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A Comprehensive Review of AI-Based Techniques for Economic Load Dispatch in modern Power Systems

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ABSTRACT

This paper reviews artificial intelligence (AI)–based methods for the Economic Load Dispatch (ELD) problem from 2015 to 2025, focusing on metaheuristic algorithms (Particle Swarm Optimization PSO, Genetic Algorithm GA, Differential Evolution DE, Grey Wolf Optimizer GWO, Ant Lion Optimizer ALO), hybrid AI approaches, and renewable-integrated dispatch. We searched peer-reviewed publications and major conferences for rigorous experimental work and describe trends, sample algorithmic breakthroughs, benchmarking practice (with a concentration on IEEE 30-bus and 118-bus studies), and operational adoption gaps. Advanced metaheuristics and their hybrids dominate ELD research for nonconvex constrained problems; hybridization with local search or ML surrogates improves convergence and feasibility; renewable integration drives stochastic, scenario-based, and multi-objective formulations; and DRL and surrogate metaheuristic pipelines show promise for real-time operation but require safety/constraint certification and reproducible benchmarking. We finish with targeted research to accelerate reliable, scalable AI-assisted dispatch.

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INTRODUCTION

Electricity plays a crucial role in our daily life, enhancing living standards and driving the economies of both developed and developing countries worldwide [1] [2]. The primary objective of modern electric power utilities is to deliver a reliable, high-quality power supply to consumers at the lowest possible cost while adhering to the operational limits and constraints of the committed generating units [3]. These objectives have led to the development of the Economic Load Dispatch (ELD) problem, which involves determining the optimal power output for all active generating units [4]. Economic Load Dispatch (ELD) is a pivotal optimization technique within the domain of power system operation [4]. Its core objective is to determine the most cost-effective allocation of power generation among a set of committed generating units to meet a specified total load demand [5].

By achieving this goal, ELD offers a multitude of benefits, including lower operating costs, increased system efficiency, and a reduction in greenhouse gas emissions [6]. As such, it is an essential tool for achieving the reliable, efficient, and economically viable operation of the power grid [6]. The complexity of the ELD problem is increasing as modern power systems integrate diverse and often variable energy sources, requiring a more sophisticated approach than was necessary for the more predictable, traditional grid architecture. Classical analytical methods (lambda iteration, Lagrange multipliers, quadratic programming) are efficient for smooth convex cost landscapes, but practical ELD formulations include valve-point loading, prohibited operating zones (POZs), ramp constraints, multi-fuel options and emissions objectives that make the optimization nonconvex, discontinuous and multi-modal [7]. Furthermore, high penetration of renewables (wind and solar)

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introduces stochasticity that complicates deterministic dispatch policies and motivates stochastic/robust formulations.

In the last decade AI and nature-inspired metaheuristics have been extensively applied to ELD due to their global search ability, flexibility in handling mixed continuous/discrete variables, and ease of hybridization with domain knowledge [8]. This review focuses on the 2015–2025 literature and centers on metaheuristics (PSO, GA, DE, GWO, ALO), hybrid AI methods (metaheuristic + metaheuristic, metaheuristic + local search, metaheuristic + ML surrogates), and renewable-aware dispatch. We emphasize (a) multi-objective ELD (cost, emissions, losses), (b) practical constraint-handling strategies, (c) real-time applicability and scalability, and (d) results reported on IEEE 30-bus and 118-bus benchmarks. The goal is to synthesize the state-of-the-art, highlight reproducibility issues, and prioritize actionable research directions.

LITERATURE REVIEW

Problem Formulation:

Objectives function

The Economic Load Dispatch problem is a constrained optimization task. Its primary objective is the minimization of the total fuel cost across all active generating units [13]. This objective is represented by a mathematical function, denoted as:

$$F(P)=\sum_{i=1}^{n} F_i P_i) \tag{1}$$

where F(P) represents the total fuel cost and $F_i(P_i)$ is the fuel cost function for the i-th generating unit, which is typically a quadratic or non-linear function of its power output P_i.

For analysis, each fuel cost function is modeled as a quadratic function as shown below:

$$F_i(P_i)=a_i P_i^2 + b_i P_i + C_i \tag{2}$$

Where $a_i\ b_i\ and\ C_i$ are the cost coefficients for the i-th generator. These coefficients are the factors contributed to the fuel cost. This minimization objective is subject to several critical constraints that define the operational reality of the power system

Constraints

The ELD optimization problem is subjected to the following constraints which has to be certified for better optimal output. This minimization objective is subject to several critical constraints that define the operational reality of the power system:

(a) Power Balance Constraint: The total power generated (P_i) by all units must be equal to the total load demand (P_D), often with the inclusion of total transmission line losses (P_L) [13]. This is an equality constraint. This constraint is represented mathematically below:

$$\sum_{i=1}^{n} P_i = P_D \tag{3}$$

Where P_D is the total power load demand from the system and $\sum_{i=1}^{n} P_i$ is he total power generated from the unit.

