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Reliability Improvement on Power Distribution Systems by Network Reconfiguration: A Matheuristic Approach to Clustering Electrical Consumers

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Abstract:- This paper proposes the clustering of consumers into subsets through network reconfiguration procedures, combining mathematical and heuristic methods. The mixed-integer linear programming (MILP) model consists of two submodels applied separately to the electrical network, focusing on solving the consumer clustering problem. The modeling framework is divided into two interdependent and mutually influenced levels. At the upper level, the goal is to preserve the radial topology of the network, while the lower level is responsible for the electrical validation of the proposed clusters, ensured through power flow calculations. Mathematically, the upper level ensures the radial configuration of the network based on load flow, while the lower level confirms the electrical magnitudes associated with the new load allocations. The objective of the proposed approach is to minimize the line loading rate and the system reliability indices. To indirectly represent the clustering of consumers, a generalized minimum-cost multi-flow network model was adopted, directly reflecting the new topological structure of the electrical circuits. Network modification corresponds to the degree of each consumer's association with the power sources and is guided by a heuristic evaluation based on minimum-cost energy paths. Additionally, a path construction strategy was implemented to maximize energy delivery at the lowest cost. The computational implementation of the model demonstrates its effectiveness in generating solutions that reduce line loading costs and significantly improve system reliability. The combination of MILP modeling, the use of multiple flows, and the validation of results through power flow simulations represents a technically relevant contribution compared to existing literature. The results obtained demonstrate the benefits of the proposed matheuristic for the planning and efficient operation of radial distribution systems.

Keywords: *Clustering electrical customers, Network reconfiguration, Multiple Flows, Matheuristic approach.*

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1. Introduction

The main function of an electric power system is to supply electricity to consumers continuously and with quality, without compromising operational conditions and desired performance limits [1]–[3]. However, the increasing demand for electricity in recent years [2] has challenged traditional power transmission methods, leading to necessary changes in the search for solutions that ensure system reliability as one of the main issues [4].

On the supply side, the provision of an economical and reliable service is directly related to the planning of distribution systems by electric utility companies, which are increasingly incorporating new monitoring technologies and adopting various strategic models that prioritize service efficiency and the reduction of operational costs [2], [5], [6].

On the demand side, with thousands of consumers being supplied, it is unfeasible to solve an electric circuit that individually represents each of these consumers or even to study their energy supply conditions in isolation [7].

This study aims to develop and apply a mathematical heuristic method based on mixed-integer linear programming (MILP) to address the problem of consumer clustering in electric power distribution networks, focusing on optimizing network reliability and improving the performance of distribution systems.

Although there is extensive literature on consumer clustering, commonly adopted approaches do not robustly consider future scenarios that could influence the reduction of equipment failure rates, focusing mainly on historical data [8], [9]. This gap opens opportunities for the development of new approaches that can enhance both the reliability and the operational efficiency of the networks.

The problem of reconfiguring power distribution networks usually involves minimizing technical losses and ensuring compliance with specific operational conditions that must be maintained, such as: radial topology, voltage level constraints, and conductor loading limits [10]–[14].

It is important to highlight that this study presents methodological variations compared to the research in [15]–[22], as one of its particularities lies in the approach that considers losses as a critical factor in the optimization problem, but without treating it as an objective function to be minimized. Instead, the model limits losses to acceptable levels while optimizing other objectives, such as line loading rates and the network reliability index, focusing on minimizing historical SAIDI rather than failure rates.

The main challenge addressed in this study relates to optimizing consumer clustering, constrained by their electrical interconnection characteristics and the operational conditions of distribution networks.

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From a clustering problem perspective, any set of consumers is theoretically possible. However, the interconnections determined by the electric system's protection devices impose constraints on these possibilities. Thus, the problem involves solving a combinatorial optimization model that must descend to a feasibility level that necessarily analyzes the technical limitations of the electric system and the arrangement of sets, such as losses, voltage, power, etc.

Additionally, there is a need to maximize network reliability, estimated based on the SAIDI (System Average Interruption Duration Index), selected as the typical and widely used index in the reconfiguration process [8], [23], without compromising other critical factors such as efficiency and operational cost.

The originality of this research lies in the formulation of a matheuristic approach capable of efficiently understanding and solving the consumer clustering problem in the context of electrical distribution systems. Unlike conventional approaches, which typically address clustering and network reconfiguration separately or rely on loosely structured heuristics, this work proposes a hierarchical decomposition of the problem into two interdependent levels: the strategic level (upper), responsible for clustering decisions, and the operational level (lower), focused on network reconfiguration and the evaluation of solution feasibility. These levels influence each other and are coordinated by a mathematical model based on Mixed-Integer Linear Programming (MILP), closely aligned with the structure proposed in Saki et al. [4], while incorporating significant methodological advances.

The technique combines neighborhood structures with heuristic search mechanisms and a rigorous evaluation of solutions through the underlying mathematical model. This integration defines the approach as a matheuristic, enabling the efficient exploration of the feasible solution space in highly combinatorial problems. Despite the potential of such techniques, their application remains limited in the energy systems optimization literature [35]. In particular, the lack of consolidated mathematical formulations for the clustering problem highlights the contribution of this work, which proposes a unified framework to jointly address consumer clustering and network reconfiguration in a coordinated manner. This innovative approach offers greater flexibility and improved solution quality, while ensuring compliance with system operational constraints and reducing computational cost compared to purely exact methods.

The main contributions of the method include:

1. The proposal of a matheuristic MILP-based method that maximizes network reliability and optimizes the performance of distribution substations and their respective feeders.

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2. The introduction of a multi-objective optimization approach that incorporates the nonlinear convergence of the reliability index (SAIDI) into the exact optimization problem and an evaluation architecture supported by a metric based on minimizing the loading rate under demand.
3. The development of a solution to the clustering problem that focuses on optimizing generalized network flow, exploring multiple minimum-cost flows.
4. Mathematical algorithm that integrates mathematical programming and heuristic techniques to coordinate the clustering problem and network reconfiguration using a set of neighborhood structures.

The remainder of this paper is organized as follows. Section 2 provides an overview of the literature on research related to methods used for electrical consumer clustering and network reconfiguration. Section 3 presents the proposed methodology, detailing the problem formulation, the mathematical model, and the solution algorithm. Section 4 presents the numerical results and their analysis. Finally, Section 5 concludes the paper and suggests directions for future research.

2. State of the art on reconfiguration of distribution networks and electrical consumers clustering problem

Distribution network reconfiguration is a widely used strategy, both in short-term planning and in emergency situations, contributing to improved operation, reduced interruption time and frequency, and increased reliability in electricity supply [24]–[28].

The classical study by Baran and Wu [10] laid the groundwork for formulating the problem as an optimization subject to operational constraints. Since then, various approaches have been proposed focusing on different objectives such as loss reduction, voltage improvement, load balancing, and service continuity.

