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IMPROVING POWER GRID NETWORK ROBUSTNESS BY OPTIMIZED SWITCH ALLOCATION: A LARGE-SCALE CASE STUDY IN BRAZIL

APRIMORAMENTO DA ROBUSTEZ DE REDES DE DISTRIBUIÇÃO DE ENERGIA POR ALOCAÇÃO OTIMIZADA DE CHAVES DE PROTEÇÃO: UM ESTUDO DE CASO EM LARGA ESCALA NO BRASIL

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ABSTRACT

Radial distribution networks are inherently vulnerable to cascading outages: a single fault on an unprotected lateral can trip the feeder breaker and de-energize thousands of consumers. Optimally placing protective switches to segment these networks is an NP-hard combinatorial problem whose exact formulation scales at $O(2^N)$, making it intractable for real utility-scale grids. We propose a scalable graph-theoretic heuristic based on a Cumulative Downstream Load (CDL) metric that identifies the electrical backbone of each feeder through a two-pass tree traversal in $O(N)$ time. The method exploits a formal isomorphism between radial power flow and hydrological stream ordering (Horton-Strahler), treating the feeder as a “reverse river” where load accumulates from consumers to the substation. Applied to the full distribution network of COPEL, a major Brazilian utility encompassing approximately 3.8 million nodes and 2,415 feeders, the algorithm proposed 6,979 switch locations across 1,757 feeders in under five minutes on commodity hardware. Of these, 92.6% correspond to genuinely unprotected locations, while the remaining 7.4% independently confirm devices already placed by utility engineers. In aggregate, the proposed allocation would protect over 349,000 backbone consumer units from unnecessary cascading outages while isolating over one million lateral consumer units into properly segmented fault zones, with a highly skewed per-switch impact distribution that enables priority-based phased deployment. The results demonstrate that linear-time network science heuristics can deliver actionable infrastructure recommendations at scales where conventional optimization methods fail to converge.

Keywords: Power distribution network; Switch allocation; Network robustness; Graph theory; Cumulative downstream load.

RESUMO

Redes de distribuição radiais são intrinsecamente vulneráveis a interrupções em cascata: uma única falta em um ramal desprotegido pode atuar o disjuntor do alimentador e desenergizar milhares de consumidores. A alocação ótima de chaves de proteção para segmentar essas redes é um problema combinatório NP-difícil cuja formulação exata escala em $O(2^N)$, tornando-a intratável em redes reais de porte concessionário. Propõe-se uma heurística escalável, fundamentada em teoria dos grafos, baseada na métrica de Carga Acumulada a Jusante (CDL, *Cumulative Downstream Load*), que identifica a espinha dorsal elétrica de cada alimentador por meio de uma travessia de árvore em duas passagens com tempo $O(N)$. O método explora um isomorfismo formal entre o fluxo de potência radial e a ordenação hidrológica de cursos d'água (Horton-Strahler), tratando o alimentador como um “rio invertido”, no qual a carga se acumula dos consumidores em direção à subestação. Aplicado à rede de distribuição completa da COPEL, uma grande distribuidora brasileira com aproximadamente 3,8 milhões de nós e 2.415 alimentadores, o algoritmo propôs 6.979 locais de instalação de chaves em 1.757 alimentadores em menos de cinco minutos em hardware convencional. Desses, 92,6% correspondem a locais genuinamente desprotegidos, enquanto os 7,4% restantes confirmam, de forma independente, dispositivos já instalados por engenheiros da distribuidora. No agregado, a alocação proposta protegeria mais de 349.000 unidades consumidoras da espinha dorsal contra interrupções em cascata desnecessárias, ao mesmo tempo que isolaria mais de um milhão de unidades consumidoras de ramais em zonas de falta adequadamente segmentadas, com uma distribuição de impacto por chave fortemente assimétrica que viabiliza uma implantação faseada por prioridade. Os resultados demonstram que heurísticas

de ciência de redes com tempo linear podem gerar recomendações de infraestrutura acionáveis em escalas nas quais métodos convencionais de otimização não convergem.

