Data Engineering and Applications

Review Paper

From Algorithms to Applications: Data-Centric Optimization for Distributed Power System Energy Management

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Abstract. With the rapid advancement of computer-driven optimization and artificial intelligence, energy management in distributed power systems (DPS) has emerged as a critical research focus in the power and energy sector. This review systematically summarizes recent progress in optimization algorithms for distributed power systems, highlighting their theoretical foundations, methodological diversity, and practical applications. First, traditional mathematical programming approaches are outlined, discussing their advantages in ensuring solution rigor while highlighting inherent limitations in handling nonlinearity and large-scale problems. Subsequently, the global search capabilities and adaptability of mainstream metaheuristic and swarm intelligence algorithms are evaluated, with detailed analysis of AI- and machine learning-based methods enabling data-driven forecasting and adaptive control. A comparative assessment of centralized versus distributed optimization frameworks follows, highlighting trade-offs between scalability, data privacy, and real-time responsiveness. Representative applications in microgrid dispatch, energy storage, renewable grid integration, multi-energy coupling, and demand response are critically reviewed, with a focus on operational benefits and deployment challenges. Finally, key theoretical controversies are explored, including scalability barriers, privacy and security concerns, and issues related to model interpretability and engineering standardization. Looking ahead, the paper identifies future research trends: the convergence of edge and cloud computing, federated learning, cyber-physical collaborative optimization, and the pursuit of autonomous self-healing energy systems. This comprehensive analysis aims to provide researchers and practitioners with a structured reference, foster the exchange of ideas, and support the sustainable development of distributed energy management.

Keywords: *Data-Centric Optimization, Distributed Power Systems, Machine Learning, Energy Management*

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Introduction

The global energy landscape is undergoing unprecedented and profound transformation, driven by three irreversible trends: the continuous rise of renewable energy penetration in the global power mix, the accelerated shift from traditional centralized to distributed power generation models, and the digital and intelligent upgrade across the entire power system chain. Traditional power grids, long centered on large-scale fossil fuel power plants like coal and gas and reliant on a "long-distance transmission, centralized control" model, are now rapidly evolving into new power network configurations where Distributed Power Systems (DPS) play a crucial role. Within this system, diverse energy resources—including solar photovoltaic arrays, distributed wind turbines, electrochemical storage devices, micro-gas turbines, and responsive loads with flexible regulation capabilities—are no longer confined to single power generation points. Instead, they are geographically dispersed and predominantly deployed directly at the consumer side or near load centers, achieving a "close proximity match" between energy production and consumption [1–3]. This structural shift is both an urgent necessity to address global climate change, reduce greenhouse gas emissions, and advance the energy system toward carbon neutrality, as well as an inevitable choice to enhance grid resilience against extreme weather and geopolitical risks, improve power supply reliability, and meet users' demands for personalized, efficient energy services.

However, the widespread adoption of distributed power systems (DPS) has introduced unprecedented complexity and challenges to energy management. Unlike centralized systems with relatively simple structures and clear control logic, distributed energy systems require the coordinated management of numerous highly heterogeneous energy resources—These resources exhibit significant differences in technical characteristics (intermittency of PV, charging/discharging constraints of energy storage), ownership (residential PV, commercial/industrial energy storage, public microgrids), and operational objectives (economic efficiency, environmental sustainability, autonomy). They often operate within complex environments characterized by uncertainty, dynamic changes, and partially observable information [4,5]. Specifically, the strong randomness of renewable generation influenced by natural conditions like sunlight and wind speed, bidirectional power flow fluctuations between distributed sources and the main grid, and the involvement of multiple stakeholders—including prosumers, power aggregators, microgrid operators, and distribution network companies—collectively create multifaceted management challenges. These challenges manifest primarily in four key areas: achieving precise real-time balancing of supply and demand power to prevent frequency fluctuations; implementing global optimization scheduling of Distributed Energy Resources (DER) to enhance overall utilization efficiency; employing technological means to integrate greater renewable energy penetration while reducing reliance on fossil fuels; and ensuring critical system performance metrics—such as voltage stability and power flow security—under complex operational fluctuations [6].

Against this backdrop, optimization algorithms have emerged as the core technological tools and fundamental support for tackling energy management challenges in distributed power systems. Starting from early mathematical programming methods (linear programming, integer programming) applied to linear problems such as economic dispatch and unit combination in traditional grids, optimization techniques have continuously evolved alongside increasing system complexity. They have progressively gained the capability to solve multi-objective, nonlinear, and high-dimensional complex problems. Today's modern optimization methodology has become increasingly diversified. It not only encompasses refined classical linear and nonlinear programming algorithms but also incorporates metaheuristic algorithms—including genetic algorithms, particle swarm optimization, ant colony optimization—and AI-based intelligent optimization methods such as deep learning-driven predictive optimization and reinforcement learning-driven dynamic scheduling. These advanced algorithms effectively handle high-dimensional decision spaces, non-convex constraints, and uncertainty factors that traditional methods struggle with [7,8]. Leveraging robust computational and optimization capabilities, they provide critical technological support for advanced functions in distributed power systems. These include real-time dynamic scheduling, refined demand response management, implementation of distributed energy trading mechanisms, and coordinated control among multiple microgrids. Consequently, they establish a solid computational foundation for building future power systems characterized by operational efficiency, cost control, and environmental sustainability.