In recent years, reliability has emerged as a central criterion in reconfiguration models. Ghasemi [8] and Anteneh et al. [13] proposed methodologies that incorporate metrics such as SAIDI and SAIFI into the problem formulation. Sarantakos et al. [9] highlighted the importance of including substation reliability in the decision-making process.

To address the combinatorial complexity of the reconfiguration problem, several authors have explored computational intelligence techniques and mathematical programming methods. Kahouli et al. [29] applied genetic algorithms combined with particle swarm optimization to achieve greater reliability and reduce energy losses.

Guo et al. [30] developed mixed-integer programming models aimed at networks incorporating distributed generation and storage. Wang et al. [31] proposed a method to assess the reliability of distribution networks with distributed generation, considering feeder fault recovery and network reconfiguration. Ahmed et al. [32] applied a hybrid algorithm combining gravitational search and binary particle swarm optimization, focusing on optimizing reliability indices through network reconfiguration. Agrawal et al. [33] investigated underground network reconfiguration considering dynamic failure rates.

In recent years, matheuristics have gained prominence as promising alternatives to tackle the high complexity of operational problems in distribution networks [34], [35]. These approaches combine heuristic algorithms with mathematical models, aiming for a balance between solution quality and computational effort.

In this context, Yumbla et al. [34] proposed a matheuristic approach based on neighborhood search for optimal operational planning in active distribution systems, integrating multiple operational resources in a MISOCP model and obtaining good results in IEEE 69- and 118-bus networks. Similarly, Home-Ortiz et al. [35] presented a matheuristic approach to solve the optimal power flow (OPF) problem, integrating variable neighborhood descent (VND) with classical optimization methods. Their proposal stood out for its ability to find efficient solutions with lower computational cost, especially in large-scale systems.

The integration of advanced optimization techniques and data analysis has proven promising in the context of active distribution systems. While matheuristic approaches like those proposed by Ghasemi [8], Anteneh et al. [13], Sarantakos et al. [9] e Wang et al. [31] emphasized the importance of reliability, Yumbla et al. [34] e Home-Ortiz et al. [35], demonstrated efficiency in solving complex problems such as optimal operational planning and OPF, reducing computational cost in large networks. The use of clustering methods complements these strategies by enabling the identification of consumption patterns and the classification of consumers into homogeneous clusters [36]–[38]. This synergy between optimization and exploratory data analysis allows for the development of smarter, more adaptive solutions capable of considering both the operational characteristics of the network and the diverse behaviors of users [39]–[45].

When applied to power utilities, clustering enables intelligent management of consumer behavior, improving power quality assessments and aiding in the early detection of abnormal energy usage (outliers) that could compromise the reliability of the power grid [39], [41], [46], thereby optimizing the distribution system and the quality of the service provided [38], [47], [48].

Although practical applications of clustering analysis can be found in various fields [49], [50], the concept of consumer clustering in the energy sector is justified by the infeasibility of solving an electric circuit that represents the individual conditions and habits of all supplied consumers. Characterized by highly unpredictable individual load patterns, the utility's service area is typically divided into multiple substations [39], [51], [52].

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A classic partition-based clustering algorithm, the K-means method is commonly used to explore consumer load profile characteristics [41]–[44], [53]–[55]. Studies such as those by Hsu [42], Li et al. [56] and Cai et al. [44] employ K-means to model energy consumption in residential buildings. However, methods like K-means have limitations, such as the need to predefine the number of clusters and sensitivity to centroid initialization.

Queiroga et al. [49] on the other hand, employed a metaheuristic approach based on the Continuous Greedy Randomized Adaptive Search Procedure (C-GRASP) to solve a partitioning clustering problem aiming to find high-quality solutions with lower intra-cluster distance.

Unlike other clustering algorithms found in the literature, Falabretti e Sabbatin [52], employed MILP to simultaneously optimize energy efficiency and service continuity, focusing on distribution network planning aspects to minimize energy losses, preserve existing network layout, and improve reliability. According to Salyani et al. [57], MILP models have been widely used in recent studies to ensure optimization of the obtained results.

Electric grid reliability is a crucial aspect for the power sector. Some studies use clustering techniques to assess reliability by representing the network as a graph [58] for topological similarity analysis, combined with statistical techniques that help identify network components that impact overall reliability, supporting system-wide improvement decisions.

Moreover, multi-objective approaches aim to optimize the clustering process by exploring information from minimum spanning trees and redefining the problem into subsets, allowing for more computationally efficient processing to find clustering solutions [37].

Clustering has also been applied to manage uncertainties in new loads, such as distributed generation (DG) and electric vehicles (EVs). For instance, Yaghoubi-Nia et al. [59] proposed a clustering-based method for optimized DG and charging station allocation, modeling the stochastic behavior of these elements to maximize reliability. This application underscores the relevance of clustering to modern planning and operational challenges.

In Gomes et al. [7], the consumer clustering problem was solved using a MILP-based approach oriented to substation reclustering, aiming to maximize the reliability of the power distribution system. The complex optimization of distribution networks presented in this work finds precedents in studies such as Garcia e França [60], who addressed service restoration using local search heuristics.

With a structural characteristic similar to this research, Bertazzi et al. [61] applied a Mixed-Integer Linear Programming (MILP) model to solve a multi-depot inventory routing challenge. The proposed approach follows a three-phase matheuristic: first, customers are clustered into clusters based on critical stock levels; then, routes are planned for each cluster; and finally, a binary linear programming model is solved to obtain a feasible solution.

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This study adopts the concept of boundary consumers, but in contrast to Bertazzi et al. [61], employs a different clustering method focused on the interconnections determined by distribution circuits and the natural clustering of consumers near each feeder. Additionally, while Bertazzi et al. [61] generated two types of routes (intra-cluster and inter-cluster), this study, due to the particularities of electric networks, only considers inter-cluster paths.

Fathabadi [62] proposed a method for reconfiguring power distribution networks to obtain the optimal configuration determined by a modified clustering algorithm. Other relevant contributions include Schmitz et al. [63], with a matheuristic for islanding scenarios, and Nguyen et al. [15] and Mukhopadhyay and Das [16], who used hybrid strategies for generation allocation and reconfiguration.

Distribution network reconfiguration inherently modifies the network's topology, while clustering can be used to adjust load distribution among feeders. Therefore, the combination of reconfiguration and consumer clustering constitutes an effective strategy for optimizing the power system.

Despite recent advances, it is observed that most studies address clustering and reconfiguration separately. The proposal of this paper aims to fill this gap through a matheuristic approach that integrates consumer clustering with system reliability optimization. The literature review highlights the importance and wide application of consumer clustering to optimize the electrical system and the quality of the service provided.

Clustering analysis is frequently emphasized in the power systems literature to model the behavior of different types of electricity consumers. This approach allows clustering consumers with similar characteristics across various aspects, such as consumer size, economic activity, and, most importantly, their energy consumption patterns [43], [44], [54], [55].