Palavras-chave: Rede de distribuição de energia; Alocação de chaves; Robustez de redes; Teoria dos grafos; Carga acumulada a jusante.

1. INTRODUCTION

The modernization of electrical power systems is increasingly defined by a paradigm shift from static reliability, focused on the probability of component failure, to dynamic robustness, which characterizes the system's ability to withstand, adapt to, and recover from high-impact, low-probability events (Albert; Jeong; Barabási, 2000; Holmgren, 2006). As distribution networks (DNs) grow in complexity, driven by the integration of Distributed Energy Resources (DERs) and the expanding footprint of urban electrification, the topological structure of these grids becomes a primary determinant of their resilience (Pagani; Aiello, 2013). While transmission networks are often meshed and redundant, distribution grids typically operate radially to simplify protection coordination. This tree-like topology creates a unique form of fragility: without adequate segmentation, a fault at a peripheral "leaf" node propagates upstream to the root protection device, causing a cascading failure that disconnects the entire feeder (Crucitti; Latora; Marchiori, 2004).

In the domain of power systems engineering, the terms "reliability" and "robustness" are often used interchangeably, yet distinct definitions emerge from the network science literature. Reliability is typically an operational metric, quantified by indices such as the

System Average Interruption Duration Index (SAIDI) and System Average Interruption Frequency Index (SAIFI) — regulated in Brazil as DEC and FEC, respectively (Aneel, 2024). These metrics aggregate the temporal impact of outages but often fail to capture the structural properties that necessitate such outages. Conversely, robustness is a topological property, measuring the network's ability to maintain a Giant Connected Component (GCC) following the removal of nodes or edges (Albert; Albert; Nakarado, 2004).

To improve robustness in radial grids, utilities must deploy protection switches that compartmentalize the network. This corresponds to the graph-theoretic problem of Tree Partitioning, where the objective is to isolate faults within small sub-trees (branches), preserving the functionality of the critical path (backbone) (Keller et al., 2023). However, a pervasive gap in the existing literature is the trade-off between optimality and scalability. The Switch Allocation Problem (SAP) is classically formulated as a Mixed-Integer Non-Linear Programming (MINLP) problem (Jooshaki et al., 2024). While exact optimization guarantees global optimality, it is computationally prohibitive for large-scale networks, exhibiting exponential complexity ($O(2^N)$) that renders it intractable for utility-wide datasets containing millions of nodes.

This paper proposes and validates a scalable graph-theoretic heuristic to bridge this gap. We hypothesize that the electrical “Backbone” of a distribution feeder can be identified via a Cumulative Downstream Load (CDL) metric, which acts as a proxy for Load Centrality. This approach reveals a profound isomorphism between power distribution grids and geomorphological river networks, specifically relating to Horton-Strahler stream ordering and Shreve Magnitude (Horton, 1945; Shreve, 1966). By treating the feeder as a “reverse river” where load accumulates from consumers (sources) to the substation (sink), we can identify critical topological vulnerabilities with linear time complexity ($O(N)$).

We present a large-scale case study applied to the full distribution network of COPEL (Companhia Paranaense de Energia), a major Brazilian utility. The dataset encompasses approximately 3.8 million nodes and 2,415 feeders, a scale significantly larger than typical academic benchmarks (e.g., IEEE 123-bus) (Hartmann et al., 2025). Our methodology utilizes an automated network reprocessing to correct GIS inconsistencies — such as spurious loops and disconnected islands — before applying the CDL heuristic to propose optimal switch locations.

The main contributions of this work are:

- The translation of abstract network science concepts (Load Centrality, Percolation) into actionable engineering heuristics for Switch Allocation.

- A formal definition of the isomorphism between radial power flow and hydrological stream ordering, providing a theoretical basis for heuristic backbone extraction.

- A validation of the methodology on a massive real-world dataset (Brazil), demonstrating that $O(N)$ heuristics can achieve significant robustness improvements where $O(2^N)$ optimization methods fail to converge.

The remainder of this paper is organized as follows: Section 2 details the graph-theoretic framework and the CDL algorithm. Section 3 describes the data processing and inconsistency correction pipeline.

