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OPTIMIZING N-1 CONTINGENCY RANKINGS USING A NATURE-INSPIRED MODIFIED SINE COSINE ALGORITHM

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ABSTRACT: Ensuring the reliability and sustainability of power systems is essential for maintaining efficient and uninterrupted operations, especially under varying load conditions and potential faults. This study tackles the critical task of contingency ranking by evaluating the severity of disturbances caused by transmission line disconnections. Such evaluations enable power system operators to make informed and strategic decisions during real-time scenarios. A novel approach utilizing the Modified Sine Cosine Algorithm (MSCA), a nature-inspired metaheuristic optimization technique, is proposed to resolve (N-1) contingency rankings efficiently. The MSCA method is validated using the IEEE 30-bus test case, focusing on optimal parameter tuning for population size, iterations, and key variables. Results demonstrate that MSCA achieves a high capture ratio of 96.67%, explores only 8.33×10^{-7}% of the search space, and requires a processing time of 3.69 seconds. Compared with established methods such as Ant Colony Optimization (ACO) and Genetic Algorithm (GA), MSCA exhibits superior computational efficiency while maintaining competitive accuracy. These findings underline the potential of MSCA in real-time applications where speed and precision are critical. By closely matching manual contingency rankings, the proposed method integrates reliability assessment and optimization techniques, offering practical value for improving system resilience and reducing risks associated with disruptions. This research advances state-of-the-art power system reliability assessment and optimization approaches, providing operators and planners with a robust tool for addressing complex contingency challenges.

ABSTRAK: Memastikan keandalan dan kelestarian sistem tenaga elektrik adalah penting untuk mengekalkan operasi yang cekap dan tidak terganggu, terutamanya dalam menghadapi keadaan beban yang berubah-ubah dan kemungkinan kerosakan. Kajian ini menangani tugas kritikal dalam perangkingan kontingensi dengan menilai tahap keparahan gangguan yang disebabkan oleh pemutusan talian penghantaran. Penilaian sebegini membolehkan pengendali sistem tenaga membuat keputusan yang berinformasi dan strategik dalam senario masa nyata. Pendekatan baharu yang menggunakan Modified Sine Cosine Algorithm (MSCA), satu teknik pengoptimuman metaheuristik yang diilhamkan oleh alam, dicadangkan untuk menyelesaikan perangkingan kontingensi (N-1) dengan cekap. Kaedah MSCA ini disahkan menggunakan kes ujian IEEE 30-bus dengan memberi tumpuan kepada penalaan parameter optimum untuk saiz populasi, iterasi, dan pemboleh ubah utama. Keputusan menunjukkan bahawa MSCA mencapai nisbah tangkapan yang tinggi sebanyak 96.67%, hanya meneroka 8.33×10^{-7}% daripada ruang pencarian, dan memerlukan masa pemprosesan sebanyak 3.69 saat.

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Berbanding dengan kaedah sedia ada seperti Ant Colony Optimization (ACO) dan Genetic Algorithm (GA), MSCA menunjukkan kecekapan pengiraan yang unggul sambil mengekalkan ketepatan yang kompetitif. Penemuan ini menekankan potensi MSCA dalam aplikasi masa nyata di mana kelajuan dan ketepatan adalah kritikal. Dengan hasil yang hampir menyamai perangkingan kontingensi manual, kaedah yang dicadangkan ini mengintegrasikan penilaian keandalan dan teknik pengoptimuman, memberikan nilai praktikal untuk meningkatkan daya tahan sistem dan mengurangkan risiko yang berkaitan dengan gangguan. Penyelidikan ini memajukan pendekatan terkini dalam penilaian keandalan sistem tenaga dan pengoptimuman, menyediakan pengendali dan perancang dengan alat yang kukuh untuk menangani cabaran kontingensi yang kompleks.

KEYWORDS: *contingency analysis, contingency ranking, sin cos algorithm, metaheuristic technique, nature-inspired.*

1. INTRODUCTION

Contingency analysis plays a vital role in ensuring the reliability and security of electrical power systems. It involves assessing potential disruptions to critical system components and evaluating their impacts on power flow and bus voltage. These disruptions can significantly change power flow patterns and voltage profiles throughout the network, requiring proactive measures to uphold system stability and operational reliability [1-3].

Contingency analysis is vital for simulating adverse power flow scenarios and triggering appropriate alarm systems to prevent operational violations. Identifying vulnerable nodes and high-risk transmission paths is essential for implementing effective preventive measures and managing risks in power systems [4, 5]. Traditionally, computational methods have been utilized to evaluate power networks' resilience. Various optimization techniques, including nature-inspired algorithms like Ant Colony Optimization (ACO) [6] and Genetic Algorithm (GA) [7], have been applied to enhance the effectiveness of contingency analysis. Additionally, machine learning approaches such as Artificial Neural Networks and Deep Learning models, encompassing Convolutional and Recurrent Neural Networks, have demonstrated their utility in enhancing prediction and classification tasks in power systems [8-11].

Despite these advancements, optimizing contingency ranking remains challenging due to computational complexity, scalability for large-scale systems, and the need to balance accuracy with efficiency [12-14]. Innovative approaches that efficiently prioritize critical contingencies while maintaining computational feasibility are crucial. Advanced metaheuristic optimization algorithms like the Modified Sin Cos Algorithm (MSCA) have shown promise in addressing such challenges by leveraging mathematical trigonometric functions for optimization [15-17]. The MSCA builds upon the foundational principles of the Sine Cosine Algorithm (SCA), addressing its limitations and extending its applicability to complex optimization challenges. The SCA employs mathematical models based on sine and cosine functions to dynamically balance exploration and exploitation, generating candidate solutions that converge toward the global optimum. While SCA effectively maintains this balance, its dependency on uniform sinusoidal movements can lead to premature convergence in highly nonlinear or unstructured search spaces. Similar challenges were highlighted in population-based optimization algorithms in [17], emphasizing the importance of adaptive mechanisms for step size and solution interactions to enhance global search capabilities. In response to these insights, MSCA integrates advanced modifications such as probabilistic selection, mutation strategies, and enhanced parameter tuning to overcome local optima entrapment, improve computational efficiency, and ensure robustness across diverse problem domains. These enhancements make

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MSCA a superior alternative for addressing complex, large-scale optimization tasks in power system contingency analysis.

This study proposes using MSCA to optimize (N-1) contingency rankings, providing a reliable and computationally efficient solution for real-time decision-making. The methodology is validated using the IEEE 30-bus test case. MSCA achieves competitive performance in key metrics such as accuracy, processing time, and search space efficiency compared to ACO and other state-of-the-art methods [18, 19]. By demonstrating the robustness and scalability of MSCA, this research contributes to advancing power system reliability assessment and optimization techniques, offering practical value for utility providers in minimizing risks and improving network resilience.

2. SINE COSINE OPTIMIZATION ALGORITHM

Optimization is finding an effective and reliable approach based on performance within given constraints. Mathematically, optimization involves determining the minimum or maximum of a function subject to constraints. A set of values that satisfies all constraints constitutes a viable solution. Optimization problems are found across all fields of study, making the development of optimization techniques highly significant and a compelling research direction for many scholars. Due to limitations of conventional optimization paradigms, such as local optima stagnation and reliance on derivatives of the search space, interest in stochastic optimization approaches has grown over the last two decades.

In contingency ranking optimization, algorithms are required to explore the search space for the best solution to the problem at hand. The best value of the global optimum is retained as a reference throughout the optimization process. This process consistently updates the positions of solutions, tending to move toward the most promising regions of the search space. In this context, the Sine Cosine Algorithm (SCA) is a flexible and versatile algorithm applicable to various optimization problems [15, 16].

