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Review

Economic Dispatch Techniques Under Varying Load and Renewable Integration Scenarios: A Systematic Review

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Abstract: Economic Dispatch (ED) is a vital optimization problem in power systems, focused on minimizing generation cost while satisfying operational and environmental constraints. The increasing integration of renewable energy sources such as wind, solar, and hydro has made ED more complex due to intermittency, variability, and forecasting challenges, necessitating advanced optimization frameworks beyond conventional mathematical programming. This review analyzes ED approaches under varying load and renewable integration conditions, drawing on peer-reviewed literature from IEEE Xplore, ScienceDirect, Springer, Elsevier, and Scopus (2013–2025). Classical methods like lambda iteration and quadratic programming remain effective for small-scale convex ED problems but fail to address nonlinearities and renewable-related uncertainties. Meta-heuristic algorithms, including Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Differential Evolution (DE), effectively solve nonconvex problems but face limitations in convergence speed and scalability. Hybrid frameworks, particularly those incorporating artificial intelligence and fuzzy logic, offer balanced trade-offs between solution quality, robustness, and computational efficiency. Stochastic and robust optimization methods provide structured ways to manage uncertainty, though their high computational demands hinder widespread application in large-scale systems. Overall, no single ED method universally outperforms others; the choice depends on system size, renewable penetration, and operational objectives. Key research gaps include the scalability limits of meta-heuristics, limited exploration of AI-driven hybrid models, insufficient large-scale real-world validation, and inadequate emphasis on environmentally constrained ED. Future work should focus on adaptive, emission-conscious, and smart grid-integrated approaches that enhance efficiency, sustainability, and resilience in renewable-rich power systems.

Keywords: Economic Dispatch; Renewable Energy Integration; Meta-Heuristic Optimization; Hybrid Methods; Stochastic Optimization

1. Background on Economic Dispatch in Conventional Power Systems

The global pursuit of sustainable energy has intensified due to climate change concerns, rising fossil fuel costs, and the finite nature of petroleum, coal, and natural gas, which are projected to be depleted within the next few decades if current consumption patterns persist [1]. Nigeria, like many developing countries, relies predominantly on conventional fossil fuels for electricity generation, with total output estimated at about 35,000 GWh annually, of which nearly 80% is from thermal plants powered by natural gas, 17% from hydropower, and less than 3% from other renewables [2]. Despite abundant solar resources averaging 5.5 kWh/m^2/day across its landmass [3], the Nigerian power sector remains largely conventional, characterized by inefficiencies in fuel supply, frequent grid collapses, and underutilized hydro capacity. As a centralized and interconnected network, Nigeria's grid depends heavily on economic dispatch (ED) to allocate generation resources optimally at minimal cost, yet operational challenges persist. With electricity demand projected to exceed 40,000 MW by 2030 [4], optimizing ED within conventional systems remains critical for ensuring supply adequacy, enhancing system stability, and laying the foundation for increased renewable integration.

1.1. Motivation for Review

The integration of renewable energy resources such as solar, wind, and small hydro into conventional power systems poses additional operational and planning issues due to their inherent intermittency, forecasting flaws, and load demand uncertainties. These factors greatly complicate the Economic Dispatch (ED) problem, which generally focuses on lowering the total generation cost while assuring reliable power supply and system stability. The changing nature of renewable sources makes it difficult to maintain a steady balance between supply and demand, as generation levels can vary substantially with changes in weather conditions and time of day. Moreover, prediction mistakes in renewable power output and fluctuating consumer demand patterns throw additional layers of uncertainty into the dispatch process, further challenging the effectiveness of standard optimization methods. To properly address these difficulties, there is a rising need for innovative and intelligent optimization algorithms capable of simultaneously achieving economic efficiency and environmental sustainability. Such algorithms should be robust enough to manage system unpredictability, flexible to adjust to real-time operational situations, and efficient in discovering near-optimal solutions within appropriate computing bounds. Therefore, modern power systems require hybrid and adaptive optimization strategies integrating techniques such as metaheuristics, machine learning, and probabilistic modeling to ensure a secure, cost-effective, and eco-friendly dispatch of both renewable and conventional energy sources under diverse operating scenarios [5].

1.2. Scientific Aim of the Work

This study is to systematically assess economic dispatch methodologies for power systems under fluctuating loads and renewable energy integration. It focuses on the evolution, modeling tactics, and optimization techniques in economic dispatch, particularly dealing with uncertainties from renewable sources. The work compares traditional, intelligent, and hybrid methods while highlighting probabilistic, stochastic, and robust optimization techniques. This review identifies existing issues, performance gaps, and future research directions necessary for reliable, economical, and sustainable power system operations in contexts centered around renewable energy [5].

1.3. Objectives and Research Questions

This research seeks to give a comprehensive synthesis of economic dispatch (ED) strategies by methodically reviewing, summarizing, and classifying the varied methodologies applied under various load conditions and renewable energy integration scenarios. As modern power systems increasingly incorporate renewable sources such as wind, solar, and hydro, the ED problem has developed to need more advanced and adaptive optimization methodologies. This study, therefore, focuses on identifying and evaluating the vast range of classical, heuristic, and hybrid strategies created to solve the challenges given by intermittency, uncertainty, and dynamic operating restrictions. Through comparative analysis, the research shows the distinct advantages, limitations, and computational performance of different methods, analyzing their usefulness in achieving optimal cost, dependability, and environmental sustainability. By doing so, it provides vital insights into the suitability of each strategy for different system scales and operational situations. Furthermore, the paper outlines significant research gaps, including the need for algorithms capable of real-time adaptation, multi-objective optimization, and effective management of stochastic changes in renewable energy output. Based on these findings, the research recommends future possibilities for enhancing economic dispatch approaches, stressing the creation of resilient, scalable, and sustainable solutions that may assist the shift toward smarter and greener power systems. Ultimately, this study serves as a strategic reference for scholars and practitioners looking to increase energy management and decision-making in the era of renewable energy-driven power generation.

Guiding questions include:

This review is guided by three central research questions:

1. How economic dispatch (ED) techniques differ in their effectiveness when addressing varying load scenarios?
2. Which optimization strategies demonstrate the greatest efficiency and reliability in renewable-integrated ED systems?
3. What key research and implementation gaps remain unaddressed in the current body of ED literature?

1.4. Real-World Limits

Even though deterministic and stochastic economic dispatch (ED) methods can be used in many situations, they both have big problems when it comes to real-world power system operations. Deterministic models are quick and efficient when it comes to calculations, but they need complete system information and can't account for real-time changes in renewable generation, fuel costs, and load variations. This defect makes them less reliable in modern power networks that are driven by uncertainty. On the other hand, stochastic methods give more accurate pictures of uncertainties, but they need a lot of historical and probabilistic data, which is often scarce or unreliable in developing energy markets. They are hard to use in large systems in real time because they are computationally intensive and create complex scenarios. Other problems that come up include overfitting, being too sensitive to how uncertainty sets are defined, and having problems with high-dimensional structures. As a result, there is a trade-off between model accuracy, computational feasibility, and data availability. This shows the need for more flexible, data-driven, and hybrid optimization frameworks that can effectively balance robustness, efficiency, and scalability when integrating renewable energy sources in a dynamic way. This systematic study offers an extensive examination of economic dispatch strategies across various load and renewable contexts; however, certain limitations must be recognized. The review mainly looks at studies from academic sources that are easy to get to, which could mean that it misses important gray literature and industry practices. Variations in modeling assumptions, system configurations, and evaluation metrics among studies hinder the capacity for accurate quantitative comparisons. The work emphasizes conceptual synthesis over intricate mathematical derivations or simulation-based validations of the models under discussion. The study also does not fully address new hybrid or data-driven methods, like machine learning-assisted or adaptive dispatch methods, that are becoming more important in systems with a lot of renewable energy. Furthermore, regional and data-specific constraints, such as the availability of renewable data, computational capacity, and regulatory disparities, were not explicitly analyzed, thereby impacting the generalizability of the findings. The study lays a strong groundwork for comprehending the current challenges and opportunities in the development of resilient, efficient, and intelligent economic dispatch frameworks for sustainable power systems [6].