Section 4 presents the results of the switch allocation across 2,415 feeders, and Section 5 discusses the implications for grid resilience policy and future work.

2. BACKGROUND AND THEORETICAL FRAMEWORK

This section establishes the graph-theoretic foundations used to model the distribution network, differentiates between operational reliability and topological robustness, and formally describes the isomorphism between radial power grids and hydrological systems.

2.1. Graph Representation Of Distribution Feeders

A power distribution network can be modeled as a graph $G = (V, E)$, where V represents the set of nodes (substations, transformers, poles, and consumer units) and E represents the set of edges (conductors/lines) connecting them. Unlike transmission networks, which often exhibit a meshed topology to ensure redundancy, distribution networks operate primarily as radial trees to simplify protection coordination (Pagani; Aiello, 2013).

Formally, a distribution feeder is a tree $T \subseteq G$, rooted at the substation node v_{root}. For any node $v_i \in V$, there exists a unique path from v_{root} to v_i. The flow of power is directed from the root to the leaves. However, for the purpose of robustness analysis, we treat edges as undirected when calculating connectivity, as a disconnection event isolates the subgraph regardless of flow direction.

2.2. From Reliability To Topological Robustness

Standard engineering practices quantify grid performance using reliability indices such as SAIDI (System Average Interruption Duration Index), defined as:

$$\text{SAIDI} = (\Sigma\ U_i N_i) / N_{total} \quad (1)$$

where U_i is the annual outage duration for location i, and N_i is the number of customers at location i. While effective for regulatory compliance, these metrics are retrospective and probabilistic (Aneel, 2024).

In contrast, network science defines robustness as the structural ability of the network to maintain connectivity under percolation (node/edge removal). We focus on the size of the Giant Connected Component (GCC) after a fraction f of nodes are removed. In a radial tree without switches, the removal of any edge e_{ij} partitions the tree into two disjoint components: the component containing v_{root} (energized) and the downstream component (de-energized). The vulnerability of an edge is therefore directly proportional to the size (load or number of customers) of the sub-tree it supports.

2.3. The River Network Isomorphism And Stream Ordering

A key theoretical insight of this work is the isomorphism between radial distribution grids and geomorphological river networks. Just as a river basin collects water from distributed sources to a central outlet, a distribution feeder delivers power from a central source to distributed loads.

We utilize the Horton-Strahler Stream Ordering scheme (Horton, 1945; Strahler, 1957) to characterize the hierarchical structure of the grid. In this “reverse river” analogy:

1. Leaf Nodes (End-Of-Line Consumers) Are Assigned An Order Of $\omega = 1$

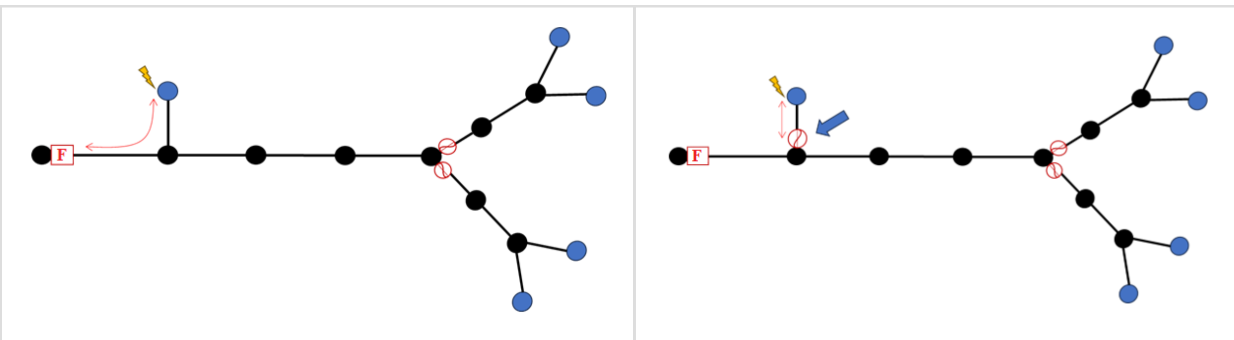
2. If two branches of order ω_1 and ω_2 meet, the upstream edge is assigned order $\max(\omega_1, \omega_2)$ if $\omega_1 \neq \omega_2$, or $\omega_1 + 1$ if $\omega_1 = \omega_2$.

