Highlights

Open-source implementation of distribution network reconfiguration methods: Analysis and comparison

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- Practical review and approach to distribution network reconfiguration methods.
- Enhances the implementation of metaheuristic methods by initializing the search with results from faster heuristic algorithms, thereby achieving faster and superior network optimization.
- Incorporating multi-objective capabilities into metaheuristic frameworks.
- Open source repository with the source code use for the paper.
- Compares the systems over long time series periods, to better quantify the global energy savings achievable through the implementation of dynamic DNR policies.

Open-source implementation of distribution network reconfiguration methods: Analysis and comparison

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Abstract

This paper presents a critical and practical approach to the evolution of distribution network reconfiguration algorithms, tracing their development from foundational heuristic methods introduced in 1975 to contemporary state-of-the-art techniques. The article systematically reviews seven different methodologies, including classical heuristic algorithms (Merlin, Baran, and others), advanced meta-heuristic methodologies (particle swarm optimization (PSO) and genetic algorithms), and purely mathematical approaches (MILP-based), analyzing their theoretical foundations, implementation strategies, computational complexity, and performance metrics based on extensive literature review and our own empirical testing.

Each methodology is assessed through standardized test systems, considering multiple objectives such as power loss minimization and voltage profile improvement. The comparative analysis reveals the strengths and limitations of each approach under various network conditions and operational constraints. Furthermore, this work provides significant value to the research community by offering an open-source repository containing documented implementations of all reviewed algorithms. This resource facilitates accessibility for newcomers to the field, promotes reproducible research, and accelerates the development of next-generation distribution network optimization solutions. The repository includes comprehensive documentation, test cases, and performance benchmarks.

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Keywords: Distribution network reconfiguration, heuristic algorithms, greedy methods, metaheuristic algorithms, genetic algorithm (GA), particle swarm optimization (PSO) algorithm, mathematical methods, mixed-integer linear

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programming (MILP)

Glossary A comprehensive list of terms used in this work.

- DNR : Distribution Network Reconfiguration
- GA : Genetic Algorithm
- PSO : Particle Swarm Optimization
- SBPSO : Selective Binary Particle Swarm Optimization
- MST : Minimum Spanning Tree
- BIBC : Bus Injection to Branch Current
- BCBV : Branch Current to Bus Voltage
- MILP : Mixed-Integer Linear Programming
- QP : Quadratic Programming

1. Introduction

The electrical grid, recognized as one of humanity's most complex and vital creations, is susceptible to failures that can affect vast populations and result in substantial economic repercussions. Having operated for over a hundred years in many nations, the grid now confronts the challenge of high DER penetration. This includes renewable energy generators and energy storage systems connected at various voltage levels. The increased variability and uncertainty caused by Distributed Energy Resources (DERs) necessitates dynamic network reconfiguration to accommodate fluctuating generation and consumption patterns and reduce power losses.

The electrical network is structured into three primary voltage levels: transmission, sub-transmission, and distribution (comprising medium voltage and low voltage). The transmission network, responsible for transporting large volumes of energy over long distances, is both critical and resilient, owing to its redundant, meshed topology and substantial investments in monitoring and control systems. The sub-transmission network, also characterized by a meshed topology, provides greater network reach, connecting the transmission network to the distribution level.

Finally, the distribution network, encompassing medium and low voltage infrastructure, includes numerous lines, varying distances, small switches, transformers, and directly links the power infrastructure to consumers.

Distribution networks can be designed with meshed topologies, but are typically operated radially by Distribution System Operators (DSOs) to simplify operation and maintenance. This radial operation simplifies protection relay coordination, reduces the complexity of protection devices, and limits short-circuit currents by avoiding loops on the network. However, this radiality constraint further complicates optimization, as solutions must adhere to Kirchhoff's laws while preventing the formation of loops.

The electrical network experiences significant energy losses, which represent a substantial inefficiency. These losses are distributed across all voltage levels and arise from both technical factors (e.g., resistive losses in cables, faulty connections, partial discharges, and unbalanced loads) and non-technical factors (e.g., energy theft and metering errors). Total power losses can reach up to 15% of the transferred energy, with an average of 8% in Europe. For instance, in Spain alone, losses amount to approximately 25 GWh annually [1], resulting in costs exceeding 2.5 billion euros based on average energy prices [2]. Given that the majority of losses occur within the distribution network, reducing these losses is a vital objective for Distribution System Operators (DSOs) and Transmission System Operators (TSOs) alike, driven by both economic and environmental considerations.

The increasing electricity demand, environmental regulations, and competitive energy markets have led to transmission and distribution systems operating under heavy load conditions, increasing concerns about distribution system losses. The imperative to maintain acceptable power quality and enhance efficiency to maximize economic benefits creates a strong incentive for the development and implementation of loss minimization techniques and innovative operational practices.

Utilities employ Distribution Network Reconfiguration (DNR) to address these challenges by adjusting network topology. This is achieved through manipulation of sectionalizing (normally closed) and tie switches (normally open). This process can optimize three different objectives, but our work focuses on reducing system losses:

1. Loss Reduction: Minimize resistive losses in conductors (e.g., I^2R) by rerouting power through shorter or higher-capacity pathways.
2. Load Balancing: Equalize feeder loading to prevent transformer overheating and extend asset lifespan.
3. Resilience Enhancement: Isolate damaged sections during faults while maximizing supply to healthy zones.

Distribution network reconfiguration (DNR) plays a crucial role in optimizing power systems [3][4]. Its objectives can include minimizing power losses[3], enhancing network stability, and effectively integrating the growing number of distributed energy resources (DERs). DNR, formulated as a non-convex binary optimization problem [5], presents significant computational challenges. Balancing solution accuracy with computational efficiency is therefore critical. This paper provides a comprehensive and accessible overview of DNR, examining its theoretical underpinnings, algorithmic methodologies, and practical applications.

The combinatorial nature of Distribution Network Reconfiguration (DNR) is a primary source of its NP-hard complexity. A network featuring (N) switches presents (2^N) possible configurations, quickly rendering exhaustive search impractical for real-world systems. This exponential growth in the search space, combined with the challenges of optimizing non-linear objective functions under various operational constraints, classifies DNR as an NP-hard problem, as cited in [6].

The advent of smart grid technologies (e.g., RTUs, SCADA, AMI) has enabled real-time DNR by providing granular load data and remote switch control. Yet, the core challenge remains: how to solve this NP-hard problem fast enough for operational decision-making? The mathematical formulation of this operational decision-making problem results in a Mixed-Integer Second-Order Cone (MISOCP) or Mixed-Integer Quadratic Programming (MIQP) problem. Due to the inclusion of binary variables, this renders it NP-hard [6] and precludes the use of efficient polynomial-time algorithms. Consequently, alternative solution strategies must be explored to achieve sufficiently fast computation. Early methods, such as the branch-and-bound approach proposed by [4], were computationally intractable for large networks, while heuristic approaches (e.g., Civanlar's load-transfer method [7]) lacked optimality guarantees. Current research predominantly focuses on metaheuristics (e.g., genetic algorithms), which continue to grapple with convergence and scalability issues. This paper aims to address these limitations through quantitative and qualitative analysis and open-source implementations.

Achieving a solution within a reasonable timeframe represents a significant challenge that has been extensively studied, yet a definitive solution remains elusive. In [4], the author introduced the first study on distribution feeder reconfiguration in 1975, employing a branch-and-bound method. However, this approach suffered from two primary drawbacks: the lack of guaranteed solution convergence and the substantial computational burden required for real-world networks. In [7], the author proposed a simplified yet innovative method for calculating loss reduction through network reconfiguration, based on approximations of loss changes during load transfer between feeders. However, this method did not guarantee global optimality, and the final solution was dependent on the initial switch configuration. Subsequently, [8] presented a power-flow-minimum heuristic algorithm for distribution feeder reconfiguration.

The heuristic methods were followed by metaheuristic methods, starting with genetic algorithms (GA) and followed by nature-based methods such as Ant Colony and Particle Swarm Optimization (PSO) [9], among others, as discussed later in this paper.

Together with algorithm and methodology papers, several reviews on DNR have been published over the years [10][11][12], with the most recent one from 2023. However, their approach has been to list and compare different methods based on the authors' reported results. A different approach has been taken by [9], focused on metaheuristic algorithms, providing a detailed description of a genetic algorithm and a comprehensive comparison of most published papers in the field.

Instead of comprehensively enumerating existing references, which has been done previously by other authors [9][12], this paper provides an in-depth, engineer-oriented review of five decades of research on distribution network reconfiguration (DNR). Specifically, it examines seven methods, along with their open-source implementations in Python.

The contributions of this paper are:

1. Systematically classifies DNR methods, emphasizing their optimization structure.
2. Provides detailed descriptions of, at least, one algorithm from each family, to introduce the different methodologies in a simple and clear manner.
3. Compares algorithmic trade-offs between computational efficiency and solution quality.
4. Includes open-source implementations to bridge theory and practice.
5. Enhances the implementation of metaheuristic methods by initializing the search with results from faster heuristic algorithms, thereby achieving faster and superior network optimization.
6. Compares the systems over long time series periods, to better quantify the global energy savings achievable through the implementation of dynamic DNR policies.

The remaining sections are structured as follows. Section 2 describes the problem statement, by describing the mathematical and physical foundations of the problem, detailing the power flow equations and the radiality constraint imposed by most distribution system operators. Section 3 details the mathematical formulation of the problem. Section 4 classifies and describes the various methodologies proposed in the literature. Section 5 presents the obtained results and the comparison between the different methods. Finally, Section 7 presents the conclusions of this paper.

2. Understanding the problem

2.1. Distribution Network Reconfiguration Objectives

Distribution Network Reconfiguration (DNR) aims to optimize system operation for enhanced reliability and economy, primarily addressing four objectives: Power Loss Reduction, Voltage Profile Optimization, Load Balancing, and Service Restoration. Of the seven methods implemented, six were initially dedicated to Power Loss Reduction, with only one's initial formulation incorporating Voltage Profile as main objective [13]. In contrast, our implementation has expanded these metaheuristic methods to be multi-objective, thereby enabling the optimization of both power losses and voltage profile.

2.1.1. Power Loss Reduction

Minimizes resistive losses (P_{loss}) through optimal path selection:

$$\min \sum_{k=1}^{N_l} I_k^2 R_k \quad \forall k \in N_l \tag{1}$$

where I_k is the current on line k, which is constrained by its line ampacity $I_k \leq I_k^{max}$, R_k is the resistance of that line, and N_l is the number of lines in the electrical network.

