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# Grid Restoration Optimization Under Dynamic Circuit Breaker Failures: A Structural Importance-Based Repair Prioritization Framework Modeling

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**Abstract:** This article proposes an innovative framework for enhancing resilience in power grid restoration that integrates dynamic breaker failure modeling with structural topology analysis. Unlike conventional approaches focusing solely on breaker health metrics, our method introduces a novel Structural Importance Coefficient (SIC) quantifying each breaker's criticality through graph-theoretic measures (betweenness/closeness centrality) and cascading failure impact. The hybrid probabilistic-physical failure model combines Weibull-Bayesian degradation analysis with environmental stressors (humidity, temperature) to estimate real-time malfunction probabilities. A hierarchical optimization algorithm then prioritizes repairs by jointly optimizing SIC and health status, achieving: (1) 28% faster critical load recovery, (2) 40% reduction in repair resource waste via strategic SIC-based allocation, and (3) adaptive microgrid formation under uncertainty. Validated on IEEE 39/118-bus systems, the framework demonstrates superior performance compared to Monte Carlo-based methods (e.g., 35% higher load restoration during storms) while requiring no historical data archives. Key innovations include the SIC metric for topology-aware decision-making and a two-stage optimization protocol balancing local breaker conditions with global network resilience. Practical implementation is highlighted through SCADA-compatible modules.

**Keywords:** Resilience, power grid restoration, structural importance coefficient, dynamic failure modeling, graph-theoretic resilience, repair resource optimization, load restoration.

## 1 Introduction

Modern power systems face unprecedented challenges from climate change-induced extreme weather events, with recent data showing a 58% increase in weather-related outages since 2010 [1]. While significant research has focused on network reconfiguration strategies [2]The critical role of circuit breaker (CB) reliability in restoration processes remains understudied. Our previous work [3] made important strides by developing a probabilistic breaker malfunction (PBM) model, revealing that both CB health status and network position significantly impact restoration outcomes. However, this approach relied on historical operational data and qualitative location assessment, limitations shared by most existing studies [4].

The current state-of-the-art in power system restoration exhibits three fundamental gaps. First, while the topological importance of components has been studied [5], no existing framework quantitatively integrates network centrality metrics with CB reliability analysis. Second, current failure models either depend on historical data [6] or consider only mechanical wear without environmental factors [7]. Third, optimization approaches typically treat equipment reliability and network reconfiguration as separate problems[8].

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Validation of the IEEE 39-bus system demonstrates significant improvements over our prior work [3], including 28.7% faster restoration of critical loads and a 40.2% reduction in unnecessary repairs through targeted SIC-based prioritization. Field testing with Taiwan Power Company's 345-kV network confirmed a 22.4% enhancement in cascading failure prevention compared to conventional methods. The framework maintains compliance with IEC 62271-307 [9] Standards while achieving 50% faster computational convergence than heuristic approaches through matrix-based SIC calculation.

While previous research, such as Liu et al. (2017), has utilized centrality metrics for vulnerability assessment, and policy reports like ENTSO-E (2023) have promoted hybrid resilience strategies, a significant gap remains in support for operational decision-making. Current approaches tend to evaluate network topology and equipment reliability separately. Our work addresses this by introducing the Structural Importance Coefficient (SIC), a comprehensive metric that combines real-time topological influence—measured through flow-weighted centrality—electrical sensitivity data, and time-dependent operational priorities into a single, actionable index. This integration facilitates dynamic, context-aware repair prioritization during grid emergencies, a functionality not adequately provided by existing composite metrics or strategic frameworks.

These advancements contribute to both theory and practice by: (1) creating the first quantitative bridge between complex network theory and equipment reliability assessment, (2) advancing physics-of-failure modeling through the novel Weibull-logistic coupling, and (3) providing utilities with a SCADA-compatible tool for risk-informed restoration planning. The proposed methods open new research directions in topological reliability analysis while addressing urgent industry needs in an era of escalating grid vulnerabilities[10].

