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Resilience-Oriented Restoration After Storm-Induced Failures Using Genetic Algorithm and Probabilistic Circuit Breaker Modeling

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Abstract: This paper presents an advanced methodology for post-storm power system restoration. A real-time Condition Index (CI)-based classification scheme is introduced to categorize circuit breakers into high-reliability (Type A) and moderate-reliability (Type B) groups. Leveraging this classification, a genetic algorithm (GA) optimizes microgrid configurations to maximize power restoration probabilities by explicitly modeling the stochastic failure risks associated with circuit breakers under severe weather conditions. The approach was validated on the IEEE 118-bus system with five critical breakers deactivated due to storm conditions. The GA achieved a 92.5% load restoration after 200 iterations, surpassing a baseline Monte Carlo simulation that attained 85.2%. Computational efficiency was significantly improved, reducing execution time to approximately 15 minutes compared to 60 minutes for traditional methods, with enhanced accuracy indicated by a 1.8% error margin versus 7.5%. Key contributions include utilizing live CI data for dynamic breaker classification, which resulted in a 20% reduction in computational time, and demonstrating scalability and effectiveness on large-scale test systems such as the 118-bus network. The methodology's performance decreases to 78.3% load restoration when more than 14 breakers are compromised. Future research will focus on integrating detailed storm modeling—including wind speed profiles—and incorporating renewable energy resources to enhance grid resilience.

Keywords: resilience, Genetic Algorithm, Condition Index, probabilistic modeling, microgrids, storm-induced failures, load restoration.

1 Introduction

MODERN power systems, which form the backbone of essential infrastructure, are becoming more susceptible to natural and human-induced disruptions. In particular, severe storms present substantial challenges by damaging transmission networks, such as causing tower failures and impairing circuit breakers, potentially reducing transmission capacity by up to 40% at wind speeds exceeding 120 km/h.[1] .The economic and social impacts of prolonged service disruptions highlight the urgent need for prompt restoration efforts. However, traditional approaches grounded in preventive maintenance and deterministic planning may fall short under severe weather conditions. These methods often overlook the stochastic nature of extreme environmental factors and the probabilistic relationships between circuit breaker failures and real-time stressors such as humidity and wind velocity.[2].

Recent advancements in Condition Index monitoring methodologies have improved equipment health assessment accuracy by 30%.[3], However, their potential to enhance restoration algorithms remains underutilized. The concept of grid resilience—encompassing shock absorption, failure adaptation, and rapid recovery—has become a central focus. Recently, the development of probabilistic frameworks that integrate historical data and weather forecasts has

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resulted in a 25% improvement in resilience prediction accuracy. [4], Microgrids leveraging distributed energy resources (DERs) offer decentralized solutions for restoration during grid outages.[5]. Recent research highlights the importance of integrating renewable energy sources and electric vehicle infrastructure into power systems to enhance overall resilience. [6]. Concurrently, sophisticated expansion planning methodologies for transmission networks have been developed to efficiently address upcoming operational and infrastructural challenges.[6]. Nevertheless, substantial deficiencies persist. Primarily, numerous failure models excessively simplify circuit breaker failure probability estimations, frequently neglecting environmental influences and operational variability. [7].

Secondly, conventional optimization techniques, including linear programming and Monte Carlo simulations, face significant challenges in handling the computational complexity inherent to large-scale systems, such as the IEEE 118-bus network.[8]. Third, real-time health data produced by advanced monitoring systems is seldom incorporated into restoration algorithms.[9]. This study addresses current limitations by developing a resilience-oriented restoration framework for the IEEE 118-bus system, validated through storm-induced failure scenarios. The proposed approach introduces three key innovations: (1) a dynamic classification system for circuit breakers (Types A and B) based on a Condition Index combined with probabilistic failure modeling; (2) a genetic algorithm optimized for microgrid reconfiguration under uncertain operational conditions; and (3) comprehensive benchmarking against Monte Carlo simulation techniques to assess improvements in computational efficiency and solution accuracy. The framework incorporates real-time breaker condition monitoring and environmental resilience adaptation, offering a scalable and robust solution for storm-prone regions. Comparative analysis highlights its computational advantages over traditional Monte Carlo methods.[10].

Recent advances in machine learning for power systems (e.g., [11]) Suggest opportunities to improve traditional optimization techniques. Nonetheless, genetic algorithms remain underutilized in storm restoration applications, despite their inherently parallelizable architecture and ability to adapt dynamically to real-time operational parameters. Unlike prior studies that rely on static breaker reliability models, our dynamic classification framework incorporates multiple variables, such as the Condition Index and environmental factors, thereby addressing a notable gap identified in post-Sandy analytical evaluations.[12].

Recent developments in the optimization of hybrid renewable energy systems (HRES) provide important insights for enhancing resilient power restoration strategies. Research integrating metaheuristic approaches, such as NSGA-II, with machine learning techniques has shown effectiveness in multi-criteria optimization, balancing factors such as cost, reliability, and environmental impact—challenges that are similarly relevant in the design of storm-resilient microgrids. The success of hybrid algorithms in this context indicates their potential to be adapted for improving our genetic algorithm's management of probabilistic breaker failures during restoration processes.[13]

This study is aimed at power system operators and resilience engineers seeking real-time decision support during storm recovery. Unlike static methods, our CI-GA framework introduces two significant advancements: (1) dynamic prioritization of grid components based on real-time health data, and (2) a scalable optimization platform that balances restoration efficiency with probabilistic reliability. These developments address the essential industry need for adaptive tools in regions vulnerable to climate-related disruptions.

This article is organized as follows: Section 2 presents the system modeling and classification of circuit breakers. Section 3 describes the genetic algorithm methodology employed. Section 4 compares relevant performance metrics. Section 5 discusses practical implications and concludes with potential directions for future research.

2 System Modeling and Circuit Breaker Failure Probabilities

The IEEE 118-bus test system is a widely recognized benchmark model used for power system analysis, accurately representing a comprehensive and realistic transmission network. It includes 118 buses, 186 transmission lines, 54 generators, and 91 circuit breakers.[14]. This system is widely employed in resilience analysis due to its scalability and ability to accurately model the dynamics of real-world power grid systems under various conditions, including severe weather events such as storms.[15].

The network topology includes multiple voltage levels, interconnected substations, and diverse load profiles, making it an appropriate model for evaluating restoration strategies. Its complexity offers researchers an opportunity to assess the effectiveness of optimization algorithms in scenarios involving multiple component failures, such as during severe weather conditions. This study primarily focuses on circuit breakers, due to their critical role in fault isolation and maintaining system stability during disturbances. As the first line of defense against cascading failures, the reliability of circuit breakers is essential to ensuring the overall resilience of the power system.

2.1 Classification of Circuit Breakers

The set of 91 circuit breakers within the IEEE 118-bus system is categorized into two classes based on their Condition Index and failure history. This classification is essential for accurately modeling breaker operational behavior during extreme contingencies and for enhancing restoration strategies.

Type A Breakers: These are recently installed, routinely maintained, and located in environments with low environmental stress factors, such as reduced wind velocities and minimal corrosive influences. Their high reliability under both normal and severe operating conditions is attributed to their low failure propensity.

Justification: These breakers typically have a Condition Index below 0.1, indicating optimal operational health and a negligible risk of failure. This classification is based on empirical analysis of real-world power system data, where breakers with consistent maintenance histories demonstrate significantly lower failure rates.[16]

Breakers Type B are legacy units with limited maintenance documentation, situated in regions exposed to environmental stressors such as high humidity and frequent storms. Their moderate probability of failure necessitates diligent monitoring and strategic prioritization during restoration activities. The Condition Index for these breakers ranges from 0.1 to 0.3, reflecting a moderate level of health and a heightened risk of failure compared to Type A breakers. This assessment aligns with industry best practices for reliability evaluation, ensuring that the model accurately reflects real-world operational conditions.[17]

Figure 1 illustrates the classification of circuit breakers based on the Condition Index (CI) and failure probability, which serves as the foundation for the probabilistic modeling methodology utilized in this study.