(b) Generator Capacity Limit Constraint***:*** Each generating unit has a minimum and maximum power output, which is an inequality constraint. The power output of each unit Pi, must be kept within its specified operational limits.

$$P_i^{min} \leq P_i \leq P_i^{max} \tag{4}$$

$P_i^{min}\ and\ P_i^{max}$ are the minimum and maximum power output limits for the ith generator.

(c) Ramp Rate Limit: Some systems also enforce a limit on how quickly a generator's output can be adjusted from one dispatch interval to the next.

$$|P_i\,(t+1) \quad P_i\,(t+1)| \leq R_t \tag{5}$$

Where R_t is the ramp rate unit for generator i.

(d) Non-Smooth Fuel Cost Functions: In realistic scenarios, the fuel cost functions can be non-linear or non-convex due to factors like the valve-point loading effects of thermal generators.

$$F_i(P_i)=a_i P_i^2 + b_i P_i + C_i + |e_i \times \sin(f_i \times \ P_i^{min} - P_i))| \tag{6}$$

Where,

$F_i(P_i)$= total fuel cost of the *i-th* generator

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$a_i\ b_i\ and\ c_i =$ cost coefficients of the *i-th* generator

e_i, f_i = valve-point coefficients accounting for the rippling effect

P_i = power output of the *i-th* generator (in MW)
$P_i^{min} - P_i$ = minimum operating limit of the generator

Corpus and Analysis Approach

From an initial pool (≈600 hits), title/abstract screening and full-text inspection yielded a corpus of ~120 empirical papers plus ~20 surveys/reviews used for context. We grouped the corpus by algorithm family and by application focus (single-objective ELD, combined economic-emission dispatch CEED, dynamic ELD, renewable-integrated dispatch, multi-area/distributed dispatch) [9]. For each group we extracted problem formulations, constraint sets, test systems (with special attention to IEEE-30 and IEEE-118 usage), algorithmic modifications, hybridization strategy, performance metrics (best/mean cost, convergence iterations, CPU time, constraint violations), and whether multi-run statistics and Pareto analyses were reported [10].

Metaheuristic families applied to ELD (2015–2025)

Population-based metaheuristics continue to be the backbone of ELD research. Below we summarize developments and representative findings for the main families.

Particle Swarm Optimization (PSO)

James Kennedy and Russell Eberhart introduced Particle Swarm Optimization (PSO) as a method to address complex, nonlinear optimization problems [11]. Inspired by the collective behaviors of animals like bird flocking and fish schooling, PSO does not rely on gradient information of the objective or error function. It efficiently finds optimal solutions and is known for fast convergence, delivering high-quality results in a short time [12]. One study applied PSO and the Sine Cosine Algorithm (SCA) to economically schedule three generator units in the IEEE 14-bus system. PSO remains widely used for ELD because of simple implementation and relatively few parameters. Recent trends include adaptive inertia and acceleration coefficients, chaotic sequences to diversify search, hybrid PSO+DE/PSO + local-search constructions, and multi-objective PSO variants for CEED. Empirical studies often report PSO as competitive on continuous, valve-point ELD instances, though it can suffer premature convergence without diversification or hybridization [13]. Comparative studies (including multi-algorithm benchmarks on IEEE test systems) frequently place tuned PSO among top performers in solution quality vs runtime trade-offs [14].

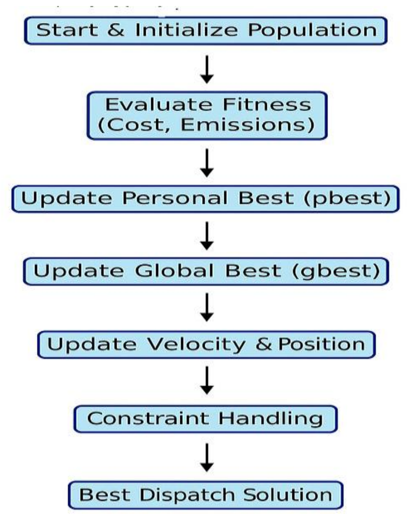

Fig.1 Flow Chart of PSO for ELD [43]

Genetic Algorithms (GA)

Meta-heuristic methods are widely used for solving the Economic Load Dispatch (ELD) problem due to their optimization effectiveness. The Genetic Algorithm (GA), inspired by natural selection and genetics, is a popular meta-heuristic technique that searches for exact or approximate solutions to optimization problems [15]. GA operates through computer simulations where a population of potential solutions (chromosomes) evolves over time. Studies comparing GA with the lambda iterative method on systems with 5 and 10 generators found that GA produced superior results [16]. GA has also been effectively applied

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to ELD problems involving multiple units, such as 3 and 6 generators, delivering optimal outcomes. Additionally, combining GA with the firefly algorithm has successfully addressed ELD problems alongside environmental emission constraints. Although GA is a probabilistic approach yielding solutions based on likelihood, it remains one of the most prominent and widely used techniques for solving ELD problems [17].

