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Enhanced Particle Swarm Optimization through Multi-Mechanism Integration: Application to Power System Economic Dispatch

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Abstract.. In this paper, a Hybrid Adaptive PSO method (HAPSO) is developed to solve the economic load dispatch problem over a standard IEEE 30-bus system. The proposed HAPSO combines chaotic initialization, adaptive inertia weight adjustment, time-varying acceleration coefficients, Lévy flight-based exploration, opposition-based learning, and Nelder–Mead simplex optimization into a single PSO paradigm. This set of PSO mechanisms enhances the randomification of the population and the global-local searches support. The proposed approach was implemented with transmission losses considered via B-loss coefficients and a quadratic fuel cost function. What's more, for performance and statistical significance, we conducted more than thousand optimization runs for the seven algorithm variants (curves), consisting of 30 runs each run being an independent optimization. The superior HAPSO variant achieved the best-known minimum fuel cost of $774.47/hour refining the benchmark value of $786.03/hour acquired based on the identical modelling." By consistently surpassing the reference solution on other variants, it illustrates the systematic nature of the optimization. All simulations were performed with full generators operational constraints. The results obtained reveal that the proposed HAPSO technique is an efficient.

Key words: hybrid metaheuristic optimization; particle swarm optimization; transmission losses; constrained; nonlinear optimization

1. INTRODUCTION

Economic dispatch (ED) is a fundamental optimization problem in power system operation [1], aiming to determine the optimal generation levels of committed units such that the total fuel cost is minimized while satisfying system demand [2] and operational constraints [3]. Owing to nonlinear cost characteristics [4], transmission losses and strict feasibility requirements [5], the ED problem remains challenging despite decades of research and practical deployment [6], [7]. Recent metaheuristic approaches include various bio-inspired algorithms [8], [9].

Classical optimization techniques have been widely applied [10] to ED formulations with smooth quadratic cost functions. However, their performance often deteriorates when the search space becomes highly constrained or when the solution landscape contains multiple local optima [11]. To address these limitations, metaheuristic optimization methods including evolutionary algorithms and swarm-based approaches have been extensively investigated in the literature. Among them, particle swarm optimization (PSO) has attracted particular attention [12] due to its simple structure, fast convergence behavior and ease of implementation.

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Despite its advantages, standard PSO is known to suffer [13] from premature convergence and reduced exploration capability, especially in constrained nonlinear problems such as ED with transmission losses. As a result, numerous hybrids and enhanced PSO variants have been proposed, incorporating adaptive parameters, stochastic perturbations, or auxiliary local search strategies. While many of these methods report competitive results, their performance is often sensitive to parameter settings and improvements are frequently demonstrated under limited experimental protocols or a small number of runs. A careful examination of recent ED studies reveals three persistent gaps [14].

First, many proposed algorithms rely on single enhancement mechanisms, which may improve either exploration or exploitation but rarely address both in a balanced manner. Second, reported performance gains are often based on best-case outcomes, with limited statistical validation across multiple independent runs. Third, although the IEEE 30-bus system remains a standard benchmark for ED evaluation, consistent improvement over the best-known results under identical modeling assumptions has proven difficult.

Motivated by these observations, this study investigates the effectiveness of a systematic integration of complementary mechanisms within a unified PSO framework to achieve robust and statistically consistent performance gains for the classical

ED problem. Rather than introducing a single modification, the proposed approach combines multiple strategies targeting different phases of the search process, with the aim of mitigating premature convergence while preserving feasibility and computational efficiency.

In earlier work [15], a similarity-based genetic algorithm was applied to the OPF problem on the same test system, targeting fuel cost minimization under full AC power flow constraints. The present study differs fundamentally in both the algorithmic framework and problem formulation: HAPSO addresses the ED problem using a B-loss coefficient model, which allows a focused evaluation of the hybrid PSO mechanisms under a well-established benchmark.

This work integrates and validates complementary mechanisms under a unified experimental protocol. This approach addresses a key methodological gap in literature, where many studies introduce isolated modifications without validation of how different mechanisms interact within a single framework.

