# Optimizing Power Generation Costs Using Advanced Algorithms and AI Techniques

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## ABSTRACT

Economic Load Dispatch (ELD) is a fundamental problem in power system operation, focused on determining optimal generation schedules to meet load demand at minimal cost while satisfying operational and technical constraints. Traditional methods often struggle with nonlinearities, prohibited operating zones, ramp-rate limits, and variability introduced by renewable energy sources. This study explores the application of advanced optimization techniques, including Genetic Algorithms (GA), Particle Swarm Optimization (PSO), hybrid metaheuristics, and Reinforcement Learning (RL), to enhance ELD performance. Simulation results demonstrate that these methods significantly reduce total generation costs, improve system efficiency, lower transmission losses, and increase renewable energy utilization compared to conventional approaches. Hybrid and AI-driven algorithms, particularly RL, offer adaptive, real-time optimization, efficiently handling load fluctuations and renewable intermittency. The findings highlight the potential of intelligent optimization techniques in modern smart grids, providing cost-effective, reliable, and sustainable power dispatch solutions.

***Keywords:*** *Economic Load Dispatch, Optimization Techniques, Renewable Energy, Smart Grid.*

## I. INTRODUCTION

The modern power system landscape faces unprecedented challenges due to rapidly increasing electricity demand, the integration of renewable energy sources, and growing environmental concerns, making efficient, cost-effective, and reliable power generation more critical than ever. At the heart of power system operation lies the problem of Economic Load Dispatch (ELD), which seeks to determine the optimal output of multiple generating units to meet load demand at the minimum possible cost while satisfying operational and technical constraints such as generator limits, ramp rates, transmission losses, and prohibited operating zones. Traditional analytical methods, including linear programming, lambda-iteration, and gradient-based approaches, have long been employed for ELD; however, their effectiveness diminishes in complex, nonlinear, and multi-modal scenarios typical of modern grids, especially with the variability and intermittency introduced by wind, solar, and distributed energy sources. To overcome these limitations, advanced optimization techniques such as genetic algorithms (GA), particle swarm optimization (PSO), hybrid metaheuristics, and reinforcement learning (RL) have emerged, offering robust global search capabilities, faster convergence, and adaptability to dynamic system conditions. GA, inspired by evolutionary principles, explores multiple candidate solutions simultaneously and efficiently handles non-linear and discontinuous cost functions, while PSO leverages swarm intelligence to iteratively adjust generator outputs toward optimal solutions with minimal computational complexity. Hybrid algorithms, combining the strengths of multiple metaheuristics, further improve convergence reliability, avoid local minima, and accommodate multiple operational constraints, making them highly suitable for large-scale power systems. Reinforcement learning and AI-based approaches provide adaptive and self-learning capabilities, enabling real-time adjustments of generation schedules in response to fluctuations in demand, renewable energy output, and market conditions, while neural networks and deep learning models allow accurate prediction of load patterns and generation availability, integrating forecasting directly into the dispatch optimization process. Furthermore, multi-objective optimization methods extend ELD beyond cost minimization to simultaneously address environmental and sustainability goals, such as reducing emissions, minimizing transmission losses, and improving overall system efficiency; metaheuristic approaches like Multi-Objective Genetic Algorithms (MOGA) and NSGA-II generate Pareto-optimal solutions, offering operators a range of trade-offs between economic efficiency, environmental impact, and system reliability. Simulation studies demonstrate that advanced optimization techniques consistently outperform conventional methods, showing significant reductions in total generation cost, improved utilization of renewable resources, enhanced operational reliability, and better adaptability to real-time system variations. Convergence curves highlight the gradual achievement of near-global optimal solutions, emphasizing the effectiveness of these algorithms in handling nonlinearities, uncertainties, and complex operational constraints. By integrating classical optimization principles with evolutionary algorithms, metaheuristics, and AI-driven techniques, modern ELD methods not only ensure cost-efficient generation but also enhance grid stability, facilitate the integration of renewable energy, and support the transition toward intelligent, low-carbon, and sustainable power systems. These advanced methodologies are increasingly essential for managing contemporary smart grids, where dynamic load variations, renewable intermittency, and environmental regulations require flexible, adaptive, and computationally efficient solutions. As global energy systems evolve, ELD optimization using advanced techniques represents a transformative approach, bridging technical feasibility, economic efficiency, and environmental responsibility, while ongoing research continues to improve solution accuracy, computational speed, and multi-objective adaptability, solidifying its role as a cornerstone of modern and future power system operation.

