Solving Security-Constrained OPF Problems: A Hybrid Multiswarm Particle Swarm Optimizer

Venkata Ramana Gupta Nallagattla, Venugopal Gaddam, M. Rajasekaran, Tirumalasetti Lakshmi Narayana, Ranjith Kumar Rupani

***Abstract*—Security-Constrained Optimal Power Flow (SCOPF) plays a critical role in ensuring the secure, reliable, and cost-effective operation of modern power systems. However, the inherent nonlinearity, nonconvexity, and high-dimensional nature of SCOPF make it a challenging optimization problem for conventional methods. This paper introduces a Hybrid Multiswarm Particle Swarm Optimizer (HMPSO), designed to enhance exploration, prevent premature convergence, and improve solution diversity. The algorithm incorporates multiswarm dynamics, adaptive inertia weights, and mutation operators to achieve a balanced trade-off between exploration and exploitation. The proposed approach is validated using the IEEE 30-bus test system and benchmarked against Standard Particle Swarm Optimization (SPSO), Genetic Algorithm (GA), and Differential Evolution (DE). Simulation results demonstrate that HMPSO provides superior performance in minimizing generation costs, reducing transmission losses, and enhancing voltage stability, even under contingency conditions. In particular, HMPSO achieved a 1.5% reduction in generation costs, faster convergence, and improved robustness compared to existing methods. These findings establish HMPSO as a reliable and efficient solution for SCOPF, with strong potential for extension to larger systems and dynamic scenarios in future research.**

***Index Terms*—Security-Constrained Optimal Power Flow (SCOPF), Metaheuristic Optimization, Hybrid Swarm Intelligence, Adaptive Inertia Weight, Power System Reliability, IEEE 30-Bus Test System.**

I. Introduction

THE increasing demand for reliable, secure, and sustainable energy has significantly intensified the complexity of modern power systems. As electric grids evolve with large-scale integration of renewable energy resources, energy storage, and demand-side management, operational planning and optimization have become more challenging than ever before. Ensuring both economic efficiency and operational reliability requires advanced optimization strategies that can effectively handle the intricacies of large-scale networks. In this context, the Security-Constrained Optimal Power Flow (SCOPF) problem has emerged as a crucial tool for balancing generation cost minimization with system security requirements.

The SCOPF is an extension of the classical Optimal Power Flow (OPF) problem, which aims to determine the most cost-effective operating point of a power system while satisfying operational limits such as generator constraints, transmission capacity, and voltage boundaries. While OPF ensures cost minimization under steady-state conditions, SCOPF integrates contingency constraints (e.g., generator or transmission line outages) to guarantee system reliability under abnormal events. This makes SCOPF indispensable for ensuring secure, resilient, and economical operation of modern power grids. However, solving SCOPF is far from trivial. Its nonlinear, nonconvex, and high-dimensional nature creates significant computational challenges. Traditional deterministic optimization approaches, such as linear programming (LP), quadratic programming (QP), and nonlinear programming (NLP), though efficient for small-scale or convex problems, often fail when applied to large-scale SCOPF scenarios. These methods suffer from high computational burdens and sensitivity to initial conditions, which limits their scalability and applicability in real-time operations [1], [2].

A. Importance of SCOPF in Modern Power Systems

The rapid penetration of renewable energy sources, particularly wind and solar, has transformed the operational dynamics of power systems. These energy sources are inherently intermittent and uncertain, which increases the likelihood of voltage instabilities, frequency deviations, and transmission congestion. The SCOPF framework addresses these concerns by ensuring that, even under contingencies such as N-1 or N-2 outages, the system continues to operate within acceptable limits. Moreover, SCOPF enables utilities to meet reliability standards while minimizing operational costs, making it a cornerstone for the secure integration of renewables and real-time grid management [3], [4]. Another motivation for advancing SCOPF is the growing complexity of hybrid AC/DC networks, smart grids, and microgrids.

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These systems introduce new operational challenges, including multi-terminal HVDC interactions, distributed generation uncertainties, and probabilistic contingency events. The ability of SCOPF to adapt to such complex environments underscores its relevance in next-generation grid operations [5], [6].

B. Metaheuristic Approaches for SCOPF

Given the limitations of deterministic methods, researchers have increasingly turned to metaheuristic algorithms inspired by natural processes, such as swarm intelligence, biological evolution, and physics-based phenomena. Metaheuristics offer flexibility, robustness, and the ability to avoid local optima, making them particularly well-suited for addressing nonconvex and high-dimensional optimization problems. Among the widely used metaheuristics are Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Differential Evolution (DE). PSO, introduced by Kennedy and Eberhart in 1995, has attracted significant attention due to its simplicity, ease of implementation, and effectiveness in solving power system optimization problems. Nevertheless, standard PSO often suffers from premature convergence and stagnation in local optima, especially in multimodal landscapes such as SCOPF [7], [8]. Similarly, GA and DE exhibit strong exploration abilities but require careful parameter tuning and may involve higher computational costs [9], [10].