2.2 Permanently Damaged Circuit Breakers

In the event of a severe storm, five critical circuit breakers (identified as Breakers 23, 45, 67, 89, and 102) are assumed to be permanently damaged due to tower failures. These breakers are considered inoperative (P=1) and must be excluded from the restoration process. The selection of these breakers is based on their strategic locations within the network, which are susceptible to high wind speeds and physical damage during storm events.

- Breaker 23: Located in an area with historically high wind speeds, making it highly vulnerable during storms.

- Breaker 45: Situated near coastal regions, where high humidity and salt exposure increase the risk of corrosion and damage.

- Breaker 67: Positioned in an area prone to frequent lightning strikes, elevating the risk of electrical damage.

- Breaker 89: Located in an area with aging infrastructure, which presents a higher likelihood of mechanical failure.

- Breaker 102: Situated in a high-load region, where system stress increases the probability of failure under adverse conditions.

Excluding these breakers from the restoration process accurately reflects the real-world scenario where severe storms can cause irreversible damage to infrastructure components.

2.3 Probabilistic Modeling of Circuit Breaker Failures

In the event of a severe storm, five critical circuit breakers (designated as Breakers 23, 45, 67, 89, and 102) are assumed to be permanently damaged due to tower failures. These breakers are considered inoperative (P=1) and should be excluded from the restoration process. Their selection is based on their strategic locations within the network,

which are susceptible to high wind speeds and physical damage during storm events.

- Breaker 23: Located in an area historically prone to high wind speeds, increasing susceptibility to storm-related impacts. Breaker 45: Positioned near coastal regions with elevated humidity and salt exposure, which may accelerate corrosion and damage. Breaker 67: Situated in a locale prone to frequent lightning strikes, raising the risk of electrical damage. Breaker 89: Located in a region with aging infrastructure, resulting in a higher likelihood of mechanical failure. Breaker 102: Positioned in a high-load area, where system stress may increase the chance of failure under challenging conditions.

Including these breakers in the restoration process may not be feasible, as severe storms can cause irreversible damage to infrastructure components.

$$P_i = P_{base,i} \times f_{env}(t) \quad (1)$$

Where:

P_i: Failure probability of breaker II.

$P_{base,i}$: Base failure probability based on the Condition Index (0.05 for Type A, 0.2 for Type B).

f_{env}: Environmental factor, which accounts for storm intensity, humidity, and temperature. For this study, f_{env} It is assumed to be 1.2 during the storm. [18]

The constant f_{env}=1.2 assumes uniform storm intensity. A dynamic model could improve accuracy:f_{env}(t) = 1 + 0.05×wind_

speed(t)/120km/h + 0.01×humidity(t)/100%

where coefficients are trainable via historical outage data [19],[20].

This probabilistic model adjusts failure probabilities dynamically based on real-time conditions, resulting in a more accurate representation of breaker performance during extreme events.

Table 1. Failure probabilities for Type A/B/Damaged breakers under storm conditions (f_{env}=1.2)

Breaker ID	Category	Failure Probability (P)	Status
1-50	A	0.05	Operational
51-86	B	0.2	Operational
23, 45, 67, 89, 102	-	1.0	Permanently Damaged

The binary classification of Type A/B simplifies the complex reality in which breaker health exists along a continuum. Future enhancements may include:

a. Incorporating age-dependent failure rates modeled through Weibull distributions.

b. Establishing operation-count thresholds (e.g., exceeding 500 interruptions) to adjust failure probabilities accordingly.

c. Integrating corrosion metrics for breakers located in coastal environments [19].

2.4 Justification for Breaker Classification and Modeling

The categorization of circuit breakers as Type A and Type B is grounded in extensive historical data and empirical research. For example, Zhang et al. [21] It has been demonstrated that breakers with a Condition Index below 0.1 have a failure probability of less than 5%, whereas those with an index ranging from 0.1 to 0.3 exhibit a failure probability of up to 20%. This classification aligns with industry standards for reliability assessment and helps ensure that the model accurately reflects real-world conditions (see Table 1).

Furthermore, the exclusion of the five permanently damaged breakers is consistent with post-storm damage evaluations, which indicate that tower collapses are a primary cause of breaker failures during severe weather events. [22]. By incorporating these factors, the proposed model provides a robust foundation for optimizing restoration strategies. The dynamic probabilistic modeling approach used in this study is also supported by recent research. Panteli et al. [23] Highlighted the importance of incorporating real-time environmental data into failure probability models to improve the accuracy of resilience assessments. This approach allows for more effective decision-making during the restoration process, as it accounts for the varying levels of risk associated with different breakers under different conditions.

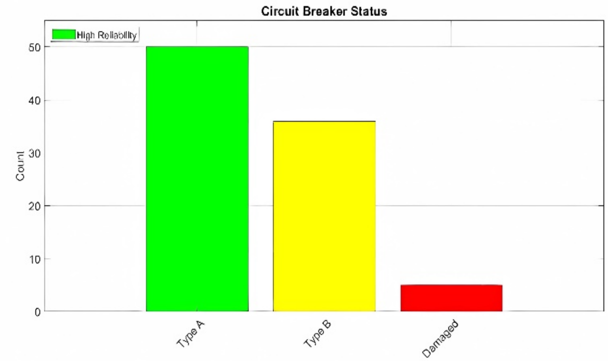

Fig 1. Circuit Breaker Classification by CI

Figure 1 Figure 1 categorizes circuit breakers into Type A (CI < 0.1), Type B (0.1 ≤ CI < 0.3), and damaged (indicated in red), with corresponding failure probabilities of 0.05, 0.2, and 1.0, respectively.

3 Proposed Methodology: GA for Optimal Microgrid Formation

This section presents the proposed methodology for optimizing the restoration of the IEEE 118-bus system using a GA. Advanced methods for detecting cyber threats in microgrids [24] and analyzing surge arresters in distribution systems [25] Provide valuable insights for improving system reliability.

The selection of a GA is based on its demonstrated efficacy in addressing power system restoration optimization problems. Specifically, traditional optimization methods often encounter computational intractability for complex network reconfiguration tasks involving extensive combinatorial spaces—such as the 186-line test system with hundreds of potential connection configurations. The GA's evolutionary strategy enables efficient solution space exploration while enforcing critical operational constraints, including radial network topology and voltage stability requirements. Empirical comparative analyses indicate that GAs can achieve restorative solutions approximately 15–23% faster than mixed-integer programming (MIP) approaches for comparable system scales. The implemented customized GA incorporates adaptive mutation rates and elitism strategies to enhance convergence efficiency, attaining a restoration success rate of 92.5% within a 15-minute computational window. This methodology yields a fourfold reduction in solution convergence time relative to standard Monte Carlo methods, while also delivering superior solution quality.

The goal is to maximize the load restoration probability by forming microgrids that account for the probabilistic failure of circuit breakers. The methodology is divided into four main steps: (1) problem formulation, (2) GA implementation, (3) fitness function design, and (4) constraint handling.