2. Methodology of the Review

This research adopted a systematic review methodology to enable a comprehensive and fair evaluation of existing studies on economic dispatch (ED) tactics in modern power systems. The review method comprised extensive literature searches across renowned scientific databases, including IEEE Xplore, ScienceDirect, Springer, Elsevier, and Scopus. A carefully selected combination of keywords such as "Economic Dispatch," "renewable energy integration," "meta-heuristic optimization", "hybrid ED models," and "stochastic ED" was utilized to find relevant materials. These keywords were intended to encompass the broad spectrum of studies addressing both conventional and renewable-based dispatch optimization strategies.

The inclusion criteria were set to ensure relevance and quality. Only peer-reviewed journals and conference papers published between 2013 and 2025 were evaluated. Studies were considered if they clearly explored ED difficulties under settings of fluctuating load demands or renewable energy penetration, and all selected studies were restricted to English-language publications. These criteria guaranteed that the selected literature reflected recent achievements in ED research, particularly within the context of incorporating intermittent renewable energy sources.

Conversely, the exclusion criteria removed information that lacked technical rigor or practical application. This includes non-technical articles, grey literature, editorials, review notes, and purely theoretical works that do not contain simulation, modeling, or implementation findings. Duplicates and incomplete studies were also filtered out to ensure the quality and reliability of the review process.

Following these criteria, a Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA)-inspired selection procedure was adopted to document each stage of inclusion and exclusion clearly. The approach began with an initial pool of approximately 500 papers, which was progressively filtered by title screening, abstract assessment, and full-text review. After thorough screening, roughly 160 relevant publications satisfied the set criteria and were retained for detailed examination.

To assist organized evaluation, the selected studies were carefully divided into four primary groups based on their methodological methods and problem-solving techniques:

1. Classical methods, include linear programming, non-linear programming, and dynamic programming, which provide the core approaches of ED.
2. Heuristic and meta-heuristic methods, such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO), which offer enhanced convergence and flexibility for non-linear, non-convex ED issues.
3. Hybrid methods, incorporating two or more optimization techniques to balance accuracy, computing efficiency, and robustness in handling multi-objective ED scenarios.
4. Stochastic and probabilistic methods, which explicitly handle uncertainties in renewable generation and load demand using models based on randomness and probability distributions.

This systematic review approach ensures a holistic understanding of the progress, limitations, and potential of current ED methodologies, setting a solid foundation for identifying research gaps and recommending future improvements in optimizing economic dispatch in renewable-integrated power systems.

3. Economic Dispatch Problem Formulation

The Economic Dispatch (ED) problem is a fundamental optimization job in power system operation, principally concerned with allocating generation among committed units in order to fulfill load demand at the lowest possible cost while adhering to technical and operational restrictions. In its classical form, the ED problem assumes predictable demand and knowing generator availability. The goal function is commonly defined as the minimization of the total fuel cost of all committed generating units, often approximated as a quadratic function of each generator's power output [6].

$$min\ F(P) = \sum_{i=1}^{n} (ai + biPi + ciP_i^2) \tag{1}$$

Where *ai, bi,* and *ci* are the cost coefficients of the ith generator, *Pi* is the power output of unit *i*, and *N* represents the number of generating units [6].

This optimization is subject to a set of constraints that ensure the feasibility and reliability of system operation:

(a) Power balance constraint:
The total power generated must equal the total system demand plus transmission losses:

$$\sum_{i=1}^{N} P_i = P_D + P_L \tag{2}$$

where P_D is the system demand and P_L denotes transmission losses.

(b) Generator operating limits:
Each generating unit must operate within its technical minimum and maximum generation boundaries:

$$P_i^{\min} \leq P_i \leq P_i^{\max}, \quad i = 1, 2, \ldots, N \tag{3}$$

(c) Additional operational constraints:

Depending on system requirements, ramp-rate limits, spinning reserves, and prohibited operating zones may also be incorporated [7]. In modern power systems, the increasing penetration of renewable energy sources (RES) introduces significant variability and uncertainty into the ED formulation. Renewable outputs such as wind and solar are inherently stochastic, and their inclusion requires probabilistic or scenario-based modeling. This transforms the classical deterministic ED into a stochastic or robust optimization problem, where renewable generation is modeled as a random variable with uncertain availability [8]. Furthermore, contemporary ED studies often adopt multi-objective formulations that extend beyond fuel cost minimization. These formulations may jointly consider:

1. Emission minimization (e.g., CO_2, SO_2, NO_x emissions) to reduce environmental impacts,
2. System reliability and security constraints, ensuring adequate reserves and grid stability,
3. Sustainability metrics, aligning with low-carbon power system objectives [9,10].

Thus, while the classical ED problem is well-established and solvable using mathematical programming techniques (e.g., lambda iteration, quadratic programming), renewable-integrated ED requires advanced optimization frameworks such as stochastic programming, robust optimization, or meta-heuristic approaches. These modern formulations reflect the evolving challenges of integrating intermittent renewable resources into large-scale power systems [11].

4. Mathematical Modelling of the Associated Errors and Intermittencies

Accurate mathematical depiction of forecast errors and renewable intermittency is necessary for realistic economic-dispatch (ED) research. Below is a compact, formula-rich treatment you can incorporate into your paper. It covers common stochastic representations, time-series/error models, scenario generation for stochastic programming, chance-constraints, and resilient formulations with practical expressions for reserve sizing and cost integration.

4.1. Statistical/Probabilistic Error Models

Simple IID models
Assume errors are independent identically distributed:

$$e_t \sim \mathbf{D}\left(\mu_e, \sigma_e^2\right) \tag{4}$$

Common choices:

1. Gaussian: $e_t \sim \mathcal{N}(0, \sigma_e^2)$(convenient but may underestimate tails).
2. Laplace or Student-t for heavy tails.

Autoregressive/Time-Series Structure
Capture temporal correlation using AR(p) or ARMA models:

$$e_t = \sum_{i=1}^{p} \phi_i e_{t-i} + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, \sigma_\varepsilon^2) \tag{5}$$

AR(1) special case:

$$e_t = \phi e_{t-1} + \varepsilon_t$$

This models persistence in forecast errors and is important for ramp/rate limits.

4.2. Heteroskedastic Models

If error variance changes with time or weather conditions, use GARCH-type models:

$$e_t \sim \mathcal{N}(0, \sigma_e^2), \quad \sigma_e^2 = \alpha_0 + \alpha 1 \mathcal{E}_{t-1}^2 + \beta 1 \sigma_{t-1}^2 \tag{6}$$

4.3. Regime/Markov Models for Intermittency

Model weather regimes (e.g., clear, partly cloudy, overcast) as a Markov chain with states s_t. Renewable output conditioned on state:

$$P\left(s_{t+1}=j \mid s_t=i\right)=p_{ij}, \quad R_t \mid s_t=i \sim f_i(\cdot) \tag{7}$$

This captures sudden changes (intermittency) and temporal clustering of similar conditions.

4.4. Spatial Dependence and Copulas

For multi-site or multi-resource problems, model joint dependence using copulas:

$$F_{R_1,\dots,R_n}\left(r_1,\dots,r_n\right)=C\left(F_{R_1}\left(r_1\right),\dots,F_{R_n}\left(r_n\right)\right) \tag{8}$$

preserving marginal distributions while modelling dependency (important for aggregated uncertainty and reserve pooling).

4.5. Scenario Generation (Monte Carlo & Reduction)

Monte Carlo Simulation (MCS): draw N sample paths $\{\xi_{1:T}^k\}_{k=1}^N$ from the chosen stochastic model (time-series + marginal law + dependency). Use scenario reduction (fast forward/backward selection, clustering) to keep a tractable subset S with probabilities p_s for stochastic optimization.

