Power Distribution Network Reconfiguration Based on Energy Loss Reduction by Graph Theory

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Most of the investment in the power industry is devoted to enhance and improve the capacity and reliability of the power distribution network, which in turn imposes significant costs on electric power companies to compensate for network loss. Furthermore, in competitive electricity markets, the customers expect the least cost for high-quality power delivery. Distribution feeder reconfiguration, given its complex and discrete nature, is the most suitable and economical approach to reduce energy loss and consequently, improve operational conditions in the management of power distribution networks. In this paper, we propose an optimization method, which schedules annual reconfiguration subject to energy loss constraint and determines the impact of loss reduction caused by the optimization. Various cases, including the presence and absence of distributed generation sources, as well as the uncertainty issues of these sources, have been studied. The proposed method is applied for distribution feeder reconfiguration to minimize the annual loss in two sample distribution IEEE network networks with 33 and 118 buses. The results show that the proposed graph theory-based method, independent of the distribution network dimension and scale, can reconfigure the networks for the minimum loss in the network lines when the load condition varies suddenly or a network fault is created.

Keywords: *Distribution System, Energy Loss Reduction, Network Reconfiguration, Graph Theory.*

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Nomenclature

Indices	Description
J	Set of annual unit periods
S	Sections of the year
L	Load demand
$\mathcal{X}$	Feasible configuration set
η	Efficiency of the proposed method
λ	Load growth factor
α	Weighting factor in optimization
γ	Constraint violation penalty
M	Set of Switches
C	Set of component numbers

Parameters	Description
S_t	Set of operational periods
T_T	Acceptable reconfiguration time per year
S_{comp}	Set of component-wise feasible configurations
P_{Lj}	Load demand in operational period j
f_{loss}	Objective function to minimize energy loss
E_{loss}	Energy loss in each configuration
T_{switch}	Switching time for reconfiguration
C_{switch}	Cost of Switching operation
P_{reconf}	Power loss after reconfiguration
P_{init}	Initial power loss before reconfiguration
P_{loss}	Total power loss in the distribution network
V_i	Voltage magnitude at bus i
I_{ij}	Current flowing in branch i, j
R_{ij}	Resistance of branch i, j
X_{ij}	Reactance of branch i, j
S_i	Apparent power at bus i
P_i	Active power at bus i
Q_i	Reactive power at bus i
P_{DG}	Power output of distributed generation (DG)
V_{min}	Minimum allowable voltage magnitude
V_{max}	Maximum allowable voltage magnitude

I_{max}	Maximum allowable branch current

Abbreviation	Description
NOB	Normally open branches (tie switches)
NOC	Normally closed branches (sectionalizing switches)
ZDD	Zero-suppressed binary decision diagram
B&B	Branch and Bound algorithm
ENS	Energy Not Supplied

1. Introduction

Electric power systems are very complex and have experienced rapid progress in recent decades. The primary goal of the electric power industry, as an infrastructural and fundamental industry in the country, is to provide suitable electric power for the consumers. Reducing the dependence on the power grid for energy transmission results in an increase in energy efficiency, as the losses incurred during transmission are reduced. In addition to this, utilizing renewable energy sources and minimizing losses leads to a reduction in carbon dioxide emissions [1, 2]. The distribution system connects the transmission part to the end customer, and consequently, is the nearest part to the subscribers. From the generation to consumption level, a power system includes four general levels of electric power generation in power plants, electric power transmission from high-voltage levels toward load centers, electric power sub-transmission system, and medium- and low-voltage distribution feeder. Moreover, Distribution Automation System (DAS) allows remote controlling, monitoring, and management, as well as real-time transmission of the required commands to the deployed equipment of the distribution network in long distances. Before the introduction of the DAS, restoration programs were rarely used; however, by growing worldwide development of the modern distribution networks, the probability of fault and consequently, outage for one or multiple regions increased and therefore, modern power distribution companies started network monitoring. It can be said that the smart distribution network is developed based on the DAS. This focused the attention on more efficient and affordable restoration programs. A smart distribution system should be restored in the least possible time to resume power delivery to the subscribers. Upgrading the manual switches to Remote-Controlled Switches (RCSs) improves the restoration capability. However, operational and economical requirements should be considered for the deployment of the RCSs [3]. To achieve high levels of reliability and minimize investment costs can be considered as the main challenges of the distribution system optimization [4, 5]. In other words, the determination of the optimal number and location of the switches in the DAS is an important factor for reliability and economical requirements [6]. In competitive electricity markets, the customers expect the least cost for a high-quality power delivery, which may require extra investment and more complex operational techniques to increase security in power systems [7-9].

1.1. Motivation

Studies indicate that power losses within distribution networks contribute approximately 70% of total system losses and nearly 13% of overall power generation [10]. With rising electricity costs, efforts to mitigate these losses are gaining traction [11]. The electrical distribution network (DN) is responsible for transmitting power from the main grid to end consumers via lateral and sub-lateral feeders. Radial distribution networks (RDNs), which may have limited meshing, are commonly utilized due to their cost-effectiveness and simplified protection schemes [12]. However, because each feeder in an RDN receives power in a single direction from the substation, its radial configuration, coupled with a higher resistance-to-reactance ratio relative to transmission systems, leads to significant power dissipation and voltage reduction [13, 14].

Among the most effective techniques proposed to enhance distribution network efficiency are network reconfiguration and the integration of distributed generation (DG). The RDN structure includes sectionalizing switches, which correspond to normally closed branches (NCB), and tie switches, representing normally open branches (NOB). Adjusting the status of these branches alters the network's topology while maintaining its radial structure [15]. This modification redistributes power flow, optimizing load distribution across feeders and contributing to power loss reduction, voltage stability, and improved reliability. Moreover, incorporating DG units during network reconfiguration further enhances these benefits, leading to substantial improvements in voltage regulation and efficiency. Consequently, the simultaneous implementation of DG integration and network reconfiguration significantly strengthens the overall performance, resilience, and power quality of the RDN [16, 17]. To overcome these issues, extensive research has introduced various strategies for reconfiguring distribution networks. These methods are designed to optimize power system performance by minimizing energy losses, mitigating bus voltage deviations, and enhancing voltage stability throughout the network.

