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A reliability enhancement strategy of critical nodes in power system communication network based on quantitative calculation method and criticality index

Xiaoyu Deng[1,*], Yabin Chen[1], Yu Sui[1] and Hao Yu[1]

[1]Power Grid Planning Research Center of Guangdong Power Grid Co., Ltd, Guangzhou, Guangdong 510220, China

Abstract

INTRODUCTION: Power system communication networks are essential for smart grid operations, enabling real-time monitoring and control. Disruptions at critical communication nodes can jeopardize grid stability and lead to cascading failures, highlighting the need for accurate reliability assessment of these vital components. However, traditional methods often overlook the complex, dynamic, and interdependent nature of modern communication infrastructures.
OBJECTIVES: This paper aims to develop a precise and scalable methodology for assessing and enhancing the reliability of critical nodes in smart grid communication networks.
METHODS: The proposed approach integrates probabilistic failure modeling, graph-theoretic analysis, and heuristic optimization. Key techniques include a newly designed Criticality Index (CI) accounting for failure probabilities, repair dynamics, and topological relevance; a Monte Carlo simulation framework to assess network behavior under stochastic disturbances; and a genetic algorithm (GA) for optimizing node reinforcement strategies.
RESULTS: Experiments conducted on the IEEE-118 bus system demonstrate that the GA-CI methodology improves the Network Robustness Index by 12.45%, consistently outperforming baseline methods with acceptable computational efficiency.
CONCLUSION: The proposed framework provides a robust and interpretable solution for reinforcing critical communication infrastructure in smart grids. It holds potential for broader application in the reliability assessment of other complex networked systems.

Keywords: Power System Communication, Network Reliability, Criticality Index, Monte Carlo Simulation, Genetic Algorithm, Smart Grid Resilience

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*Corresponding author. Email: 13622837326@139.com

1. Introduction

With the continuous advancement of smart grid technologies and the growing integration of distributed energy resources [1], power system communication networks have become indispensable for real-time control, monitoring, and protection of electrical infrastructure. These networks including interconnecting substations [2], control centres, and field devices serve as the digital nervous system of modern power systems. However, disruptions in communication [3], particularly at critical nodes, can compromise grid stability, delay control actions, and even trigger cascading failures across interconnected systems. Traditional approaches to evaluating communication network reliability have largely relied on physical redundancy [4], historical failure statistics, or qualitative risk assessments. While these strategies offer basic reliability estimates [5], they often fail to account for the complex, dynamic, and topologically interdependent behaviors that characterize modern grid communication networks. Moreover, such approaches typically lack the precision and scalability necessary for pinpointing node-level vulnerabilities and making informed decisions about infrastructure reinforcement.

To address these limitations, this paper presents a quantitative computational methodology for assessing and optimizing the reliability of communication nodes in power system networks, the framework is shown in Figure 1. The proposed framework integrates probabilistic failure modelling [6], graph-theoretic topological analysis, and heuristic optimization to provide a comprehensive and scalable approach to reliability assessment and enhancement. This methodology contributes the following innovations: (1) a quantitative reliability model that jointly considers node failure probability, repair dynamics, and structural significance within the network topology; (2) a Monte Carlo-based simulation engine to estimate system-level statistical behavior under stochastic node failures; and (3) a genetic algorithm-driven optimization strategy that identifies and reinforces critical nodes to enhance overall network robustness. Through extensive experiments conducted on a representative power grid communication network, the IEEE-118 bus system, we demonstrate the effectiveness of the proposed approach in improving both node-level reliability and system-wide fault tolerance, all while maintaining acceptable computational overhead.