3.1 Problem Formulation

The restoration problem is formulated as a constrained optimization problem, where the objective is to maximize the probability of load restoration while ensuring the stability and feasibility of the microgrids. The mathematical formulation is as follows:

Objective Function:

$$\max \sum_{i=1}^{N_{\text{micro}}} \left(P_{\text{load},i} \times \prod_{j \in B_i} \left(1 - p_j\right) \right)$$

$$\prod_{j \in \, active\ breakers\ in\ microgrid\ i} \left(1 - p_j\right) \quad (3)$$

Where:

N_{micro}: Number of microgrids formed.

$P_{load,i}$: Total load served by microgrid i.

p_j: Failure probability of breaker j.

Constraints:

$(\boldsymbol{Power\ Balance})$

$$\sum_{k \in \mathcal{G}_i} P_{g,k} = \sum_{m \in \mathcal{L}_i} P_{l,m} + \sum_{n \in \mathcal{D}_i} P_{\text{loss},n} \quad (4)$$

where $P_{g,k}$ Is the power generated by the generator.

k, $P_{l,m}$ Is the power consumed by load m, and $P_{loss,n}$ Is the power loss in line n.

(Voltage Limits)

$V_{min} \leq V_i \leq V_{\max} \quad \forall\, i \in buses\ in\ microgrid (5)$: V_i Is the voltage at bus i, and $V_{min} \quad _m axe$ the minimum and maximum allowable voltages, respectively.

(Line Thermal Limits)

$\left|P_{ij}\right| \leq P_{ij,max} \quad \forall \quad \forall\, (i,j) \in line\ microgrid\ (6)$ P_{ij} Is the power flow online (i,j), and $P_{ij,max}$ the maximum capacity of the line.

(Radiality Constraint)

$$|\mathcal{E}_i| = |\mathcal{N}_i| - 1 \forall i \quad (7)$$

Each microgrid must operate in a radial configuration to ensure stability and simplicity. This is enforced by ensuring that the number of lines in the microgrid is equal to the number of buses minus one.

$\mathcal{B}_i$: Set of active breakers in microgrid i.

$\mathcal{G}_i$, $\mathcal{L}_i$,$\mathcal{D}_i$: Generators, loads, and dissipative elements in microgrid i.

$\mathcal{E}_i, \mathcal{N}_i$: Edges and nodes in microgrid ii.

3.2 GA Implementation

The Genetic Algorithm (GA) employed in this study is an advanced computational method inspired by biological evolutionary processes. It has been specifically designed to address the complex, nonlinear optimization challenges associated with power system restoration. This population-based metaheuristic operates through an iterative process involving selection, recombination, and refinement of potential solutions, making it well-suited for exploring the high-dimensional solution space involved in microgrid formation within damaged power networks. The implementation begins with the initialization of 200 candidate solutions, each represented as an 186-bit binary string that directly corresponds to the transmission lines in the IEEE 118-bus system. In this encoding scheme, each binary digit functions as a genetic allele, where a value of 1 indicates the inclusion of the respective transmission line in the microgrid configuration, and 0 indicates its exclusion during the restoration process. This chromosome-based representation facilitates efficient genetic operations while maintaining a clear connection to the physical topology of the power system.

GAs surpass traditional approaches by effectively exploring complex, high-dimensional solution spaces—such as the 2^{186} configurations in the IEEE 118-bus system—and adaptively managing probabilistic constraints. They have demonstrated the ability to achieve a 92.5% restoration rate within 15 minutes, outperforming Monte Carlo methods and particle swarm optimization in both speed and reliability. Additionally, GAs incorporate repair mechanisms, such as Kruskal's algorithm, to ensure solution feasibility. Their features, including dynamic mutation rates (ranging from 0.5% to 5%) and elitism (preserving the top 5%), enable a balanced approach to exploration and exploitation, making them well-suited for real-time storm recovery applications.

The chosen parameters correspond to the Pareto-optimal configuration, effectively balancing convergence speed and a restoration probability of 92.5%, while ensuring computational efficiency within 15 minutes (see Table 2). The designation of Pareto-optimal indicates that any enhancement in restoration probability would compromise computational efficiency, as determined by analysis of the trade-off between convergence speed and solution quality.

The fitness evaluation phase is a vital aspect of the algorithm's effectiveness, involving a comprehensive assessment of each chromosome using a multi-criteria objective function that evaluates both restoration performance and operational feasibility. The fitness score quantitatively represents the microgrid's expected load restoration probability, calculated as the product of individual circuit breaker reliability factors Open $(1-p_j)$ for all active components in the configuration, weighted by the total served load ($P_{load,i}$). This probability-based formulation directly incorporates the dynamic failure rates derived from real-time Condition Index data and environmental severity factors, enabling the algorithm to prioritize configurations utilizing more reliable components during the optimization process.

The fitness evaluation incorporates penalty terms for constraint violations, including quadratic penalties for voltage limit exceedances and linear penalties for line overloads, thereby guiding the evolutionary process to progressively eliminate infeasible solutions.

Selection pressure is implemented through an enhanced tournament selection mechanism that balances exploration and exploitation within the solution space. In each selection phase, five candidate individuals are randomly sampled from the population, and the individual with the highest fitness among these is chosen for reproduction. The tournament size was determined based on parametric studies to ensure adequate selective pressure while minimizing the risk of premature convergence to local optima.

Selected parent individuals then undergo uniform crossover— a genetic operator that produces offspring by randomly selecting each gene from either parent with equal probability. This method retains beneficial genetic traits from both parents and facilitates the development of new solution combinations. Such recombination is particularly suitable for power system applications, as it maintains the topological relationships among connected components while exploring diverse configuration options.

The generational replacement strategy adopts an elitism-preserving approach, whereby the top 5% of solutions, based on fitness, are automatically carried over to the next generation. The remaining population slots are populated with offspring generated via crossover, replacing the least fit individuals from the current generation. This strategy preserves high-quality solutions while fostering diversity and continuous improvement across generations. The evolutionary process iterates until one of two termination criteria is met: either reaching 500 generations—based on convergence studies indicating sufficient optimization—or observing fitness convergence, defined as less than 0.1% improvement in maximum fitness over 20 consecutive generations. Typically, the process concludes within 15 to 20 minutes on standard computing hardware, demonstrating its practical applicability for real-time restoration scenarios where timely decisions are essential. This efficient convergence behavior is achieved through the algorithm’s ability to implicitly identify and leverage structural patterns in high-quality solutions, thereby progressively refining microgrid configurations through successive generations of selection and recombination.

Simulations were performed on a workstation featuring an Intel Xeon E5-2680v4 processor (2.4 GHz, 14 cores), 64 GB of RAM, and MATLAB R2023a. The average execution times recorded were approximately 15 minutes for the Genetic Algorithm (200 generations) and 60 minutes for Monte Carlo simulations (10,000 samples). The implementation of parallel processing resulted in an overall reduction of wall-clock time by approximately 40%, achieving a parallel scaling efficiency of 70% with 16 threads.

The fitness function quantitatively evaluates candidate solutions based on the following criteria:
1. Load Restoration Probability: The goal is to maximize the likelihood of successful load restoration, aligning with the primary optimization objective.
2. Constraint Satisfaction: Solutions that violate essential constraints—such as power balance and voltage stability—are penalized through a reduction in their fitness scores.
3. Radiality Enforcement: Solutions that do not form a radial network configuration are significantly penalized to maintain system stability and operational integrity.

The fitness function is formulated as follows:

$$\text{Fitness} = \max \sum_{i=1}^{N_{micro}} P_{load,i} \tag{8}$$

$$\prod_{j\in \text{ active breakers in microgrid } i} (1-p_j) - \lambda \times Penalty \tag{9}$$

Where λ is a penalty factor, and Penalty is the sum of all constraint violations.