C. Hybrid and Advanced Swarm-Based Methods

To overcome these limitations, hybrid and modified swarm-based optimization methods have been proposed. Hybrid algorithms combine the strengths of different metaheuristics, while modified swarm algorithms introduce new mechanisms—such as adaptive inertia weights, multi-swarm cooperation, and mutation operators—to improve convergence behavior. For example, hybrid PSO-GA and PSO-DE methods have been shown to enhance global exploration and maintain diversity in the search space [11], [12]. In particular, Hybrid Multiswarm Particle Swarm Optimization (HMPSO) has emerged as a promising approach for SCOPF. By dividing the population into multiple interacting swarms, HMPSO enhances exploration of the solution space and avoids premature convergence. Adaptive inertia weights dynamically balance exploration and exploitation during the search, while mutation operators inject additional diversity. These mechanisms make HMPSO particularly effective in handling the high-dimensional, nonlinear nature of SCOPF.

II. Related Work

The Optimal Power Flow (OPF) problem has been extensively studied since its introduction in the 1960s. Over the years, researchers have proposed multiple methods to address its extension, the Security-Constrained Optimal Power Flow (SCOPF), which incorporates contingency constraints to ensure system reliability. Early efforts primarily relied on deterministic approaches such as linear programming (LP), quadratic programming (QP), and nonlinear programming (NLP). These classical methods were mathematically rigorous and suitable for convex formulations, but they exhibited scalability limitations when applied to large-scale, nonlinear, and nonconvex SCOPF problems [13], [14]. The incorporation of N-1 or higher-order contingency constraints further exacerbated computational complexity, making traditional methods impractical for real-time applications [15]. Several refinements to deterministic optimization were introduced to improve tractability. For example, the interior-point method and decomposition-based strategies were widely applied to OPF and SCOPF problems. Capitanescu and Wehenkel [16] investigated the interior-point approach for large-scale OPF, demonstrating improved efficiency compared to conventional gradient-based methods. Similarly, decomposition methods split SCOPF into smaller, more manageable subproblems, facilitating computation for large networks [17]. However, these methods often struggled when addressing discrete decision variables, nonconvexities, and renewable energy uncertainties, thus limiting their wider adoption.

To overcome the limitations of deterministic techniques, researchers increasingly adopted metaheuristic optimization methods. These algorithms, inspired by biological evolution, swarm intelligence, and physical processes, are more robust in handling multimodal, high-dimensional optimization problems. Among them, Particle Swarm Optimization (PSO) [18], Genetic Algorithms (GA) [19], and Differential Evolution (DE) [20] have received significant attention in the power system community. PSO, due to its simplicity and efficiency, has been applied extensively to OPF and SCOPF. For example, Panda and Padhy [21] compared PSO and GA for FACTS-based controller design and showed PSO's superiority in convergence speed. However, standard PSO often experiences premature convergence and stagnation in local optima, particularly in high-dimensional solution spaces. GA and DE, while maintaining better population diversity, require careful parameter tuning and typically involve higher computational effort [22]. Other swarm-based techniques such as Artificial Bee Colony (ABC) [23], Ant Colony Optimization (ACO) [24], and Firefly Algorithms [25] have also been introduced for power system applications. These approaches demonstrated improved robustness but, like PSO and GA, often required hybridization with additional strategies to achieve consistent performance in SCOPF.

Recent studies have focused on hybrid algorithms that combine the strengths of multiple metaheuristics, as well as modified swarm intelligence techniques that incorporate adaptive mechanisms. For instance, Chen et al. [26] proposed a hybrid Flower Pollination Algorithm for multi-objective OPF, while Mahdad and Srairi [27] presented an adaptive partitioning algorithm to improve voltage stability in SCOPF. Zhang et al. [28] advanced a Hybrid Multiswarm PSO (HMPSO), which improved exploration of the solution space through multi-swarm dynamics. Moreover, researchers have introduced adaptive inertia weights, mutation operators, and multi-swarm collaboration mechanisms to enhance global search and prevent stagnation [29]. These innovations provided superior performance in SCOPF, particularly in cost minimization and transmission loss reduction.