2.1.2. Voltage Profile

A significant effect of the radial topology is increased voltage loss due to voltage drops in the cables, so maintaining the voltages within the DSO's limits can be another objective in the optimization process:

$$V_i \in [V_{min}, V_{max}] \quad \forall i \in N_b \tag{2}$$

where V_i is the voltage at bus i measured in pu, N_b is the number of buses in the electrical network, while V_{min} and V_{max} are the maximum and minimum voltages defined by the DSO.

2.1.3. Load Balancing

When aiming to reduce system losses or maintain the voltage profile, there's a risk that some lines might be configured to operate very close to their maximum capacity, while others carry only a small percentage of their load. It's important for the DSO (Distribution System Operator) to keep all lines as balanced as possible. This increases the system's resilience against events like load increases or line failures, which could otherwise lead to dangerous situations.

2.1.4. Service Restoration

The critical post-fault objective restores power to the maximum number of customers (with energy) while isolating faults. Mathematically, this maximizes:

$$\max \sum_{i=1}^{N_b} w_i x_i \tag{3}$$

where w_i is the customer weight, $x_i \in \{0, 1\}$ indicates service status at bus i, $\forall i \in N_b$, and N_b is the number of buses in the electrical network.

2.2. Solution Strategies for Distribution Optimization

Distribution Network Reconfiguration (DNR) offers a means to optimize network operation, yet it is not the sole solution available to utilities. Enhancements can similarly be achieved during the planning stage through the inclusion of additional shunt capacitors or distributed generation (DG) assets; however, these alternatives typically entail greater CAPEX expenses, while DNR primarily entails OPEX expenses.

2.2.1. Shunt Capacitor Placement

This approach [11] improves systems by compensating reactive power and stabilizing voltage. This method requires installing fixed capacitors at specific locations. Benefits include reduced losses and better voltage profiles, though these goals may sometimes conflict. Limitations include high upfront costs, static nature, need for placement analysis, and large incremental adjustments.

2.2.2. DG Allocation

DG Allocation [11] strategically positions distributed generation sources close to consumers, which minimizes energy transmission distances and consequently reduces power losses. Furthermore, DGs enhance voltage profiles by increasing voltage levels at the far ends of the network and alleviating cable loading. However, the integration of DGs can introduce potential challenges related to reverse power flow. Similar to Shunt Capacitor Placement, implementing DG Allocation necessitates substantial financial investment and represents a static infrastructure solution.

2.2.3. Distribution Network Reconfiguration (DNR)

It alters network topology via switch exchanges, offering flexibility at minimal cost. It reduces losses, improves voltage profiles, and isolates faults. The challenge lies in finding optimal configurations due to non-convex discrete problems that conventional methods cannot easily solve. Implementation needs no new infrastructure, using existing switches automated in smart grids.

The authors are aware of the limited life of switches when they operate under load. Future work will investigate adapting the base strategies to account for the available electrical elements, as mentioned in Section 7.

2.3. Intuition behind the DNR methods

To clearly exemplify the DNR problem, we will use the IEEE 14-bus system, shown in Fig. 1. This network comprises 14 buses, 20 lines, 5 generators, and 11 loads, and includes 7 loops. The objective of DNR methods is to achieve a radial architecture by opening 7 switches to eliminate the loops, selecting the switches to open or close, such that the total network losses are minimized.

We will denote the line names as follows: the line connecting buses 6 and 12 is named '6_12_1'. If multiple lines connect the same two buses, the trailing number will enumerate them.

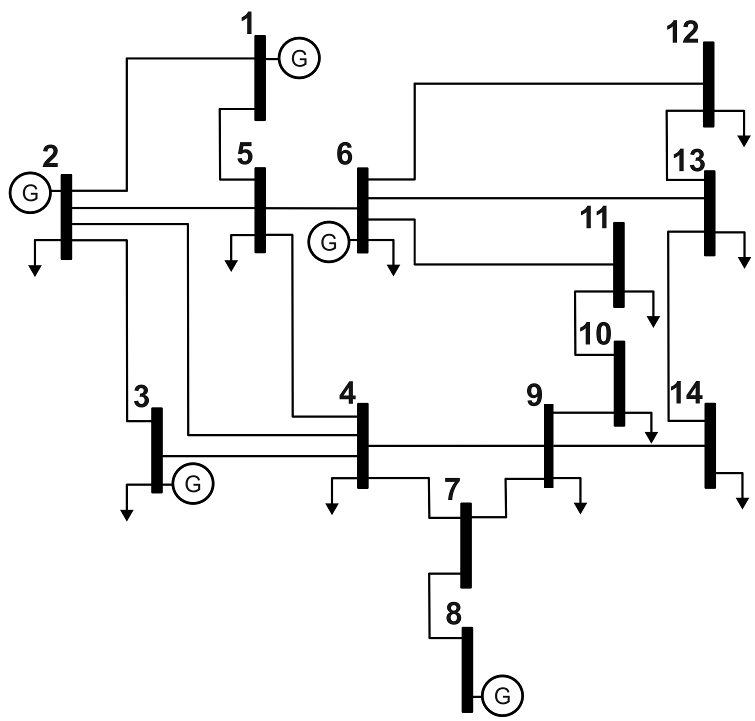
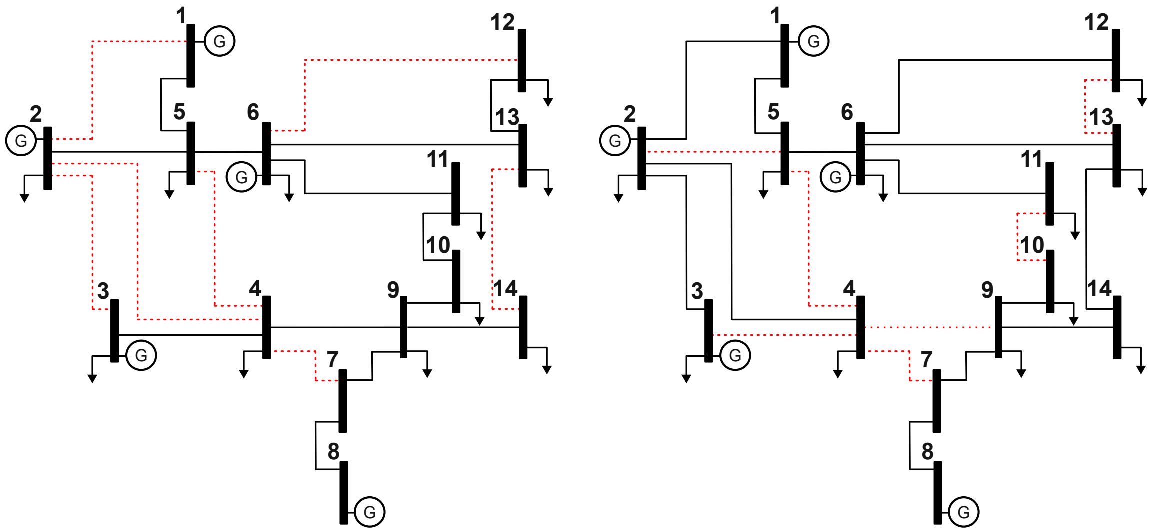


Figure 1: IEEE 14-bus case, with all switches closed and losses equal to 13.34 MW

If we choose a random combination of switches, Fig. 2, such as disconnecting the lines *['6_12_1', '13_14_1', '2_4_1','4_5_1','4_7_1','2_3_1','1_2_1']*, the losses will be 115.23 MW with a voltage range between 1.09 and 0.815 p.u.



(a) Non-optimal configuration with losses equal to 115.23 MW.

(b) Near-optimal configuration with losses equal to 28.91 MW.

Figure 2: IEEE 14-bus case non-optimal and near-optimal configurations. Disabled lines in red.

Executing the method formulated by [4] chooses the lines *['2_5_1', '3_4_1', '4_5_1', '4_7_1', '4_9_1', '10_11_1', '12_13_1']*, Fig. 2. This solution achieves 28.91 MW of losses, maintains network radiality, and improves the voltage profile to a range of 0.958 to 1.09 p.u., resulting in lower losses and enhanced network parameters.

3. Mathematical Formulation and Constraints

Distribution Network Reconfiguration (DNR) can be formulated as a traditional optimization problem requiring the definition of specific terms. Subsequently, we will outline the optimization equations and discuss the various approaches employed by authors to calculate network losses using different power flow calculation methods.

3.1. Optimization Framework

The DNR problem is defined as:

$$\min_{x} \quad f(x) \quad \text{(objective function, i.e. network losses)} \tag{4}$$

$$\text{s.t.} \quad g(x) = 0 \quad \text{(Power flow equations)} \tag{5}$$

$$h(x) \leq 0 \quad \text{(Operational limits)} \tag{6}$$

$$x \in \{0,1\}^{N_s} \quad \text{(Switch states)} \tag{7}$$

3.2. Power Flow Models

The selection of the equations to be used in the optimization objective function (4) and constraints (5,6,7) is a key decision in the solution process, as different authors have chosen different methods, affecting both the resolution time and accuracy:

3.2.1. Kirchhoff's Power Flow Equations

The power flow equations, defined by Kirchhoff's laws [14], are applicable to any network regardless of its topology. They can be solved by methods like Newton-Raphson [15], among others. However, authors have applied a variety of relaxations in order to obtain solutions for the DNR problem [3][5][16], as explained in Section 4.2 and Section 4.3:

$$P_i = \sum_k |V_i||V_k|(G_{ik}\cos\theta_{ik} + B_{ik}\sin\theta_{ik}) \tag{8}$$

$$Q_i = \sum_k |V_i||V_k|(G_{ik}\sin\theta_{ik} - B_{ik}\cos\theta_{ik}) \tag{9}$$

where P_i is the active power flow between buses i and k, Q_i is the reactive power flow between buses i and k, V_i is the voltage at bus i, V_k is the voltage at bus k, G_{ik} is the conductance of the line between buses i and k, B_{ik} is the susceptance of the line between buses i and k, θ_{ik} is the phase angle difference between buses i and k.