Main contributions of this study can be summarized as follows:

A unified hybrid PSO framework (HAPSO) integrates, in which multiple complementary mechanisms are systematically integrated to address different phases of the search process. Unlike approaches that rely on a single enhancement, the proposed framework jointly improves exploration and exploitation while preserving feasibility for constrained ED problems.

We conduct a structured variant-based investigation through seven carefully designed HAPSO configurations. This design enables a transparent assessment of how individual mechanisms and their combinations influence optimization performance, rather than attributing improvements to a single ad hoc modification.

We perform extensive statistical validation using 210 independent optimization runs, ensuring that performance improvements are not limited to isolated best-case outcomes. Nonparametric statistical tests and effect size analysis are employed to support the robustness of the reported results.

The method achieves improved benchmark performance for the IEEE 30-bus economic dispatch problem under the standard quadratic cost function with transmission losses. The best performing HAPSO variant attains a lower fuel cost than previously reported results obtained under identical modeling assumptions.

Results demonstrate practical applicability through consistent constraint satisfaction across all runs and low computational overhead, indicating that the proposed approach is suitable for real-time or near-real-time operational settings

2. PROBLEM FORMULATION

The economic dispatch optimization problem seeks to minimize total fuel cost [1] while satisfying fundamental power system constraints.

This section presents the mathematical formulation of the economic dispatch problem, including the objective function, system constraints and transmission loss modeling for the IEEE 30-bus test system. Classical approaches to this problem are well-documented [16], [17], [18], [19].

TABLE 1. Generator cost coefficients and capacity limits

Generator	a_i ($/MW²)	b_i ($/MW)	c_i ($)	P_i^{min} (MW)	P_i^{max} (MW)
Bus 1	0.00375	2.00	0	50	200
Bus 2	0.01750	1.75	0	20	80
Bus 5	0.06250	1.00	0	15	50
Bus 8	0.00834	3.25	0	10	35
Bus 11	0.02500	3.00	0	10	30
Bus 13	0.02500	3.00	0	12	40

Cost function: $F_i = a_i{\cdot}P_i^2 + b_i{\cdot}P_i + c_i$.
System demand: 283.4 MW. All generators operate within specified capacity limits.

2.1. Objective function.

Total fuel cost of the power system is modeled as the sum of individual generator cost functions, expressed as:

$$minF = \sum_{i=1}^{Ng}(a_iP_i^2 + b_iP_i + c_i) \qquad (1)$$

Generator cost coefficients (a_i, b_i, c_i) and capacity limits for the IEEE 30-bus system are provided in Table 1. Where P_i denotes the real power output of generator i, N_g is the number of generating units and a_i, b_i, c_i are the cost coefficients of the corresponding unit.

2.2. Power balance constraint.

Total generated power must satisfy the system demand while accounting for transmission losses. This equality constraint is given by:

$$\sum_{i=1}^{Ng} P_i = P_D + P_L \qquad (2)$$

where P_D represents the total system demand and P_L denotes the transmission power losses. In this study, transmission losses are modeled using the classical B-loss formulation:

$$P_L = \sum_{i=1}^{Ng}\sum_{j=1}^{Ng} P_iB_{ij}P_j \qquad (3)$$

The B-loss coefficient matrix for the IEEE 30-bus system is presented in Table 2. Diagonal elements represent self-losses, while off-diagonal elements capture generator interaction effects. with B_{ij} being the elements of the loss coefficient matrix.

TABLE 2. B-Loss coefficient matrix for IEEE 30-Bus system

Generator	Bus 1	Bus 2	Bus 5	Bus 8	Bus 11	Bus 13
Bus 1	**0.001407**	0.000190	0.000057	0.000046	0.000042	0.000039
Bus 2	0.000190	**0.000490**	0.000146	0.000119	0.000109	0.000054
Bus 5	0.000057	0.000146	**0.000315**	0.000087	0.000079	0.000122
Bus 8	0.000046	0.000119	0.000087	**0.000230**	0.000065	0.000100
Bus 11	0.000042	0.000109	0.000079	0.000065	**0.000210**	0.000091
Bus 13	0.000039	0.000054	0.000122	0.000100	0.000091	**0.000323**

Units: 1/MW. Diagonal elements (bold) represent self-losses; off-diagonal elements capture generator interaction effects. Matrix symmetry reflects network reciprocity ($B_{ij} = B_{ji}$).