The SCA is a population-based metaheuristic algorithm inspired by sine and cosine functions. Unlike other population-based algorithms, SCA divides optimization into exploration and exploitation phases. It uses pure sine and cosine functions to control the steps in these phases [20]. During exploration, SCA searches widely across the solution space to identify promising areas. In contrast, exploitation refines solutions by focusing on specific areas near optimal points to improve accuracy and proximity to the global optimum.

SCA achieves exploration by leveraging sine and cosine functions, which create significant positional changes in candidate solutions. Exploitation reduces the amplitude of sine and cosine functions, resulting in smaller, more directed positional changes. This mechanism enables SCA to balance exploration and exploitation, although its dependency on sinusoidal functions sometimes makes it prone to local optima trapping due to its uniform search patterns.

Mathematically, SCA updates candidate solutions using a single mathematical expression and random numbers, as shown in Eq. 1, as follows [16]:

$$X_i^{t+1} = \begin{cases} X_i^t + r_1 \cdot \sin(r_2) \cdot |r_3 \cdot P_i^t - X_i^t|, & if\ r_4 < 0.5 \\ X_i^t + r_1 \cdot \cos(r_2) \cdot |r_3 \cdot P_i^t - X_i^t| & if\ r_4 \geq 0.5 \end{cases} \tag{1}$$

where X_i^{t+1} is the new position of the solution, a scaling factor or step size multiplier, r_2 is a random number used within the sine and cosine functions in radians, r_3 acts as a scaling factor or weight that adjusts the magnitude of the difference between P_i^t and X_i^t, r_4 is a random number used for probabilistic decision-making and P_i^t is the best-known position at iteration

t. The balance between exploration and exploitation is achieved by automatically adjusting the range of sine and cosine functions through Eq. (2):

$$r_1 = a - \frac{t \cdot a}{T} \tag{2}$$

where T is the maximum number of iterations, t is the current iteration, and a is a constant.

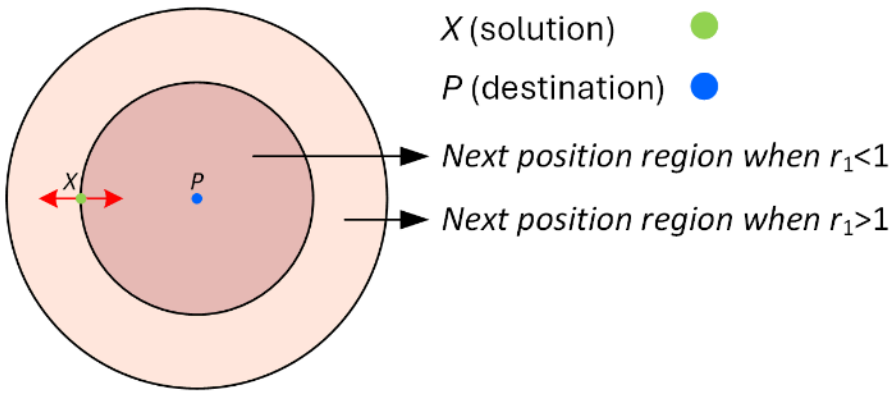

Figure 1. Position Determination using the SCA Algorithm

Figure 1 illustrates the Sin Cos Algorithm (SCA) mechanism for determining the next position of a candidate solution (X) in the search space relative to the global best solution (P). The figure highlights two key regions in the search space: the *inner region*, which represents potential positions when the random parameter $r_1 < 1$, and the *outer region* shows potential positions when $r_1 > 1$. Using sine and cosine functions, SCA adjusts the movement of X toward or away from P, ensuring broad exploration and precise exploitation of the search space. In the *exploration phase*, r_1 is set to values outside the range of -1 to 1, enabling the algorithm to search widely for promising areas. During the *exploitation phase*, r_1 is restricted to values between -1 and 1, focusing on refining solutions around the most promising regions to approach the global optimum.

This mechanism enables SCA to balance exploration and exploitation, reducing the risk of premature convergence to local optima. The algorithm dynamically transitions between these phases by adapting each iteration's sine and cosine functions range. While SCA is effective for many optimization problems, its reliance on absolute values and sinusoidal patterns may limit performance in highly nonlinear or unstructured difficulties, particularly in high-dimensional spaces. Enhancements such as hybrid approaches and empirical adjustments to the search process have been proposed to address these limitations, ensuring effective global searches and faster convergence. Figure 1 visually encapsulates these dynamics, emphasizing SCA's adaptability and potential for solving complex optimization problems.

While the Sine Cosine Algorithm is a promising optimization approach, it faces limitations when dealing with highly nonlinear and unstructured problems. The reliance on absolute values in traditional SCA for position updates can lead to premature convergence, causing the algorithm to become trapped in local optima and fail to identify the global optimum. Additionally, the search path employed by the SCA needs to be more directed to guide the algorithm effectively toward the optimal solution. As problem dimensionality increases, the convergence speed of the SCA tends to decline, further limiting its effectiveness. Recent studies have highlighted the need for linear search paths and empirical parameter adjustments to enhance SCA performance in challenging scenarios [21].

Research efforts to address these challenges have evolved along three primary directions: improving existing SCA techniques, developing entirely new algorithms, and hybridizing SCA with other optimization methods. SCA enhancement integrates stochastic and mathematical operators to improve convergence and search efficiency [22]. On the other hand, novel algorithms aim to introduce entirely new frameworks to overcome SCA's inherent limitations. Hybrid metaheuristic approaches, such as PSO-GA, PSO-ACO, and GA-DE, represent the most popular research avenue, combining SCA with other optimization techniques to balance exploration and exploitation effectively [23, 24]. By adopting linear search paths and empirically tuned parameters, researchers have proposed ways to improve the global search capabilities of SCA, resulting in more stable solutions and reduced risks of local optima trapping [25].

3. MODIFIED SINE COSINE ALGORITHM FOR POWER SYSTEM STATIC SECURITY ANALYSIS

The Modified Sine Cosine Algorithm (MSCA) represents a significant enhancement over the traditional Sin Cos Algorithm (SCA), aimed at improving efficiency and accuracy in identifying optimal solutions. In the context of static security analysis for power systems, particularly for N-1 contingency analysis, MSCA provides a robust framework for optimizing resource allocation and improving network stability. This algorithm addresses the limitations of the traditional SCA by integrating advanced mechanisms such as mutation, probabilistic selection, and more potent population-based strategies to overcome local optima trapping, a common challenge in SCA applications [26, 27].

The MSCA enhances the original SCA, as shown in Eq. (1), by replacing the scaling factor r_1 with a dynamic parameter a, which controls the amplitude. Additionally, the MCSCA introduces the d parameter, which regulates the distance between candidate solutions and the global best position, adding an extra layer of adaptability to improve search efficiency. MSCA can be formulated as follows:

$$X_i^{t+1} = \begin{cases} X_i^t + a \cdot \sin(r_2) \cdot |r_3 \cdot P_i^t - X_i^t|, & if\ r_4 < 0.5 \\ X_i^t + a \cdot \cos(r_2) \cdot |r_3 \cdot P_i^t - X_i^t| & if\ r_4 \geq 0.5 \end{cases} \tag{3}$$

where X_i^{t+1} is the new position of the solution, a is a dynamic amplitude control parameter replacing r_1 in the original SCA, updated as

$$a = a_{max}\left(1 - \frac{t}{t_{max}}\right) \tag{4}$$

where t is the current iteration t_{max} is the maximum number of iterations, and a_{max} is a predefined constant that depends on the problem domain and the desired balance between exploration and exploitation. In this paper, a_{max} was set to 1 to provide more conservative exploration. The d parameter is a distance regulation parameter integrated into $|r_3 \cdot P_i^t - X_i^t|$, modifying the search direction and step size. It can be expressed as:

$$d = |P_i^t - X_i^t| \cdot \left(1 - \frac{t}{t_{max}}\right) \tag{5}$$

This modification ensures that that a decreases over iterations to prioritize local exploitation in later stages, while d dynamically scales the search steps based on proximity to the global best position. Together, these parameters improve the algorithm's capability to explore the search space broadly during the initial stages and converge efficiently as the optimization progresses. The integration of a and d is further analyzed in Section 5.4, where their impact on the performance metrics, including Capture Ratio, Processing Time, and Search Scan Space Percentage, is evaluated. The three critical metrics will be discussed subsequently.

