	57.7 kVAR
SAIFI	0.621	0.515
SAIDI	3.46	3.14
CAIDI	5.57	6.1
ASAI	0.99	0.99
ENS	17209 kWh	15816kWh
AENS	3.44 kWh	3.16kWh

Table 4.16: Gothatar Feeder Initial operating cost

Parameter	Base Value	Reconfigured value
Loss Cost	118091.72 $	114017.34 $
Utility Energy Interruption Cost	1720.99 8 $	1581.64 $
Customer Energy Interruption Cost	34419.90 $	210974 $
Interruption Event Cost	254408.57 $	31632.86$
Total Cost	408641.18 $	358206.14 $

Parameters used of optimization algorithm was:

Population Size: 50

Maximum Iteration: 200

Stall Generations: 20

For Genetic algorithm following additional parameters were used:

Mutatiion Probability: 0.1

Cross over probability: 0.5

Parents Portion: 0.3

For Particle swarm optimization, following coefficients were used

C1:0.5, C2:0.3 and W:0.9

For Cucko Search algorithm, following parameters were taken

Assigned Probability: 0.25

Levy Parameter: 1.5

The optimal solution was reached by GA, PSO, and CSA each time on the run while GWO did not converge most of the time. The convergence issue was mostly because the optimization problem is non-continuous. Only looking for a strictly radial solution makes search space extremely sparse. GA's mutation seems to help individual solutions to jump between such sparse spaces particularly well as GA was significantly faster in providing solutions than the rest of the algorithms.

Table 4.17: Comparison of Optimization Algorithm on Gothatar Feeder Radial reconfiguration

SN	GA			PSO			CSA			GWO		
	iteration	time(m)	time per iteration	iteration	time(m)	time per iteration	iteration	time(m)	time per iteration	iteration	time(m)	time per iteration
1	49	122.5	2.5	65	1092	16.8	73	6416.7	87.9	NA	NA	NA
2	55	137.5	2.5	67	1051.9	15.7	82	5920.4	72.2	95	8740	92
3	62	148.8	2.4	92	1766.4	19.2	88	6635.2	75.4	NA	NA	NA
4	49	122.5	2.5	43	700.9	16.3	64	5203.2	81.3	NA	NA	NA
5	51	127.5	2.5	83	1560.4	18.8	79	6422.7	81.3	87	531.1	115.6
6	55	154	2.8	88	1672	19.0	77	6360.2	82.6	92	9954.4	108.2
7	57	153.9	2.7	96	1843.2	19.2	84	7417.2	88.3	NA	NA	NA
8	43	120.4	2.8	53	1044.1	19.7	63	6652.8	105.6	96	9878.4	102.9
9	45	126	2.8	58	1165.8	20.1	74	6837.6	92.4	NA	NA	NA
10	47	136.3	2.9	72	1360.8	18.9	91	8017.1	88.1	NA	NA	NA
Average	51.3	134.94	2.64	71.7	1325.75	18.37	77.5	6588.31	85.51	92.5	9185.25	99.3