Given the rapid proliferation of distributed power systems (DPS) and the urgent need for efficient energy management, coupled with the critical role optimization algorithms play in addressing system complexity, there is an urgent need for a comprehensive and up-to-date survey to systematically review the latest research advances in this field. This paper focuses on two core configurations—grid-connected and islanded microgrids—to provide a systematic review of optimization techniques applied to energy management in distributed power systems. Specifically, the reviewed algorithms span an extensive spectrum: they encompass classical mathematical programming methods such as linear programming, mixed-integer programming, and nonlinear programming—approaches that retain irreplaceable advantages in structured problems due to their rigorous mathematical foundations; It also encompasses metaheuristic approaches like genetic algorithms, particle swarm optimization, ant colony optimization, and their hybrid derivatives, which excel in global search and complex constraint adaptation. Additionally, it incorporates AI/ML-driven optimization techniques such as reinforcement learning and deep learning guided by predictive control, demonstrating unique potential in handling dynamic environments and uncertainty. Furthermore, it encompasses distributed and decentralized optimization frameworks represented by consensus algorithms and multi-agent systems, which offer novel approaches for collaborative management and privacy protection in large-scale systems.

This review aims to achieve multiple core objectives: First, to thoroughly explore the theoretical foundations and technological evolution of various mainstream optimization algorithms in distributed power system energy management; Second, it systematically analyzes the inherent strengths, application limitations, and typical use cases of different algorithms, conducting comparative performance evaluations based on specific research outcomes. Third, it clearly identifies key bottlenecks that current algorithms must overcome for practical engineering deployment, including scalability challenges during system expansion, data privacy protection issues in multi-agent collaboration, and model interpretability problems stemming from the "black box" nature of AI algorithms. Finally, it highlights emerging research trends and future technological directions poised to advance optimization-based energy management in distributed power systems [9,10].

The remainder of this paper is organized as follows. Section 2 reviews core optimization methods and assesses their applicability to the specific requirements of smart grids. In Section 3, we discuss the application of these algorithms in energy management for distributed power systems (DPS), such as microgrid dispatch, renewable energy integration, and demand response. Section 4 addresses current theoretical debates and critical issues in this field. Section 5 explores future research directions, focusing on technological trends that may influence next-generation distributed energy management systems. Finally, Section 6 summarizes the paper's key findings and their implications for research and practice

Core Optimization Technologies and Adaptability to Smart Grids

Classical Mathematical Programming Methods

The core of distributed power system (DPS) energy management optimization has historically relied on mathematical programming, a domain that offers rigor and interpretability for deterministic and stochastic problems. Linear Programming (LP) and Mixed-Integer Linear Programming (MILP) provide foundational tools for scheduling and dispatch in power networks. LP models are valuable for problems with linear objective functions and constraints, as in classical economic dispatch formulations [11]. MILP extends LP by incorporating binary or integer variables, thus enabling the modeling of unit commitment, start-up/shutdown logic, and grid topology decisions [12]. Nonlinear Programming (NLP) and Dynamic Programming (DP) address the inherent nonlinearities and temporal coupling present in distributed energy resources (DERs) and multi-period optimization. NLP accommodates quadratic and more complex objective functions, such as those arising from power flow equations and storage dynamics [13]. DP is particularly suited for sequential decision-making over multiple time-steps, supporting optimal scheduling of storage and demand response under uncertainty [14]. The general mathematical formulation of the DPS energy management problem is typically cast as:

$$\begin{aligned} \min_{x,u} \quad & f(x,u) \\ \text{s.t} \quad & g(x,u) = 0 \\ & h(x,u) \leq 0 \\ & x \in X, u \in U \end{aligned} \tag{1}$$

where x denotes the state variables, u the control variables, $f(\cdot)$ the objective (e.g., cost or emission minimization), $g(\cdot)$ equality constraints (e.g., power balance), $h(\cdot)$ inequality constraints (e.g., capacity limits), and X, U the feasible sets [15].

Classical approaches have been widely implemented in microgrid scheduling, economic dispatch, and unit commitment [16]. LP/MILP-based models have demonstrated scalability and precision in short-term operation. NLP and DP provide a more accurate representation of distributed network physics and storage management. However, these methods face notable limitations. The computational burden grows rapidly with system size and complexity, particularly for MILP and DP. The deterministic nature of most classical methods hampers their adaptability to stochastic renewable generation and real-time disturbances [17]. Table 1 illustrates the principal features and comparative advantages of LP, MILP, NLP, and DP in DPS energy management.

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Table 1. Comparison of classical optimization methods for DPS energy management

Method	Mathematical Nature	Typical Objective	Variables Type	Constraint Handling	Scalability	Solution Guarantee	Handling Nonlinearity	Temporal Coupling	Common Applications	Main Limitations
LP	Linear	Cost Minimization	Continuous	Linear	High	Global Optimum	Poor	Static or Single Period	Economic Dispatch	Linear Assumptions
MILP	Linear	Cost Unit Commitment	Mixed Binary or Integer	Linear	Medium	Global Optimum	Poor	Static or Single Period	Unit Commitment Switching	Computationally Intensive
NLP	Nonlinear	Cost Losses	Continuous	Nonlinear	Low to Medium	Local or Global (rare)	Good	Static or Single Period	Power Flow Storage Scheduling	Local Minima Complexity
DP	Recursive	Multi-stage Cost	Discrete or Continuous	Flexible	Low	Global Optimum	Good	Dynamic	Storage Demand Response	Curse of Dimensionality
QP	Quadratic	Quadratic Cost	Continuous	Linear or Quadratic	Medium	Global Optimum	Limited	Static or Single Period	Security Constrained Economic Dispatch	Limited to Quadratic Form
SOCP	Convex	Loss Minimization	Continuous	Convex	Medium	Global Optimum	Good	Static or Single Period	Optimal Power Flow Voltage Control	Convexity Required
MINLP	Mixed Nonlinear	Cost Unit Commitment Losses	Mixed	Nonlinear	Low	Local or Global (rare)	Good	Static or Single Period	Combined Heat and Power	Very High Complexity
MIP	Mixed Integer	Unit Commitment Scheduling	Mixed	Linear or Nonlinear	Medium	Global Optimum	Limited	Static or Single Period	Microgrid Scheduling	Large Scale Hard to Solve
Stochastic LP	Linear Probabilistic	Expected Cost	Continuous	Linear	Medium	Global Optimum	Limited	Dynamic	Renewable Uncertainty	Scenario Explosion
Robust Opt.	Set based	Worst case Cost	Continuous or Mixed	Flexible	Medium	Robust Solution	Limited	Static or Dynamic	Uncertainty Management	Conservative Solutions