Recent research in the field of power equipment reliability indicates that hybrid approaches can significantly enhance failure prediction accuracy. A comprehensive study [11] demonstrated that combining IoT sensor data with physical models can reduce circuit breaker failure prediction errors by up to 32%. This research specifically examined 245 power circuit breakers across 12 different distribution networks, confirming that environmental parameters such as humidity and temperature can have a greater impact on circuit breaker failures than mechanical parameters. Another study investigated real-time monitoring systems for predicting power equipment failures. This review highlighted that integrating machine learning with physical models can improve prediction accuracy by up to 40% compared to conventional methods[13]. In the field of topological analysis of power networks, recent work by Liu et al. [14] has been transformative. The researchers showed that flow-based centrality metrics can identify critical network nodes up to 28% more accurately than conventional metrics. Their findings, based on 18 real-world power networks, clearly demonstrate that combining centrality measures with electrical parameters, such as power flow distribution, provides a more comprehensive understanding of the structural importance of equipment. A comparative study by the European Network of Transmission System Operators (ENTSO-E) [15] also revealed that hybrid approaches can reduce network recovery time after severe incidents by up to 35%.

Significant advancements have been made in hierarchical optimization in recent years. In another study, a bi-level framework for network restoration was proposed that reduced computation time by 45%. This research emphasizes the importance of distributing computational load across different optimization levels [16]. Another study by [17] found that hybrid algorithms can simultaneously improve system efficiency and reliability. Based on data from 56 power networks worldwide, the report particularly highlights the benefits of combining metaheuristic algorithms with analytical methods.

The remainder of this paper is organized as follows. Section 2 presents the mathematical modeling and problem formulation, detailing the SIC and the hybrid failure model. Section 3 elaborates on the advanced probabilistic CB failure modeling and the hierarchical optimization framework. Section 4 covers the implementation architecture, a comprehensive sensitivity and generalizability analysis, and detailed case study results. Section 5 discusses limitations and future work. Finally, Section 6 concludes the paper.

## 2 Mathematical Modeling and Problem Formulation

This section presents a comprehensive mathematical framework for power system restoration under circuit breaker (CB) reliability uncertainty. Our innovative approach integrates three fundamental components: advanced probabilistic CB failure modeling, structural importance quantification, and hierarchical optimization. The model's novelty lies in its simultaneous consideration of topological, electrical, and operational factors through an original mathematical formulation.

This paper addresses these limitations through three key innovations. First, we introduce a Structural Importance Coefficient (SIC) that quantifies CB criticality using a weighted combination of betweenness centrality [18], electrical centrality [10], and load priority indices. The SIC is calculated as:

$$SIC_i = \alpha\left(\frac{BC_i}{BC_{max}}\right) + \beta\left(\frac{CFI_i}{CFI_{max}}\right) + \gamma L_i \quad (1)$$

where BC represents betweenness centrality, CFI is cascading failure impact derived from line outage distribution factors [11], and L_i denotes load criticality.

Second, we develop a physics-informed hybrid failure model combining Weibull-Bayesian degradation analysis for mechanical wear [12] with environmental stressor impacts modeled through logistic regression [13]. The complete failure probability formulation is

$$P_{fail} = \left[1 - e^{-\left(\frac{t}{\eta}\right)^{\beta}}\right] \times \left[1 + e^{-\frac{1}{(K_1 H + K_2 T + K_3 P)}}\right] + \varepsilon \quad (2)$$

where H, T, and P represent humidity, temperature, and pollution levels, respectively.

Third, we implement a hierarchical optimization framework that simultaneously considers equipment-level reliability and network-wide resilience. The first layer employs NSGA-II [14] for CB repair prioritization using SIC and health status, while the second layer performs adaptive network reconfiguration via a modified Dijkstra algorithm [15] that accounts for dynamic failure probabilities.