3.2.2. DistFlow Equations

DistFlow equations [17] are a set of equations based on Kirchhoff's laws, specifically tailored to the characteristics of distribution grids, such as their radial or weakly meshed topology. They can be solved using the recursive Forward (10)-(12)/Backward (13)-(17) sweep method, which allows for a non-derivative solution and faster computation.

$$P_{i+1} = P_i - r_i\frac{P_i^2 + Q_i^2}{V_i^2} - P_{Li+1} \tag{10}$$

$$Q_{i+1} = Q_i - x_i\frac{P_i^2 + Q_i^2}{V_i^2} - Q_{Li+1} \tag{11}$$

$$V_{i+1}^2 = V_i^2 - 2(r_iP_i + x_iQ_i) + (r_i^2 + x_i^2)\frac{P_i^2 + Q_i^2}{V_i^2} \tag{12}$$

$$P_{i-1} = P_i + r_i\frac{P_i'^2 + Q_i'^2}{V_i^2} + P_{Li} \tag{13}$$

$$Q_{i-1} = Q_i + x_i \frac{P_i'^2 + Q_i'^2}{V_i^2} + Q_{Li} \tag{14}$$

$$V_{i-1}^2 = V_i^2 + 2(r_i P_i' + x_i Q_i' + (r_i^2 + x_i^2) \frac{P_i'^2 + Q_i'^2}{V_i^2} \tag{15}$$

$$P_i' = P_i + P_{Li} \tag{16}$$

$$Q_i' = Q_i + Q_{Li} \tag{17}$$

where P_i is the active power flow between buses i and $i+1$, Q_i is the reactive power flow between buses i and $i+1$, P_{Li} is the active power flow for the loads at bus i, Q_{Li} is the reactive power for the loads at bus i, V_i is the voltage at bus i, r_i is the resistance of the line between buses i and $i+1$, x_i is the reactance of the line between buses i and $i+1$.

During the backward sweep, powers/currents are aggregated node by node from the network extremities to the substation, while during the forward sweep, voltages are calculated from the slack bus at the main substation to the feeder extremities.

A simplified version was formulated by [3] to achieve even faster solutions, by not considering the quadratic terms of the losses during the forward (10)(11) and backward passes (13)(14), and later considering the voltage equal to 1 p.u. in the final power losses calculation.

3.2.3. Direct Load Flow (DLF)

The method proposed by [18], is based on the bus-injection to branch-current (BIBC) and branch-current to bus-voltage (BCBV) matrices. It is solved by a fast recursive process, achieving a non-derivative solution simply by multiplying matrices based on the admittances and the network's interconnection:

$$[B] = [BIBC][I] \tag{18}$$

$$[\Delta V] = [BCBV][BIBC][I] \tag{19}$$

3.2.4. Summary of Power Flow calculation methods

Power flow solutions present a trade-off between accuracy and computational expense. Kirchhoff's laws when solved by Newton-Raphson method achieve the highest accuracy but at the highest computational cost. In contrast, Direct Load Flow (DLF) equations offer the fastest solution at the expense of lower accuracy. Positioned in the middle, the DistFlow method provides a balance of both computational effort and accuracy.

Considering that solving the power flow equations is the most time-consuming task within network reconfiguration methods, as this operation can be done iteratively for tens or hundreds of times, the choice of how to solve these equations directly impacts the solution time. For this reason, some authors choose to apply certain relaxations, assumptions, or simplifications to the equations to improve the power flow solution time. The most common approaches include:

- Assuming cable losses are negligible compared to loads, allowing them to be omitted from the equations.
- Setting voltages in all nodes to 1 per unit (pu).
- Considering only the real part of the equations (as commonly done in older works).

In heuristic methods, the equations are manipulated as part of the decision-making process [3][7], whereas metaheuristics typically use an external solver to obtain the objective function result. Mathematical approaches [5][16] utilize these Kirchhoff's equations as constraints or objectives, as detailed in Section 4.2.

Each author selects the objective function based on their decision criteria, with the most common being the minimization of power losses in the network, but other criteria could include voltage margins, switching costs, or a combination of weighted objectives.

3.3. Network radiality

Special attention has been given to the definition of radiality in the network and its translation into mathematical equations that can be easily incorporated into the decision-making process.

A radial network requires that there are no loops in the topology, which can be mathematically defined as:

$$N_{lines} \; = \; N_{buses} - N_{con} \tag{20}$$

where N_{lines} is the number of available lines, N_{buses} is the number of buses and N_{con} is the number of connections between the network and the main transmission or subtransmission grid.

However, this condition alone is not sufficient; it also requires that all buses are energized.

In heuristic and metaheuristic approaches, the radiality constraint is verified by equation (20), while ensuring that no nodes are disconnected or de-energized after each decision or selection step. In contrast, mathematical optimization methods require the radiality constraint to be integrated into a mathematical equation, as defined by [5] and [19]. This point will be discussed in more detail in Section 4.

3.4. Graph Theory

Electrical networks can be modeled as undirected graphs, $G(V,E)$, where nodes correspond to network buses, and edges represent the lines connecting them [20]. This representation allows graph optimization methods and algorithms to be readily applied to electrical systems. For the Distribution Network Reconfiguration (DNR) problem, the most suitable algorithms are those designed to find the Minimum Spanning Tree (MST)[13], such as Kruskal's [21] or Prim's [22] algorithms. These ensure the radial structure of the distribution system while optimizing the paths based on various criteria, such as line impedance or the current flowing through the lines, which are used as edge weights.

4. Methods Review

4.1. Solution Approaches Classification

The evolution of DNR methodologies can be categorized into four distinct paradigms, as detailed in Table 1

Table 1: Methods summary

Heuristic Methods	The foundational methods in DNR employ rule-based approaches that utilize network physics and practical rules derived from network-specific knowledge	• Branch exchange algorithms • Loop-based algorithms • Minimum Spanning Tree based methods	• Fast computation (polynomial time complexity) • Intuitive physical interpretation • Local optima convergence • Dependency on initial conditions	[3][4][7][13]
Metaheuristic Methods	Nature-inspired optimization techniques, which include genetic and swarm intelligence approaches	• Genetic Algorithms (GA) • Particle Swarm Optimization (PSO) • Ant Colony Optimization (ACO) • Simulated Annealing (SA)	• No guarantee of global optimality • Fitness evaluation via power flow solutions • Population-based search	[9][23][24]
Mathematical Programming	Exact optimization methods providing rigorous solutions	• Mixed-Integer Linear Programming (MILP) • Mixed-integer quadratic programming (QP) • Second-order cone programming (SOCP)	• NP-hard problem complexity • Approximation/relaxation techniques often required • Incorporation of radiality constraints (Eq. 20)	[5][6][16]
Data-driven algorithms	Emerging data-driven techniques that have been gaining prominence in the last few years [9]	• Supervised and unsupervised neural networks • Reinforcement learning for dynamic reconfiguration	• Increased computational cost during the training stage • Extremely fast solution in run time operation • Capability to learn and generalize complex non-linear relationships • Black-box nature with limited explainability	[25][26]

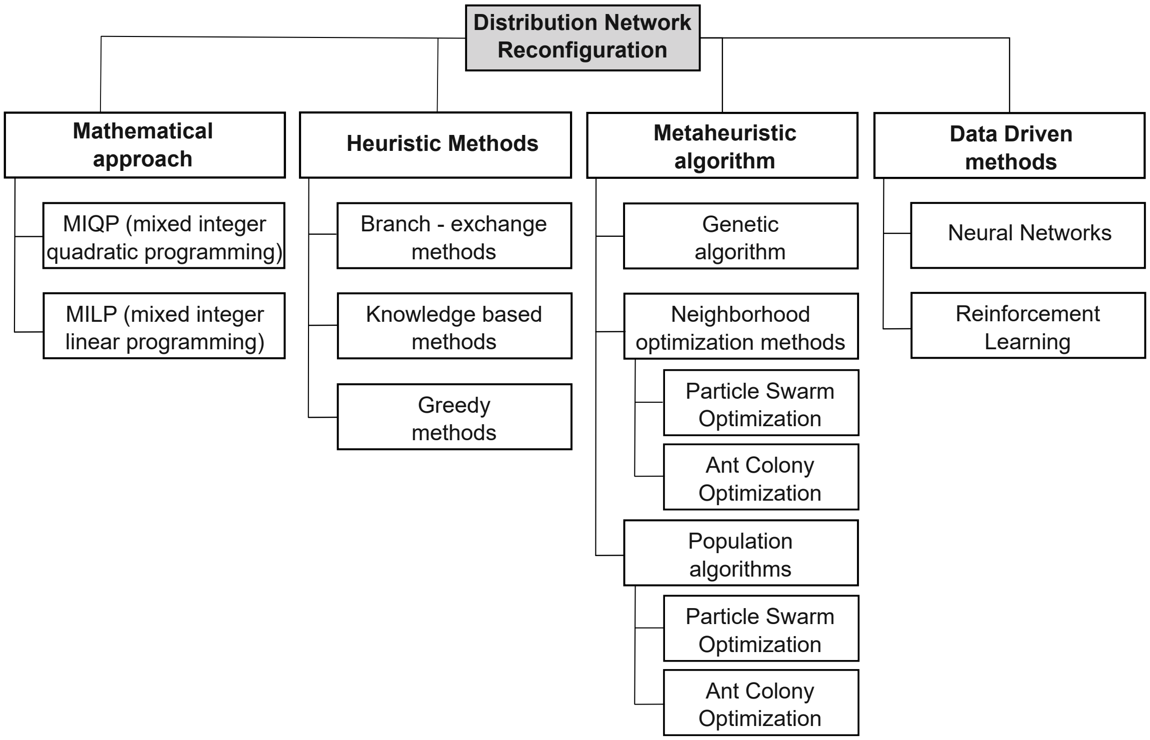


Figure 3: Distribution Network Reconfiguration Methodologies

4.2. Mathematical techniques

The most straightforward approach to solving the DNR problem would be to use mathematical methods based on the power flow equations. However, its mixed-integer nonlinear nature, which renders it a highly combinatorial problem, makes its solution a challenging task.

Mathematical methods possess a key advantage compared to heuristic and meta-heuristic techniques (which will be discussed in Sections 4.3 and 4.4): they can obtain globally optimal solutions if the problem can be transformed into a convex problem through relaxations. oreover, they do not require any tuning or random initialization that could lead to suboptimal or inconsistent solutions.

