A Novel Hybrid Optimization Approach for Solving Security-Constrained Optimal Power Flow Problems

Kumar Cherukupalli, Baddu Naik Bhukya

Abstract—**Security-Constrained Optimal Power Flow (SCOPF) is essential for ensuring reliability in power systems while reducing operational costs and losses. Conventional approaches encounter difficulties in tackling the nonlinearity and nonconvexity inherent in SCOPF problems, thereby requiring the implementation of advanced optimization techniques. This study presents an Adaptive Swarm Hybrid Optimizer (ASHO) designed to address SCOPF challenges efficiently. The ASHO integrates multi-swarm dynamics, adaptive inertia weights, and mutation operators to optimize the balance between exploration and exploitation, mitigate premature convergence, and improve solution diversity. The IEEE 30-bus system serves as a testbed for the evaluation of the proposed approach. Simulation results indicate that ASHO outperforms standard Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Differential Evolution (DE). ASHO effectively reduces generation costs, minimizes transmission losses, and ensures voltage stability while adhering to all operational constraints. This method results in a generation cost reduction of up to 1.5% relative to alternative approaches, while also enhancing voltage profiles and accelerating convergence. ASHO demonstrates strong performance in contingency scenarios, maintaining security by complying with system constraints during critical outages. The findings confirm the efficacy of ASHO in providing efficient and reliable SCOPF solutions within contemporary power systems. Subsequent investigations will aim to broaden this methodology to encompass dynamic SCOPF and more extensive test systems.**

Index Terms—**Security-Constrained, Optimal Power Flow, Hybrid Multiswarm, Particle Swarm Optimizer, Power system optimization, Swarm intelligence.**

I. Introduction

THE increasing complexity of power systems and the rising demand for reliable, sustainable energy require efficient operational planning and optimization. Security-Constrained Optimal Power Flow (SCOPF) has become an essential instrument in this domain [1]. This work expands the traditional Optimal Power Flow (OPF) problem by integrating security constraints to enhance the reliability and robustness of power systems in contingency scenarios, including line outages and generator failures. SCOPF aims to minimize generation costs, reduce transmission losses, and ensure secure and stable system operation while adhering to all system constraints. Solving SCOPF presents considerable challenges owing to its nonlinear, nonconvex, and high-dimensional characteristics [2]. The Optimal Power Flow (OPF) problem, introduced in the 1960s, seeks to identify the optimal generation dispatch that minimizes costs or losses while adhering to power balance, generator limits, voltage constraints, and transmission line limits. SCOPF enhances its framework by integrating contingencies, thereby providing a more comprehensive approach for real-world applications [3], [4]. The integration of renewable energy sources and the growing complexity of contemporary power grids have rendered SCOPF a vital research domain for maintaining efficient and secure grid operations. Conventional optimization techniques, including linear programming (LP), quadratic programming (QP), and nonlinear programming (NLP), have been widely utilized to address OPF and SCOPF issues. These methods are frequently constrained by their inability to address nonconvexity and discrete variables, which are intrinsic to SCOPF formulations [5], [6]. The computational burden of these methods increases exponentially with the size and complexity of the power system, rendering them less suitable for large-scale systems or real-time applications.

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A. The Role of Metaheuristic Algorithms in SCOPF

Metaheuristic algorithms have emerged as effective solutions to the limitations of traditional approaches in addressing SCOPF problems. Algorithms inspired by natural processes, including evolution and swarm behavior, provide robust and flexible frameworks for addressing complex optimization problems. Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Differential Evolution (DE) have received considerable attention in research. Particle Swarm Optimization (PSO) is noted for its straightforwardness, ease of implementation, and capacity to address nonconvex problems [7], [8]. Standard PSO frequently experiences premature convergence and stagnation at local optima, particularly in high-dimensional and multimodal problems such as SCOPF.