Clustering methods have evolved from classical techniques such as K-means to more advanced approaches like MILP models and metaheuristics, which are capable of handling multiple objectives and specific network constraints. Additionally, network graph representation and reliability analysis techniques contribute to more efficient power system management.

This article proposes a consumer clustering method, with a focus on the practical application of techniques, by addressing the challenge of clustering consumers across substation feeders, considering the natural clustering that emerges from the resolution of generalized multi-load flows. The proposed method goes beyond clustering consumers based solely on similarities and has the potential to contribute to the equitable distribution of network reliability.

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3. Methodology

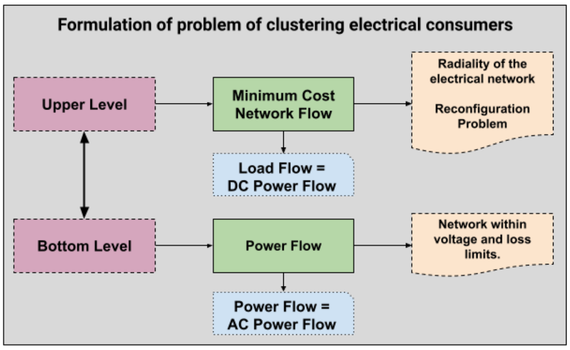
This section describes the methodological framework adopted in this study. First, the problem is formally characterized in the context of clustering electrical consumers via distribution network reconfiguration. Then, a multilevel MILP-based model is introduced, including its upper and lower-level components. Following that, the algorithmic structure of the proposed matheuristic is detailed, including its logical flow and decision-making process.

3.1 Problem Description

The approach adopted in this work involves the characterization of distribution circuits constrained by the conditions of the electrical configuration and the existence of original sets of consumers, which consequently require the decomposition of the network into subsets for consumer clustering.

The problem in question concerns the clustering of consumers within an electric network composed of branches originating from substations, known as feeders. The structure used to formulate the problem is simplified in Figure 1.

Figure 1 - Multilevel formulation of the problem



The structure describes a hierarchical two-level process: upper and lower levels. It begins with cost optimization in the power network at the upper level, followed by power flow calculation at the lower level, which is responsible for validating the results obtained from the upper level.

This subdivision allows the clustering problem to be solved in the form of a MILP while ensuring the radiality of the network. Additionally, the clustering problem formulation incorporates a mathematical heuristic that functions as a coordination and parameterization tool, representing a procedure that adjusts these models to achieve the desired outcomes.

3.2 Upper-Level MILP Formulation

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The intrinsic relevance lies in the complex nature of this problem in its broader context. When addressed as a clustering problem, the main focus is on optimizing two distinct types of flows: energy (Equation 1) and indices (Equation 2).

This process models the problem as a generalized network flow challenge with multiple flows, connecting subsets of consumers to the feeders. Furthermore, it incorporates specific functionalities related to radiality and network configuration adjustments (reconfiguration). The feeders, in turn, are connected to the substations, which represent the defined sets.

The generalized network flow occurs within a distribution network defined as $G = (B, A)$, where $A = (i, j), \forall i, j \in B, (i \neq j)$defines the arcs (lines) as ordered pairs of nodes, with i and j belonging to B and distinct from each other. Additionally, A_S is a subset of lines derived from the substations and therefore $A_S \subset A$. This structure is represented by the following compact formulation:

$$Min \sum c_{ij} \cdot k_{ij}^{(2)} \tag{1}$$

$$Min \sum_{i \in V_T, i \neq j} \sum_{j \in V_S} \left| k_{ij}^{(1)} - k_{ji}^{(1)} \right| + \sum_{k \in V_T, k \neq j} \sum_{j \in V_S} \left| k_{kj}^{(1)} - k_{jk}^{(1)} \right| \tag{2}$$

This formulation focuses on maximizing the overall system performance by considering both the harmonization of aggregated reliability indices ($k^{(1)}$) from consumer subsets and the minimization of operational costs (c_{ij}) associated with energy flows ($k_{ij}^{(2)}$).

Specifically, the objective function in Equation (1) minimizes the total cost (c_{ij}) associated with the movement of energy flows ($k_{ij}^{(2)}$) corresponding to the pairs (i, j) in A. The second objective function, in Equation (2), minimizes the set of discrepancies among the aggregated flows of specific reliability indices ($k_{ij}^{(1)}$) along the path from V_T to V_S for all $(i, j) pairs$.

The outcome of this process is a set of load flows estimated under a simplified approach that assumes ideal conditions according to the DC Power Flow model. In this context, voltage drops along the lines are neglected, and therefore, there is no need to compute nonlinear power flow interactions.

To traverse the network and identify the maximum flow value between a source node and a target node (and vice versa), the optimization of the available capacity usage is performed using the Ford-Fulkerson algorithm, which is widely applied in maximum flow problems due to its advantages [64], [65]. A detailed description of this solution can be found in [64].

The execution of the power flow is subject to the following constraints:

$$k_{ij}^{(2)} \le CAP_{ij} \cdot \gamma_{ij}, \forall_{(i,j)} \in A \tag{3}$$

$$\sum_{j \in B} k_{ij}^{(k)} - \sum_{j \in B} k_{ji}^{(k)} = OD_i^{(k)}, \forall_i \in B, \forall k \in K \tag{4}$$

$$\sum_{j \in B} k_{ij}^{(k)} = OD_i^{(k)}, \forall_i \in B, \forall k \in K \tag{5}$$

$$M \cdot \left(1 - \gamma_{ij}\right) + k_{ij}^{(2)} \ge \varphi, \forall k \in K, \varphi \in \{0, 10^{-5}\} \tag{6}$$

$$-M \cdot \gamma_{ij} + k_{ij}^{(2)} \le 0, \forall k \in K \tag{7}$$

$$k_{ij}^{(1)} \le SAIDI_{lim} \cdot \gamma_{ij} \tag{8}$$

$$\gamma_{ij} \in \{0,1\}, (i,j) \in A \tag{9}$$

Constraint (3) ensures that the energy flow ($k_{ij}^{(2)}$) through a given line (i,j) does not exceed its maximum allowable capacity (CAP_{ij}), thereby guaranteeing that network operation remains within safe and feasible limits.

Flow conservation within the network, expressed by constraint (4), is known as the balance constraint. This condition states that the difference between the total incoming and outgoing flows at a node i for a specific type of flow k must equal the supply or demand at that node for the same flow type. Essentially, this maintains the balance between what enters and leaves each node.

Equation (5) specifies that the total amount of flow of type k entering node iii must exactly match the supply or demand of node i for that specific flow type.

Constraints (6) and (7) define the relationship between the presence or absence of energy flow on a line (i,j), governed by the binary variable $\gamma_{i,j} \in \{0,1\}$. The activation of one constraint implies the deactivation of the other.