This topological ordering allows us to identify the "Main Stem" or electrical backbone of the feeder without relying on complex electrical impedance calculations. This aligns with the concept of *Load Centrality*, where the importance of a node is determined by the cumulative weight of its downstream descendants (analogous to the *Shreve Magnitude* in hydrology (Shreve, 1966)).

2.4. The Switch Allocation Problem (SAP)

The objective of the Switch Allocation Problem is to place a limited set of k switches on edges in E to minimize the total unserved load (or customers) during faults. Let $S \subset E$ be the set of edges equipped with switches. When a fault occurs on edge $e \in E$, the protection system isolates the smallest subtree containing e bounded by switches in S. Figure 1 illustrates this problem on a simple network, and how a good switch allocation can prevent network disconnection.

Figure 1. Impact of fault location and protection devices on feeder operation.



(**a**) A short circuit on a lateral line trips the feeder (F), causing the entire network to be de-energized.	(**b**) A protective switching device installed on the branch allows isolation of the faulted lateral.

Source: prepared by the authors.

Finding the optimal set S is a combinatorial optimization problem. For a graph with $|E|$ edges, the search space for placing k switches is $C(|E|, k)$. This is computationally isomorphic to the p-median problem or the set covering problem, which are known to be NP-hard (Abedi; Vahidi; Hosseinian, 2013). Given the scale of our case study ($N \approx 3.8 \times 10^6$), exact optimization methods such as Mixed-Integer Linear Programming (MILP) are intractable ($O(2^N)$ complexity). This necessitates the heuristic approach based on the Cumulative Downstream Load (CDL) centrality described in the following sections.

3. METHODOLOGY

The methodology adopted in this study bridges the gap between theoretical network science and practical power systems engineering. It is structured into three sequential stages: (1) Data Acquisition and Graph Modeling, encompassing a rigorous network preprocessing; (2) Topological Backbone Identification via the Cumulative Downstream Load (CDL) metric; and (3) A heuristic Switch Allocation algorithm designed for linear-time scalability.

3.1. Data Acquisition And Graph Modeling

The dataset was obtained from the Geographic Information System (GIS) of Companhia Paranaense de Energia (COPEL), encompassing the entire distribution network of the state of Paraná, Brazil. The raw data includes spatial and electrical attributes for approximately 3.8 million nodes, representing poles, transformers, and switching devices, organized into 2,415 distinct distribution feeders.

To model the physical network as a mathematical graph $G = (V, E)$, we mapped "Significant Points" (points of electrical significance such as poles and transformers) to the set of vertices V, and "Primary Segments" (conductors connecting these points) to the set of edges E. Attributes such as the number of connected consumers ($N_{\text{customers}}$) and installed transformer power (P_{kVA}) were associated with the respective nodes.

3.1.1. Network Preprocessing

Real-world utility datasets inevitably contain topological errors due to manual data entry or synchronization lags between field operations and GIS updates. Before analysis, an automated network preprocessing pipeline was applied to correct three primary classes of inconsistencies:

- **Disconnected Islands:** Subgraphs physically disconnected from the main feeder source (substation) were identified and flagged. If an island contained load but no source, it was treated as a data error and excluded from the flow calculations to prevent algorithm divergence.

- **Spurious Loops:** Although distribution grids may have physical loops for reconfiguration, they operate radially. Cycles formed by incorrectly closed switches in the database were broken by virtually opening the switch with the highest topological depth, enforcing the tree constraint $T \subseteq G$.

- **Orphan Nodes:** Vertices with missing connectivity attributes (e.g., null upstream pointers) were analyzed. If they represented negligible load (e.g., streetlights without consumers), they were pruned; otherwise, they were flagged for manual review by utility engineers.