3.1. Capture Ratio

The capture ratio quantifies the algorithm's ability to identify optimal or near-optimal solutions across multiple iterations consistently. For MSCA, a high capture ratio signifies its effectiveness in converging to optimal solutions across diverse test functions. In the context of power system security, the capture ratio measures the algorithm's accuracy in identifying the most critical contingencies that could affect the system. This ratio is calculated using Eq. (6):

$$T_{cr} = \frac{k_p}{Q} \times 100 \tag{6}$$

where T_{cr} is the capture ratio, k_p is the number of the most severe contingencies captured in the top p positions of the list and Q is the total number of severe contingencies evaluated. A higher capture ratio indicates the algorithm's superior ability to rank contingencies accurately, ensuring the reliability of the contingency analysis framework.

3.2. Processing Time

Processing time measures the algorithm's total duration to complete the optimization process, from initialization to reaching an optimal solution or termination criteria. For MSCA, processing time is critical in assessing its suitability for real-time applications, particularly in scenarios requiring rapid analysis of contingencies. Efficient algorithms with shorter processing times are preferable for time-sensitive applications in power systems. In this study, the processing time of MSCA is compared against established methods such as Ant Colony Optimization (ACO) and Genetic Algorithms (GA) under identical conditions (number of iterations and computational resources).

3.3. Search Scan Space Percentage

Search Scan Space Percentage evaluates the extent of the search space the algorithm explores during optimization. This metric is crucial for understanding the balance between exploration (searching broadly across the solution space) and exploitation (focusing on refining the most promising areas). Search Scan Space Percentage is calculated using Eq. (7):

$$peb_i = \frac{qia_i}{C_k^r} \tag{7}$$

where peb_i is the percentage of the search space explored at iteration i, qia_i is the number of contingencies evaluated up to iteration i, and C_k^r is the total possible combinations of contingencies. Lower Search Scan Space Percentage values indicate higher efficiency, as fewer power flow calculations are required to achieve the desired optimization level. MSCA leverages its enhanced exploration and exploitation mechanisms to minimize Search Scan Space Percentage, making it a more computationally efficient algorithm.

The MSCA provides clear advantages over traditional algorithms by addressing the key limitations of SCA. Its probabilistic selection and mutation strategies reduce the risk of premature convergence, ensuring a more thorough search space exploration. Its improved processing efficiency makes it suitable for real-time power system contingency analysis applications, where rapid and accurate decision-making is critical. Including advanced metrics such as Capture Ratio, Processing Time, and Search Scan Space Percentage ensures that the algorithm's performance can be rigorously assessed, demonstrating its potential to set new benchmarks in power system optimization. MSCA establishes itself as a reliable tool for static security analysis in modern power systems by offering a balanced trade-off between accuracy, efficiency, and robustness.

4. SECURITY INDEX ANALYSIS

The Security Index (SI) is a critical parameter used to quantify the impact of contingency scenarios on the overall performance of a power system. It provides a numerical representation of the severity of disruptions caused by the disconnection of transmission lines or other contingencies, enabling the prioritization of ranking for mitigation strategies. While SI does not explicitly describe the type of violations or disturbances, it captures the magnitude of their impact on system performance. Higher SI values correspond to more significant risks, indicating more severe contingencies. To calculate SI, contingencies are ranked based on performance indices, enabling practical risk assessment and prioritization.

This study leverages the MSCA to optimize the ranking of contingencies using SI, improving upon traditional approaches. After simulating the outage of specific lines, voltage performance indices are calculated using Matlab. These indices then rank the contingencies based on their respective SI values. By integrating MSCA, a nature-inspired optimization algorithm, this research addresses limitations in traditional methods and compares the results against other nature-inspired algorithms. The enhanced optimization capabilities of MSCA ensure a more accurate and efficient ranking of critical contingencies, offering significant improvements in static security analysis for power systems.

The SI used in this study is formulated to normalize and quantify upper and lower voltage and power flow limit violations. It is calculated using Eq. (8):

$$SI = \left[\sum_i \left(\frac{d_{v,i}^u}{g_{v,i}^u}\right)^{2n} + \sum_i \left(\frac{d_{v,i}^l}{g_{v,i}^l}\right)^{2n} + \sum_i \left(\frac{d_{p,j}}{g_{p,j}}\right)^{2n}\right]^{\frac{1}{2n}} \tag{8}$$

Here, $d_{v,i}^u$ and $d_{v,i}^l$ represent normalized upper and lower voltage limit violations beyond alarm thresholds while $d_{p,j}$ represents normalized power flow limit violations. Normalization factors ($g_{v,i}^u$, $g_{v,i}^l$, and $g_{p,j}$) ensure that the SI values are dimensionless and comparable across different contingencies.

The normalized voltage limit violations are calculated as follows:

$$d_{v,i}^u = \begin{cases} \frac{V_i - F_i^u}{V_i^d}, & if\ V_i > F_i^u \\ 0, & if\ V_i \le F_i^u \end{cases} \tag{9}$$

$$d_{v,i}^l = \begin{cases} \frac{F_i^l - V_i}{V_i^d}, & if\ V_i < F_i^l \\ 0, & if\ V_i \ge F_i^l \end{cases} \tag{10}$$

where V_i is the voltage magnitude at a bus, F_i^u, F_i^l is the upper and lower alarm limits, and V_i^d is the desired bus voltage. The corresponding normalization factors for voltage are given as:

$$g_{v,i}^u = \frac{V_i - F_i^u}{V_i^d},\ g_{v,i}^l = \frac{F_i^l - V_i}{V_i^d} \tag{11}$$

Power flow limit violations are calculated using:

$$d_{p,j} = \begin{cases} \frac{|P_j| - P_{F_j}}{Base\ MVA}, & if\ |P_j| > P_{F_j} \\ 0, & if\ |P_j| \leq P_{F_j} \end{cases} \tag{12}$$

$$g_{pj} = \frac{P_{P_j} - P_{F_j}}{Based\ MVA} \tag{13}$$

where P_j is the actual power flow, P_{F_j} is the alarm limit for power flow, and $Base\ MVA$ is the base power for normalization.

By incorporating these detailed normalization factors, the Security Index accounts for voltage and power flow violations in a dimensionless and comparable manner. It ensures consistency and reliability in ranking contingencies. Using MSCA, this study optimizes the process of ranking these contingencies, improving computational efficiency and accuracy. MSCA's ability to avoid local optima and explore the solution space thoroughly ensures that critical contingencies with the highest SI values are identified accurately. This approach not only enhances the reliability of the power system but also enables real-time decision-making, making MSCA a valuable tool for static security analysis.

