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Optimal Reconfiguration of Medium Voltage Distribution Networks: A MINLP Approach with Power Loss Minimization

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ABSTRACT

This paper presents a comprehensive framework for optimizing medium voltage distribution networks, addressing the challenges of energy loss reduction, voltage stability, and operational cost minimization. The study combines methodologies from two complementary approaches: one focusing on the optimal reconfiguration of radial distribution networks using Mixed-Integer Nonlinear Programming (MINLP) models implemented in the General Algebraic Modeling System (GAMS), and the other highlighting advanced strategies for distributed generation (DG) integration and reactive power compensation. The proposed MINLP formulation employs branch-to-node incidence, enabling accurate representation of active and reactive power flows as functions of real and imaginary voltage and current components. By merging these approaches, the unified framework not only minimizes total power losses but also enhances voltage profiles and supports sustainable network operations. Case studies on IEEE-standard networks validate the effectiveness of the methodology, demonstrating its potential to address the complex challenges of modern power distribution systems.

1. Introduction

Electrical distribution networks constitute the largest and most critical component of modern power systems, responsible for delivering electricity from substations to end-users at medium voltage levels [1,2]. These networks, which typically operate at voltages ranging from 11.4 kV to 13.8 kV, are fundamental for the commercialization of electricity services [3]. However, their operational characteristics present significant challenges, including substantial power losses, voltage instability, and limited adaptability to modern energy demands [4]. Radial distribution networks, widely adopted by utilities for their simplicity and cost-effectiveness, are particularly prone to inefficiencies. This topology minimizes infrastructure investments by reducing the need for complex coordination of protective devices such as reclosers, sectionalizers, and fuses.

Despite these benefits, the inherent structure of radial networks introduces several operational drawbacks [5]:

- The extensive length of feeders combined with medium voltages results in higher resistance/reactance ratios compared to transmission systems. In countries like Colombia, where distribution grids often extend over rural and geographically dispersed areas, power losses can range between 6% and 15% of the total energy purchased in the spot market.

- Nodes farthest from the substation experience significant voltage drops, which adversely affect the quality and reliability of electricity delivery.
- Traditional radial networks lack the flexibility to accommodate modern demands, including renewable energy integration, bidirectional power flows, and dynamic load variations.

The modernization of electrical distribution networks necessitates advanced strategies to address these challenges [6, 7]. Optimal restructuring of distribution systems is a critical operational task aimed at enhancing the performance of power grids [8]. This process involves, minimizing energy losses across the network, improving voltage profiles to ensure stable and reliable electricity delivery, balancing loads to reduce strain on critical components and reducing operational costs while maintaining service quality. Beyond traditional optimization techniques, the evolving energy landscape introduces additional complexities [9]. Future distribution networks must accommodate unconventional operating conditions such as probabilistic loads, distributed renewable energy sources, small-scale generation, and the increasing prevalence of bidirectional power flows [10, 11]. These changes require the adoption of real-time monitoring and control systems to ensure efficient and sustainable operations. Despite extensive research in this field, significant gaps remain. While many studies focus on solution techniques, they often overlook the importance of accurate mathematical formulations to represent real-world problems effectively [12]. The ability to model and solve these optimization problems is essential for addressing practical challenges, particularly in the context of reconfigurable distribution networks [13]. Reconfiguration, which involves determining the optimal subset of network conductors while ensuring a radial structure, is a particularly complex problem [14-16]. It requires balancing multiple objectives, including power flow optimization, voltage regulation, and operational constraints. Traditional approaches often rely on heuristic or metaheuristic methods, which, while effective for solving complex problems, lack the rigor and accuracy provided by mathematically robust formulations. This gap underscores the need for precise models that can be efficiently solved using modern computational tools [17, 18]. MINLP offers a powerful framework for addressing this complexity [19-22]. By incorporating branch-to-node incidence matrices, active and reactive power flows can be accurately represented using real and imaginary components of voltages and currents [23-25]. This approach eliminates the need for trigonometric functions, reducing nonlinearity and improving computational efficiency.