Metaheuristic and Swarm Intelligence Algorithms

The limitations of mathematical programming in handling highly nonlinear, non-convex, and high-dimensional problems have motivated the adoption of metaheuristic and swarm intelligence algorithms in DPS optimization. Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) have attracted significant attention for their global search capabilities and robustness to local minima [18]. GA employs evolutionary operators—selection, crossover, mutation—to explore the solution space, showing effectiveness in DER scheduling and demand-side management. PSO mimics social behavior of particles, achieving rapid convergence in parameter tuning and multi-objective optimization. ACO, inspired by the foraging behavior of ants, is successfully utilized in network reconfiguration and distributed routing.

Hybrid metaheuristics, integrating the strengths of different algorithms, offer enhanced solution quality and convergence speed. Multi-objective variants, such as NSGA-II and MOPSO, enable simultaneous optimization of cost, emissions, and reliability, generating Pareto optimal fronts for operator decision-making [19]. Parameter sensitivity is a key concern, as improper tuning can result in premature convergence or excessive computational time. Recent literature highlights adaptive parameter control and hybridization as promising directions for improving metaheuristic performance [20]. Table 2 provides a synthesis of metaheuristic algorithms and their application domains within DPS energy management.

AI and Machine Learning-Based Optimization

The proliferation of data and computational resources has catalyzed the introduction of artificial intelligence (AI) and machine learning (ML) methods for DPS optimization. Deep Neural Networks (DNNs), Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs) are leveraged for load forecasting, renewable generation prediction, and system state estimation [21]. Reinforcement Learning (RL), particularly Deep RL (DRL) and multi-agent RL, enables real-time, adaptive control strategies that learn optimal policies through interaction with dynamic environments [22]. These methods are capable of handling complex, nonlinear mappings and exploiting high-dimensional input data, surpassing the capabilities of traditional approaches in dynamic, uncertain scenarios.

Explainability and real-time adaptation remain central challenges. While DNNs and RL algorithms deliver superior empirical performance, their black-box nature complicates validation and regulatory acceptance. Efforts to enhance interpretability through feature attribution and surrogate modeling are ongoing [23]. Real-time adaptation is increasingly realized through online learning and transfer learning, which allow models to adjust to evolving grid states and user preferences. Figure 1 illustrates a typical architecture for AI-driven energy management in distributed power systems, highlighting the integration of forecasting, optimization, and control modules.