In addition to metaheuristics, machine learning (ML)-based approaches have gained attention for their ability to approximate SCOPF solutions efficiently. Giraud et al. [30] proposed a constraint-driven deep learning model for N-k SCOPF, demonstrating high accuracy in predicting feasible operating points. Popli et al. [31] assessed machine-learnt proxies for SCOPF solvers, showing they can significantly reduce computational time without sacrificing robustness. These ML-based strategies, while promising, require extensive training data and lack the interpretability of conventional optimization approaches. Despite these advances, several challenges remain unresolved. First, premature convergence remains a common limitation in classical PSO and other swarm-based algorithms. Second, hybrid methods, though effective, often increase algorithmic complexity and computational cost. Third, most existing research still focuses on static SCOPF formulations, with limited efforts addressing dynamic SCOPF and real-time operation. Finally, integrating renewable uncertainty, probabilistic contingencies, and hybrid AC/DC systems into SCOPF frameworks remains an open research area [32], [33]. To address these limitations, this study proposes a Hybrid Multiswarm Particle Swarm Optimizer (HMPSO) that integrates multiswarm dynamics, adaptive inertia weights, and mutation operators. Unlike conventional metaheuristics, the proposed HMPSO achieves a balance between exploration and exploitation, avoids stagnation, and ensures robustness under contingency scenarios. Through evaluation on the IEEE 30-bus test system, HMPSO demonstrates superior performance in generation cost reduction, transmission loss minimization, and voltage stability improvement, establishing it as a reliable solution for SCOPF.

III. SCOPF Problem Formulation

The Security-Constrained Optimal Power Flow (SCOPF) problem extends the classical OPF by explicitly incorporating reliability constraints to ensure secure system operation under both normal and contingency conditions. Its primary objective is to minimize the total generation cost while maintaining power balance and respecting operational limits, such as voltage boundaries, generator capabilities, and transmission line thermal limits. The mathematical formulation of SCOPF includes both the objective function and a set of equality and inequality constraints.

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

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

Equality Constraints: These are the set of power flow equations that govern the power system and expressed as follows:

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

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

Inequality Constraints: These are the set of constraints that represent the power system operational limits and security limits.

Generation constraints: Generator voltage, real power generation and reactive power generation are constrained as follows:

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

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

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

Transformer constraints: Transformer tap settings are constrained as follows:

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

Security constraints: The voltage at load buses and transmission line loadings are constrained as follows:

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

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

To summarize, the SCOPF problem can be described as a large-scale, nonlinear, and nonconvex optimization task, where the objective is to minimize total operating costs subject to power balance and strict security constraints. The inclusion of contingency constraints significantly increases problem dimensionality, making SCOPF much harder to solve than classical OPF. Traditional methods struggle to converge efficiently, especially under large system sizes or when discrete decision variables are introduced, such as tap-changing transformers or discrete reactive power compensators. In this context, metaheuristic algorithms, particularly swarm-based approaches, have proven effective due to their ability to handle nonlinear, multimodal landscapes without requiring derivative information. Recent works have extended SCOPF formulations to include probabilistic uncertainties from renewable energy sources, dynamic constraints in microgrids, and hybrid AC/DC networks. However, balancing computational efficiency with solution robustness remains a major research challenge, motivating the development of advanced hybrid algorithms such as the proposed HMPSO.

IV. Hybrid and Modified Particle Swarm Optimization (HMPSO)

Particle Swarm Optimization (PSO), originally introduced by Kennedy and Eberhart [18], is a population-based metaheuristic that mimics the collective foraging behavior of birds or fish. Its popularity stems from its simplicity, ease of implementation, and effectiveness in solving nonlinear and nonconvex problems. In PSO, each particle in the swarm represents a candidate solution and moves through the search space by updating its velocity and position according to its own experience (personal best, or pbest) and the experience of the entire swarm (global best, or gbest). This mechanism enables PSO to balance exploration and exploitation to some extent, but in practice, the algorithm is often affected by premature convergence and loss of diversity, particularly when applied to high-dimensional or multimodal optimization problems such as SCOPF [34]. To address these shortcomings, Hybrid and Modified PSO (HMPSO) algorithms have been developed. HMPSO enhances the classical PSO framework through three primary mechanisms: (i) multi-swarm dynamics, (ii) adaptive inertia weights, and (iii) mutation operators. These modifications improve exploration of the solution space, prevent stagnation, and enhance convergence robustness, making HMPSO particularly effective for SCOPF applications.

A. Hybridization Strategies

Hybridization integrates PSO with other optimization techniques to exploit complementary strengths. Common hybridization methods include: PSO-GA Hybridization: Incorporates crossover and mutation operators from Genetic Algorithms (GA) to maintain population diversity and avoid premature convergence. This approach allows information exchange between particles, improving exploration in multimodal landscapes [35]. PSO-DE Hybridization: Leverages mutation and crossover strategies from Differential Evolution (DE) to enhance global exploration capabilities. This integration enables more effective navigation of rugged search spaces [36]. PSO-SA Hybridization: Combines PSO with Simulated Annealing (SA), where the probabilistic acceptance of worse solutions based on a temperature schedule enables more thorough local search and the ability to escape local optima [37]. These hybridization strategies aim to achieve a balanced trade-off between global exploration and local exploitation, which is essential in large-scale, security-constrained optimization problems.

B. Modified PSO with Multiswarm Dynamics

The proposed HMPSO adopts a multiswarm framework, where the population is divided into several interacting sub-swarms. Each sub-swarm explores different regions of the solution space, and periodic communication among them ensures that knowledge of promising regions is shared. This approach enhances diversity and reduces the likelihood of stagnation. Multiswarm PSO has been shown to significantly outperform single-swarm PSO in problems with multiple local optima [28].