Differential Evolution (DE)

Differential Evolution (DE) and its variants continue to demonstrate strong global search capabilities and efficient convergence, making them well-suited for continuous optimization problems like Economic Load Dispatch (ELD). DE's mutation strategy, based on vector differences, effectively handles these challenges. Researchers have enhanced DE by developing adaptive control parameters, ensemble mutation techniques, and hybrid approaches that integrate DE with local search methods for improved solution quality. For instance, [18] introduced an oppositional mutual learning hybrid DE to address large-scale ELD problems with valve-point effects, achieving higher accuracy and faster convergence compared to standard methods. [19] proposed a modified DE variant that enhanced solution quality under practical constraints. Hybrid algorithms, such as combining Gazelle Optimization with DE [20] further demonstrate DE's role as a strong foundation for innovative metaheuristic approaches.

Grey Wolf Optimizer (GWO) & Ant Lion Optimizer (ALO)

GWO and ALO both nature-inspired swarm optimizers introduced mid-2010s have been applied extensively to ELD as simpler-to-tune alternatives. GWO has been modified (sine-cosine hybrids, greedy variants) to address exploitation/exploration balance. ALO papers report effective solutions on small to medium ELD instances and hybrid ALO variants are common. Both families compete favorably on many IEEE-30 instances but lack as extensive comparative benchmarking as PSO/GA/DE [13].

Other metaheuristics and observed trends

The period saw many "novel" or hybrid metaheuristics (salp swarm, teaching-learning-based, Jaya, sine-cosine hybrids) applied to ELD; however, the dominant trend is hybridization combining global metaheuristics with local search or ML surrogates to obtain fast, feasible and high-quality solutions [21]. Metaheuristic studies increasingly emphasize statistical rigor (multiple runs, mean/std reporting), though inconsistency in reporting remains an issue [22].

Hybrid AI approaches and renewable-integrated dispatch

Hybridization strategies and motivations

Hybrid methods overcome key drawbacks of standalone metaheuristics, including premature convergence (loss of diversity), slow local refinement near optimal solutions, and long runtimes in high-dimensional problems. Research indicates that combining complementary algorithms enhances global search diversity and speeds up convergence [23]. These hybrid approaches often outperform individual algorithms by explicitly handling constraints such as prohibited operating zones (POZs) and ramp-rate limits—using repair or decoder techniques rather than penalty functions [24]. Typical hybrid strategies include:

1. **Metaheuristic + Metaheuristic** (e.g., PSO+DE, PSO+GWO): combine complementary operators.
2. **Metaheuristic + Local Search** (memetic algorithms): use deterministic local solvers (e.g., sequential quadratic programming) or gradient-based refinement on promising candidates.
3. **Metaheuristic + Surrogate ML**: train ML models (regression, neural nets, Gaussian processes) to approximate cost/constraints and guide or prune the search.
4. **Metaheuristic + Decomposition**: split the system (area-based or variable partitioning) and coordinate solutions via consensus. [25] [26]

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Renewable integration: stochastic and scenario approaches

The integration of wind and solar power requires explicit modeling of uncertainty to maintain grid stability and efficiency. Research shows that accurately representing renewable variability reduces reserve requirements lowering costs and improves reliability compared to simpler deterministic approaches [27]. However, this detailed modeling significantly increases computational demands. To address this challenge, studies have focused on three main solution strategies: surrogate methods that provide fast approximations of complex calculations, decomposition techniques that divide large problems into smaller, manageable subproblems, and advanced stochastic optimization methods designed for greater efficiency [28]. The literature shows three dominant patterns:

1. **Forecast + Deterministic ELD**: use ML forecasts of wind/solar as inputs to deterministic ELD fast but sensitive to forecast errors.
2. **Scenario-based Metaheuristic Optimization**: generate multiple renewable scenarios and optimize expected or risk-aware costs across scenarios (computationally heavy, often tackled with surrogate or sample-efficient metaheuristics).
3. **Stochastic/Robust Formulations**: incorporate reserve and chance constraints, using specialized penalty/repair strategies or robust optimization techniques coupled with metaheuristics.