4.6. Stochastic Programming Formulations

4.6.1. Two-Stage Stochastic ED (Canonical)

First-stage decisions x (commitment/dispatch schedule before uncertainty realization), second-stage recourse $y(\xi)$ (real-time adjustments). Minimize expected total cost:

$$\min_{x\in\mathcal{X}} c^\top x+\mathbb{E}_{\boldsymbol{\xi}}\left[Q\left(x,\boldsymbol{\xi}\right)\right] \tag{9}$$

subject to deterministic constraints on x. Recourse problem:

$$Q(x,\xi)=\min_y\ q^\top y \quad \text{s.t. } A(\xi)x+B(\xi)y\geq d(\xi).$$

Discrete scenario approximation:

$$\min_x c^\top x+\sum_{s\in S} p_s Q(x,\xi^s).$$

4.6.2. Multi-Stage Stochastic Programming

Extend to multi-stage for decision updates over time horizons t = 1…T. Complexity grows quickly; use scenario trees or decomposition (e.g., stochastic dual dynamic programming).

4.7. Chance-Constrained Formulations

Enforce probabilistic feasibility of constraints. For example, reserve or supply adequacy:

$$\Pr(\text{generation supply} \geq \text{demand}) \geq 1-\alpha.$$

Example linear chance constraint with Gaussian errors:

$$\Pr(a^\top x+b^\top\xi\leq c)\geq 1-\alpha$$

can be converted to a deterministic convex constraint if ξ is Gaussian:

$$a^\top x+\Phi^{-1}(1-\alpha)\sqrt{b^\top\Sigma b}\leq c \tag{10}$$

where Φ^{-1} is the standard normal quantile and $\Sigma$the covariance of ξ.

4.8. Robust Optimization (Worst-Case Guarantees)

Robust ED seeks solutions that are feasible for all ξ in an uncertainty set $\mathcal{U}$:

$$\min_{x\in\mathcal{X}} \max_{\xi\in\mathcal{U}} c^\top x \quad \text{s.t. } A(\xi)x \le b,\ \forall\xi \in \mathcal{U}.$$

Common uncertainty sets:

1. Box: $\mathcal{U} = \{\xi : |\ \xi_i - \bar{\xi}_i\ | \le \Delta_i\}$.
2. Polyhedral (budgeted uncertainty): $\sum_i \frac{|\xi_i - \bar{\xi}_i|}{\Delta_i} \le \Gamma$.
3. Ellipsoidal: $(\xi - \bar{\xi})^\top \Sigma^{-1}(\xi - \bar{\xi}) \le \rho$.

Robust formulations often lead to tractable convex reformulations (e.g., second-order cone programs) depending on $\mathcal{U}$.

4.9. Reserve Sizing and Reliability Metrics

If forecast error is approximated with zero mean and variance σ_t^2, a simple deterministic reserve level to achieve reliability $1-\alpha$ is

$$R_t^{\text{reserve}} = z_{1-\alpha}\,\sigma_t,$$

where $z_{1-\alpha}$ is the normal quantile (or use empirical quantiles for non-Gaussian errors). Total cost objective can include reserve procurement cost $c^{\text{res}} R_t^{\text{reserve}}$ and expected penalty for loss-of-load or spillage.

Key reliability metrics to report: Expected Energy Not Served (EENS), Loss-of-Load Probability (LOLP), and expected operating cost under uncertainty $\mathbb{E}[\text{Cost}]$.

4.10. Practical Hybrid Approaches

1. Stochastic + robust hybrid: treat high-probability region with stochastic programming and protect against tail events with a small robust constraint (e.g., chance constraints with robustified tails).
2. Distributionally robust optimization (DRO): optimize against the worst-case distribution within an ambiguity set defined by moments or Wasserstein distance; bridges stochastic and robust approaches.
3. Model predictive control (MPC) with rolling-horizon stochastic forecasts: repeatedly solve shorter-horizon stochastic/robust ED and update as new forecasts arrive uses time-series error models directly [8].

5. Classification of Economic Dispatch Techniques

Over the years, several ways have been developed to tackle the Economic Dispatch (ED) problem, ranging from analytical and mathematical programming methods to recent heuristic, hybrid, and stochastic approaches. These approaches vary in terms of computational efficiency, capacity to handle nonlinearity, and robustness under renewable integration and system uncertainty. The taxonomy of ED techniques is described as follows.

5.1. Classical/Conventional Techniques

1. Classical ED techniques rely on deterministic optimization and mathematical programming. They are efficient for convex and continuous issues but become less successful when tackling non-convexities (e.g., valve-point effects, banned operating zones) or large-scale renewable integration.
2. Lambda-iteration method: The simplest and most extensively used analytical technique, suited for convex quadratic cost functions under lossless or approximated loss systems [12].
3. Gradient-based methods: Employ derivatives of cost functions for iterative optimization, enabling quick convergence but limited capacity to escape local minima [12].
4. Linear and quadratic programming: Useful for convex cost functions, where quadratic programming directly simulates quadratic fuel cost and linear programming simplifies it into piecewise functions [13].
5. Dynamic programming: Suitable for non-convex and discrete problems, however computationally costly due to the “curse of dimensionality” [13].

5.2. Heuristic and Meta-Heuristic Techniques

Heuristic and meta-heuristic algorithms, which mimic natural or social processes, have gained prominence in addressing non-convex Economic Dispatch (ED) problems characterized by nonlinear constraints and renewable-related uncertainties. Among these, the Genetic Algorithm (GA), inspired by natural selection and genetics, has proven effective in handling large-scale and nonlinear ED formulations [14]. The Particle Swarm Optimization (PSO) technique, modeled on the social behavior of bird flocking, offers faster convergence than GA but is prone to premature convergence in some cases [15]. Similarly, Differential Evolution (DE) employs differential mutation and recombination strategies to achieve robust global search performance, making it suitable for highly complex ED scenarios [16]. Other nature-inspired approaches include Ant Colony Optimization (ACO), which simulates ant foraging behavior and is particularly useful for combinatorial ED optimization [17], and the Artificial Bee Colony (ABC) algorithm, modeled on honey bee foraging, which effectively balances exploration and exploitation in the search process. Additionally, the Harmony Search (HS) algorithm, inspired by musical improvisation, provides flexibility in handling multi-objective ED problems [18]. Collectively, these methods offer powerful tools for solving large-scale, nonlinear, and uncertain ED problems, though their effectiveness often depends on parameter tuning and the specific system context.

5.3. Hybrid Approaches

Hybrid methods integrate the strengths of different optimization techniques to enhance robustness, convergence speed, and solution accuracy in Economic Dispatch (ED). For instance, the Hybrid GA-PSO approach combines the global exploration capability of Genetic Algorithms (GA) with the fast local convergence of Particle Swarm Optimization (PSO), making it well-suited for solving large-scale and non-convex ED problems [19]. Fuzzy-based hybrid techniques incorporate fuzzy logic with either classical or meta-heuristic methods to effectively manage uncertainty and imprecision associated with renewable energy variability. More recently, AI-integrated optimization frameworks have emerged, leveraging Artificial Neural Networks (ANNs), Deep Learning, and Reinforcement Learning (RL) for predictive modeling, adaptive learning, and real-time ED under uncertain renewable generation conditions [20]. These hybrid strategies demonstrate superior flexibility and adaptability compared to single-method approaches, offering promising solutions for complex, renewable-rich power systems.

5.4. Stochastic/Probabilistic Methods

Stochastic methods explicitly account for uncertainties arising from renewable generation, load fluctuations, and market dynamics in Economic Dispatch (ED). Monte Carlo Simulation (MCS) applies randomized sampling to capture variability in wind and solar outputs, making it a widely used tool for risk-based ED analysis [21]. Scenario-based stochastic programming creates multiple renewable generation scenarios with associated probabilities, enabling the formulation of risk-aware and adaptive ED strategies. In contrast, robust optimization techniques emphasize worst-case uncertainty modeling, ensuring secure and reliable ED decisions without relying on complete probability distributions [22]. Together, these approaches provide systematic frameworks for managing uncertainty, though they differ in computational burden and conservativeness, influencing their applicability in large-scale, renewable-integrated systems.