3.2. Backbone Identification Via CDL

Central to our approach is the identification of the electrical "Backbone" (or Main Stem) of each feeder. Unlike impedance-based methods, which require complete electrical parameters often missing in GIS data, we utilize the Cumulative Downstream Load (CDL) metric. This method leverages the isomorphism between radial power flow and hydrological networks described by Horton (1945) and Shreve (1966).

The CDL algorithm operates in two passes with $O(N)$ complexity:

1. **Upstream Aggregation (Post-Order Traversal):** We traverse the tree from leaves to root. For every node v, the cumulative load L_v is calculated recursively:

$$L_v = l_v + \Sigma_{c \in \mathrm{children}(v)} L_c \quad (2)$$

where l_v is the local load (number of customers) directly connected to node v, and *children*(v) are the downstream nodes connected to v.

2. **Downstream Classification (Pre-Order Traversal):** Starting from the substation (root), the algorithm identifies the path of "heaviest flow". At any branching node v, the edge connecting to the child c_{max} with the highest L_c is classified as part of the

Backbone. All other edges connecting to children $c_i \neq c_{max}$ are classified as the start of "Laterals" (or tributaries).

This topological classification allows us to decompose a complex feeder into a hierarchy of a main backbone and subordinate laterals, effectively reducing the search space for switch placement from the entire edge set E to the set of lateral entry points.

3.3. Scalable Switch Allocation Heuristic

The optimization goal is to maximize the robust segmentation of the grid. We define an "Unprotected Lateral" as a branch that, upon detecting a fault, causes the disconnection of the Backbone due to the lack of an isolating device at its origin.

The heuristic allocation algorithm proceeds as follows:

1. **Candidate Identification:** For every node v identified as a branching point off the Backbone, the algorithm examines the edge leading to the Lateral.

2. **Existing Protection Check:** The algorithm queries the database for existing protection devices (fuses, reclosers, or sectionalizers) on the lateral edge. If a device exists, the lateral is considered "Protected".

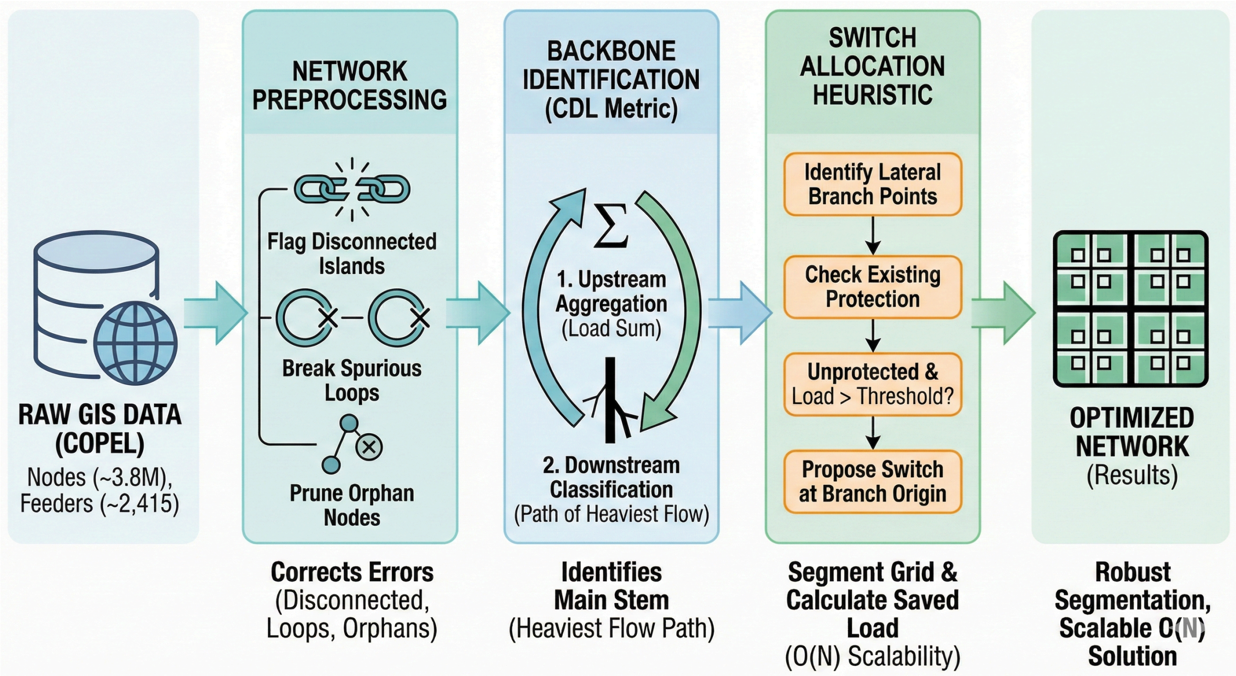
3. **Allocation Criteria:** If the lateral is unprotected and its cumulative load $L_{lateral}$ exceeds a utility-defined threshold (e.g., $L_{lateral} > 0$), a new switch is proposed at the coordinate immediately downstream of the branching point.