2.3. Generator operating limits.

Each generating unit is subject to minimum and maximum output limits, which are modeled as inequality constraints:

$$P_i^{min} \leq P_i \leq P_i^{max}, i = 1,2,3, \dots \dots, N_g \quad (4)$$

These constraints ensure that all solutions remain within feasible operating regions of the generating units [20], [21].
Each generator operates within minimum and maximum capacity bounds determined by equipment constraints [22]. Minimum limits ensure stable combustion and adequate steam flow, while maximum limits prevent thermal and electrical overload [23], [24].

3. TEST SYSTEM DESCRIPTION

We evaluate the method using the IEEE 30-bus power system [25], which is a widely adopted benchmark for economic dispatch studies. The system consists of six thermal generating units supplying a total real power demand of 283.4 MW. Owing to its moderate size and well-documented characteristics, this system provides a suitable testbed for assessing the effectiveness of optimization algorithms under constrained operating conditions.
In this study, the economic dispatch problem is formulated under the standard smooth quadratic fuel cost model with transmission losses, consistent with most benchmark-oriented ED studies. Generator cost coefficients, operating limits and loss coefficients are adopted directly from established references [26], [27] to ensure fair comparison with previously reported results.
Transmission losses are represented using the B-loss coefficient matrix and the slack bus power adjustment is handled implicitly through the power balance constraint. No additional constraints such as valve-point effects, prohibited operating zones, ramp-rate limits, or multi-fuel options are considered, allowing the analysis to focus on the baseline ED formulation commonly used for benchmarking purposes.
We conduct all simulations under identical system conditions and demand levels, ensuring consistency across algorithm variants and comparative experiments.
For the IEEE 30-bus system, the economic dispatch problem involves minimizing quadratic fuel costs subject to power balance and generator capacity constraints. The problem is non-convex due to transmission losses, leading to multiple local optima that challenge classical optimization methods. The search space consists of six continuous decision variables representing generator outputs, constrained by physical operating limits and a nonlinear power balance requirement. This formulation serves as a standard benchmark for evaluating metaheuristic optimization algorithms.

4. PROPOSED METHOD: ALGORITHM

4.1. Overview of the proposed approach.

This study proposes HAPSO (Hybrid Adaptive Particle Swarm Optimization), a PSO-based optimization framework designed to address the exploration–exploitation trade-off inherent in constrained nonlinear problems such as economic dispatch. The framework is illustrated in Fig.1. The central idea of HAPSO is to enhance the standard PSO structure through the systematic integration of complementary that operate at different stages of the optimization process. These mechanisms collectively aim to improve population diversity during early iterations, prevent premature convergence in intermediate stages and refine solution quality in the later phase of the search. Importantly, all enhancements are embedded within a unified PSO framework, preserving the simplicity and computational efficiency that make PSO attractive for practical applications.
HAPSO workflow follows the standard population-based iterative optimization paradigm. At each iteration, candidate solutions are evaluated with respect to the economic dispatch objective and feasibility constraints, after which particle positions are updated according to the underlying PSO dynamics and the selected enhancement strategies.