5. RESULTS AND DISCUSSION

This section presents the proposed Modified Sin Cos Algorithm (MSCA) results and analysis for contingency ranking in the IEEE 30-bus power system. The experimental setup, including the dataset, software, and hardware, is detailed to ensure reproducibility. Comparative simulations using manual contingency ranking, Ant Colony Optimization (ACO), and the original Sin Cos Algorithm (SCA) are conducted to evaluate the performance of MSCA. Key metrics such as capture ratio, search space scan percentage, and processing time are analyzed to assess the effectiveness and efficiency of each method. A benchmarking analysis highlights the advantages of MSCA against state-of-the-art algorithms, providing insights into its potential for real-world applications.

5.1. Simulation Setup

The IEEE 30-bus system, depicted in Figure 2, serves as the dataset for this study. It is a standard benchmark for power system analysis and contingency ranking, consisting of 30 buses, 41 lines, and detailed data for transmission lines, generation, and loads. The system includes:

- *One slack bus* is located at bus 1.
- *Five generator buses* are located at buses 2, 5, 8, 11, and 13.
- *Twenty-four load buses* represent the demand points across the network.

The network's connectivity is illustrated in Figure 2, where the red numbers represent the line indices, and the black numbers represent the bus indices. This structure captures the operational complexity of modern power grids, making it ideal for evaluating contingency ranking methods such as manual ranking, ACO, SCA, and the proposed MSCA.

The experiments were conducted using MATPOWER within the Matlab/Octave environment [28], a reliable tool known for its robustness and accuracy in solving power system optimization problems, particularly for $N - 1$ contingency analysis. The computational hardware used was a Dell Inspiron 15 Laptop equipped with a 12th Gen Intel Core i5-1235U processor for efficient computation, 16 GB DDR4 RAM to handle memory-intensive

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simulations, and a 512 GB SSD for fast data access and storage. This combination of hardware and software ensured the smooth execution of simulations, enabling a comprehensive analysis of the IEEE 30-bus system and an accurate evaluation of the performance of the optimization algorithms tested.

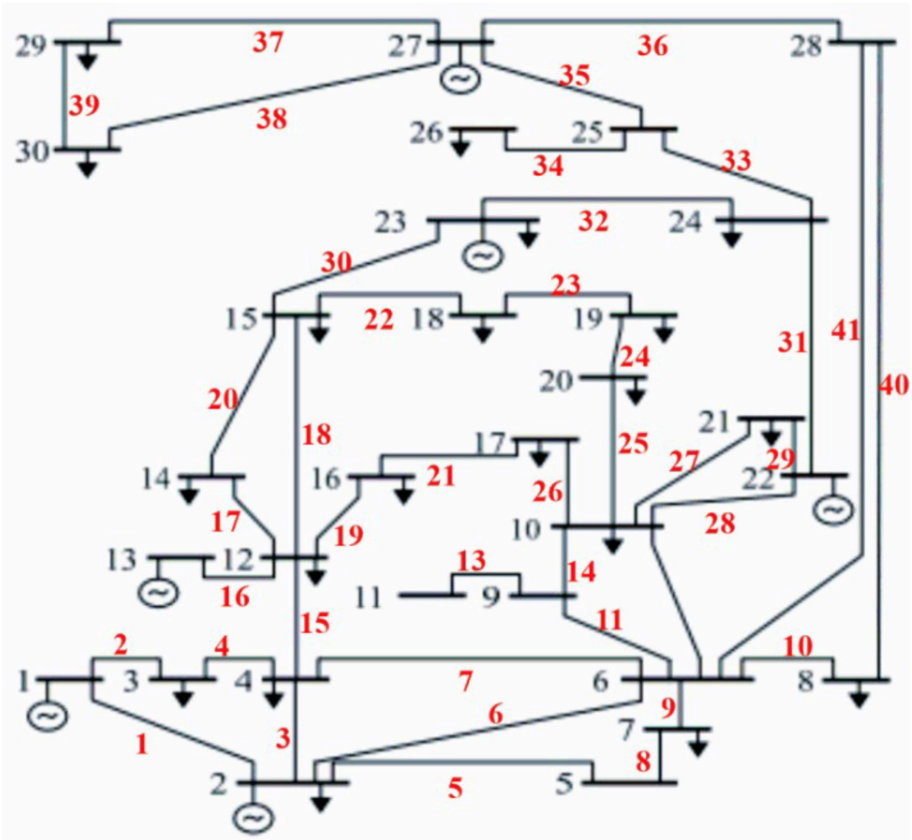

Figure 2. Line Diagram of IEEE 30-Bus System

The experimental setup involves simulating N-1 contingency scenarios on the IEEE 30-bus power system to compare the performance of three methods: manual ranking, Ant Colony Optimization (ACO), and the Sin Cos Algorithm (SCA). These simulations aim to evaluate the effectiveness of the proposed Modified Sin Cos Algorithm (MSCA). The IEEE 30-bus system, a widely used benchmark model, consists of 30 buses, 41 transmission lines, 5 generator buses, and 24 load buses. Manual ranking calculates the voltage performance index for each transmission line for each scenario sequentially using MATPOWER. At the same time, ACO and SCA automate the ranking process with various parameters, such as population size, iterations, and algorithm-specific variables (e.g., Alpha and Beta for ACO; a and d for SCA). Each method's performance is analyzed using three key metrics: capture ratio, processing time, and search space scan percentage.

This simulation scenario provides a comprehensive framework for analyzing contingency ranking methods. The study addresses real-world operational challenges using the IEEE 30-bus system and N-1 contingencies, ensuring practical relevance. Comparing manual and automated methods (ACO and SCA) highlights the benefits of optimization techniques in improving efficiency and accuracy. Additionally, the scenario allows for the benchmarking of MSCA against established methods, validating its capability as a superior tool for contingency analysis in power systems. These results demonstrate the potential of MSCA to enhance contingency ranking with better computational efficiency and accuracy, making it an effective solution for modern power systems.

5.2. Manual Contingency Ranking As Simulation Baseline

Manual contingency ranking was conducted by disconnecting individual transmission lines in the IEEE 30-bus system ($N-1$ contingency analysis). Each line was removed one by one, starting from the first to the last, and the voltage performance index for each scenario was calculated using MATPOWER in the Matlab/Octave software environment. The results were then ranked in descending order, from the highest to the lowest voltage performance index, to identify the most critical contingencies. The transmission line associated with the highest performance index represents the most severe contingency scenario. The results of this manual ranking process are presented in Table 1.

Table 1. Manual Contingency Ranking Results for IEEE 30-Bus System

Ranking	Line Number	From Bus	To Bus	Security Index
1	36	28	27	56.5915
2	37	27	29	56.5443
3	38	27	30	56.5441
4	34	25	26	56.5434
5	9	6	7	56.5430
6	33	24	25	56.5416
7	39	29	30	56.5411
8	11	6	9	56.5409
9	29	21	22	56.5407
10	32	23	24	56.5407
11	10	6	8	56.5405
12	20	14	15	56.5405
13	23	18	19	56.5404
14	31	22	24	56.5404
15	21	16	17	56.5402
16	8	5	7	56.5399
17	41	6	28	56.5399
18	4	3	4	56.5398
19	24	19	20	56.5398
20	40	8	28	56.5398
21	28	10	22	56.5395
22	26	10	17	56.5394
23	30	15	23	56.5393
24	35	25	27	56.5392
25	12	6	10	56.5391
26	22	15	18	56.5387
27	25	10	20	56.5378
28	7	4	6	56.5374
29	17	12	14	56.5374
30	27	10	21	56.5374
31	19	12	16	56.5371
32	3	2	4	56.5369
33	5	2	5	56.5365
34	6	2	6	56.5365
35	2	1	3	56.5361
36	15	4	12	56.5330
37	18	12	15	56.5325
38	1	1	2	56.5309
39	13	9	11	56.5309
40	16	12	13	56.5308
41	14	9	10	56.5300

Table 1 indicates that the most critical contingency occurs on line 36, which connects bus 28 to bus 27. Its security index of 56.5915 earns it the top ranking. On the other hand, the least critical contingency occurs on line 14, which connects bus 9 to bus 10, with the lowest voltage performance index of 56.53. These rankings provide a clear picture of the relative severity of each contingency scenario within the IEEE 30-bus system.