4. **Metric Computation:** For each proposed switch, the algorithm computes two metrics: (a) the number of downstream lateral consumers whose faults are now contained within the branch, and (b) the number of exposed backbone consumers — those on the backbone segment between the lateral branch point and the nearest existing upstream protection device — who would otherwise lose service when a lateral fault cascades.

This heuristic approach avoids the combinatorial explosion of Mixed-Integer Non-Linear Programming (MINLP). While MINLP methods scale at $O(2^N)$, our graph traversal and heuristic decision-making scale at $O(N)$, enabling the processing of the entire 3.8-million-node state network in minutes rather than weeks.

The implementation utilized the Python ecosystem, specifically GeoPandas (Jordahl et al., 2025) for spatial manipulation and Folium (Python Visualization, 2025) for result visualization and validation by utility engineers.

Figure 2. Proposed approach.



Source: prepared by the authors.

4. RESULTS AND DISCUSSION

The CDL heuristic was applied to the full COPEL distribution network, encompassing 2,415 feeders and approximately 3.8 million nodes across the state of Paraná, Brazil. The algorithm executed in linear time, completing the backbone identification and switch allocation for the entire network in under five minutes on commodity hardware, confirming the practical scalability of the $O(N)$ approach.

4.1. Switch Allocation Output

The algorithm produced 6,979 switch proposals distributed across 1,757 feeders (72.8% of all feeders). The remaining 658 feeders either already possess sufficient protection at all lateral entry points or contain no unprotected laterals with non-zero downstream load. Of the proposed locations, 6,462 (92.6%) correspond to edges without any existing protection device, representing genuine new infrastructure requirements. The remaining 517 locations (7.4%) coincide with positions already occupied by existing switching devices (reclosers, sectionalizers, or fuses) recorded in the GIS database, providing an independent validation that the algorithm converges on the same critical topological points identified by utility engineers.

Table 1 summarizes the key quantitative metrics of the allocation output. On average, each feeder with proposed switches receives approximately 4 new devices (median: 3), with a range from 1 to 23 switches per feeder, reflecting the heterogeneous complexity of the network topology.

Table 1. Summary of CDL switch allocation results for the COPEL distribution network.

Metric	Value	Unit
Network scope		
Total feeders analyzed	2,415	feeders
Feeders with at least one proposed switch	1,757	feeders
Proposed switches		
Total switch proposals	6,979	switches
New installations required	6,462	switches
Existing devices confirmed by algorithm	517	switches
Mean switches per affected feeder	3.97	switches/feeder
Median switches per affected feeder	3	switches/feeder
Maximum switches in a single feeder	23	switches
Consumer impact (per-fault)		

Downstream lateral consumers (fault zone isolated)	1,038,262	consumer units
Exposed backbone consumers (protected from outage)	349,622	consumer units
Mean lateral consumers isolated per switch	148.8	consumer units
Mean backbone consumers protected per switch	50.1	consumer units
Backbone exposure mitigated		
Total exposed backbone length mitigated	3,034.5	km
Total exposed backbone poles mitigated	74,014	poles
Mean exposed backbone length mitigated per switch	434.8	m

Source: prepared by the authors.