1.2. Main Contribution

The main contribution of this paper is the development of a graph theory-based optimization method for power distribution network reconfiguration to minimize annual energy loss. The proposed method schedules annual reconfiguration while considering energy loss constraints and evaluates the impact of loss reduction through optimization. Prominent contributions include:

- Providing an approach that finds the optimum configuration for operational periods using the Branch and Bound (B&B) Algorithm and Zero-suppressed Binary Decision Diagram (ZDD).
- The method applies graph theory to model and analyze distribution network reconfiguration, ensuring efficient search and feasibility checking of configurations.
- The study examines network reconfiguration with and without DG sources, incorporating their uncertainties in the optimization process.
- The method is independent of network dimension and scale, making it suitable for large-scale power networks, such as the 33-bus and 118-bus IEEE benchmark systems.
- Simulation results demonstrate that the proposed method reduces power losses more effectively than existing methods. Also, it improves voltage profiles in distribution networks. Additionally, that enhances network reliability by reducing undelivered energy.

1.3. Paper Organization

This paper is organized as follows: Section 2 describes the theoretical fundamentals for power distribution network reconfiguration and relevant literature. Section 3 details the proposed method and algorithm. Section 4 summarizes the simulation and analytical results. Section 5 concludes the paper.

2. Theoretical Fundamentals

The concept of Power Distribution Network Reconfiguration (DNR) and its Various Processes

First, it should be noted that the reconfiguration of feeders involves changing their topological structure by altering the open/closes states in sectionalizing and tie switches. Medium-voltage distribution feeders are reconfigured for different load levels. Achieving the optimal reconfiguration in the least possible time is the most significant factor in distribution feeders. The distribution feeder should be analyzed to check the closed/open states of the power switches in the least possible time, without any fault and subject to constraints of the power network. Reconfiguration, as an affordable but valuable strategy, can be used to efficiently improve the behaviors of the subscribers in the electric distribution network to meet various pre-defined goals. Moreover, the reconfiguration problem is intrinsically modeled as a discrete nonlinear program, whose accurate solution requires powerful optimization techniques. Recently, many researchers have studied this mixed-integer nonlinear optimization problem and proposed appropriate and effective solution methods; however, there is no guarantee that the proposed methods can effectively explore the search space of the problem and achieve all the pre-defined objectives [18]. In DNR, the network topology is altered such that its radial structure is preserved while the system performance is improved [19]. DNR is generally categorized into two classes: Dynamic DNR and static DNR. In static DNR, the long-term configuration of the distribution feeders is determined in the planning stage to achieve the intended goals subject to a set of fixed conditions. The static FDR is an offline method, where the time constraints do not intervene in the reconfiguration process. However, in the more valuable method of dynamic DNR, the DAS periodically solves and runs the reconfiguration process to meet time-varying conditions of the load and network. Reconfiguration speed and power restoration service are two important parameters, which should be addressed in the online dynamic DNR method. In the design of electric distribution networks, the planning process effectively affects the power quality and required expenditures. As discussed in [20], the network planning problem in power systems conventionally includes a comprehensive comparison between various developed states of the system, which are created according to the system cost.

2.1. The Objectives of the DNR Problem

Power System Loss Reduction

Since the system loss imposes extra operational costs on power distribution companies, loss reduction is the primary objective of the DNR problem [21]. The DNR is capable of altering the direction of the power flowing toward the loads such that the overall network loss is reduced.

System Voltage Profile Improvement

The radial distribution network configuration has many advantages. The distribution network is designed with a ring or mesh topology but utilized radially [22]. This may lead to a voltage drop for the loads at the end of the feeder. DNR can be used to change the load distribution in the system and minimize the extra load of some transmission lines. As a result, the high voltage drop in the system is avoided.

Other Objectives of the DNR Problem

Load balance between feeders and phases, improving the reliability and restoration service of the distribution system, fault isolation and load restoration, increasing loadability, increasing the possibility of DG source placement, improving power quality and voltage indicators, and reducing operational expenditures are among other objectives of the DNR problem.

2.2. Relevant Literature

Distribution networks or microgrids that can be reconfigured act as smart networks that are flexible and controllable compared to traditional energy networks. This issue leads to stability and social welfare and energy flexibility in the restructuring of power systems [23]. The history of the reconfiguration problem in power systems shows that the first official researches on loss reduction were conducted by Back and Merlin in 1975 using B&B and sequential switch opening methods [24].