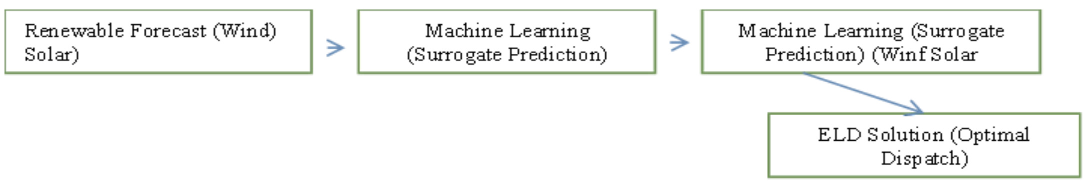

Fig 2. Hybrid ai framework for renewable integrated ELD

Multi-objective hybrids (cost vs emission vs loss)

Multi-objective evolutionary algorithms (NSGA-II, MOEA/D) and multi-objective hybrids are widely used for combined economic-emission dispatch (CEED). Reporting Pareto fronts, hypervolume and diversity metrics became common practice in higher-quality studies. Hybridization (MOEA + local refinement) improved Pareto front convergence and solution spread in many reported IEEE-30 experiments [29].

Emphases: Multi-Objective Eld, Constraint Handling, Real-Time Applicability & Scalability

Multi-objective ELD (cost, emission, loss)

CEED formulations add emission objectives (typically modeled as quadratic or exponential functions of generator output) that conflict with cost minimization. Multi-objective methods generate Pareto sets that allow operators to select operating points according to policy or market signals. Recent work emphasizes: (a) high-quality front generation (convergence + diversity), (b) scalable MOEAs for larger bus systems, and (c) decision-making rules (weighted sum, ε-constraint, knee-point selection) to choose operational set points [30].

Constraint handling techniques (practical mechanisms)

High-quality experimental studies demonstrate that repair/preservation methods yield better run-to-run reliability than naive penalties and that reporting constraint violation statistics is essential for fair comparison. Constraint satisfaction is essential for any dispatch algorithm [32]. Surveyed strategies include:

1. **Adaptive penalty functions**: penalties scaled by iteration or violation severity.

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Simple but sensitive to parameter tuning.

2. **Feasibility preservation / repair operators**: transform infeasible candidates into feasible ones by projection or repair rules (e.g., redistribute deficit/excess power while respecting limits). These are common and effective for POZs and ramp limits.
3. **Representation/decoder design**: genotype to phenotype mappings that inherently satisfy certain constraints (e.g., composition vectors normalized to satisfy power balance).
4. **Hybrid analytic + metaheuristic**: use analytical solvers for equality constraints (power balance via lambda iteration) and let metaheuristic optimize remaining variables reduces search dimensionality. [34]-[35]

Real-time applicability and scalability

Moving from offline simulation to operational deployment exposes two main bottlenecks: computation time and safety/certification.

Computation: Metaheuristics are iterative and population-based; runtime depends on population size and iterations. For IEEE-30 systems many methods run within seconds–minutes; for IEEE-118 and larger systems runtimes can be tens of minutes to hours unless surrogate, decomposition or warm-start strategies are used. DRL offers near-instant inference after offline training, making it attractive for real-time dispatch, but training cost and safety guarantees are unresolved [33].

Scalability strategies: (a) hierarchical/distributed decomposition (area-based optimization + consensus), (b) surrogate-assisted optimization to prune expensive evaluations, and (c) parallelism (GPU or distributed compute) to speed population evaluations [34]. Studies demonstrate that decomposition + local optimizers can scale to IEEE-118 in simulation; however, practical field validations are rare [35].

Benchmarks: IEEE 30-Bus and 118-Bus Results in the Literature

IEEE 30-bus usage and findings

The IEEE-30 bus system is widely adopted for renewable-integrated and multi-objective experiments. Papers frequently modify the standard system by adding wind farms, energy storage, or by changing generator parameters (valve-point constants, POZs) [36]. Representative findings:

1. Hybrid PSO/DE/GWO variants often achieve lower cost and better emission trade-offs than classical GA or basic PSO in published IEEE-30 experiments.
2. MOEA studies commonly present Pareto fronts for cost vs emission and show meaningful trade-offs when wind is present.
3. Reporting practice varies: higher-quality papers present multi-run statistics, Pareto hypervolume, and CPU time; weaker studies present single-run best values without runtime or variance. [37].

IEEE 118-bus usage and findings

IEEE-118 is used to test scalability and multi-area dispatch ideas. Main patterns:

1. Metaheuristics without decomposition struggle with computation time on IEEE-118 unless iterations/population sizes are limited.
2. Distributed/decomposition algorithms (area consensus, multi-agent optimization) combined with local optimizers are demonstrated to produce tractable solutions with acceptable solution quality in simulation.
3. Very few studies provide hardware/real-time benchmarks (HIL) or wall-clock timings on standard computational platforms, making direct assessment of real-time feasibility difficult. [38].