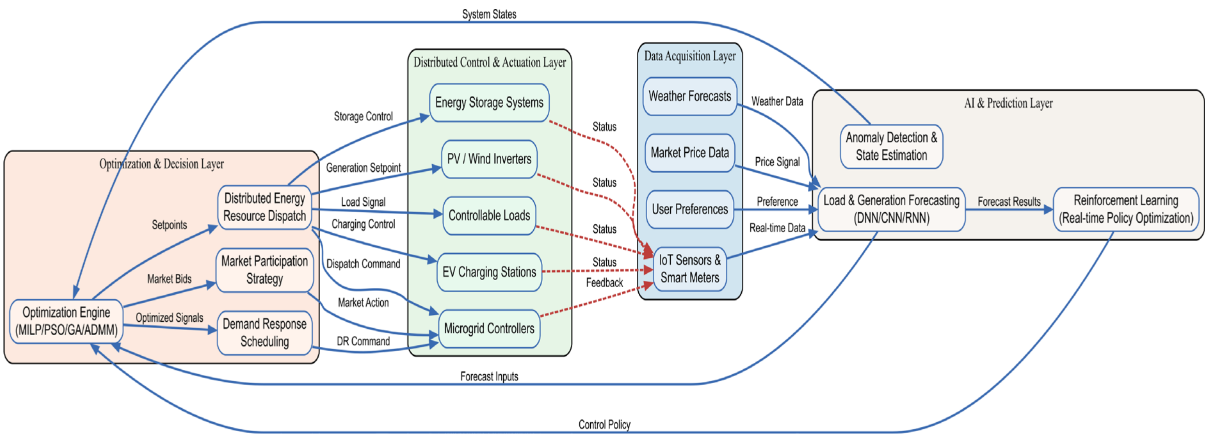

Figure 1 Architecture of AI-driven energy management in DPS

Table 2. Metaheuristic algorithms and their application in DPS

Algorithm	Search Strategy	Encoding	Objective Handling	Multi-objective Support	Adaptivity	Convergence Speed	Typical Applications	Scalability	Parameter Sensitivity	Hybridization Potential	Main Weaknesses
GA	Evolutionary	Binary or Real	Single or multi-objective	Yes NSGA-II High	High	Moderate	DER Scheduling DG Placement	Good	Medium	High	Premature Convergence
PSO	Swarm Intelligence	Real	Single or multi-objective	Yes MOPSO	High	Fast	Storage Optimization Load Dispatch	Good	Medium	Medium	Local Optima Trap
ACO	Probabilistic	Path based	Routing Scheduling	Yes	Moderate	Moderate	Network Reconfiguration	Medium	High	Medium	Slow for Large Problems
ABC	Swarm Intelligence	Real	Cost Losses	Limited	Moderate	Moderate	Power Loss Minimization	Medium	High	Medium	Stagnation Risk
DE	Evolutionary	Real	Single or multi-objective	Yes	Moderate	Fast	Renewable Integration	Good	Medium	High	Scaling Issues
SA	Probabilistic	Real or Discrete	Cost Minimization	Limited	Low	Slow	Unit Commitment	Low	Low	Low	Slow Convergence
TS	Memory based	Real or Discrete	Scheduling Routing	Limited	Low	Moderate	Microgrid Scheduling	Low	Low	Low	Trapping in Cycles
Hybrid GA-PSO	Hybrid	Real or Binary	Multi-objective	Yes	High	Fast	Multi-energy Optimization	Good	Medium	Very High	Complex Implementation
NSGA-II	Evolutionary	Real or Binary	Multi-objective	Yes	High	Moderate	Pareto Front Generation	Good	Medium	High	Non-deterministic
MOPSO	Swarm Intelligence	Real	Multi-objective	Yes	High	Fast	Multi-objective Dispatch	Good	Medium	High	Parameter Tuning

Distributed and Decentralized Optimization

Distributed and decentralized optimization frameworks have emerged as indispensable in the context of large-scale, geographically dispersed DPS. Consensus algorithms and the Alternating Direction Method of Multipliers (ADMM) decompose the global optimization problem into subproblems solved locally by individual agents, facilitating scalability and privacy preservation [24]. Multi-agent systems and federated learning further enhance autonomy and robustness by enabling agents to learn and coordinate without centralized data aggregation. These paradigms are particularly relevant for peer-to-peer energy trading, local voltage regulation, and federated microgrid control.

Communication and privacy issues pose significant technical barriers. Reliable, low-latency communication channels are essential for convergence and stability. Privacy-preserving mechanisms, such as differential privacy and secure multiparty computation, are being developed to address data security and regulatory compliance [25]. Table 3 compares distributed and centralized optimization, outlining their respective advantages and disadvantages in terms of scalability, privacy, and operational resilience.

Table 3. Distributed vs. centralized optimization: Pros and cons (CSV format)

Aspect	Centralized Optimization	Distributed or Decentralized Optimization
Scalability	Limited for large scale systems	Excellent supports large scale and expansion
Data Privacy	Requires data centralization low privacy	Local data processing high privacy
Communication Load	Central server bottleneck high data transfer	Peer to peer local communication scalable load
Fault Tolerance	Single point of failure risk	High resilience local autonomy
Computational Load	Centralized needs powerful server	Distributed among agents parallelizable
Real-time Response	Limited by central processing and communication delay	Fast local decisions possible
Implementation	Easier to manage mature software	Complex coordination emerging standards
Adaptability	Less adaptive to dynamic changes	Highly adaptive to local disturbances
Optimality	Global optimality possible if tractable	May yield suboptimal but feasible solutions
Security Risks	Vulnerable to centralized attacks	More robust but exposed to communication security issues
Application Scope	Small or medium microgrid well instrumented systems	Large scale peer to peer trading federated microgrids
Example Algorithms	LP MILP NLP DP	Consensus ADMM Multi agent RL Distributed PSO

Applications of Optimization Algorithms in DPS Energy Management

The deployment of advanced optimization algorithms has fundamentally transformed the operational landscape of distributed power systems (DPS), enabling precise scheduling, resource allocation, and system-level coordination. The following subsections review the key applications of these algorithms in microgrid scheduling, storage and renewables integration, multi-energy coupling, and demand response—each representing a cornerstone of intelligent energy management. The interplay between algorithmic sophistication and practical deployment continues to drive both academic inquiry and industrial innovation [26].

Microgrid Energy Management Scheduling

Microgrid energy management is a quintessential application of optimization in DPS, where the goal is to coordinate distributed energy resources (DERs), storage units, and controllable loads to achieve cost-efficient, reliable, and sustainable operations. Day-ahead and real-time scheduling constitute the dual pillars of microgrid optimization.

Day-ahead and Real-time Optimization

Day-ahead scheduling is formulated as a multi-period optimization problem, typically solved using MILP, dynamic programming, or advanced metaheuristics. The objective incorporates operational cost minimization, emission reduction, and reliability constraints. Real-time optimization, on the other hand, addresses intra-day uncertainties—such as load fluctuations and renewable generation variability—by leveraging receding-horizon control, stochastic programming, and reinforcement learning-based adaptation [27]. Algorithmic frameworks must balance computational tractability with solution quality, particularly under high renewable penetration scenarios.

Case Studies and Practical Implementations

Recent field demonstrations validate the efficacy of hybrid optimization approaches, including combined MILP-PSO and deep reinforcement learning, in microgrid control centers. Studies show improved operational economics and enhanced resilience, particularly in islanded and grid-connected modes. Results from commercial testbeds highlight the significance of interoperability and distributed execution. Figure 2 presents a flowchart of the microgrid scheduling optimization process, illustrating the integration of forecasting, optimization, and real-time control modules. The workflow integrates forecasting, multi-objective optimization, and distributed control, forming a closed-loop scheduling mechanism for robust microgrid operation.

