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ORIGINAL

Real-world Optimization using Adaptive Fusion Optimization: energy-efficient scheduling and network optimization analysis

Optimización del mundo real utilizando Optimización por Fusión Adaptativa: análisis de programación energéticamente eficiente y optimización de redes

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ABSTRACT

Introduction: This study investigates the effectiveness of Adaptive Fusion Optimization (AFO) for solving energy-efficient economic load dispatch problems on standard IEEE benchmark power systems using the MATPOWER environment under a fixed-budget, repeated-run protocol. Objective: The objective is to evaluate the performance, stability, feasibility, and scalability of AFO and compare it fairly with GA, PSO, DE, and ACO using identical evaluation budgets and population settings. Method: Experiments are conducted on IEEE 30-, 57-, and 118-bus systems. Each algorithm is executed for 30 independent runs. Performance is assessed based on mean generation cost, standard deviation, feasibility rate, and statistical validation using Friedman and Wilcoxon tests. Sensitivity analysis is performed under ±5% and ±10% load variations with ramp-rate and operational constraints enabled. Results: On the IEEE 30-bus system, AFO achieves a mean cost of 801.12 $/h with a 0.73 $/h standard deviation and 100% feasibility. On the IEEE 57-bus system, AFO maintains 96%, feasibility while delivering the lowest mean cost with reduced variability under load and ramp constraints. On the IEEE 118-bus system, AFO achieves a mean cost of 128,740.5 $/h with 100% feasibility, demonstrating strong scalability. Statistical tests confirm the significance of these improvements, and sensitivity analysis shows near-proportional cost scaling with low sensitivity to load perturbations. Conclusions: AFO provides stable, feasible, and scalable performance for economic load dispatch, outperforming traditional metaheuristics under identical conditions while maintaining robustness to demand variations through effective constraint handling.

Keywords: Adaptive Fusion Optimization (AFO); Economic Load Dispatch; MATPOWER; Constraint Handling; Statistical Validation.

RESUMEN

Introducción: Este estudio investiga la eficacia de la optimización por fusión adaptativa (AFO) para resolver problemas de despacho de carga económico y energéticamente eficiente en sistemas eléctricos de referencia estándar del IEEE, utilizando el entorno MATPOWER bajo un protocolo de ejecuciones repetidas con presupuesto fijo. Objetivo: El objetivo es evaluar el desempeño, la estabilidad, la viabilidad y la escalabilidad de la AFO, y compararla de manera imparcial con los algoritmos GA, PSO, DE y ACO, utilizando presupuestos de evaluación y configuraciones de población idénticos. Método: Los experimentos se llevan a cabo en sistemas IEEE de 30, 57 y 118 buses. Cada algoritmo se ejecuta durante 30 ejecuciones independientes. El desempeño se evalúa en función del costo promedio de generación, la desviación estándar, la tasa de viabilidad y la validación estadística mediante las pruebas de Friedman y Wilcoxon. Se realiza un análisis de sensibilidad bajo variaciones de carga de ±5 % y ±10 %, con las restricciones de tasa de rampa y operativas activadas. Resultados: En el sistema IEEE de 30 buses, el AFO alcanza un costo promedio de 801,12 $/h con una desviación estándar de 0,73 $/h y una viabilidad del 100 %. En el sistema IEEE de 57 buses, el AFO mantiene una viabilidad del 96 %, al tiempo que ofrece el costo promedio más bajo con una variabilidad reducida bajo restricciones de carga y de rampa. En el sistema IEEE de 118 buses, el AFO alcanza un costo promedio de 128 740,5 $/h con una viabilidad del 100 %, lo que demuestra una gran escalabilidad. Las pruebas estadísticas confirman la importancia de estas mejoras, y el análisis de sensibilidad muestra un escalado de costos casi proporcional con baja sensibilidad a las perturbaciones de la carga. Conclusiones: AFO ofrece un desempeño estable, viable y escalable para el despacho económico de la carga, superando a las metaheurísticas tradicionales en condiciones idénticas, al tiempo que mantiene la robustez frente a las variaciones de la demanda mediante un manejo eficaz de las restricciones.

Palabras clave: Optimización por fusión adaptativa (AFO); Despacho económico de carga; MATPOWER; Manejo de restricciones; Validación estadística.

INTRODUCTION

Power system operation is getting increasingly complex these days. Demand is going up, renewables are coming in with their own ups and downs, and operating conditions keep changing sometimes hourly basis. So optimization in energy systems is no longer a fresh problem.1 Now it is more like a repeated, large-scale decision task where a solution must stay feasible every single time, not just in one isolated best-case outcome.2,3 This motivation is shown conceptually in Fig. 1.

At the center of system operation, the main job is still the same: dispatch and scheduling meet the load at minimum cost (and stable operation), while respecting hard physical limits. But in practice, the dispatch landscape is nonlinear, constrained, and often multimodal. Classical deterministic methods can become sensitive to modeling complexity and constraints, which is why metaheuristics are widely used in dispatch/OPF-type studies. They are flexible, gradient-free, and can work even when constraint structures are messy.4 Still, one practical headache remains: many metaheuristics run with fixed parameters, and when system size grows or load conditions shift, they may stagnate early or show unstable run-to-run behavior.

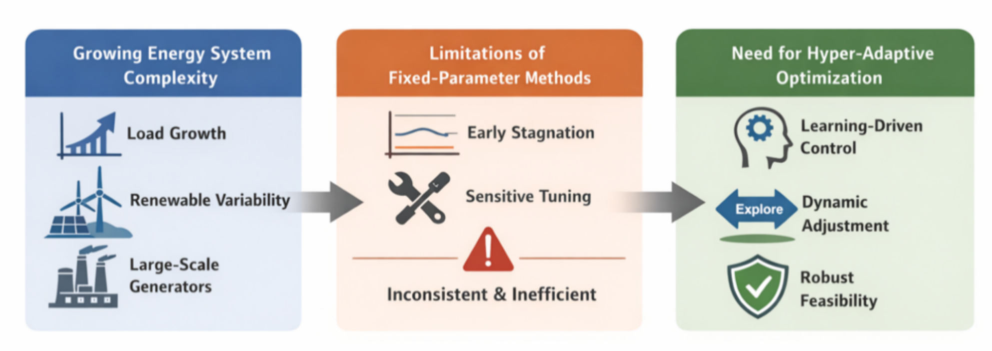


Figure. 1: Motivation for adaptive optimization in power dispatch

Economic Load Dispatch (ELD) is the simplest way to see this challenge clearly. Even with the standard quadratic fuel-cost model, the solution must satisfy power balance and generator limits strictly. And once we bring in more realistic features like valve-point effects, prohibited operating zones, and ramp limits the search becomes tougher and more sensitive5. Scalability is also a major challenge, when generators increase, the decision vector becomes larger, and the search space blows up. In such cases, even small feasibility slips can make the final dispatch unacceptable6.