When $\gamma_{i,j} = 0$, the line (i,j) is inactive, and its value becomes significantly larger than φ, effectively disabling constraint (6). This constraint enforces that the energy flow must be

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greater than or equal to a minimum constant value $\varphi \in \{0, 10^{-5}\}$, regardless of the high cost (M) associated with flow activation.

If the index $\gamma_{i,j} = 1$, then constraint (7) is deactivated. This constraint ensures that, if the flow is active, it does not exceed a maximum value denoted by M.

Constraint (8) represents the estimation of the maximum flow of indices, defined by the total quantity of indices of the nodes in set B. This equation links the energy flows and the index flows. If $\gamma_{i,j} = 0$, there is no index flow; if $\gamma_{i,j} = 1$ t must respect the flow limit, thus establishing the association between energy and reliability indices.

Finally, constraint (9) defines the domain of $(\gamma_{i,j})$, where A is the set of all ordered pairs (i) and (j), indicating that $\{0,1\}$is the set of all possible values that $\gamma_{i,j}$ can assume. Here, $\gamma_{i,j}$ is a binary decision variable that indicates whether there is energy flow online (i,j) $(\gamma_{i,j} = 1)$ or not $(\gamma_{i,j} = 0)$. Thus, the clustering problem can be formulated as a mixed-integer linear programming (MILP) problem.

However, once the radial network is identified, regardless of perturbations in the allocation of consumers to feeders, the integrity of the paths must be preserved. To ensure this, the radiality constraint is introduced in Equation (10) [18].

$$\sum_{(i,j)\in A} \gamma_{ij} \leq n_b - 1, \forall (ij) \in B \tag{10}$$

The definition in (10) ensures that each connection between two vertices occurs through a single line and requires that the number of active lines $\gamma_{i,j} = 1$ must be less than or equal to $n_b - 1$, maintaining the necessary condition for the new network configuration to preserve the radial operation of the electrical distribution system [8], [66]–[69].

Once the constraints are satisfied, a process for constructing the set of efficient (non-dominated) solutions is initiated. To support this process, it is necessary to have a data structure capable of: (a) verifying whether a solution is dominated or non-dominated, (b) including a solution in the set, and (c) replacing dominated solutions with a candidate solution.

The function in (11) combines the two objectives, z_1 and z_2 with ε controlling the relative importance of each one.

$$Min \varepsilon \cdot z_1 + (1 - \varepsilon) \cdot z_2, 0 \leq \varepsilon \leq 1 \tag{11}$$

The optimization using the ε-constrained method involves finding non-dominated solutions in the two-dimensional space defined by z_1 e z_2. When $\varepsilon = 0$, the objective function z_2, is prioritized, focusing on minimizing the energy flow. Conversely, when $\varepsilon = 1$, the objective function is simplified to z_1, prioritizing the minimization of the SAIDI reliability index.

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However, this does not guarantee that other system requirements are met, since the power flow has not yet been executed.

3.3 Bottom-Level Power Flow Validation

The resolution of the generalized network flow necessarily requires consideration of the second level within the multilevel structure of the mathematical heuristic approach. The adjustments and verification of the effects of this planning are then carried out at the lower level, where a new solution emerges as a candidate for efficiency.

At the lower level, the power flow is executed. Additionally, important constraints are applied to ensure that the system operates within safe limits: one to enforce the allowable voltage range in distribution systems, as formulated in Equation (12) [20], [70], [71]; and another (Equation 13), which imposes a limit on technical energy losses (P_{loss}) for each proposed configuration [13].

$$0{,}95 \leq V_i \leq 1{,}05 \tag{12}$$

$$\sum_{(i,j)\in A} \left(R_{ij} \cdot \frac{(P_{ij})^2 + (Q_{ij})^2}{(V_{ij})^2} \right) \leq P_{loss} \tag{13}$$

The objective of the power flow solution is to validate the main consumer clustering problem at the upper level, ensuring system stability and efficiency; otherwise, the process returns to the upper level.

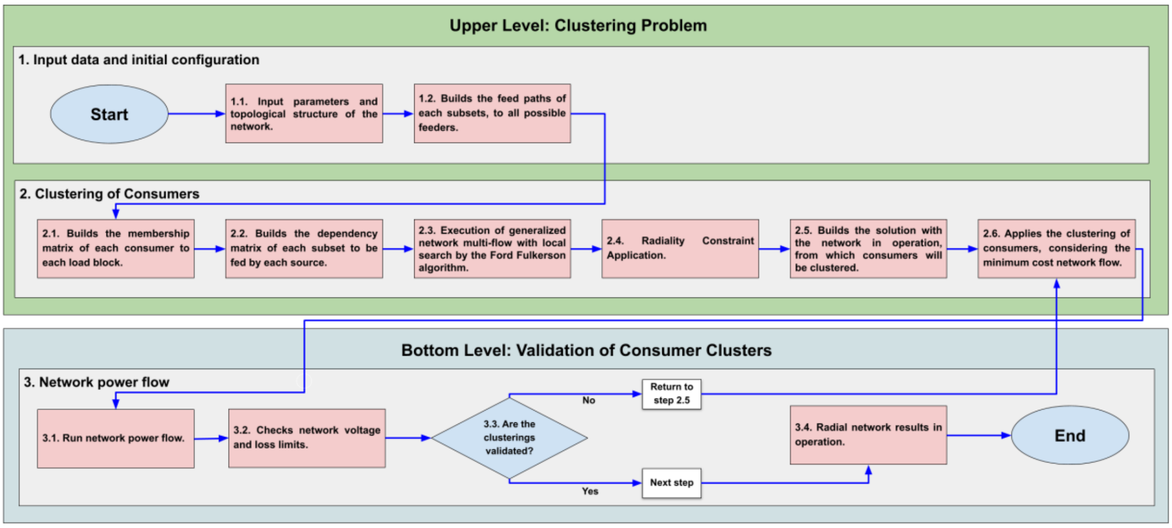
3.4 *Proposed Matheuristic Framework*

This paper proposes a customized MILP-based method to address the challenge associated with the natural clustering of consumers in electrical networks. The solution is highly constrained by the conditions of the electrical network and includes the reorganization of the network topology into clusters, aiming to maximize system performance through the optimization of energy flow and reliability index flow.

The process involves the use of a hybrid matheuristic approach based on two hierarchical levels: the upper level, responsible for coordinating the clustering problem, and the lower level, which validates the clustering results through power flow analysis.

The application framework of the method is conducted as shown in Figure 2, which describes the sequential steps of the proposed mathematical algorithm.

Figure 2 - Flowchart of solution processes for clustering consumers in the distribution system.



The method is derived from the approaches proposed by Gomes et al. [7] and Garcia and França [60], which were originally developed to address the challenges of substation reclustering and neighborhood optimization related to service restoration, respectively.