The manual ranking results also serve as a baseline for comparing the performance of optimization methods used for contingency ranking. The primary focus of this study is to evaluate the effectiveness of different optimization methods, such as Ant Colony Optimization (ACO) and the Modified Sin Cos Algorithm (MSCA), in identifying the top 20 most critical contingencies. For simplicity, the top 20 rankings in Table 1, highlighted in grey, represent the actual severity levels of the contingencies. These rankings are used as a reference for validating the accuracy of the capture ratio calculated by the optimization algorithms. This process ensures that the proposed methods are rigorously evaluated against a reliable benchmark.

5.3. Contingency Ranking Simulation Using the Ant Colony Optimization Method

The Ant Colony Optimization (ACO) method was applied to the IEEE 30-bus system to evaluate its performance in contingency ranking. ACO relies on ants' probabilistic selection of solutions (paths) based on pheromone trails and heuristic factors. During the iterative process, pheromones are updated to reflect the quality of the solutions, guiding ants toward better paths over time. Key parameters influencing ACO's performance include Alpha (pheromone influence), Beta (heuristic influence), population size (number of ants), and the number of iterations. This study conducted ACO simulations 50 times for each parameter variation, and the average capture ratio was calculated as the primary performance metric.

5.3.1. Ranking Based on Alpha and Beta Variations

The justification for testing the performance of ACO by simultaneously varying both Alpha and Beta lies in the fundamental role these parameters play in balancing exploration and exploitation during the search process. Alpha determines the influence of pheromone trails, guiding ants based on the solutions discovered in prior iterations. At the same time, Beta controls the weight given to heuristic factors, encouraging ants to explore promising solutions based on their immediate value. Simultaneous variation of these parameters enables a comprehensive assessment of how their interplay affects the algorithm's ability to discover high-quality solutions effectively.

Using 41 ants ensures a diverse population of solution candidates, which promotes broad exploration of the search space and reduces the likelihood of premature convergence to local optima. Similarly, setting the number of iterations to 82 allows the algorithm to refine its exploration and exploitation balance over multiple cycles, giving it sufficient opportunity to converge toward optimal solutions. This configuration evaluates the algorithm's robustness across various parameter settings, ensuring the findings are generalizable and informative for real-world applications.

The results in Table 2 demonstrate that the ACO algorithm achieves its best capture ratio of 98.80% when both Alpha and Beta are set to 2. It indicates that at moderate values, the balance between pheromone influence (Alpha) and heuristic influence (Beta) is optimized, enabling the ants to explore the solution space effectively while focusing on promising areas. This balanced interplay ensures that pheromone trails guide the algorithm efficiently without overemphasizing the influence of heuristic factors. Such a result underscores the importance of carefully tuning these parameters to achieve optimal performance in contingency ranking.

Table 2. Processing Time, Search Space Scan Percentage, and Capture Ratio for ACO with Simultaneous Alpha and Beta Variations

Alpha and Beta	**Processing Time (seconds)**	**Search Space Scan Percentage (%)**	**Capture Ratio (%)**
1	100.23	1.25×10^{-6}	87.30
2	**101.00**	$\mathbf{1.25 \times 10^{-6}}$	**98.80**
3	109.02	1.25×10^{-6}	93.43
4	111.32	1.25×10^{-6}	92.56
5	113.42	1.25×10^{-6}	93.30

As Alpha and Beta values increase beyond 2, the capture ratio declines. For instance, at Alpha and Beta set to 3, the capture ratio decreases to 93.43%, and further reductions are observed at values of 4 and 5, where the capture ratios are 92.56% and 93.30%, respectively. These declines suggest that excessive pheromone and heuristic influence can disrupt the balance between exploration and exploitation. When both factors are overemphasized, the algorithm may focus too narrowly on certain paths, leading to premature convergence on suboptimal solutions and an inability to explore new, potentially better solutions in the search space.

The processing time exhibits a linear increase as Alpha and Beta values rise. Starting at 100.23 seconds for Alpha and Beta set to 1, the processing time grows to 113.42 seconds when these parameters are set to 5. This increase in computational cost reflects the additional effort required for the ants to process pheromone trails and heuristic factors under high Alpha and Beta settings. Notably, the marginal increase in capture ratio from 93.43% to 93.30% (Alpha and Beta values of 3 to 5) does not justify the significantly higher processing time. It highlights the trade-off between accuracy and efficiency, where over-tuning parameters leads to diminishing returns in performance at the cost of greater computational resources.

Interestingly, the search space scan percentage remains constant at 1.25×10^{-6} % across all Alpha and Beta variations. This consistency suggests that the algorithm explores a fixed proportion of the solution space regardless of parameter changes. While this uniformity ensures that a comparable scope of the search space is analyzed, it also highlights a limitation in ACO's adaptability, where the extent of exploration is not directly influenced by Alpha and Beta variations. It may contribute to the decline in capture ratio at higher parameter values, as the algorithm becomes less capable of compensating for over-concentration on specific areas of the search space.

Table 2 highlights the critical importance of parameter tuning in ACO. The optimal balance achieved at Alpha and Beta values of 2 demonstrates the algorithm's ability to navigate the trade-offs between exploration and exploitation effectively. However, the decline in capture ratio at higher parameter values underscores the risk of overemphasizing pheromones or heuristic factors, limiting the algorithm's ability to generalize effectively. Additionally, the linear increase in processing time at higher parameter values reveals the computational cost of over-tuning, emphasizing the need for careful consideration of efficiency in real-time applications. Finally, the static search space scan percentage indicates that while ACO maintains consistent exploration across the solution space, its adaptability could be improved to better respond to parameter variations.

5.3.2. Ranking with One Parameter Constant

This section evaluates the performance of the ACO algorithm by varying one parameter—either Alpha or Beta—while keeping the other constant at 1. Alpha represents the influence of pheromones in guiding the ants toward promising solutions, while Beta represents the influence of heuristic factors in the decision-making process. The experiments utilized 41 ants and 82 iterations to ensure sufficient exploration and exploitation of the search space. The results, shown in Table 3, provide insights into how Alpha and Beta individually affect the algorithm's performance metrics: processing time, search space scan percentage, and capture ratio.

Table 3. Processing Time, Search Space Scan Percentage, and Capture Ratio for ACO with One Parameter Constant

Alpha	Beta	Processing Time (seconds)	Search Space Scan Percentage (%)	Capture Ratio (%)
1	1	109.30	1.25×10^{-6}	87.30
2	**1**	**110.40**	$\mathbf{1.25 \times 10^{-6}}$	**95.50**
3	1	111.10	1.25×10^{-6}	94.46
4	1	111.98	1.25×10^{-6}	94.32
5	1	112.50	1.25×10^{-6}	95.40
1	2	110.39	1.25×10^{-6}	90.30
1	3	111.12	1.25×10^{-6}	89.40
1	4	111.94	1.25×10^{-6}	90.12
1	5	112.52	1.25×10^{-6}	91.20

When Alpha was varied while Beta was kept constant at 1, the capture ratio improved as Alpha increased, reaching a peak of 95.5% at Alpha = 2. Beyond this value, the capture ratio exhibited slight fluctuations, indicating diminishing returns. Similarly, when Beta was varied while Alpha was kept constant at 1, the highest capture ratio of 91.2% occurred at Beta = 5. It suggests that both pheromones and heuristic factors are critical in guiding the algorithm, but their contributions reach an optimal balance when Alpha and Beta are moderately increased. The values of Alpha (α) and Beta (β) influence the ACO algorithm's balance between pheromone intensity and heuristic factors. A high Alpha value makes the ants overly reliant on pheromone trails, which can lead to premature convergence in local optima. Conversely, a high Beta value causes the ants to focus excessively on heuristic factors, neglecting pheromone trails. These extremes disrupt the balance necessary for effective exploration and exploitation, limiting the algorithm's ability to find optimal solutions. This behavior is evident in the results, where moderate increases in Alpha and Beta produce the best performance metrics.