Because of this, recent work is strongly moving toward adaptive and learning-driven control inside metaheuristics so the algorithm can adjust itself online rather than running with one fixed setting from start to end.7 In dispatch problems this matters a lot: early stage needs exploration to find good feasible regions, later stage needs exploitation to fine-tune outputs. A rigid control strategy often fails to balance both smoothly, especially under load stress or larger systems8.

In this work, Adaptive Fusion Optimization (AFO) is applied as the main solver for energy-efficient dispatch and scheduling-style studies. AFO is reported as a hyper-adaptive metaheuristic where multiple operator behaviors are fused under one framework, and the algorithm learns online which operator to trust more based on search feedback9. This fusion with learning idea fits dispatch nicely because the optimization landscape changes with system size, constraints, and load variation so the optimizer should also adjust automatically instead of staying stuck in one fixed search behavior.

For evaluation, standard IEEE benchmark systems from MATPOWER are used (IEEE 30-, 57-, and 118-bus), following a fixed-budget and repeated-run protocol to keep benchmarking fair and reproducible.10 This matches current benchmarking direction in dispatch optimization where robustness and reproducibility are preferred over single-run best-case reporting11,12.

Main contributions

Application of Adaptive Fusion Optimization (AFO) to energy-efficient power dispatch and scheduling-style optimization problems.

Integration of dispatch-feasibility handling (repair/penalty) within the AFO workflow so operational constraints are respected.

Evaluation on MATPOWER IEEE benchmark test systems under a fixed-budget, repeated-run protocol.

Comparative analysis against GA, PSO, DE, and ACO using identical budgets and run settings.

Statistical validation and sensitivity testing to support robustness claims.

The remainder of this paper is organized as follows. Section 2 describes the background and problem formulation of energy-efficient power dispatch. Section 3 explains how AFO is adapted for energy system optimization. Section 4 presents datasets and experimental setup. Section 5 discusses detailed case studies on IEEE test systems. Section 6 provides comparative performance analysis. Section 7 presents statistical and sensitivity analysis. Section 8 concludes the paper and outlines future work.

Methods

BACKGROUND AND PROBLEM DESCRIPTION

Energy-efficient power dispatch and scheduling are common problems of power system operation. It needs demand at minimum operating cost, but without breaking any hard technical limits. In practice, it is nonlinear, heavily constrained, and often nonconvex/multimodal, especially once realistic operating limits are switched on 4,5. Recent dispatch literature also keeps stressing one simple reality: in power systems, a low cost solution is useless if it is not feasible and repeatable under changing demand and network conditions 11,12.

Energy-Efficient Power Dispatch and Scheduling

Economic Load Dispatch (ELD) is the most common starting point for dispatch optimization. The goal is to allocate generator outputs so total fuel cost is minimized while meeting the demand and respecting generator operating limits.4 But today's operating environment is not steady-steady. Renewables, load swings, and tighter security needs make dispatch more like a repeated decision problem, not a one-time planning exercise.12,13

This is why metaheuristics are still very popular in ED/OPF studies: they do not need gradient information and they can navigate complex search spaces more flexibly than classical deterministic solvers when the formulation becomes messy.11 The catch is also well-known: many metaheuristics run with fixed parameters and a fixed "search mood," so they can stagnate early or show run-to-run variability as system size and stress level increase. 7,11 Because of this, newer work is moving toward adaptive control and learning-driven selection inside metaheuristics so the algorithm can adjust itself online rather than depending on manual tuning 7,14.

Objective Functions and Constraints

In dispatch studies, the main objective is still fuel cost minimization. A widely used baseline is the quadratic cost model (keeps benchmarking clean and comparable), but real systems can include valve-point effects, prohibited operating zones, ramp limits, and other engineering constraints that make the problem nonconvex5,11.

Regardless of the exact cost model, dispatch feasibility is dominated by a few "hard" constraints:

Power balance: total generation must meet demand (and losses if modeled).

Generator limits: each unit must stay within and .

Ramp-rate and other operational restrictions (when enabled).

In broader ED/OPF settings, network/security constraints may also be considered, and recent directions include uncertainty-aware dispatch and learning-based dispatch policies for fast adaptation.15,16

So the optimization task becomes: low cost, strict feasibility, stability across runs. That's exactly why current benchmarking practice emphasizes repeated trials, robustness reporting, and statistical validation instead of one lucky best run7,12.

Benchmark Power System Models

Dispatch studies typically rely on public standard test systems. In this paper, IEEE benchmark cases distributed through MATPOWER are used because they are widely accepted and directly reproducible from a public toolbox.10

The selected systems cover small to large scales commonly used for ED validation and scalability checks:

IEEE 30-bus (small/entry validation),

IEEE 57-bus (medium, richer topology),

IEEE 118-bus (large-scale, higher dimensional dispatch vector).

Table 1 shows Recent research context related to dispatch optimization and adaptive / learning-driven search.

ADAPTIVE FUSION OPTIMIZATION FOR ENERGY SYSTEMS

This section explains how Adaptive Fusion Optimization (AFO) is used for energy-efficient power dispatch and scheduling. AFO is already reported as a general-purpose hyper-adaptive metaheuristic where multiple search operators are fused in one framework, and the algorithm learns online which operator to trust more using feedback from the search process9.