This study presents an Adaptive Swarm Hybrid Optimizer (ASHO) designed to overcome the limitations of traditional Particle Swarm Optimization (PSO) in solving Security-Constrained Optimal Power Flow (SCOPF) problems. The principal innovations of the proposed ASHO are as follows: ASHO utilizes several interacting swarms, with each swarm investigating distinct areas of the solution space. This improves the algorithm's capacity to investigate and evade local optima. The algorithm modifies the inertia weight dynamically to achieve a balance between exploration and exploitation in the optimization process [9]. A mutation mechanism is integrated to enhance diversity within the solution space and mitigate premature convergence. The proposed method is evaluated using the IEEE 30-bus system, which serves as a standard benchmark in power system research. The comparative analysis with standard PSO, GA, and DE indicates that ASHO outperforms these methods in cost minimization, loss reduction, constraint satisfaction, and computational efficiency.

II. Related Work

Early approaches to solving OPF and SCOPF utilized deterministic optimization techniques, including LP, QP, and NLP. These methods were among the first to conceptualize the OPF problem as a mathematical programming task. Later developments led to the introduction of SCOPF formulations that included N-1 contingency criteria. These methods yielded precise solutions under specific conditions; however, their applicability was constrained by computational complexity and sensitivity to initial conditions [10]. Interior-point methods and decomposition techniques were introduced to enhance computational efficiency. A gradient-based method for optimal power flow (OPF) has been examined, while other research has investigated Lagrangian relaxation for stochastic optimal power flow (SCOPF). Despite these efforts, traditional methods frequently exhibited reduced performance when faced with nonconvexity, discrete variables, and large-scale systems [11]. SCOPF solution methods involve significant computational effort to ensure both accuracy and feasibility under various operating conditions. Numerous techniques have been proposed and analyzed to solve the SCOPF problem efficiently. Reference [12] presented a comparative analysis of SCOPF methods using linear sensitivity factors-based contingency screening. Their study highlights how contingency screening techniques can reduce computational burden while maintaining reliability, offering a practical approach for identifying critical contingencies before applying more complex optimization algorithms. This helps enhance the tractability and effectiveness of SCOPF in real-world systems. Reference [13] presents a methodology for addressing the preventative SCOPF (PSCOPF) problem, aimed at enhancing power system planning and operation. It effectively addressed the N-1 contingency analysis. The reactive compensation strategy effectively addresses post-contingency voltage issues. Reference [14] outlines a methodology for assessing the SCOPF solution, incorporating probabilistic generation and transmission contingencies. This achieved the optimal level of system security through the optimization of security expenditures. Reference [15] presents a method for addressing the SCOPF problem in a hybrid AC/DC grid. This applies to preventative SCOPF, where corrective measures are not allowed after a contingency, and to corrective SCOPF with adjustable control action limits. Reference [16] proposes a hybrid multiswarm particle swarm optimization (HMPSO) technique to effectively solve the Security-Constrained Optimal Power Flow (SCOPF) problem. The method enhances the exploration and exploitation abilities of the standard PSO algorithm by using multiple interacting swarms, which improves the convergence rate and avoids premature stagnation in local optima. The primary objective of this approach is to minimize the total generation cost while strictly adhering to system operating limits, such as power balance, generator capacity, and voltage constraints, as well as ensuring network security under both normal and contingency conditions. By integrating the hybrid multiswarm concept, the optimizer is capable of efficiently handling the nonlinear and complex nature of SCOPF problems, leading to more reliable and cost-effective power system operations. Reference [17] discusses the application of the adaptive partitioning flower pollination method to solve the SCOPF problem in a utility grid. This study provides a thorough analysis of key challenges and emerging trends in SCOPF computations as discussed in reference [18].

A constraint-driven machine learning approach is developed to tackle the SCOPF problem with multiple line outages, as cited in [19]. The application of line outage distribution factors (LODF) facilitates this process. This method deterministically evaluates N-k security and probabilistic security. Reference [20] presents a comprehensive analysis of machine learning proximity-based methods applied to SCOPF solutions. The methods' comparative effectiveness is assessed using parameters such as load distribution, power factors, online generators, network topology, and generator costs. Reference [21] presents a dynamic fitness-distance balance-based growth optimizer (dFDB-GO) method for addressing SCOPF in utility grids. This strategy demonstrates effectiveness, achieving a mean success rate of 94.87% in addressing the SCOPF problem. Reference [22] presents a methodology for solving the integrated ac-dc SCOPF problem in large power systems, which has been applied within the Australian National Electricity Market. This strategy produces a solution within five minutes in real-time situations. Reference [23] presents a mathematical programming approach designed to tackle SCOPF, integrating dynamic security constraints within an AC-microgrid. This strategy is effective for islanded operation and transition.