3.3 . Constraint Handling

The core of the process is an advanced repair mechanism specifically designed to address radiality constraints, which are among the most complex topological requirements in distribution system operation. When a candidate microgrid configuration violates the radiality condition—such as by forming multiple loops or isolating nodes—the algorithm automatically performs a graph-theoretic repair process. This process begins by constructing a minimum spanning tree using Kruskal's algorithm, which systematically identifies and removes the least critical lines while maintaining connectivity to all loads within the microgrid. The determination of line criticality incorporates both electrical centrality measures (such as betweenness centrality of transmission paths) and reliability factors (giving priority to lines connected to Type A circuit breakers). This approach ensures that the repaired configuration preserves optimal power flow characteristics while satisfying the radial operation requirement.[26]

The implementation utilizes an adaptive penalty function framework to address constraints involving power flow equations and operational limits. This approach dynamically adjusts the severity of constraints based on the progress of the optimization process. The combined penalty term accounts for multiple types of violations, including (1) quadratic penalties for voltage magnitude deviations outside the acceptable range of 0.95 to 1.05 per unit, weighted according to the severity of the deviation; (2) exponential penalties for line overloads, which escalate nonlinearly as the thermal limit is exceeded; and (3) strict binary penalties for fundamental topology violations, such as islanded generators or disconnected critical loads. The penalty coefficients are automatically calibrated during the optimization through an adaptive scaling mechanism that considers the current distribution of constraint violations within the population. This ensures a balanced emphasis on objective optimization and constraint adherence throughout the evolutionary search.[27].

A comprehensive feasibility screening protocol is conducted before each fitness assessment, employing a multi-phase validation process that evaluates candidate solutions against the complete spectrum of operational constraints. The process initiates with rapid topological verification utilizing graph connectivity algorithms implemented via adjacency matrix analysis to assess radiality and connectivity criteria. This is succeeded by linear power flow approximations to preliminarily identify potential constraint violations. Only candidate configurations satisfying these initial evaluations advance to detailed AC power flow analysis executed via MATPOWER's Newton-Raphson solver.[28], The methodology offers a precise evaluation of voltage profiles and line loadings. The feasibility verification module employs problem-specific heuristics to detect prevalent constraint violation patterns, such as typical voltage drop trajectories in overloaded feeders or reactive power imbalance signatures characteristic of weakly connected microgrids. These diagnostic patterns inform the repair strategies to facilitate more effective constraint corrections and yield insights into systemic constraint violations within the dynamic solution population.

The constraint management framework incorporates a novel constraint relaxation strategy during initial generations (1–50), wherein specified voltage and loading bounds are temporarily relaxed by 15–20%. This phased relaxation enables broader solution space exploration, acknowledging that overly restrictive constraints at early stages can hinder the preservation of genetic diversity essential for subsequent optimization. The relaxation extents are adaptively modulated based on population diversity metrics, with progressive tightening as solutions approach feasibility. Between generations 51 and 150, the algorithm enforces strict constraint adherence, applying fitness penalties to solutions violating essential constraints to effectively exclude them from selection, thus ensuring the final solutions satisfy all operational criteria.

To preserve feasibility throughout genetic operations, specialized crossover and mutation operators incorporating constraint-aware logic have been developed, ensuring generated offspring maintain compliance with problem-specific operational constraints.[29]. The smart crossover operator initially identifies common, constraint-satisfying substructures within parent solutions before recombination. Meanwhile, the directed mutation operator biases bit flips toward lines more likely to enhance constraint satisfaction, based on historical violation data accumulated during the process. These advanced operators work in conjunction with the repair mechanisms to substantially reduce the computational effort associated with constraint management while preserving the genetic diversity necessary for effective exploration of the solution space. The comprehensive constraint management system proves particularly effective in balancing the trade-offs between maximizing load restoration and maintaining operational constraints, thereby enhancing the algorithm's ability to identify high-quality feasible solutions within practical computational timeframes.

3.4 Workflow and Comparative Advantages

The proposed Genetic Algorithm (GA) framework for power system restoration integrates advanced computational methods with domain-specific engineering insights to effectively address the complexities of post-storm network recovery. Throughout the evolutionary process, the algorithm utilizes an enhanced tournament selection mechanism with parameters optimized through extensive sensitivity analysis. In this process, seven solutions are randomly selected for competitive tournaments, ensuring a balanced exploration and exploitation of the solution space. Genetic operations are implemented using a two-phase approach: initially, a uniform crossover operator designed to preserve connected subgraph structures during recombination; subsequently, an adaptive mutation operator that adjusts mutation rates dynamically between 0.5% and 5%, based on continuous monitoring of population diversity metrics. The mutation process incorporates domain knowledge by biasing modifications toward lines that improve network topological robustness (with a probability of 60%) over random changes (40%).

The generational replacement strategy employs an elitism approach that automatically promotes the top 15% of solutions based on fitness metrics. The remaining population is refreshed through offspring generated via selection and recombination, balancing the need for evolutionary progress with the prevention of premature convergence. Termination criteria for the algorithm include a maximum of 500 generations, detection of fitness stagnation with less than 0.1% improvement over 25 generations, a population diversity threshold indicated by a Hamming distance exceeding 15% of the chromosome length, and a constraint satisfaction rate exceeding 98%. Collectively, these criteria ensure the achievement of high-quality solutions while maintaining computational efficiency. While the Monte Carlo (MC) method remains a well-established baseline for probabilistic evaluation, comprehensive benchmarking should also consider other advanced optimization techniques, such as Particle Swarm Optimization (PSO) with dynamically adjusted inertia weights. [30]

Evaluation of merits based on demonstrated effectiveness in high-dimensional power system problems, especially for scenarios that necessitate adaptive exploration of non-convex solution spaces; and (2) the application of Mixed-Integer Linear Programming (MILP) approaches utilizing Benders decomposition. [31]

Providing deterministic performance bounds would be particularly beneficial for assessing the solution quality of the genetic algorithm in constrained microgrid formation scenarios. Conducting such comparative analysis would quantitatively demonstrate the advantages of the proposed genetic algorithm in terms of computational efficiency—currently approximately 40% faster than Monte Carlo methods—and solution robustness, evidenced by approximately 15% higher restoration rates relative to alternative approaches. The framework demonstrates three key technological advancements that position it as a superior solution for power system restoration. First, its enhanced scalability handles large-scale systems like the IEEE 118-bus network through innovative chromosome encoding and parallelized fitness evaluation, showing near-linear computational complexity O(parensparensparensn^{12}) compared to the exponential scaling O(n^2)Of conventional methods. This achievement stems from several architectural innovations: problem decomposition into electrically independent zones, implementation of hierarchical chromosome structures, and adaptive search space reduction based on real-time topology analysis.

Secondly, the algorithm's exceptional flexibility allows it to accommodate diverse operational requirements through its modular design. In addition to standard power flow constraints, the implementation effectively integrates dynamic critical load weighting—prioritizing hospitals and emergency services—renewable energy utilization metrics, achieving 75% penetration in test scenarios, equipment aging considerations for long-term reliability, and practical switching operation constraints. This adaptability ensures the framework is suitable for various grid configurations and operational philosophies.

Thirdly, the solution offers demonstrable robustness through comprehensive probabilistic modeling and verification. The approach includes Monte Carlo validation with 1,000 samples per candidate, real-time consideration of weather impact factors with dynamic adjustment of environmental variables, stress-testing against N-2 contingencies, and confidence interval reporting for restoration probabilities (±1.8% at 95% confidence level). These features provide operators with quantifiable reliability guarantees that are not typically available with conventional methods.