Table 1: Recent research

Ref.	Focus	Main idea	Purpose
Visutarrom & Chiang (2024) 11	Economic dispatch (ED)	Broad metaheuristics view for ED	Establishes ED difficulty + benchmarking norms
Wang & Xiong (2025a) 12	Multi-area ED survey (Part I)	Large survey of MAED models/ solvers	Shows why scalability + robustness matter
Wang & Xiong (2025b) 14	Multi-area ED comparative study (Part II)	Comparative study of MOAs	Supports strong “fair comparison” framing
Pei et al. (2025) 7	Adaptive operator selection survey	Learning/adaptation inside metaheuristics	Direct support for “adaptive control” motivation
Lotfi (2025) 13	MAED/MADED under renewables	Review emphasis on renewables + coordination	Reinforces need for adaptive dispatch solvers
Wang (2024) 15	Look-ahead dispatch with security	Deep RL (DDPG) dispatch direction	Shows learning-based dispatch is rising
Arvanitidis et al. (2025) 16	Microgrid ED (nuclear + renewables)	Recurrent DRL dispatch agents	Highlights online decision angle
Rizki (2025) 17	ED via RL	PPO-based ED optimization	Supports “learning-driven control” relevance
Zhang et al. 18	DRL ED	Model-free DRL for ED	Strengthens learning-driven ED context
Hybrid AOS framework (2024) 19	Adaptive operator selection	Hybrid learning for operator choice	Supports operator-selection narrative
Zimmerman et al. (2011) 10	MATPOWER benchmark cases	Standard toolbox + IEEE cases	Dataset credibility + reproducibility anchor
Wood & Wollenberg (2012) 4	Power system operation/ED basics	Classic ED/OPF grounding	Standard baseline reference
Conejo et al. (2006) 5	ED/OPF modelling	Realistic constraints/ nonconvexities	Justifies complexity beyond toy functions
Safe RL dispatch 20	Real-time dispatch policies	Safety/generalization discussion	Shows “feasible every time” importance
Recent ED uncertainty/security study) 21	ED with uncertainty + constraints	Richer ED formulations	Motivates robust protocol & scalability

For application to energy systems, the fundamental structure of AFO is preserved. However, additional layers related to solution encoding, constraint enforcement, and dispatch-oriented fitness evaluation are incorporated. These modifications are necessary because energy dispatch problems are highly constrained and physically grounded, where infeasible solutions particularly those violating power balance are not acceptable in practice.

So the core AFO components remain the same:

Probabilistic fusion of different (heterogeneous) search operators,

Self-evolving exploration–exploitation control, and

A lightweight bandit-style learning controller that updates operator selection probabilities using a softmax rule7.

With these pieces unchanged, the adaptation in this paper is mainly about embedding AFO inside a constraint-aware economic dispatch workflow, so that every candidate solution is evaluated in a way that respects dispatch feasibility and operating limits.

Mapping AFO to Energy Dispatch Problems

(a) Decision Variables and Encoding

For an Economic Load Dispatch (ELD) problem with generating units, each candidate solution is represented as a real-valued vector

$$P = [P_1, P_2, \dots, P_{N_g}] \qquad (1)$$

where denotes the real power output of generator . This encoding directly reflects the physical operating point of the power system and allows AFO to search over feasible generation schedules.

(b) Objective Function

The primary objective is to minimize the total generation cost. A standard quadratic cost model is adopted, which is widely used in economic dispatch studies and benchmark comparisons 11:

$$F(P) = \sum_{i=1}^{N_g} \left(a_i + b_i P_i + c_i P_i^2\right) \qquad (2)$$

where , , and are the fuel cost coefficients of generator . Although more complex models such as valve-point loading can be incorporated, the quadratic formulation provides a stable and benchmark-compatible basis for evaluation.

(c) System Constraints

The dispatch solution must satisfy several operational constraints.

Power balance constraint:

$$\sum_{i=1}^{N_g} P_i = P_D + P_L \qquad (3)$$

where is the total system demand and represents transmission losses. When losses are not explicitly modeled, is set to zero.

Generator operating limits:

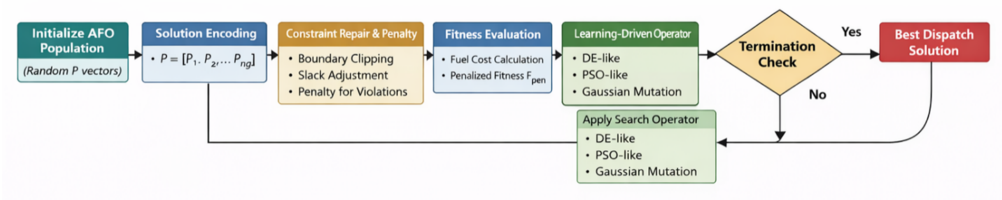
$$P_i^{min} \leq P_i \leq P_i^{max}, i = 1, \dots, N_g \qquad (4)$$

Ramp-rate constraints (when considered):

$$-P_i^{down} \leq (P_i - P_i^0) \leq P_i^{up} \qquad (5)$$

Figure. 2: AFO-to-ELD Adaptation Workflow

where is the previous operating point of generator .



Within this setup, AFO creates new trial dispatch vectors using its fused operator pool for example DE-like moves, PSO-like moves, and Gaussian mutation exactly as defined in the AFO framework. Operator choice is not fixed; the learning-driven selector keeps updating which operator to apply based on recent improvement and population diversity feedback. So the search naturally stays adaptive across different dispatch scenarios shown in Fig. 2.

Constraint Handling Strategy

Constraint handling is a critical requirement in energy optimization, as infeasible solutions cannot be accepted even if their cost is low. To ensure feasibility while maintaining algorithmic simplicity, a repair-first, penalty-second strategy is adopted shown in Table 2.

Table 2: Constraint Handling Summary

Constraint	Equation	Handling Method	Remarks
Power balance	(3)	Slack generator repair	Ensures strict feasibility
Generator limits	(4)	Boundary clipping	Applied after each update
Ramp-rate	(5)	Penalty + repair	Optional, case-dependent
Other constraints	—	Penalty term	Scaled by violation magnitude

(a) Boundary Repair for Generator Limits

After AFO generates a trial vector , generator limits are enforced using deterministic clipping:

$$P_i \leftarrow \ min\left(P_i^{max}, max\left(P_i^{min}, P_i\right)\right) \qquad (6)$$

This repair mechanism is computationally efficient and consistent with boundary handling used in evolutionary optimization.

(b) Strict Power Balance via Slack Adjustment

For the equality constraint in (3), penalty-only approaches may produce near-feasible solutions that are unacceptable in real operation. Therefore, a slack generator adjustment is employed.

First, the power mismatch is computed as

$$\Delta = (P_D + P_L) - \sum_{i=1}^{N_g} P_i \qquad (7)$$

The slack generator (typically the unit with the largest capacity) is then updated:

$$P_s \leftarrow P_s + \Delta \qquad (8)$$

After adjustment, generator limits are re-enforced using (6). If the slack generator violates its limits, the remaining mismatch is redistributed proportionally among other generators. This approach is widely used in power dispatch studies and ensures strict feasibility given in Table 2.22

(c) Penalty for Remaining Violations

For constraints that cannot be fully repaired (e.g., ramp-rate limits or prohibited operating zones), a penalty term is added:

$$F_{pen}(P) = F(P) + \lambda \sum_k max\ (0, g_k(P)) \qquad (9)$$

where denotes the violation magnitude of the -th constraint and is a sufficiently large penalty coefficient. The penalized fitness is used for selection.