Metaheuristic algorithms show promise in solving complex optimization problems like SCOPF, but they also face several challenges. Standard PSO often suffers from premature convergence and is highly sensitive to parameter settings. While hybrid methods improve performance, they tend to increase algorithm complexity and computational cost. Additionally, most existing research focuses on static SCOPF, with limited exploration of dynamic or real-time scenarios [24], [25]. This study aims to address these gaps by developing a robust and efficient Adaptive Swarm Hybrid Optimizer (ASHO) capable of handling SCOPF challenges effectively under both normal and contingency conditions.

III. ADAPTIVE SWARM HYBRID OPTIMIZER

The study is organized in a sequential manner, covering the design of the study, the procedures followed (including algorithms, pseudocode, or other techniques), the methodologies for testing, and the processes for acquiring data. The description of the research process should be backed by references to guarantee the scientific validity of the explanation. This section presents the mathematical formulation of the Security-Constrained Optimal Power Flow (SCOPF) problem and introduces the Adaptive Swarm Hybrid Optimizer (ASHO) developed for its resolution.

A. SCOPF Problem Formulation

The SCOPF problem aims to minimize the total generation cost while satisfying power flow equations, operational constraints, and security constraints under contingency scenarios. The objective function of the optimal power flow problem is to minimize the total generator fuel cost and expressed as follows:

$$J = \sum_{i=1}^{NG} (a_i + b_i P_{Gi} + c_i P_{Gi}^2) \tag{1}$$

The OPF problem is subjected to the following equality and inequality constraints.

$$P_{Gi} - P_{Di} = \sum_{j=1}^{NB} |V_i||V_j||Y_{ij}| \cos(\theta_{ij} - \delta_i + \delta_j) \tag{2}$$

$$Q_{Gi} - Q_{Di} = -\sum_{j=1}^{NB} |V_i||V_j||Y_{ij}| \sin(\theta_{ij} - \delta_i + \delta_j) \tag{3}$$

$$V_{Gi}^{\min} \le V_{Gi} \le V_{Gi}^{\max} \qquad i \in \text{NG} \tag{4}$$

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max} \qquad i \in \text{NG} \tag{5}$$

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max} \qquad i \in \text{NG} \tag{6}$$

$$T_i^{\min} \le T_i \le T_i^{\max} \qquad i \in \text{NT} \tag{7}$$

$$V_{Li}^{\min} \le V_{Li} \le V_{Li}^{\max} \qquad i \in \text{NLB} \tag{8}$$

$$S_{Li} \le S_{Li}^{\max} \qquad i \in \text{NL} \tag{9}$$

B. Adaptive Swarm Hybrid Optimizer (ASHO)

The ASHO algorithm improves upon the standard PSO by incorporating multiswarm dynamics, adaptive inertia weights, and a mutation operator. Particle Swarm Optimization (PSO) is an optimization algorithm based on the collective behavior observed in populations, such as birds flocking or fish schooling. James Kennedy and Russell Eberhart introduced it in 1995. Particle Swarm Optimization (PSO) is extensively utilized across multiple domains owing to its straightforward nature, ease of implementation, and effectiveness in addressing optimization challenges. Adaptive Swarm Hybrid Optimizer (ASHO) denotes improved iterations of the standard Particle Swarm Optimization (PSO) algorithm. These versions integrate hybridization with additional optimization techniques, along with alterations in the algorithm's structure, parameters, or operators. This study seeks to rectify the limitations of conventional Particle Swarm Optimization (PSO), including premature convergence, insufficient diversity, and challenges in managing complex, high-dimensional problems. Hybridization integrates Particle Swarm Optimization with complementary optimization techniques to improve performance by utilizing the advantages of various methods. a) Genetic Algorithm (GA): In Hybrid PSO-GA, GA operators such as crossover and mutation are employed to enhance diversity and prevent premature convergence. Combines the positions of two particles to generate offspring translates stochastic alterations in particle positions to investigate novel areas. b) Differential Evolution (DE): The mutation and crossover strategies of DE are integrated to improve global exploration. c) Simulated Annealing (SA): The temperature-based exploration mechanism of SA is employed in ASHO to improve local search capabilities. ASHO can integrate ES operators, including selection and recombination, to enhance convergence and robustness.