This research integrates two complementary methodologies to develop a comprehensive framework for optimizing distribution networks. A mathematical approach employing MINLP to reconfigure radial networks, minimizing total power losses while adhering to operational constraints. Techniques to improve network efficiency, reliability, and adaptability under dynamic operating conditions. The primary objective is to bridge the gap between theoretical modeling and practical implementation by providing a robust, scalable, and adaptable solution for modern power systems. The proposed framework not only enhances operational efficiency but also equips engineers with the tools to develop accurate models and solve complex optimization problems using general-purpose solvers.

The contributions of this research are threefold, A rigorous MINLP model that accurately captures the complexities of distribution network reconfiguration, ensuring global optimization, the use of GAMS, a versatile and powerful optimization platform, to solve large-scale problems efficiently, the framework is designed to accommodate emerging challenges in the energy sector, including the integration of renewable energy sources, real-time control systems, and sustainability metrics. By addressing these critical aspects, this study aims to advance the field of power distribution optimization, providing a foundation for future research and practical applications in modern energy systems.

The use of rectangular representation for voltage and current variables significantly outperforms polar representation and heuristic/metaheuristic strategies by eliminating trigonometric functions, thereby reducing nonlinearity and improving computational efficiency. This approach minimizes numerical errors, provides more accurate modeling of power flows, and enhances solution reliability. Unlike polar representation, which can introduce rounding errors and complexity, rectangular representation ensures precision by directly using real and imaginary components. Combined with MINLP techniques, it enables global optimization, addressing the limitations of heuristic methods that often converge to local solutions. These advantages make rectangular representation a superior choice for accurate and scalable optimization of distribution networks. The method proposed in "Optimal Reconfiguration of Medium Voltage Distribution Networks: A MINLP Approach with Power Loss Minimization" stands out for its mathematical precision, ability to achieve global optimization, and adaptability to the dynamic conditions of modern energy systems. The MINLP model accurately minimizes power losses and voltage deviations while directly addressing operational constraints through a robust framework. Leveraging advanced optimization tools like GAMS, it efficiently solves large-scale problems. Moreover, it bridges the gap between theoretical modeling and practical applications by addressing modern energy demands such as renewable energy integration, real-time control, and sustainability. These attributes make the MINLP approach a comprehensive and scalable solution for optimizing distribution networks.

In the second part of this study, the contents of the formulation of the problems and the preparation of the objective function are presented, in the third part, methodology and mathematical modeling are shared. In the fourth part, case studies and results are presented in detail.

2. Problem Formulation

The optimal reconfiguration of AC distribution feeders is a classical problem in power system analysis, requiring a balance between mathematical rigor and practical implementation. This problem involves identifying the optimal subset of conductors that forms a radial network, ensuring compliance with operational constraints such as power balance, voltage regulation, and network topology. The objective is to minimize active power losses, while maintaining:

- Ensuring active and reactive power equilibrium at all nodes.
- Keeping node voltages within ±10% of nominal levels.
- Preserving the tree-like structure of the network to simplify the coordination of protective devices.

Mathematically, this problem is formulated as a MINLP model. The MINLP approach addresses the dual nature of the problem by combining binary variables for determining network configurations with continuous variables for power flow and voltage calculations [26]. While metaheuristic optimization strategies have been widely used to solve this problem, they often focus on sequential steps, employing a master-slave structure where the metaheuristic approach guides the search, and the power flow solution refines the configuration. Despite their practical success, these strategies frequently neglect the importance of accurate mathematical representation. Classical formulations often rely on trigonometric functions to represent voltage profiles, introducing strong nonlinearities that increase computational complexity and the likelihood of convergence to local optima [27]. This research proposes an alternative mathematical formulation to overcome these limitations. By using a rectangular representation of voltage and current variables, the model avoids trigonometric functions, reducing nonlinearity and enhancing computational efficiency. Additionally, binary variables are incorporated to determine the required subset of conductors, ensuring minimal power losses across all branches of the network. The proposed MINLP model represents a novel contribution to the field, addressing a gap in the specialized literature and providing a robust framework for distribution network reconfiguration.