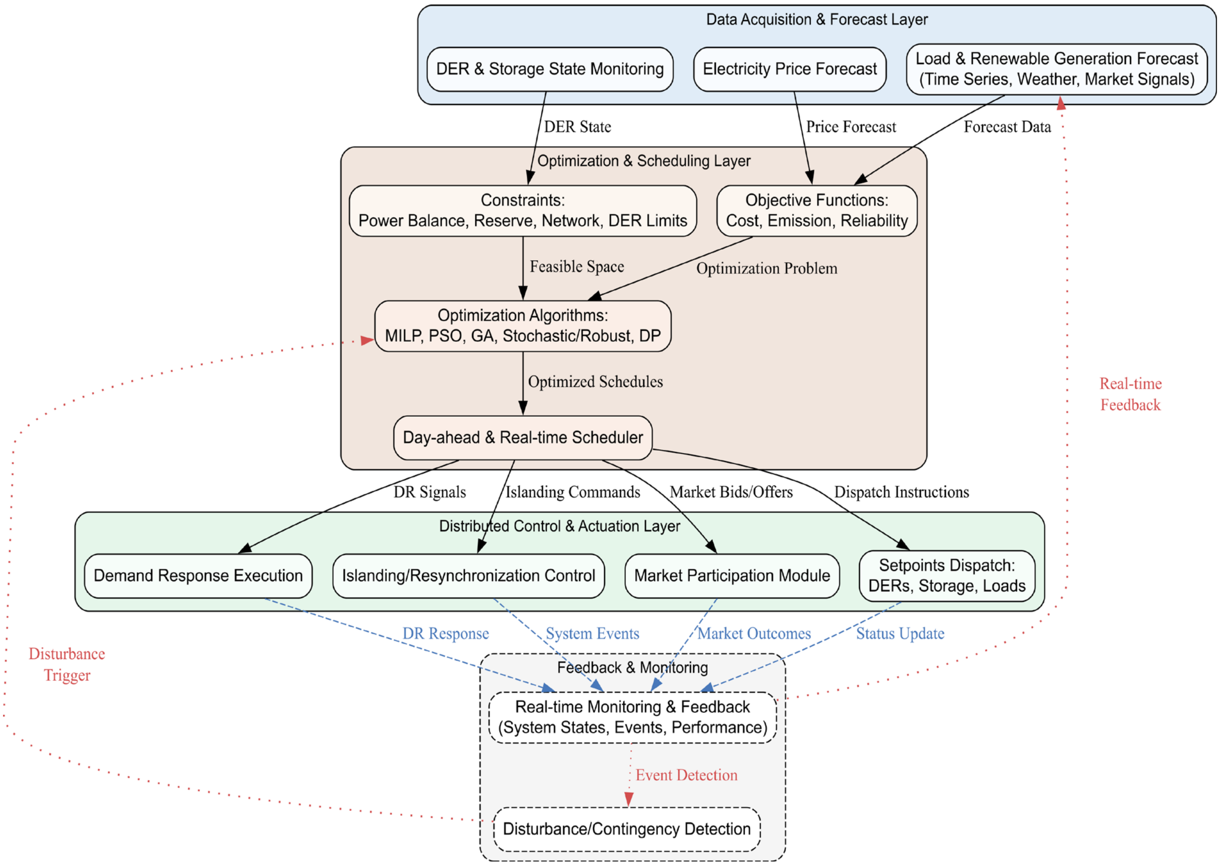

Figure 2 Microgrid scheduling optimization flowchart.

Energy Storage and Renewable Integration

The proliferation of energy storage systems and variable renewables has intensified the need for robust optimization schemes that ensure system flexibility and adequacy.

Optimization for Battery and Storage Systems

Optimal sizing, placement, and dispatch of batteries are formulated as mixed-integer nonlinear programming tasks. Algorithms such as genetic algorithms, PSO, and ADMM are widely employed to account for nonlinear degradation models, time-of-use tariffs, and network constraints [28]. Coordinated battery scheduling enhances energy arbitrage, peak-shaving, and frequency regulation capabilities, directly supporting grid stability.

Handling Renewable Energy Uncertainty

Renewable generation introduces stochasticity that challenges deterministic scheduling paradigms. Scenario-based stochastic programming, robust optimization, and probabilistic forecasting are increasingly utilized to hedge against forecast errors and enable risk-informed decision-making. Recent comparative studies highlight those metaheuristics, when combined with probabilistic models, significantly outperform classical methods in terms of solution robustness and computational efficiency [29]. Table 4 provides a performance comparison of leading optimization algorithms applied to storage and renewable integration, referencing empirical benchmarks from recent literature.

Table 4. Performance comparison of algorithms for storage and renewables.

Algorithm	Solution Quality	Computational Time	Robustness to Uncertainty	Scalability	Practical Deployment	Reference
MILP	High	Medium-High	Medium	Medium	Widely Used	[30]
PSO	High	Medium	High	High	Field Pilots	[31]
GA	Medium-High	Medium-High	Medium-High	High	Demonstrations	[32]
Stochastic Programming	High	High	High	Medium	Limited	[33]
Robust Optimization	Medium	Medium	Very High	Medium	Increasing	[34]
ADMM	High	Low-Medium	High	Very High	Emerging	[35]

Multi-energy and Coupled Systems

As energy systems become increasingly integrated, the optimization of multi-energy systems (MES)—combining electricity, gas, and heat—has emerged as a critical research frontier.