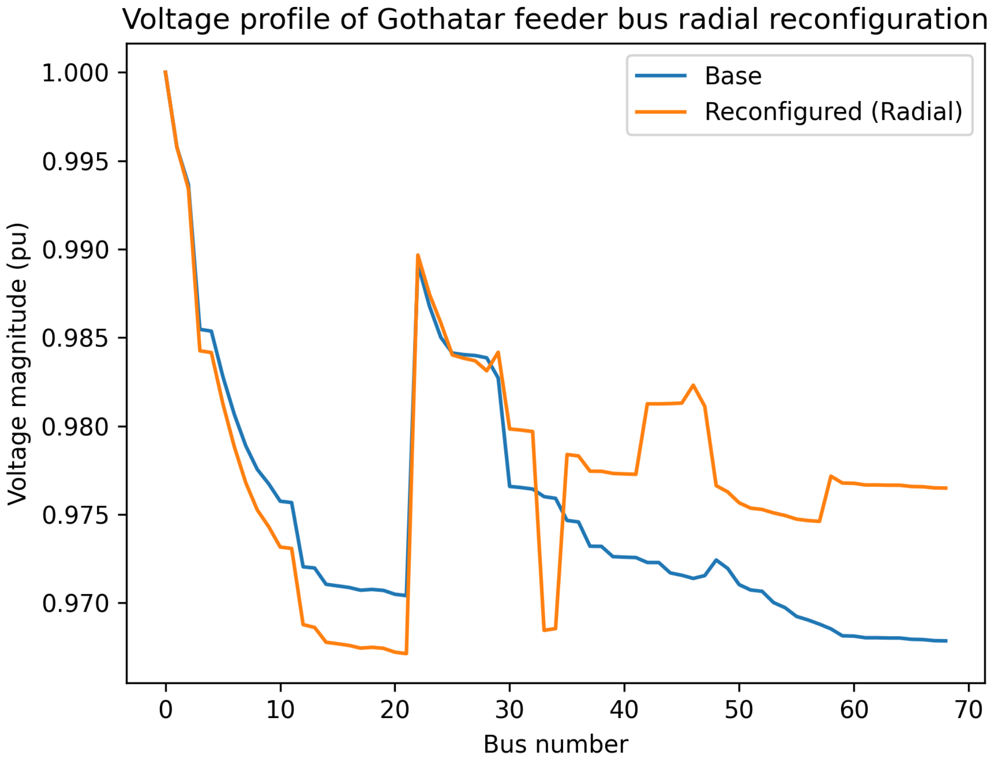

Figure 4.13: Gothatar Feeder radial reconfigured system voltage profile

As expected radial reconfigured system has a better voltage profile than the base system but not as much better as the looped system as shown in figure 4.7. The same is the case for branch loss of the system shown in figure 4.8.

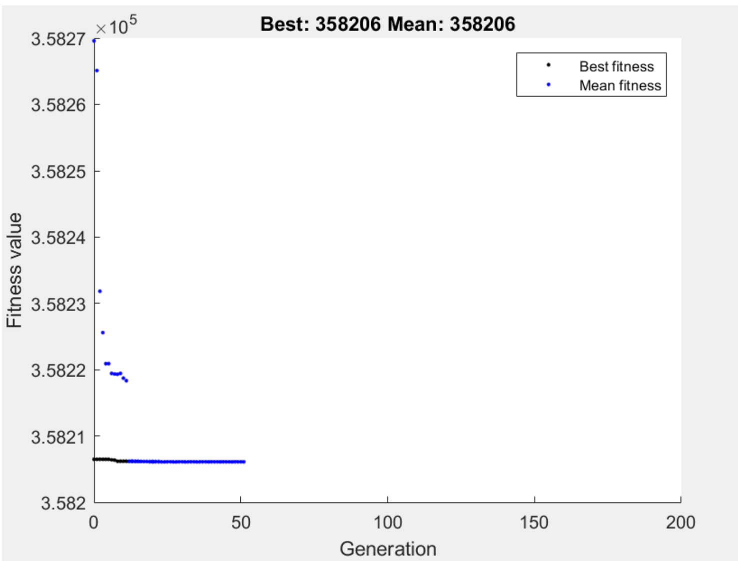

Figure 4.14: GA convergence Graph for a sample run

Figure 4.14 shows a convergence profile for GA in a sample optimization run. The Hit ratio for three of algorithms including GA, PSO and CSA was 1, while for GWO, it was much poor at only 0.4. This indicates that further modifications might be needed for GWO for successfully using in optimization involving power systems.