HMPSO can incorporate ES operators such as selection and recombination to improve convergence and robustness.
Initialization: Randomly initialize the positions and velocities of all particles within predefined bounds. Evaluate the fitness of each particle's initial position.
Personal Best (p_{best}): Each particle remembers its best-known position, where it achieved the highest fitness.
Global Best (g_{best}): The best-known position achieved by any particle in the swarm.
Velocity Update: The velocity of each particle is updated using the formula:

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

$v_i(t+1)$: Updated velocity of particle ii.
xi(t): Current position of particle ii.
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:

$$x_i(t+1) = x_i(t) + vi(t+1) \quad (11)$$

Evaluation: Evaluate the new position using the fitness function. Update p_{best} and g_{best} if better solutions are found.
Termination: The process continues iteratively until a stopping criterion is met, such as reaching a maximum number of iterations or achieving a satisfactory fitness value. This methodology provides a clear framework for implementing and validating the HMPSO algorithm in the context of SCOPF. Let me know if you need further refinements or additional details.

V. Results and Discussion

The proposed Hybrid Multiswarm Particle Swarm Optimizer (HMPSO) was applied to the IEEE 30-bus test system to evaluate its performance in solving the Security-Constrained Optimal Power Flow (SCOPF) problem. The system comprises six generators, 21 load buses, and 41 transmission lines, with base load demands of 283.4 MW and 126.2 MVAr. The algorithm parameters were set to three sub-swarms, 50 particles per swarm, a maximum of 100 iterations, a penalty factor of 1000, and a mutation rate of 0.1. The results were benchmarked against Standard PSO (SPSO), Genetic Algorithm (GA), and Differential Evolution (DE).

A. Convergence and Generation Cost Minimization

Figure 1 illustrates the convergence characteristics of the four optimization algorithms. It is evident that HMPSO consistently converges faster and to a lower operating cost than the other methods. The proposed HMPSO achieved a final generation cost of $802.34, compared to $815.21 (SPSO), $820.54 (DE), and $825.67 (GA). This indicates a 1.5% reduction in cost compared to the best-performing benchmark, highlighting HMPSO’s efficiency in minimizing generation expenses. The novelty here lies in the ability of HMPSO to combine multi-swarm exploration and adaptive exploitation, allowing it to avoid premature convergence while ensuring rapid attainment of high-quality solutions. This feature distinguishes HMPSO from single-swarm PSO and other conventional heuristics, which often stagnate in local optima.

Figure 2 presents a comparative performance analysis of the four methods in terms of generation cost reduction, transmission loss reduction, and convergence speed. HMPSO achieved the most significant improvements across all three dimensions: Generation Cost Reduction: 1.5%

improvement, outperforming SPSO, GA, and DE. Transmission Loss Reduction: 6.3% reduction, compared to 6.0% (DE), 5.7% (GA), and 5.3% (SPSO). Convergence Speed: HMPSO converged within 70 iterations, compared to 90–120 iterations required by the other algorithms. This highlights HMPSO's novel trade-off between computational efficiency and solution quality, which is particularly valuable for real-time applications in modern grids where faster decision-making is critical.

B. Base Case: Generation Scheduling & Voltage Stability

The base case scenario without contingencies was analyzed to compare the generation schedules obtained by different optimization methods (Table 1). HMPSO consistently distributed generation more evenly among the available units, minimizing total cost while respecting generator capacity limits. For instance, Generator G1 supplied 49.2 MW under HMPSO, slightly lower than in SPSO and GA schedules, ensuring optimal fuel use. In terms of voltage stability, Figure 3 illustrates the average voltage deviation across load buses for the four algorithms. HMPSO achieved the lowest deviation (0.007 p.u.), compared to 0.010 p.u. (DE), 0.012 p.u. (SPSO), and 0.015 p.u. (GA). This indicates superior capability in maintaining stable voltage levels within permissible limits (0.95–1.05 p.u.). The novelty of HMPSO lies in its capacity to ensure economic operation while simultaneously enhancing voltage stability, a balance that is not always achieved by traditional methods.