To solve this complex optimization problem, the GAMS is employed as the computational platform. GAMS enables the formulation and solution of large-scale nonlinear programming problems, focusing on the correctness of the mathematical model rather than the solution technique [28]. This approach is particularly valuable for power system engineers and students, as it emphasizes the importance of accurate problem representation over heuristic-driven solutions. By presenting a comprehensive formulation of the reconfiguration problem, this research bridges the gap between theoretical modeling and practical application, providing a scalable and efficient solution for modern distribution networks. The optimization of radial distribution networks involves determining the optimal configuration of branches, nodes, and devices while adhering to technical and economic constraints. The goal is to achieve a balance between operational efficiency and cost-effectiveness [29]. The comparison between the proposed MINLP approach and metaheuristic techniques, such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA), highlights significant advantages in terms of computational efficiency and accuracy. Metaheuristic methods often rely on iterative, heuristic-driven search processes that can effectively navigate complex solution spaces but are prone to converging on local optima, especially in problems with high nonlinearity, such as distribution network reconfiguration [30]. These methods typically adopt a master-slave structure, where the optimization algorithm guides the search, and a power flow solver refines the results. However, this sequential process can be computationally intensive and lacks precision in mathematical representation. In contrast, the MINLP model eliminates trigonometric functions by employing a rectangular representation of voltage and current variables, significantly reducing nonlinearity and computational complexity. By incorporating binary variables for network configuration and continuous variables for power flow, the MINLP approach provides a mathematically rigorous and globally optimized solution. Additionally, tools like GAMS allow for precise problem formulation, ensuring scalability and efficiency in solving large-scale optimization problems. While PSO and GA are effective for exploratory searches, the MINLP model's ability to directly represent operational constraints and achieve global optimization makes it a superior choice for accurate and efficient reconfiguration of AC distribution networks.

2.1. Objective Function

The primary objective is to minimize the total cost function, expressed as:

$$minimize\ Z = Z_{losses} + Z_{operation} + Z_{investment} \tag{1}$$

where: Z_{losses}: Represents the costs due to energy losses in the network, $Z_{operation}$: Captures operational and maintenance expenses and $Z_{investment}$: Accounts for the capital costs of new infrastructure and devices.

2.2.Constraints

Key constraints ensure the feasibility and reliability of the optimized network:

Power Flow Equations: These equations ensure power balance at all nodes.

$$P_i^{gen} - P_i^{gen} = \sum_j P_{ij}\, , Q_i^{gen} - Q_i^{gen} = \sum_j Q_{ij} \tag{2}$$

Voltage Limits:Maintain acceptable voltage levels across the network.

$$V_{min} \leq V_i \leq V_{max} \tag{3}$$

Radial Topology Enforcement: The network must retain its tree structure, ensuring simplicity and reliability.

Device Capacity Limits:

$$S_{DG} \leq S_{max} \tag{4}$$

3. Methodology

3.1 Mathematical Modeling

The proposed methodology adopts a rectangular representation for voltage and current variables, avoiding the nonlinearities introduced by trigonometric functions. This approach reduces computational complexity and ensures global optimization.

3.2 Implementation in GAMS

GAMS is utilized to model and solve the optimization problem, leveraging its capabilities for handling complex, large-scale problems. Binary variables represent line reconfiguration, while continuous variables describe power flows and voltages. Power balance, radial topology, and voltage limits are explicitly modeled. The BONMIN solver is employed for its efficiency in handling mixed-integer nonlinear problems.

3.3 Simulation Scenarios

The model is tested under various operational conditions:

- Base Case: Network performance without optimization.
- Reconfiguration: Optimization of branch and node connections to minimize losses.
- DG and D-STATCOM Integration: Strategic placement of devices to enhance reliability and voltage profiles.

3.4. Case Study: IEEE 33-Node System

The IEEE 33-node distribution network is a standard test system widely used for analyzing and optimizing power distribution networks shown as Figure 1. The network consists of 33 nodes (or buses) and 32 branches (or lines) connecting these nodes. Below is a detailed explanation of the network's structure, components, and key parameters.