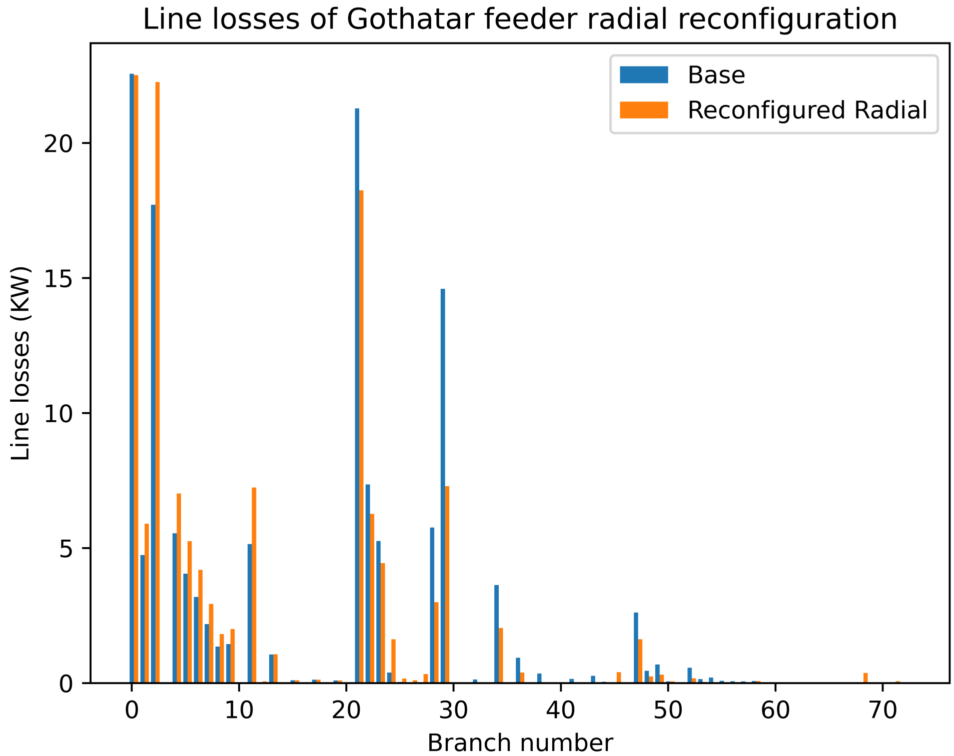

Figure 4.15: Active power loss of Gothatar feeder radial reconfiguration

The optimization was rerun for varying CIC charges to study how that would affect optimization results. Only GA was considered for this additional optimization as GA was faster to run. The results are presented in table 4.18.

Table 4.18: CIC rate variation in radial reconfiguration in Gothatar feeder

CIC Rate	Affected Lines			
	From Bus	To Bus	Previous State	Current Sate
1$/kWh	28	46	Open	Closed
	36	37	Closed	Open
1.5$/kWh	28	46	Open	Closed
	36	37	Closed	Open
2$/kWh	28	46	Open	Closed
	37	58	Open	Closed
	13	34	Open	Closed
	39	42	Closed	Open
	57	58	Closed	Open

	30	33	Closed	Open
2.5$/kWh	28	46	Open	Closed
	37	58	Open	Closed
	13	34	Open	Closed
	39	42	Closed	Open
	57	58	Closed	Open
	30	33	Closed	Open
3$/kWh	28	46	Open	Closed
	37	58	Open	Closed
	13	34	Open	Closed
	39	42	Closed	Open
	57	58	Closed	Open
	30	33	Closed	Open

We see two sets of results based on CIC values of below 2$ Per kWh and above it. The differences in operating parameters are shown in table 4.19.

Table 4.19: Operating Condition Comparision

Parameter	Base Value	Above 2$/kWh	Below 2$/kWh
Active Power Loss	134.81kW	130.15 kW	128.32kW
Reactive Power Loss	63.15 kVAR	57.7 kVAR	52.9kVAR
SAIFI	0.621	0.515	0.572
SAIDI	3.46	3.14	3.35
CAIDI	5.57	6.1	5.85
ASAI	0.99	0.99	.99
ENS	17209 kWh	15816kWh	16382 kWh
AENS	3.44 kWh	3.16kWh	3.27kWh

Results show that at a low CIC rate, optimization favored reducing system power loss rather than improving reliability, as loss cost becomes more significant than reliability cost. A reverse case happens when CIC is increased.

CHAPTER FIVE

Conclusions and Recommendations

5.1 Conclusion

This work has compared different optimization algorithms for use in distribution system restructuring. GA, PSO, CSA, and GWO are considered for comparison in this study. Each of those algorithms has their own characteristic and perform better than other for a specific type of problem. These algorithms were used on two different test systems for multiple times to get generalized timing results. The total operating loss cost of the system was taken as a minimization objective. Total loss cost comprised of active power loss, Interruption costs and Energy not Supplied costs. The distribution system is optimized while maintaining and discarding strict radiality.