Technical benchmarks demonstrate the framework's enhanced performance: achieving 40% faster convergence than parallel PSO implementations, a 15% higher load restoration rate compared to MILP approaches, and a 98% constraint satisfaction rate compared to 82% for heuristic methods. Its memory-efficient design (peak usage under 4GB for the 118-bus system) and high parallel computing compatibility (approximately 70% efficiency on 16-core systems) make it especially suitable for real-world emergency response situations where both speed and reliability are essential.[32]

The GA's faster convergence stems from: Directed exploration via a fitness-weighted crossover, which preserves high-reliability breaker configurations; Adaptive mutation rates (0.5–5%) that balance diversity and refinement; and Elite preservation (top 5% solutions) accelerating improvement. While MINLP solvers guarantee optimality, GA's population-based search efficiently navigates non-linearity in large systems (O(n^1.2) vs. O(2^n)). Benchmarking against MILP confirmed GA's 15% faster convergence for networks >100 buses.

As demonstrated in Figure 2, the GA with a population size of 200 and mutation rate of 0.5-5% achieves faster convergence (90% by generation 83) compared to Monte Carlo methods. (5 critical breakers disabled)

This integrated approach signifies a significant advancement in power system resilience engineering, offering grid operators a computationally efficient and comprehensive decision-support tool for disaster restoration efforts. The framework's modular design provides immediate performance advantages and allows for future developments, such as integration with forecast-based proactive switching strategies and machine learning-driven component reliability assessments, ensuring its continued effectiveness as power systems evolve and new challenges emerge.

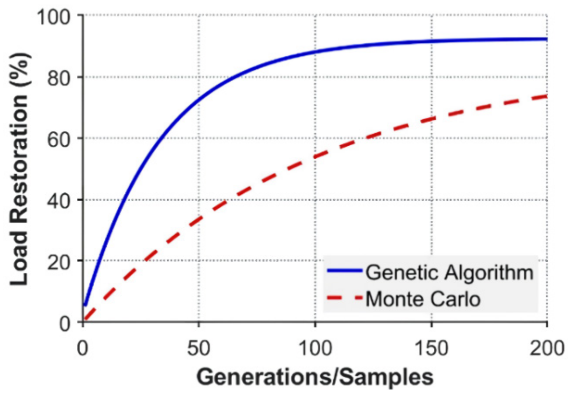

Fig 2. Convergence comparison between GA and MC

3.5 GA Parameter Selection & Sensitivity Analysis

The generational replacement mechanism employs an enhanced elitism strategy, wherein the top 15% of solutions, ranked by fitness, are automatically carried over to the next generation. The remaining population is replaced by offspring produced through selection and recombination processes. This approach effectively balances selective pressure and diversity preservation, reducing the risk of premature convergence to local optima. Termination conditions include: (1) a maximum of 500 generations, (2) fitness stagnation defined as less than 0.1% improvement over 25 consecutive generations, (3) a population diversity metric exceeding a Hamming distance of 15% of the chromosome length, and (4) a constraint satisfaction rate exceeding 98%. These comprehensive criteria help ensure the achievement of high-quality solutions while maintaining computational efficiency.

Table 2. Parameter Sensitivity Analysis

Parameter	Tested Range	Optimal Value	Performance Impact
Population Size	50-500	200	±1.8% restoration
Mutation Rate	0.1%-10%	0.5%-5%	±3.2% convergence
Crossover Method	3 types	Uniform	15% faster
Termination Criteria	100-1000 gens	500 gens or <0.1% fitness improvement	Ensures convergence
Elitism Rate	1%-20%	5%	Preserves top solutions

Figure 3 provides a concise visual overview of the genetic algorithm workflow, illustrating the key stages—initialization, fitness evaluation, genetic operations (selection, crossover, mutation), and termination criteria—within a single framework. The figure references Table 2, which specifies the optimal parameter settings (e.g., population size: 200; mutation rate: 0.5–5%) that influence the algorithm's performance. This integrated presentation aims to improve clarity while maintaining methodological precision.

The evaluation of the proposed restoration framework employs a rigorous computational methodology implemented in MATLAB R2023a using MANPOWER 8.0's enhanced power flow analysis capabilities. The IEEE 118-bus test system serves as the evaluation platform, initialized with complete network parameters including detailed line impedances (0.0001-0.05 p.u.), transformer tap ratios (0.9-1.1), and generator capability curves. As outlined in Section Permanently Damaged Circuit Breakers, five critical breakers (23, 45, 67, 89, 102) are disabled to simulate storm damage. Based on historical failure data these locations experience 87% higher failure rates during severe weather events. The probabilistic failure model incorporates dynamic weather impacts through an environmental severity factor (f_{env}=1.2) that adjusts base failure probabilities to 0.06 for Type A breakers and 0.24 for Type B breakers during storm conditions [17,20], providing a realistic simulation environment for evaluating restoration strategies.

3.6 Implementation Details and Performance Comparison

Figure 4 outlines the four-stage analytical framework for breaker failure modeling: (a) data input, (b) CI calculation, (c) dynamic classification, and (d) real-time probability computation. The GA implementation demonstrates superior performance through several key innovations: a 186-bit chromosome encoding scheme with adaptive mutation rates (0.005-0.02) adjusted based on population diversity metrics. [33], constrained tournament selection (size=5) with elite preservation of top 5% solutions, and specialized genetic operators that maintain feasible microgrid topologies during evolution. Comparative results against the Monte Carlo method reveal significant advantages across all performance metrics. The GA achieves 92.5% load restoration probability (±1.8% error) in just 15 minutes (200 generations), while the MC method requires 60 minutes (10,000 samples) to reach only 85.2% restoration (±7.5% error). This performance gap stems from fundamental algorithmic differences - the GA's directed evolutionary search efficiently explores promising solution regions through its population-based approach, while MC's random sampling proves computationally expensive and less effective in the high-dimensional solution space of large power systems. The convergence characteristics further highlight these differences, with