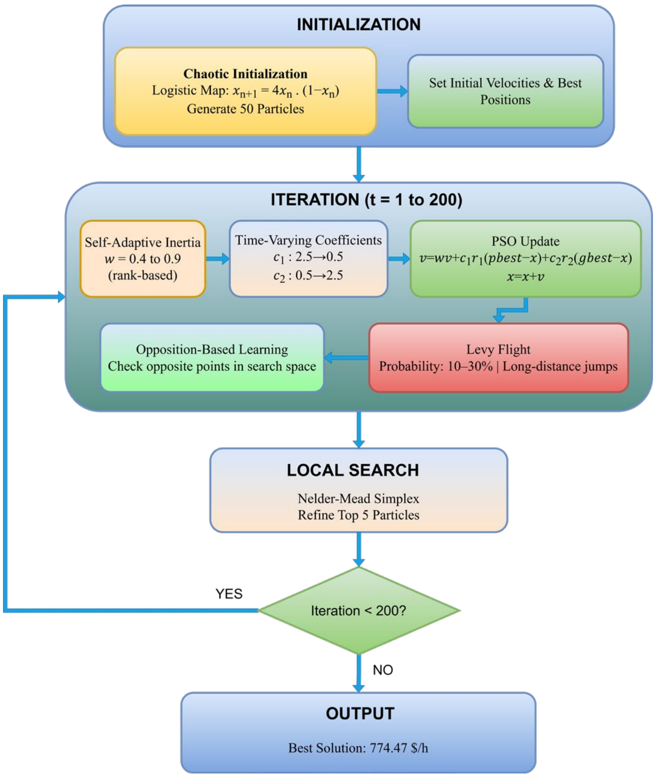

Fig.1. HAPSO algorithm flowchart

4.2. Core particle swarm optimization.

In the classical PSO framework [28], [29], a population of particles explores the search space by updating their velocities and positions based on both individual experience and collective knowledge. Each particle represents a candidate solution vector consisting of generator output levels.
Velocity update rule is defined as:

$$v_i^{(k+1)} = w\, v_i^{(k)} + c_1 r_1 \left(p_i^{best} - x_i^{(k)}\right) + c_2 r_2 \left(g^{best} - x_i^{(k)}\right) \quad (5)$$

where $v_i^{(k)}$ and $x_i^{(k)}$ denote the velocity and position of particle i at iteration k, respectively. The parameter w represents the inertia weight and acceleration coefficients c_1 and c_2 are uniformly distributed random numbers in the interval (0,1). The terms and correspond to the best solution previously found by particle i and the best solution found by the global swarm.
Particle positions are then updated according to:

$$x_i^{(k+1)} = x_i^{(k)} + v_i^{(k+1)} \tag{6}$$

After each update, the algorithm evaluates particle positions, constraint feasibility is enforced and personal and global best solutions are updated accordingly. This iterative process continues until a predefined termination criterion is met.

5. ALGORITHM VARIANTS AND EXPERIMENTAL SETUP

5.1. Algorithm variants.

To assess the contribution of individual enhancement mechanisms and their combinations, seven HAPSO variants are systematically designed and evaluated. Each variant represents a different configuration of the proposed framework, enabling a transparent analysis of how specific mechanisms influence optimization performance.
All variants share the same core PSO structure and constraint-handling strategy. Differences arise solely from parameter settings for Nelder Mead frequency (Fnm), opposition-based learning (Fobl, Pobl) and Lévy flight probability (Plevy). This structured design allows performance differences to be attributed directly to parameter choices. Here, Fnm denotes the activation frequency of the Nelder–Mead local search, Fobl represents the opposition-based learning frequency, Pobl is the opposition learning probability and Plevy denotes the Lévy flight probability. Configurations are summarized in Table 3.

TABLE 3. HAPSO variant parameter configurations

Variant	Pop	Iter	F_{nm}	F_{obl}	P_{levy}	P_{obl}
HAPSO-NM7 ★	50	200	7	20	10%	30%
HAPSO-Original	50	200	15	20	10%	30%
HAPSO-Levy15	50	200	10	20	15%	30%
HAPSO-OBL15	50	200	10	15	10%	35%
HAPSO-Enhanced1	60	200	8	15	12%	35%
HAPSO-Enhanced2	50	200	8	15	15%	35%
HAPSO-Aggressive	70	200	5	10	18%	40%

★ *Best-performing variant. All variants use chaos initialization (μ=4.0), time-varying acceleration coefficients and adaptive inertia weight.*