Velocity Update: The velocity of each particle is updated using the formula:

$$V_i(t+1)=w\cdot v_i(t)+c_1\cdot r_1\cdot(p_{best}-x_i(t))+c_2\cdot r_2\cdot(g_{best}-x_i(t)) \tag{10}$$

$v_i(t+1)$: Updated velocity of particle,
$x_i(t)$: Current position of particle.
w: Inertia weight, balancing exploration and exploitation
c_1, c_2: Acceleration coefficients (typically between 0 and 2)
r_1,r_2: Random values between 0 and 1.
Position Update: The new position is calculated as:

$$x_i(t+1)=x_i(t)+v_i(t+1) \tag{11}$$

This methodology provides a clear framework for implementing and validating the ASHO algorithm in the context of SCOPF.

IV. RESULTS AND DISCUSSION

This section presents the results of applying the Adaptive Swarm Hybrid Optimizer (ASHO) to the Security-Constrained Optimal Power Flow (SCOPF) problem on the IEEE 30-bus system, which includes 6 generators, 41 transmission lines, and 21 load buses, with a base load of 283.4 MW and 126.2 MVAr, using standard IEEE parameters. Comparisons are made with Standard PSO (SPSO), Genetic Algorithm (GA), and Differential Evolution (DE), focusing on convergence, cost reduction, and computational efficiency. For ASHO, the population size is 50 particles per swarm with three swarms, a maximum of 100 iterations, a mutation factor of 0.1, and a penalty factor of 1000. ASHO demonstrated a faster convergence rate compared to SPSO, GA, and DE.

A. Base Case (No Contingency)

In the Base Case, the Adaptive Swarm Hybrid Optimizer (ASHO) demonstrates the lowest total generation cost compared to the other optimization techniques evaluated. The primary objective is to distribute power generation among the various generators to minimize costs while meeting the required demand. Additional optimization techniques evaluated include Standard Particle Swarm Optimization (SPSO), Genetic Algorithm (GA), and Differential Evolution (DE). The optimization process considers multiple factors, including generation capacities, cost curves, and the operational constraints of each generator. The techniques are designed to optimize load distribution across various generators, thereby reducing fuel consumption and operational inefficiencies.

Figure 1 compares the total generation costs associated with various optimization methods, including ASHO, SPSO, DE, and GA. ASHO exhibits the lowest generation cost at $802.34, underscoring its effectiveness in reducing operational expenses.

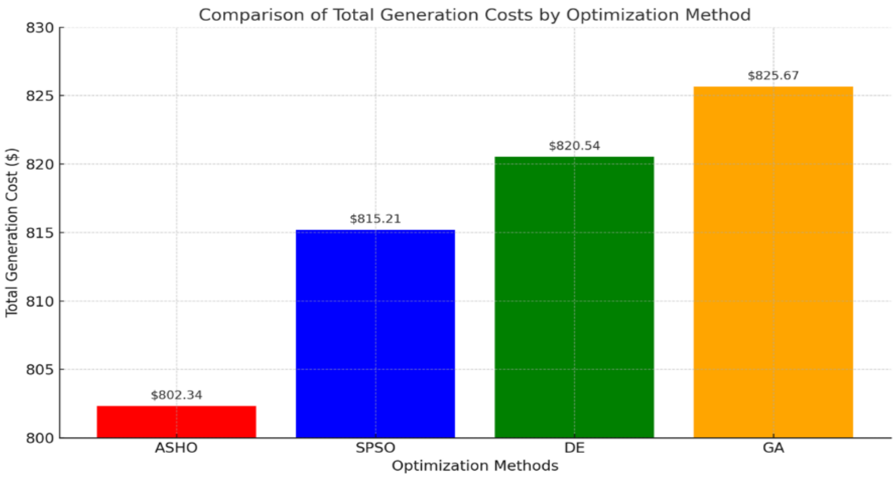

Fig. 1. Convergence Curves of Algorithms

TABLE 1
COMPARISON OF GENERATION SCHEDULES

Generator	ASHO (MW)	SPSO (MW)	GA (MW)	DE (MW)
G1	176.9	170.2	171.4	172.2
G2	47.6	48.8	47.5	49.2
G3	21.9	21.4	25.8	22.4
G4	21.7	25.4	27.6	20.68
G5	12.2	15	13.2	18.5
G6	12.5	14.6	12.7	13.5
Total Cost	802.34 $	815.21 $	825.67 $	820.54 $