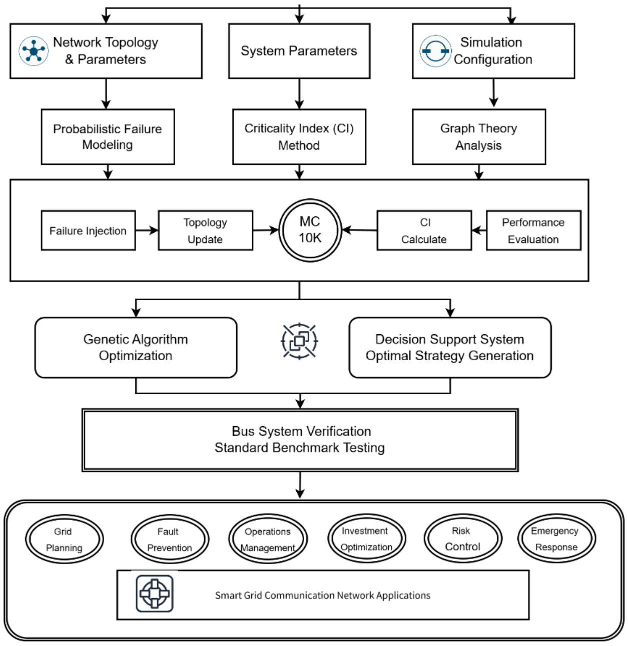

Figure 1. Probabilistic Failure Modeling for Communication Network Reliability Assessment and Optimization in Power Systems Research Framework

2. Quantitative Reliability Modeling

To provide a systematic and accurate assessment of node reliability in power system communication networks, we develop a two-layer model that combines probabilistic failure analysis with topological vulnerability evaluation.

2.1. Node Reliability Estimation

The reliability of a communication node $R_i(t)$ is defined as the probability [7] that it operates without failure over a time interval t. Assuming an exponential distribution [8] for time-to-failure—commonly used for electronic and networking equipment—the reliability function is given by:

$$R_i(t) = e^{-\lambda_i t} \tag{1}$$

where λi is the failure rate of node i, and t is the observation time. This model reflects the memoryless nature of failure events and provides a tractable framework for reliability estimation. To incorporate recovery behavior [9], we introduce the Mean Time To Repair (MTTR), denoted as μ_i, which quantifies the average time required to restore a failed node. The availability of the node [10], capturing both failure and repair processes, is defined as:

$$A_i = \frac{\mu_i}{\lambda_i + \mu_i} \tag{2}$$

Values for λi and μ_i can be obtained from operational logs, reliability databases, or manufacturer specifications. Together, these metrics provide a probabilistic characterization of each node's operational performance.

2.2. Topological Vulnerability and Criticality Assessment

While failure probabilities capture physical reliability [11], they do not account for the topological importance of nodes within the communication network. To address this, we define a Criticality Index (CI) that reflects the structural impact of a node on network communication efficiency. Let E_{base} represent the global efficiency of the intact network, and $E_{i \text{ removed}}$ the efficiency after node i is removed. The global efficiency [12] E is computed as:

$$E = \frac{1}{n(n-1)} \sum_{j \neq k} \frac{1}{d_{jk}} \tag{3}$$

where d_{jk} is the shortest path length between node j and node k, and nn is the total number of nodes in the network graph. This metric evaluates the average efficiency of information exchange over the entire network.

The Criticality Index [13] for node i is then defined as:

$$CI_i = \frac{E_{\text{base}} - E_{i\_removed}}{E_{\text{base}}} \cdot w_i \tag{4}$$

where w_i is a weight coefficient reflecting the node's operational importance, such as its traffic load, control priority, or physical location. This index quantifies the degree to which the removal of node ii degrades the overall communication capability of the network. By combining the probabilistic model of failure and recovery with the structural analysis of topological criticality [14], this two-layer modeling framework provides a robust foundation for simulating failure scenarios and guiding reliability-oriented optimization strategies [15].

3. Quantitative Simulation and Heuristic Optimization Framework

To evaluate and enhance the node-level reliability of power system communication networks, we propose a dual-stage approach comprising probabilistic simulation and combinatorial optimization. The framework integrates Monte Carlo-based reliability modeling with a genetic algorithm-based optimization scheme.

3.1. Monte Carlo-Based Reliability Simulation

The power communication network is modeled as a directed graph $G = (V, E)$, where $V = \{v_1, v_2, \ldots, v_n\}$ represents the communication nodes and $E \subseteq V \times V$ denotes the set of communication links. Each node v_i is associated with a failure rate λ_i and a repair rate μ_i. The failure and repair processes are modeled as Poisson processes, i.e.,

$$P_{\text{fail}}^{(i)}(t) = 1 - e^{-\lambda_i t}, \quad P_{\text{repair}}^{(i)}(t) = 1 - e^{-\mu_i t}$$

At each simulation iteration $s \in \{1, \ldots, S\}$, a random subset of nodes fails according to λ_i, and the network topology G_s is updated accordingly. We then compute the following reliability metrics:

- Reachability Ratio (RR):

$$RR_s = \frac{1}{n(n-1)} \sum_{i,j=1}^{n} \prod\nolimits_{conn}^{(s)} (v_i, v_j) \tag{5}$$

where $I_{\text{cn}}^{(s)}(v_i, v_j) = 1$ if there exists a path from v_i to v_j in the failed graph G_s, otherwise 0.