The processing time for each scenario increased with larger Alpha or Beta values. It can be attributed to the additional computational effort required to process larger pheromone trails or more detailed heuristic evaluations. For example, the processing time rose from 109.3 seconds at Alpha = 1 to 112.5 seconds at Alpha = 5. A similar trend was observed when the Beta was varied. These findings highlight a trade-off between accuracy (capture ratio) and computational efficiency (processing time), emphasizing the need for careful parameter tuning in real-world applications where computational resources are limited.

The search space scan percentage remained constant across all tested Alpha and Beta values, demonstrating that the algorithm maintained a consistent level of exploration in the solution space. This consistency suggests that variations in Alpha and Beta primarily affect how ants prioritize pheromone trails and heuristic factors rather than the overall breadth of the search. However, the diminishing improvements in capture ratio at higher parameter values indicate that the algorithm may overemphasize one factor while underutilizing the other, leading to inefficiencies in solution refinement.

Critically, these results underline the importance of balancing pheromone and heuristic influences in ACO. When Alpha or Beta values are set too high, the algorithm risks overfitting to certain paths, potentially converging prematurely on suboptimal solutions. Conversely, when these parameters are too low, the algorithm may fail to exploit high-quality solutions effectively, leading to lower capture ratios. Therefore, the optimal settings for Alpha and Beta—identified here as 2—strike a balance between exploration and exploitation, ensuring robust and efficient contingency ranking.

The experiments demonstrate that ACO's performance is highly sensitive to the balance between Alpha and Beta. While both parameters independently contribute to the algorithm's effectiveness, their interplay determines the overall quality of the solutions. The findings emphasize the need for adaptive parameter tuning for optimal performance in dynamic and resource-constrained environments, such as real-time power system contingency ranking. In subsequent analyses, these results provide a strong foundation for comparing ACO to alternative algorithms, such as the MSCA.

5.3.3. Ranking with Iteration and Population Variations

The third experiment investigates the performance of the ACO algorithm by varying the population size (number of ants) and the number of iterations. These parameters significantly impact the algorithm's ability to explore the solution space and converge to optimal solutions. The experiments were conducted with Alpha and Beta fixed at 2, as these values provided the best balance of pheromone and heuristic influence in prior tests. The results, summarized in Tables 4 and 5, demonstrate the interplay between population size, iterations, processing time, search space scan percentage, and capture ratio.

Table 4. Processing Time, Search Space Scan Percentage, and Capture Ratio for ACO with Varying Population Sizes at 100 Iterations

Alpha and Beta	**Population Size**	**Processing Time (seconds)**	**Search Space Scan Percentage (%)**	**Capture Ratio (%)**
2	5	16.38	1.867×10^{-7}	83.4
2	10	37.78	3.72×10^{-7}	87.4
2	20	59.19	7.43×10^{-7}	89.2
2	**40**	**80.60**	$\mathbf{1.49 \times 10^{-6}}$	**92.3**
2	80	102.00	2.97×10^{-6}	91.9

As shown in Table 4, when the number of ants (population size) was increased from 5 to 80 while keeping the number of iterations constant at 100, the capture ratio improved significantly, reaching a maximum of 92.3% at a population size of 40. Beyond this value, the capture ratio slightly declined to 91.9% at a population size of 80. It indicates an optimal population size exists, where the algorithm balances sufficient exploration and efficient pheromone reinforcement. However, larger populations require more pheromone updates and solution evaluations, leading to a proportional increase in processing time, which rose from 16.38 seconds at a population size of 5 to 102 seconds at 80 ants. This trade-off highlights the need to carefully tune the population size for efficient operation in time-sensitive applications.

As shown in Table 4, when the number of ants (population size) was increased from 5 to 80 while keeping the number of iterations constant at 100, the capture ratio improved significantly, reaching a maximum of 92.3% at a population size of 40. Beyond this value, the capture ratio slightly declined to 91.9% at a population size of 80. It indicates an optimal population size exists, where the algorithm balances sufficient exploration and efficient

pheromone reinforcement. However, larger populations require more pheromone updates and solution evaluations, leading to a proportional increase in processing time, which rose from 16.38 seconds at a population size of 5 to 102 seconds at 80 ants. This trade-off highlights the need to carefully tune the population size for efficient operation in time-sensitive applications.

Table 5. Processing Time, Search Space Scan Percentage, and Capture Ratio for ACO with Varying Iterations at 10 Population Size

Alpha	Iterations	Processing Time (seconds)	Search Space Scan Percentage (%)	Capture Ratio (%)
2	10	3.34	13.72×10^{-8}	60.40
2	40	12.00	22.30×10^{-8}	65.83
2	70	20.67	30.80×10^{-8}	82.60
2	**100**	**29.30**	$\mathbf{3.940 \times 10^{-7}}$	**89.90**
2	130	38.00	4.80×10^{-7}	89.80

For iterations, the results showed that increasing the number from 10 to 130 while keeping the population size constant at 10 led to a steady improvement in the capture ratio, peaking at 89.9% at 100 iterations. Beyond this point, the capture ratio plateaued, indicating diminishing returns with further increases in iterations. Processing time increased proportionally with iterations, rising from 3.34 seconds at 10 to 38 seconds at 130 iterations. Similarly, the search space scan percentage grew consistently, reflecting the algorithm's broader solution space exploration. These findings suggest that increasing iterations enhances solution quality up to a certain point, beyond which additional computational effort yields minimal benefits.

The experiments highlight a critical trade-off between population size and iterations. Larger populations improve the algorithm's ability to explore diverse regions of the solution space in parallel but at the cost of increased processing time. On the other hand, more iterations allow the ants to refine their solutions and converge to better optima, but the incremental improvements diminish as the solution space becomes saturated. Balancing these two parameters is essential to achieve high capture ratios without excessive computational overhead.

The search space scan percentage provides valuable insights into the algorithm's exploration efficiency. When either population size or iterations increased, the search space scan percentage rose significantly, indicating thorough coverage of potential solutions. For instance, at 100 iterations with a population size of 10, the scan percentage reached 3.94×10^{-7}%. However, this exhaustive exploration also increases computational demands. The challenge lies in ensuring that the algorithm explores the search space sufficiently to avoid local optima while maintaining computational efficiency. The diminishing improvements in capture ratio at higher parameter values suggest that the algorithm reached an effective saturation point, beyond which additional exploration yielded negligible gains.

The results underscore the importance of parameter tuning in ACO. For real-time applications, such as contingency ranking in power systems, selecting the optimal combination of population size and iterations is crucial. While higher values improve solution quality, the associated increase in processing time may render the algorithm unsuitable for time-sensitive tasks. This study's population size of 40 and 100 iterations emerged as a practical balance, achieving a high capture ratio of 92.3% with reasonable computational effort. These findings establish a solid benchmark for evaluating alternative optimization methods in contingency ranking scenarios, such as the Modified Sin Cos Algorithm (MSCA).