4.2. Consumer Protection Analysis

The primary impact metric captures two distinct effects of each proposed switch. First, the downstream lateral consumers isolated (1,038,262 in total): these are the consumer units on the lateral branch that define the fault zone. Without the switch, a fault anywhere on this branch would propagate upstream and trip the nearest protection device — potentially the feeder breaker itself — cascading the outage to the backbone and beyond. The switch confines such faults to the lateral, preventing this propagation. Note that these consumers lose power in either scenario when a fault occurs on their branch; the switch does not protect them from their own faults, but rather prevents their faults from affecting the rest of the network.

Second, the exposed backbone consumers protected from outage (349,622 in total): these are the actual beneficiaries of the switch — consumer units on the backbone segment between the lateral branch point and the nearest existing upstream protection device. This segment represents the “blast radius” on the backbone side: the consumers who would unnecessarily lose service when a lateral fault cascades upstream. This count is deliberately conservative, reflecting only the vulnerable backbone stretch up to the first existing protection device rather than the entire feeder above the switch.

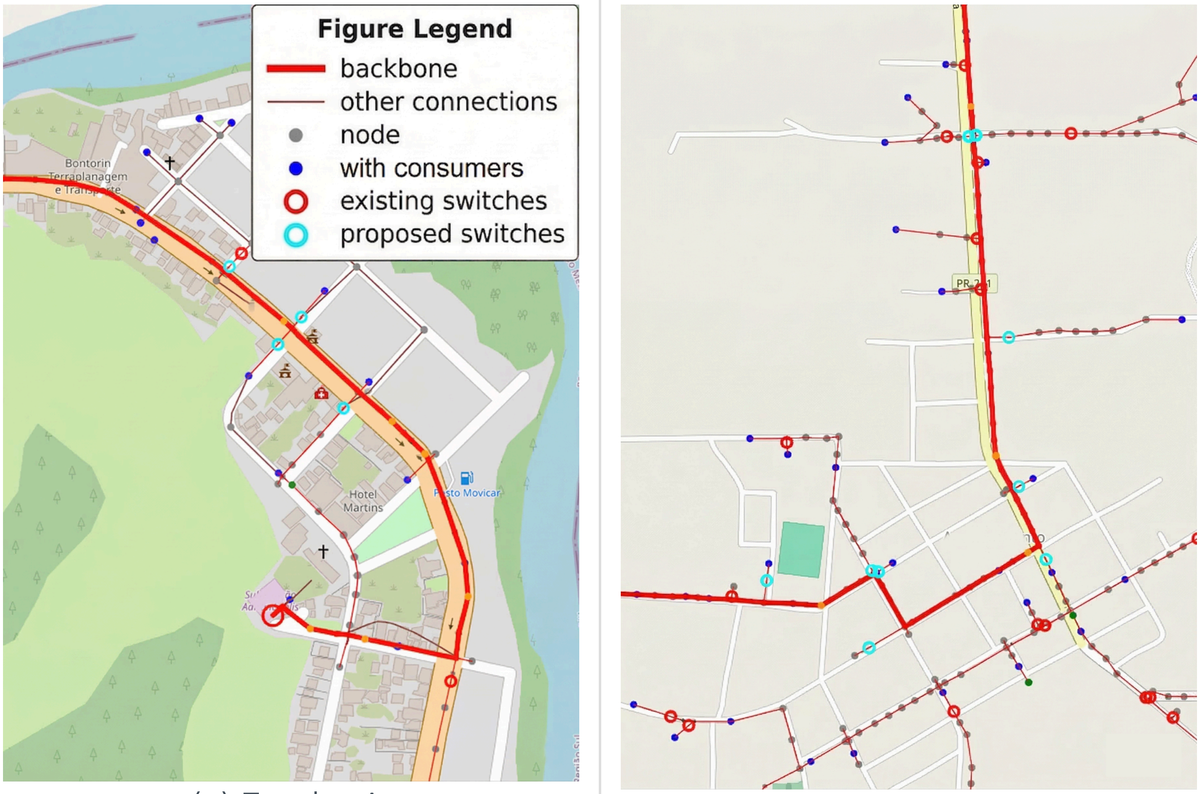
On a per-switch basis, the mean number of backbone consumers protected is 50.1 (median: 23), though the distribution is highly skewed, with 10% of switches protecting more than 127 backbone consumers and 1% protecting over 415 each. This skewness reflects the heterogeneous load density of the network: a minority of high-impact switch placements — at the entry points of densely loaded laterals near the substation — yield disproportionate robustness gains. The top-priority switches should therefore be allocated first in any phased deployment strategy.