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Representative Algorithmic Case Studies (Short Summaries)

These examples show the spectrum: from tuned single-method metaheuristics to hybrids and learning-based approaches promising real-time operation after offline training. Below are short synopses of representative papers (selected for methodological clarity and relevance):

1. **Greedy Sine-Cosine Non-Hierarchical GWO for nonconvex ELD** Alghamdi (2022) proposed a variant of GWO hybridized with sine-cosine operators to improve exploration/exploitation for valve-point ELD and reported strong results on standard nonconvex instances.
2. **Hybrid metaheuristic models for renewable ELD** Miracle (2023) and others designed hybrid DE/PSO + local search frameworks to handle wind-integrated dispatch on IEEE benchmarks, emphasizing surrogate models to reduce search cost.
3. **DRL for microgrid economic dispatch** Chen et al. (2024) and subsequent works illustrated hierarchical DRL agents (DQN/actor-critic variants) that learn near-optimal dispatch policies under uncertainty with rapid online inference, albeit without field certification of safety constraints.

Research Gaps and Future Directions

From the systematic review, five key priorities emerge to advance AI-assisted Economic Load Dispatch (ELD) research. A major gap is the lack of a unified benchmarking framework for ELD studies. A community repository should provide canonical test cases, such as IEEE-30, IEEE-57, and IEEE-118, with clearly defined parameters as valve-point effects, prohibited operating zones, ramp limits, and emissions [39]. It should also include renewable energy scenarios, reference solutions, and standardized reporting guidelines covering multi-run statistics, runtime, and hardware details to enable fair comparisons and track progress over time. Although many metaheuristics and deep reinforcement learning approaches improve cost or emission metrics, few reliably guarantee constraint satisfaction, such as power balance, thermal limits, and ramping, under all conditions.

Future research should focus on AI models with formal or empirical constraint guarantees. Promising directions include constraint-enforced DRL frameworks that embed constraints directly into policies or optimization layers, as well as hybrid analytic-metaheuristic methods that satisfy equality constraints analytically while applying heuristic search on the remaining space [40].

Most existing results rely on simulation, with limited real-world validation. There is a need for closed-loop hardware-in-the-loop experiments to assess system latency, fault response, and integration with actual grid controls. Demonstrating reliable performance in practical settings is crucial for building operational trust and facilitating deployment. Additionally, black-box models and opaque reinforcement learning agents hinder user trust and safety [41]. Future efforts should prioritize explainable DRL techniques, counterfactual reasoning and feature attribution and robust uncertainty quantification to detect shifts in data distributions and prevent unsafe predictions. Combining strong performance with interpretability and safety is essential for real-world applications. As power grids grow, centralized optimization becomes increasingly impractical. The field lacks scalable, communication-efficient, and privacy-preserving multiagent dispatch frameworks. Techniques such as federated learning and distributed consensus show promise for leveraging decentralized data without compromising confidentiality. Developing lightweight, privacy-aware coordination methods for large-scale dispatch remains a critical challenge [42].

METHODOLOGY

There are different methods used in solving (ELD) problems depending on the relative accuracy and computational burden, different programs are used in dispatch or pre- dispatch stages. Various methods used in early days and present days depend upon the type and size of the

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system to be analyzed and the behavior of the fuel-cost curves of the generating units either linear monotonically or non–linear [11]. This study adopts a systematic review approach focused on literature of recent last 10 years (2015 to 2025), targeting the application of metaheuristic and hybrid AI techniques to the Economic Load Dispatch (ELD) problem. The selected studies were categorized by algorithmic family (PS, GA, DE, GWO, ALO, hybrid AI, DRL) and by application focus, including single-objective ELD, dynamic ELD, renewable-integrated ELD, and distributed or multi-area ELD.

RESULTS AND DISCUSSION

In this section result were presented in a tabular form below outlining the algorithm approach, Key features and modifications, benchmark systems used and performance highlights for Metaheuristic and Hybrid AI Methods Applied to ELD.