Results shown indicate GA is by far a better choice for such sort of optimization work. GA operated at less than 50% of the compute time of the next best algorithm. On the other hand, PSO and CSA too did an okay job. Both were able to consistently find solutions albeit slower than GA. GWO on the other hand struggled to find optimal solutions, not converging or converging on local minima instead of global many times. As search space is heavily discontinuous and the nature of the solution is discrete, algorithms that favor continuous/gradual progression instead of sudden movement suffer. GA's mutation seems to help a lot in such a discontinuous search space. PSO and CSA took more time in calculating the next generation of individuals and hence their performance suffered time-wise.

Overall GA was clear algorithm of choice for most power system optimization problems, as most requirement share similar problem formulation and discrete search space.

5.2 Recomendations

This work can be extended further by adding more optimization algorithms into consideration. Modifications can be suggested for subpar algorithms that can enhance their performance. In this work, radiality is maintained by a set of non-linear equations that eliminate loops. Other techniques can be used to ensure radiality. Optimization objectives can be changed to enhance a specific type of reliability only instead of trying to optimize all at once. Interruption costs considered are fairly basic for now, customers can be segregated and different tiers of interruption cost rates can be used for different sectors of customers.

Appendix

IEEE 33bus BW system Bus Data [28]

Bus No	V Mag (pu)	Vang (degree)	P (MW)	Q (Mvar)
1	1	0	-3.91768	-2.43514
2	0.997032	0.014481	0.1	0.06
3	0.982938	0.096042	0.09	0.04
4	0.975456	0.161651	0.12	0.08
5	0.968059	0.228285	0.06	0.03
6	0.949658	0.133853	0.06	0.02
7	0.946173	-0.09647	0.2	0.1
8	0.941328	-0.0604	0.2	0.1
9	0.935059	-0.13348	0.06	0.02
10	0.929244	-0.19601	0.06	0.02
11	0.928384	-0.18876	0.045	0.03
12	0.926885	-0.17727	0.06	0.035
13	0.920772	-0.26859	0.06	0.035
14	0.918505	-0.34727	0.12	0.08
15	0.917093	-0.38495	0.06	0.01
16	0.915725	-0.40821	0.06	0.02
17	0.913698	-0.48547	0.06	0.02
18	0.91309	-0.49506	0.09	0.04
19	0.996504	0.003651	0.09	0.04
20	0.992926	-0.06333	0.09	0.04
21	0.992222	-0.08269	0.09	0.04
22	0.991584	-0.10303	0.09	0.04
23	0.979352	0.06508	0.09	0.05
24	0.972681	-0.02365	0.42	0.2
25	0.969356	-0.06736	0.42	0.2
26	0.947729	0.17331	0.06	0.025
27	0.945165	0.229463	0.06	0.025
28	0.933726	0.312409	0.06	0.02
29	0.925507	0.390314	0.12	0.07
30	0.92195	0.495586	0.2	0.6
31	0.917789	0.411178	0.15	0.07
32	0.916873	0.388135	0.21	0.1
33	0.91659	0.380405	0.06	0.04