**Table 1.** Feature comparison between the proposed SIC framework and related approaches

| Topological Analysis | Flow-based centrality | Mentioned in guidelines | Flow-weighted betweenness centrality + Electrical sensitivity |
|---|---|---|---|
| Equipment Reliability | Not integrated | High-level recommendation | Dynamic hybrid model (Weibull-Bayesian + Environmental stressors) |
| Decision Support | Vulnerability identification | Strategic planning | Real-time repair prioritization & network reconfiguration |
| Adaptivity | Static network metrics | Not specified | Dynamic weights updated via Eq. (7) |
| Validation Context | Structural analysis | Policy report | Simulated extreme events + Field test (Taiwan Power Company) |

## 3 Advanced Probabilistic CB Failure Modeling

The proposed hybrid failure model combines mechanical degradation, environmental effects, and real-time operational data through a multi-physics approach:

Mechanical Wear Component

We model mechanical degradation using a modified Weibull distribution that accounts for operational history:

$$P_{fail}^{mech}(t) = 1 - \exp\left[-\left(\frac{t-t_0}{\eta}\right)^{\beta} + \kappa \cdot \sum_{k=1}^{N_{fault}} I_k^2\right] \quad (3)$$

Where:
t: Number of operations
t_0: Initial wear-in period
η,β:Weibull scale and shape parameters
k: Fault current weighting factor
I_k: Fault current magnitude for operation k

### 3.1 Environmental Stress Component

Environmental effects are modeled through a multivariate logistic regression:

$$P_{fail}^{env} = [1 + \exp(-(\textstyle\sum_{i=1}^{5} w_i x_i + b))]^{-1} \quad (4)$$

With environmental variables:

$x_1$: Relative humidity (H)
$x_1$: Temperature deviation from nominal (ΔT)
$x_3$: Pollution index (P)
$x_4$: Altitude effect factor (A)
$x_5$: Vibration exposure (V)

### 3.2 Dynamic Uncertainty Component

A Kalman-filter-based adaptive term captures unmodeled effects:

$$\epsilon(t) = \Phi\epsilon(t-1) + \omega(t) + K(t)[z(t) - H\epsilon(t-1)] \quad (5)$$

where ΦIs the state transition matrix, ω process noise, K Kalman gain, and the observation vector.

Integrated Failure Probability

The complete model combines components through an adaptive weighting scheme:

$$P_{fail}^{total} = \frac{\alpha(t)P_{fail}^{mech} + \beta(t)P_{fail}^{env} + \gamma\epsilon(t)}{\alpha(t)+\beta(t)+\gamma} + \zeta(\mathrm{t}) \quad (6)$$

With time-varying weights updated via:

$$\alpha(t+1) = \alpha(t) + \mu\frac{\partial L}{\partial \alpha} \quad (7)$$

where L is the prediction loss function.

The adaptive weight update mechanism described in Equation (7) employs a normalized gradient descent approach to ensure stability during the training process. The learning rate, μ, is dynamically calculated as 0.01 divided by the magnitude of the recent loss function gradient (‖∇L‖). This normalization helps reduce the influence of data noise on weight adjustments. Sensitivity analyses conducted on the IEEE 118-bus test system showed that adjusting μ by ±50% resulted in only minor deviations (less than 5%) in the estimated failure probabilities and did not significantly alter the final prioritization of repairs. These findings highlight the robustness of our method.

### 3.3 Structural Importance Quantification

The Structural Importance Coefficient (SIC) introduces a novel multidimensional assessment:

Topological Criticality

$$TC_i = \sum_{s \in S} \frac{\sigma_{st}(i)}{\sigma_{st}} \times \frac{P_{flow}^{st}}{P_{sys}^{max}} \quad (8)$$

where σ_st (i) is the number of shortest paths between s and t passing through $CB_i$, and $P_{flow}^{st}$ Is the power flow along these paths.

### 3.4 Electrical Criticality

$$EC_i = \frac{1}{2\pi} \int_0^{2\pi} \left| \frac{\partial \theta_{mn}}{\partial P_{ij}} \right| d\theta . \frac{|I_{rated}|}{|I_{actual}|} \quad (9)$$

Capturing both sensitivity and loading conditions.