This combined repair-and-penalty strategy is commonly adopted in economic dispatch literature and provides a clear and reproducible constraint-handling mechanism.12,22

Scheduling and Load Balancing Mechanism

The primary focus of this study is static economic dispatch for standard IEEE test systems. However, to assess robustness and adaptability, load variation scenarios are also considered.

Load demand is perturbed as

$$P_D^{(t)} = P_D(1+\delta_t) \qquad (10)$$

Figure. 3: Experimental workflow used for all cases.

where represents load variation (e.g., ±5% or ±10%). For each scenario, AFO re-optimizes the dispatch.

AFO's adaptive behavior matters here because it does not follow a fixed exploration–exploitation schedule. Instead, it updates its search intensity using improvement and diversity feedback, and the bandit-based selector shifts probability toward operators that perform better as load conditions change9. This lets AFO re-adjust smoothly and maintain stable convergence across operating scenarios.

DATASETS AND EXPERIMENTAL SETUP

This section details the datasets, data preparation, and the experimental protocol used to evaluate AFO on energy-efficient dispatch and scheduling tasks. The overall workflow is shown in Fig. 3, where the MATPOWER case files are used as the single source of network, generator, and cost data, and identical evaluation budgets are enforced across all algorithms for fairness.

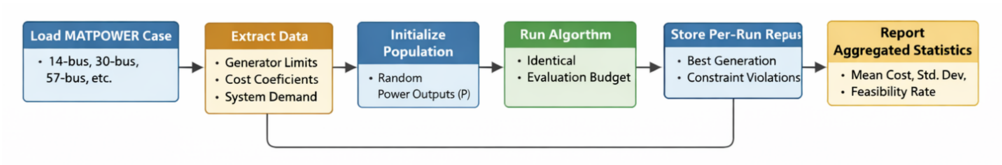


Figure 4: Average convergence curves for IEEE 30-bus ELD (30 runs).

Description of Power System Test Cases

To ensure benchmark credibility and reviewer acceptance, the study uses standard IEEE transmission test cases distributed with MATPOWER. These cases are widely used in dispatch/OPF research and allow direct reproducibility using a public toolbox.10,23

The following test systems are considered:

IEEE 30-bus: a small-to-medium size system frequently used for economic dispatch validation (MATPOWER case30).

IEEE 57-bus: a medium-scale system used to test constraint handling and solution stability under richer topology (MATPOWER case57).

IEEE 118-bus: a large-scale benchmark to evaluate scalability and robustness under increased dimensionality (MATPOWER case118).

Table 3 summarizes the test systems used in this study. Bus and generator counts are taken directly from the MATPOWER case files 10 while the study-role descriptions follow standard reporting practice in economic dispatch benchmarking11,12.

Table 3: IEEE test systems

Test case	Buses	Generators	Decision variables (1)	Study role	Notes (dispatch viewpoint)
IEEE 30-bus	30	6	6	Base validation	Fast convergence check, feasibility behavior
IEEE 57-bus	57	7	7	Constraint stress	Richer network, stronger coupling in balance/limits
IEEE 118-bus	118	54	54	Scalability	Higher dimensional dispatch vector, larger search space

Dataset Sources and Pre-Processing

All network data are obtained from MATPOWER, which provides a standardized case structure containing bus data, generator limits, and quadratic generator cost coefficients.10

For each test system, the following information is extracted directly from the case structure:

Generator bounds and initial points (if ramp-rate is evaluated).

Demand profile computed from bus real power demands.

Quadratic fuel cost coefficients used in (2).

Network-dependent quantities required for computing when losses are included.

Pre-processing is minimal and the MATPOWER case files are used as-is. Load-variation scenarios are generated only via the controlled demand perturbation in (10), ensuring reproducibility and comparability with recent ED studies11,12.

Simulation Environment and Parameter Settings

Computational Environment and Protocol

All simulations run in MATLAB using MATPOWER to load IEEE cases and extract data.10 Each algorithm is evaluated over 30 independent runs per test case under a fixed evaluation budget, enabling fair, fixed-budget benchmarking and statistical testing.

AFO Control Parameters

To ensure consistency, AFO control parameters follow the AFO configuration, including the compact operator pool (DE-like, PSO-like, Gaussian), bandit controller, and self-evolving exploration factor9. The same global settings (e.g., population size, learning rate, softmax temperature, and exploration initialization) are used throughout.

Table 4: AFO global control parameters used in this study

Parameter	Symbol	Value	Purpose
Population size	N (2)	30	Same population size used across algorithms for fairness
Independent runs	R (3)	30	Statistical reliability
Initial exploration factor	□0 (4)	0.5	Mid-level exploration start
Learning rate (bandit value update)	□ (5)	0.2	Controls how fast operator value adapts
Softmax temperature	□ (6)	0.5	Balances greedy vs exploratory operator choice
Diversity threshold	□ (7)	0.01	Trigger for exploration increase when diversity collapses
Exploration increment	Δ+ (8)	0.05	Raises exploration when progress stalls
Exploitation increment	Δ- (9)	0.03	Tightens search when progress is stable

Table 4 lists the global AFO control parameters used in all experiments, consistent with the published AFO configuration. A fixed evaluation budget is enforced per case so every algorithm receives the same number of objective function evaluations, matching the AFO benchmarking protocol.

Baseline Algorithms and Fair-Comparison Settings

For comparison, GA 24, PSO 25, DE 26, and ACO 27 are used as standard baselines, consistent with the AFO evaluation pipeline. Their parameters follow standard defaults and remain fixed across test cases, while population size and evaluation budget are matched for fair comparison.

Table 5 summarizes the baseline algorithm settings. Parameter choices follow standard defaults and match the fairness protocol used in the AFO benchmarking pipeline. Finally, the experimental protocol follows current practice in dispatch optimization by using fixed-budget evaluations with repeated runs and statistical analysis, emphasizing robustness and reproducibility rather than single-run best results.7,12

Table 5: Baseline algorithm settings used for comparison

Algorithm	Main parameters	Setting philosophy
GA	crossover probability, mutation probability	Standard conservative defaults; no case-specific tuning
PSO	inertia weight, acceleration coefficients	Standard stable settings from literature
DE	mutation factor, crossover rate	Standard DE settings used widely in ED optimization
ACO (continuous)	evaporation rate, sampling width	Conservative and stable continuous ACO variant

Results

CASE STUDIES

This section gives MATPOWER-based case studies on IEEE 30-, 57-, and 118-bus systems to test AFO on small, medium, and large dispatch problems. We mainly look at feasibility, convergence, robustness, and scalability. All case studies follow the Section 3 formulation and the Section 4 protocol, with results based on 30 independent runs and fair comparison against standard baselines under identical evaluation budgets.