Integrated Electricity-Gas-Heat Optimization

The MES optimization problem is inherently large-scale and multi-domain, requiring coordinated scheduling across sectors. MILP, decomposition, and distributed optimization methods are prominent, enabling joint consideration of network constraints, conversion efficiencies, and multi-carrier storage. Coupled modeling frameworks facilitate the holistic minimization of system-wide operational costs and emissions [36].

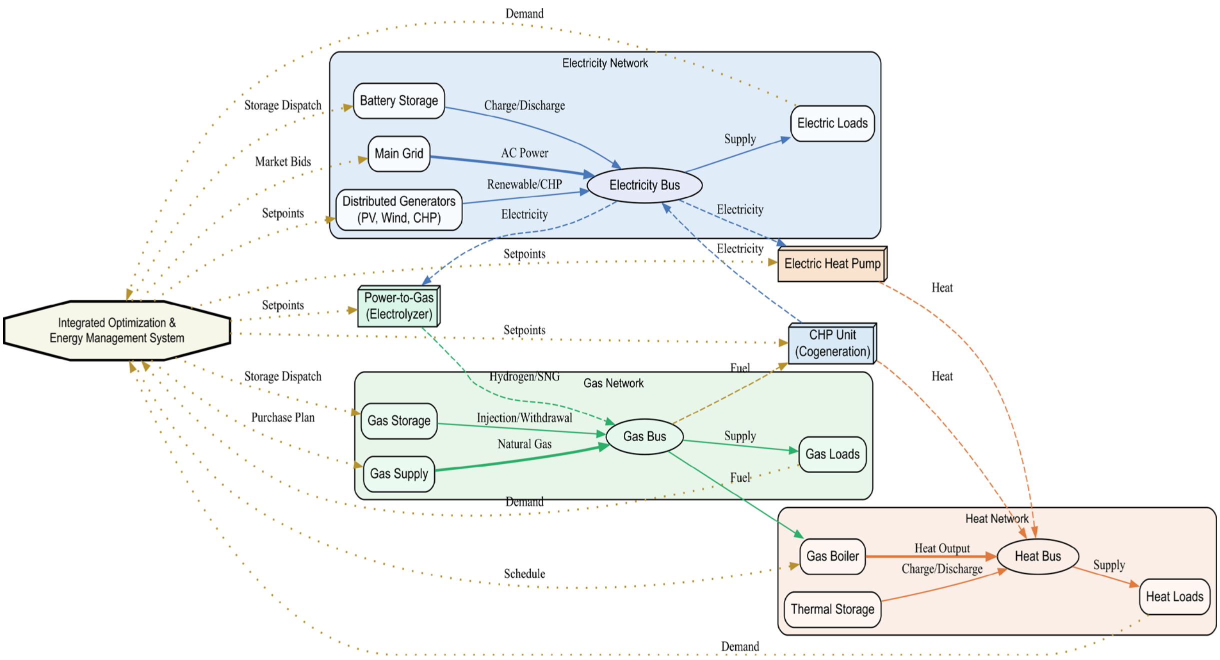

Figure 3 Integrated energy system schematic.

Sector Coupling and Flexibility Analysis

Sector coupling unlocks additional flexibility, particularly through power-to-gas and combined heat and power units. Optimization algorithms assess cross-sectoral synergies, quantifying the value of temporal and spatial flexibility. Recent advances in ADMM-based distributed coordination and multi-agent reinforcement learning have demonstrated superior scalability and adaptability in integrated system operations. Figure 3 provides a schematic representation of an integrated energy system, highlighting the interconnections and optimization interfaces between electricity, gas, and heat domains.

The schematic illustrates the coupling of electricity, gas, and heat networks in a typical integrated energy system. Sector-coupling devices—including CHP units, power-to-gas electrolyzers, and electric heat pumps—enable multi-energy flow, while the optimization and management layer coordinates setpoints and schedules across all subsystems. This structure supports holistic energy management and flexibility provision in modern multi-carrier energy networks.

Demand Response and User-side Management

Demand response (DR) represents a pivotal mechanism for enhancing system flexibility and economic efficiency in DPS.

Demand-side Bidding and Flexibility

DR optimization models capture user-side flexibility through load-shifting, real-time pricing, and automated bidding strategies. MILP and metaheuristics are widely applied for aggregating distributed flexibility resources and optimizing participation in electricity markets. Empirical studies report significant cost savings, peak load reduction, and improved system reliability.

Privacy-preserving Optimization Approaches

As user data becomes increasingly critical in DR programs, privacy-preserving optimization has gained traction. Federated learning, secure multi-party computation, and distributed optimization frameworks enable energy management without direct data sharing, thus addressing regulatory and ethical concerns. Comparative analysis reveals that such approaches retain high solution quality while minimizing privacy risks.

Key Challenges and Theoretical Controversies

The integration of optimization and artificial intelligence into distributed power systems (DPS) energy management has spurred remarkable progress, yet it also introduces new theoretical and engineering challenges. This section systematically reviews four primary dimensions of ongoing debate and technical difficulty: scalability and computational complexity, data privacy and security, model interpretability and reliability, and the engineering deployment gap. The following analysis synthesizes findings across the literature to highlight both unresolved issues and emerging research frontiers [37].

Scalability and Computational Complexity

The expansion of DPS from isolated microgrids to interconnected regional systems has significantly increased the dimensionality and coupling of optimization problems. Scalability remains a critical barrier, with the computational tractability of mainstream algorithms under continuous scrutiny.