Line Data of Gothatar Feeder

From Bus	To Bus	Length(km)	R/Km	X/km
0	1	0.14	0.5524	0.3

1	2	0.12	0.9289	0.3
2	3	0.48	0.9289	0.3
3	4	0.19	0.9289	0.3
3	5	0.16	0.9289	0.3
5	6	0.14	0.9289	0.3
6	7	0.13	0.9289	0.3
7	8	0.10	0.9289	0.3
8	9	0.06	0.9289	0.3
9	10	0.08	0.9289	0.3
10	11	0.13	0.9289	0.3
10	12	0.34	0.9289	0.3
12	13	0.07	0.5524	0.3
12	14	0.16	0.5524	0.3
14	15	0.18	0.5524	0.3
14	16	0.05	0.5524	0.3
16	17	0.13	0.5524	0.3
14	18	0.08	0.9289	0.3
18	19	0.09	0.9289	0.3
18	20	0.10	0.9289	0.3
20	21	0.08	0.9289	0.3
1	22	0.35	0.5524	0.3
22	23	0.13	0.5524	0.3
23	24	0.10	0.5524	0.3
24	25	0.34	0.5524	0.3
25	26	0.04	0.5524	0.3
26	27	0.04	0.5524	0.3
27	28	0.16	0.5524	0.3
24	29	0.16	0.5524	0.3
29	30	0.44	0.5524	0.3
30	31	0.04	0.5524	0.3
31	32	0.10	0.5524	0.3
30	33	0.44	0.5524	0.3
33	34	0.15	0.5524	0.3
30	35	0.17	0.5524	0.3
35	36	0.17	0.5524	0.3
35	37	0.39	0.5524	0.3
37	38	0.02	0.9289	0.3

37	39	0.17	0.5524	0.3
39	40	0.03	0.9289	0.3
40	41	0.04	0.9289	0.3
39	42	0.12	0.5524	0.3
42	43	0.03	0.9289	0.3
42	44	0.22	0.5524	0.3
44	45	0.06	0.5524	0.3
45	46	0.44	0.5524	0.3
44	47	0.36	0.5524	0.3
35	48	0.32	0.5524	0.3
48	49	0.08	0.5524	0.3
49	50	0.21	0.5524	0.3
50	51	0.17	0.9289	0.3
51	52	0.05	0.9289	0.3
50	53	0.31	0.5524	0.3
53	54	0.10	0.5524	0.3
54	55	0.20	0.5524	0.3
55	56	0.08	0.5524	0.3
56	57	0.13	0.5524	0.3
57	58	0.19	0.5524	0.3
58	59	0.34	0.5524	0.3
59	60	0.10	0.9289	0.3
59	61	0.07	0.9289	0.3
61	62	0.13	0.9289	0.3
61	63	0.01	0.5524	0.3
63	64	0.01	0.9289	0.3
63	65	0.08	0.5524	0.3
65	66	0.01	0.9289	0.3
66	67	0.10	0.5524	0.3
67	68	0.06	0.5524	0.3
28	46	0.30	0.5524	0.3
13	34	0.05	0.5524	0.3
15	49	0.10	0.5524	0.3
37	58	0.20	0.5524	0.3
47	68	0.30	0.5524	0.3

Load Data of Gothatar Feeder

Bus	Pload (MW)	Qload (MVAR)
0	0.00	0.00
1	0.06	0.05
2	0.07	0.07
3	0.00	0.00
4	0.05	0.05
5	0.18	0.09
6	0.09	0.05
7	0.12	0.08
8	0.00	0.00
9	0.13	0.11
10	0.00	0.00
11	0.06	0.05
12	0.00	0.00
13	0.16	0.11
14	0.00	0.00
15	0.07	0.06
16	0.40	0.17
17	0.17	0.16
18	0.00	0.00
19	0.06	0.05
20	0.21	0.09
21	0.09	0.09
22	0.12	0.10
23	0.12	0.12
24	0.00	0.00
25	0.01	0.00
26	0.18	0.10
27	0.12	0.05
28	0.14	0.07
29	0.13	0.06
30	0.00	0.00
31	0.14	0.05
32	0.14	0.07
33	0.11	0.07
34	0.10	0.08

35	0.00	0.00
36	0.09	0.03
37	0.00	0.00
38	0.04	0.03
39	0.00	0.00
40	0.06	0.04
41	0.06	0.03
42	0.00	0.00
43	0.01	0.01
44	0.00	0.00
45	0.27	0.22
46	0.07	0.03
47	0.07	0.04
48	0.22	0.09
49	0.17	0.15
50	0.00	0.00
51	0.03	0.03
52	0.16	0.05
53	0.05	0.04
54	0.09	0.03
55	0.00	0.00
56	0.10	0.07
57	0.05	0.04
58	0.04	0.04
59	0.00	0.00
60	0.02	0.02
61	0.00	0.00
62	0.00	0.00
63	0.00	0.00
64	0.01	0.00
65	0.00	0.00
66	0.06	0.03
67	0.06	0.05
68	0.03	0.02

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