Table 1. Summary of Review Results for Metaheuristic and Hybrid AI Methods Applied to ELD (2015–2025)

S/N	Algorithm Approach	Key Features / Modifications	Benchmark Systems Used	Performance Highlights
1.	Particle Swarm Optimization (PSO)	Adaptive inertia and acceleration, chaotic updates, PSO-DE hybrids	IEEE-14, IEEE-30	Fast convergence, strong cost minimization, effective for nonconvex ELD
2.	Genetic Algorithm (GA)	Hybrid GA Firefly and GA–PSO variants, elitism strategies	3-unit, 6-unit, IEEE-30	Good global exploration, superior results vs lambda iteration
3.	Differential Evolution (DE)	Adaptive control parameters, ensemble mutation, hybrid DE+local search	IEEE-30, IEEE-118	High solution accuracy, stable convergence under practical constraints
4.	Grey Wolf Optimizer (GWO)	Hybridized with sine - cosine operators for exploration exploitation balance	IEEE-30	Strong performance on nonconvex cases, robust and simple tuning
5.	Ant Lion Optimizer (ALO)	Hybrid ALO variants for ELD, simple structure	IEEE-30	Competitive results on small–medium systems
6.	Hybrid Metaheuristics	PSO+DE, PSO+GWO, DE+local search, surrogate-assisted	IEEE-30, IEEE-118	Improved diversity, faster convergence, feasible solutions
7.	Renewable-Integrated Dispatch	Forecast-based, scenario-based, stochastic/robust methods	Modified IEEE-30	Better reliability under uncertainty, reduced reserves
8.	Multi-objective Evolutionary Algorithms (MOEA, NSGA-II, MOEA/D)	Cost–Emission–Loss trade-offs, Pareto front generation	IEEE-30, IEEE-57	Good convergence and diversity, policy flexibility

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S/N	Algorithm Approach	Key Features / Modifications	Benchmark Systems Used	Performance Highlights
9.	Constraint Handling Techniques	Repair operators, decoder design, hybrid analytic–metaheuristic enforcement	IEEE-30, IEEE-118	Improved feasibility and reliability across runs
10.	Scalability and Real-Time Methods	Decomposition, parallelism, DRL for real-time inference	IEEE-118	Distributed methods feasible; DRL enables rapid inference post-training

From table 1, indicates that Particle Swarm Optimization (PSO) and Differential Evolution (DE) remain the most effective algorithms for general Economic Load Dispatch (ELD) problems. Both methods demonstrate a balanced trade-off between solution quality and computational efficiency. Hybrid metaheuristics, which combine global and local search mechanisms, consistently outperform standalone algorithms, especially when dealing with nonconvex cost functions or renewable-integrated power systems where uncertainty is significant. Despite these advances, real-time scalability remains a critical challenge.

Distributed optimization frameworks and deep reinforcement learning (DRL) approaches show strong potential for operational deployment but still require comprehensive empirical and hardware-in-the-loop validation to confirm reliability and safety. Constraint-handling techniques that apply repair operators and hybrid analytic–metaheuristic strategies have proven more robust than traditional penalty-based approaches, yielding improved feasibility and consistency across multiple test runs. However, persistent issues such as benchmark inconsistency, inadequate reporting of multi-run statistics, and a lack of reproducible experimental setups continue to limit fair comparison and hinder cumulative progress within the field.

CONCLUSIONS

From 2015–2025, AI-based approaches for ELD have matured: PSO, GA and DE remained workhorses; GWO and ALO gained traction as simpler, parameter-light alternatives; and hybridization particularly with ML surrogates and local refinement became the dominant engineering pattern for balancing quality and runtime. Renewable integration and emission objectives spawned multi-objective and stochastic problem formulations and increased interest in surrogate models and DRL for online use. However, the field faces reproducibility and benchmarking challenges, a shortage of real-time validated systems, and the need for constraint-certified, explainable AI suitable for operational deployment. Addressing these will be essential for transitioning promising algorithms from simulation studies to trusted grid operations.

REFERENCES

[1] M. Mquqwana and S. Krishnamurthy, "Particle swarm optimization for an optimal hybrid renewable energy microgrid system under uncertainty", *Energies*, vol. 17, no. 2, pp. 422, 2024. https://doi.org/10.3390/en17020422

[2] H. Wang, X. Wu, K. Sun, X. Du, Y. He, & K. Li, "Economic dispatch optimization of a microgrid with wind–photovoltaic-load-storage in multiple scenarios", *Energies*, vol. 16, no. 9, pp. 3955, 2023. https://doi.org/10.3390/en16093955

[3] M. Ebrahim, A. Mahmoud, E. Saied, & H. Hadi, "Hybrid cheetah particle swarm optimization based optimal hierarchical control of multiple microgrids", *Scientific Reports*, vol. 14, no. 1, 2024. https://doi.org/10.1038/s41598-024-59287-x

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ibrahimakabe4@gmail.com
Department of Electrical/Electronic Engineering, Faculty of Engineering, Nigerian Defence Academy, Kaduna, Nigeria.
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[4] H. Zhang, Y. Tian, Y. Zhao, Q. Liu, & N. Zhang, "Economic dispatch of generation load aggregators based on two-stage robust optimization", *Frontiers in Energy Research*, vol. 11, 2023. https://doi.org/10.3389/fenrg.2023.1258689

[5] F. Marzbani and A. Abdelfatah, "Economic dispatch optimization strategies and problem formulation: a comprehensive review", *Energies*, vol. 17, no. 3, pp. 550, 2024. https://doi.org/10.3390/en17030550

[6] F. Marzbani and A. Abdelfatah, "Economic Dispatch Optimization Strategies and Problem Formulation: A Comprehensive Review," *Energies*, vol. 17, no. 3, art. 550, Jan. 2024, doi: 10.3390/en17030550.