Large-scale System Coordination

Coordinating thousands of distributed energy resources (DERs), storage units, and controllable loads exacerbates the curse of dimensionality in both centralized and distributed optimization frameworks. Decomposition techniques, such as Lagrangian relaxation and ADMM, have improved problem partitioning and parallelism, yet they often introduce convergence and feasibility trade-offs. Hierarchical and multi-agent architectures further enhance modularity, but their performance degrades with increased inter-agent communication and network latency [38].

Real-time Optimization Constraints

Real-time market participation and frequency regulation demand sub-second optimization cycles, challenging even the most efficient metaheuristics and convex solvers. Research shows that surrogate models and fast linear approximations can accelerate computation, but at the expense of solution fidelity and robustness. Hybrid approaches, which combine offline scenario analysis with online receding-horizon control, partially mitigate timing constraints but add algorithmic complexity [39]. Table 5 provides a comparative assessment of scalability across mainstream optimization algorithms, synthesizing empirical and theoretical results from recent studies [40].

Data Privacy and Security

The proliferation of user-level data and distributed optimization protocols has brought privacy and cybersecurity to the forefront of DPS research. Theoretical and practical vulnerabilities are under ongoing investigation.

Privacy-preserving Optimization

Preserving customer privacy in demand response and distributed scheduling is frequently achieved using aggregation, differential privacy, and cryptographic methods. Despite advances, federated learning and homomorphic encryption remain computationally intensive and can degrade solution quality. The literature documents a fundamental trade-off between privacy preservation and optimization efficiency in real-world deployments [41].

Attack-resilient Distributed Algorithms

Distributed consensus and optimization algorithms are inherently vulnerable to data injection, replay, and denial-of-service attacks. Recent research proposes resilient consensus protocols and anomaly detection layers, but adversarial actors can still compromise convergence and system stability. The lack of standardized security benchmarks further complicates comparative analysis across algorithmic approaches [42].

Model Interpretability and Reliability

The adoption of AI-based optimization solvers has triggered debate over explainability, trustworthiness, and operational transparency.

Explainability of AI-based Solutions

Black-box models, including deep reinforcement learning and ensemble metaheuristics, often outperform classical approaches in high-dimensional dynamic environments. However, their decision logic is rarely transparent, limiting operator trust and regulatory acceptance. Recent work introduces post-hoc explainability tools, such as SHAP values and surrogate interpretable models, but these are often insufficient in safety-critical applications [43].

4.3.2 Black-box vs. White-box Models

White-box optimization, grounded in physical laws and explicit constraints, offers superior interpretability but struggles with modeling uncertainty and system complexity. Black-box approaches adapt more flexibly to nonlinearity and incomplete data, yet lack formal performance guarantees. The field remains divided over the optimal balance between transparency and adaptivity, with some advocating hybrid frameworks that combine both paradigms [44].

4.4 Engineering Deployment and Standardization

Translating theoretical advances into operational systems remains a persistent challenge, hindered by gaps in standardization and benchmarking.

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Table 5. Scalability comparison of mainstream algorithms for DPS energy management.

Algorithm	Problem Size Tolerance	Distributed Capability	Real-time Feasibility	Memory Requirement	Communication Overhead	Convergence Guarantee	Field-Proven Scalability	Reference
MILP	Medium	Limited	Low	High	Low	Yes (Global)	Microgrids	[40]
NLP	Small-Medium	Limited	Low	High	Low	Local	Small-scale	[40]
DP	Small	No	Very Low	Very High	None	Yes (Global)	Toy examples	[41]
PSO	Large	Yes	Medium	Moderate	Moderate	No	Pilot projects	[41]
GA	Large	Yes	Medium	Moderate	Moderate	No	Demonstrations	[42]
ADMM	Very Large	Yes	High	Low	High	Yes (Convex)	Regional grids	[42]
TS	Medium	Limited	Medium-Low	Moderate	Low	No	Case studies	[43]
Robust Opt.	Medium	Possible	Medium-Low	High	Low	Yes	Limited	[43]
Stochastic Prog.	Small-Medium	Possible	Low	Very High	Low	Yes	Research stage	[44]
Multi-agent RL	Very Large	Yes	High	Moderate	High	No	Simulations	[45]

4.4.1 From Simulation to Real-world Application

Many optimization frameworks demonstrate impressive results in simulation but face substantial obstacles in hardware integration, legacy system compatibility, and cyber-physical interface stability. Field deployments reveal a mismatch between algorithmic assumptions and real-world constraints, including communication delays, measurement noise, and actuator limits. Industry experience suggests that iterative co-design of algorithms and hardware is essential for successful scaling [45].

4.4.2 Standardization and Benchmarking Needs

The absence of universally accepted benchmarks and performance metrics impedes objective comparison and technology transfer. Diverse test systems, inconsistent data granularity, and nonuniform evaluation criteria create barriers to reproducibility and cross-validation. Recent initiatives advocate for open-source testbeds, standardized datasets, and protocol harmonization to accelerate field adoption and regulatory approval [37].

5. Future Research Trends

The rapidly evolving landscape of distributed power systems (DPS) continues to drive both theoretical advancement and practical innovation in energy management. As the complexity and interconnectedness of modern energy networks increase, future research is expected to be shaped by cross-disciplinary integration, adaptive intelligence, and heightened attention to cyber-physical resilience. This section outlines several pivotal directions for the next generation of optimization-based DPS energy management, synthesizing recent scholarly consensus and highlighting open questions [46].