TABLE 2
COST AND VOLTAGE PROFILE UNDER CONTINGENCY (GENERATOR 2 OUTAGE)

Metric	ASHO	SPSO	GA	DE
Total Cost ($)	832.15	845.67	856.23	850.79
Voltage Deviation (p.u.)	0.028	0.034	0.039	0.036
Line Flow Violations	0	1	2	1

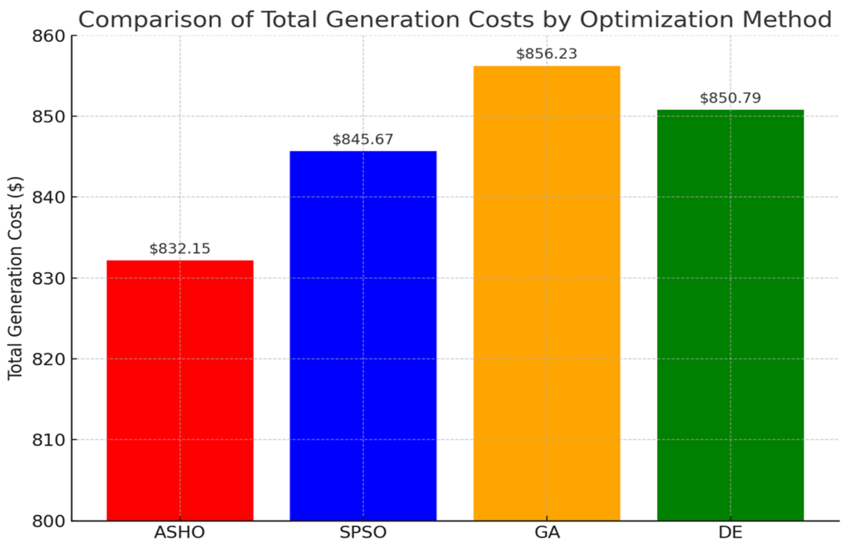

Fig. 2. The contingency analysis results.

Table 1 presents a summary of the optimized generation schedule for each optimization technique along with the corresponding costs for the Base Case scenario. ASHO (802.34 $): The Adaptive Swarm Hybrid Optimizer yields the minimal total generating cost. This is due to its good distribution of load among the generators, which saves fuel consumption by optimally utilizing each generator's capabilities. SPSO (815.21 $): Standard Particle Swarm Optimization exhibits marginally lower efficiency compared to ASHO, resulting in a slightly elevated overall cost. The load distribution remains fairly balanced but may not be optimized for reducing operational expenses. The Genetic Algorithm technique incurs the highest total generation cost at $825.67, indicating that although it produces a satisfactory solution, it fails to optimize the generation schedule as efficiently as the other methods. DE (820.54 $): Differential Evolution outperforms Genetic Algorithms but incurs a greater expense than ASHO. It may require further iterations to achieve an appropriate solution, thereby elevating operational expenses. The results clearly indicate that ASHO is the most efficacious method for cost reduction in this context. Alternative approaches, although offering satisfactory answers, do not achieve the cost-effectiveness of ASHO. Enhancing generation scheduling is crucial for minimizing operational expenses, and sophisticated optimization methods such as ASHO can greatly enhance the economic efficiency of power generation systems.