One of the earliest references for solving the DNR problem using mathematical optimization processes is presented in [27], published in 1996, which employed linear programming. The formulation is given by

$$[A][P_f] = [P] \tag{21}$$

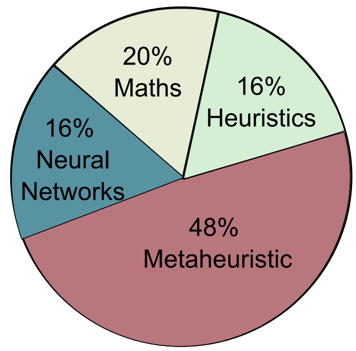


Figure 4: Percentage of the different DNR methods on the technical literature, based on the information given in [9] and other papers

where A is the node-to-branch reduced incidence matrix, P_f is the branch flow vector, and [P] is the nodal injection vector, excluding the reference node.

If there are N buses, only N-1 out of L lines need to be connected (20). However, the [A] matrix will change for each choice of N-1 lines while maintaining radiality and connectivity. The article establishes resistive losses as the objective function, focusing solely on real power. Its main challenge lies in maintaining radiality, achieved through the use of an extended matrix.

Instead of purely linear programming, other approaches such as [28], which focus on communication networks but propose theoretical foundations applicable to distribution networks, suggest using the branch-and-bound method. This search method is adapted to the binary nature of communication networks and can also be applied to energy distribution networks, emphasizing efficient pruning of all possible configurations.

The DNR problem can utilize methods developed for Optimal Power Flow (OPF), a well-established field aiming to minimize one or more objective functions, typically to minimize the generation costs. However, in the case of the DNR, power losses are used as objective function. However, the added complexity lies in determining the status of switches, represented as binary variables, which makes it a Mixed-Integer Non Linear Programming (MILNP) problem.

Many authors focus on applying relaxations to the quadratic equations of power flow, converting them into linear equations suitable linear programming solvers. This includes Mixed-Integer Linear Programming (MILP), which integrates power flow equations and network operational constraints.

Two prominent works in the field, [29] and [30], propose different approaches using Piecewise Linear Functions (PLF) to linearize the quadratic equations that relate power, voltage and current. This linearization process, however, adds complexity to the solution when combined with binary variables defining switch status. PLFs can effectively linearize these equations, enabling their use in MILP formulations. In [29], the author introduces a novel method for modeling switches based on the definition of all possible paths between nodes and substations. Each path is mathematically represented by a binary variable, ensuring radiality while simultaneously defining switch statuses.

In later papers, the process has been refined and expanded to more sophisticated methods, such as mixed-integer conic programming [5]. Nevertheless, the primary focus and concern remains on the radiality constraint, which is the most challenging to represent mathematically, as highlighted in [19]. Other papers [31] propose the use of planar graph representations to ensure radiality while employing a Mixed-Integer Quadratic Programming (MIQP) formulation. Recent works, such as those published in 2024 [32] and [33], continue to explore these challenges.

The necessary and sufficient conditions for radiality in a graph, and thus for the existence of a spanning tree, are rigorously established through the calculation of the determinant of the branch-to-node incidence matrix [27]. Nevertheless, mathematical optimization techniques are generally incapable of incorporating determinants directly as constraints, thus necessitating their expression through alternative mathematical formulations. One of the main contributions to this topic is presented in [19], where the authors define radiality as satisfying two simultaneous conditions:

- Condition 1: The network configuration must form no loops.
- Condition 2: The network configuration must have all buses connected.

In [5] and [33], the authors propose using variables B_{ij} and B_{ji} to indicate power flow direction. These variables satisfy:

$$B_{ij} + B_{ji} = 1 \tag{22}$$

where $B_{ij} = 0$ indicates no flow from bus i to bus j. When both, $B_{ij} = 0$ and $B_{ji} = 0$, it means there is no current in the line, so it is disconnected.

An interesting contribution to the problem was provided by [16] and [30]. The authors proposed adding a binary signal within a simplified set of equations, along with piecewise linearization, to enable the use of MILP. They also introduced a “path-to-node” incidence concept, which allows for the compact and efficient formulation of both radiality and electrical constraints.

4.2.1. QP and SOC implementations

In our work, we have based our implementation on [6], where the authors propose a set of equations to define radiality similar to [5], but also introduce a third variable y_{ij} that defines the state of the line or its associated switch. The problem is then solved by two different approaches: first by Quadratic Programming (QP), without considering the physical limits, such as minimum bus voltage or maximum line current, and later, with Second-Order Cone Programming (SOCP), where the physical constraints are added to the set of constraints.

The most significant contribution of this proposal [6] is the mathematical definition of radiality, where three key variables are introduced:

- z_{ij} and z_{ji}: To define the current flow direction
- y_{ij}: To indicates whether the current is active (switch closed)

Alongside the radiality constraints, the power flow equations are formulated with different relaxations for each approach:

- For Quadratic Programming (QP), the equations consider only resistance (a simplification of the full impedance model).
- For Second-Order Cone Programming (SOCP), the equations are extended to incorporate the full impedance model.

In our implementation, we used Python with the Pyomo library, [34] [35] for formulating constraint and objective functions, and employing the [36] solver to obtain the final solution.

4.3. Heuristic techniques

Heuristic methods leverage domain-specific knowledge of distribution systems to efficiently find feasible configurations, though they typically yielding locally optimal solutions. These approaches offer computational advantages over metaheuristics by incorporating electrical system insights directly into their decision-making processes, as will be explained in this section.

4.3.1. Methodological Categories

The literature classifies heuristic DNR methods into three principal approaches:

- Branch Exchange: Iterative switch swapping from an initial configuration.
  - Operates on an existing radial topology.

  - Uses sensitivity metrics for switch selection.

- Loop Cutting: Systematic opening of switches in meshed networks.
  - Begins with all switches closed.
  - Prioritizes branches by current magnitude.

- Greedy Graph Methods: These methods utilize methods like Kruskal's [21] or Prim's [22] algorithms to find a minimum spanning tree or radial configuration based on electrical parameters such as cable impedance or current or power in a given configuration. The decision-making process in these methods can be specifically tailored by the author or implemented using standard algorithms like Prim's or Kruskal's.

The first proposed heuristic method was a loop cutting algorithm by [4], which selects branches for opening based solely on their minimum current. After selecting a branch, the algorithm ensures no nodes remain disconnected and repeats the process (see Fig. 5). This method was later refined by [37], incorporating AC power flow calculations and network constraints, for particular use during network planning phase.

Two other key studies, conducted by [7] in 1988 and [3] in 1989, were based on the Branch Exchange method. These works innovated both in heuristic reconfiguration methods and, more importantly, in power flow estimation techniques. These advancements were crucial at a time when computational capacities were limited, accelerating decision-making processes. In [3], the author dedicates a significant portion to defining simplified DistFlow equations, as explained in Section 1. Later, in 1992, [8] improved the method for selecting the lines to be opened.

The Branch Exchange algorithm has continued to be studied and updated to this day, as evidenced by recent papers such as [38], where authors use BIBC/BVBC matrices to speed up load flow calculations (similar to Civanlar's approach [7]), and [39], published in 2023.

Another area of study involves greedy methods for achieving minimum spanning trees based on graph theory, which aim to select the optimal branches for opening or closing based on localized decision parameters. These methods employ algorithms like Prim's and Kruskal's, as seen in [40] and [41], where authors use decision parameters ranging from line impedance to line active power.

This paper has selected and implemented five different heuristic methods for comparison, as they demonstrate fundamentally different approaches to solving the problem. This contrasts with mathematical methods, where changes primarily involve the description of constraints while the core problem remains the same:

- Loop Cutting: [4]
- Branch Exchange: [3]
- Branch Exchange: [38]
- Greedy Minimum Spanning Tree: [13]
- Brute Force: [20]

4.3.2. Loop Cutting

The first implemented method in this review is the proposal by [4] in 1975 (shown in Figure 5). This method starts with all switches closed; the algorithm then calculates the network power flow and lists all branches in ascending order based on their current. It then chooses branches starting from the one with the lowest current and disconnects them sequentially, ensuring that the resulting network maintains radiality. After disconnecting a branch and generating a valid network configuration, the power flow is recalculated, and the process repeats until the number of open lines equals the number of buses minus one (20).

4.3.3. Branch Exchange

The selected Branch Exchange method is based on the algorithm proposed by [38], represented in Fig. 6, and which builds upon earlier proposals by [3] and [7]. The main feature of the algorithm, compared to the other implemented algorithms, is that its optimization objective is to improve the voltage profile rather than directly reducing losses. It starts with a valid radial configuration and iteratively exchanges tie switches. It compares the voltages at the nodes connected by the tie switch, and the algorithm opens the line connected to the node with the higher voltage. One of the key elements in [38] is the use of BIBC/BVBC matrices for efficient power flow calculation in distribution networks. The authors start with a network configuration compliant with constraints and perform a power flow calculation to determine the voltages at each node. They then analyze each tie switch by comparing the voltages at its connected nodes. Depending on whether the sending or receiving node has the higher voltage, the algorithm decides on the exchange of the tie switch to optimize network performance. The power flow is recalculated after each change, and if the system performance improves, the change is reatined; otherwise, the algorithm proceeds to the next tie switch.