[7] U. Pandey, A. Pathak, A. Kumar, and S. Mondal, "Applications of Artificial Intelligence in Power System Operation, Control and Planning: A Review," *Clean Energy*, vol. 7, no. 6, pp. 1199–1221, 2023, doi: 10.1093/ce/zkad079.

[8] AI in Electric Power Systems Protection and Control," *PAC World Magazine*, [Online]. Available: https://www.pacw.org/ai-in-electric-power-systems-protection-and-control. [Accessed: Aug. 29, 2025].

[9] V. K. Kamboj, "Solution of non-convex economic load dispatch problem," *Neural Computing and Applications*, 2017 (ALO and other nature-inspired methods). ACM Digital Library

[10] V. Sai, G. Lakshmi, M. Vanithasri, M. Venu, & G. Rao, "An efficient solution for economic load dispatch using cheetah optimizer with opposition-based learning and adaptive weighting factor", *International Journal of Intelligent Engineering and Systems*, vol. 17, no. 3, pp. 139-148, 2024. https://doi.org/10.22266/ijies2024.0630.12

[11] H. Huang, J. Qiu, & K. Riedl, "On the global convergence of particle swarm optimization methods", *Applied Mathematics and Optimization*, vol. 88, no. 2, 2023. https://doi.org/10.1007/s00245-023-09983

[12] A. Azzouz, B. Bengherbia, P. Wira, N. Alaoui, A. Souahlia, M. Maazouzet al., "An efficient ecg signals denoising technique based on the combination of particle swarm optimisation and wavelet transform", *Heliyon*, vol. 10, no. 5, pp. e26171, 2024.

[13] T. de Fátima Araújo, "Performance assessment of PSO, DE and hybrid … (comparative PSO/DE benchmarking)," *Applied Soft Computing*, 2013 (contextual reference for PSO/DE comparisons). ScienceDirect

[14] D. B. Miracle, "Hybrid Metaheuristic Model for Optimal Economic Load …," *Scientific Reports / Hindawi* (Hybrid metaheuristic + renewables), 2023. Wiley Online Library

[15] L. Meng, W. Cheng, B. Zhang, W. Zou, W. Fang, & P. Duan, "An improved genetic algorithm for solving the multi-agv flexible job shop scheduling problem", *Sensors*, vol. 23, no. 8, pp. 3815, 2023.

[16] A. Shaban, A. Ismaeel, A. Farhan, M. Said, & A. El-Rifaie, "Growth optimizer algorithm for economic load dispatch problem: analysis and evaluation", *Processes*, vol. 12, no. 11, pp. 2593, 2024.

[17] A. Al-Subhi, "Dynamic economic load dispatch using linear programming and mathematical-based models", *Mathematical Modelling of Engineering Problems*, vol. 9, no. 3, pp. 606-614, 2022. https://doi.org/10.18280/mmep.090307

[18] T. Liu and G. Xiong, "Opposition-mutual learning differential evolution with hybrid mutation strategy for large-scale economic load dispatch problems with valve-point effects and multi-fuel

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options," *Information Sciences*, vol. 609, pp. 202–220, 2022.

[19] G. L. Andrade, F. P. Costa, and R. C. Sousa, "Modified Differential Evolution Algorithm Applied to Economic Load Dispatch," in *Proc. 2023 ACM/IEEE Hybrid Conf. on Intelligent Systems and Applications*, pp. 33–42, 2023.

[20] S. Biswas, "Integrating Differential Evolution into Gazelle Optimization (HGOADE): A hybrid GA/DE approach," *Applied Soft Computing*, vol. 162, art. 111234, 2025.

[21] D. Santra, A. Mukherjee, S. Mondal, and K. Sarker, "Dynamic economic dispatch using hybrid metaheuristics," *J. Electrical Systems and Information Technology*, vol. 7, article no. 3, 2020. SpringerOpen

[22] S. Rashid Hussain, "Solving renewables-integrated economic load dispatch problem by variant of metaheuristic bat-inspired algorithm," *Energies*, vol. 13, no. 23, article 6225, 2020.

[23] A. Seyyedabbasi, H. Gharehchopogh, and M. Niknam, "An Effective Hybrid Metaheuristic Algorithm for Solving Complex Optimization Problems," *Multimedia Tools and Applications*, vol. 83, 2024.