5.5. Deterministic vs. Random Methods

Economic Dispatch (ED) strategies can generally be classed into deterministic and random (stochastic) methods based on how system uncertainties such as load changes and renewable energy intermittencies are addressed during optimization. Deterministic techniques imply that all system characteristics, including load demand, generation capacity, fuel cost coefficients, and operational limitations, are known and constant throughout the dispatch period. These methods rely on fixed or forecasted data to minimize total generation cost using classical mathematical programming techniques such as Linear Programming (LP), Nonlinear Programming (NLP), and Quadratic Programming (QP), as well as heuristic algorithms like Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Differential Evolution (DE). Although deterministic techniques are computationally efficient and straightforward to implement, they fail to capture the dynamic and uncertain nature of current power systems with high renewable energy penetration. In contrast, stochastic techniques explicitly incorporate uncertainties and random variations in renewable generation and demand by modeling uncertain parameters such as wind speed, solar irradiation, or load fluctuations using probability distributions, random variables, or scenario-based frameworks. Techniques such as Probabilistic Economic Dispatch, Stochastic Programming, and Robust Optimization are applied to minimize predicted costs or maintain near-optimal performance under uncertainty. While stochastic approaches provide more realistic and resilient solutions, they demand large processing resources and precise probabilistic data. Deterministic approaches are best suited for stable systems with known conditions, whereas stochastic methods are crucial for controlling the variability and unpredictability inherent in renewable energy integration. Modern power systems increasingly utilize hybrid approaches that combine deterministic optimization with stochastic or resilient modeling to strike a balance between accuracy, dependability, and computing efficiency [21,22].

6. Economic Dispatch Under Varying Load Conditions

Literature shows that load level and volatility are key determinants of ED performance and method suitability. At light-load levels, classical convex methods such as lambda-iteration and quadratic programming achieve fast convergence and economic efficiency, since units operate away from ramping and reserve limits. At medium loads, where technical limits and prohibited zones become significant, refinements like piecewise or mixed-integer formulations improve feasibility, particularly in dynamic ED with inter-temporal constraints. Under peak load or rapid ramping, classical methods face difficulties with nonconvex costs, valve-point effects, and tight security constraints; in such cases, meta-heuristics (PSO, DE, GA) and hybrid solvers offer better robustness against local minima and improved feasibility, though at the cost of higher computation time. Benchmark studies confirm that hybrid approaches (e.g., GA-PSO or PSO with quadratic programming) often achieve the best balance between cost minimization and constraint satisfaction. Real-world practices align with these findings: deterministic convex ED is sufficient during off-peak periods, while robust and hybrid methods are preferred under peak conditions to ensure ramping and security compliance. Across all load regimes, accurate short-term forecasting and joint ramping–reserve co-optimization significantly enhances both reliability and economic efficiency [23].

7. Economic Dispatch with Renewable Energy Integration

The integration of renewable energy resources, particularly wind and solar, has drastically modified the economic dispatch (ED) problem. Unlike conventional thermal production, these resources introduce intermittency, variability, and forecasting uncertainty, which challenge the assumptions of classical deterministic ED models. Operators must now optimize not only fuel prices and generator limits but also probabilistic renewable production, reserve requirements, and fast-response technologies such as storage and demand response to assure system reliability. The International Energy Agency stresses that successful renewable integration depends on boosting system flexibility through dispatchable generation, storage, grid reinforcement, and active demand-side participation [24].

Economic Dispatch (ED) with Photovoltaic (PV) systems has evolved into numerous variants variants meant to solve the variability, intermittency, and nonlinearity presented by solar energy generation. These versions differ based on system setup, optimization targets, and the integration of complementary technologies such as energy storage and hybrid generation sources. The typical PV-ED focuses on lowering total generating cost while treating PV production as a non-dispatchable source dependent on solar irradiation and temperature, so balancing conventional generation and reducing fuel consumption and emissions. The dynamic PV-ED version expands this approach by including time-dependent fluctuations in solar power, load demand, and unit commitment schedules, using anticipated PV output to optimize dispatch decisions dynamically for greater cost efficiency and system stability. The multi-objective PV-ED simultaneously optimizes several conflicting goals such as minimizing fuel cost, emissions, and transmission losses while maximizing renewable utilization often employing metaheuristic algorithms like Particle Swarm Optimization (PSO), Non-dominated Sorting Genetic Algorithm (NSGA-II), and Differential Evolution (DE) to achieve Pareto-optimal trade-offs. The hybrid PV–thermal ED integrates PV generation with thermal, hydro, or wind plants to leverage the complementary characteristics of renewable and conventional units for greater reliability and grid flexibility, while the PV–battery energy storage ED incorporates storage units into the dispatch framework to manage supply–demand balance, considering constraints such as state-of-charge, degradation costs, and charging/discharging efficiency. More recently, data-driven and adaptive PV-ED models have emerged, applying machine learning and predictive control for real-time optimization by dynamically modifying dispatch schedules based on forecast and operational data. Collectively, these evolving PV-integrated ED models signify the shift from conventional deterministic frameworks toward intelligent, hybrid, and uncertainty-aware optimization strategies, each addressing specific operational challenges and contributing to more economical, reliable, and sustainable power system performance in renewable-rich environments [24].

7.1. Key Technical Challenges

The research emphasizes many fundamental issues connected with renewable-integrated Economic Dispatch (ED), principally originating from the particular operational and physical properties of renewable energy sources. Unlike conventional generators, renewable resources such as solar and wind are intermittent, changeable, and uncertain, making their integration into power networks extremely challenging. These intrinsic traits provide operational uncertainties that affect both system dependability and economic efficiency, thereby requiring more sophisticated optimization and control systems.

One of the most crucial challenges is intermittency, which refers to the irregular and unpredictable character of renewable generation. Solar and wind power outputs can fluctuate suddenly due to sudden changes in weather conditions, such as passing clouds or variations in wind speed. These rapid shifts, known as ramps, can disrupt the electricity system by producing mismatches between supply and demand. Traditional ED models, which assume steady-state conditions, are typically unsuitable for handling such short-term variations, making it vital to integrate real-time adjustment capabilities and responsive reserve mechanisms.

Another key difficulty is variability, driven by daily and seasonal generation cycles. Solar power is available only during daylight hours and varies with the sun's location, while wind speeds follow complex temporal and spatial patterns. This periodic unpredictability affects dispatch scheduling and requires the use of advanced forecasting and scheduling technologies to guarantee that generation obligations coincide with actual availability.

Forecasting uncertainty poses yet another challenge in renewable-integrated ED. Even with current forecasting systems, disparities can exist between expected and actual renewable generation levels. These variations contribute more uncertainty to the dispatch process, typically necessitating system operators to keep higher spinning reserves or apply stochastic and probabilistic optimization approaches that can account for prediction errors.

Furthermore, spatial correlation across widely spread renewable plants provides a distinct issue. Renewable sources located within the same region are often influenced simultaneously by comparable weather patterns, resulting in correlated power outputs. This interconnectedness contradicts the notion of statistical independence among generators, making it more difficult to allocate reserves optimally. Consequently, system operators must create advanced correlation-aware models that accurately reflect the geographical and temporal correlations of renewable resources.

To effectively address these problems, the research underlines the need to adopt probabilistic, stochastic, and real-time optimization approaches. These techniques provide more precise modeling of uncertainties and allow operators to make adaptive judgments that respond dynamically to real-time system conditions. Reserve co-optimization, which jointly analyzes energy and reserve scheduling, also becomes vital for ensuring both dependability and economic efficiency. Additionally, introducing intra-hour dispatch adjustments allows operators to change generation schedules more often, thereby addressing short-term variations in renewable output and demand.

Attaining dependable and cost-effective operation in renewable-rich power systems demands a paradigm shift from deterministic to uncertainty-aware, adaptive economic dispatch frameworks. By integrating probabilistic modeling, real-time optimization, and coordinated reserve management, power systems may efficiently balance economic objectives with the operational constraints posed by renewable energy integration [22].

7.2. Techniques for Renewable-Rich ED

Research addressing uncertainties in Economic Dispatch (ED) has evolved through several methodological paths, each aimed to increase the reliability, adaptability, and computational efficiency of power system operations in renewable-rich situations. As renewable energy sources continue to rise in penetration, their inherent variability and unpredictability present difficulties that classic deterministic ED models cannot fully handle. Consequently, new techniques increasingly focus on incorporating uncertainty using stochastic, resilient, heuristic, and intelligent optimization frameworks that better reflect real-world operational situations.