Compared to conventional mathematical and heuristic approaches, intelligent optimization methods demonstrate superior performance in handling large-scale, non-linear problems [25, 26]. Recent research has explored various metaheuristic algorithms for optimizing DG placement and network reconfiguration in RDNs, targeting objectives such as power loss minimization, voltage deviation reduction, voltage stability enhancement, and cost optimization. For instance, the Modified Whale Optimization Algorithm (MWOA) has been utilized to simultaneously optimize DG and capacitor placement while improving voltage profiles and reducing power losses [27]. Similarly, the Plant Growth Simulation (PGS) and Particle Swarm Optimization (PSO) algorithms have been applied to optimize DG allocation and RDN reconfiguration, with validation performed on IEEE 33- and 69-bus systems [28]. Also, the Improved Equilibrium Optimization Algorithm (IEOA) has been applied to optimize RDN reconfiguration and DG allocation under different loading conditions, achieving voltage profile improvements and power loss reductions [29]. Additionally, the Artificial Ecosystem Optimizer (AEO) has been employed for reconfiguring an actual Egyptian RDN, integrating DG and capacitor placement across multiple loading scenarios to enhance efficiency and reliability [30]. Other studies have explored hybrid optimization techniques, such as a combination of the Grey Wolf Optimizer (GWO) and PSO, to evaluate various standalone and hybrid DG allocation scenarios with reconfiguration [31]. To mitigate power losses and voltage fluctuations across different scenarios—including independent reconfiguration, standalone DG integration, and various hybrid configurations—the Salp Swarm Algorithm (SSA) has been implemented [32]. Additionally, the Self-Adaptive Fireworks Algorithm (SAFWA), combined with the Iterative Game-Based Algorithm (IGBA), has been introduced to optimize RDN reconfiguration and DG placement for improved efficiency and reduced power dissipation [33]. Additionally, an adaptive modified whale optimization algorithm (AMWOA) has been employed to improve the voltage stability index (VSI) and reduce power losses, incorporating probabilistic load variations and different power factors for DG units [34]. Further studies have explored alternative approaches, such as the enhanced Elitist-Jaya algorithm, which considers the impact of four dependent load models under increasing demand conditions [35]. To optimize RDN reconfiguration and DG allocation under various scenarios, researchers have introduced advanced optimization techniques. An enhanced sine-cosine algorithm (ESCA) has been proposed to evaluate performance based on economic, technical, and reliability indices [36]. A hybrid method utilizing binary PSO for reconfiguration and conventional PSO for DG placement has also been investigated [37]. An improved sine-cosine algorithm (ISCA) has also been developed to optimize RDN performance by reducing real power losses and improving VSI across different load levels [38]. The Modified Marine Predators Optimizer (MMPO) in [39] has further been utilized to address the reconfiguration problem under varying loading conditions, while in [40] the Butterfly Optimization (BO) technique has been implemented to improve network loadability and reduce power losses. In [41] the Tabu Search Algorithm (TSA) has been applied to optimize reconfiguration while accounting for DG reactive power generation, switching costs, and power loss expenses. Similarly, the Moth-Flame Optimization (MFO) technique has been employed to integrate solar and wind energy sources, with the objective of minimizing power losses and enhancing the voltage profile and VSI [42]. Also, in [43] the Geometric Mean Optimization (GMO) technique has been introduced to address both single- and multi-objective optimization problems, evaluating various reconfiguration and DG placement scenarios based on different DG types and load levels. Furthermore, in [44] an advanced Ant Colony Optimization Algorithm (ACOA) has been utilized for RDN reconfiguration with multiple DG integrations, resulting in significant power loss reduction, voltage drop minimization, enhanced VSI, and improved system reliability. For multi-objective optimization, an improved Black Widow Optimization Algorithm (IBWOA) has been developed to optimize DG allocation and dynamic network reconfiguration, considering power loss reduction, voltage regulation, and carbon emission minimization [45]. In this approach, DeepSCN has been applied to forecast DG power output and RDN load variations. The Arithmetic Optimization Algorithm (AOA) has been employed to optimize network reconfiguration while improving the VSI and reducing voltage deviation and power loss [46]. Additionally, an improved Symbiotic Organism Search (ISOS) algorithm has been introduced for optimizing RDN reconfiguration and DG placement to achieve loss reduction [47]. In [48] a modified Particle Swarm Optimization (MPSO) approach, incorporating graph theory, has been proposed to minimize active power losses by reconfiguring the network and strategically placing multiple DG units of different types.

An efficient Modified Tabu Search (MTS)-based meta-heuristic procedure for the DNR problem has been proposed in [49],where the active loss is effectively reduced by activating and deactivating the sectionalizing switches. In this procedure, Kirchhoff's algebraic method is also used to check the radially of the system topology. As reported in the paper, the outstanding feature of the MTS method is its convergence speed to the global optimum or a near-optimal solution. Considering the costs of active and reactive powers in the deregulated electricity market with the maximum operational reliability, the Non-dominated Sorting Genetic Algorithm (NSGA) is used in [50] to reconfigure a radial distribution feeder to minimize the operational expenditures. In [51], the authors propose a Cuckoo Search Algorithm (CSA)-based metaheuristic method for DNR to minimize active power loss and increase voltage level. Compared to the other schemes, the proposed method has fewer control parameters and is more effective for optimization.

Table 1 provides a comparative analysis of pertinent research works and evaluates them in relation to the methodology proposed in this study.

Table 1. Brief Summary of Relevant Literature

Operational Planning Aspects	Optimization Approach	Assessed Advantages	Ref.
Initial methodology for tackling loss reduction in distribution networks	B&B combined with sequential switch opening methods.	Technical: Basis for subsequent research; Economic: Initial insights into cost reduction.	[24]
Power loss reduction	Modified Whale Optimization Algorithm (MWOA)	Technical: Improved voltage stability and loss reduction.	[27]
Power loss reduction	Plant Growth Simulation (PGS) and Particle Swarm Optimization (PSO)	Technical: Enhanced load balancing and efficiency.	[28]
Power loss reduction and total VSI improvement	Improved Equilibrium Optimization Algorithm (IEOA)	Technical: Reduced loss, enhanced voltage profile.	[29]
Power loss reduction	Artificial Ecosystem Optimizer (AEO)	Technical: Improved efficiency and network resilience.	[30]
Power loss reduction	Grey Wolf Optimizer (GWO) and Particle Swarm Optimization (PSO)	Technical: Optimization of power flow and loss reduction.	[31]
Power loss reduction	Salp Swarm Algorithm (SSA)	Technical: Higher reliability and operational flexibility.	[32]
Power loss reduction	Self-Adaptive Fireworks Algorithm (SAFWA) and Iterative Game-Based Algorithm (IGBA)	Technical: Efficient network reconfiguration with improved stability.	[33]
Power loss reduction	Adaptive Modified Whale Optimization Algorithm (AMWOA)	Technical: Better voltage regulation and loss minimization.	[34]
Power loss and Maximum loadability	Elitist–Jaya Algorithm	Technical: Increased system loadability and efficiency.	[35]
Power loss and Operating costs reduction	Enhanced Sine-Cosine Algorithm (ESCA)	Technical: Enhanced reliability; Economic: Cost savings.	[36]
Power loss reduction	Binary PSO and Conventional PSO	Technical: Effective optimization for energy loss minimization.	[37]
Power loss and VSI improvement	Improved Sine-Cosine Algorithm (ISCA)	Technical: Improved voltage stability index.	[38]
Power loss reduction	Modified Marine Predators Optimizer (MMPO)	Technical: Load distribution optimization and loss reduction.	[39]
Power loss reduction, System loadability, and DG penetration level	Butterfly Optimization (BO)	Technical: Increased penetration of distributed energy resources.	[40]
Operating costs reduction	Tabu Search Algorithm (TSA)	Technical: Reduced switching costs; Economic: Minimized operational expenditures.	[41]
Power loss, VSI, and Voltage deviation improvement	Moth-Flame Optimization (MFO)	Technical: Enhanced voltage stability and reduced energy loss.	[42]
Power loss, VSI, and Voltage deviation	Geometric Mean Optimization (GMO)	Technical: Optimized grid operation and improved efficiency.	[43]
Power loss and Voltage deviation reduction	Ant Colony Optimization Algorithm (ACOA)	Technical: More effective energy distribution.	[44]
Power loss, Voltage deviation, and Carbon emission reduction	Improved Black Widow Optimization Algorithm (IBWOA)	Technical & Environmental: Sustainable energy operation.	[45]
Power loss, VSI, and Voltage deviation improvement	Arithmetic Optimization Algorithm (AOA)	Technical: Enhanced voltage regulation.	[46]