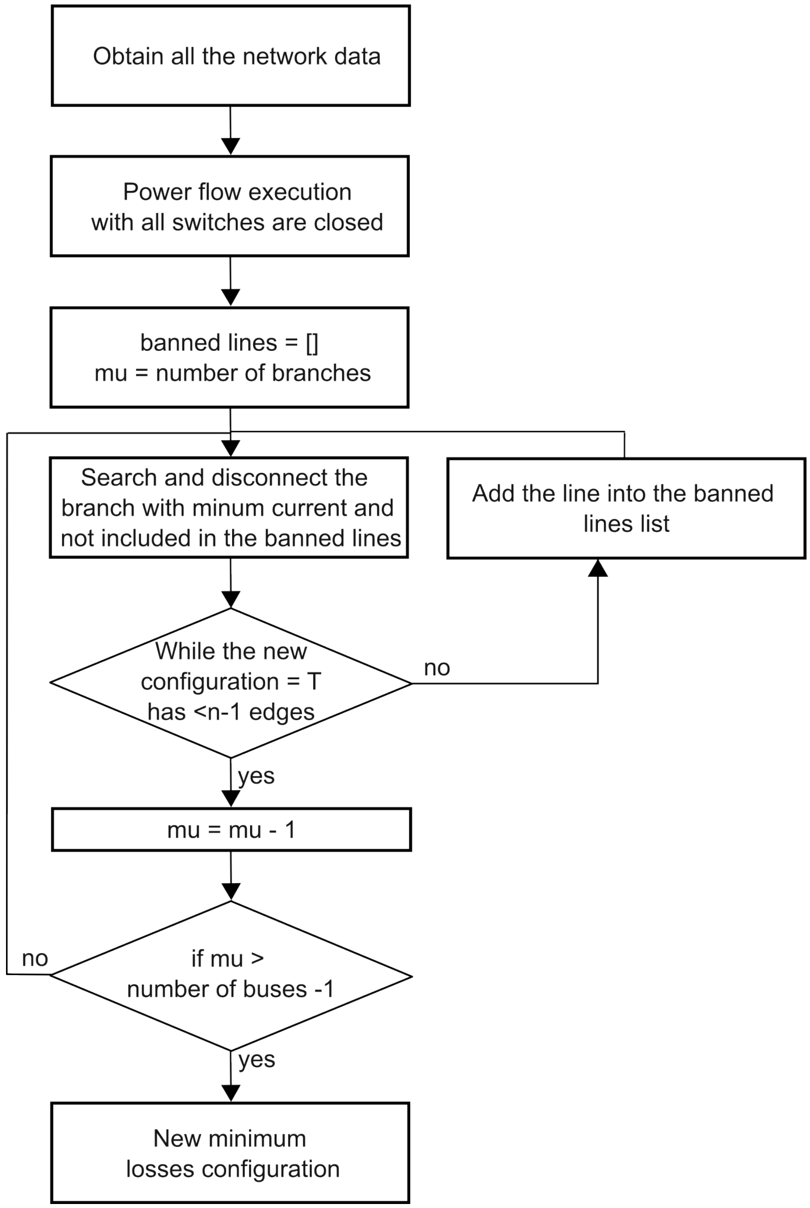


Figure 5: Heuristic algorithm based on "Search for a minimal loss operating spanning tree configuration in an urban power distribution system" by Merlin et al. [4]

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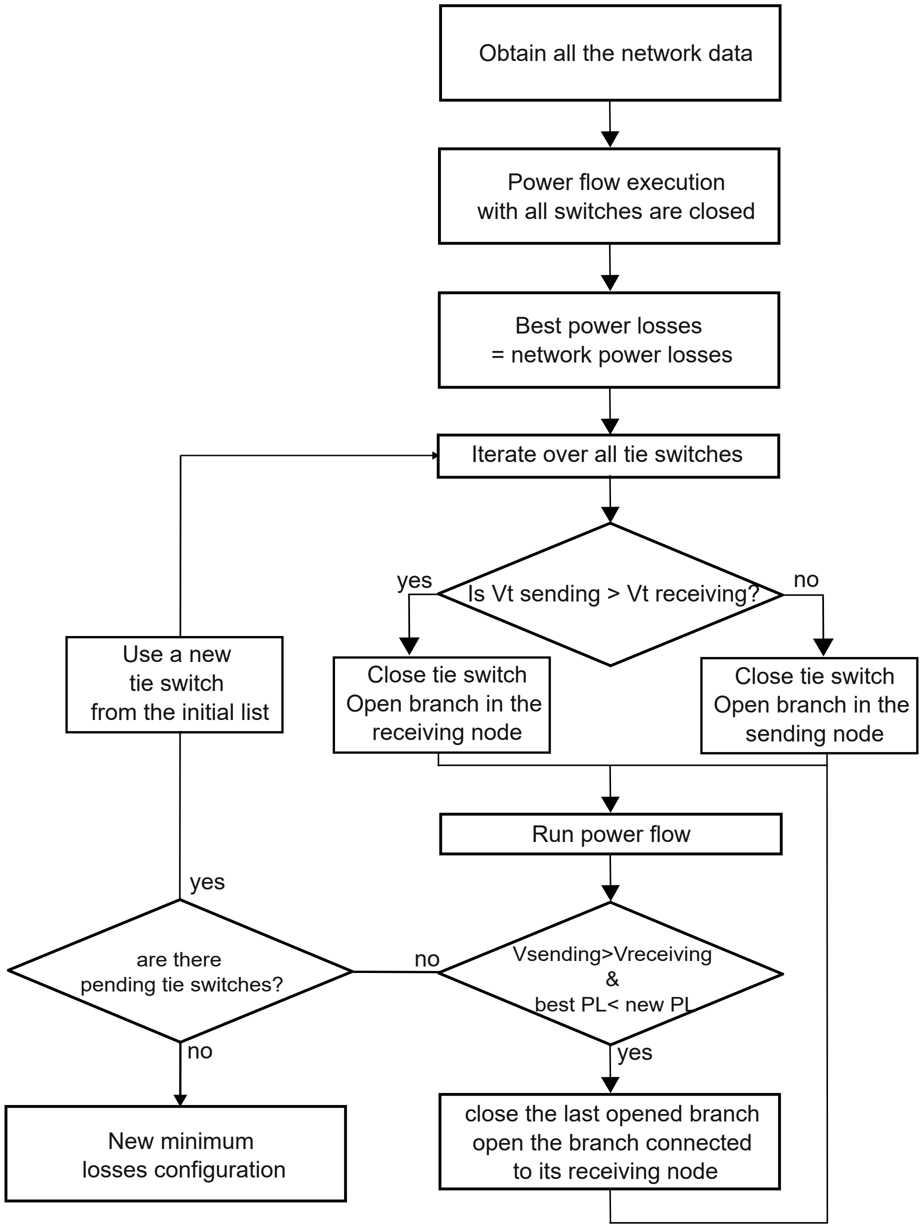

Figure 6: Flow diagram of "An effective network reconfiguration approach of radial distribution system for loss minimization and voltage profile improvement" by [38]

4.3.4. Greedy MST Method

The authors in [13] propose a graph-based method using Kruskal's algorithm to find the minimum spanning tree (MST) for distribution network reconfiguration. The algorithm begins by calculating the power flow with all switches closed and assigns weights to graph edges based on the inverse of the active power of the branches. Kruskal's MST algorithm is then applied to these weighted edges, which progressively adds edges to the spanning tree based on their weights, ensuring that no cycles are created. This process is illustrated in Fig. 7. The authors experimented with various weighting policies and found that using the inverse of active power produced comparable results to more complex metaheuristic algorithms such as genetic algorithms and harmony search.

The implementation performed in the present paper is based on [13] but includes the option to use different MST algorithms, such as Prim's or Boruvka's, while the weight can be chosen between the current or the power on the lines. The best results have been obtained with current on the line, with a significant improvement compared to using active power.

An alternative heuristic approach is proposed by [20], that employs a modified Minimum Spanning Tree (MST) method to exhaustively search all valid spanning trees in a network using a brute-force strategy. This ensures that the optimal radial solution is identified. Morton's method simplifies power flow calculations by converting the model into a constant-current load-based representation. This modification facilitates a more efficient evaluation of network configurations while retaining the advantages of a spanning tree approach.

4.4. Metaheuristic Methods

4.4.1. Methodological Categories

Metaheuristic algorithms constitute a significant portion of research in distribution network reconfiguration (DNR), accounting for over 58% of studies according to [9].

Metaheuristic methods iteratively optimize problems without using derivative information, thereby simplifying computational processes. They often emulate natural processes like genetic evolution or the behaviors of animal collectives (e.g., bird swarms, ant colonies) to find near-optimal solutions.

The pioneering metaheuristic algorithm for DNR was the Genetic Algorithm (GA), which evolves an initial population through crossover, mutation, and selection based on a fitness function to minimize or maximize objectives. GA was first applied to DNR in 1992 [42] and gained popularity in the 2000s with refinements such as faster power flow calculations [43] and multi-objective approaches [23].

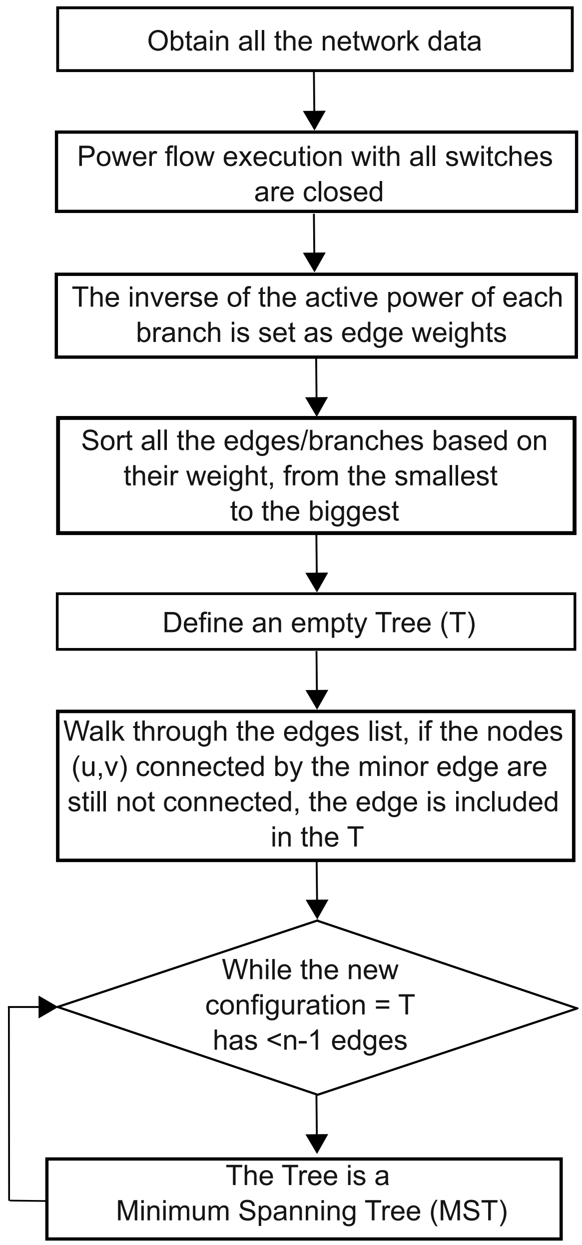

Figure 7: Flow diagram of "A minimal spanning tree algorithm for distribution network configuration" by [13]

Population-based algorithms such as Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) iteratively improve solutions based on candidate positions and values, converging towards optimal solutions.

Other metaheuristic algorithms applied to DNR include Ant Colony Optimization, Simulated Annealing, Immune Algorithms, Plant Growth Simulation Algorithm, Honey Bee Mating Optimization, Artificial Bee Colony Algorithm, and Gravitational Search Algorithm, among others. Recent studies have explored newer algorithms such as Harris Hawk Optimization and Jaya Algorithm [44][45].

Despite their effectiveness, metaheuristic algorithms heavily depend on chosen parameters and the initial conditions, which can influence their performance significantly.