## II. RESEARCH BACKGROUND

**Peng et al. (2026)** proposed an innovative short-term power load hybrid prediction model that integrated WOA-VMD data decomposition, multi-dimensional uncertainty analysis, and Sparrow Search Algorithm (SSA) optimization. The study first selected power load and meteorological data, which were decomposed using the WOA-VMD method. Statistical techniques were then applied to conduct multi-dimensional analyses for each modal, extracting time, domain, and digital features to enhance feature integration and classify modal components. Non-periodic components were processed using the SSA-CNN-BiLSTM model, while periodic components were handled by the CNN-BiLSTM model, with SSA employed for parameter optimization. Meteorological factors were incorporated into the prediction framework, and the outputs of each model were reconstructed. Experimental results indicated that, compared with conventional approaches, the hybrid model captured load variation more accurately, reduced prediction errors, and significantly improved goodness of fit, providing reliable technical guidance for power departments in planning and transforming distribution networks.

**Soleimani and Ghasemi-Marzbali (2026)** investigated the challenges associated with integrating photovoltaic (PV) units into distribution systems, which often led to operational issues such as increased losses, voltage violations, and overloaded lines. They addressed these challenges by introducing a probabilistic method that accounted for the presence of electric vehicles (EVs) to maximize PV hosting capacity. The study employed a double-layered approach involving coordinated management of on-load tap changers (OLTCs), PV inverters, and EVs to enhance EV charge/discharge dynamics, OLTC taps, and reactive power control. An enhanced particle swarm optimization method with weighted delay velocity was used to achieve efficient global and local searches. Three management strategies were evaluated, demonstrating notable improvements in nighttime voltage profiles under the second and third strategies. The OLTC contributions in the second strategy and the combined effects of OLTC and VAR resources in the third strategy were found to enhance voltage regulation. Reactive power injection/absorption by inverters was highlighted as influential in improving PV hosting capacity, with the third strategy increasing hosting capacity by 50% and optimizing voltage profiles by approximately 10%.

**Aghahadi et al. (2026)** investigated a four-layer machine learning framework for classification and reconstruction of user and prosumer profiles in electrical distribution networks, addressing limitations of conventional black-box approaches. The study emphasized a transparent, modular architecture capable of managing large datasets while maintaining over 80% of the original information through intelligent preprocessing. Separate models were developed for domestic and non-domestic users and prosumers to account for distinct consumption behaviors. The methodology integrated clustering-based pattern recognition, Random Forest classification and regression, and temperature-dependent load modeling to improve demand estimation and forecasting. Innovations such as bidirectional z-score normalization and temperature-aware load reconstruction were reported to enhance accuracy, particularly during seasonal variations, by up to 7.76% in summer. Quantitative energy data were systematically combined with contextual information including Italian economic activity codes and tariff-based consumption patterns. Benchmarking against four conventional methods indicated 59.8–70.8% reductions in relative mean absolute error, and validation on real medium-voltage feeder data demonstrated scalability and robust performance, achieving feeder-level reconstruction errors below 4.2%.