Power loss reduction	Improved Symbiotic Organism Search (ISOS)	Technical: Greater efficiency in power distribution.	[47]
Power loss reduction	Modified Particle Swarm Optimization (MPSO)	Technical: Optimized reconfiguration and DG placement.	[48]
Distribution system reconfiguration for active loss reduction	Modified Tabu Search (MTS)	Technical: Rapid convergence to near-optimal solutions.	[49]
Reconfiguration in deregulated electricity markets for cost minimization	Non-dominated Sorting Genetic Algorithm (NSGA)	Economic: Reduced operational expenditures; Technical: Enhanced reliability.	[50]
Voltage profile improvement and Loss minimization in distribution networks	Cuckoo Search Algorithm (CSA)	Technical: Effective voltage control and reduced power dissipation.	[51]

2.3. DNR Process Operational Scheduling

At first in 1993, Chen et al., the authors of [52], proposed the idea of systematic and operational programming for minimizing annual energy loss. Their proposed method utilizes season-based reconfiguration; where for each of the seasons, the most optimal reconfiguration is selected. However, their proposed method does not account for reconfiguration periods in which the network is being reconfigured. In [53, 54], a scheduling method has been proposed to determine the optimal configurations, while also accounting for the reconfiguration periods. The authors of [55], consider hourly loss-minimized feeder reconfiguration as an application of DAS, which can lead to substantial savings in service delivery. According to what reported in [56], seasonal, daily, and hourly reconfiguration incorporating customer time-varying diversified load characteristics reduces the loss in distribution systems. Moreover, in [57] it is shown how utilizing reconfigurations based on minimal loss in various distribution systems can help to evaluate the advantages of online reconfiguration, considering the time-varying nature of loads, using daily load profiles in each bus of the system. Reconfiguration may reduce the lifetime of the switches, which not only imposes high operational expenditures for the mentioned reconfiguration methods but also incorporates physical constraints limiting the number of reconfigurations [58]. Finally, according to the above-mentioned reports, frequent reconfiguration such as hourly reconfiguration [55, 56], may create overvoltage transients [57].

2.4. Reducing the Annual Energy Loss

A common distribution system includes several sets of transmission lines located near to the switches, junctions, or feeding points. Considering the corresponding hourly load curve, a single load is assigned to each section, which provides enough time for the exact analysis of the energy loss [59]. Each of the load section has a uniform distribution over the line as a load with a constant current [60]. Moreover, it is assumed that the acceptable reconfiguration time per year, $\bar{k}$, is known. S is a reconfiguration period, which is a subset of annual unit periods set (n-day or n-week periods) $J = \{1, \dots, n\}$. The periods in S sections of the year J are divided into consecutive periods $\{J_k\}$, where $k \in \{1, \dots, |S|+1\}$, and each is named operational period. The existing switches of the distribution network are denoted by $M = \{s_1, \dots, s_m\}$.

In distribution networks, the electrical and topological constraints should be satisfied in the reconfiguration of each operational period. Considering the topological constraints, the reconfiguration creates a radial structure, without any loop, where each of the sections is only connected to a single point of feeding. However, there are a couple of main electrical limitations:

- The first one is that the lines' currents must be in the permitted range.
- The second one is that the voltage drop in each section should be also in the permitted range.

In the current study, in order to satisfy the topological and electrical restrictions of hourly loads in a year, an operational restriction is introduced. Therefore, the problem of minimizing the annual energy loss, shown as $Loss_j$ is expressed as follows [61]:

$$\min_{S,\{X_k\}} f(S,\{X_k\}:J) = \sum_{k=1}^{|S|+1} \sum_{j \in J_k} Loss_j(X_k) \qquad (1)$$

subject to the constraints

$$S \in \{S \subseteq J - \{1\} : |S| \le \bar{k}\} \qquad (2)$$

$$X_k \in \chi, \chi = \{X \subseteq M : IsFeasible(X)\} \qquad (3)$$

, where $Loss_j\ (X_k)$ is the loss in configuration X_k during period j, which in fact is considered as the overall loss of power for each hour t of the period j. (2) and (3) show the reconfiguration time and operational constraints, respectively.