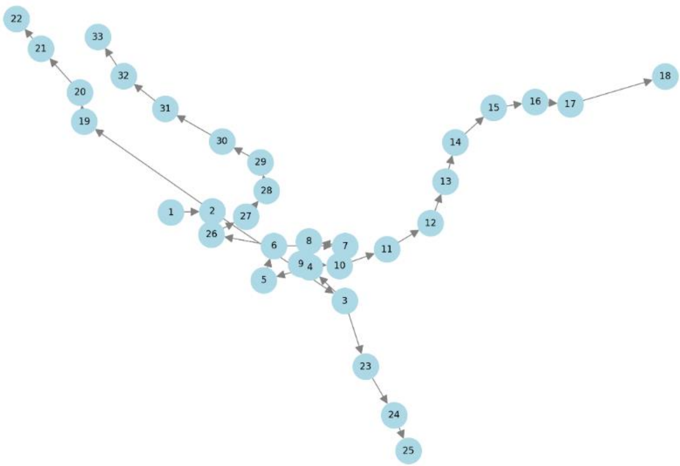

Figure 1. IEEE 33-Node Distribution Network

Nodes (Buses), Each node represents a point in the network where power is either supplied (source node) or consumed (load nodes). Slack Bus, Node 1 acts as the reference or slack bus, maintaining a fixed voltage magnitude and angle. Load Buses, Remaining nodes (2 to 33) are load buses where active and reactive power demands are specified. Branches (Lines), The 32 branches connect the nodes in a radial topology, meaning there are no closed loops. Each branch has electrical parameters, including resistance (R) and reactance (X), which contribute to power losses and voltage drops the parameters of test model shown in Table 1. The nominal voltage of the network is 12.66 kV. Voltage magnitudes at each node must remain within a permissible range (±10% of nominal voltage, i.e., 11.4 kV to 13.93 kV). Each branch is characterized by its resistance (R) and reactance (X). These parameters define the impedance of the line, influencing power flow and losses. Each load bus has a specified active power (P) and reactive power (Q) demand in kW and kVar, respectively. Active Power Flow, Represents the actual power consumed by loads or losses in the network. Combined active and reactive power losses across all branches contribute to the network's overall inefficiency.

Table 1. Parameters of Test Model

Branch	From Node	To Node	Resistance (R)	Reactance (X)	Load (P,Q)
1	1	2	0.092 Ohms	0.047 Ohms	100 kW, 60 kVar
2	2	3	0.493 Ohms	0.251 Ohms	90 kW, 40 kVar
3	3	4	0.366 Ohms	0.186 Ohms	120 kW, 80 kVar
…	…	…	…	…	…
32	32	33	0.748 Ohms	0.380 Ohms	60 kW, 30 kVar

Optimization of the IEEE 33-node system aims to Minimize Power Losses. Reconfigure branches or integrate devices like DGs and shunt capacitors to reduce losses. Improve Voltage Profiles, ensure all node voltages remain within the specified range. Balance Load Distribution, avoid overloading specific branches or nodes.

3.5.GAMS-Based Implementation

The optimization model is implemented in GAMS, leveraging its compact structure and powerful solvers such as BONMIN and DICOPT. GAMS excels in handling large-scale problems with mixed variables (binary, integer, and continuous) and provides a structured approach to define variables, constraints, and objective functions. Figure 2 illustrates the GAMS workflow for network reconfiguration.

Algorithm outlines the implementation steps:

- Define network parameters, including node voltages, branch resistances, and load demands.
- Set optimization variables, such as power flows, voltages, and binary indicators for branch status.
- Formulate the objective function and constraints.
- Solve the MINLP model using GAMS solvers.

This section presents the optimization strategy adopted to solve the problem of optimal reconstruction of AC networks with a MINLP model described. For this purpose, the general algebraic modeling system is used as the solution technique. GAMS software is a powerful tool that allows solving complex optimization models, including linear and mixed integer programming, quadratic programming, and general nonlinear programming models with mixed variables (e.g., binary, integer).

The main advantages of using GAMS software in mathematical optimization can be summarized as follows: It works with a compact structure, i.e., it uses sets that contain information about the number of variables and the size of the solution space. In addition, information about the system is introduced using matrices, vectors, and scalars, and these can be assigned to the domain of the set. It is possible to distinguish the nature of the variables intervening in the mathematical model, namely discrete (integer),

binary, continuous and positive variables. Figure 2 shows the flow chart for the proposed GAMS implementation.
In this case, the problem is optimized and the system is closed. Also, please: Start, start and use it if you want to use it again. Define Network Parameters, Optimize the model in the first place and then select the parameters you want. These parameters include the structure of the network, capacity limits, connections and other necessary information about the problem. Set Optimization Variables, Problems can be solved in the future. This way, the function optimizes the size of your device.