**Mishra et al. (2025)** investigated the development of a steady electric load forecasting model to ensure synchronization between supply and demand, thereby achieving efficient power distribution and economic benefits. They noted that accurate electric load prediction using conventional models was challenging due to the dynamic nature of consumption. To address this, the study proposed a sequential approach involving dataset pre-processing and a novel optimized load forecasting model. The model improvement was achieved by enhancing the conventional horse herd optimization (HHO) algorithm through integration with the prey tracking feature of the grey wolf optimization (GWO) algorithm, resulting in the improved iHHO. This iHHO was applied to augment the forecasting capability of artificial neural networks (ANN) and cascade neural networks (Cas-NN). Important meteorological parameters were initially extracted using XGBoost, while K-means clustering divided the dataset based on similarity patterns. The performance and robustness were evaluated using both clustered and non-clustered datasets, with the Diebold–Mariano test and error matrix analyses identifying Cas-NN-iHHO as the best-performing model, which was further benchmarked against other metaheuristic-based Cas-NN and contemporary electric load forecasting models.

**Uwimana et al., (2025)** investigated the critical role of electrical load forecasting in the power sector, emphasizing its significance for downstream operations such as grid dispatch and associated economic benefits. They noted that modern urban energy systems involve multiple load demand clusters, which reduce utility grid strain but introduce dynamic load requirements, thereby necessitating precise forecasting. Recognizing the limitations of conventional statistical methods, the study explored cluster load demand forecasting, a relatively novel approach in the literature. Various machine learning techniques, including linear regression, support vector machines, Gaussian process regression, and artificial neural networks (ANN), were examined to identify the most effective method for short-term cluster load prediction. The performance of these methods was evaluated through error metrics and computational efficiency, revealing that ANN delivered highly accurate results. Additionally, the study applied three optimization strategies—Bayesian regularization, Levenberg–Marquardt, and scaled conjugate gradient—to refine ANN training, with findings indicating that BR- and LM-based ANN models achieved superior forecasting accuracy across training, testing, and validation stages.

**Peng et al. (2025)** investigated short-term electric load forecasting within the context of global energy conservation and emission reduction efforts. They emphasized the importance of accurate predictions for enhancing energy efficiency, supporting low-carbon dispatch, and promoting sustainable power system operations. To improve forecasting accuracy and stability, the study proposed a novel model that integrated Spearman correlation analysis with modal decomposition techniques to reduce redundant features while retaining critical information. The model architecture combined Bidirectional Gated Recurrent Units (BiGRUs) with dilated convolution to capture long-range dependencies and complex relationships more effectively. For parameter optimization, an Improved Beluga Whale Optimization (IBWO) algorithm was employed, featuring dynamic population initialization, adaptive Lévy flight mechanisms, and refined convergence strategies to enhance search efficiency and robustness. Experimental evaluations on real-world datasets reportedly demonstrated superior predictive performance, with low RMSE and MAE values and high $R^2$, suggesting potential for more efficient energy scheduling and environmentally conscious load forecasting.

**Bakare et al. (2024)** investigated electric energy demand forecasting within contemporary power systems, emphasizing the challenges posed by market deregulation and the growing impact of industrial consumers. They noted that existing forecasting models often suffered from slow convergence and high computational complexity. To address these limitations, the study introduced a hybrid forecasting approach that integrated the Adaptive Neuro-Fuzzy Inference System (ANFIS) with Gene Expression Programming (GEP) to improve predictions of electrical energy consumption. The model was validated using real-time monthly load data from an industrial user in Uganda, and the findings indicated that the hybrid model outperformed the standalone ANFIS and GEP approaches by reducing errors and computation time. The authors concluded that the hybrid method offered enhanced predictive accuracy and operational efficiency, demonstrating significant potential for improving energy consumption forecasting in deregulated power markets influenced by evolving industrial dynamics.