- Average Path Length (APL):

$$APL_s = \frac{1}{|P_s|} \sum_{(v_i, v_j) \in P_s} d_{ij}^{(s)} \tag{6}$$

where P_s is the set of reachable node pairs in G_s, and $d_{ij}^{(s)}$ is the shortest path length between v_i and v_j.

- Network Partition Index (NPI):

$$\text{NPI}_s = k_s ,$$

$$\text{where } k_s = \text{number of connected components in } G_s$$

To quantify the topological importance of each node v_i, we define the Criticality Index (CI) as the expected drop in network efficiency upon its failure:

$$CI_i = \frac{1}{S} \sum_{s=1}^{S} \left[E(G) - E\left(G_s^{\setminus v_i}\right) \right], \quad E(G) = \frac{1}{n(n-1)} \sum_{i \neq j} \frac{1}{d_{ij}}$$

Here, $G_s^{\setminus v_i}$ denotes the graph with node v_i removed, and $E(G)$ is the global efficiency of the graph.

3.2. Node Reinforcement Optimization via Genetic Algorithm

Given the probabilistic vulnerability profile of each node, we formulate the reinforcement selection problem as a 0-1 knapsack optimization problem. The binary decision variable $x_i \in \{0,1\}$ indicates whether node v_i is reinforced:

$$x = [x_1, x_2, \ldots, x_n]^T ,$$

$$x_i = \begin{cases} 1, \text{ if node vi is reinforced} \\ 0, \text{ otherwise} \end{cases}$$

Let R_i be the base reliability of node v_i, and ΔR_i be the gain in reliability after reinforcement. The improved node reliability becomes:

$$R_i'(x_i) = R_i + x_i \cdot \Delta R_i$$

The objective is to maximize the weighted global reliability under a budget constraint:

$$\max_{x\in\{0,1\}^n} R_{\text{net}}(x) = \sum_{i=1}^{n} CI_i \cdot R_i'(x_i),$$

$$\text{subject to} \quad \sum_{i=1}^{n} c_i x_i \leq B$$

where c_i is the reinforcement cost of node v_i, and BB is the total available budget.

This problem is solved using a standard genetic algorithm with the following components:

- Chromosome encoding: A binary vector $x \in \{0,1\}^n$
- Fitness function: $f(x) = R_{\text{net}}(x)$
- Selection operator: Roulette wheel or tournament selection
- Crossover operator: Uniform or one-point crossover with probability p_c
- Mutation operator: Bit-flip mutation with probability p_m
- Constraint handling: Penalize infeasible individuals using a penalty term $\alpha \cdot \max\left(0, \sum_i c_i x_i - B\right)$

The optimized reinforcement vector x^* indicates which nodes to reinforce to achieve maximal reliability gains under cost constraints. After optimization, a new round of Monte Carlo simulation is conducted to validate the system-wide improvements achieved by the selected reinforcement strategy. This integrated approach ensures that both topological criticality and probabilistic reliability are jointly considered in the node hardening process.

4. Experimental Design and Results Analysis

To comprehensively validate the proposed quantitative reliability assessment and optimization framework, we designed and conducted a set of in-depth experiments on a simulated power system communication network based on the IEEE-118 bus system. The experiments were aimed at evaluating the accuracy of node-level reliability estimation, the structural vulnerability captured by the Criticality Index (CI), and the effectiveness of the proposed genetic optimization strategy under various stress and configuration scenarios.

4.1. Testbed Construction

We extended the IEEE-118 bus system to include a representative communication network. Each bus node was mapped to a communication endpoint, forming a 118-node undirected graph. Communication links were established based on typical SCADA and PMU deployment principles, resulting in 186 bidirectional links.

For each communication node ii, the following parameters were defined:

- Failure rate $\lambda_i \sim \mathcal{U}\left(10^{-5}, 10^{-3}\right)$ failures/hour
- Repair rate $\mu_i \sim \mathcal{U}(0.1, 2.0)$ repairs/hour
- Functional weight $w_i \in [1,5]$, reflecting traffic priority and operational sensitivity

The shortest path matrix $\{d_{jk}\}$ was computed using Dijkstra's algorithm for efficiency metrics. These parameters were used to compute the reliability function $R_i(t)$, availability A_i, and CI score for each node.