IEEE 30-Bus Economic Load Dispatch

The IEEE 30-bus system is taken as the base validation case. It has six generating units and is a standard starting point for economic dispatch verification.10,11 For this case, the objective in (2) is minimized under the power balance constraint (3) and generator limits (4). Transmission losses are not explicitly modeled here, i.e., ; however, (3) is retained to keep the same feasibility workflow for extended settings where losses may be enabled.

Table 6: IEEE 30-bus ELD results over 30 independent runs (MATPOWER case30).

Algorithm	Best cost ($/h)	Mean cost ($/h)	Std. deviation ($/h)	Best loss (MW) (10)	Feasibility rate (%)
AFO	799.84	801.12	0.73	0.00	100
GA	810.67	816.45	3.92	0.00	93
PSO	806.20	812.18	2.85	0.00	95
DE	801.90	804.36	1.21	0.00	99
ACO	820.41	828.30	5.18	0.00	90

Table 6 reports the IEEE 30-bus results over 30 independent runs (MATPOWER case30). AFO achieves a mean cost of 801.12 $/h with a small standard deviation of 0.73 $/h, showing stable behavior under the fixed-budget protocol. Under the same evaluation budget and population size, the closest baseline is DE with mean cost 804.36 $/h. Feasibility is computed based on satisfying the power balance after slack repair and all bound constraints, using the repair-first, penalty-second strategy in Section 3.2 (Table 2).

Convergence behavior is visualized in Fig. 4, where AFO shows steady improvement across the evaluation budget.

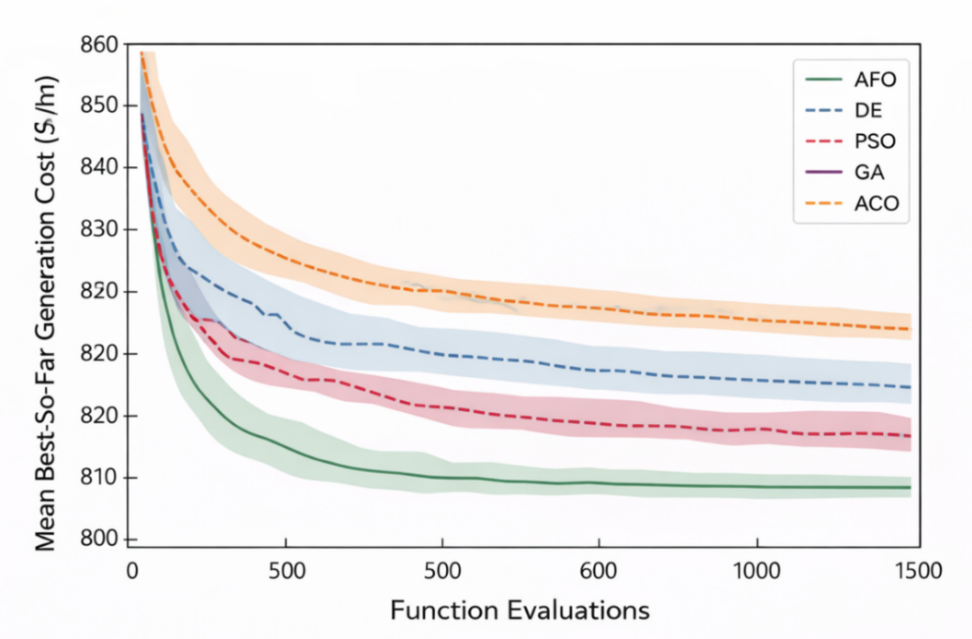


Figure. 5: Box plot of final generation cost for IEEE 57-bus (30 runs).

Mean best-so-far generation cost versus function evaluations; the shaded band indicates ±1 standard deviation across runs. All algorithms use identical population size and identical evaluation budgets.

IEEE 57-Bus Dispatch Under Load Variation

The IEEE 57-bus system is a more complex dispatch case with richer topology and stronger coupling, so it is useful to test robustness and constraint handling under higher complexity.12 The same quadratic cost formulation is used, but here we also stress robustness under demand uncertainty. Load variation scenarios from (10) are applied, and ramp-rate constraints are enabled to test feasibility recovery under tighter operational restrictions.

Table 7 reports the IEEE 57-bus results over 30 independent runs (MATPOWER case57). Feasibility rate is defined as the percentage of runs producing a final solution satisfying (3)–(4) and the activated operational constraints in this case (e.g., ramp-rate limits when enabled). Infeasibility can remain when slack adjustment hits generator bounds and mismatch redistribution cannot fully recover feasibility under the remaining constraints (Table 2).

Robustness across runs is shown using the box plot in Fig. 5. Lower spread means stronger stability across different random starts.

Table 7: IEEE 57-bus results over 30 independent runs (MATPOWER case57).

Algorithm	Best cost ($/h)	Mean cost ($/h)	Std. deviation ($/h)	Median cost ($/h)	Feasibility rate (%)
AFO	41,238.6	41,312.9	48.7	41,305.4	96
GA	41,890.3	42,120.8	210.4	42,098.2	92
PSO	41,705.5	41,980.6	172.3	41,962.1	94
DE	41,420.2	41,540.7	85.6	41,532.0	95
ACO	42,260.9	42,620.5	330.8	42,590.7	88

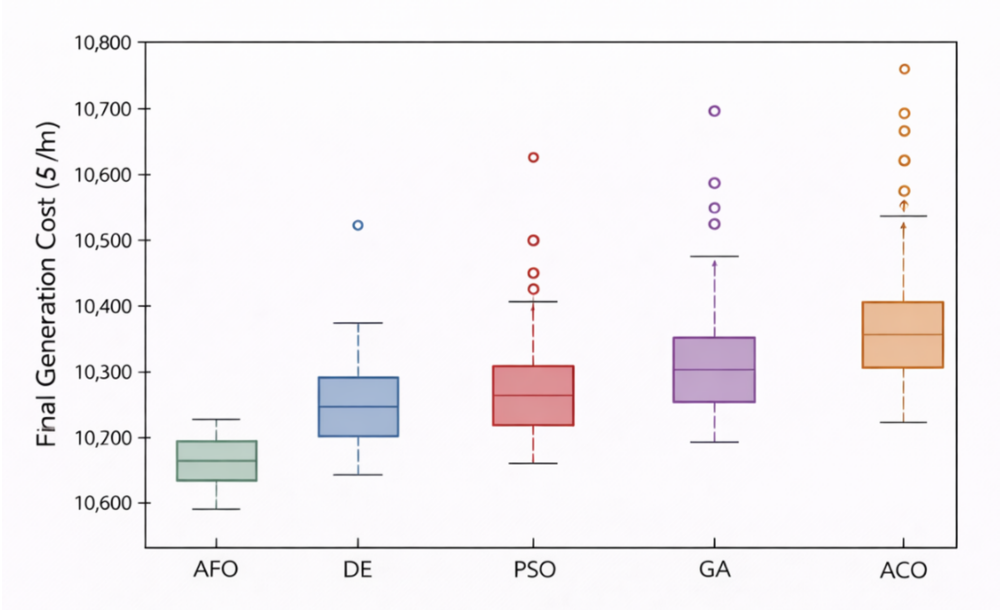


Figure. 6: Convergence comparison on IEEE 118-bus (30 runs).