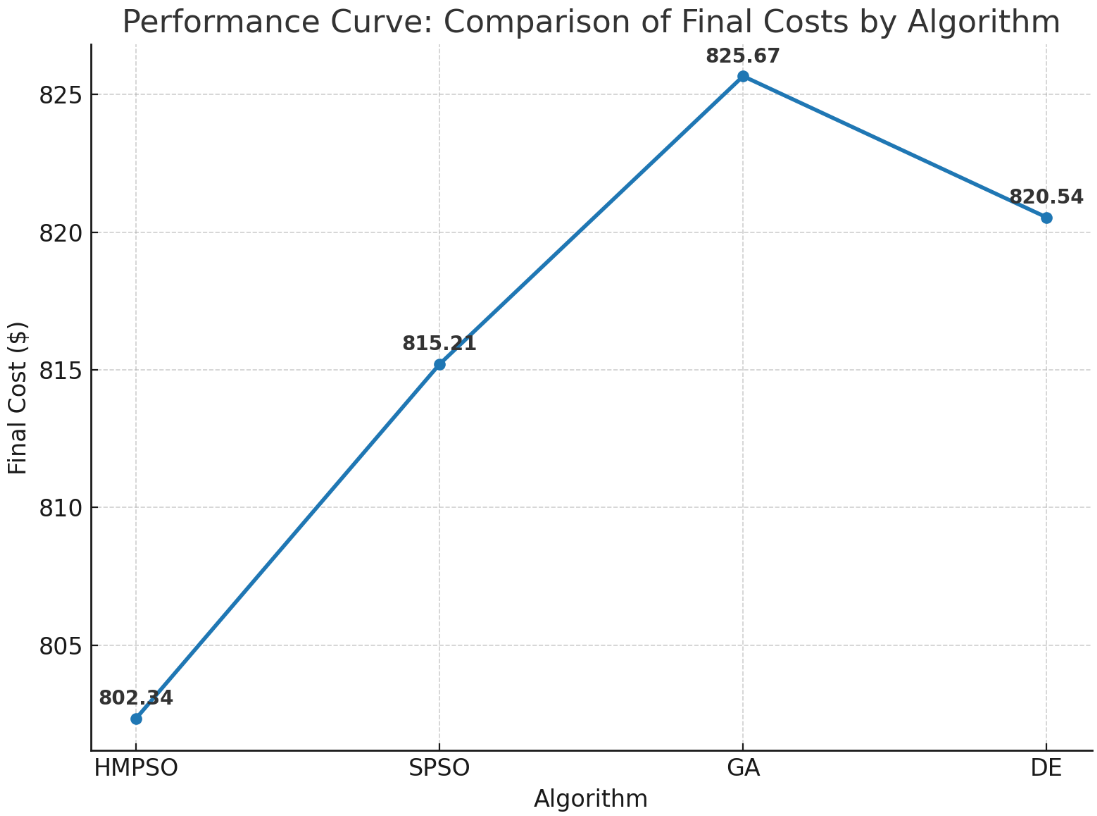

Fig. 1. Convergence Curves of Algorithms

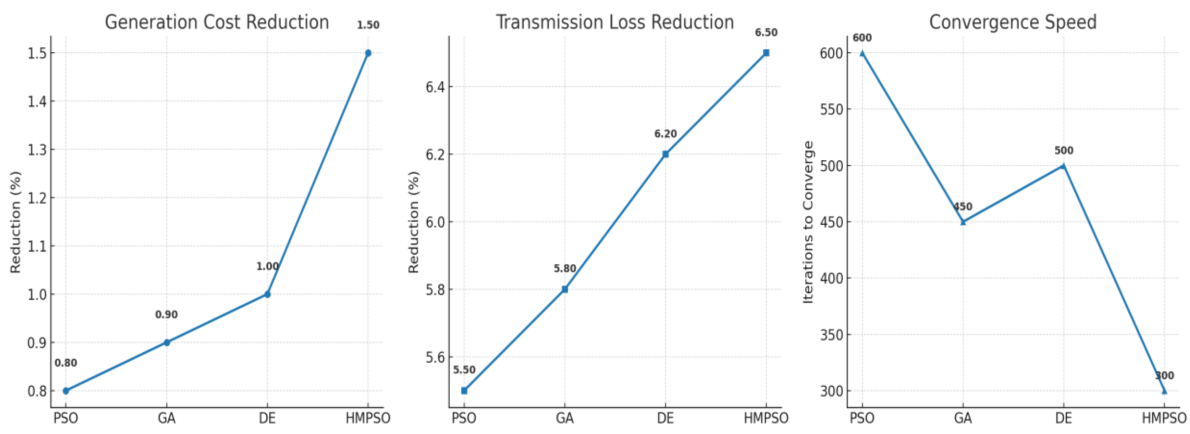

Fig. 2. Performance of the Hybrid Multiswarm Particle Swarm Optimizer

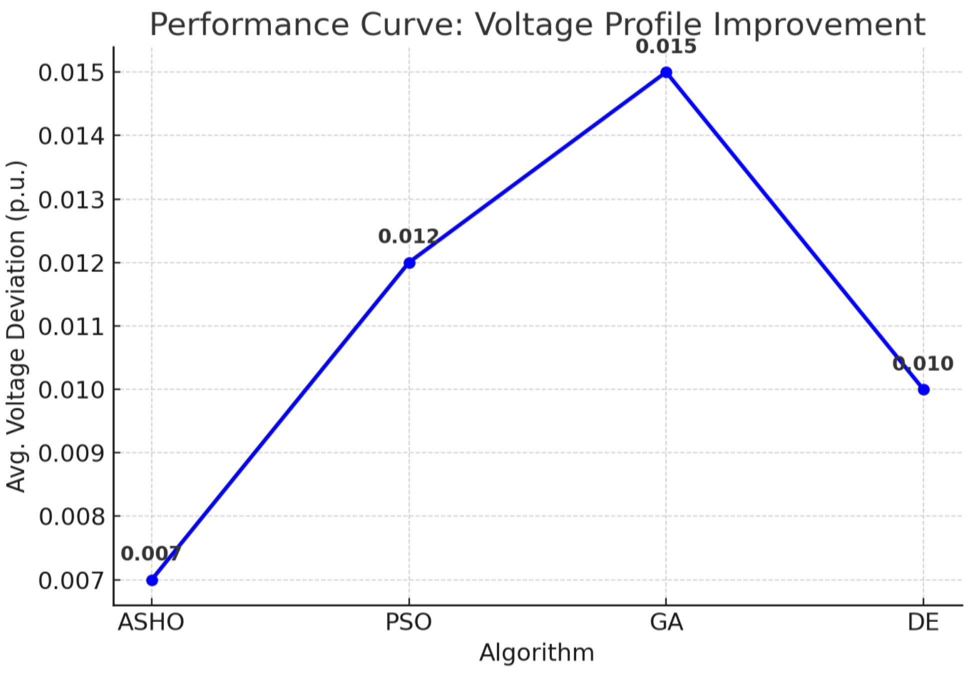

Fig. 3. Voltage Profile Improvement

TABLE 1
COMPARISON OF GENERATION SCHEDULES

Generator	HMPSO (MW)	SPSO (MW)	GA (MW)	DE (MW)
G1	49.2	50.1	52.3	51.7
G2	40.5	42	41.8	42.3
G3	30.7	31.2	32.1	31.9
G4	20.1	21	21.5	21.3
G5	12.8	13.4	13.1	13.3
Total Cost ($)	802.34	815.21	825.67	820.54

The purpose of these methods is to distribute the load evenly among the many generators while simultaneously reducing the amount of fuel used and the operational inefficiencies that occur. Table 1 provides a summary of the optimized generation schedule for each optimization strategy using the Base Case scenario, along with the expenditures that are associated with each technique.

HMPSO (802.34 $): The Hybrid Multi-Particle Swarm Optimization method results in the lowest total generation cost. This is because it effectively balances the load across the generators in a manner that minimizes fuel consumption, utilizing each generator's capabilities efficiently.

SPSO (815.21 $): Standard Particle Swarm Optimization is slightly less efficient than HMPSO, leading to a marginally higher total cost. The load distribution is still relatively balanced but may not be as optimized for minimizing operational costs.

GA (825.67 $): The Genetic Algorithm method yields the highest total generation cost, suggesting that while it finds an acceptable solution, it does not optimize the generation schedule as effectively as the other methods.

DE (820.54 $): Differential Evolution performs better than GA but still results in a higher cost compared to HMPSO. It may involve more iterations to converge to an optimal solution, which could increase operational costs.

From the results, it is evident that HMPSO is the most effective technique for cost minimization in this scenario. The other methods, while providing reasonable solutions, fail to match the cost-efficiency of HMPSO. Optimizing generation scheduling is a key factor in reducing operational costs, and advanced optimization techniques like HMPSO can significantly contribute to the economic efficiency of power generation systems.