For this study, the following two metaheuristic methods were selected:

- Genetic Algorithm (GA) [23]: Utilized for its effective multi-objective optimization approach.
- Selective Binary Particle Swarm Optimization (SBPSO) [24]: Chosen for its capability in discrete solution space optimization.

4.4.2. Genetic Algorithm

The paper by [23] introduces a traditional Genetic Algorithm (GA), illustrated in Fig. 8, and described in detail below.

The algorithm begins by generating an initial population of N_{pop} candidates. Specifically, N_{sbe} candidates are derived from an initial radial configuration using the Successive Branch Exchange Algorithm (SBEA) based on [3]. The remaining candidates are generated by a greedy minimum spanning tree method employing Kruskal's algorithm, where each branch is assigned a random weight for each candidate to ensure a random exploration of the action space.

Once the initial population is established, each candidate's fitness function is evaluated. The fitness function is defined as the inverse of the power loss plus one to prevent division by zero. Candidates are sorted based on their fitness values from highest to lowest, and the top N_{el} elite candidates are selected to proceed. The remaining candidates are replaced with new candidates generated through crossover operations between elite candidate pairs, followed by mutations with a probability of (P_{mut}).

This iterative process continues for N_{iter} iterations, and the candidate with the highest fitness is selected as the solution to the Distribution Network Reconfiguration (DNR) problem.

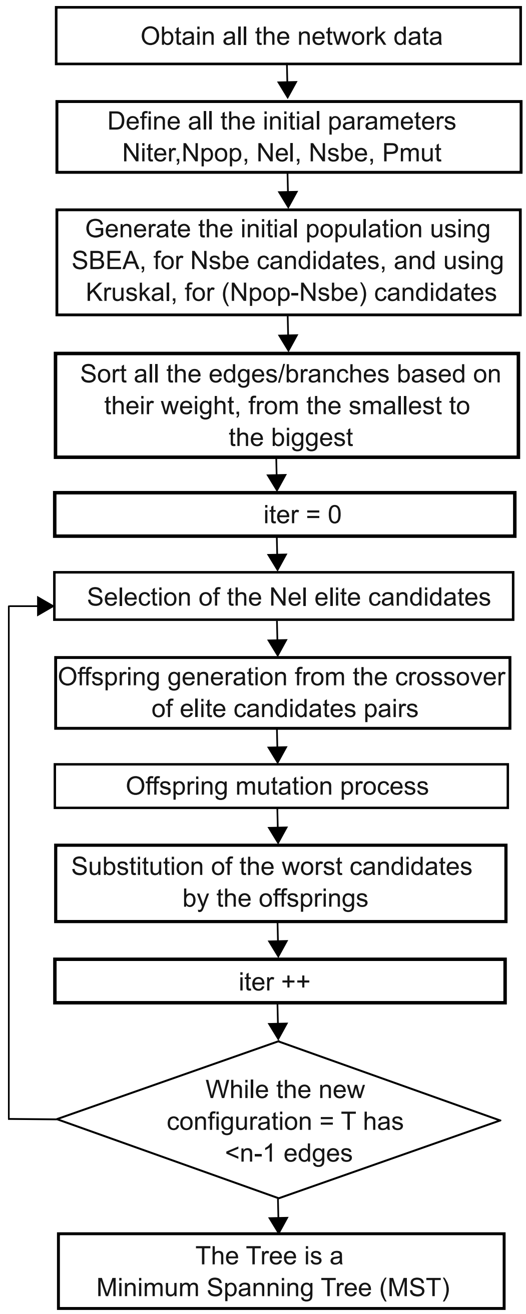

Figure 8: Genetic Algorithm based on the paper "Optimal Reconfiguration of Distribution Networks Using Hybrid Heuristic-Genetic Algorithm" by [23]

4.4.3. Selective Binary Particle Swarm Optimization

The Particle Swarm Optimization (PSO) algorithm was first introduced by [46] and has been applied to the Distribution Network Reconfiguration (DNR) problem since the 2000s. Initial works such as [47] utilized the Binary Particle Swarm Optimization (BPSO) formulation, which was later enhanced by [24] by introducing a technique for efficiently selecting the line to disconnect. Comparative studies such as [48] provide valuable insights into different PSO implementations.

The algorithm proposed by [24], depicted in Fig. 9, starts by gathering all network information, defining configuration parameters, and generating a random list of valid candidates. Each candidate adheres to radiality constraints (i.e., no loops and all nodes connected), and is represented by a list of open switches. The algorithm defines the search dimension as the number of loops to be opened, and the search space is defined by the available switches at each loop.

Once the initial candidates are defined, the fitness function, which represents network losses, is evaluated through power flow calculations. The best global candidate is identified as the one with lowest losses.

Subsequently, the algorithm computes the velocity of each candidate using the equations originally proposed by [46]:

$$v_{id}^{k+1} = w v_{id}^{k} + c_1 r_1 (pb_{id}^{k} - x_{id}^{k}) + c_2 r_2 (gb_{d}^{k} - x_{id}^{k}) \tag{23}$$

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \tag{24}$$

$$\text{sigmoid}(v_{id}^{k+1}) = \frac{1}{1 + \exp(-v_{id}^{k+1})} \tag{25}$$

where $id = 1, 2, \ldots, n$ represents the population or set of swarm particles, and w, c_1, c_2, r_1, r_2 are inertia, acceleration and randomness constants, respectively, and k the iteration up to N_{iter} iterations.

The authors proposed a modification to search within the action space, composed of switches available at each loop, by adjusting the sigmoid equation of BPSO (eq. 25), resulting in Selective Binary Particle Swarm Optimization (SBPSO):

$$\text{sigmoid}(v_{id}^{k+1}) = d_n \frac{1}{1 + \exp(-v_{id}^{k+1})} \tag{26}$$

where d_n represents the search space in the loop, ensuring that the selection of the new line to be opened is conducted appropriately.

$$x_{id}^{k+1} = \begin{cases} s_{d1} & \text{if sigmoid}(v_{id}^{k+1}) < 1 \\ s_{d2} & \text{if sigmoid}(v_{id}^{k+1}) < 2 \\ s_{d3} & \text{if sigmoid}(v_{id}^{k+1}) < 3 \\ \vdots & \\ s_{d_n} & \text{if sigmoid}(v_{id}^{k+1}) < d_n \end{cases} \tag{27}$$

After selecting a new line to open, the fitness function is recalculated. If any candidate improves upon the global candidate's fitness value, that candidate becomes the new global solution.

This iterative process continues for N_{iter} iterations, with the final global candidate determined as the algorithm's solution.

5. Results Comparison and Discussion

5.1. Simulation Scenarios

The compared papers were implemented in Python, made open-source [49] and evaluated across five distinct distribution network scenarios:

- 16-bus network ([7], 1998), a distribution network composed of 16 buses, 3 substation connections, 20 MV lines, 14 loads and 5 generators
- 33-bus network ([3], 1989), Fig. 10, a distribution network composed of 33 buses, 1 substation connection, 37 MV lines and 33 loads
- 69-bus network ([3], 1989), a distribution network composed of 69 buses, 74 MV lines and 48 loads
- 118-bus network ([50]IEEE standard), a segment of the American Electric Power system (in the U.S. Midwest) with 118 buses, 175 MV lines 118 loads and 54 generators.
- Simbench Urban Network ([25] 1-HVMV-urban-2.203-0-no_sw): a realistic rural-urban network with 196 buses, 215 lines, 194 loads, and 219 generators (biomass, hydroelectric, PV, and wind). This scenario included one-year time-series data (15-minute intervals) for load and generation, providing a robust test case for dynamic network reconfiguration (DNR) aimed at achieving energy savings. Figure 11

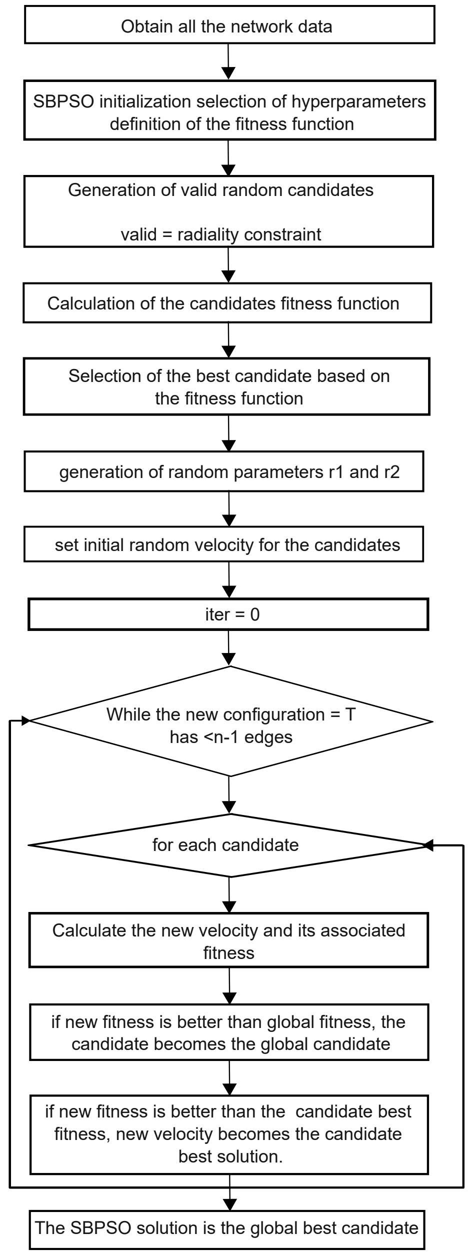

Figure 9: Selective Binary Particle Swarm Optimization (SBPSO) algorithm based on [24], "Reconfiguration for loss reduction of distribution systems using selective particle swarm optimization"

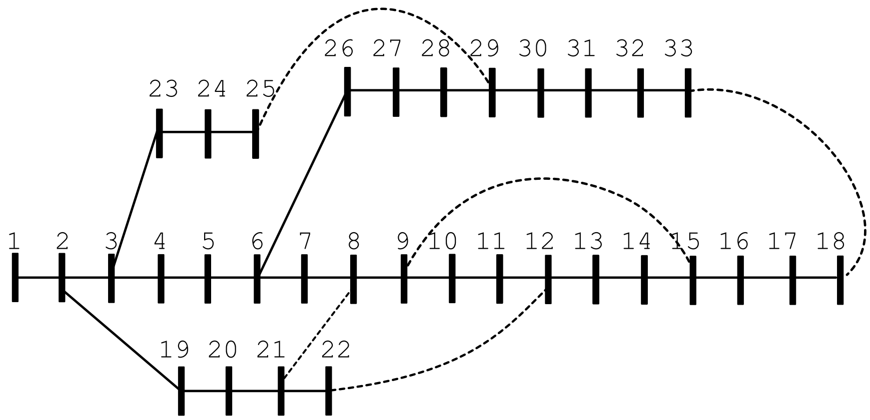

Figure 10: 33 bus distribution case defined by [3], with discontinuous lines for the default Tie Lines