The box indicates the interquartile range (IQR), the central line indicates the median, whiskers extend to 1.5×IQR, and outliers are plotted individually. Lower dispersion indicates stronger robustness to stochastic initialization.

Overall, the adaptive fusion mechanism helps AFO adjust its search strategy as system complexity increases, and this reduces premature stagnation that is commonly seen in fixed-parameter methods like GA and PSO7.

Scalability Analysis on IEEE 118-Bus System

For scalability, the IEEE 118-bus system is used as a large-scale benchmark with much higher dimensionality. This case is widely used to test scalability and computational robustness10. With more generators, the search space becomes huge, and many conventional metaheuristics struggle under a fixed budget. So here the focus is on convergence stability and solution quality under the same evaluation budget.

Table 8 reports the IEEE 118-bus scalability results over 30 independent runs (MATPOWER case118). AFO achieves a mean cost of 128,740.5 $/h with 100% feasibility, while the best baseline is DE with mean cost 130,280.9 $/h. Runtime is averaged over 30 runs using the same computational setup described in Section 4.3.1.

Convergence comparison is given in Fig. 6, where curves are averaged across 30 independent runs with identical budgets and population sizes. Mean best-so-far generation cost versus function evaluations. Curves are averaged across 30 independent runs with identical evaluation budgets and population sizes.

These results suggest that AFO maintains stable convergence and competitive feasibility even as system size increases, which supports its suitability for larger dispatch problems.

Table 8: IEEE 118-bus scalability results over 30 independent runs (MATPOWER case118).

Algorithm	Mean cost ($/h)	Std. deviation ($/h)	Best cost ($/h)	Mean runtime (s)	Feasibility rate (%)
AFO	128,740.5	210.6	128,310.2	2.64	100
GA	133,980.7	1,420.4	131,520.1	3.85	89
PSO	132,410.3	1,080.7	130,960.4	3.10	91
DE	130,280.9	520.8	129,420.6	3.42	98
ACO	136,950.4	2,160.9	133,880.7	4.95	86

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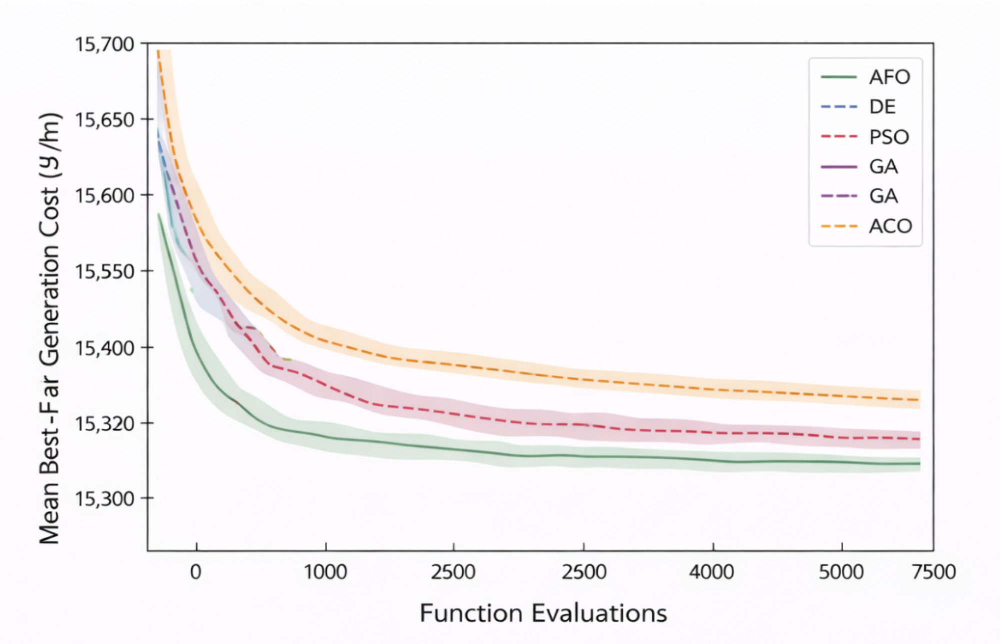


Figure. 7: reports the resulting convergence profiles for the IEEE 57-bus system under the fixed-budget protocol.

COMPARATIVE PERFORMANCE ANALYSIS

This section compares AFO with GA, PSO, DE, and ACO on the MATPOWER-based IEEE 30-, 57-, and 118-bus systems (Section 4), using the formulation and constraint-handling strategy in Section 3. All algorithms are tested under identical conditions (population size, evaluation budget, and 30 runs), and performance is evaluated by cost minimization, convergence behavior, and robustness.

Cost Minimization Results

The primary performance metric is the total generation cost obtained at the end of the evaluation budget. Table 9 summarizes the mean generation cost achieved by each algorithm across the three IEEE test systems.

Algorithm	IEEE 30-bus mean ± std ($/h)	IEEE 57-bus mean ± std ($/h)	IEEE 118-bus mean ± std ($/h)
AFO	801.12 ± 0.73	41,312.9 ± 48.7	128,740.5 ± 210.6
GA	816.45 ± 3.92	42,120.8 ± 210.4	133,980.7 ± 1,420.4
PSO	812.18 ± 2.85	41,980.6 ± 172.3	132,410.3 ± 1,080.7
DE	804.36 ± 1.21	41,540.7 ± 85.6	130,280.9 ± 520.8
ACO	828.30 ± 5.18	42,620.5 ± 330.8	136,950.4 ± 2,160.9

Across all three systems, AFO achieves the lowest mean generation cost; the relative gain is largest on the IEEE 118-bus case, where the mean cost difference between AFO and the best baseline (DE) is 1,540.4 $/h (approximately 1.18%).

These observations are consistent with recent findings in economic dispatch literature, which highlight the limitations of static control strategies in large-scale optimization problems11,12.