In aggregate, the proposed allocation would protect 349,622 backbone consumer units from unnecessary cascading outages while isolating 1,038,262 lateral consumer units into properly segmented fault zones. This demonstrates that even a single round of heuristic-guided switch installation can yield substantial system-wide robustness improvements.

4.3. Qualitative Validation

Figure 3 illustrates a representative example of the algorithm's output applied to two real COPEL feeders. Location names were removed/blurred to preserve the company's data privacy. The backbone (red line), automatically identified via the CDL maximum-flow path, closely follows the main arterial corridor of the feeder, consistent with engineering intuition and the river-network analogy. Proposed switches (cyan markers) are placed at the entry points of all unprotected laterals branching off this backbone, while existing protection devices (red circles) are shown for reference. The spatial coherence of the proposed placements, concentrating near population centers with higher lateral load, provides qualitative confirmation that the CDL heuristic captures the topologically critical locations without requiring explicit electrical parameter data.

Figure 3. Representative output of the CDL backbone identification and switch allocation algorithm applied to two real feeders in Brazil. The backbone (bold red line), identified as the maximum cumulative downstream load path, forms the main arterial stem of the feeder. Thin red lines represent lateral branches. Blue dots indicate nodes (poles) with directly connected consumers; gray dots indicate intermediate poles. Proposed switch locations (cyan circles) are placed at the origin of each unprotected lateral branching off the backbone. Existing protection devices already present in the GIS database (red circles) are shown for reference.



(**a**) Feeder A.

(**b**) Feeder B.

Source: prepared by the authors.

5. CONCLUSION

This work presented a scalable graph-theoretic approach for protective switch allocation in radial power distribution networks. By defining a Cumulative Downstream Load (CDL) metric and exploiting the formal isomorphism between radial power flow and hydrological stream ordering, we showed that the electrical backbone of a feeder can be identified through a simple two-pass tree traversal in linear time. This backbone then directly reveals the topologically critical lateral entry points where protective devices yield the greatest robustness gains.

Applied to the full distribution network of COPEL — encompassing approximately 3.8 million nodes across 2,415 feeders in the state of Paraná, Brazil — the method proposed 6,979 switch locations in under five minutes on commodity hardware. The algorithm independently converged on 517 positions already occupied by existing protection devices, providing empirical validation that the CDL heuristic captures the same critical points identified by experienced utility engineers. In aggregate, the proposed switches would protect over 349,000 backbone consumer units from unnecessary cascading outages while isolating over one million lateral consumer units into properly segmented fault zones, with a highly skewed impact distribution: the top 1% of switches each protect over 415 backbone consumers, enabling a cost-effective phased deployment strategy.

The key contribution is demonstrating that $O(N)$ network science heuristics can produce actionable infrastructure recommendations at scales where exact $O(2^N)$ optimization methods are computationally intractable. The river-network analogy, grounded in Horton-Strahler stream ordering, provides both an intuitive theoretical framework and a practical algorithmic basis that requires no electrical impedance data beyond what is available in standard GIS databases.

Several avenues for future work emerge from this study. First, the current heuristic treats all faults as equally probable; incorporating historical fault-frequency data or vegetation-proximity indices could refine the prioritization of switch placements. Second, extending the framework to account for Normally Open switches and network reconfiguration would allow the methodology to optimize not only fault isolation but also post-fault service restoration. Third, coupling the CDL backbone identification with reliability indices such as SAIDI/SAIFI (DEC/FEC) would enable a direct quantification of regulatory compliance improvements. Finally, the observed isomorphism between power grids and river networks invites further investigation into whether other hydrological concepts — such as bifurcation ratios or drainage density — can yield additional insights into distribution network design and vulnerability assessment.

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