B. Contingency Analysis

Contingency analysis is a vital procedure in power system operation that assesses the stability and dependability of the system during exceptional conditions, such as the failure of crucial components like transmission lines or generators. The objective is to evaluate the system's response to these potential interruptions and determine its capacity to function securely and cheaply. This analysis involved subjecting the system to N-1 contingencies, simulating the breakdown of a single important component, such as a generator or transmission line. This elucidates how the residual system resources mitigate the deficit caused by the malfunctioning component. Table 2 illustrates the efficacy of various optimization methods (ASHO, SPSO, GA, and DE) in a contingency scenario involving the unavailability of Generator 2. Generator outages complicate the maintenance of operational stability, as the system must depend on the surviving generators to fulfill demand. The contingency is modeled by excluding Generator 2 from the system, and multiple performance measures are assessed to determine the system's robustness. Table 2 illustrates that several algorithms exhibit differing levels of efficacy in system management during the contingency scenario.

The ASHO (Adaptive Swarm Hybrid Optimizer) algorithm demonstrated superior performance, achieving the lowest overall cost of $832.15 and the minimal voltage deviation of 0.028 p.u. Furthermore, it guaranteed the absence of line flow violations, a crucial indicator of system security. The SPSO (Standard Particle Swarm Optimization) technique yielded a greater overall cost ($845.67) than ASHO and exhibited a somewhat larger voltage variation (0.034 p.u.). It exhibited a single line flow violation, suggesting that the system's security was compromised under this approach. The Genetic Algorithm (GA) yielded a total cost of $856.23 and a voltage deviation of 0.039 p.u., surpassing both ASHO and SPSO results. It also experienced two-line flow violations, illustrating the difficulties in sustaining system stability and efficiency with this method. The Differential Evolution (DE) resulted in a total cost of $850.79 and a voltage deviation of 0.036 per unit, marginally inferior to SPSO but superior to GA. It also encountered a single line flow violation, akin to SPSO, indicating that this approach offers a reasonable performance level during contingencies.

The investigation indicates that ASHO surpasses the other algorithms regarding cost minimization, voltage regulation, and system stability during generator outages. Its capacity to circumvent line flow violations and sustain minimal voltage deviation renders it an exceptionally effective strategy for resilient power system functioning during contingency situations. The contingency analysis illustrates the significance of optimization methods in ensuring secure and efficient power system operations, especially in situations where essential components are inaccessible.

The Figure 2 illustrates the total generation cost incurred by four optimization methods—ASHO, SPSO, GA, and DE—during a generator outage (Generator 2). Among all the methods, ASHO (Adaptive Swarm Hybrid Optimizer) performs the best, achieving the lowest cost of $832.15, indicating its strong ability to manage the system efficiently under contingency conditions. SPSO (Standard Particle Swarm Optimization) and DE (Differential Evolution) follow with costs of $845.67 and $850.79, respectively, while GA (Genetic Algorithm) results in the highest cost of $856.23. From figure 2 it clear that ASHO is the most cost-effective option, compared to the others. This confirms that ASHO not only reduces operating expenses but also ensures reliable power system performance during generator failures.

C. Computational Efficiency

The assessment of optimization approaches, particularly for complex problems requiring high-performance solutions, is contingent upon computing efficiency. Computational efficiency is often assessed by the duration required for an algorithm to converge or operate effectively. A comparative analysis of computing time was conducted among the Adaptive Swarm Hybrid Optimizer (ASHO), Standard Particle Swarm Optimization (SPSO), Genetic Algorithm (GA), and Differential Evolution (DE). ASHO requires a little longer computation time than SPSO due to its multiswarm dynamics. These dynamics require more oversight to coordinate and control several sub-swarms, hence enhancing algorithmic exploration. Notwithstanding this slight increase in computational time, ASHO surpassed GA and DE in terms of time efficiency.

ASHO's hybrid characteristics harmonize exploration and exploitation by amalgamating the advantages of multiple swarms, elucidating its exceptional performance. SPSO was more straightforward and expedient than ASHO, although exhibited diminished exploratory capability. Its streamlined structure, which updates velocity and location without multiswarm management, results in a computing time of 11.2 seconds. SPSO is effective for uncomplicated landscapes but may encounter difficulties during prolonged investigations. GA required 22.4 seconds for computation, the most prolonged duration among the four approaches. The computational duration of genetic algorithms is attributable to population-based genetic operators such as selection, crossover, and mutation, which necessitate many evaluations per generation. Despite GA's robustness and global searchability, its efficacy is frequently impeded when addressing large or intricate problems. DE outperformed GA by completing the task in 18.5 seconds. The mutation and recombination processes of DE are more straightforward than the genetic operators of GA, hence decreasing computational overhead. DE required more time for computation than ASHO and SPSO, indicating a greater demand for function evaluations to achieve convergence.