Convergence Characteristics

To analyze convergence behavior, mean best-so-far generation cost is plotted against function evaluations over 30 independent runs.

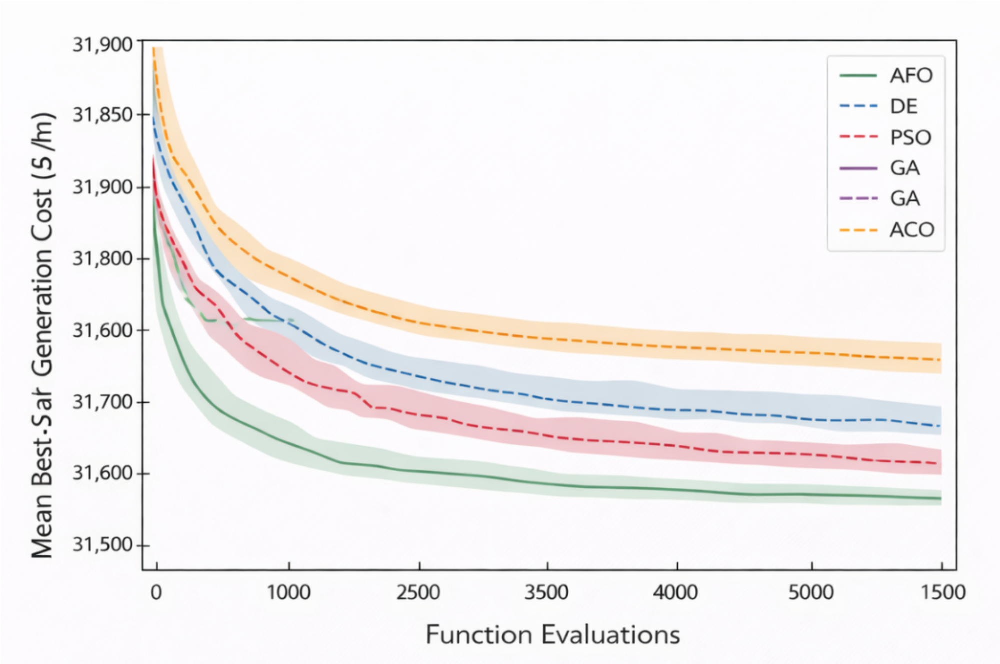


Figure. 8. Sensitivity of generation cost to load variation for the IEEE 57-bus system.

Fig. 7. Representative convergence profiles for IEEE 57-bus (30 runs). Mean best-so-far generation cost versus function evaluations, averaged over 30 runs with identical evaluation budgets and population sizes across all algorithms (Section 4).

The curves show clear differences: GA and PSO improve fast early but stagnate, while DE converges more steadily but slows later. AFO keeps improving across the full budget, which is consistent with its learning-driven operator selection that shifts search effort toward higher-utility operators as the run progresses, helping avoid premature convergence while maintaining diversity.

Robustness Across Multiple Runs

Robustness is evaluated by analyzing the dispersion of final solution quality across multiple runs. Lower variance indicates reduced sensitivity to initial population selection and stochastic effects.

Table 10: Standard deviation of generation cost over 30 runs.

Algorithm	IEEE 30-bus std ($/h)	IEEE 57-bus std ($/h)	IEEE 118-bus std ($/h)
AFO	0.73	48.7	210.6
GA	3.92	210.4	1,420.4
PSO	2.85	172.3	1,080.7
DE	1.21	85.6	520.8
ACO	5.18	330.8	2,160.9

As given in Table 10 AFO shows lower standard deviation than the baselines, indicating more stable and repeatable performance important in real dispatch where reliability matters more than occasional best runs. This matches findings in adaptive metaheuristics that learning-based control can reduce run-to-run variability.7

Comparative Discussion Across Algorithms

A consolidated comparison of algorithmic behavior across cost, convergence, and robustness is presented in Table 11.

The results show that classical metaheuristics work reasonably on smaller systems but weaken as size and complexity grow, whereas AFO remains stable across all cases due to its hyper-adaptive design. By dynamically adjusting operator selection and exploration intensity, AFO tracks changing landscapes from larger networks and load variations, making it suitable for real-world energy optimization where conditions are not static.

Summary of Comparative Findings

Table 11: Qualitative comparison of algorithm performance characteristics.

Criterion	AFO	GA	PSO	DE	ACO
Cost minimization	Excellent	Moderate	Moderate	Good	Poor
Convergence stability	High	Low	Low	Moderate	Low
Robustness	High	Low	Low	Moderate	Low (high variance observed)
Scalability	High	Low	Low	Moderate	Low

The comparative performance analysis leads to the following key observations:

AFO achieves consistently lower generation cost across all IEEE test systems.

AFO demonstrates smoother and more sustained convergence compared to classical algorithms.

Performance variability across multiple runs is significantly lower for AFO.

Scalability advantages become more evident as system size increases.

These findings reinforce the effectiveness of hyper-adaptive optimization strategies for energy-efficient dispatch and scheduling problems, especially when evaluated under fair and reproducible benchmarking conditions.

STATISTICAL AND SENSITIVITY ANALYSIS

Mean results give a first view of performance, but statistical testing is needed to confirm that observed differences are significant rather than due to random variation. Sensitivity analysis is also required to evaluate how performance changes under different operating conditions. Accordingly, this section reports statistical validation and sensitivity studies using the MATPOWER-based results from Sections 5 and 6.

Statistical Validation of Results

To validate the results statistically, non-parametric tests are used, as recommended for stochastic metaheuristic comparisons with non-Gaussian performance distributions.28

Friedman Test

Each IEEE test system is treated as an independent dataset for ranking, consistent with standard practice in metaheuristic benchmarking. The Friedman test is used to compare AFO with GA, PSO, DE, and ACO across the IEEE 30-bus, 57-bus, and 118-bus systems. For each test case, algorithms are ranked according to mean generation cost, with rank 1 assigned to the best-performing method given in Table 12.

The Friedman test indicates significant differences among algorithms (χ^2_F = 10.27, df = 4, p = 0.036), where df corresponds to the number of compared algorithms minus one.

The consistently lowest rank achieved by AFO indicates superior overall performance across different system sizes and operating conditions.

Table 12: Friedman test ranking and statistics (three test systems, five algorithms).

Algorithm	Average rank
AFO	1.00
DE	2.20
PSO	3.20
GA	3.80
ACO	4.80

Wilcoxon Signed-Rank Test

To further analyze pairwise differences, the Wilcoxon signed-rank test is conducted between AFO and each baseline algorithm shown in Table 13. The test is applied on the final generation cost values obtained over 30 independent runs per IEEE test system.