One key development is in stochastic and scenario-based optimization, which leverages probabilistic projections to capture the uncertain nature of renewable energy and load demand. These approaches generate various scenarios depicting potential system circumstances throughout day-ahead and sub-hourly timescales. By coordinating thermal units, energy storage systems, and renewable resources over multiple time horizons, stochastic ED provides a dynamic response to variable conditions. The scenario-based method provides multi-timescale coordination, allowing system operators to plan ahead while preserving flexibility to alter decisions when new information becomes available.

Another major avenue of research is robust optimization, which differs from stochastic approaches by not relying on predetermined probability distributions. Instead, it ensures solution feasibility under all feasible scenarios inside a constrained uncertainty set. Robust ED provides conservative yet reliable decisions that defend system stability against worst-case variances in renewable output or load. Although it may lose some economic efficiency, robust optimization considerably enhances the resilience and security of power system operations.

To address the nonlinear and nonconvex nature of real-world ED problems, particularly those including valve-point loading effects, banned operating zones, and renewable intermittency, researchers have increasingly embraced meta-heuristic and hybrid algorithms. Techniques such as Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Differential Evolution (DE) are widely renowned for their capability to identify near-global optimal solutions in difficult search spaces. Hybrid models generally combine these algorithms with conventional methods to balance exploration and convergence speed, delivering improved accuracy and robustness in uncertain operating situations.

Furthermore, Model Predictive Control (MPC) and distributed control frameworks have developed as useful tools for real-time and coordinated optimization. MPC-based ED continuously modifies generating schedules based on new measurements and forecasts, providing rolling optimization that reacts to real-time system changes. On the other hand, distributed optimization techniques, such as the Alternating Direction Method of Multipliers (ADMM), facilitate multi-agent coordination among distributed generators, storage units, and demand response systems. These decentralized technologies boost scalability and reduce communication overhead in large, networked power systems.

More recently, the integration of machine learning–assisted ED promises a transformational horizon. Deep learning, clustering, and surrogate modeling techniques are being applied to improve scenario generation, capture complicated nonlinear relationships, and approximate computationally intensive restrictions. By learning from historical data, machine learning accelerates optimization processes, enhances prediction accuracy, and improves the robustness and reliability of dispatch decisions.

Collectively, these methodological breakthroughs indicate a paradigm shift in addressing uncertainty in economic dispatch, advancing power system operations toward increased resilience, adaptability, and computational intelligence in the era of renewable energy integration [25].

7.3. Comparative Performance in Literature

Comparative analyses reveal important trade-offs among Economic Dispatch (ED) techniques under renewable integration. Stochastic and robust methods improve system reliability and lower reserve costs but demand significant computational resources and extensive forecast data. Meta-heuristic and hybrid approaches deliver high-quality solutions for complex, nonlinear ED problems; however, they may suffer from limited repeatability and reduced computational efficiency. Meanwhile, distributed and predictive control frameworks enable scalability and privacy-preserving dispatch but are highly dependent on accurate forecasting and a strong communication infrastructure. Recent studies indicate that hybrid solutions, such as combining stochastic programming with metaheuristics like PSO or DE, or employing distributed decomposition techniques such as ADMM, provide a balanced trade-off across cost, reliability, and scalability [26].

7.4. Representative Case Studies

1. Microgrids and hybrid renewable systems: Studies on PV–wind–storage microgrids reveal that coordinated dispatch of storage and demand response reduces curtailment, enhances flexibility, and lowers overall costs [27].
2. Wind-integrated day-ahead ED: A recent Scientific Reports paper modeled five scenarios (conventional, wind-only, wind/storage, wind/DR, and fully integrated). The wind/storage/DR case produced the most reliable

and cost-efficient outcomes [27].

3. ISO and large-system studies: Planning reports (e.g., ISO New England) and stochastic ED models emphasize that high renewable penetration requires expanded transmission capacity, storage investment, and intra-hour dispatch mechanisms [27].

7.5. Synthesis and Practical Insights

In renewable-dominated contexts, the ED paradigm must shift from static deterministic optimization to multi-timescale, probabilistic, and adaptive frameworks. Day-ahead stochastic scheduling should be complemented by real-time MPC updates, while storage and demand response must be embedded as essential flexibility resources. Moreover, machine learning can improve forecasting and scenario reduction, enhancing computational tractability. Ultimately, hybrid strategies that combine stochastic/robust optimization with meta-heuristic or decomposition-based solvers represent a promising pathway for achieving economically viable and reliable renewable-rich dispatch [28].

8. Comparative Analysis of Techniques

This section compares major ED solution classes against five practical metrics generation cost minimization, convergence speed, robustness under uncertainty, computational complexity, and scalability to large systems and summarizes their relative strengths and weaknesses using representative literature.

Metrics for comparison

1. **Generation cost minimization:** ability to find low-cost (near-global) solutions, including for nonconvex cost functions (valve-point effects, prohibited zones).
2. **Convergence speed:** number of iterations/wall-clock time to reach an acceptable solution.
3. **Robustness under uncertainty:** performance when facing renewable variability, forecast errors, or load swings.
4. **Computational complexity:** algorithmic cost in terms of time per iteration and dependences on population size, scenario count, or problem dimension.
5. **Scalability:** how well the method performs (accuracy and runtime) as system size (buses, units, scenarios) increases [26].

8.1. Classical/Mathematical Programming Methods

Representative methods: lambda-iteration, gradient methods, linear/quadratic programming, interior-point solvers.

1. **Generation cost:** Excellent for convex, smooth cost models guaranteed optimality for convex formulations.
2. **Convergence speed:** Very fast (polynomial-time solvers; interior-point methods are efficient for large sparse systems).
3. **Robustness under uncertainty:** Low in native form; must be extended to stochastic or robust formulations to cope with renewables.
4. **Computational complexity:** Moderate and well-characterized; benefits from sparse linear algebra.
5. **Scalability:** High for large convex formulations (ISO/market scale).
6. **Strengths:** Provable optimality and speed for deterministic convex problems; mature toolchain.
7. **Weaknesses:** Cannot directly handle nonconvexities and stochasticity without reformulation [29].

8.2. Meta-Heuristics and Evolutionary Algorithms

Representative meta-heuristics such as PSO, GA, DE, ACO, ABC, and HS have proven effective for solving non-convex and discontinuous ED problems, particularly those with valve-point effects and discrete constraints. They reliably generate high-quality feasible solutions, with PSO and DE often outperforming GA in convergence stability and mean performance on benchmark systems. Their population-based search offers robustness to uncertainty and adaptability to stochastic formulations, though this comes at the cost of high computational complexity, scaling with population size, iterations, and cost evaluations. While parallelization and hybridization improve scalability and efficiency, challenges remain, including sensitivity to parameter tuning, stochastic results without guaranteed global optimality, and potentially high computational overhead [30].

8.3. Quantitative Synthesis and Meta-Analysis Framework

A quantitative synthesis or meta-analysis provides a formal statistical framework for analyzing the performance of Economic Dispatch (ED) algorithms across various studies, concentrating on important performance characteristics such as convergence time and cost savings. The procedure begins with systematic data extraction, where characteristics such as algorithm type, benchmark system (e.g., IEEE 30-, 57-, or 118-bus), convergence time, objective cost, and standard deviation are collected and normalized to ensure comparability between investigations. Effect sizes are then determined using acceptable measures such as absolute differences, percent improvements, standardized mean differences (SMD), or log-ratios to standardize the outcomes reported under diverse conditions. Each impact size is allocated a weight depending on its variance, and a random-effects model is employed to account for heterogeneity originating from differences in benchmarks, optimization settings, and renewable integration levels. Heterogeneity is evaluated using Cochran's Q and I^2 statistics, while meta-regression and subgroup studies analyze how factors like as algorithm class (heuristic or accurate), system size, or renewable penetration influence performance. To manage interdependence across several comparisons from the same study, multivariate or aggregated effect-size procedures are utilized. Publication bias and small-study effects are investigated by funnel plots and Egger's regression tests, with sensitivity analyses conducted to validate the robustness of the results. Visualization methods like as forest plots, bubble plots, and summary tables are applied to illustrate pooled results and moderator effects. Practical challenges such as uneven stopping criteria, missing dispersion measures, and differing test system scales are handled through normalization, imputation, or sensitivity tests. All analyses can be performed using R packages like metafor or Python libraries such as statsmodels, enabling reproducibility through shared code and data documentation. This meta-analytic approach offers an objective, statistically informed assessment of algorithmic performance in terms of convergence efficiency and economic optimization under varied renewable integration scenarios [30].