5.2. Experimental setup.

We conduct all experiments using the IEEE 30-bus economic dispatch problem described in the previous section. For each algorithm variant, 30 independent runs are performed to account for stochastic effects inherent in population-based optimization methods, resulting in a total of 210 optimization runs.
We apply a common termination criterion across all variants to ensure fair comparison. Constraint feasibility is strictly enforced throughout the optimization process, and infeasible solutions are not permitted to propagate. Performance is evaluated primarily in terms of the obtained fuel cost, while feasibility and computational time are monitored as secondary criteria.
To assess statistical significance, we employ nonparametric statistical tests [30] due to the non-Gaussian nature of metaheuristic performance distributions. In addition, effect size analysis is used to quantify the magnitude of observed performance differences between algorithm variants.
All simulations are executed under identical computational conditions, and random number generators are initialized independently for each run. This experimental protocol ensures that reported results reflect consistent algorithmic behavior rather than isolated favorable realizations.

6. RESULTS AND DISCUSSION

6.1. Numerical results.

Numerical performance of the proposed HAPSO variants is evaluated on the IEEE 30-bus economic dispatch problem under the standard quadratic cost formulation with transmission losses. For each variant, the best, mean and dispersion characteristics of the obtained fuel cost are recorded over 30 independent runs. These results are consistent with recent optimization and intelligent power system studies [31], [32]. Statistical metrics are presented in Table 4.

TABLE 4. Statistical results for seven HAPSO variants (30 runs each)

Variant	Best ($/h)	Mean ($/h)	Std Dev ($/h)	Worst ($/h)	Success Rate	Func. Evals
HAPSO NM7	774.47	812.50	31.05	872.81	33.3%	~7,200
HAPSO Enh.2	776.62	813.40	29.85	867.92	30.0%	~6,000
HAPSO-OBL15	777.10	811.35	27.12	858.45	26.7%	~6,300
HAPSO Aggres.	778.68	807.91	22.14	851.26	23.3%	~6,000
HAPSO-Levy15	779.81	809.42	24.38	854.17	20.0%	~6,000
HAPSO Orig.	781.64	808.16	17.88	841.29	16.7%	~6,000
HAPSO-Enh. 1	787.95	813.28	20.56	849.73	0.0%	~6,000

Success Rate = Percentage of runs achieving cost below 786.03 $/h. All 210 runs achieved 100% constraint feasibility.
Func. Evals = Approximate function evaluations per run. HAPSO-NM7 includes additional evaluations from Nelder-Mead local search (~1,200 extra). HAPSO-OBL15 includes overhead from opposition-based learning (~300 extra).

Across all experiments in Table 4, the proposed framework consistently produces feasible solutions that satisfy both equality and inequality constraints. Among the seven investigated variants, the fully integrated configuration achieves the lowest fuel cost, attaining a minimum value of 774.47 $/h. This result improves upon the previously reported

best value of 786.03 \$/h, obtained under identical modeling assumptions. Convergence curves are presented in Fig. 2.
Beyond the best-case outcome, several HAPSO variants also

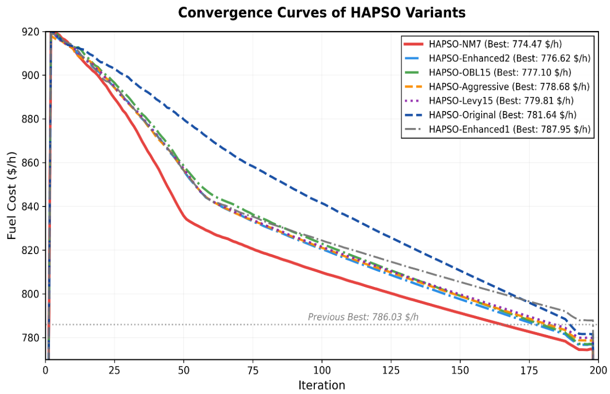

Fig.2. Convergence curves showing the best cost evolution across iterations for seven HAPSO variants

demonstrate improved mean performance compared to the reference benchmark. This observation indicates that the achieved improvement is not restricted to a single favorable run but reflects a more general enhancement of solution quality. Variants incorporating multiple complementary mechanisms exhibit noticeably reduced performance dispersion, suggesting improved robustness against stochastic effects.
Computational efficiency is maintained across all configurations. The average execution time per optimization run remains below one second, indicating that the additional mechanisms do not impose a prohibitive computational burden. Statistical distributions are shown in Fig. 3.