5.4. Contingency Ranking Simulation Using Modified Sine Cosine Algorithm

The Modified Sine Cosine Algorithm (MSCA) was employed to simulate contingency ranking in the IEEE 30-bus system, focusing on its effectiveness under varying parameter configurations. MSCA builds upon the Sine Cosine Algorithm (SCA) by leveraging sinusoidal functions to explore and exploit the solution space. Key parameters influencing the algorithm's performance include a and d (amplitude and distance control parameters), population size, and the number of iterations. Each configuration was tested 50 times, and the most frequently observed capture ratio in the iterations was selected for evaluation.

Optimization algorithms like MSCA aim to strike a balance between exploration, which involves searching broadly across the solution space, and exploitation, which refines solutions around promising areas. The sinusoidal functions in MSCA enable this balance, but their efficiency depends significantly on the values of a (denoted as r_1) and d (denoted as r_3). Selecting appropriate parameter values ensures the algorithm's robustness, minimizing the risk of premature convergence or suboptimal performance.

The parameter a regulates the amplitude of sinusoidal movements in the solution space. Higher values of a increase the range of individual position changes during iterations, enhancing the algorithm's exploratory capacity. However, excessively high values of a can introduce randomness, causing the population to drift away from optimal solutions. It underscores the necessity of carefully tuning a to balance broad exploration with precise exploitation. Optimal values allow the algorithm to explore widely without losing focus on high-quality solutions, which is crucial in complex systems like the IEEE 30-bus power grid.

Similarly, d affects the distance individuals move relative to the current best position during iterations. Higher values encourage broader exploration but may also lead to instability, with individuals deviating significantly from optimal regions. Conversely, excessively low values of d can result in limited exploration, trapping the algorithm in local optima. It highlights the importance of tuning d to achieve a dynamic balance between moving towards global optima and thoroughly exploring the search space.

By varying a and d systematically, the MSCA can adapt its search behavior to the complexities of contingency ranking in power systems. Properly calibrated, the algorithm comprehensively explores potential contingencies while focusing computational resources on the most critical scenarios. MSCA is particularly suited for optimizing large-scale, nonlinear systems like power grids, where balancing exploration and exploitation is essential for accurate and efficient contingency ranking.

5.4.1. Ranking with MSCA by Varying the Amplitude and Distance Control Parameters

The MSCA was evaluated under varying configurations of the amplitude control parameter (a) and the distance control parameter (d). These parameters are critical in determining the algorithm's ability to balance exploration and exploitation of the solution space. A total of 50 trials were conducted for each parameter variation, with the most frequently observed capture ratio used as the primary evaluation metric. The population size was set to 250, and the number of iterations was fixed at 500 to allow sufficient search space exploration. The results are summarized in Table 6, highlighting the interplay between parameter values and the algorithm's performance metrics, including processing time, search space scan percentage, and capture ratio.

Table 6. Processing Time, Search Space Scan Percentage, and Capture Ratio for MSCA for Variations in a and d

a	d	Processing Time (seconds)	Search Space Scan Percentage (%)	Capture Ratio (%)	Number of Identified Lines
1	0.1	18.06	0.0028736	93.3	28
2	0.1	17.82	100.0	100.0	30
3	0.1	17.95	100.0	100.0	30
4	0.1	17.89	0.0028736	93.3	28
5	0.1	18.65	100.0	100.0	30
1	0.2	18.18	100.0	100.0	30
1	0.3	18.12	100.0	100.0	30
1	0.4	18.67	100.0	100.0	30
1	0.5	18.67	100.0	100.0	30

The amplitude parameter (a) influences the scale of sinusoidal movements in the algorithm, directly impacting its exploratory capabilities. Higher values of a enable broader exploration by allowing larger positional changes during iterations, reducing the risk of getting trapped in local optima. However, excessively high values can result in random movements, inefficiently exploiting promising areas in the search space. The results in Table 6 demonstrate that when $a = 2,3,5$, the algorithm achieved a 100% capture ratio and search space scan percentage, indicating that these values provide an optimal balance for contingency ranking tasks.

The distance control parameter (d) regulates the magnitude of individual movements relative to the best-known solution, thereby influencing local exploitation. Smaller d values focus the search on refining solutions within a narrow region, while larger values promote more exploratory movements. The results indicate that values of $d = 0.1$ consistently achieved 100% search space coverage for $a = 2,3,5$, demonstrating the parameter's effectiveness in balancing localized refinement with broader exploration. In contrast, when $d = 0.1$ for $a = 1$, the search space scan percentage dropped significantly to 0.0028%, highlighting the algorithm's sensitivity to suboptimal parameter combinations.

Interestingly, despite achieving 100% capture ratio and search space coverage in several configurations, the algorithm exhibited stable processing times between 17.8 and 18.6 seconds. This consistency indicates that MSCA can efficiently explore the solution space without incurring excessive computational overhead, even when varying the amplitude and distance control parameters. However, low search space coverage was observed for specific configurations (e.g., $a = 1, d = 0.1$), suggesting that suboptimal parameter tuning may lead to reduced algorithmic efficiency and potentially overlooked solutions.

A notable difference between MSCA and previously tested algorithms, such as Ant Colony Optimization (ACO), lies in the comprehensive search space coverage achieved by MSCA. While ACO exhibited extremely low search space percentages in earlier tests, MSCA consistently covered the complete solution space under optimal configurations. It underscores the robustness of the sinusoidal-based exploration mechanisms in MSCA, which allow it to effectively navigate complex, nonlinear solution spaces such as those encountered in power system contingency ranking.

The experiments highlight the importance of carefully tuning the amplitude (a) and distance control (d) parameters to optimize MSCA's performance. The findings demonstrate that MSCA can identify all critical contingencies in the IEEE 30-bus system while maintaining efficient computational performance. By achieving a 100% capture ratio and search space scan percentage in several configurations, MSCA establishes itself as a reliable tool for contingency ranking. Future work could explore adaptive parameter tuning to adjust dynamically a and d during execution, further enhancing MSCA's robustness and applicability across diverse optimization problems.

5.4.2. Ranking with MSCA by Varying the Number of Iterations and Population Size

This section evaluates the performance of the MSCA by systematically varying the number of iterations and population size. These parameters are critical in determining the algorithm's ability to balance computational efficiency with optimization accuracy. Iterations define the number of updates made during the search process, while population size represents the number of candidate solutions explored simultaneously. The experiments used fixed parameter values of $a = 1$ and $d = 0.1$ to isolate the impact of iterations and population size. The results are summarized in Tables 7 and 8.

Table 7. Processing Time, Search Space Scan Percentage, and Capture Ratio for MSCA for Variations in Population Size at 250 Iterations.

Population Size	Processing Time (seconds)	Search Space Scan Percentage (%)	Capture Ratio (%)	Number of Identified Lines
50	1.82	2.87×10^{-8}	93.33	28
100	3.70	8.33×10^{-7}	96.67	29
150	5.53	1.25×10^{-6}	96.67	28
200	7.37	100.00	100.00	30
250	8.98	1.47	93.33	28

Table 7 demonstrates a clear trend where increasing population size improves the capture ratio and search space coverage but at the expense of processing time. For a fixed number of iterations (250), the capture ratio increased from 93.33% with a population size of 50 to 100% with a population size of 200. It indicates that larger populations enhance the algorithm's ability to explore diverse areas of the search space and identify critical contingencies accurately. However, processing time increased proportionally with population size, reflecting the higher computational demands of managing and evaluating a larger number of candidate solutions.