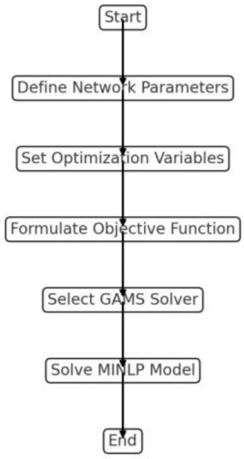

Figure 2. GAMS application flowchart

Formulate Objective Function, The goal of the optimization is determined and expressed mathematically. For example, goals such as minimizing the cost, increasing efficiency or reducing energy consumption are formulated as the objective function. Select GAMS Solver, Optimize Problems, GAMS platform on which it can be used. In this step, special solvers for problems such as nonlinear MINLP can be preferred. Solve MINLP Model, The mathematical model created using the selected GAMS solver is solved. In this step, optimized results are obtained. End, then you will be able to use it later. This way, the problem is optimized when it comes to the sun. GAMS is available, with the latest model and optimization, it is not necessary to use it.

Multiple solution techniques are available to address the mathematical optimization model for the reconfiguration of radial distribution networks. Among these techniques, methods based on interior point algorithms and branch-and-bound approaches are commonly used due to their efficiency in solving large-scale optimization problems. These methods are well-suited for handling the different types of programming structures encountered in power system optimization, such as: LP, Suitable for problems with linear objective functions and constraints.

NLP, Used when the problem includes nonlinear relationships between variables, such as power flow equations. MILP, Employed when the problem involves both continuous variables (e.g., voltages, power flows) and discrete variables (e.g., switch states). MINLP, a hybrid approach for problems that combine nonlinearity with discrete decision variables, making it ideal for complex power system reconfiguration tasks. Figure 2 illustrates the implementation flowchart for optimal reconfiguration in radial distribution networks using an MINLP formulation and the GAMS. This flowchart provides a step-by-step representation of the process, from defining network parameters and variables to solving the optimization model and extracting results. The load information for this test feeder, including active and reactive power demands at each node, is summarized in Table 1. This information forms the basis for defining the optimization problem, which aims to minimize power losses, maintain voltage regulation, and ensure compliance with operational constraints. By leveraging the capabilities of GAMS, the proposed model efficiently handles the complexity of the optimization problem, providing a robust solution framework for real-world applications in power distribution networks.

4. Case Studies and Results

4.1 System Description

The integrated framework was validated using IEEE-standard networks, A 10-node DC system, focusing on conductor optimization and 33-node and 69-node AC systems, highlighting reconfiguration, DG integration, and reactive power compensation. The optimization yielded significant performance improvements shown in Table 2.

Table 2. Performance Metrics for IEEE 33-Node System

Scenario	Total Losses (kW)	Voltage Deviation (%)	Cost Reduction (%)
Base Case	202.67	±10%	0%
Network Reconfiguration	172.27	±5%	15%
DG Integration	151.50	±3%	25%
D-STATCOM Integration	143.00	±2%	30%

The results highlight the substantial improvements achieved through the integrated framework. Network reconfiguration alone reduced total power losses by 15% (from 202.67 kW to 172.27 kW) and voltage deviation to ±5%, while DG integration further reduced losses by 25% (to 151.50 kW) and improved voltage deviation to ±3%. The addition of D-STATCOM devices resulted in the most significant improvements, with total losses decreasing by 30% (to 143.00 kW) and voltage deviation stabilizing at ±2%, alongside notable cost reductions. These numerical outcomes underscore the effectiveness of the framework in minimizing losses, stabilizing voltage, and lowering operational costs, making it a robust and scalable solution for modern power distribution challenges.