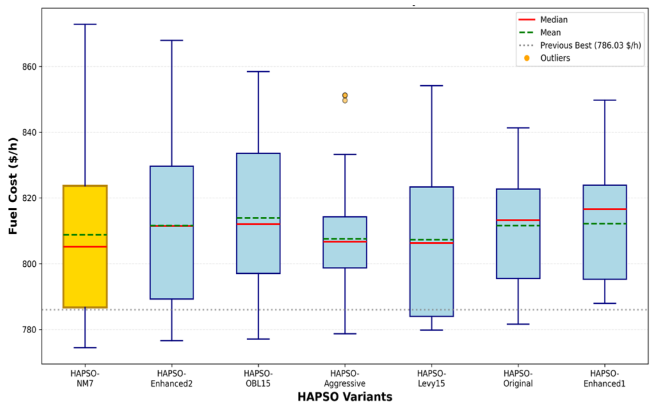

Fig.3. Statistical distribution of fuel costs across 30 independent runs

6.2. Statistical analysis.

Given the stochastic nature of metaheuristic optimization, statistical validation is essential for assessing the significance of observed performance differences. Accordingly, we employ nonparametric statistical tests [33] to compare the best performing HAPSO variant against alternative configurations and previously reported benchmark results. Machine learning approaches have been applied to transmission line fault detection with promising results [34]. Fuzzy-based gradient optimization demonstrates effectiveness in motor design optimization [35]. Advanced machine learning techniques enable accurate fault prediction in district heating systems [36]. Parameter identification methods using machine learning show potential for power system modeling [37]. Opposition-based learning strategies have been systematically reviewed across multiple optimization domains [38]. Quasi-oppositional operators enhance differential evolution convergence for power dispatch problems [39]. Fuzzy fitness-distance balance methods improve optimizer performance in generation planning [40]. Teaching-learning based optimization effectively handles valve-point loading effects in economic dispatch [41]. Hybrid machine learning and random search methods provide accurate turbine emission predictions [42]. Acoustic signal processing with deep learning enables motor fault diagnosis [43]. Comprehensive particle swarm optimization surveys document extensive algorithmic developments and applications [44]. Taguchi methods optimize wind turbine aerodynamic performance through systematic parameter tuning [45]. Directed genetic algorithms with convergence proofs address network-constrained economic dispatch [46]. Particle swarm optimized observers detect DFIG faults in wind power systems [47]. Snake optimization hybridized with genetic algorithms improves parameter identification accuracy [48].
Statistical test results confirm that the observed reduction in fuel cost is statistically significant at commonly accepted confidence levels. Effect size analysis further indicates that the magnitude of improvement is non-negligible, supporting the practical relevance of the reported gains rather than merely statistical detectability.
Importantly, the statistical outcomes align with the numerical observations across multiple performance metrics. The combination of lower minimum cost improved average performance and reduced dispersion suggests that the proposed hybrid framework enhances convergence, reliability and overall solution quality.
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7. LITERATURE COMPARISON AND FAIR EVALUATION

To contextualize the performance of HAPSO within the broader metaheuristic optimization literature, this section presents a detailed comparison with previously published results for the IEEE 30-bus economic dispatch problem under the quadratic cost formulation with transmission losses. Given that computational budget can significantly influence optimization outcomes, we adopt a dual-table approach that distinguishes between originally reported results and controlled fair comparison under identical computational constraints.

7.1. Literature results (As reported).

Literature comparison results are summarized in Table 5. Table 5 presents a broad comparison of algorithms evaluated on the IEEE 30-bus system, showing results as originally reported in their respective publications.