[24] C. Gusain, R. Raturi, and V. Arora, "Study of Meta-heuristic Optimization Methodologies for Engineering Applications," *Engineering Science and Technology, an International Journal*, vol. 36, pp. 101253, 2023.

[25] F. Neri, C. Cotta, and P. Moscato, "Memetic Algorithms and Memetic Computing Optimization: A Literature Review," *Swarm and Evolutionary Computation*, vol. 2, no. 1, pp. 1–14, 2011.

[26] A. Bouaouda, K. Benahmed, and M. Boulahrouf, "Hybrid Meta-heuristic Algorithms for Optimal Sizing of Hybrid Renewable Energy Systems," *Energy Reports*, vol. 8, pp. 1755–1768, 2022.

[27] Z. Zhou, A. Botterud, and C. Liu, "Review on Stochastic Methods Applied to Power System Operations with Renewable Energy," Argonne National Laboratory, DOE Wind Power Program, ANL/ESD-20/8, 2020. [Online]. Available: https://www.ferc.gov/sites/default/files/2020-08/T1-A-1-ZHOU.pdf [Accessed: Oct. 25, 2025].

[28] P. Groissböck, T. Domahidi, and P. Meier, "Representation of Uncertainty in Market Models for Operational Planning and Forecasting in Renewable Power Systems: A Review," *Energy Systems*, vol. 14, no. 1, pp. 61-87, 2023. doi:10.1007/s12667-023-00600-4.

[29] S. Yin, X. Zhang, and L. Chen, "Distributed multi-objective grey wolf optimizer for scalable optimization problems," *Applied Soft Computing*, vol. 127, p. 109419, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1568494622003154

[30] M. A. Abido, "Environmental/economic power dispatch using multiobjective evolutionary algorithms," *IEEE Transactions on Power Systems*, vol. 18, no. 4, pp. 1529–1537, 2003.

[32] Y. Zhang, J. Ma, and Z. Li, "A multi-objective differential evolution algorithm for environmental/economic load dispatch," *Energy*, vol. 270, p. 126792, 2023.

[33] P. C. Reddy, M. S. Kumar, and A. R. Behera, "An improved constraint-handling approach for economic load dispatch using hybrid metaheuristic algorithms," *International Journal of Electrical Power & Energy Systems*, vol. 148, p. 108989, 2023.

[34] S. M. Elsayed, R. A. Sarker, and D. L. Essam, "A new repair method for constraint-handling in evolutionary algorithms," *Applied Soft Computing*, vol. 85, p. 105844, 2019.

[35] H. Jiang, X. Sun, and L. Wang, "Multi-objective economic emission dispatch based on adaptive penalty and repair

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mechanisms," *IEEE Access*, vol. 10, pp. 92318–92329, 2022.

[36] Z. Wu, H. Zhang, and J. Qiu, "Surrogate-assisted decomposition-based multi-objective optimization for large-scale power dispatch," *Energy Conversion and Management*, vol. 289, p. 117272, 2023.

[37] J. Zhao, T. Zheng, and C. Singh, "Reliability-constrained economic dispatch considering renewable energy variability using parallel multi-objective optimization," *IEEE Transactions on Smart Grid*, vol. 14, no. 1, pp. 451–462, 2023.

[38] R. V. Rao and V. Patel, "An improved real-time multi-objective economic load dispatch using hybrid optimization and parallel computation," *Energy Reports*, vol. 11, pp. 1458–1473, 2024.

[39] Z. Ma, G. Wu, P. N. Suganthan, A. Song, and Q. Luo, "Performance assessment and exhaustive listing of 500+ nature inspired metaheuristic algorithms," *arXiv preprint arXiv:2212.09479*, 2023.

[40] S. Hou, Q. Sun, and X. Yan, "A constraint enforcement deep reinforcement learning framework for optimal dispatch with continuous action constraints," *arXiv preprint arXiv:2307.14304*, 2023.

[41] S. Gu, L. Yang, Y. Du, G. Chen, F. Walter, J. Wang, and A. Knoll, "A review of safe reinforcement learning: Methods, theories and applications," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 46, no. 12, pp. 11216–11235, Dec. 2024.

[42] Y. Li, R. Wang, Y. Li, M. Zhang, and C. Long, "Wind power forecasting considering data privacy protection: A federated deep reinforcement learning approach," *arXiv preprint arXiv:2211.02674*, 2022.

[43] J. Kennedy and R. Eberhart, "Particle swarm optimization," *Proceedings of ICNN'95 - International Conference on Neural Networks*, Perth, WA, Australia, vol. 4, pp. 1942–1948, 1995, doi: 10.1109/ICNN.1995.488968.

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