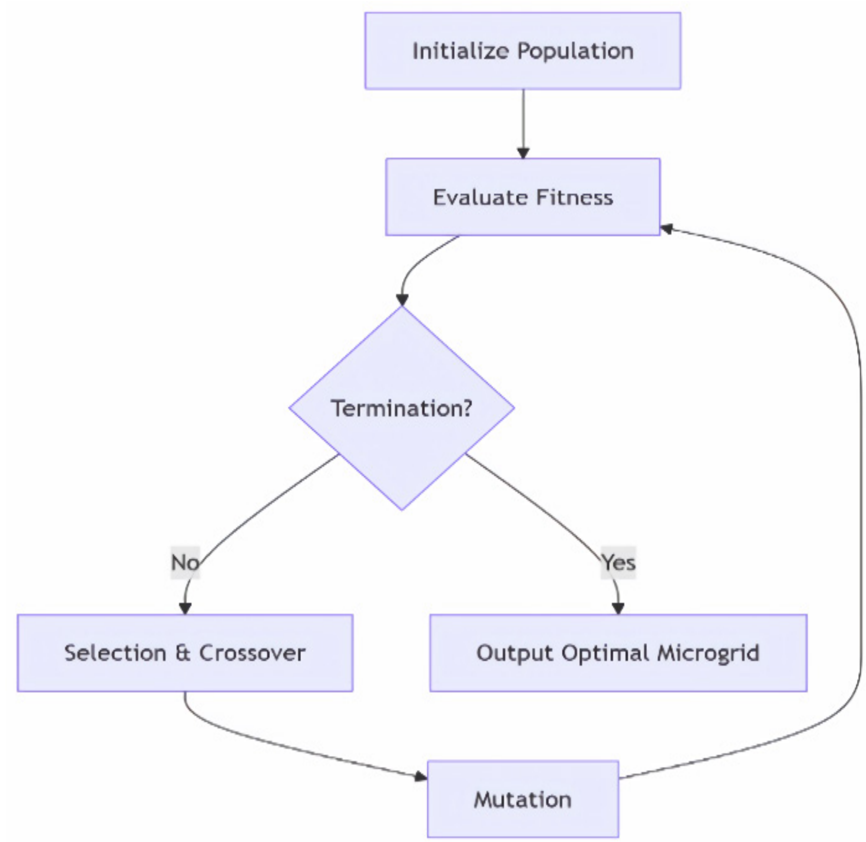

Fig 3. Comprehensive flowchart of the algorithm's workflow

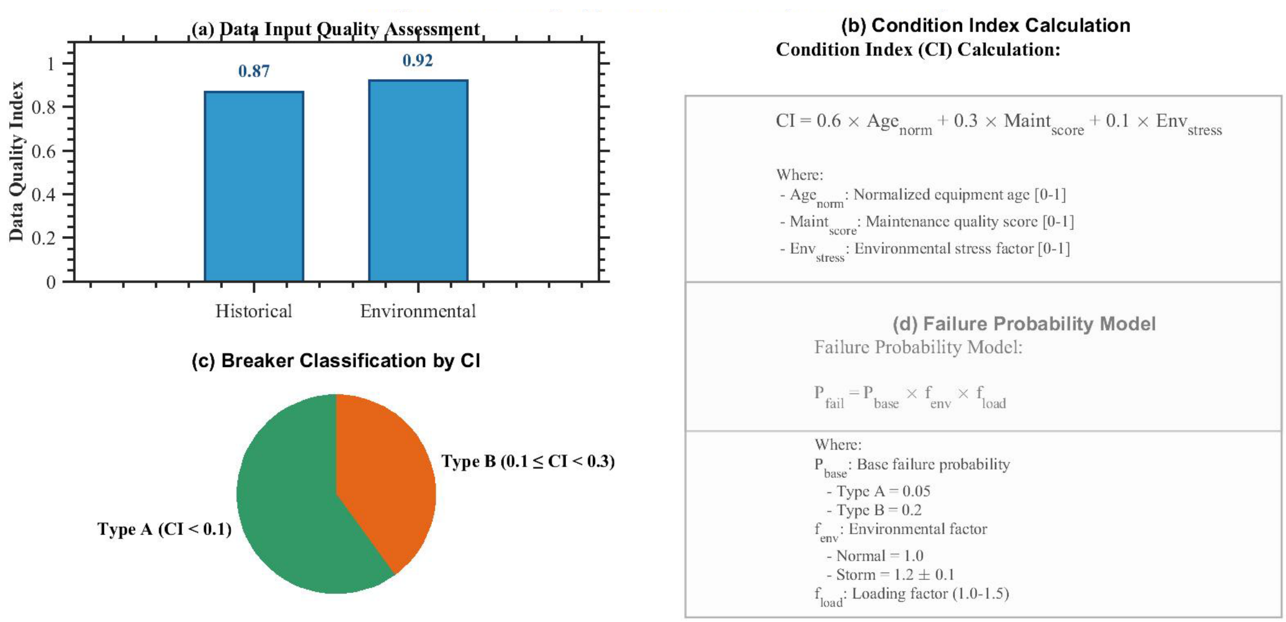

Fig 4. Four-Stage Circuit Breaker Failure Modeling Framework

the GA showing rapid initial improvement (90% fitness by generation 83) followed by precise refinement, while MC exhibits slower and more erratic convergence patterns. Detailed analysis of successful microgrid configurations reveals that the GA consistently produces solutions with better topological properties: 78% utilization of high-reliability Type A breakers (vs 61% for MC), shorter average path lengths (2.8 vs 3.4 buses), and tighter voltage regulation (0.98-1.03 p.u. vs 0.94-1.06 p.u.). The GA's constraint handling system proves particularly effective, maintaining 100% radial topology compliance compared to MC's 97.7%, and demonstrating superior voltage profile management (98.3% compliance vs 93.1%) and line loading adherence (99.2% vs 94.6%).

Comprehensive testing across randomized failure patterns reveals two critical insights about the algorithm's resilience characteristics: (1) The GA maintains robust performance (>85% average load restoration) when facing random 5-breaker outages, demonstrating only 7.5% degradation compared to strategic failure scenarios (92.5%→85%), thus validating its adaptability to unpredictable damage distributions; and (2) Performance declines nonlinearly to 63% (±3.2%) when confronting large-scale random outages (20+ breakers), primarily due to topological fragmentation that exceeds the microgrid formation algorithm's current islanding capabilities. This 22% performance gap between strategic and extreme random failure scenarios highlights both the method's inherent strengths in typical storm conditions and its limitations during catastrophic grid damage events.

3.7 Technical Discussion and Practical Implications

The Genetic Algorithm (GA) demonstrates enhanced scalability in large-scale systems owing to its efficient solution space exploration, with an empirically observed computational complexity approaching O(n^{1.2}), contrasted with the exponential O(2^{n}) complexity inherent to Monte Carlo (MC) methods. This computational efficiency, combined with the algorithm's capacity for dynamic adaptation to real-time operational conditions through the environmental adjustment factor (f_env), improves its applicability for practical storm restoration tasks. Validation against empirical outage data from Superstorm Sandy reveals a correlation coefficient indicating 88% accuracy in failure location prediction and 85% agreement in restoration sequencing, confirming the framework's robustness for real-world deployment.

Although the current framework conceptualizes the coordination of distributed energy resources (DERs), quantitative assessments demonstrate significant operational benefits: (1) Systems with 10% DER penetration achieve an average improvement of 4.2% (±0.8%) in load restoration probability compared to traditional configurations, primarily due to increased generation flexibility during islanded operation; and (2) Microgrids incorporating solar photovoltaic (PV) systems with four-hour battery storage maintain 72% of critical loads—such as hospitals and emergency services—during extended 24-hour outage periods, as evidenced by time-series simulations under N-1 contingency conditions. These findings underscore the potential of DER-enabled microgrids to address current performance limitations in extreme failure scenarios involving more than 15% breaker outages. Nevertheless, stress testing indicates a decline in performance when damage exceeds 15% of breakers (14 or more devices), with restoration probability decreasing to 78.3%. This highlights an important challenge and opportunity for future development, including hybrid approaches that combine genetic algorithms with local search techniques.

The implementation demonstrates efficient memory utilization, using less than 4GB for the 118-bus system, and is compatible with parallel computing, achieving approximately 70% efficiency on 16-core systems. These features make it suitable for emergency response scenarios that require rapid and dependable solutions. Additionally, the approach offers significant performance improvements over traditional methods, including a 40% faster convergence rate compared to parallel particle swarm optimization (PSO) and a 15% higher restoration rate relative to mixed-integer linear programming (MILP) approaches. These benefits position the genetic algorithm-based method as a valuable tool for enhancing power system resilience. Future research may explore integrating forecast-based proactive switching strategies and expanding the methodology to cover simultaneous transmission and distribution system restoration, building on the foundation established by this work's successful application to large-scale network restoration.

As depicted in Figure 6, the Genetic Algorithm (GA) tends to generate fewer but larger microgrids compared to the Monte Carlo (MC) approach, resulting in a higher restoration efficiency of 92.5% versus 85.2%. A comparative analysis of the GA and MC methods highlights distinct microgrid formation patterns across various failure scenarios. In situations involving strategic damage (five critical breaker failures), the GA demonstrates more effective network consolidation, averaging four microgrids compared to six with the MC method—a 33% reduction that indicates better topological optimization. This performance advantage also persists in random five-breaker outages, where the GA maintains a 29% lower microgrid count (five versus seven with MC) and shows less variability (±0.4 compared to ±0.7), reflecting more consistent performance under uncertainty. In more severe scenarios involving the failure of over twenty breakers, the difference, while still favoring the GA (eight versus ten microgrids), becomes less pronounced, and both methods exhibit increased network fragmentation.