At the upper level, the fundamental principle consists of tackling the consumer clustering problem by optimizing distribution network indices. This is achieved indirectly through restricted load transfers, employing multiple minimum-cost flows [72].

Given the network $G = (B, A)$, where B represents the set of network nodes and A represents the set of lines connecting these nodes to various feeders, each line has an associated cost for load transfer. Therefore, the operation of load transfer is formulated under capacity constraints for each connection i, j and each feeder.

In assigning flows, an objective function seeks to minimize the line loading rate ($k_{ij}^{(2)}$) through the costs associated with energy flow transfers between consumers and feeders, while a second objective function aims to minimize discrepancies in index flows to ensure an equitable redistribution of the SAIDI index ($k_{ij}^{(1)}$), thus guaranteeing system reliability.

Once consumer-to-feeder flow assignments are quantified, perturbations in these flows result in the need to reassign consumers from one feeder to another. This effectively simulates the consumer redirection process. Each feeder serves a specific set of consumers, clustering those in close proximity or with some relationship to the serving feeder.

The process models the problem as a generalized network flow based on spanning trees, incorporating specific features of radiality and configuration adjustments [73]. Several constraints are applied to ensure the feasibility and safety of network operation. Capacity,

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flow balance, and energy conservation constraints are imposed to limit energy flow and maintain balance between supply and demand at each node.

Additional constraints ensure that connections between nodes remain radial, preserving path integrity, thus, a path with N_b nodes consists of $N_b - 1$ lines. The nature of the optimal solution to the network flow problem provides efficient and cost-effective allocation of consumers to feeders, resulting in natural clusterings based on proximity and feeder association.

The sequence of switching operations is determined based on the spanning tree. The constraints dictate that the reconfigured distribution network must maintain radiality, voltage levels must remain within the acceptable range of 0,95 to 1,05 pu and power losses must be within allowable limits.

Other situations may arise; however, ensuring that the load flow is supported depends on the problem definition at the lower hierarchical level. There may be cases where flows exceed feeder capacity, which must be carefully addressed. In such cases, electrical constraints (12) and (13) must be identified and satisfied.

Clustering involves decomposing the network G, composed of B and A, into subsets SS_k of G, with k distinct clusters delimited by electrical devices. By decomposing the network into subsets (SS_k), the search space during reconfiguration is reduced from B to SS_k and each SS_i is assigned to a tree-structured set encompassing a cluster of consumers with distinct characteristics but sharing the same power supply.

Each consumer node associated with a subset is no longer considered individually, but becomes a single load node (SS_k) allowing exploration of network topology information and enabling a solution with acceptable computational time [15], [37], [74], [75].

Internal lines within the subsets are disregarded in order to reduce the combinatorial complexity of the path search algorithms. However, all lines, including internal ones, are considered in the power flow calculation. In other words, the full network is used for power flow analysis, while the path search algorithm operates on the network resulting from the predefined subsets.

The manipulation of the distribution network topology is based on the generalized spanning tree that enables identification of subsets and their electrical connections (i, j) from an additional, non-substitutive topology.

The load flow is computed considering the current network and the location of existing feeders (F). A binary variable defines $\gamma_{i,j} = 1$ if a demand point $OD_i^{(k)}$ is served by an existing feeder ($fe \in F$), or $\gamma_{i,j} = 0$ otherwise.

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The multi-objective optimization problem lies in identifying a set of solutions representing trade-offs between different objectives, known as Pareto-optimal solutions or non-dominated solutions [76].

This optimization procedure is based on a dominance relationship. Given two solution vectors z_1 and z_2, which respectively represent the minimization of the SAIDI index flow and the minimization of energy flow, a feasible solution z_1 dominates another feasible solution z_2 if and only $z_1 \leqslant z_2$ for all objectives, and $z_1 < z_2$ r for at least one objective. When a solution is not dominated by any other, it is considered non-dominated [76]–[78].

This procedure is closely linked to the reconfiguration problem and consequently to the reliability index. Once the reconfiguration problem is solved at the upper level, a Pareto front is obtained, identifying the set of non-dominated solutions (Pareto solutions) that represent different variables of interest.

The approximate Pareto front is analyzed to identify solutions that offer the best balance among the considered objectives. The essence of this technique consists in selecting a primary objective to be minimized or maximized, while treating the other objectives as constraints for that primary objective. By systematically varying the constraint bounds, different solutions to the primary objective can be obtained, resulting in the construction of the so-called Pareto front [79], [80].

The interdependent effects of the targeted functions, defined in (1) and (2), are investigated using the ε-constraint technique to solve the multi-objective consumer clustering problem. The solution prioritizes the minimization of SAIDI as the primary objective, while energy flow cost is treated as a secondary objective.

Minimizing objective function z1z_1z1 is justified by its association with improving the performance of the power distribution system, with an emphasis on equitable distribution of the SAIDI index flow [3], [14], [69], [81]–[83].

As adjustments are made, it is essential that the constraints of the power distribution network—such as radial structure, feeder capacity, acceptable voltage range across nodes, and power loss limits—are practically satisfied in the reconfigured network. Consequently, variations in the system require the execution of power flow analysis, which not only verifies the updated electrical values but also validates the newly formed consumer clusterings.

The choice of a matheuristic strategy over classical metaheuristics (e.g., GA, PSO) or exact MILP solvers is justified by its capacity to balance solution quality and computational efficiency. While exact approaches often suffer from scalability issues in large-scale networks, the proposed hybrid model ensures convergence to high-quality solutions in acceptable runtime. Moreover, the two-level decomposition enables simultaneous respect for radiality and power constraints, which is not always guaranteed by metaheuristics alone.

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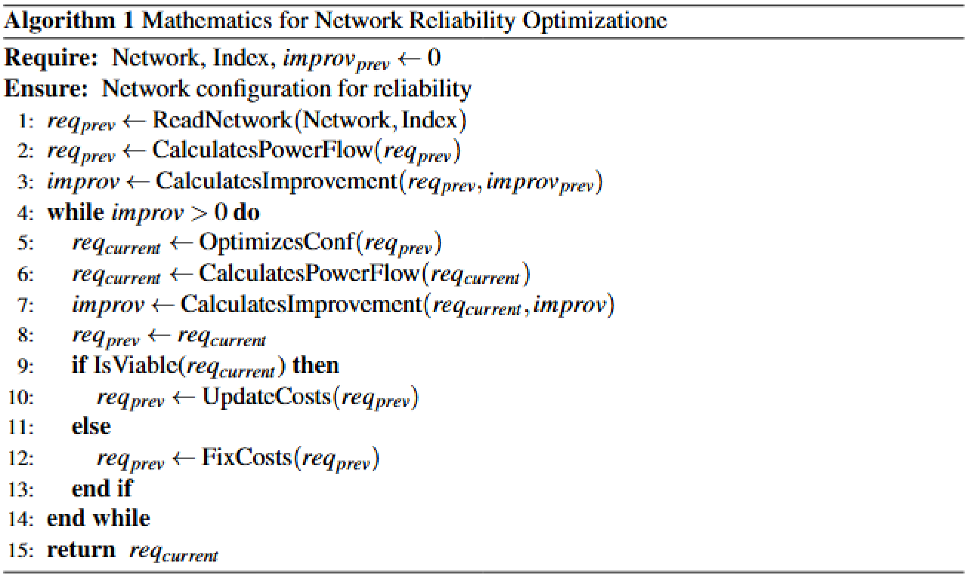
3.5 Algorithm Description

Based on the mathematical formulation previously presented, the matheuristic algorithm is now developed to optimize reliability in electric power distribution systems through the topological reconfiguration of the network. The proposed approach integrates heuristic strategies with the systematic evaluation of a mixed-integer linear programming (MILP) model, enabling the simultaneous fulfillment of technical and operational criteria such as cost minimization, reliability index balancing, and compliance with electrical and structural constraints.