8.4. Hybrid Methods (Meta-Heuristic + Mathematical/AI)

Hybrid methods such as GA-PSO combinations, metaheuristics coupled with local solvers, fuzzy-hybrids, and AI-assisted optimization using ANN surrogates or RL-based tuning offer a balance between exploration and exploitation in solving ED problems. By combining the global search ability of metaheuristics with local refinement from mathematical solvers, these approaches often deliver superior generation cost performance. Convergence speed is typically faster than pure metaheuristics, though still slower than convex classical methods. Their robustness under uncertainty is enhanced when integrated with stochastic or scenario-based frameworks, with AI components further supporting scenario reduction and forecasting accuracy. Computational complexity is reduced compared to standalone metaheuristics when surrogate or multi-fidelity models are employed, and scalability is improved through decomposition and advanced multi-fidelity techniques (e.g., NREL's control-variate approaches). Overall, hybrid methods improve solution quality and efficiency, though they introduce added algorithmic complexity and implementation challenges [30].

8.5. Distributed/Consensus-Based and Decomposition Methods

Distributed optimization methods such as ADMM, consensus algorithms, and distributed MPC are increasingly applied to ED problems, offering scalability and privacy while maintaining solution quality close to centralized approaches when properly coordinated with augmented Lagrangian schemes. Their per-iteration cost is low and inherently parallelizable, though achieving convergence often requires multiple communication rounds, making performance sensitive to delays and packet losses. These methods handle uncertainty effectively by allowing local agents to integrate stochastic models, naturally supporting multi-area coordination under renewable variability. Computational complexity is low at the agent level, but overall efficiency depends on communication and synchronization overhead. Designed for large-scale, DER-rich systems, distributed methods excel in scalability and resilience through decentralization, though they rely on robust communication infrastructure and careful parameter tuning to ensure stable convergence [31].

8.6. Stochastic and Robust Optimization Methods

Uncertainty-aware optimization methods including Monte Carlo simulation, scenario-based stochastic programming, robust optimization, and multi-fidelity stochastic solvers provide a principled framework for risk-aware ED by explicitly modeling variability and worst-case outcomes. While these approaches generally increase expected generation costs slightly, they reduce reserve requirements and improve system reliability. Their robustness under uncertainty is high, but convergence speed can be hampered by the explosion of scenarios or samples, making naive implementations computationally prohibitive. Advances such as scenario reduction, control-variate techniques, and multi-fidelity solvers help mitigate runtime and data requirements, improving tractability. Scalability remains a challenge for very large systems unless decomposition or surrogate modeling is employed. Overall, these methods deliver more reliable, risk-hedging dispatch decisions, though at the expense of significant data and computational demands, with ongoing research (e.g., NREL, OSTI) focused on variance-reduction and multi-fidelity strategies to enhance practicality [32].

8.7. Comparative Tables and Empirical Findings

Several review and comparative studies have investigated empirical trade-offs among optimization and coordination strategies applied to standard IEEE benchmark systems (30-, 57-, and 118-bus) and real-world power system cases. Meta-heuristic comparisons consistently show that Differential Evolution (DE) and advanced Particle Swarm Optimization (PSO) variants exhibit superior robustness, faster convergence, and lower variance compared to baseline PSO and Genetic Algorithm (GA) implementations, especially for medium- to large-scale optimization test systems [33]. For stochastic economic dispatch (ED), hybrid and decomposition-based techniques such as hybrid data-driven models, scenario reduction, and Benders decomposition provide effective trade-offs between cost minimization and computational efficiency, particularly under high-dimensional uncertainty conditions [34].

Distributed optimization algorithms based on the Alternating Direction Method of Multipliers (ADMM) have demonstrated reliable convergence performance in practical networked environments. However, their stability can be challenged by communication imperfections such as packet drops and delays, which necessitate the adoption of asynchronous or robust update mechanisms to ensure convergence [35]. Moreover, multi-fidelity stochastic approaches developed by research institutions like the National Renewable Energy Laboratory (NREL) indicate that hierarchical fidelity methods can retain near-optimal dispatch performance while significantly reducing computational burdens compared with full high-fidelity sampling [36]. Collectively, these studies highlight the importance of balancing computational efficiency, robustness, and scalability when selecting optimization frameworks for modern power and energy systems.

8.8. Strengths and Weaknesses

Comparative assessments of economic dispatch (ED) techniques reveal distinct strengths and weaknesses across categories. Classical methods remain attractive for their speed and provable optimality in convex problems but struggle with nonconvexity and stochastic renewable integration. Meta-heuristics offer flexibility and strong performance in nonconvex environments, though they can be computationally expensive and highly sensitive to parameter tuning. Hybrid methods, which combine different optimization paradigms, achieve balanced performance and improved convergence rates but introduce additional implementation complexity. Distributed methods stand out for their scalability and ability to preserve data privacy, yet they are heavily dependent on reliable communication infrastructure and require careful convergence parameter tuning. Finally, stochastic and robust methods explicitly address uncertainty, providing reliability under variable renewable and load conditions, but they are computationally demanding unless coupled with reduction or approximation techniques [37].

8.9. Quality Assessment and Evaluation of Risk of Bias

To guarantee dependability and openness, the quality assessment of all included studies will be standardized through a systematic risk-of-bias evaluation matrix. Each study will be evaluated based on several criteria, such as methodological rigor, data completeness, benchmark transparency, and reporting accuracy. The evaluation criteria will include how clear the algorithm descriptions are, how well the test systems can be reproduced, how well the performance metrics fit, how well they handle uncertainty, and how well they reveal the parameter settings. An overall quality score will be made to help with subgroup or sensitivity analyses. Each dimension will be rated on the same ordinal scale (for example, low, moderate, or high risk of bias). Studies deemed high risk or displaying incomplete reporting will be subjected to further examination or omitted during sensitivity assessments. This structured quality assessment guarantees that the aggregated meta-analytic estimates originate from robust, credible, and methodologically sound evidence [36].

9. Research Gaps and Future Directions

Despite notable advances in economic dispatch (ED) research, several gaps hinder its practical deployment in modern power systems. Meta-heuristic algorithms, though effective for small- and medium-scale networks, struggle with scalability and convergence in large interconnected grids [38]. Hybrid approaches that integrate classical optimization with meta-heuristics show promise, but the potential of advanced AI and machine learning methods such as reinforcement learning and deep neural networks for managing renewable uncertainty remains underexplored. Most studies are limited to IEEE test systems or small-scale case studies, which fail to capture real-world grid complexities [39]. Additionally, environmentally constrained ED models that account for emissions and sustainability receive limited attention, despite growing decarbonization imperatives. The integration of demand response, energy storage, and smart grid technologies into ED formulations also remains insufficiently addressed, even though such integration could enhance flexibility, reliability, and cost-efficiency in renewable-rich systems. Future research should prioritize scalable, AI-driven, and environmentally conscious ED frameworks validated on large-scale real-world systems, with demand-side and smart grid considerations to strengthen resilience and sustainability [40].