2.5. Binary Decision Graph

In this section, presents a zero-suppressed binary decision diagram, a.k.a. a ZDD. This diagram is a data structure where a set of combinations can be stored [62]. It is worth mentioning that ZDD is expressed in the form of a directed acyclic graph or DAG, which includes sink nodes, the internal nodes, and a root node. Moreover, each of the internal nodes corresponds to a binary variable representing the on/off states of the corresponding switch. In other words, each internal node has two edges (zero and one). Each of the paths from the root node to the sink node indicates a set of combinations. For instance, the ZDD given in **Fig. 1**, shows the combination set $\{\{s_1, s_2\}, \{s_2, s_3\}, \{s_3, s_4\}, \{s_2, s_3, s_4\}\}$. An obvious feature of the ZDD is that certain operators can be calculated for two ZDDs without suppressing the existing combinations. In the current study, ZDD is utilized in order to realize the following objectives:

- Counting the possible reconfigurations as the whole network
- Counting the possible configurations as a part of the network
- Checking the feasibility of the intended reconfiguration

In **Fig. 1**, each of the diagrams depicts a single ZDD, and $\top$ denotes the upper sink node. Each of the ZDDs indicates the following set of combinations. In order to realize the first two goals, a couple of binary operators are utilized for the ZDD: and the second one is the meet operator the first one is the intersection parameter [62], and the second one is the meet operator [63]. The selected sets of different combinations; namely F and G, provide the intersection operator as $F \cap G$, which can be seen in **Fig. 1a.** Moreover, the meet operation provides the set of combination shown below and in **Fig. 1b.**:

$$F \sqcap G = \{\alpha \cap \beta : \alpha \in F, \beta \in G\} \qquad (4)$$

For the third objective, the search and membership inquiry [62] are used to determine if the ZDD includes the set of given switches or not.

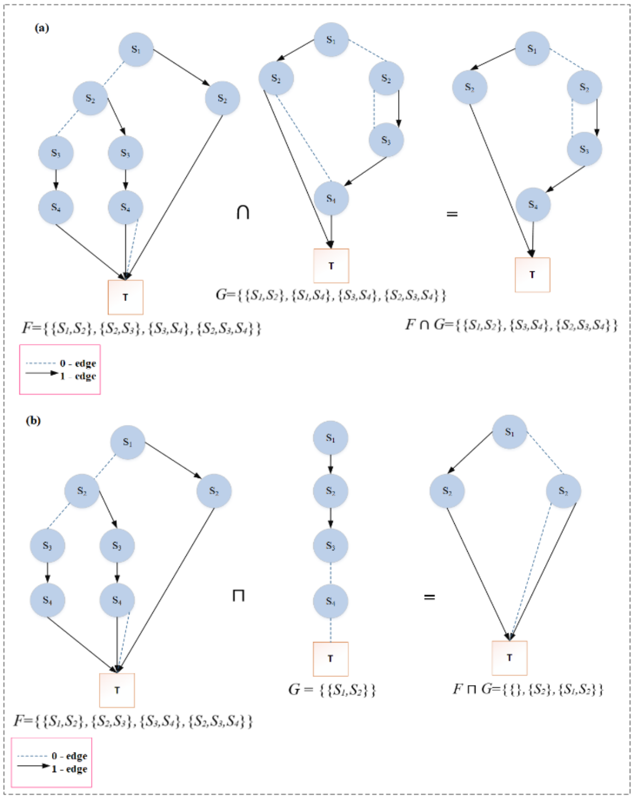

Fig. 1. An example for (a) intersection operation (b) meet operation in the corresponding ZDD [61]

3. The Proposed Method and Algorithm

In this method, the network is divided into small components, whose mutual dependencies are theoretically limited. The proposed method has two steps. In the first step, optimized configurations are obtained for each of the operational periods. The main objective of this phase involves computing the outcomes of the traditional optimization method for each of the periods. Using this matrix, the optimum configuration is attained for all operational periods. In the second step, the number of periods and allowed reconfigurations grow exponentially. Therefore, the B&B Algorithm is used to find the optimum configurations [61].

3.1. Finding the Optimum Configuration for All Operational Periods

3.1.1. Evaluating Common Configurations for Feasibility

Firstly, the component-wise optimal configurations are obtained. Then, a common configuration is derived from the optimized configurations which are based on individual components. A common configuration can be considered as the optimized configuration for the entire network if it can satisfy the operational requirements. Nevertheless, as the common configuration is not capable of always satisfying the operational requirements, the proposed method will evaluate the possibility of each common configuration. If a common configuration is not feasible, then the traditional method, as in [64], will be utilized for identifying the optimized configuration for the entire network. The feasibility of the common configuration is rapidly checked using the property of the ZDD, which includes all possible configurations.

3.1.2. Listing the Possible Configurations for a Year

The method, which creates two ZDDs independently, is used for network configuration [64], where one ZDD corresponds to the configurations satisfying the topological constraints $\mathcal{X}^{topol}$, and the other relates to the configurations satisfying the electrical constraints $\mathcal{X}^{elec}$. Considering the intersection of $\mathcal{X}^{topol}$ and $\mathcal{X}^{elec}$,

$$\mathcal{X} = \mathcal{X}^{\text{topol}} \bigcap_{t=1}^{T} \mathcal{X}_{\text{t}}^{\text{elec}} \qquad (5)$$

, where $\mathcal{X}$ denotes the set of feasible configurations and $\mathcal{X}_c$ shows the set of component-wise feasible configurations for component c. The component-wise feasible configurations are extracted from $\mathcal{X}$. M_c denotes the set of available switches in component c. The component-wise feasible configurations are

$$\mathcal{X}_c = \mathcal{X} \sqcap \{M_c\} \qquad (6)$$

3.1.3. Energy Loss Matrix

The energy loss matrix is defined as

$$A_c = \left(a_{c,ij}\right) 1 \leq i \leq |\mathcal{X}_c|\,, i \leq j \leq n \qquad (7)$$

, where i denotes the number of component-wise feasible configurations and $a_{c,\text{ij}}$ indicates the energy loss of configuration i in period j.

3.2. Branch and Bound Algorithm

B&B is an incidental counting algorithm, where the solutions of an optimization problem are represented by nodes of a decision tree. The B&B algorithm includes two parts of branching and bounding. The branching is the process of converting a problem into several subproblems. The bounding strategy used in the proposed B&B algorithm is based on a lower bound approach.