The matheuristic approach efficiently explores the feasible solution space in complex networks, delivering high-quality results with lower computational cost compared to purely exact methods.

Algorithm 1 presents the pseudocode of the proposed algorithm, outlining in a structured manner the execution steps and logical decisions involved, thus facilitating the understanding of the procedure's underlying logic.

Algorithm 1 - Algorithm for the proposed approach



Algorithm 1 Mathematics for Network Reliability Optimizatione

```
Require: Network, Index, $improv_{prev} \leftarrow 0$
Ensure: Network configuration for reliability
 1: $req_{prev} \leftarrow$ ReadNetwork(Network, Index)
 2: $req_{prev} \leftarrow$ CalculatesPowerFlow($req_{prev}$)
 3: $improv \leftarrow$ CalculatesImprovement($req_{prev}$, $improv_{prev}$)
 4: while $improv > 0$ do
 5:     $req_{current} \leftarrow$ OptimizesConf($req_{prev}$)
 6:     $req_{current} \leftarrow$ CalculatesPowerFlow($req_{current}$)
 7:     $improv \leftarrow$ CalculatesImprovement($req_{current}$, $improv$)
 8:     $req_{prev} \leftarrow req_{current}$
 9:     if IsViable($req_{current}$) then
10:         $req_{prev} \leftarrow$ UpdateCosts($req_{prev}$)
11:     else
12:         $req_{prev} \leftarrow$ FixCosts($req_{prev}$)
13:     end if
14: end while
15: return $req_{current}$
```

The algorithm begins by reading the current network structure and the reliability indices provided as input (Network,Index as well as initializing the value of the previous improvement ($improv_{prev} \leftarrow 0$) — as described in the pre-step of the pseudocode. Based on this input, an initial solution is constructed ($req_{prev} \leftarrow ReadNetwork(Network, Index)$), representing the current topology of the network (line 1).

Next, the power flow is calculated for this configuration ($req_{prev} \leftarrow CalculatesPowerFlow(req_{prev})$, line 2), considering operational constraints such as line

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capacity limits (i, j (Equation 3) and load balancing at each node in the network (Equations 4 and 5). Subsequently, the quality of the initial solution is evaluated ($improv \leftarrow CalculatesImprovement$, line 3) based on a composite objective function that incorporates the costs associated with energy flows (Equation 1, z_1) and the discrepancies between the reliability indices of the various nodes (Equation 2, z_2). The weighting between these two criteria is adjusted using Equation 11, which combines the objectives into a single parametric expression, based on the value of ε.

Following the evaluation of the initial solution, the algorithm enters an iterative cycle ($while improv > 0$, line 4) that continuously searches for improvements. In each iteration, a new network configuration is generated ($req_{current} \leftarrow OptimizesConf(req_{prev})$, line 5) through structural changes in the topology, controlled by the binary variables γ_{ij}, which indicate the activation or deactivation of connections between nodes. This new configuration is then re-evaluated by recalculating the power flow ($req_{current} \leftarrow CalculatesPowerFlow(req_{current})$, line 6), and the improvement obtained in relation to the previous solution is measured ($improv \leftarrow CalculatesImprovement(req_{current}, improv)$, line 7). If there is a significant improvement, the new solution replaces the previous one as the starting point for the next iteration ($req_{prev} \leftarrow req_{current}$, line 8).

The technical feasibility of the new configuration is then verified ($if IsViable(req_{current})$ line 9), ensuring that all mathematical model constraints are respected. Among these constraints are: voltage limits at the buses (Equation 12), total technical power losses (Equation 13), radial structure of the topology (Equation 10), and compliance with regulatory reliability limits such as SAIDI (Equation 8).

If the solution is feasible, its costs and indices are updated ($req_{prev} \leftarrow UpdateCosts(req_{prev})$, line 10); otherwise (under the "*else*" condition, line 11), cost corrections are applied ($req_{prev} \leftarrow FixCosts(req_{prev})$, line 12), to adjust the configuration and make it compatible with operational criteria. This process is repeated as long as performance gains in the objective function are observed (line 13).

At the end of the iterations, when no new configuration offers relevant improvement, the algorithm performs a refinement step, consolidated by the final correction function ($req_{prev} \leftarrow FixCosts(req_{prev})$, line 14), which includes cost adjustments and final feasibility checks. Finally, the best configuration found ($req_{current}$) is returned as the optimal or satisfactory solution (line 15).

The consistency between the proposed algorithm and the underlying mathematical model is ensured by a direct correspondence between computational decisions and the formal elements of the equations. The decision variables ($k_{ij}^{(1)}$, $k_{ij}^{(2)}$, γ_{ij}) are implicitly used in the generation, evaluation, and selection processes of the solutions. Furthermore, all structural and

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operational constraints of the model — related to network topology, power flow, technical losses, and reliability limits — are respected throughout every stage of the heuristic.

To facilitate the understanding of the correspondence between the steps of the proposed matheuristic algorithm and the formal elements of the mathematical model, Table 1 presents a summary of the relationship between the main operational blocks of the algorithm and the equations used in the problem formulation.

Table 1 - Relationship between blocks and equations of the proposed algorithm.