Table 8. Processing Time, Search Space Scan Percentage, and Capture Ratio for MSCA for Variations in Iterations at 500 Population Size.

Iterations	Processing Time (seconds)	Search Space Scan Percentage (%)	Capture Ratio (%)	Number of Identified Lines
25	2.20	8.77×10^{-7}	83.33	25
50	8.85	8.33×10^{-7}	96.67	29
100	7.98	100	100	30
250	20.61	100	100	30

Table 8 highlights the impact of varying the number of iterations while keeping the population size constant at 500. As the number of iterations increased, the capture ratio and search space coverage improved, reaching 100% with 100 or more iterations. This result underscores the importance of sufficient iterations to refine the search process and identify all critical contingencies. However, the processing time increased significantly, particularly for 250 iterations, indicating the trade-off between optimization accuracy and computational efficiency.

The findings reveal that population size and iterations contribute significantly to MSCA's performance, but their effects differ. Larger populations enhance diversity and prevent premature convergence, while more iterations allow deeper exploration and refinement of candidate solutions. Notably, the configuration with 500 iterations and a population size of 200 achieved a 100% capture ratio and search space coverage with a processing time of 20.61 seconds, representing an optimal balance for this dataset.

MSCA demonstrates superior adaptability and robustness in balancing exploration and exploitation compared to other algorithms, such as ACO. When carefully tuned parameters, the results show that MSCA can achieve comprehensive search space coverage with fewer computational resources. The ability to scale performance with increasing population size and iterations highlights its potential for handling complex optimization problems in power systems.

The study confirms that fine-tuning population size and iterations are essential for optimizing MSCA's performance in real-world applications. The trade-offs observed between computational efficiency and optimization accuracy suggest that parameter selection should be guided by the problem's specific requirements, such as the search space size and the criticality of timely results. Future work could explore adaptive parameter adjustment strategies to dynamically balance these trade-offs, further enhancing MSCA's applicability in contingency ranking tasks.

5.5. Comparative Analysis

Contingency ranking is a critical component of power system reliability analysis, requiring algorithms that can efficiently prioritize system vulnerabilities during N-1 contingency scenarios. Nature-inspired algorithms like Ant Colony Optimization (ACO) and Modified Sine Cosine Algorithm (MSCA) have addressed this complex optimization task. ACO leverages pheromone-based heuristics to guide its search process, while MSCA employs sinusoidal dynamics with added modifications to balance exploration and exploitation. Table 9 compares these algorithms, focusing on key metrics: processing time, search space scan percentage, and capture ratio.

Table 9. Comparison of Nature-Inspired Algorithms for Contingency Ranking.

Algorithm Type	**Simulation Parameters**	**Processing Time (seconds)**	**Search Space Scan Percentage (%)**	**Capture Ratio (%)**
ACO	Iterations = 82, Population = 41, Alpha = 2, Beta = 2	101.00	1.25×10^{-6}	98.8
MSCA	Iterations = 250, Population = 100, $a = 1$, $d = 0.1$	3.70	8.33×10^{-7}	96.7

The metrics in Table 9 are carefully selected to capture the performance characteristics of the algorithms. Processing Time measures computational efficiency, a crucial factor for real-time applications. At the same time, the Search Space Scan Percentage quantifies the extent of solution space exploration, reflecting the algorithm's robustness against local optima. Capture Ratio assesses the accuracy of identifying high-impact contingencies, showcasing the algorithm's effectiveness in prioritization. These metrics comprehensively evaluate each algorithm's strengths and limitations, enabling informed decisions on their application in power system optimization tasks.

ACO and MSCA exhibit distinct performance characteristics across key metrics. Processing Time highlights the computational efficiency of MSCA, which completes in 3.7 seconds compared to ACO's 101 seconds. MSCA's reliance on straightforward sinusoidal equations ensures minimal computational overhead, making it ideal for real-time applications, unlike ACO, whose iterative pheromone updates and probabilistic path selection result in significant processing delays. Regarding Search Space Scan Percentage, ACO demonstrates a narrower exploration focus (1.25×10^{-6} %) compared to MSCA's broader search coverage (8.33×10^{-7} %). While ACO's focused search improves accuracy in identifying critical contingencies, it may reduce robustness in high-dimensional or irregular solution spaces, where MSCA's adaptability becomes an advantage. Capture Ratio, a measure of accuracy, sees ACO slightly outperforming MSCA (98.8% vs. 96.7%), attributed to its pheromone-guided optimization. However, the marginal accuracy gain does not offset ACO's significantly higher computational cost, positioning MSCA as a more balanced and efficient option, especially for time-sensitive applications. These comparisons underscore the trade-offs between accuracy, computational efficiency, and robustness in applying nature-inspired algorithms for contingency ranking.

The MSCA enhances the standard SCA through targeted modifications that significantly improve its performance. By integrating sinusoidal dynamics with adjustable parameters (a=1, d=0.1), MSCA achieves a balanced trade-off between exploration and exploitation, effectively mitigating the risk of entrapment in local optima. Its reliance on simple mathematical functions ensures computational simplicity, enabling scalability to larger power system models while maintaining efficiency. Additionally, its broader search space coverage enhances robustness, making it well-suited for diverse optimization problems, including those with irregular or high-dimensional solution spaces. Comparative results underscore MSCA's computational efficiency and robust exploration as key advantages for contingency ranking tasks. In real-world applications, such as large-scale power systems with stringent computational constraints, MSCA provides a practical and efficient solution without significant accuracy trade-offs. While ACO's slightly higher accuracy may be advantageous in scenarios demanding precision and abundant computational resources, MSCA strikes a compelling balance between performance and practicality.

6. CONCLUSIONS

The study highlights the Modified Sine Cosine Algorithm (MSCA) as an efficient and robust tool for contingency ranking in power system reliability assessment. Leveraging simple sinusoidal dynamics and carefully adjusted parameters (a=1, d=0.1), MSCA achieves a notable balance between exploration and exploitation. The algorithm demonstrates superior computational efficiency, achieving a significantly faster processing time of only 3.7 seconds compared to 101 seconds for Ant Colony Optimization (ACO), making it particularly advantageous for real-time applications. Furthermore, MSCA demonstrates broader search space coverage (8.33×10^{-7} %) compared to ACO's narrower exploration focus (1.25×10^{-6} %), indicating its superior robustness in navigating irregular or high-dimensional solution spaces. While ACO achieves a marginally higher capture ratio (98.8% vs. 96.7% for MSCA), this improvement comes at a significantly higher computational cost, rendering ACO less practical for scenarios with strict time constraints or large-scale systems. MSCA's near-equivalent accuracy, faster computation, and scalability underscore its viability for modern power systems requiring efficient and adaptable solutions. These results solidify MSCA's position as a competitive alternative to ACO, addressing critical challenges such as local optima entrapment and the computational burden often faced in optimization problems. The comparative analysis confirms that MSCA's strengths lie in its ability to deliver rapid, accurate, and scalable solutions, making it suitable for diverse power system applications. Its adaptability and computational simplicity make it an attractive choice for dynamic and high-stakes environments where real-time decision-making is paramount. Future research will enhance MSCA's capabilities by integrating hybrid optimization techniques, potentially combining MSCA with other metaheuristic methods to improve accuracy and adaptability in handling large-scale and dynamic power system challenges. Additionally, future studies could explore translating algorithmic performance into economic terms, such as the cost of increased processing time, providing a broader perspective on the real-world trade-offs associated with optimization techniques. This extension would offer valuable insights into the cost-benefit analysis of deploying MSCA in practical scenarios.

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