3.3. Using the Branch and Bound Algorithm for the Optimization of Reconfiguration Periods

The optimization is accomplished using the B&B algorithm, where the solution space is comprehensively searched. Here, the notion of an improvement value is introduced, while a critical lower bound is obtained. The branch and bound algorithm consist of two operations; namely, the branching and the bounding.

- *Branching operation*

The branching operation, which is based on considering the reconfiguration periods as the search space of the algorithm, i.e. $\mathcal{S} = \mathcal{P}(J - \{1\})$, involves the process of dividing a particular search space, $\mathcal{S}_l$, into two subsets:

$$\begin{cases} \mathcal{S}_{l_1} = \{S \in \mathcal{S}_l : j \in S\} \\ \mathcal{S}_{l_2} = \{S \in \mathcal{S}_l : j \notin S\} \end{cases} \qquad (8)$$

In this paper, P_{l_1} and P_{l_2} represent the subproblems corresponding to the search spaces $\mathcal{S}_{l_1}$ and $\mathcal{S}_{l_1}$, respectively.

- *Bounding operation*

In this part, a lower bound is acquired for a sub-problem. Moreover, two dimensions of the annual reconfiguration problem are dealt with in the design of the lower bound. The first aspect is the load diversity among the seasons, and the second one is that the optimization is accomplished over a set of consecutive periods.

- *Searching for reconfiguration periods by utilizing the B&B algorithm*

The B&B algorithm is utilized through an iterative procedure of branching and bounding operations. At first, the branching operation starts using the depth-first search, whose stop conditions are: 1. It can be observed that the search space fails to satisfy the accepted reconfiguration time, i.e. 2. Moreover, the lower bound for the sub-problem, P_l, is greater than its current value. Here's a detailed breakdown of how this proposed algorithm works:

Steps of proposed algorithm for DNR

Start: Begin the process.
Input Data:
- Gather network topology.
- Load profiles.
- Distributed Generation (DG) characteristics.
- Energy loss constraints.
- Initial Configuration:
- Set initial state for the distribution network.

Algorithm Selection:
- Choose optimization algorithm (e.g., B&B, ZDD).

Evaluate Current Configuration:
- Calculate power losses and voltage profiles.

Check Optimization Conditions:
➢ Are energy loss constraints met?
➢ Are voltage profiles acceptable?

❖ { If Yes: → Return to Monitoring State for any changes.
❖ { If No: → Proceed to Reconfiguration.

Reconfigure Network:
- Change the states of sectionalizing and tie switches to alter the network topology.
- Redistribute power flow based on new topology.

Simulate New Configuration:
- Run simulations to assess impact on energy loss and voltage stability.

Comparison:
- Compare new results with previous configuration.
- Determine if further reconfiguration is needed.

Output Results:
- Present the optimal configuration with minimized energy loss and improved voltage profiles.

End: Conclude the algorithm.

3.4. Data for DG Units

The DG units considered in this research study are traditional distributed generators. The critical parameters of the DG units are:

- Location: DG units are optimally located at the best buses in the IEEE 33-bus and 118-bus test systems to achieve maximum loss reduction and enhance voltage profiles.
- Capacity: The capacity of the DG units is changing with network load, and values are chosen based on average test cases and sensible operating constraints.
- Power Factor: DGs have a defined power factor, thus they are compatible with the voltage and reactive power support requirements of the distribution network.

3.4.1 Load Level Data

The load levels for the IEEE 33-bus and 118-bus networks are obtained from standard benchmark datasets widely used in power system studies. Table 3 provides an overview of the critical parameters and characteristics associated with DG units and the associated load profiles in network reconfiguration. The data includes:

- *Hourly Load Profiles:* The study considers realistic daily and seasonal variations in power demand, with load levels categorized into peak, off-peak, and intermediate periods.
- *Voltage and Power Demand:* Load demand at each bus is modeled based on historical data and practical system studies to ensure accurate representation of distribution system behavior.
- *Load Growth Scenarios:* Future load growth trends are incorporated into the analysis, reflecting increasing demand over time.

Table 3. DG Units and Load Levels Data

DG Capacity	Varies with network load; values are typically chosen based on average test cases (e.g., 100 kW, 200 kW, 300 kW)
Power Factor	Typically set between 0.8 to 1.0 to comply with voltage/reactive power requirements.
Hourly Load Profiles	Example loads might be categorized as: Peak (e.g., 200 kW), Off-Peak (e.g., 100 kW), Intermediate (e.g., 150 kW).
Voltage and Power Demand	Modeled loads at each bus could be obtained from historical data (e.g., 20-25 kV for distribution networks).
Load Growth Scenarios	The projected growth could range from 3% to 5% annually based on renewable energy trends.
Uncertainty Scenarios	Assumed maximum variations: 10%, 20%, and 50% fluctuation in both DG output and load demand.

3.4.2 Uncertainty Scenarios

To account for the inherent uncertainties in DG output and load variations, the study employs probabilistic models and scenario-based analysis. Uncertainty scenarios are created by varying DG output and load demand within defined probability bounds. The optimization approach ensures that network reconfiguration is robust across all scenarios.

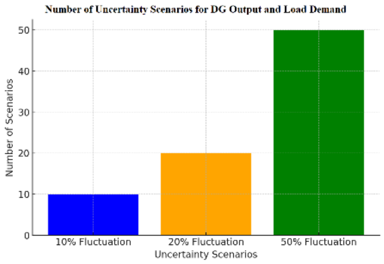

Fig. 2. Number of uncertainty scenarios for DG output and load

demand

Figure 2 illustrates the number of uncertainty scenarios for DG output and load demand, considering 10%, 20%, and 50% fluctuations.

4. Simulation and Analytical Results

4.1. Simulation Results in 33-bus IEEE Network

The proposed method is applied for the network reconfiguration to minimize the annual power loss in the benchmark 33-bus IEEE network shown in **Fig. 3**. The network parameters including the line and load impedances are given in [65].