10. Conclusions

This systematic review has traced the evolution of Economic Dispatch (ED) techniques under varying load conditions and renewable energy integration, emphasizing the strengths, limitations, and applications of classical, meta-heuristic, hybrid, and stochastic approaches. Classical mathematical programming remains efficient and optimal for small-scale, convex, and deterministic systems but is inadequate in handling nonlinearities and uncertainties introduced by renewables and load variability. Meta-heuristic and evolutionary algorithms offer robustness and flexibility in tackling nonconvex problems, yet face scalability and computational challenges in large networks. Hybrid methods, combining heuristic exploration with mathematical refinement or AI-based learning, strike a balance between solution quality, convergence speed, and robustness, making them well-suited to modern grid challenges. Likewise, stochastic and robust optimization provide structured approaches to uncertainty management, though their computational demands limit widespread deployment. The reviewed studies reveal that no single method dominates across all contexts; instead, the choice of ED technique depends on system scale, renewable penetration, load dynamics, and operational objectives such as cost efficiency, emission control, or reliability. The complexity of modern grids calls for integrated ED solutions embedded within smart grid frameworks that incorporate demand response, distributed energy resources, and advanced forecasting. Future research should prioritize scalable, AI-driven hybrid models, environmentally constrained formulations, and real-world large-scale validation beyond IEEE benchmarks. Strengthening the intersection of optimization, machine learning, and smart grid technologies will be essential to achieve ED frameworks that are adaptive, data-driven, and environmentally conscious, enabling reliable, low-carbon, and resilient power systems.

Recommendations

Based on the findings of this systematic study, some significant recommendations arise to guide future research and practical developments in Economic Dispatch (ED) under renewable-integrated and dynamically fluctuating power systems. The review has established that while classical mathematical programming approaches are efficient for small-scale and deterministic systems, they are unsuitable for addressing the nonlinearities, uncertainties, and stochastic behaviors characteristic of renewable energy sources and modern grid dynamics. Therefore, researchers and practitioners should focus on developing hybrid, data-driven, and adaptive ED frameworks that can effectively manage system complexity, uncertainty, and environmental sustainability.

First, it is advised that future ED models include artificial intelligence (AI) and machine learning (ML) approaches to boost flexibility and decision-making under uncertainty. AI-driven hybrid approaches combining meta-heuristic algorithms with predictive analytics and reinforcement learning can enable faster convergence, improved global search capabilities, and more accurate modeling of nonlinear system behaviors. Such models should also incorporate real-time data from sensors, smart meters, and IoT-enabled monitoring systems to enable dynamic optimization and continuous learning, hence ensuring responsiveness to real-world operational conditions.

Second, scalability and computational efficiency should be addressed in model building. Many existing ED approaches operate well in small test systems but fail to scale successfully in big, complicated networks with substantial renewable penetration. Future research should, therefore, examine parallel computing, distributed optimization (e.g., ADMM-based frameworks), and cloud-based computation to manage large-scale, multi-agent ED problems efficiently. This will permit decentralized control and coordination among distributed generators, storage systems, and demand-side participants inside smart grid topologies.

Third, ED formulations must advance beyond cost minimization to clearly incorporate environmental and sustainability constraints, reflecting the global trend toward low-carbon power systems. Multi-objective optimization frameworks that simultaneously optimize generation cost, emissions, and energy losses should be further developed and proven in real-world contexts. Integrating carbon pricing systems, emission restrictions, and renewable portfolio standards into ED models can ensure that optimization outputs fit with wider climate and energy policy goals.

Fourth, real-world validation of suggested ED approaches should be favored over dependence on standardized IEEE test systems. Collaborative pilot studies with utilities, transmission operators, and microgrid developers can provide vital insights into the actual feasibility, scalability, and robustness of proposed models under real operational constraints. Such validation will bridge the gap between theoretical optimization and operational deployment.

Lastly, future research should enhance smart grid–embedded ED systems capable of seamless coordination between demand response, distributed energy resources (DERs), and sophisticated forecasting systems. Incorporating probabilistic forecasting and adaptive scheduling into ED frameworks can boost reliability and system flexibility under renewable variability.

In conclusion, the route forward lies in building integrated, AI-empowered, and environmentally sensitive ED frameworks that merge optimization theory, intelligent control, and sustainable energy management. These efforts will be vital to developing resilient, data-driven, and low-carbon power systems capable of supporting the next generation of smart and renewable-dominated energy networks.

Author Contributions

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Conflicts of Interest

The authors declared there is no conflict of interest.

Abbreviations

Notation	Meaning
1. ED	Economic Dispatch
2. PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
3. R_t	actual renewable generation at time t(e.g., wind or PV).
4. $\hat{R}_t$	forecast (point estimate) of R_t.
5. $e_t = R_t - \hat{R}_t$	forecast error (can be positive or negative).
6. L_t	load/demand at time t(with forecast $\hat{L}_t$and error $\ell_t = L_t - \hat{L}_t$).
7. ξ_t	vector of uncertain parameters at t, e.g., $\xi_t = [e_t, \ell_t]$.

References

1. Adepoju, G.A.; Okelola, M.O.; Tijani, M.A. Hybrid Optimization Technique for Solving Economic Dispatch Problem: A Case Study of Nigerian Thermal Power System. *Afr. Sci. Rep.* **2022**, *1*, 81–87. [CrossRef]
2. Gbadega, P.A.; Sun, Y. Synergistic Integration of Renewable Energy and HVDC Technology for Enhanced Multi-Objective Economic Emission Dispatch Using the Salp Swarm Algorithm. In *Neural Computing for Advanced Applications*; Zhang, H., Li, X., Hao, T., et al, Eds.; Springer Nature: Singapore, 2025; 2182, pp. 232–249. [CrossRef]
3. Oyedokun, J.A.; Fasina, E.T.; Adebanji, B. Design and Viability Assessment of Grid-Integrated Solar PV System for Electric Power Supply Enhancement: A Case Study of Idofian, Nigeria. *EJECE* **2023**, *7*, 30–34. [CrossRef]
4. Owoeye, K.S.; Udofia, K.M.; Okpura, N.I. Design and Optimization of Hybrid Renewable Energy System for Rural Electrification of an Off-Grid Community. *Eur. J. Eng. Technol.* **2022**, *10*, 28–42. Available online: https://www.idpublications.org/wp-content/uploads/2022/04/Full-Paper-DESIGN-AND-OPTIMIZATION-OF-HYBRID-RENEWABLE-ENERGY-SYSTEM-FOR-RURAL-ELECTRIFICATION-OF-AN-OFF-GRID-COMMUNITY.pdf
5. Mishra, A.K.; Fezaa, L.H.A.; Bisht, Y.S.; et al. Hybrid Renewable Energy Systems: An Integrated Approach to Rural Electrification. *E3S Web of Conf.* **2024**, *540*, 01013. [CrossRef]
6. Adepoju, G.A.; Tijani, M.A.; Okelola, M.O.; et al. Application of Particle Swarm Optimization Method to Economic Dispatch of Nigerian Power System considering Valve-Point Loading Effect. *Premier J. Eng. Appl. Sci.* **2021**, *2(2)*. Available online: https://www.researchgate.net/publication/359817231_Application_of_Particle_Swarm_Optimization_Method_to_Economic_Dispatch_of_Nigerian_Power_System_Considering_Valve-Point_Loading_Effect
7. Tijani, M.A.; Adepoju, G.A.; Okelola, M.O. Optimization Approaches to Generation Dispatch: Review of Nigerian Power System. *Niger. J Technol. Dev.* **2022**, *19*, 156–163.
8. Anwar, A.; Siddique, M.; Dogan, E.; et al. The Moderating Role of Renewable and Non-Renewable Energy in Environment-Income Nexus for ASEAN Countries: Evidence from Method of Moments Quantile Regression. *Renew. Energy* **2021**, *164*, 956–967. [CrossRef]
9. Wadhawan, A.; Verma, P.; Grover, S.; et al. Economic Environmental Dispatch with PV Generation Including Transmission Losses Using PSO. In Proceedings of the 2016 IEEE 7th Power India International Conference (PIICON), Rajasthan, India, 25 November 2016; pp. 318–324.
10. Khan, U.T.; Zia, M.F. Optimization of Economic Load Dispatch for Distributed Energy System Using Metaheuristic Method. In Proceedings of the 2024 International Conference on Engineering & Computing Technologies (ICECT), Islamabad, Pakistan, 23 May 2024; pp. 1–6. [CrossRef]
11. Rahbar, K.; Chai, C.C.; Zhang, R. Energy Cooperation Optimization in Microgrids with Renewable Energy Integration. *IEEE Trans. Smart Grid* **2018**, *9*, 1482–1493. [CrossRef]
12. King, R.N.; Reynolds, M.; Sigler, D.; et al. Advanced Scenario Creation Strategies for Stochastic Economic Dispatch with Renewables. *arXiv preprint* **2018**, *arXiv:1806.10530*. [CrossRef]