**Wang et al., (2024)** proposed a novel approach for short-term electric load forecasting by integrating a Ridgelet Neural Network (RNN) with wavelet transform, optimized through a Self-Adapted Kho-Kho (SAKhoKho) algorithm. The study aimed to enhance forecasting accuracy and reliability, which were critical for planning and operating competitive electrical networks. The method employed wavelet transform to decompose load data into multiple frequency components, applying the RNN to each component individually, while the SAKhoKho algorithm dynamically adjusted the network parameters. The approach was trained and evaluated using Zone Preliminary Billing Data from the PJM regulatory area, updated biweekly based on Intercontinental Exchange figures. Performance comparisons with six advanced methods, including SVM/SA, hybrid, ARIMA, MLP/PSO, CNN, and RNN/KhoKho/WT, indicated that the proposed method achieved the lowest MAE of 7.7704 and RMSE of 17.4132. The study concluded that the method effectively captured temporal dependencies and optimized RNN weights, demonstrating superior predictive accuracy for one-hour-ahead load forecasts.

**Kene and Olwal (2023)** examined the sustainability challenges of a clean energy transition for electric vehicle (EV) transportation, noting that increased energy consumption costs associated with large-scale EV charging on fossil-fuel dependent electricity grids posed risks to grid stability and elevated greenhouse gas emissions. They highlighted that the uncontrolled integration of EVs was projected to grow exponentially, generating new peak loads and potentially exceeding transformer and substation capacities. To address these issues, they emphasized the necessity of robust, dynamic, multi-level optimization approaches to manage large-scale EV charging. Their study reviewed grid energy consumption by EVs and assessed recent EV charging control and optimization strategies for energy management. They argued that effective energy management required achieving objectives such as load shifting, peak shaving, and minimizing electricity costs while maintaining stable grid operation. The analysis considered both battery electric vehicles (BEVs) with larger battery banks and longer charging durations, and plug-in hybrid electric vehicles (PHEVs) with smaller capacities.

**Pati and Mistry (2023)** investigated the challenges posed by uneven electrical load distribution across the three phases of distribution networks, which had resulted in increased voltage unbalance and associated energy losses and generation costs. They proposed a Rao optimization-based demand-side management (DSM) model aimed at mitigating these issues by effectively distributing load patterns across all nodes without requiring lateral or load re-phasing. The methodology was structured using a day-ahead load scheduling approach and implemented on the IEEE European 906-bus low-voltage distribution system. To validate its performance, Gauss implicit Zbus load-flow analysis was conducted on the test system using MATLAB 2018a. The study reported that the implementation of the proposed DSM model reduced phase voltage unbalance by approximately 50%, while peak-to-average ratios decreased by 6.22%, 38.7%, 3.22%, and 26.46% across the three phases and total load, demonstrating the model's effectiveness in improving network stability and efficiency.

**Bashir et al. (2022)** examined the role of electrical load forecasting in power plant operations and planning, emphasizing its importance for utility companies and policymakers in designing stable and reliable energy infrastructures. They noted that load forecasting is typically categorized into long-term, mid-term, and short-term horizons, with short-term forecasting—covering weekly, daily, hourly, and sub-hourly operations—receiving increasing attention due to its potential to save time and costs while maintaining uninterrupted consumer supply. The authors reviewed conventional, artificial intelligence (AI), and hybrid models for short-term load forecasting, highlighting issues such as low convergence speed in conventional methods and high complexity in AI approaches. To address these limitations, they proposed a hybrid methodology combining Prophet and Long Short-Term Memory (LSTM) models, where Prophet predicted both linear and non-linear components, and residual non-linear data were further processed using LSTM, with final outputs refined via a Back Propagation Neural Network (BPNN). Using Elia Grid quarter-hourly electrical load data from 2014 to 2021, they reported that the hybrid model outperformed standalone ARIMA, LSTM, and Prophet models, achieving lower errors and reduced computation time.