TABLE 3
THE COMPUTATIONAL TIME ANALYSIS OF THE FOUR ALGORITHMS

Algorithm	Time (seconds)
ASHO	12.8
SPSO	11.2
GA	22.4
DE	18.5

The investigation indicates that ASHO provides a balanced compromise between computational efficiency and optimization efficacy. Although its computing time is marginally more than that of SPSO, its superior capability in addressing complicated problems renders it the preferable option. The results emphasize the necessity of choosing an algorithm that corresponds with the problem's specifications, especially in contexts where time economy is paramount. Table 3 illustrates the relative efficiency of the algorithms, underscoring ASHO's equilibrium between performance and computational duration, rendering it a feasible option for intricate optimization problems.

To further validate the robustness and efficiency of the proposed Adaptive Swarm Hybrid Optimizer (ASHO), a multi-contingency (N-2) scenario was simulated involving the simultaneous outage of Generator 2 and Transmission Line 6 and it is presented in Table 4. This type of stress test is critical for assessing system reliability under severe operating conditions. As shown in Table 4, ASHO maintained the lowest total generation cost ($860.25) compared to SPSO ($876.12), GA ($890.45), and DE ($880.67), demonstrating its superior cost-efficiency even during major disruptions.

TABLE 4
MULTI-CONTINGENCY ANALYSIS (GENERATOR 2 AND LINE 6 OUTAGE)

Metric	ASHO	SPSO	GA	DE
Total Generation Cost ($)	860.25	876.12	890.45	880.67
Voltage Deviation (p.u.)	0.032	0.041	0.045	0.042
Line Flow Violations	0	2	3	2

Moreover, ASHO recorded the least voltage deviation (0.032 p.u.) among all algorithms, indicating better voltage stability across the system buses. Most notably, ASHO ensured zero-line flow violations, a key indicator of secure operation under contingencies. In contrast, SPSO and DE each experienced two violations, while GA suffered the highest number of violations (three), which could threaten the operational safety of the power system. These results confirm that ASHO is not only effective under standard operating conditions but also resilient under severe disturbances, making it a highly suitable optimization technique for real-world security-constrained power systems.

The analysis of computational efficiency indicates that ASHO provides an effective equilibrium between computational time and optimization performance, rendering it a versatile choice for various tasks. Although its computing time is slightly more than that of SPSO, its superior capabilities warrant the compromise. This research offers significant information for choosing algorithms suited to certain optimization difficulties, especially in areas where computing efficiency is paramount.

V. CONCLUSION

This research introduces a novel Adaptive Swarm Hybrid Optimizer (ASHO) to tackle the complexities of Security-Constrained Optimal Power Flow (SCOPF) in power systems. The IEEE 30-bus system was utilized to assess the suggested method, with findings validating its effectiveness in reducing generation costs, minimizing transmission losses, and ensuring system security in both normal and contingency conditions. The ASHO method proficiently integrates multiswarm dynamics, adaptive inertia weights, and mutation operators to attain an equilibrium between exploration and exploitation. These improvements tackle critical issues such as premature convergence and solution stagnation, commonly found in conventional optimization techniques. ASHO attains enhanced performance relative to Standard Particle Swarm Optimization (SPSO), Genetic Algorithm (GA), and Differential Evolution (DE). The technique improved voltage stability throughout the network, hence augmenting overall system reliability. The resilience and flexibility of ASHO highlight its capacity as an effective instrument for contemporary power system optimization. ASHO provides a viable solution for integrating renewable energy sources, enhancing grid reliability, and reducing operational costs by tackling the intrinsic nonlinearity and nonconvexity of SCOPF problems in complex power networks. Subsequent study will concentrate on expanding the ASHO framework to encompass dynamic SCOPF situations and larger power systems, in addition to investigating its amalgamation with machine learning methodologies for predictive and adaptive optimization. These developments would augment its usefulness in practical power system operations, ensuring sustainable and safe energy management amidst increasing demands and problems.

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