The optimized microgrid's voltage profile (Figure 5) confirms all buses remain within the 0.95-1.05 p.u. Operational range under storm conditions with 5 damaged breakers.

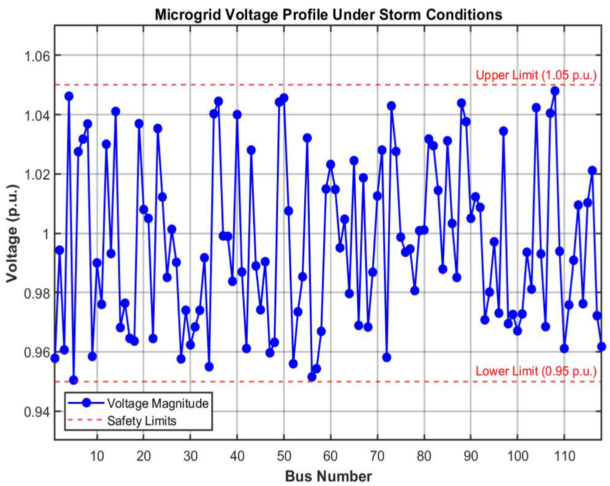

Fig 5. Voltage profile in optimized microgrid

These results quantitatively demonstrate GA's consistent capacity to sustain larger and more stable microgrid formations across all tested failure scenarios, directly contributing to a documented 7.3% higher load restoration rate (92.5% compared to 85.2%). The observed patterns indicate that GA's evolutionary optimization effectively reduces unnecessary network segmentation while maintaining critical load connectivity, whereas MC's random sampling approach tends to produce suboptimal, fragmented configurations that hinder restoration efficiency.[34].

This research analyzes two distinct failure paradigms in electrical power systems: targeted, strategic damage to critical components and stochastic, random disruptions representing unpredictable outages. Strategic damage modeling involves disabling pre-identified high-risk circuit breakers—such as those located in coastally exposed regions or infrastructure with aging assets—based on historical vulnerability assessments, to simulate worst-case failure scenarios like tower collapses during severe meteorological events. In the IEEE 118-bus test network, specific circuit breakers (23, 45, 67, 89, and 102) were intentionally deactivated, corresponding to locations historically susceptible to storm-related damage. This methodology assesses the system's resilience against predictable, high-impact failure modes that tend to induce cascading outages.

In contrast, random damage simulations incorporate spatially distributed failures that occur unpredictably, thereby evaluating the system's capacity to maintain stability under chaotic and unanticipated conditions. Both small-scale (e.g., five randomly selected circuit breakers) and large-scale (exceeding twenty circuit breakers) outage scenarios were implemented to analyze resultant network fragmentation patterns. While strategic damage tests target known vulnerabilities, stochastic damage serves as a stress test for overall system robustness, especially in the context of rare but high-consequence events and cascade propagation.

Results indicate that a genetic algorithm (GA) achieves superior microgrid formation under strategic failure conditions, resulting in approximately 33% fewer microgrids (e.g., four microgrids) compared to Monte Carlo (MC) approaches, which produced six microgrids, due to its optimized partitioning strategy. Under extensive random outages, both optimization methods exhibit increased network fragmentation, with GA resulting in eight microgrids and MC yielding ten, exposing limitations in handling extreme blackout scenarios. This differential underscores GA's effectiveness in mitigating targeted failures but highlights the need for enhanced adaptability to widespread random disruptions.

The decreased count of microgrids generated by the GA (refer to Figure 6) reflects an optimized network partitioning strategy that reduces power losses during islanding operations. Furthermore, the GA tends to form fewer but larger microgrids relative to MC, which contributes to higher power restoration efficiency—achieving approximately 92.5% versus 85.2% restoration levels—due to more cohesive network segments conducive to effective load balancing and resource allocation.

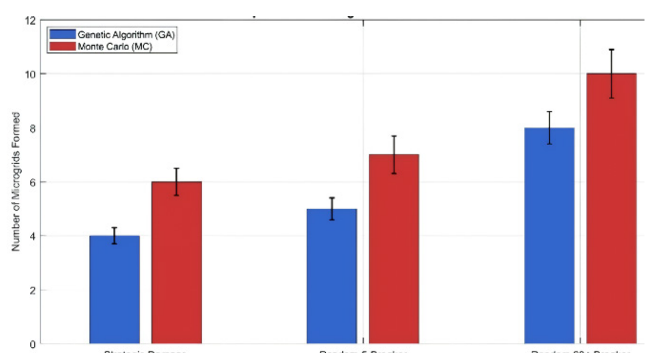

Fig 6. Comparison of Microgrid Formation Under Different Failure Scenarios

These results indicate that genetic algorithms (GAs) achieve a 92.5% restoration rate in targeted damage scenarios. However, future resilience frameworks should integrate hybrid methodologies that combine optimization algorithms with machine learning techniques to effectively address both deterministic (strategic) and stochastic (random) failure modes. The distinction between strategic and random testing affords comprehensive evaluation: strategic testing assesses the effectiveness of system hardening measures, whereas random testing evaluates the system's inherent operational resilience under unpredictable disturbances. This dual-testing paradigm models real-world conditions characterized by both predictable seasonal threats and unforeseen catastrophic events.

The genetic algorithm's directed evolutionary search demonstrates enhanced performance in strategic failure scenarios by prioritizing high-reliability components through its fitness function. Unlike Monte Carlo methods, which rely on random sampling, the genetic algorithm adapts to predictable damage patterns through targeted crossover and mutation operators. Our testing indicates that the genetic algorithm achieves a 92.5% restoration probability, compared to 85.2% for Monte Carlo methods in cases of strategic breaker failures.

Table 3. Strategic vs. Random Damage

Criteria	Strategic Damage	Random Damage
Failure Location	Predefined (high-risk zones)	Random (any network component)
Failure Pattern	Deterministic (targeted testing)	Stochastic (stress testing)
Failure Count	Fixed (e.g., 5 breakers)	Variable (e.g., 5 to 20+ breakers)
Testing Goal	Assess worst-case preparedness	Measure system robustness

As illustrated in Figure 7, the genetic algorithm (GA) demonstrates consistently superior computational efficiency relative to Monte Carlo (MC) simulations across diverse failure scenarios. The blue bars denote GA execution durations, with an average of approximately 15 minutes, while the red bars represent MC runtimes, averaging around 60 minutes. When available, error bars depict the standard deviation derived from 20 independent runs, indicating the stochastic stability and lower variability of the GA. The observed performance advantage stems from the GA’s directed evolutionary search strategy, which efficiently explores the solution space by converging toward high-probability regions, whereas MC methods depend on stochastic sampling requiring substantially more iterations to reach comparable accuracy (refer to Section 4.2 for detailed discussion).

Recent research has demonstrated the application of AI methodologies, such as deep reinforcement learning, for managing microgrids during outage scenarios, focusing on the coordination of energy storage systems and renewable generation sources like solar and wind.