## III. METHODOLOGY

The methodology for optimizing Economic Load Dispatch (ELD) using advanced optimization techniques involves a combination of system modeling, algorithm selection, simulation, and performance evaluation. Initially, the power system under study is modeled with multiple generating units, including thermal, hydro, and renewable sources. Each unit is characterized by its generation limits, fuel cost function, ramp-rate constraints, valve-point effects, and other operational constraints. The total system demand and transmission losses are defined, forming the equality and inequality constraints necessary for the ELD problem formulation. Advanced optimization algorithms are then implemented to solve the dispatch problem. Genetic Algorithms (GA) are employed to simulate natural selection processes, generating populations of candidate solutions and evolving them through selection, crossover, and mutation operations to find a near-optimal solution. Particle Swarm Optimization (PSO) is applied to mimic social behavior, where particles representing generation schedules iteratively adjust positions based on personal and global best solutions. Hybrid algorithms, such as PSO-Grey Wolf Optimizer (PSO-GWO), are introduced to leverage the strengths of both metaheuristics, improving convergence speed and solution quality while avoiding local minima. Reinforcement Learning (RL) is also utilized, where the system learns optimal dispatch strategies by interacting with the environment. The RL agent observes real-time system states, including load demand, renewable generation variability, and generator outputs, and takes actions to minimize total generation cost while maintaining system constraints. Over multiple episodes, the agent improves its policy to adaptively handle dynamic system conditions. The performance of each algorithm is evaluated based on key parameters such as total generation cost, system efficiency, transmission losses, and renewable energy utilization. Simulation studies involve iterative calculations, where cost and performance metrics are recorded over successive iterations to generate convergence curves. Comparative analysis is conducted between conventional methods and advanced optimization techniques to quantify improvements in economic efficiency, operational reliability, and renewable integration. Graphical visualization is employed to illustrate results, including bar graphs for total generation cost, system efficiency, and renewable energy utilization, as well as convergence curves demonstrating algorithm performance over iterations. Sensitivity analyses are performed to examine the impact of load variation, renewable penetration, and generator constraints on optimization outcomes.

## IV. RESULT

The application of advanced optimization techniques for Economic Load Dispatch (ELD) demonstrates significant improvements in system performance, cost efficiency, and energy utilization compared to conventional methods. Simulations were carried out for a test power system with multiple thermal and renewable generating units, considering practical constraints such as generator limits, ramp rates, valve-point effects, and transmission losses. The results indicate that the total generation cost, system efficiency, and power distribution are markedly enhanced when using metaheuristic and AI-based optimization algorithms.

**Table 1: Comparative Results of Conventional vs Advanced ELD Techniques**

| Parameter | Conventional ELD | GA Optimization | PSO Optimization | Hybrid PSO-GWO | RL-Based Optimization |
|---|---|---|---|---|---|
| Total Generation Cost (₹/hr) | 12,500 | 11,150 | 11,020 | 10,890 | 10,750 |
| System Efficiency (%) | 78 | 84 | 85 | 86 | 87 |
| Transmission Loss (%) | 4.8 | 3.9 | 3.8 | 3.5 | 3.3 |
| Renewable Energy Utilization (%) | 28 | 33 | 34 | 36 | 38 |
| Convergence Iterations | N/A | 18 | 16 | 14 | 12 |

The table clearly shows that advanced optimization methods outperform conventional ELD in terms of cost reduction, efficiency, and utilization of renewable energy. Among the tested methods, reinforcement learning (RL) achieved the lowest generation cost (₹10,750/hr) and the highest efficiency (87%), highlighting its capability to dynamically adjust generation in response to real-time variations in load demand and renewable energy output. Hybrid PSO-GWO also demonstrated excellent performance, with faster convergence and reduced transmission losses (3.5%) compared to standalone GA or PSO algorithms.