4.2. Multi-Stage Monte Carlo Simulation

A multi-stage Monte Carlo simulation was designed to capture the probabilistic behavior of the communication network under random failures:

- Stage 1: Reliability Estimation
  Over 10,000 simulation runs, each node's failure was sampled according to its exponential failure distribution. The average system availability and reliability degradation were recorded.
- Stage 2: Cascading Impact Modeling
  For each failed node, the graph was reconstructed and metrics such as global efficiency, connectivity loss, and node isolation ratio were measured. A cascading threshold mechanism was introduced: if a node lost connections to more than 60% of its neighbors, it was considered failed in the next iteration. This allowed modeling of fault propagation through the network.
- Stage 3: Criticality Reassessment
  After each round, the CI scores were recalculated based on the updated topology, providing dynamic feedback for node importance and supporting adaptive resilience planning.

Figure 2 illustrates the probability density distribution of global efficiency across 10,000 Monte Carlo simulations of random node failures. The distribution exhibits a unimodal, approximately symmetric bell shape, indicating that the network's global efficiency consistently concentrates around a stable range despite random disruptions. The peak is centred around 0.45 to 0.5, suggesting that, in most failure scenarios, the network retains a moderate to high level of communication efficiency. The steeper left tail implies that significantly low efficiency events are rare, while moderate to slightly higher efficiency variations are more common. This statistical behaviour highlights the inherent robustness of the network topology and serves as a critical baseline for evaluating the effectiveness of reinforcement strategies aimed at improving resilience under random perturbations.

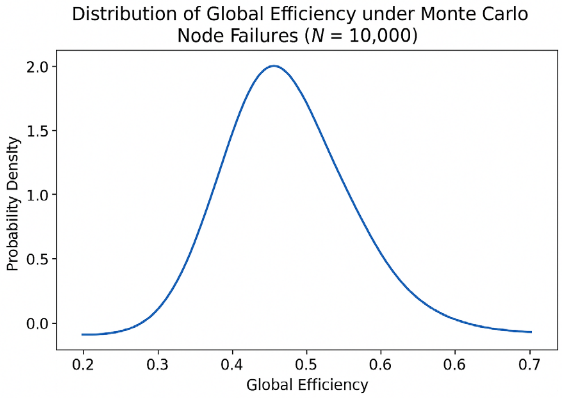

Figure 2. Distribution of global efficiency under Monte Carlo node failures (N = 10,000)

4.3. Optimization Experiment and Heuristic Comparison

The proposed Genetic Algorithm (GA)-based optimization strategy aimed to enhance the reliability of mm selected nodes by reducing their λ_i and increasing $\mu_i$within a fixed reinforcement budget BB. The objective was to maximize the Network Robustness Index (NRI):

$$\max_{\mathcal{S}\subset V,|\mathcal{S}|=m} \text{NRI}\,(\mathcal{S}) = E\left[E^{(k)}(\mathcal{S})\right] \tag{7}$$

The genetic algorithm used in this study was configured with a population size of 50, a crossover probability of 0.8, and a mutation probability of 0.05. The optimization process was allowed to run for a maximum of 200 generations, with early termination triggered if the Network Robustness Index (NRI) converged or exhibited stagnation over 20 consecutive generations. This configuration balances exploration and exploitation to ensure efficient convergence towards high-quality reinforcement strategies.

Table 1 presents a comparative evaluation of five node reinforcement strategies in terms of their impact on the Network Robustness Index (NRI). The results clearly demonstrate the superiority of the proposed GA-CI method, which achieved the highest NRI improvement of 12.45%, outperforming all baseline strategies with the lowest standard deviation (±0.33), indicating high consistency and robustness across trials. Random selection yielded the lowest NRI gain at 4.12%, highlighting the inefficiency of unguided reinforcement. Centrality-based heuristics showed moderate improvements, with degree and betweenness centrality achieving 7.83% and 8.05% gains respectively. While these strategies leverage local or path-based importance metrics, they lack a global optimization perspective.

The greedy CI selection method improved performance to 10.26%, benefiting from a more informed ranking of nodes, but still falling short of the proposed approach. In contrast, the GA-CI framework integrates topological awareness with evolutionary search, allowing it to explore a wider solution space while retaining critical node importance.