Blocks	Equations	Central Theme
Lines 1–3	(1), (2), (3), (11)	Construction and evaluation of the initial solution
Lines 4–5	(6), (10)	Generation of new topologies
Line 6	(3), (4), (5), (12), (13)	Calculation of power flows
Line 7	(1), (2), (11)	Reevaluation of the objective function
Lines 9–11 (condicional)	(4) a (9), (12), (13)	Feasibility check and adjustments
Line 13-15	—	Finalization and return of the best solution

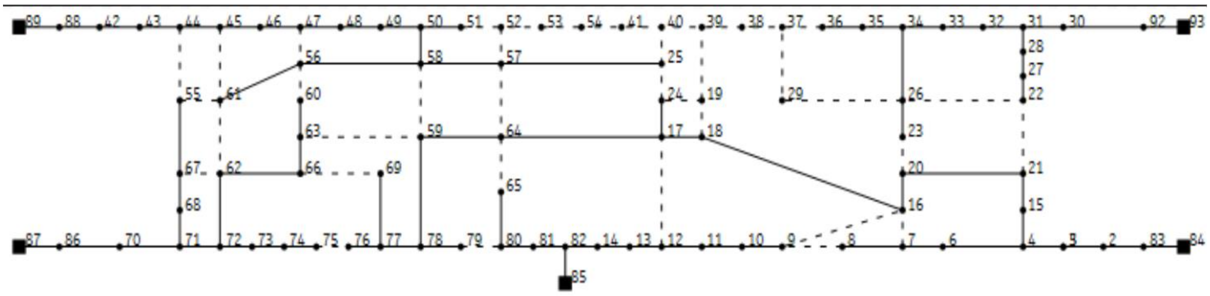
This association highlights how algorithmic decisions are directly supported by the model's constraints and objectives, ensuring consistency between the computational approach and the theoretical foundations of reliability optimization in distribution networks.

Thus, the proposed matheuristic approach constitutes an effective hybrid strategy for the network reconfiguration problem with a focus on reliability. By combining heuristic elements with rigorous mathematical evaluation, the algorithm delivers high technical-operational performance with reduced computational cost, making it especially suitable for application in large-scale systems where purely exact methods become infeasible.

3.6 *Case Study*

The proposed MILP method is validated through simulations conducted on the radial distribution system depicted in Figure 3.

Figure 3 - Topological representation of the system in use.



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The network is the same as that used in the applications developed by the authors in [84], [85]. The analyzed system is a distribution network comprising five substations and six feeders, totaling an initial active power of 28,621 kW. The circuit is characterized by a tree-structured network comprising 90 nodes and lines, all considered sectionalizing switches. At each node, a load is connected and may potentially have its primary feeder changed.

Voltage magnitude, active and reactive power flowing into or out of the nodes, and total system power losses are obtained as outputs from the power flow approach.

The heuristic presented in Figure 2 has its control parameters subjected to various operational scenarios and configurations, enabling a comprehensive evaluation of its performance under different conditions. Optimal scenarios are compared to initial data, and the numerical results are discussed.

The original version was modified and adjusted to create equivalent networks. These modifications aim to ensure that the test systems reflect realistic conditions of electrical networks, allowing for an accurate and appropriate assessment of the proposed approach.

4. Results and Discussion

The matheuristic approach was applied to two distinct scenarios of the distribution network, referred to as Case 1 and Case 2. Both scenarios share the same topology and operational parameters but exhibit minor variations in load profiles and initial distribution. The main computational results are presented below.

4.1 Operational Behavior of the Network

In both cases, the algorithm selectively activated approximately 25% of the network lines, forming economically optimized trajectories from the substations. Decisions were based on criteria such as minimum energy flow cost, improved reliability (reduction in SAIDI), and adherence to line capacity constraints.

The tested network comprises 79 lines, all with constant capacity (≈13,856.41), suggesting physical standardization. Many of these lines presented zero energy flow, indicating they were either deactivated or not part of the optimal solution. The active connections reflect strategic routing decisions made by the algorithm according to the defined objectives.

Figure 4 illustrates the graphical comparison between energy flow and index values for each active line in both Case 1 and Case 2. The visual representation clearly shows the correlation between the volume of energy transmitted and the strategic importance of each line, as reflected by the reliability indices.

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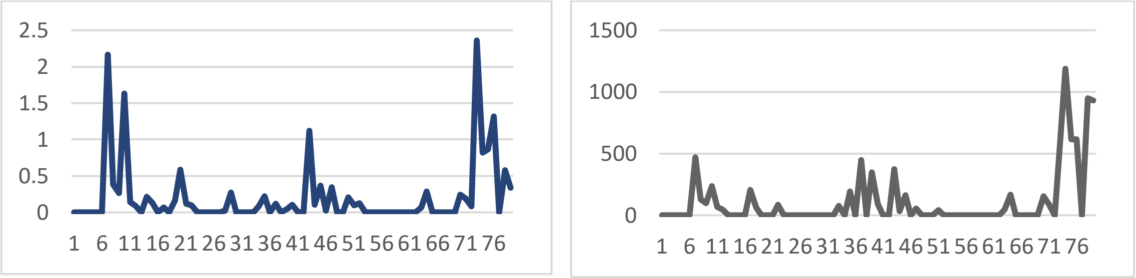
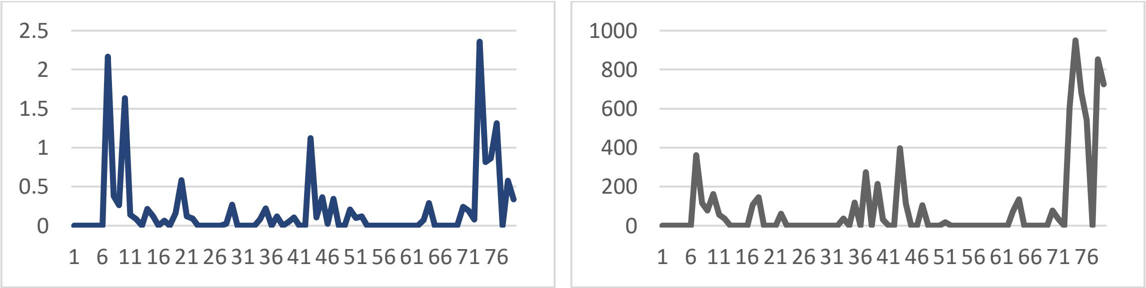
Figure 4 – Graphical Comparison: Energy Flow vs. Index Flow for Both Cases



Case 1: Energy Flow

Case 1: Reliability Index Flow



Case 2: Energy Flow

Case 2: Reliability Index Flow

Lines with high energy demand—particularly those connecting substations to load centers—also exhibit elevated index values, highlighting their critical role in the reconfiguration process. Furthermore, both cases present similar trends.

Most activated lines had energy flows below 1 MWh, especially in the network branches, indicating controlled load imbalance. Conversely, some lines with flows above 0.5 MWh were identified as critical due to both energy volume and high index values.

The joint assessment of Cases 1 and 2 demonstrates the algorithm's robustness against input variations, consistently producing high-quality solutions while respecting electrical constraints. In Case 1, 27 lines with positive flow were activated, whereas Case 2 had 23 such lines, indicating a more streamlined solution. Despite the numerical difference, the flow distribution followed similar patterns, with branched structures extending from the main substations. Table 2 below presents the main network segments identified with high values of power flow or index flow for both analyzed cases.