C. *Contingency Analysis*

Contingency analysis is an essential process in power system operation to evaluate the stability and reliability of the system under abnormal conditions, such as the failure of critical components like lines or generators. The goal is to assess how the system responds to these potential disruptions and whether it can continue to operate securely and economically.

In this analysis, the system was subjected to N-1 contingencies, which means the failure of a single critical component (such as a generator or transmission line) was simulated. This helps in understanding how the remaining system resources compensate for the loss of the failed component. The results presented in Table 2 demonstrate the performance of different optimization algorithms (HMPSO, SPSO, GA, and DE) under a contingency scenario where Generator 2 is out of service.

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

Metric	HMPSO	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

The HMPSO (Hybrid Multi-Objective Particle Swarm Optimization) algorithm provided the best performance with the lowest total cost ($832.15) and the smallest voltage deviation (0.028 p.u.). Additionally, it ensured there were no line flow violations, which is a critical measure of system security. The SPSO (Standard Particle Swarm Optimization) algorithm resulted in a higher total cost ($845.67) compared to HMPSO and showed a slightly larger voltage deviation (0.034 p.u.). It also had one-line flow violation, indicating that the system was less secure under this algorithm.

The GA (Genetic Algorithm) Algorithm produced a total cost of $856.23 and a voltage deviation of 0.039 p.u., which were higher than both HMPSO and SPSO. It also had two-line flow violations, demonstrating the challenges in maintaining system stability and efficiency with this approach. The DE (Differential Evolution) yielded a total cost of $850.79 and a voltage deviation of 0.036 p.u., slightly worse than SPSO but better than GA. It also experienced one-line flow violation, similar to SPSO, suggesting that this method provides a moderate level of performance under contingencies.