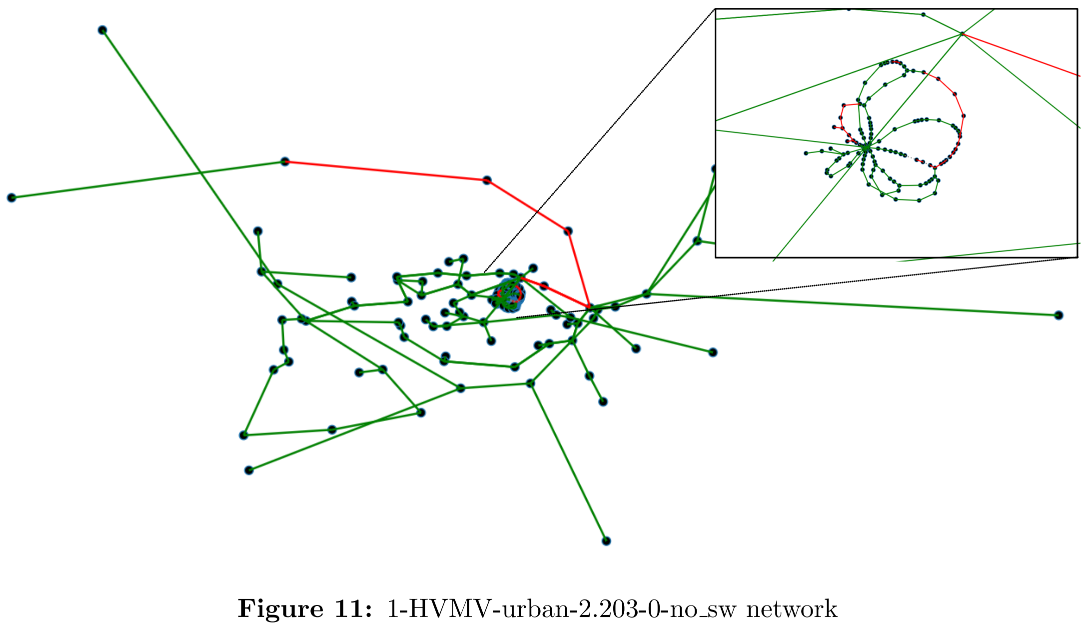

Figure 11: 1-HVMV-urban-2.203-0-no_sw network

Table 2: Execution performance for the IEEE 118 buses case

Method	Author	Technique	Objective	Losses
Heuristic	Merlin	Loop Cutting	Losses	5692 kW
Heuristic	Baran	Branch Exchange	Losses	497 kW
Metaheuristic	Jakus	GA + Baran	Losses	222 kW
Metaheuristic	Khalil	SBPSO	Losses	no solution
Heuristic	Salkuti	Voltage profile	Voltage	613 kW
Heuristic	Montoya	MST	Losses	497 kW

5.2. DNR for Power Losses Optimization results

The 16, 33, 69, and 118 bus cases were tested under nominal power conditions, while the Simbench Urban Network case was evaluated across three representative weeks (starting on days 10, 90, and 180), yielding valuable insights.

For the 16 and 33 bus networks, most algorithms (heuristics and metaheuristics) achieved near-optimal solutions, validated against a brute-force method [20] (Fig. 12). However, results varied significantly for larger networks. Notably, [23]'s genetic algorithm (GA) consistently delivered superior or optimal performance across all five cases, indicating its robustness compared to topology-dependent algorithms.

Merlin's heuristic [4] approach exhibited the poorest performance, followed by Salkuti's and Baran's algorithms. While Baran's method showed promise in time-series analysis, Khalil's SBPSO proved highly sensitive to initial loop/line selection, limiting its general applicability.

Table 3: Execution performance for the 33 buses case with nominal power

Algorithm	Type	Number of PF Calculations	Execution time (ms)
Merlin	Heuristic	20	121
Baran	Heuristic	8	4
Salkuti	Heuristic	10	5
Montoya	Heuristic	1	3
Morton	Heuristic	> 10.000	Several hours
Khalil	Metaheuristic	240	3460
Jakus	Metaheuristic	298	8410

5.3. DNR for Voltage Profile Optimization results

Fig. 12 illustrates the losses and minimum voltage for the 33, 69, 118, and Simbench Urban Networks, while Table 3 presents the 33-bus voltage profile. Jakus's

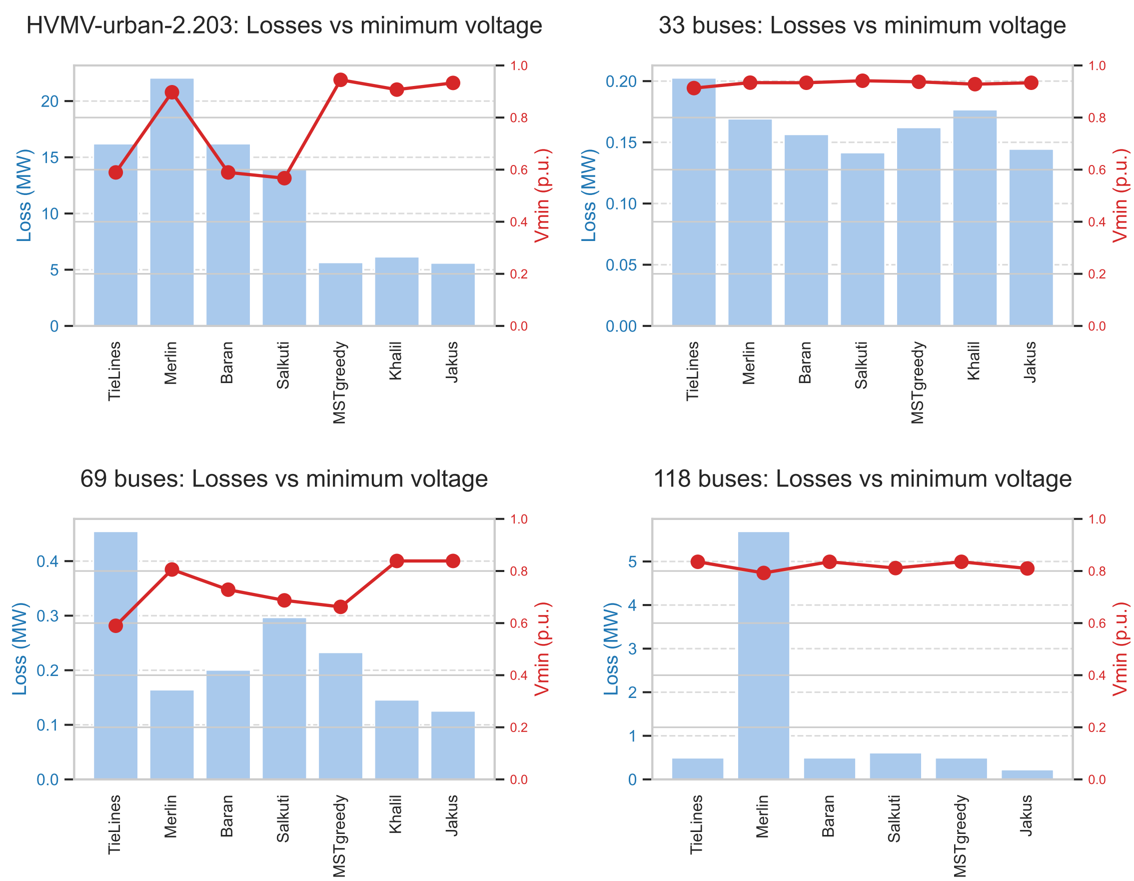

Figure 12: Evolution of the minimum voltage when minimizing the power losses, for the studied methods on the four analyzed scenarios.

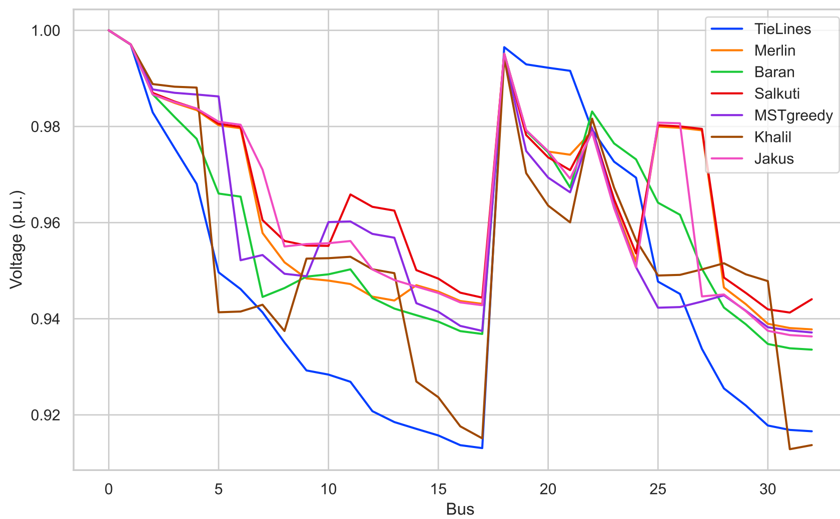

Figure 13: Voltage profile for the 33-bus case

GA effectively maintained minimum voltage, albeit at a high computational cost (Table 3), exceeding heuristic methods by an order of magnitude.

5.4. DNR for multiobjective optimization results

Extending the analysis presented in Table 3, a multiobjective optimization of Jakus's GA was conducted, balancing losses and minimum voltage (Fig. 14). Results for the Simbench Urban Network case indicated optimal performance with a fitness function emphasizing voltage profile (80–90%) over losses (10–20%).

5.5. Timeseries analysis results

The Simbench Urban Network time-series analysis (Fig. 15) compares algorithm performances over three one-week periods. Jakus's GA, initialized with the previous step's solution, achieved a 28% loss reduction (14.1 seconds), making it seven times slower than Montoya's MST (4 ms), which achieved a 15% reduction. Khalil's SBPSO, however, yielded only a 4% reduction, while Baran's achieved 18%, again highlighting topology dependence.