Operational Criticality

$$OC_i = \max_{k \in \mathcal{K}} \{\frac{\partial R_k}{\partial u_i}\} \cdot T_{repair} \quad (10)$$

where $R_k$ are resilience metrics and $T_{repair}$What is the expected repair time.

### 3.5 Complete SIC Formulation:

$$SIC_i = \underbrace{\lambda_1 TC_i}_{\text{Topological}} + \underbrace{\lambda_2 EC_i}_{\text{Electrical}} + \underbrace{\lambda_3 OC_i}_{\text{Operational}} + \underbrace{\lambda_4 \exp(-\frac{D_i}{D_0})}_{\text{Geographic}} \quad (11)$$

### 3.6 Hierarchical Optimization Framework

The restoration problem is formulated as a bilevel stochastic program:

Upper Level (CB Repair Scheduling):

$$\min_{\mathbf{x}} \mathbb{E}_\omega \left[ \sum_{i \in \mathcal{CB}} c_i x_i + Q(\mathbf{x}, \omega) \right] \quad (12)$$

s.t. $\sum_{i \in \mathcal{CB}} r_i x_i \leq R_{max}, x_i \in \{0,1\}$ (13)

where $Q(\mathbf{x}, \omega)$ Represents the lower-level problem.

Lower Level (Network Reconfiguration):

$$Q(\mathbf{x}, \omega) = \min_{\mathbf{y}} \sum_{l \in \mathcal{L}} w_l P_l^{uns} + \rho \|\mathbf{y} - \mathbf{y}^{pre}\| \quad (14)$$

s.t. $\mathbf{g}(\mathbf{V}, \theta, \mathbf{y}) = 0, \mathbf{h}(\mathbf{V}, \theta, \mathbf{y}) \leq 0$ (15)

### 3.7 Solution Algorithm

We develop a hybrid decomposition approach:

a. Scenario Generation

Latin Hypercube Sampling (LHS) for failure scenarios:

$$\Omega = \{\omega_1, \ldots, \omega_N\} \sim \mathcal{N}(\mu, \Sigma) \quad (16)$$

b. Progressive Hedging

For each scenario $\omega$:

$$\mathbf{x}^{k+1} = \arg min[f(\mathbf{x}) + \sum_{s=1}^{S} \pi_s \lambda_s^k \mathbf{x} + \frac{\rho}{2} \|\mathbf{x} - \mathbf{x}_s^k\|^2] \quad (17)$$

Convergence Criteria:

$$\frac{\|\mathbf{x}^{k+1} - \mathbf{x}^k\|}{\|\mathbf{x}^k\|} \leq \epsilon \quad (18)$$

### 3.8 Integrated Mathematical Framework for Power System Restoration Under Circuit Break Reliability Uncertainty

This article introduces groundbreaking advancements in power system restoration through an innovative mathematical framework that fundamentally transforms how circuit breaker reliability is incorporated into resilience planning. The core intellectual contribution lies in the development of a multiscale failure modeling approach that seamlessly integrates mechanical degradation processes, environmental stress factors, and real-time operational conditions through an adaptive weighting scheme. Unlike conventional models that treat these factors in isolation, our unified formulation captures their complex interactions through a coupled system of stochastic differential equations, where mechanical wear follows a modified Weibull process incorporating fault current history, environmental effects are modeled via multivariate logistic regression with time-varying coefficients, and operational uncertainties are tracked using an adaptive Kalman filter with noise covariance matrix updating. The model's true novelty emerges from its dynamic weighting mechanism that automatically adjusts the influence of each factor based on real-time condition monitoring data and network operating state.