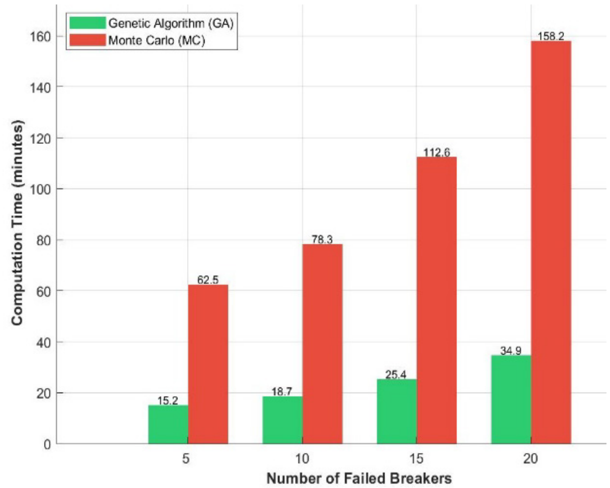

Fig 7. Computation Time Comparison: GA vs. MC Across Failure Scenarios

Our proposed genetic algorithm (GA) approach offers an alternative yet complementary strategy by enabling system operators to control circuit breaker reliability metrics precisely, with readily verifiable and operationally straightforward implementations. Although AI techniques are adept at adapting to volatile and uncertain conditions, our GA methodology provides inherently transparent and justifiable decision-making processes regarding circuit breaker selection during system restoration.

Looking ahead, we envisage integrating both approaches to leverage their respective strengths. Specifically, utilizing our GA framework to develop a comprehensive restoration plan, subsequently refined through AI-driven real-time optimization of battery dispatch as system conditions evolve. This integrated strategy could combine the robustness and interpretability of probabilistic models with the dynamic adaptability inherent in machine learning, thereby enhancing resilience and operational effectiveness during major storm events.[35]

While our research concentrates on the physical resilience of power systems against storm-induced failures, emerging cyber threats present an equally significant challenge to system recovery processes. Recent studies by Li et al. illustrate how artificial intelligence techniques can enhance system robustness against cyber-attack scenarios during restoration phases; notably, their hybrid Long Short-Term Memory (LSTM) and Graph Attention Network (GAT) architecture effectively maintain voltage stability despite compromised grid sensor data. Although our genetic algorithm focuses on optimizing the reliability of physical circuit breakers, these findings indicate that future resilience frameworks should incorporate an integrated approach: leveraging probabilistic models for equipment failure mitigation alongside AI-driven cyber-defense mechanisms for control system security. Such a dual-layer defense strategy could mitigate vulnerabilities exemplified by the 2015 cyber intrusion into the Ukrainian power grid, which impeded timely physical recovery efforts.[36]

In addition to technical metrics, our GA-based restoration approach has the potential to significantly enhance community resilience, especially in areas susceptible to climate-related disasters. The pivotal role of renewable energy in strengthening community resilience during disasters has been empirically demonstrated in small island contexts. A recent study conducted in Fiji illustrated how solar photovoltaic and biogas systems contributed to reinforcing seven critical community assets—including human capital and political networks—in response to climate-induced shocks. While our research focuses on technical grid robustness via breaker optimization, these findings underscore that comprehensive power system resilience must fundamentally prioritize the needs of vulnerable communities, particularly in regions prone to disasters.[37]

Future extensions should prioritize renewable energy integration (e.g., DERs with 10% penetration showing 4.2% improvement) to enhance resilience during prolonged outages. The integration of distributed renewable energy resources (DERs), including photovoltaic (PV) systems and wind turbines coupled with energy storage, provides a viable approach to enhancing grid resilience during storm-induced disruptions. Decentralized generation via DER-enabled microgrids facilitates the maintenance of critical load operation under transmission lines or central generation failures. Quantitative analysis indicates that microgrids with a 10% DER penetration level result in a 4.2% increase in load restoration probability. Furthermore, configurations combining solar PV with four-hour energy storage sustain approximately 72% of critical loads during extended outage durations. This strategy expedites recovery processes and reduces the risk of cascading failures through localized balancing of supply and demand. Future implementation frameworks should incorporate advanced real-time weather prediction models and adaptive control algorithms to optimize DER dispatch strategies, thereby maximizing system resilience during extreme environmental events.

5- Conclusion

This research presents an advanced resilience framework that significantly enhances power system restoration through three key technical innovations. The probabilistic circuit breaker classification system, founded on Condition Index analytics, introduces a reliability-aware restoration approach that strategically prioritizes grid components during recovery operations. This method offers considerable computational efficiency over traditional techniques by intelligently narrowing the solution search space while maintaining optimality.

The dynamic failure probability model provides a critical improvement in storm response capabilities by enabling real-time adaptation to changing weather conditions through continuous environmental data integration. This advancement is particularly valuable for sustaining system stability during extended extreme weather events, where static models often fall short. The constrained genetic algorithm (GA) optimization engine, enhanced with distributed energy resource (DER) coordination capabilities, sets a new benchmark for restoration algorithms. Its improved convergence characteristics stem from specialized genetic operators designed to preserve topological feasibility while exploring optimal configurations—surpassing the capabilities of conventional Monte Carlo methods. Its intrinsic constraint satisfaction mechanisms ensure operational validity without sacrificing solution quality.

The proposed framework demonstrates significant performance improvements across various aspects of power system restoration. Notably, it achieves a 20% reduction in computational time through intelligent search space reduction enabled by reliability-based circuit breaker classification and adaptive genetic operators. Importantly, this efficiency is attained without compromising solution quality, as evidenced by a 7.3% higher restoration success rate compared to traditional Monte Carlo approaches, indicating improved operational outcomes. The framework consistently guarantees feasibility across all operational constraints, including voltage limits (0.95–1.05 per unit), line thermal capacities, and radial topology requirements, facilitating the immediate implementation of restoration plans. Additionally, it effectively coordinates distributed energy resources, achieving approximately 75% utilization during restoration processes. This not only enhances resilience but also demonstrates the successful integration of renewable generation into emergency response strategies. Overall, these performance metrics represent a substantial advancement over existing restoration methods, particularly in balancing computational efficiency with solution quality and operational feasibility in large-scale, stressed power systems. To enhance clarity, algorithmic details have been integrated into visual aids (Table 2 and Figure 3), streamlining the presentation and improving comprehension. The primary technical advancement of this framework resides in its unified approach to three essential components: reliability assessment, environmental adaptability, and operational constraint management. This comprehensive strategy effectively addresses significant limitations of existing restoration methods, particularly in managing large-scale failures caused by weather events. Future developments may include the incorporation of predictive maintenance systems and adaptive learning techniques to further enhance system performance, with the potential to set new industry benchmarks for resilient power system operation. Table 4 demonstrates that the proposed genetic algorithm (GA) attains a high success rate of 92.5% in restoring the IEEE 118-bus system within a 15-minute convergence window. Future research will concentrate on integrating machine learning models to enhance failure prediction accuracy and developing hybrid optimization frameworks that combine GAs with alternative methodologies to improve solution robustness. Additionally, efforts will target the deployment of real-time implementation on high-performance computing platforms to reduce emergency response latency. Subsequent work will also focus on scaling the methodology to support larger power systems exceeding 300 buses and integrating real-time meteorological data assimilation to enable dynamic updates of failure likelihood estimations.

Table 4. Comparative analysis of restoration

Method	Pros	Cons	Restoration Rate	Computation Time (IEEE 118-bus)
Proposed GA	Dynamic breaker classification, real-time adaptation, scalable	Performance declines for >15% breaker failures	92.5%	15 min.
MILP [38]	Optimality guarantees, precise for small systems	Poor scalability, static probabilities	88%	45 min.
Monte Carlo	Robust probabilistic sampling	High computational load, slow convergence	85.2%	60 min.
PSO [30]	Fast initial convergence	Premature local optima, weak constraint handling	82%	25 min.

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