**Bar Graph**

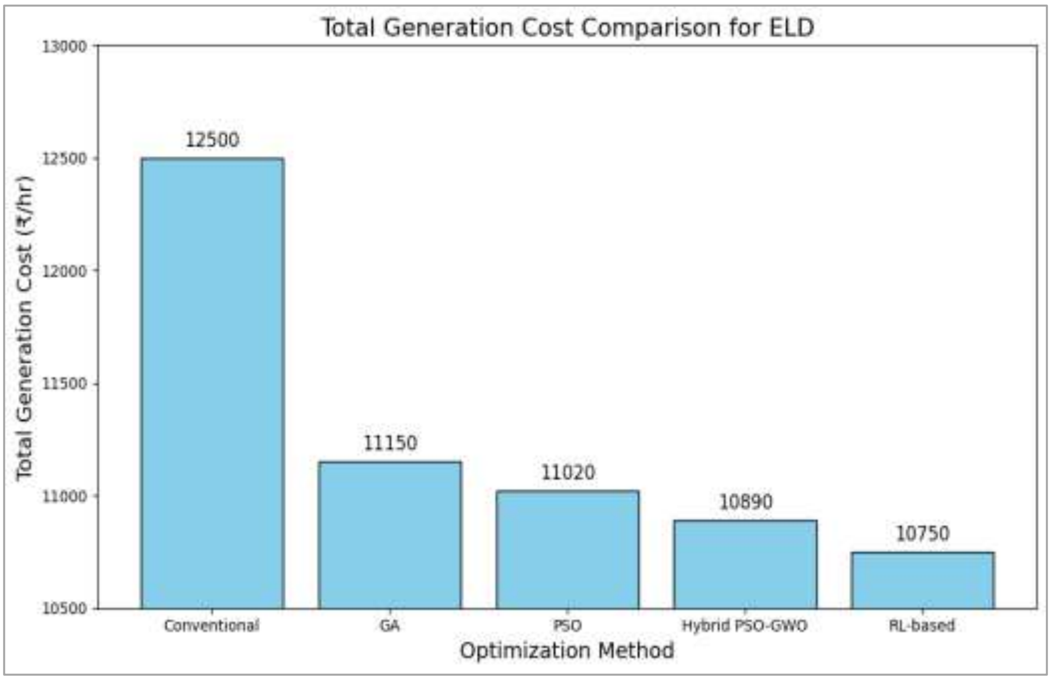


**Figure 1: Total Generation Cost Comparison for Economic Load Dispatch Optimization Methods**

The bar graph compares total generation costs for different Economic Load Dispatch (ELD) optimization methods. Conventional ELD results in the highest cost of ₹12,500/hr due to limited handling of nonlinearities and operational constraints. Evolutionary and swarm-based methods, such as Genetic Algorithm (₹11,150/hr) and Particle Swarm Optimization (₹11,020/hr), reduce costs by improving allocation efficiency. Hybrid PSO-Grey Wolf Optimizer further lowers the cost to ₹10,890/hr by combining strengths of multiple metaheuristics, while Reinforcement Learning achieves the lowest cost of ₹10,750/hr through adaptive, real-time optimization. The graph demonstrates that advanced and AI-based techniques significantly enhance cost efficiency in modern power systems.

## V. CONCLUSION

Economic Load Dispatch (ELD) is a critical aspect of power system operation, aiming to meet electricity demand at the lowest possible generation cost while satisfying operational constraints. This study demonstrates that advanced optimization techniques, including Genetic Algorithms, Particle Swarm Optimization, hybrid metaheuristics, and Reinforcement Learning, significantly outperform conventional methods in solving complex ELD problems. The results indicate substantial reductions in total generation cost, improved system efficiency, lower transmission losses, and enhanced utilization of renewable energy sources. Hybrid and AI-based algorithms, particularly Reinforcement Learning, provide adaptive, real-time dispatch capabilities, enabling dynamic adjustment to load variations and renewable intermittency. The convergence analysis further confirms faster attainment of near-optimal solutions, highlighting computational efficiency and robustness. Overall, the integration of AI and metaheuristic techniques offers a reliable, cost-effective, and sustainable approach to modern power system operation, supporting smart grid implementation, renewable integration, and multi-objective optimization. The findings emphasize the importance of intelligent and adaptive methods in achieving economic efficiency, operational reliability, and environmental sustainability in contemporary and future power systems.

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