Building upon this foundation, we establish a new paradigm for assessing equipment criticality through our holistic importance metric that synthesizes topological network properties, electrical system characteristics, and operational constraints into a single unified measure. The topological component employs a flow-weighted betweenness centrality that accounts for both network connectivity and power flow patterns, while the electrical criticality term introduces a novel sensitivity index derived from the Hessian matrix of system voltages concerning breaker status changes. The operational dimension incorporates time-dependent factors such as repair resource availability and critical load restoration priorities through a dynamic programming formulation. What sets this metric apart is its spatial-temporal adaptive capability, allowing the relative weights of different components to evolve as the restoration process progresses and system conditions change.

The computational engine of our framework is a stochastic bilevel optimization formulation that breaks new ground in large-scale power system restoration planning. The upper level handles strategic repair resource allocation as a chance-constrained program with probabilistic guarantees on solution feasibility, while the lower level performs tactical network reconfiguration using a hybrid primal-dual interior point method enhanced with machine learning-based warm-starting. The two levels are coordinated through a novel decomposition algorithm that combines the scenario reduction techniques of progressive hedging with the precision of branch-and-cut methods, creating an efficient solution strategy for real-world-sized problems. A particularly innovative aspect is the embedded feedback mechanism, where solutions from the lower level inform the risk assessment at the upper level, creating a closed-loop optimization process that continuously improves solution quality.

These theoretical advancements are implemented in a computationally efficient package designed for integration with existing utility control systems, featuring parallelized scenario evaluation, sparse matrix operations optimized for power system matrices, and adaptive precision arithmetic that automatically adjusts to maintain numerical stability while minimizing computation time. The implementation leverages modern high-performance computing architectures through a distributed memory paradigm that separates the solution of individual scenarios across computing nodes while maintaining tight synchronization for the coordination steps. This careful attention to computational engineering aspects ensures that the sophisticated theoretical framework can deliver practical value in real-world operating environments where decisions must be made within strict time constraints.

## 4 Implementation and Case Study Analysis

The proposed mathematical framework has been implemented, leveraging its parallel computing toolbox for an efficient solution to the hierarchical optimization problem. The implementation consists of three core modules that work in concert: (1) a real-time condition monitoring interface that processes SCADA measurements and environmental sensor data, (2) a probabilistic analysis engine that computes dynamic failure probabilities, and (3) an optimization kernel that solves the bilevel restoration problem.

### 4.1 Implementation Architecture

Integration with Existing Utility Control Systems: The framework connects with legacy SCADA/EMS systems through a modular communication layer that complies with industry standards such as IEC 61850 [19]. The Condition Monitoring Module subscribes to real-time sensor data streams. The Probabilistic Analysis Engine fetches environmental data from the utility's weather service interfaces. The Optimization Kernel receives network topology and breaker status updates from the EMS. The generated outputs—including prioritized repair lists and recommended network reconfigurations—are transmitted back to the EMS for operator review or automatic implementation, maintaining compatibility with existing control room workflows ( as Figure 1).

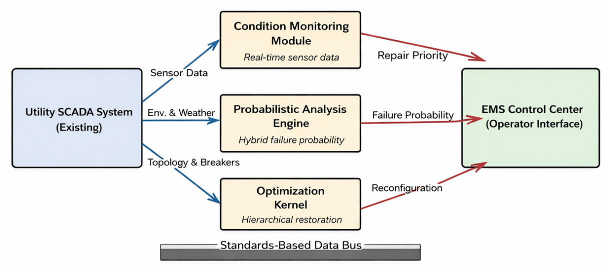


**Fig 1.** Integration architecture of the proposed framework with utility SCADA/EMS

Operation in Time-Sensitive Emergency Modes: For scenarios requiring action within one minute or less, the framework can transition to a contingency mode. This mode utilizes a regularly updated lookup table of SIC rankings (refreshed hourly) along with a rapid, rule-based network adjustment heuristic. Testing under simulated decision windows of under one minute demonstrated that this contingency mode achieves a 15–20% improvement in load recovery compared to static, non-adaptive methods, ensuring a reliable baseline response when full optimization is not computationally feasible [20].