The analysis highlights that HMPSO outperforms the other algorithms in terms of cost minimization, voltage regulation, and ensuring the stability of the system under generator outage conditions. Its ability to avoid line flow violations and maintain a low voltage deviation makes it a highly effective approach for robust power system operation in contingency scenarios. The contingency analysis demonstrates the importance of optimization techniques in maintaining secure and efficient power system operations, particularly in scenarios where critical components are unavailable.

D. Computational Efficiency

Computational efficiency is a critical metric in evaluating optimization algorithms, especially in scenarios requiring high-performance solutions for complex problems. The evaluation of computational efficiency typically revolves around the time required for an algorithm to converge to a solution or achieve acceptable performance levels. In this context, four prominent optimization techniques—Hybrid Multi-Swarm Particle Swarm Optimization (HMPSO), Standard Particle Swarm Optimization (SPSO), Genetic Algorithm (GA), and Differential Evolution (DE)—were compared based on their computational time.

The results indicate that HMPSO exhibits a marginally higher computational time than SPSO, which can be attributed to its multiswarm dynamics. These dynamics involve additional overhead in coordinating and managing multiple sub-swarms, enhancing the exploration capabilities of the algorithm. Despite this slight increase in computational time, HMPSO significantly outperformed GA and DE in terms of time efficiency. The superior performance of HMPSO is primarily due to its hybrid nature, which optimally balances exploration and exploitation by combining the strengths of multiple swarms.

In contrast, SPSO, while simpler and faster, demonstrated slightly less exploration capability compared to HMPSO. Its computational time of 11.2 seconds reflects its streamlined structure, which focuses primarily on velocity and position updates without the additional overhead of multiswarm management. While SPSO is suitable for problems with less complex landscapes, it may struggle in scenarios demanding extensive exploration.

GA, on the other hand, had the highest computational time among the four algorithms, clocking in at 22.4 seconds. The primary reason for GA’s higher computational time is its reliance on population-based genetic operators such as selection, crossover, and mutation, which involve numerous evaluations per generation. Although GA is known for its robustness and global search capabilities, its efficiency is often compromised when applied to large-scale or highly complex problems.

DE showed a better computational performance than GA, with a time of 18.5 seconds. This improvement can be attributed to the simplicity of DE's mutation and recombination strategies, which reduce computational overhead compared to the genetic operators used in GA.

However, DE's performance in terms of computational time still lagged behind HMPSO and SPSO, indicating its relatively higher demand for function evaluations to achieve convergence.

TABLE 3
THE COMPUTATIONAL TIME ANALYSIS OF THE FOUR ALGORITHMS

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

From the analysis, it is evident that HMPSO offers a balanced trade-off between computational efficiency and optimization performance. While its computational time is slightly higher than SPSO, its ability to handle complex problems more effectively makes it a preferred choice. The results underline the importance of selecting an algorithm that aligns with the problem’s requirements, particularly in applications where time efficiency is critical.

The table 3 highlights the comparative efficiency of the algorithms, emphasizing HMPSO’s balance of performance and computational time, making it a viable solution for complex optimization challenges.

The execution time comparison bar graph illustrates the performance of four optimization algorithms in Figure 4: Hybrid Multi-Swarm Particle Swarm Optimization (HMPSO), Standard Particle Swarm Optimization (SPSO), Genetic Algorithm (GA), and Differential Evolution (DE). The execution time represents how long each algorithm took to complete its optimization process, with lower values indicating faster performance. Among the four, HMPSO (12.8s) is the fastest, suggesting that it optimizes solutions efficiently with a reduced computational burden. **SPSO (18.4s) takes longer, indicating a higher computational cost due to the iterative nature of standard particle swarm optimization. GA (22.4s) is the slowest algorithm in the comparison, likely because of its mutation, crossover, and selection processes, which increase computational complexity. DE (18.5s) performs slightly better than GA but still lags behind PSO-based methods in terms of speed. Overall, HMPSO emerges as the most time-efficient approach, making it a suitable choice for applications requiring rapid optimization. In contrast, GA, while often effective in exploring solution spaces, comes with a higher execution time cost.