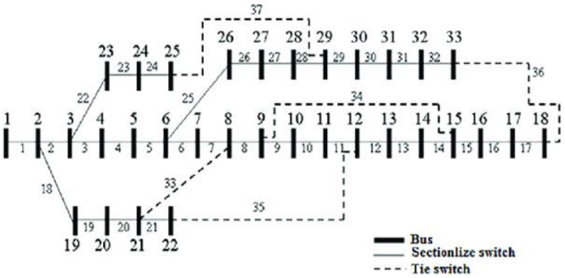

Fig. 3. 33-bus IEEE benchmark

- *The first scenario:* Reconfiguration for the minimum annual power loss in the absence of the DGs

The minimum voltage and network loss, before and after the reconfiguration, are reported in **Table 4**. As can be seen, the voltage of the busbars improves and the system power loss reduces. As can be seen, compared to the basic method without reconfiguration, the network power loss decreases to 137.892 kW corresponding to 1.75% improvement. Moreover, the proposed method provides a lower power loss and a better voltage compared to its counterpart schemes given in **Table 4**.

Table 4. Comparing the Results of the Proposed Method to those of other System Reconfiguration Schemes

Item	Open Switches	Power Loss	Power Loss Percentage	Minimum Voltage (PU)
Basic [66]	33, 34, 35, 36	202.676	5.46	0.9131
ITS [66]	7, 9, 14, 36, 37	142.165	3.83	0.9336
MPSO [66]	7, 9, 14, 32, 37	139.551	3.76	0.9378
BGA based on GT [66]	7, 9, 14, 32, 37	139.551	3.76	0.9378
Proposed Method	7, 9, 14, 28, 37	137.892	3.72	0.9417

Fig. 4 shows the busbar voltage profiles, before and after the reconfiguration, for the considered network. As shown, before the reconfiguration, some busbars have a voltage less than 0.92 PU, which corresponds to an operation in the illegal range. After the reconfiguration, the voltage profile improves in most of the busbars. As a result, the proposed graph theory-based scheme for reconfiguration and finding the best network configuration outperforms competitive counterparts. The line loading, before and after the reconfiguration, is plotted in **Fig. 5**, which shows that the reconfiguration reduces the loadings of the most lines. To get the targeted minimized annual power loss, the line loading should look like the curves in **Fig. 5**. The curves shown in **Fig. 5** illustrate the optimized line loading conditions achieved after network reconfiguration, designed to minimize annual power loss. These curves represent an average state. That figure highlights the desired load distribution across lines post-reconfiguration, which results in a lower overall network loss. While the loading may vary, the goal is to achieve a similar efficiency profile during peak loading conditions, which can be adjusted based on real-time data and forecasts.

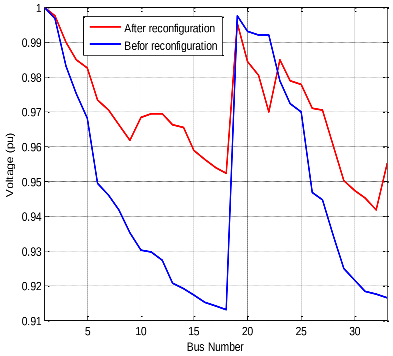

Fig. 4. Voltage Profile before and after Network Reconfiguration

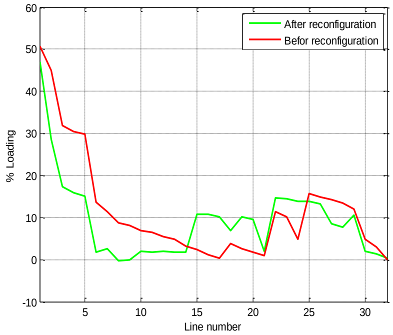

Fig. 5. Line Loading before and after Network Reconfiguration

- *The second scenario:* Reconfiguration for the minimum annual power loss in the presence of the DGs

The proposed method is compared to two counterpart schemes and the results of the reconfiguration and the amount of the annual energy not supplied (kWh/year) are collected in **Table 5**. As can be interpreted form **Table 5**, the proposed method can reduce 520.087 and 21.225 kWh/year from the energy not supplied compared to the reference schemes. In fact, network loss reduction leads to a corresponding reduction in undelivered power.

Table 5. Comparison of the Reconfiguration Results and the amount of Undelivered Power for Different Schemes

Item	**Open Switches**	**Energy not supplied (kWh/year)**
GA [67]	7, 9, 30, 34, 37	53798.300
EGSA [67]	17, 19, 34, 35, 37	53299.338
Proposed Method	7, 9, 14, 28, 37	53278.113

- *The third scenario:* Reconfiguration for the minimum annual power loss considering the uncertainty for the DG sources

The corresponding results are summarized in **Table 6**. The network configuration and deployment change in the presence of the DG units. In this scenario, the least network voltage is 0.953 PU, which is better in comparison with the scenarios without reconfiguration and DG units. Furthermore, the network loss substantially reduces in this scenario.

Table 6. Result Comparison for the Scenarios with and without DG Units

Item	DG Unit Location	Open Switches	Power Loss	Power Loss (%)	Minimum Voltage (PU)
Reconfiguration without DG [68]	-	33, 34, 35, 36, 37	202.676	5.46%	0.9131
Reconfiguration with DGs	21, 33	7, 9, 14, 36, 37	44.544	1.2%	0.954

To verify the proposed method's performance in different levels of load growth, **Fig. 6** shows the network loss curve for different load growth percentages when the network is reconfigured. As shown in **Fig. 6**, although increasing the load growth results in a higher network loss, the proposed network reconfiguration scheme considerably reduces the network loss compared to the scenario without reconfiguration capabilities. The worst-case (peak load) voltage profiles of the different busbars for three situations (after network reconfiguration, after DG installation and without reconfiguration, and after simultaneous reconfiguration and DG placement) have been compared in **Fig. 7**. As can be seen in **Fig. 7** for the peak conditions of the load, although the network reconfiguration improves the voltage profile compared to the scenario without reconfiguration, some busbars have still a voltage below the permitted limit. Moreover, the installation of the DG units in the network without reconfiguration capabilities can improve the voltage profile in comparison with the scenario, where the network is reconfigured.