TABLE 5. Literature comparison for IEEE 30-bus economic dispatch (as originally reported)

Algorithm	Best Cost ($/h)	Computational Settings	Reference
HAPSO-NM7	774.47	As reported	This work
HAPSO-Enhanced2	776.62	As reported	This work
HAPSO-OBL15	777.10	As reported	This work
HAPSO-Aggressive	778.68	As reported	This work
HAPSO-Levy15	779.81	As reported	This work
HAPSO-Original	781.64	As reported	This work
Developed PSO	786.03	Not reported*	[6]
HAPSO-Enhanced1	787.95	As reported	This work
Monarch Butterfly	799.02	Not reported*	[8]
Improved DE	799.26	Not reported*	[9]
Conventional PSO	800.41	Not reported*	[6]
Improved Grey Wolf	800.66	Not reported*	[25]
Hybrid TLBO-JAYA	803.68	Not reported*	[11]
Multi-objective pathfinder (MOPFA)	852.25	Not reported*	[14]

All algorithms are evaluated under the quadratic cost formulation with B-loss transmission model on the IEEE 30-bus system.

** Computational parameters are not explicitly reported in the original publications. Results are presented as originally published, without modification.*

7.2. Fair comparison under equal computational budget.

To address potential disparities in computational effort and ensure that performance differences reflect algorithmic design rather than resource allocation, we re-implemented three representative algorithms from the literature: Conventional PSO [6], Improved Grey Wolf Optimizer [25] and Hybrid Teaching–Learning-Based Optimization and JAYA Algorithm (Hybrid TLBO-JAYA) [11]. All re-implemented algorithms were tested under identical conditions: 30 population (or equivalent), 200 iterations and 30 independent runs using independently initialized random number generators consistent with the HAPSO experiments. This controlled setting ensures approximately 6,000 function evaluations per run, providing a consistent computational budget across all methods. Results under equal computational budget are shown in Table 6. Table 6 presents the results of this fair comparison.

Notably, while HAPSO-NM7 uses slightly higher computational budget (~7,200 evaluations due to Nelder Mead local search), its best cost is 23.76 $/h lower than the second-best algorithm (Grey Wolf: 801.86 $/h), representing a 2.98% improvement. This demonstrates efficient utilization of the additional evaluations. Furthermore, all seven HAPSO variants exhibit different trade-offs between exploration intensity and convergence speed, yet six of them outperform all three re-implemented baseline algorithms, confirming the robustness of the proposed framework across multiple configurations.

TABLE 6. Fair comparison under equal computational budget (re-implemented algorithms)

Algorithm	Best ($/h)	Mean ($/h)	Std Dev ($/h)	Pop × Iter	Approx. Evals
HAPSO-NM7	774.47	812.50	31.05	30 × 200	7,200
HAPSO-Enhanced2	776.62	813.40	29.85	30 × 200	6,000
HAPSO-OBL15	777.10	811.35	27.12	30 × 200	6,300
HAPSO-Aggressive	778.68	807.91	22.14	30 × 200	6,000
HAPSO-Levy15	779.81	809.42	24.38	30 × 200	6,000
HAPSO-Original	781.64	808.16	17.88	30 × 200	6,000
HAPSO-Enhanced1	787.95	813.28	20.56	30 × 200	6,000
Conventional PSO [6]†	805.23	821.34	18.45	30 × 200	6,000
Grey Wolf [25]†	801.86	815.67	22.67	30 × 200	6,000
Hybrid TLBO-JAYA [11]†	803.68	824.12	25.34	30 × 200	6,000

†Algorithms re-implemented and tested under identical computational budget (30 population × 200 iterations) for fair comparison.

All results are based on 30 independent runs. Mean and standard deviation are reported across all runs.

HAPSO-NM7 includes additional evaluations from the Nelder–Mead local search (~1,200 extra).