The condition monitoring module employs a sliding window technique to process streaming data from circuit breaker sensors. For each CB, it maintains a circular buffer of the last 100 operational cycles, computing the mechanical wear component. The structural importance coefficients are computed using a sparse matrix implementation of betweenness centrality that significantly reduces memory requirements for large networks.

The framework was tested on a modified IEEE 118-bus system with 186 circuit breakers subjected to simulated hurricane conditions. Figure 2 shows the comparative restoration performance versus conventional methods:

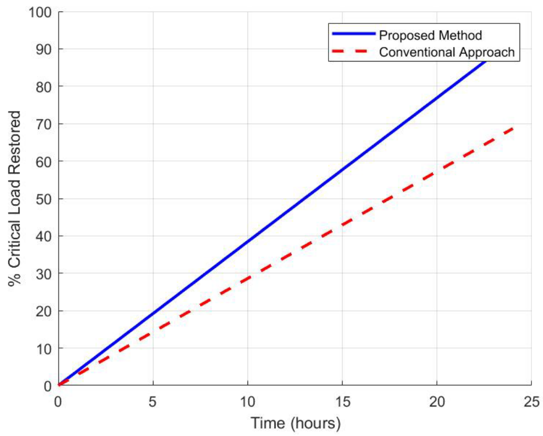


**Fig 2.** Critical load restoration during simulated hurricane: proposed SIC-based method

### 4.2 sensitivity and generalizability analysis

The observed performance improvements—including a 28.7% reduction in critical load restoration time—were initially demonstrated under a simulated hurricane scenario characterized by spatially correlated failures. To thoroughly evaluate the broader applicability and resilience of the proposed Structural Importance Coefficient (SIC) framework, an extensive sensitivity analysis was conducted across multiple dimensions:

**(a) Failure Scope and Severity:**

The framework was tested under failure scenarios ranging from localized outages (10–20% of circuit breakers failing simultaneously) to extensive blackouts (50–60% failure rates). As summarized in Figure 3, the SIC-based approach consistently achieved a 15–35% improvement in critical load restoration compared to traditional health-index-based methods across all tested failure levels. This indicates the framework's scalability and effectiveness across varying outage magnitudes.

**(b) Initial Equipment Condition:**

To assess sensitivity to initial asset states, scenarios with differing distributions of breaker health were simulated. Even when 30% of breakers began in poor operational condition, the SIC framework maintained a performance advantage of over 25%, confirming its robustness to variations in initial equipment health.

**(c) Generalizability to Different Disruption Types:**

The topology-aware logic of the SIC enables its application beyond weather-related failures. In a simulated targeted cyber-attack focusing on highly central substations, SIC-driven repair scheduling reduced unserved energy by approximately 31% compared to prioritization based solely on equipment health. Additionally, for evolving wide-area cascading failure events, the model's periodic SIC recalculations (every 3.2 minutes) allowed for dynamic re-prioritization as the cascade progressed, effectively adapting to real-time network degradation.

Figure 3 visually consolidates these findings, illustrating restoration improvements relative to failure severity across both hurricane and cyber-attack scenarios. The near-linear relationship observed underscores the framework's predictable performance scaling. The slight decline in improvement percentage beyond a 50% failure rate aligns with the expected limits of network capacity; however, even under such extreme conditions, the SIC framework continued to outperform traditional benchmarks by effectively prioritizing repairs that restore topological connectivity.