5.6. DNR results summary

Khalil's SBPSO performance was significantly affected by initial loop search space definition. Restricting tie lines to single loops hindered optimal solutions, while allowing multiple loops caused convergence issues. This sensitivity underscores the need for robust initialization strategies.

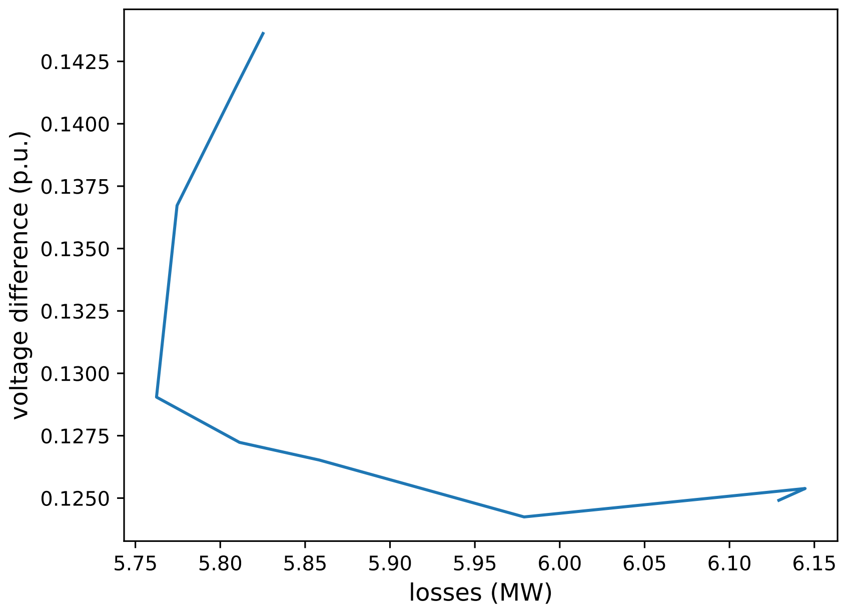

Figure 14: Pareto front between losses and minimum voltage for Simbench Urban Network case, using Jakus's genetic algorithm, under its initial conditions. Average of 100 executions.

Table 3 and Fig. 12 present the 33-bus system results (with Fig. 12 showing broader network comparisons), with particular emphasis on the number of power flow calculations (NPF) required for convergence. Unlike computational time—commonly used in literature but heavily dependent on hardware specifications—we propose NPF as a more robust and universal performance metric. This approach follows [39], who demonstrated that timing comparisons become obsolete with hardware evolution, while NPF remains valid across different computing platforms.

A summary of the tested methods can be seen in Table 4

6. Open Source Implementation

The implementation of the different algorithms tested in this paper was performed in Python. It is supported by GridCal [51] to load electrical grids from '.m' files downloaded from [52] or imported from the Simbench project [25]. Pyomo [34][35] and IPOPT [36] were used for the mathematical methods implementation.

The master class for the DNR library is DistributionNetworkReconfiguration, which groups calls to all implemented methods and manages the GridCal grid.

The code is available in Github [49] and organized in folders as follow:

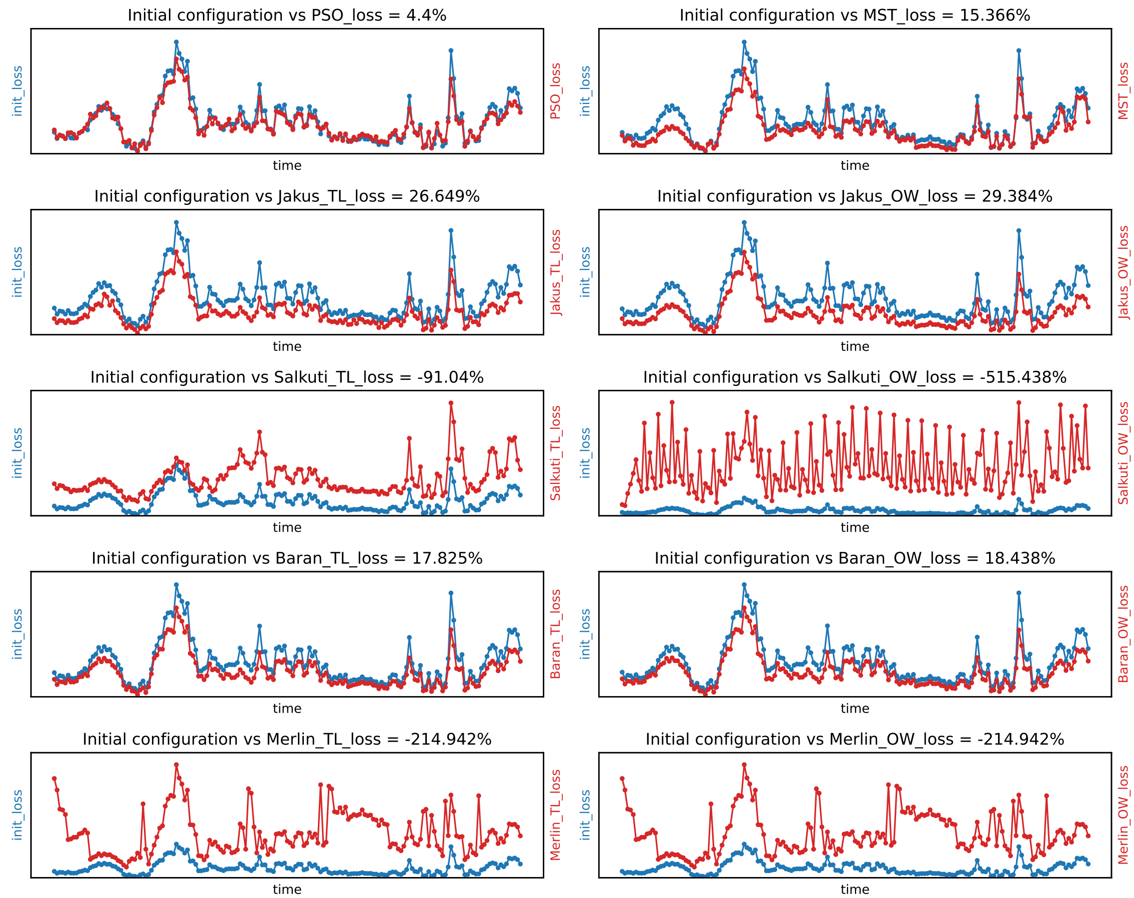

Figure 15: Methods performance for a one-week time series for the Simbench Urban Network case, using hourly samples.

```
from GridCalEngine.IO.file_handler import FileOpen

gridGC = FileOpen("case69.m").open()
dnr = DistributionNetworkReconfiguration(gridGC)
radiality = GC_utils.CheckRadialConnectedNetwork(gridGC)
disabled_lines = dnr.Solve(method="Khalil", NumCandidates
    =10)
```

Listing 1: Example of SBPSO algorithm for the 69-bus case

Table 4: Methods summary

Brute Force	Optimal but computationally infeasible for networks exceeding 33-buses.
Merlin	Historically significant but suboptimal.
Baran	Deterministic, topology-dependent branch exchange.
Montoya	Fast MST (Kruskal, line current weighting).
Salkuti	Topology-sensitive branch exchange, voltage profile-focused.
Khalil's SBPSO	Fast, initialization-dependent.
Jakus' GA	Robust, computationally intensive.
Jabr's QP	Quadratic Programming (QP) can obtain absolute optimal solutions, but our implementation has proved impractical for large networks (due to performance and convergence issues).

- src : Contains the source code for the DistributionNetworkReconfiguration class and all implemented methods, with each method in its own file.
- Examples: Jupyter Notebook (.ipynb) files with examples demonstrating the usage of the DistributionNetworkReconfiguration class. The files are commented following the philosophy of Literate Programming [53].
- Results: Files used to generate the results presented in this paper.
- docs: Markdown-based documentation.

7. Conclusions

This comprehensive study investigates and implements the most representative methodologies published for solving the Distribution Network Reconfiguration (DNR) problem, from its inception in 1975 with Merlin's pioneering work [4] to the latest state-of-the-art advancements. The research encompasses a broad spectrum of solution approaches, including heuristic, metaheuristic, and mathematical optimization methods, providing detailed analysis of their theoretical foundations, algorithmic characteristics, computational strengths, and practical limitations.

The primary objective of this research and its accompanying open-source library is to facilitate the entry of new engineers and researchers into the DNR domain by providing a comprehensive overview of existing methodologies. Furthermore, this work aims to inspire the development of novel optimization approaches that can assist utility companies in achieving superior operational performance through enhanced power loss reduction and improved voltage profile management across distribution networks.

Based on our extensive comparative analysis of the reviewed methodologies, we identified the hybrid approach combining genetic algorithms with heuristic optimization proposed by Jakus's[23] as demonstrating superior overall performance characteristics, despite requiring longer computational processing times. Our findings indicate that while traditional heuristic methods consistently produce reasonable solutions for small-scale distribution networks, their performance significantly deteriorates when applied to larger, more complex grid topologies, highlighting the need for more sophisticated optimization strategies.

This study presents a comprehensive review and practical implementation of distribution network reconfiguration methodologies, with all results and source code made publicly available via an open-source repository [49]. It should be noted that minor discrepancies between our computational results and those reported in the original publications may occur due to differences in implementation details, programming languages, computational platforms, or algorithmic parameter settings.

Our primary contributions to the field, which have been rigorously evaluated across five distinct test scenarios using comprehensive time-series analysis and multi-objective Pareto front visualization techniques, include:

- Enhanced Montoya's Minimum Spanning Tree (MST) Algorithm: Developed an improved version incorporating line current weighting factors to better reflect real-world electrical characteristics and operational constraints.

- MST-Based Initialization Strategy: Implementation a novel initialization methodology for metaheuristic algorithms using minimum spanning tree principles, which significantly improves convergence speed and solution quality.

- Multi-Objective Fitness Function Framework: Designed and implemented advanced multi-objective optimization frameworks, specifically adapted for Jakus's Genetic Algorithm and Khalil's Social-based Particle Swarm Optimization (SBPSO), enabling simultaneous optimization of multiple competing objectives such as power losses, voltage deviations, and network reliability indices

The research methodology employed rigorous benchmarking procedures using standard IEEE test systems and real-world distribution network data, ensuring the reliability and practical applicability of the proposed improvements. Statistical analysis of the results demonstrates significant performance enhancements over existing approaches, particularly in terms of solution quality and computational efficiency for medium to large-scale distribution networks.

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