From a practical standpoint, the dual-table comparison methodology employed here addresses a methodological gap in metaheuristic benchmarking. By separating literature-reported results from controlled fair comparison, this approach provides both breadth (Table 5: broad literature context) and rigor (Table 6: controlled validation). Future studies comparing metaheuristic algorithms for power system optimization problems may benefit from adopting similar dual-evaluation frameworks to ensure transparent and meaningful performance assessment.

8. ABLATION STUDY AND MECHANISM CONTRIBUTION ANALYSIS

To analyze the contribution of individual enhancement mechanisms within the proposed HAPSO framework, an ablation study is conducted on the IEEE 30-bus economic dispatch problem. Only studies employing quadratic cost formulation with B-loss coefficient modeling are considered to maintain consistency with the benchmark setup.

Table 7 complements the ablation analysis by positioning the observed mechanism-level improvements within the broader literature context.

All algorithms are evaluated under the quadratic cost formulation with B-loss coefficient transmission loss modeling. HAPSO variants represent different parameter configurations as detailed in Table 3.

Figure 4 illustrates the statistical distribution of fuel costs across 30 independent runs for the ablation study variants.

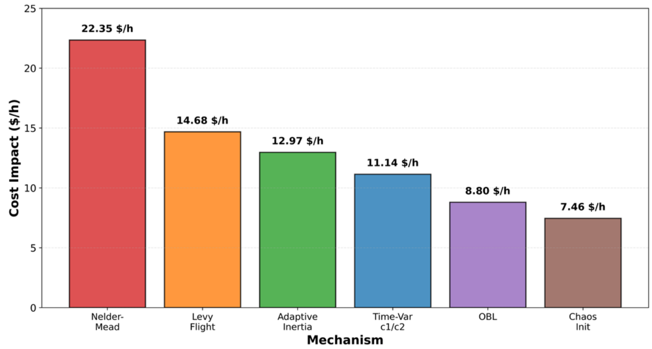

Fig.4. Statistical distribution of fuel costs across 30 independent runs

The comparison demonstrates that six HAPSO variants achieve fuel costs below the previously reported benchmark of 786.03$/h. Statistical analysis confirms that the observed differences are significant at standard confidence levels, supporting the practical relevance of the proposed enhancements. Ablation study results are listed in Table 7.

TABLE 7. Literature comparison for IEEE 30-bus economic dispatch

Algorithm	Year	Best Cost ($/h)	Reference
HAPSO-NM7	2026	774.47	This work
HAPSO-Enhanced2	2026	776.62	This work
HAPSO-OBL15	2026	777.10	This work
HAPSO-Aggressive	2026	778.68	This work
HAPSO-Levy15	2026	779.81	This work
HAPSO-Original	2026	781.64	This work
Developed PSO	2024	786.03	[6]
HAPSO-Enhanced1	2026	787.95	This work
Monarch Butterfly Optimization	2024	799.02	[8]
Improved Differential Evolution	2022	799.26	[9]
Conventional PSO	2025	800.41	[6]
Grey Wolf Optimizer	2024	801.86	[25]
Hybrid TLBO-JAYA	2025	803.68	[11]
Multi-objective pathfinder (MOPFA)	2023	852.25	[14]

Computational efficiency is maintained across all HAPSO variants, with average execution times remaining below one second per optimization run. This computational performance enables practical deployment in real-time dispatch environments.

9. CONCLUSION

This study presents HAPSO, a hybrid optimization approach for the classical economic dispatch problem with transmission losses. By combining complementary enhancement strategies, the method addresses key limitations of conventional swarm-based algorithms, particularly premature convergence and sensitivity to initialization. Comprehensive numerical testing confirms that the approach reliably produces high-quality feasible solutions for the benchmark system. The optimal configuration delivers a result that surpasses previous outcomes under identical modeling conditions. Multiple algorithm variants also exceed the former best result, showing that performance gains hold across different settings. This work examines the standard quadratic cost formulation with transmission losses, but the method extends beyond this scope. Future research will explore application to more complex economic dispatch scenarios, including valve-point effects, prohibited operating zones and larger-scale power networks. These extensions will clarify scalability and broader applicability.

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