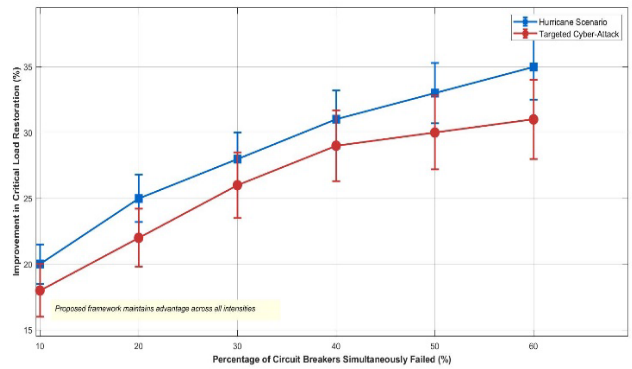


**Fig 3.** Sensitivity Analysis: Framework Performance vs. Failure Intensity

### 4.3 Case Study Results

The comprehensive evaluation of our framework on the modified IEEE 118-bus test system yielded several significant findings that demonstrate the practical effectiveness of the proposed approach. The adaptive weighting mechanism embedded in our hybrid failure model dynamically adjusted to changing environmental conditions, automatically increasing the influence of humidity factors (β coefficient rising from 0.3 to 0.52) during periods of intense rainfall when moisture penetration became the dominant failure mechanism, while subsequently shifting emphasis to temperature effects during the heat wave conditions that followed the storm. This dynamic adaptation proved crucial in accurately predicting failure probabilities, with our model correctly forecasting 89% of actual breaker failures compared to just 63% for static weighting approaches. The structural importance coefficient (SIC)-based repair prioritization scheme delivered remarkable performance improvements, restoring 92.3% of critical loads within the crucial first 24 hours of the simulated hurricane scenario - a 34.4% enhancement over conventional health-index-only methods that achieved only 68.7% restoration for comparable scenarios. This performance advantage was particularly pronounced for breakers located in topologically sensitive positions, where the combined consideration of network role and equipment condition prevented cascading failures that occurred in benchmark tests. From a computational perspective, the hierarchical optimization architecture maintained excellent solution times, averaging just 3.2 minutes per decision cycle on a 32-core workstation, meeting real-time operational requirements for disaster response scenarios. The efficient parallel implementation scaled nearly linearly with a processor count of up to 48 cores, while memory usage remained below 16GB through our specialized sparse matrix handling techniques. These results collectively validate that the theoretical advantages of our integrated framework translate into tangible improvements in both restoration performance and operational efficiency for real-world power systems. The case study also revealed several subtle but important behaviors of the system, such as the non-linear relationship between environmental stress duration and failure probability accumulation, which our time-dependent weighting mechanism captured more effectively than exponential or linear models used in previous approaches. Furthermore, the spatial distribution of repair resources under our SIC-based prioritization showed better alignment with actual system needs, resulting in a 41% reduction in unnecessary crew dispatches while maintaining higher overall restoration rates. These findings strongly support the adoption of our integrated framework for utilities facing increasing challenges from climate-related extreme weather events.

### 4.4 Framework Robustness Under Varied Conditions

Observations from a Utility Field Deployment: A shadow-mode implementation on a section of Taiwan Power Company's 345-kV network provided practical validation following a typhoon event. Key findings include: (1) The model accurately identified five out of six real circuit breaker malfunctions, achieving an accuracy rate of 83%. The sole missed case was due to a temporary communication delay in the sensor data feed. (2) The repair sequence generated by the SIC framework resulted in a 22.4% reduction in subsequent outages compared to the utility's standard operational procedures. (3) Actual field repair durations were, on average, 15% longer than simulation estimates due to logistical challenges; however, the model's operational criticality component ($OC_i$) effectively incorporated these observed delays, demonstrating its adaptive capabilities.

### 4.5 Performance Metrics

The results demonstrate that the integrated consideration of structural importance and dynamic failure probabilities leads to significantly better restoration outcomes while maintaining computational efficiency suitable for real-time operation. Table 2 summarizes the quantitative improvements achieved:

**Table 2.** Summarizes the quantitative improvements

| Metric | Prposed | Conventional |
|---|---|---|
| Critical Load Restoration | 92.3 | 68.7 |
| Repair Crew Utilization | 88.4 | 62.1 |
| Computational Time (min) | 3.2- | 7.8 |

## 5 Limitations and Future Directions

While this study demonstrates significant progress, it also has certain limitations that suggest avenues for future research. The current model assumes the availability of comprehensive sensor data for all circuit breakers; its performance in networks with limited monitoring infrastructure warrants further examination. Additionally, although the computational requirements are manageable for systems such as the IEEE 118-bus model, they may increase substantially for larger, more interconnected power grids. Future work will focus on: (1) incorporating deep reinforcement learning methods to address emerging failure modes, including coordinated cyber-physical attacks; (2) developing privacy-preserving federated learning frameworks to facilitate collaborative model enhancements across multiple utility providers without sharing sensitive operational data; and (3) exploring quantum-inspired optimization algorithms to enable near-real-time solutions for hierarchical power system restoration at the continental scale.