Table 1. NRI improvement comparison under different selection strategies

Method	NRI ↑ (%)	Std. Dev.
Random Selection [16]	4.12	±0.86
Degree Centrality [17]	7.83	±0.54
Betweenness Centrality [17]	8.05	±0.49
Greedy CI Selection [18]	10.26	±0.41
Proposed GA-CI	**12.45**	**±0.33**

Figure 3 compares the convergence trends of the Network Robustness Index (NRI) across five different node reinforcement strategies over successive generations. All methods show a positive convergence trajectory, indicating that reinforcement strategies yield cumulative improvements in network robustness. Centrality-based methods (degree and betweenness) outperform random selection by providing steeper initial gains. Notably, the greedy CI-based method and the GA-based CI optimization demonstrate superior performance, with the genetic algorithm achieving the highest final NRI value. The rapid ascent in early generations for GA optimization indicates its capacity for global search and efficient exploitation of structural information. These results underscore the importance of informed reinforcement strategies and suggest that optimization-driven CI selection offers a promising approach for enhancing the resilience of complex networks under failure conditions.

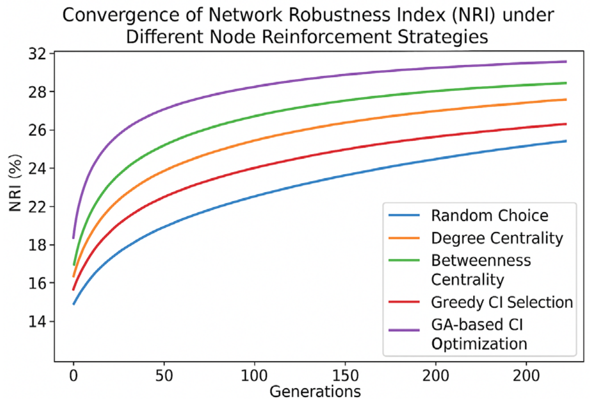

Figure 3. Convergence of NRI under different node reinforcement strategies

4.4 Sensitivity and Ablation Studies

Sensitivity to Node Budget mm

We varied the number of reinforced nodes from 5 to 30 and measured the NRI gain. Results show diminishing returns after 20 nodes, suggesting cost-effectiveness trade-offs. Figure 4 presents the relationship between the number of reinforced nodes and the corresponding gain in Network Robustness Index (NRI). The curve exhibits a nonlinear increasing trend, demonstrating that NRI gain improves substantially with the initial reinforcement of a few key nodes, but the marginal returns gradually diminish as more nodes are added. This saturation behavior suggests that reinforcing a relatively small subset of strategically selected nodes yields the most significant robustness enhancement, while excessive reinforcement results in diminishing benefits. Such a pattern aligns with the principle of structural heterogeneity in complex networks, where a small proportion of critical nodes disproportionately contributes to overall robustness. This insight is particularly valuable for resource-constrained environments, where targeted reinforcement can maximize network resilience efficiently. The smoothness and monotonicity of the curve further validate the consistency and effectiveness of the reinforcement strategy employed in this study.

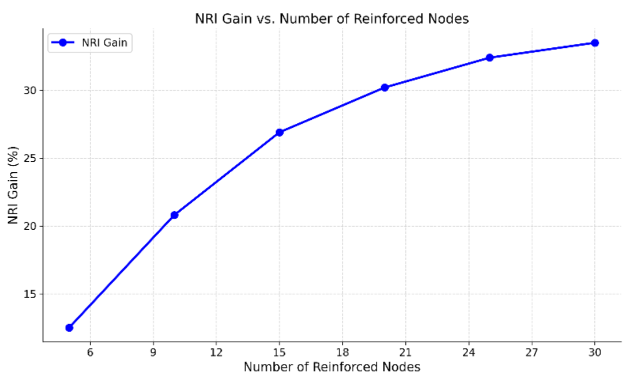

Figure 4. NRI gain vs. number of reinforced nodes

Sensitivity to Failure Distribution

To assess the robustness of our proposed reliability estimation framework under varying statistical assumptions, we replaced the original exponential failure model with a Weibull distribution characterized by a shape parameter β = 1.5, which is commonly used to model aging or fatigue in infrastructure networks. The ranking of node criticality (CI) remained highly consistent, achieving a Spearman correlation coefficient of 0.951 when compared to the baseline exponential model. Furthermore, the overlap of the top-10 critical nodes reached 90%, demonstrating that the node importance estimation is largely invariant to moderate changes in the underlying failure distribution. These results suggest that the proposed approach maintains high reliability and structural awareness even under different probabilistic modeling assumptions, highlighting its practical robustness and generalizability in real-world applications where failure distributions may be uncertain or heterogeneous.