The results demonstrate the synergy between network reconfiguration and DG placement. DG units reduced dependency on centralized generation, while D-STATCOMs improved voltage profiles and reduced losses further. Optimizing feeder connections minimized losses without additional infrastructure investments. Distributed energy sources reduced transmission losses and provided localized power support. D-STATCOMs stabilized voltage and improved power quality, significantly enhancing network performance. While the integrated framework demonstrates robust performance, challenges include computational complexity and scalability for large networks. Future research should explore are Uncertainty Modeling in renewable energy generation and load profiles, and Real-Time Applications, which is developing adaptive algorithms for dynamic network management. The integrated framework plays a critical role in supporting sustainability by reducing the carbon footprint and enhancing the resilience of power distribution networks. One of the primary contributions to sustainability is the significant reduction in power losses, which decreases the energy demand from centralized generation. This directly translates to lower fossil fuel consumption and reduced greenhouse gas (GHG) emissions, particularly in systems dependent on non-renewable energy sources. For example, the framework’s optimization strategies achieved a 30% reduction in total losses, highlighting its potential to minimize energy wastage and associated emissions. The integration of DG, especially from renewable energy sources such as solar and wind, further supports carbon footprint reduction. By offsetting carbon-intensive electricity from centralized power plants, DG integration reduces reliance on fossil fuels and provides localized power support, which minimizes energy lost during transmission. This aspect is particularly significant for geographically dispersed networks where transmission losses are typically higher. In addition to reducing emissions, the framework enhances the resilience of the distribution network. Voltage stability is significantly improved through the use of D-STATCOM devices, which mitigate voltage deviations and ensure reliable operations under varying conditions, including fluctuating renewable energy outputs. The reliance on DERs also strengthens the network by reducing dependency on centralized infrastructure, making it more robust against natural disasters or other disruptions. Furthermore, the framework’s adaptability allows it to effectively manage the variability and intermittency associated with renewable energy, ensuring stable operations even under dynamic energy generation and consumption patterns. Overall, the integrated framework aligns operational efficiency with sustainability goals by lowering carbon emissions, improving energy efficiency, and fostering a resilient and adaptive energy system capable of supporting the transition to a sustainable energy future.

5. Conclusion

The proposed optimization framework proves to be a highly effective solution for tackling the multifaceted challenges of modern power distribution networks. By adopting a mathematical modeling approach that reduces nonlinearities and leveraging the powerful capabilities of GAMS for solving MINLP problems, the framework achieves a robust and scalable methodology. The integration of network reconfiguration, distributed generation (DG), and reactive power compensation devices such as D-STATCOMs highlights its ability to optimize network performance under various operational scenarios. The case study of the IEEE 33-node system demonstrates the substantial performance enhancements enabled by the framework. The results show a 30% reduction in total power losses, improved voltage profiles with deviations stabilized at ±2%, and significant operational cost reductions. Network reconfiguration alone contributed to a 15% reduction in losses, while the integration of DG and D-STATCOMs compounded these improvements, emphasizing the synergistic effects of combined optimization strategies. Additionally, DG placement effectively reduced dependency on centralized power generation and minimized transmission losses, while D-STATCOMs ensured voltage stability and enhanced power quality. Beyond operational improvements, the framework supports long-term sustainability goals. The integration of renewable energy sources through DG reduces the reliance on fossil fuels, thereby lowering GHG emissions. For geographically dispersed networks, this localized power support mitigates the typically high transmission losses. Furthermore, the framework's focus on energy efficiency aligns with global sustainability efforts by optimizing resource utilization and minimizing energy waste. The framework also enhances the resilience of power distribution networks. Voltage stability under varying conditions, including fluctuating renewable energy outputs, is achieved through advanced reactive power compensation. This adaptability to dynamic energy generation and consumption patterns strengthens the network's robustness against potential disruptions such as natural disasters or demand surges. However, the framework is not without challenges. The computational complexity associated with large-scale networks and the scalability of the proposed solutions call for further exploration. Future research should focus on incorporating uncertainty modeling to address the variability of renewable energy generation and developing real-time adaptive algorithms for dynamic network management. These advancements will enhance the applicability of the framework to real-world systems. In conclusion, the proposed optimization framework integrates technical innovation with sustainability objectives, achieving a delicate balance between improving network efficiency, reducing environmental impact, and supporting the transition to resilient and adaptive energy systems. Its demonstrated success in optimizing power distribution networks positions it as a critical tool for future energy infrastructure development, particularly in the context of renewable energy integration and sustainable energy transitions.

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