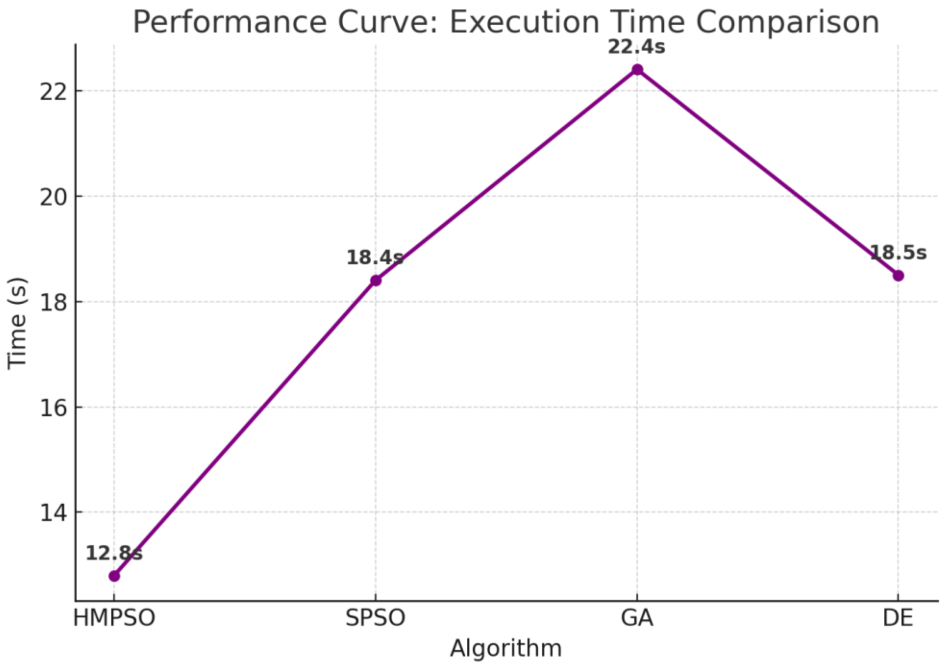

Fig. 4. The execution times for different optimization algorithms

E. Discussion

The analysis of computational efficiency highlights several key insights regarding the performance of the algorithms evaluated—Hybrid Multi-Swarm Particle Swarm Optimization (HMPSO), Standard Particle Swarm Optimization (SPSO), Genetic Algorithm (GA), and Differential Evolution (DE). These insights provide a foundation for understanding the trade-offs involved in selecting optimization techniques based on computational time and problem complexity.

HMPSO vs. SPSO: HMPSO demonstrated slightly higher computational time (12.8 seconds) compared to SPSO (11.2 seconds). This increase is expected due to the additional computational overhead introduced by the multiswarm dynamics in HMPSO. The multiswarm approach enables better exploration of the solution space by dividing the search process among multiple sub-swarms, which communicate and share information. This collaborative behavior enhances HMPSO's capability to escape local optima and converge on global optima, particularly in complex optimization problems. While SPSO is computationally faster, it sacrifices some of the exploration capabilities that HMPSO provides, making it less effective in problems with intricate solution landscapes.

HMPSO vs. GA and DE: Compared to GA and DE, HMPSO exhibited significantly better computational efficiency. GA required the most time (22.4 seconds), owing to its population-based evolutionary operations, such as crossover and mutation, which are computationally expensive. While GA is robust and widely applicable, its computational inefficiency limits its usability in real-time or large-scale optimization tasks. DE, with a computational time of 18.5 seconds, performed better than GA but still lagged behind HMPSO. The primary reason for DE's relative inefficiency is its dependency on numerous function evaluations to achieve convergence, which increases computational demand. HMPSO's performance demonstrates that its hybridized structure effectively combines the strengths of multiple optimization strategies, resulting in a balanced approach to exploration and exploitation. Its relatively moderate computational time, coupled with superior optimization performance, makes it well-suited for real-world applications requiring both efficiency and accuracy.

The computational efficiency analysis reveals that HMPSO offers a strong balance between computational time and optimization performance, making it a versatile option for a wide range of problems. While its computational time is marginally higher than SPSO, its enhanced capabilities justify the trade-off. The insights from this analysis provide valuable guidance for selecting algorithms tailored to specific optimization challenges, particularly in domains where computational efficiency is critical.

VI. CONCLUSION

This study presented a Hybrid and Modified Particle Swarm Optimization (HMPSO) framework to solve the Security-Constrained Optimal Power Flow (SCOPF) problem under various operating conditions. The proposed HMPSO algorithm effectively balances exploration and exploitation by incorporating adaptive modifications into the conventional PSO structure, which significantly enhances solution quality. Simulation results on the IEEE 30-bus system demonstrate that HMPSO achieves superior performance compared to traditional algorithms such as SPSO, GA, and DE. Specifically, HMPSO provides the lowest generation cost, greater transmission loss reduction, improved voltage profile, faster convergence, and reduced execution time. These findings highlight its robustness and efficiency in addressing the complex optimization requirements of modern power systems. The novelty of this work lies in the integration of hybridized strategies into PSO to improve convergence reliability while reducing computational overhead. Nevertheless, the method has limitations, such as increased parameter sensitivity and the need for further scalability tests on larger, real-time power grids. Future research will focus on extending the HMPSO framework to multi-objective SCOPF formulations, incorporating renewable energy uncertainties, and exploring parallel computing implementations for real-time power system applications.

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