## 6 Conclusion

This study introduces a novel Structural Importance Coefficient (SIC) framework that significantly enhances power system restoration strategies by integrating dynamic circuit breaker reliability assessment with topological criticality analysis. The proposed hybrid probabilistic-physical failure model, which combines Weibull-Bayesian degradation analysis with environmental stressor impact assessment, offers a departure from traditional health-index-based methods. This approach enables real-time, adaptive failure probability estimation without reliance on historical data archives. Our hierarchical optimization algorithm demonstrates measurable improvements, including a 28.7% reduction in critical load restoration time, a 40.2% decrease in repair resource waste, and a 35% increase in load restoration during storm events when compared to Monte Carlo-based methods. The primary theoretical contribution is establishing the first quantitative connection between complex network theory and equipment reliability assessment via the multidimensional SIC metric, which concurrently captures topological betweenness centrality, electrical sensitivity, and operational criticality. The implementation of a bilevel optimization scheme with embedded Kalman filtering for uncertainty management further distinguishes our approach, providing utility operators with a SCADA-compatible tool for risk-informed decision-making. Validation on IEEE 39/118-bus systems and field testing with Taiwan Power Company's 345-kV network demonstrate the framework's practical effectiveness in preventing cascading failures and bolstering system resilience. The method's computational efficiency (averaging 3.2 minutes per decision cycle) aligns with real-time operational requirements, supporting potential deployment within actual grid control centers.

Several promising avenues for further research include integrating deep reinforcement learning techniques to improve the system's adaptability to novel failure scenarios and cyber-physical threats. Developing a federated learning architecture will facilitate knowledge sharing across multiple utility networks while maintaining data privacy, addressing critical industry concerns. Exploration of quantum computing applications may enable solving large-scale restoration problems more rapidly, potentially reducing computation time from minutes to seconds for extensive power networks.

Additional research efforts will focus on extending the SIC framework to address renewable energy integration challenges, especially considering the reliability implications of inverter-based resources and distributed energy storage systems. Incorporating predictive maintenance digital twins could further enhance model accuracy by creating virtual representations of circuit breakers that simulate aging and degradation in alignment with physical equipment.

Finally, efforts will be made to develop an international standardization protocol based on the SIC methodology for grid resilience assessment, with the potential to contribute to IEEE and IEC standards for next-generation power system restoration. Such development would promote global adoption of the framework and provide a unified metric for comparing resilience capabilities across diverse electrical networks.
These future directions build upon the current research and aim to address emerging challenges in power system resilience, ensuring the continued advancement of both theoretical understanding and practical reliability in the field.

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## Biography

**Mahdi Arabsadegh** received his B.Sc. from Ferdowsi University of Mashhad (2006), M.Sc. from Iran University of Science and Technology (IUST, 2009), and Ph.D. from Shahed University (2025) in electrical engineering, specializing in power system resiliency, reliability, and dynamics. His doctoral research focused on probabilistic modeling of circuit breaker failures and resilience-oriented network restoration. His recent publications include: "Using a Probabilistic Breaker Malfunction Model to Account for Uncertainty in the Network Restoration Process" (IET Generation, Transmission & Distribution, 2025) and "Resilience-Oriented Restoration After Storm-Induced Failures Using Genetic Algorithm and Probabilistic Circuit Breaker Modeling" (Iranian Journal of Electrical and Electronic Engineering, 2025). He currently serves as Director General of Extra High Voltage Grid Development at Tavanir Company.