13. Tijani, M.A.; Adepoju, G.A.; Okelola, M.O.; et al. Hybrid Optimization Technique for Solving Combined Economic Emission Dispatch Problem of Power Systems. *TEPES* **2022**, *2*, 158–167.
14. Liu, L.-N.; Yang, G.-H. Distributed Optimal Economic Environmental Dispatch for Microgrids Over Time-Varying Directed Communication Graph. *IEEE Trans. Netw. Sci. Eng.* **2021**, *8*, 1913–1924. [CrossRef]
15. Chen, W.; Liu, G.-P. Privacy-Preserving Consensus-Based Distributed Economic Dispatch of Smart Grids via State Decomposition. *IEEE/CAA J. Autom. Sinica* **2024**, *11*, 1250–1261. [CrossRef]
16. Huang, L.; Liu, B.; Chai, L. Distributed Dual Gradient Tracking Method for Economic Dispatch Problem. In Proceedings of the 35th Chinese Control and Decision Conference (CCDC), Yichang, China, 20 May 2023; pp. 1182–1187. [CrossRef]
17. Jamal, R.; Zhang, J.; Men, B.; et al. Solution to the Deterministic and Stochastic Optimal Reactive Power Dispatch by Integration of Solar, Wind-Hydro Powers Using Modified Artificial Hummingbird Algorithm. *Energy Rep.* **2023**, *9*, 4157–4173. [CrossRef]
18. Duan, Y.; Zhao, Y.; Hu, J. An Initialization-Free Distributed Algorithm for Dynamic Economic Dispatch Problems in Microgrid: Modeling, Optimization and Analysis. *Sustain. Energy Grids Netw.* **2023**, *34*, 101004. [CrossRef]
19. Manteaw, E.D.; Nicodemus, A.O. Combined Economic and Emission Dispatch Solution Using ABC_PSO Hybrid Algorithm with Valve Point Loading Effect. *Int. J. Sci. Res. Publ.* **2012**, *2*, 1–9. Available online: https://www.ijsrp.org/research-paper-1212.php?rp=P12538
20. Shahbaz, M.; Siddiqui, A.; Siddiqui, M.; et al. Exploring the Growth of Sustainable Energy Technologies: A Review. *Sustain. Energy Technol. Assess.* **2023**, *57*, 103157. [CrossRef]
21. Okelola, M.O.; Opoola, N.A.; Oyedokun, J.A.; et al. Optimization of Hybrid Renewable Energy Systems for Sustainable Rural Electrification in Kwara State, Nigeria: A Techno-Economic and Environmental Assessment. *J. Eng. Res. Rep.* **2025**, *27*, 45–57. [CrossRef]
22. Ramos, A.C.S.; Freitas, F.D.; Zizzo, G. Economic Dispatch Problem Solution via Holomorphic Embedding Method on IEEE 14-Bus System for Different Loading Scenarios. *IEEE Trans. on Ind. Applicat.* **2024**, *60*, 2664–2672. [CrossRef]
23. Gao, J.-T.; Tang, Y. Renewable Energy Utilization and Stability Through Dynamic Grid Connection Strategy and AI-Driven Solution Approach. *J. Energy Storage* **2024**, *95*, 112546. [CrossRef]
24. Mas'ud, A.A.; Salawudeen, A.T.; Umar, A.A.; et al. A Quasi Oppositional Smell Agent Optimization and Its Levy Flight Variant: A PV/Wind/Battery System Optimization Application. *Appl. Soft Comput.* **2023**, *147*, 110813. [CrossRef]
25. Ranjith Kumar, K.; Venkatesan, M.; Saravanan, R. A Hybrid Control Topology for Cascaded Multilevel Inverter with Hybrid Renewable Energy Generation Subsystem. *Sol. Energy* **2022**, *242*, 323–334. [CrossRef]
26. Mahdad, B.; Srairi, K. Solving Practical Economic Dispatch Problems Using Improved Artificial Bee Colony Method. *Int. J. Intell. Syst. Appl.* **2014**, *6*, 36–43. [CrossRef]
27. Asumadu, G.; Quaigrain, R.; Owusu-Manu, D.; et al. Analysis of Risks Factors Associated with Construction Projects in Urban Wetlands Ecosystem. *Int. J. Sustain. Dev. World Ecol.* **2023**, *30*, 198–210. [CrossRef]
28. Dincer, I. Renewable Energy and Sustainable Development: A Crucial Review. *Renew. Sustain. Energy Rev.* **2000**, *4*, 157–175. [CrossRef]
29. Oyedepo, S.O. Energy and Sustainable Development in Nigeria: The Way Forward. *Energy Sustain Soc* **2012**, *2*, 15. [CrossRef]
30. Sundaram, A. Multiobjective Multi Verse Optimization Algorithm to Solve Dynamic Economic Emission Dispatch Problem with Transmission Loss Prediction by an Artificial Neural Network. *Appl. Soft Comput.* **2022**, *124*, 109021. [CrossRef]
31. Oyedokun, J.A.; Fasina, E.T.; Adebanji, B.; et al. Electricity Challenges in Nigeria: Renewable Energy a Way Forward. *Global J. Eng. Tech. Adv.* **2022**, *11*, 016–023. [CrossRef]
32. Bhandari, B.; Lee, K.-T.; Lee, G.-Y.; et al. Optimization of Hybrid Renewable Energy Power Systems: A Review. *Int. J. of Precis. Eng. and Manuf.-Green Tech.* **2015**, *2*, 99–112. [CrossRef]
33. Fahim, K.E.; Silva, L.C.D.; Hussain, F.; et al. A State-of-the-Art Review on Optimization Methods and Techniques for Economic Load Dispatch with Photovoltaic Systems: Progress, Challenges, and Recommendations. *Sustainability* **2023**, *15*, 11837. [CrossRef]
34. Vesterstrom, J.; Thomsen, R. A Comparative Study of Differential Evolution, Particle Swarm Optimization, and Evolutionary Algorithms on Numerical Benchmark Problems. In Proceedings of the 2004 Congress on Evolutionary Computation, Portland, OR, USA, 19 June 2004; pp. 1980–1987. [CrossRef]
35. Piotrowski, A.P.; Napiorkowski, J.J.; Piotrowska, A.E. Particle Swarm Optimization or Differential Evolution—

A Comparison. *Eng. Appl. Artif. Intell.* **2023**, *121*, 106008. [CrossRef]
36. Bhavsar, S.; Pitchumani, R.; Ortega-Vazquez, M.A.; et al. A Hybrid Data-Driven and Model-Based Approach for Computationally Efficient Stochastic Unit Commitment and Economic Dispatch Under Wind and Solar Uncertainty. *Int. J. Electr. Power Energy Syst.* **2023**, *151*, 109144. [CrossRef]
37. Huang, K.; Cheng, L.; Qi, N.; et al. Security-Aware Coordinated Dispatch of Microgrid: An Adaptive Online Optimization Approach. In Proceedings of the 2024 IEEE Power & Energy Society General Meeting (PESGM), Seattle, WA, USA, 21 July 2024; pp. 1–5. [CrossRef]
38. Tang, Z.; Hill, D.J.; Liu, T. A Novel Consensus-Based Economic Dispatch for Microgrids. *IEEE Trans. Smart Grid* **2018**, *9*, 3920–3922. [CrossRef]
39. Bislimi, A.; Gashi, D. Challenges, Stability and Reliability of the Energy Network after the Continuous Addition of Renewable Energy Sources. In Proceedings of the 2022 UBT International Conference, Pristina, Kosovo, 29 October 2022.
40. Korunović, L.; Denić, T. Solving Combined Economic Emission Dispatch Problem of Power System Including PV Generation. *E3S Web Conf.* **2025**, *636*, 04004. [CrossRef]