Table 2 – Main lines with the highest power flow or reliability index flow

Case	Line	Origin → Destination	Energy (MWh)	Index
1	74	82 → 85	0,817	1188
1	75	86 → 87	0,866	615,5
1	76	88 → 89	1,315	615,5

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Case	Line	Origin → Destination	Energy (MWh)	Index
1	78	90 → 91	0,579	947
1	79	92 → 93	0,335	929
2	74	82 → 85	0,817	950
2	73	83 → 84	2,359	608
2	75	86 → 87	0,866	682
2	76	88 → 89	1,315	542
2	78	90 → 91	0,580	854

Central paths, such as lines 74 (82→85), and 78 (90→91), exhibit high index values in both analyzed cases, indicating that the solution correctly identifies key points of load concentration and potential vulnerability. These segments connect substations to high-impact load areas in the system, representing strategic or failure-prone regions. Their activation, even under high criticality, demonstrates the algorithm's capability to detect and prioritize sensitive sections essential for system operation.

The evaluation of indices associated with the activated lines reveals that the algorithm selected paths that balance energy flow efficiency and reliability. In both cases, lines with the highest indices coincide with those carrying the highest flows or connecting critical regions.

4.2 Solution Efficiency and Radiality

In both cases, the connection matrix revealed successive chains with low energy and index flows, which is consistent with the radial topology of the network. For example, in Case 2, the sequence of lines from 2 to 17 (nodes 2 → 3 → 4 → 5 ... → 12) reveals a linear structure typical of a distribution branch. Moreover, Table 3 presents examples of lines with moderate flow and intermediate index values, used by the algorithm as secondary paths for load balancing:

Table 3 – Examples of lines with moderate flow and intermediate index values (case 2)

Line	Energy (MWh)	Index
35	0,222	119
37	0,119	273
39	0,047	213

The presence of such lines confirms that the model considers not only cost minimization but also operational flexibility and balance.

4.3 General comparison between Cases

Table 4 summarizes the main differences between the two evaluated cases, enabling a direct comparison of the algorithm’s reconfiguration strategies under slightly different load profiles. This synthesis highlights aspects such as the number of active lines, flow distribution, connection criticality, and the predominant operational trend. Furthermore, it shows how the algorithm balances conflicting objectives — such as reliability and energy flow — by adapting to different network conditions while maintaining radiality, performance, and solution robustness.

Table 4 – Comparison between Cases 1 and 2

Criterion	Case 1	Case 2
No. of arcs with energy > 0	27	23
Line with highest energy flow	73 (83→84): 2,359 MWh	73 (83→84): 2,359 MWh
Line with highest index	74 (82→85): 1188	74 (82→85): 950
Flow distribution	More dispersed, multiple paths	More concentrated on main paths
Avg. index of active lines	261,7	229,3
Redundancy and load balancing	Greater diversity and resilience	Less use of alternative paths
Operational tendency	Robust and balanced solution	Economically efficient solution

The variations in load allocation and indices reflect the algorithm's adaptability to different scenarios. In terms of operational efficiency, both cases avoided line overloading and respected arc capacity limits, ensuring operational safety. The activated paths maintained topological continuity, following minimally redundant yet strategically placed routes. This indicates the algorithm’s ability to balance efficiency and reliability.

While Case 1 showed greater variation in the indices of secondary lines — indicating path diversification to relieve main segments and promote higher resilience — Case 2 concentrated the indices on central lines, favoring more direct routes, with operations focused on fewer segments, yet still maintaining resilience to failures.

To complement, Table 5 presents a comparative statistical descriptive analysis of the variables of interest: energy, capacity, and indices.

Table 5 - Descriptive Analysis – Comparative summary between both cases

Statistic	Energy		Index	
	Case 1	Case 2	Case 1	Case 2
Total	20,21	20,21	11.139,00	8.693,00
Mean	0,256	0,256	141,00	110,01
Maximum	2,36	2,36	1.188,00	950,00
Standard Deviation	0,497	0,478	264,63	225,43

The values related to the total, average, and maximum energy flows are identical between the cases, indicating that the same total amount of energy was allocated, despite changes in the lines through which this energy was distributed. On the other hand, the 22% reduction in the total indicators from Case 1 to Case 2 shows an improvement in the overall network performance according to this criterion. The standard deviation also decreased, indicating a more homogeneous distribution of the indices in Case 2. Both the total and average indices are lower in this scenario, suggesting a more efficient solution.

4.4 Summary of Results

The analysis confirms that the matheuristic approach provides feasible solutions aligned with network topology and operational constraints. The model successfully:

- Maintains topological robustness by preserving radiality and respecting line capacities (no arc exceeds its limit);
- Prioritizes lines with high reliability impact and load;
- Maintains substation-level load balance;
- Adapts to varying load profiles;
- Selectively activates paths based on multiple criteria;
- Forms optimized routes from substations to terminal branches under reliability control;
- Complies with operational limits of each line.

These findings reinforce the effectiveness of the proposed multilevel approach, integrating consumer clustering and network reconfiguration. The model proves suitable for both stable operating environments and more demanding scenarios requiring simultaneous flexibility, efficiency, and reliability.

The results also demonstrate the algorithm’s adaptability to different network configurations, maintaining solution robustness and optimizing multiple objectives. Furthermore, lines with high index values represent critical points in the system and may serve as a basis for prioritizing investment and preventive maintenance strategies.

5. Conclusion

In this study, a model based on a matheuristic approach combined with a Mixed-Integer Linear Programming (MILP) formulation was proposed to enhance approximate reliability and enable a more accurate analysis of radial distribution systems.

The indirect resolution of the consumer clustering problem, at the upper level, involved the minimization of operational costs while preserving the radial topology of the network. This approach enabled the appropriate allocation of consumers to feeders through restricted load transfers. Consequently, at the lower level, it ensured an efficient reconfiguration with

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equitable distribution of reliability indices and power flow among feeders, validating the clusters formed.

To address the problem's complexity, a generalized network flow model with multiple minimum-cost flows was used to indirectly represent the clustering of consumers, directly reflecting the new topological structure of the electrical circuits. The network modification corresponded to the degree of association between consumers and feeders, guided by approximate minimum-cost flow evaluations, handled through a heuristic approach that yielded good results in terms of quality and computational efficiency.

A path construction strategy was also employed to maximize energy transfer at the lowest cost. Multi-objective decision-making was conducted using the ε-constraint method, enabling the identification of efficient (non-dominated) solutions.

The proposed model was implemented computationally, and the results demonstrated its effectiveness in producing balanced solutions, reducing line-related operational costs, and improving network reliability. This approach presented key advantages over the existing literature, such as the integration of MILP modeling, multiple flows, and electric validation based on power flow simulations.

The main contributions beyond the current literature include: the integration of clustering and reconfiguration in a unified mathematical model; the representation of consumer clustering via multiple minimum-cost flows; the inclusion of an electrical validation step coupled with the optimization process; and the robustness across different operational scenarios, ensuring solution consistency and quality.

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