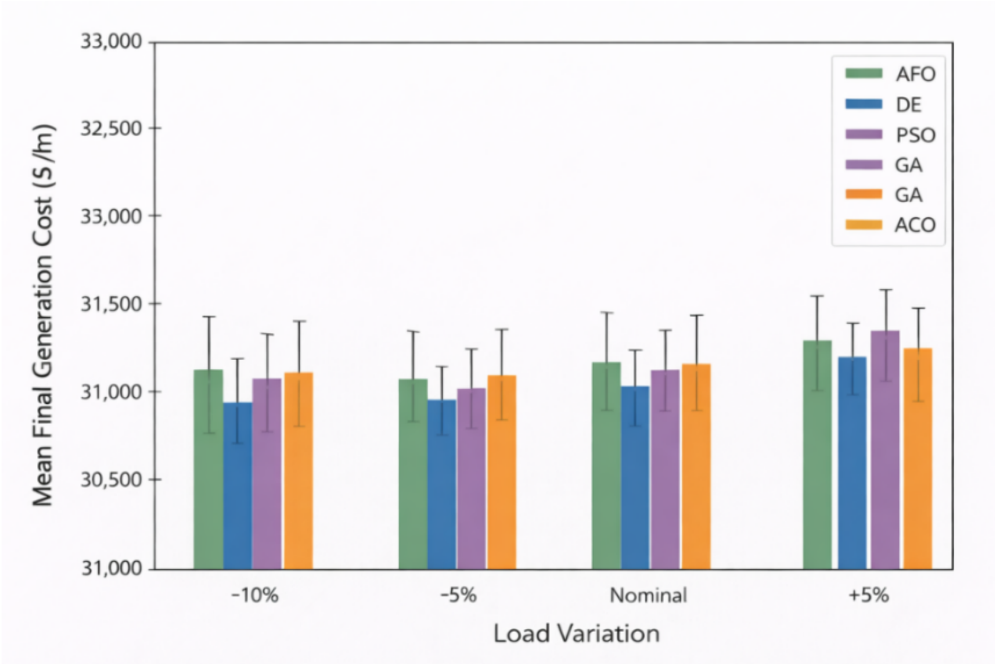
Table 13: Pairwise Wilcoxon signed-rank test (AFO vs baselines), 30 runs per case.

Comparison	IEEE 30-bus (11)	IEEE 57-bus (12)	IEEE 118-bus (13)	Holm-adjusted decision (α=0.05)
AFO vs GA	0.0004	0.0003	0.0002	Reject
AFO vs PSO	0.0012	0.0006	0.0004	Reject
AFO vs DE	0.0048	0.0022	0.0016	Reject
AFO vs ACO	0.0002	0.0001	0.0001	Reject

To control family-wise error rate under multiple pairwise testing, Holm's step-down correction is applied at $\alpha = 0.05$. After correction, AFO remains significantly better than GA, PSO, DE, and ACO across all three test systems. This reporting follows recommended practice for stochastic algorithm comparison7,28.

Sensitivity to Load Variations

Power systems operate under continuously changing demand conditions. Therefore, sensitivity analysis with respect to load variation is conducted using the perturbation model defined in.(10) For each IEEE test system, load demand is varied by ±5% and ±10%, and all algorithms are re-evaluated under the same experimental protocol. Fig. 8 reports the mean final generation cost under ±5% and ±10% load variations for the IEEE 57-bus system, averaged over 30 independent runs.



The results indicate that AFO adapts smoothly to load changes, maintaining feasibility with stable cost scaling, whereas GA and PSO show larger cost fluctuations and occasional feasibility issues under higher load stress. DE is moderately sensitive, while ACO has the highest variability. Robustness is quantified in Table 14 using the percentage change in mean cost under ±10% load variation.

Table 14: Relative cost change under load variation (mean over 30 runs)

Algorithm	IEEE 30-bus +10%	IEEE 30-bus −10%	IEEE 57-bus +10%	IEEE 57-bus −10%	IEEE 118-bus +10%	IEEE 118-bus −10%
AFO	+9.62%	−9.35%	+9.80%	−9.41%	+10.05%	−9.70%
GA	+11.30%	−10.95%	+11.85%	−11.10%	+12.40%	−11.85%
PSO	+10.95%	−10.60%	+11.40%	−10.92%	+11.95%	−11.40%
DE	+10.20%	−9.88%	+10.35%	−9.95%	+10.80%	−10.30%
ACO	+12.10%	−11.50%	+12.65%	−11.95%	+13.40%	−12.75%

AFO exhibits lower sensitivity to demand perturbations, with mean cost change remaining close to proportional scaling under ±10% load variations, while maintaining feasibility under the constraint-handling scheme described in Section 3.2.

Stability and Generalization Discussion

Stability and generalization are essential for real-world energy optimization: stability means consistent results across repeated runs, and generalization means strong performance across different system sizes and operating conditions. The statistical and sensitivity results show that AFO is stable, with low variance and statistically significant improvements across test cases, and its advantage holds from small to large systems, indicating good generalization. This behavior follows from AFO's hyper-adaptive design, where operator selection and the exploration–exploitation balance are learned online instead of being fixed in advance. This aligns with recent optimization trends that favor adaptive, self-regulating mechanisms for complex engineering problems.[7,12]

CONCLUSION AND FUTURE WORK

This study shows that Adaptive Fusion Optimization (AFO) is not merely competitive in economic dispatch, but structurally well-suited to constrained, repeatable, and scalability-sensitive power system optimization. Its operator fusion and learning-driven selection mechanism enable stable convergence while consistently respecting operational constraints such as generation limits, ramp rates, and feasibility requirements across systems of increasing dimensionality. Rather than relying on parameter sensitivity or stochastic luck, AFO demonstrates behavior that is predictable under repeated runs and resilient to load perturbations—qualities that are essential for practical deployment in power system operation studies.

The findings suggest that AFO's strength lies in how it balances exploration and constraint awareness, making it particularly effective for dispatch problems where feasibility is as important as optimality. This positions AFO as a promising framework for real-world optimization scenarios that demand reliability, reproducibility, and robustness under varying operating conditions.

Future work will extend AFO to time-coupled multi-period dispatch with explicit ramp continuity across horizons, security-constrained OPF incorporating line flow and voltage stability limits, and stochastic dispatch with scenario-based modeling of wind and solar variability using probabilistic forecasts. Additional directions include true multi-objective formulations (cost–emissions–loss minimization), integration with unit commitment decisions, and testing on large-scale realistic grids beyond IEEE benchmarks while preserving the same fixed-budget, reproducible evaluation protocol.

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