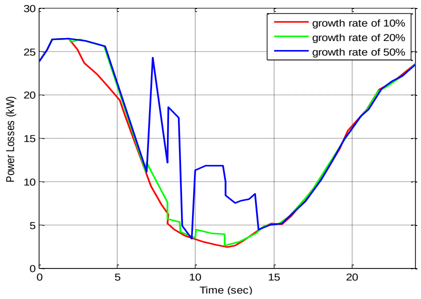

Fig. 6. Network Loss with Load Growth

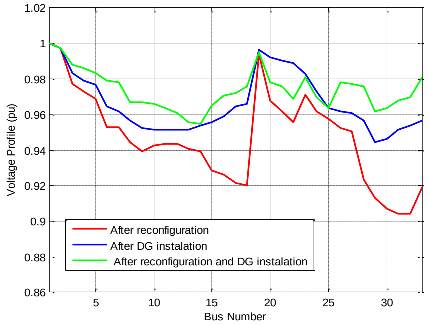

Fig. 7. Voltage Profile of the Network Busbars in Peak Load Conditions

4.2. *Simulation results in 118-bus IEEE network*

Here, the proposed method is employed to reconfigure the 118-bus IEEE benchmark network, shown in **Fig. 8**, to minimize the annual power loss. The network parameters including the line and load impedances are given in [69].

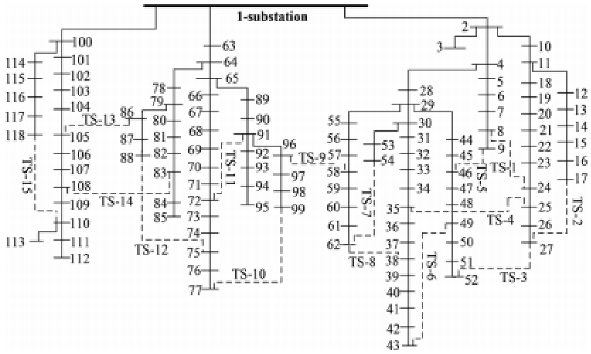

Fig. 8. 118-bus IEEE benchmark

The results of the reconfiguration in the 118-bus benchmark network are summarized in **Table 7**. As can be seen, the network configuration changes hourly following the network load variation or an occurred fault in a part of the network.

The network is reconfigured such that the total network loss is minimized in each period. Obviously, when the total network loss is minimized in each period, the overall annual loss is also minimized. The results show that the proposed graph theory-based power loss-minimized reconfiguration method, independent of the network scale and dimension, can reconfigure the distribution network for the minimum power loss when the load varies suddenly or a fault is created.

Table 7. Reconfiguration Results for 118-bus IEEE Network

Period	Open Switches	Power Loss (kW)
6.5-7	21, TS2, 34, 45, 48, 59, 95, 76, 71, 73, TS13, 82, 109	413.6
7-8.5	21, TS2, 49, 34, 45, 40, TS7, TS8, TS9, 76, 71, 73, TS13, 82, 109	441.7
8-9	21, TS2, 49, 34, 45, 40, TS7, TS8, 95, TS10, 70, 72, TS13, 82, 109	631.88
9-10	21, 15, 49, 34, 45, 40, TS7, TS8, 95, TS10, 70, 72, TS13, 82, 109	592.7
10-11	21, 15, 49, 34, 45, 40, TS7, TS8, 95, TS10, 70, 72, TS13, 82, 109	614.77
11-12	21, 15, 49, 34, 45, 40, TS7, TS8, 95, TS10, 70, 72, TS13, 82, 109	625.2
12-13	20, 15, 49, 34, 45, 40, TS7, TS8, 95, TS10, 70, 72, TS13, 82, 109	640.5
13-14	20, 15, 49, 34, 45, 40, TS7, TS8, 95, TS10, 70, 72, TS13, 82, 109	634.1
14-15	21, 15, 49, 34, 45, 39, TS10, 70, 72, TS13, 82, 109	464.5
15-15.5	21, 15, 48, 34, 45, 39, TS10, 70, 72, TS13, 82, 109	492.3
15.5 - 16	21, 15, 49, 34, 45, 40, TS7, TS8, 95, TS10, 70, 72, TS13, 82, 109	466.6

5. Conclusion

The proposed network reconfiguration method targeting the minimized annual power loss was applied in two benchmark networks with 118 and 33 buses. Considering the high costs of the power, the obtained savings due to the power loss reduction can provide economic benefits in addition to the technical advantages. The obtained power reduction and the resulted voltage improvement are more considerable for the proposed method compared to the available previously published schemes. The proposed graph theory-based network reconfiguration method outperforms its counterpart competitive schemes. The presented scheme can decrease the undelivered power in the presence of the DG sources compared to two other schemes. In fact, network loss reduction leads to a corresponding reduction in energy not supplied. Consequently, as the network reconfiguration approaches its optimum situation more, power loss reduces, undelivered power decreases, more subscribers can be covered, and network reliability improves.

Simultaneous network reconfiguration and RES placement with an objective of minimized network loss show that the network configuration changes in the presence of the DG units. The minimum network voltage improves and network loss reduces by applying this method compared to the reference scenarios without reconfiguration, and with reconfiguration in the absence of the DG sources. Therefore, in the presence of the DG sources, the proposed graph theory-based method can be used to reconfigure the network and consequently, reduce the annual power loss. When the network is loaded by an hourly time-varying load or when the network is exposed to a fault, the network reconfiguration changes accordingly such that the loss is minimized in each period, as demonstrated by simulation for the 118-bus distribution network. When the reconfiguration aims at the reduction of the network loss in each period, the annual loss is also minimized.

The results show that the proposed graph theory-based power loss-minimized reconfiguration method, independent of the network scale and dimension, can reconfigure the distribution network to minimize power loss when the network experiences a sudden load variation or a fault occurrence.

Conflict of Interest

The author declares that there is no conflict of interest that could be perceived as prejudicing the impartiality of the research reported.

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