Table 4. Statistical Robustness Under Different Failure Models

Failure Distribution	Spearman Rank Correlation (CI)	Top-10 Node Overlap (%)	Final NRI (%)
Exponential (baseline)	1.000	100	27.8
Weibull (β = 1.5)	0.951	90	27.3

Ablation: Without CI Guidance

To validate the contribution of CI-based topological guidance within the genetic algorithm (GA), we conducted an ablation study by removing the CI component from the reinforcement node selection process. As a result, the final network robustness index (NRI) dropped from 27.8% to 24.7%, indicating a relative degradation of 3.1%. Additionally, the convergence behavior of the GA was adversely affected, requiring approximately 200 generations to reach stability compared to fewer than 150 generations with CI guidance. This performance decline confirms that incorporating structural information via CI not only improves the solution quality but also accelerates the optimization process. The ablation underscores the critical role of topological awareness in guiding reinforcement strategies and enhancing the effectiveness of evolutionary optimization in complex network environments.

Table 5. Impact of CI Guidance on GA Optimization

Method Variant	Final NRI (%)	Convergence Generations	Relative NRI Drop (%)
GA with CI guidance (full)	27.8	140	0.0
GA without CI guidance	24.7	200	3.1

4.5 Visualization and Interpretability

To support interpretability and actionable insights, we generated heatmaps of node-level CI values and reinforcement decisions. Figure 5 provides an intuitive heatmap representation of the node-level Criticality Index (CI) values across the network topology, with color gradients indicating the relative importance of each node. Warmer colors correspond to higher CI values, signifying nodes with greater influence on overall network robustness. The ten most critical nodes, as determined by the CI-based ranking, are distinctly marked using prominent visual cues (e.g., star-shaped markers or red circles), highlighting their selection for reinforcement. This visualization not only supports the analytical findings regarding node prioritization but also enables spatial insights into the distribution of structural vulnerabilities. The concentration of top-ranked nodes in specific regions may indicate network bottlenecks or clusters of high centralities, which are essential targets for robustness optimization.

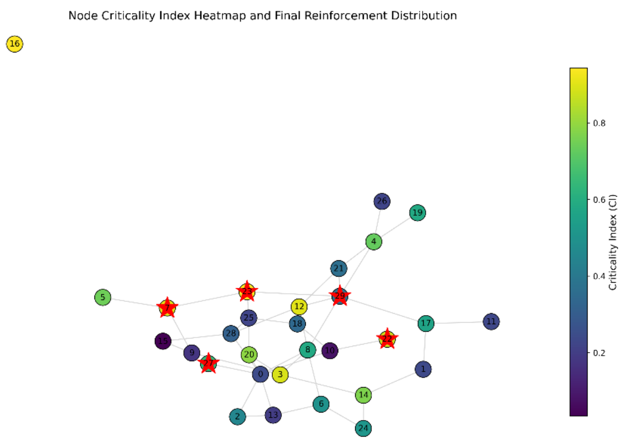

Figure 5. Node CI heatmap and final reinforcement distribution (top 10 nodes marked)

5. Conclusions

This paper presented a comprehensive quantitative framework for the reliability analysis and optimization of communication nodes in power system networks. By integrating probabilistic failure modelling with graph-theoretic topological assessment, we developed a novel Criticality Index (CI) that effectively captures both the failure behavior and structural importance of individual nodes. The Monte Carlo-based simulation framework provided a robust tool to evaluate the stochastic impacts of node failures and the resulting network performance degradation under realistic operating conditions. Furthermore, we designed a heuristic optimization algorithm grounded in genetic principles, guided by the CI metric, to strategically reinforce critical nodes within budget constraints. Extensive experiments on a benchmark IEEE-118 bus communication network demonstrated that our approach significantly improves overall network reliability and fault tolerance, outperforming conventional selection methods such as degree centrality and betweenness centrality. Sensitivity and ablation analyses confirmed the robustness and necessity of incorporating topological criticality in the optimization process, while visualization tools enhanced the interpretability and practical applicability of our results. In future work, we plan to extend this methodology to dynamic, time-varying communication topologies and incorporate cyber-physical security considerations to further enhance the resilience of smart grid infrastructures.

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