5.1 Integration of Edge and Cloud Computing

The convergence of edge and cloud computing is poised to redefine the computational fabric of DPS energy management. Edge computing facilitates ultra-low latency control, local resilience, and data privacy by enabling distributed analytics and decision-making at the device or microgrid level. Cloud platforms, in contrast, provide the scalability and storage necessary for large-scale optimization, historical data mining, and system-wide forecasting. Hybrid edge-cloud architectures are anticipated to enable seamless orchestration of computational tasks, adaptive model deployment, and real-time system monitoring. Research must address the challenges of resource allocation, task offloading, and fault tolerance in heterogeneous network environments [47].

5.2 Advances in Federated and Transfer Learning

The application of federated and transfer learning methodologies is emerging as a transformative force for privacy-preserving and data-efficient optimization in DPS. Federated learning allows collaborative model training across multiple agents or microgrids without centralizing sensitive data, thus addressing privacy and regulatory concerns. Transfer learning enables knowledge reuse across similar operational contexts, reducing the need for exhaustive retraining and expediting the adaptation to new environments. Key research topics include the development of robust aggregation protocols, quantification of transferability across heterogeneous systems, and mitigation of adversarial manipulation during decentralized learning [48].

5.3 Co-optimization with Market and Cyber-physical Security

The integration of market dynamics and cyber-physical security constraints into optimization frameworks is becoming increasingly urgent. Future research must move beyond traditional cost and network objectives to explicitly co-optimize market participation, ancillary service provision, and system resilience against cyber-physical threats. This requires a synthesis of stochastic market modeling, game theory, and attack-resilient optimization algorithms. Theoretical models must also bridge the gap between economic incentives and operational security, ensuring that market-driven actions do not inadvertently expose DPS assets to new vulnerabilities [49].

5.4 Towards Autonomous and Self-healing Energy Systems

The vision of autonomous, self-healing energy systems represents a paradigm shift for DPS management. Future architectures will leverage multi-agent reinforcement learning, distributed diagnostics, and real-time feedback to enable adaptive restoration and operational continuity in the face of disturbances. Research is expected to focus on the design of decentralized coordination protocols, robust anomaly detection mechanisms, and hierarchical control structures that enable both local autonomy and global system coherence. Achieving self-healing capabilities will depend on advances in sensor fusion, event-driven analytics, and the seamless integration of cyber and physical layers [50].

Figure 4 presents a comprehensive roadmap for future research on energy management in optimized distributed power systems (DPS), integrating technological, methodological, and systemic dimensions. It highlights the convergence of several key trends: the integration of edge-cloud computing, the application of federated learning and transfer learning techniques, collaborative optimization strategies balancing market dynamics and security constraints, and the evolution toward autonomous and self-healing energy systems.

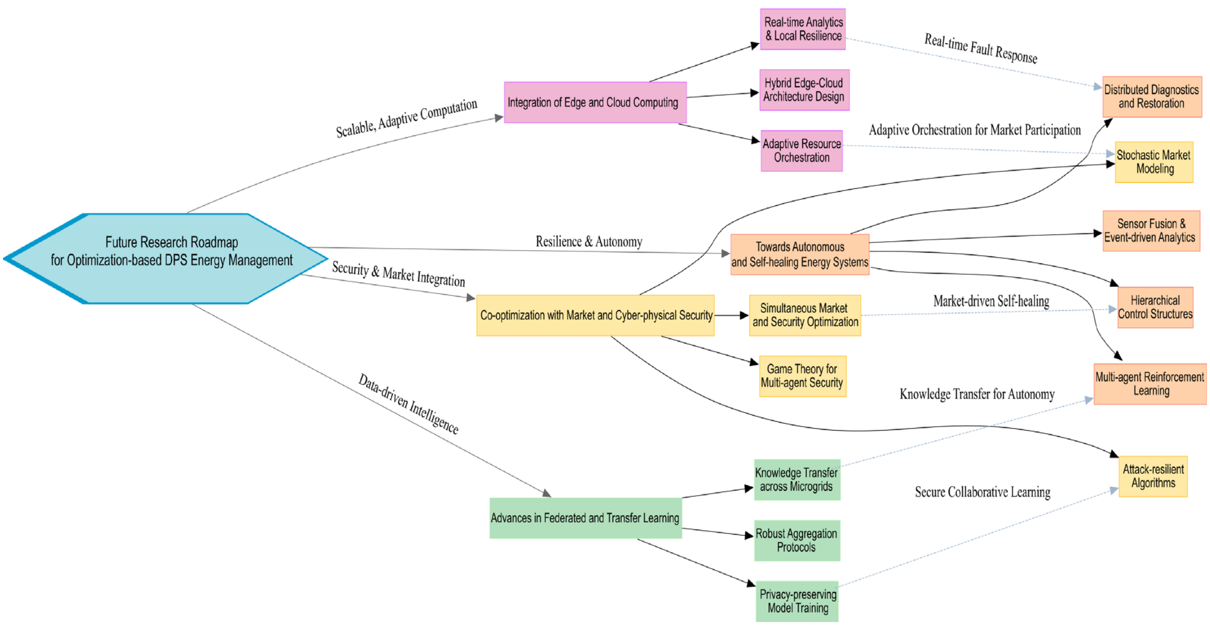

Figure 4 Future research roadmap for optimization-based DPS energy management.

6. Conclusion

This review has systematically examined the state-of-the-art in optimization-based energy management for distributed power systems (DPS), with a particular focus on algorithmic advances, integration challenges, and pressing theoretical controversies. The analysis has highlighted several core findings. The evolution from centralized to distributed and hierarchical optimization frameworks has significantly improved scalability and flexibility in DPS operation, yet has also introduced new forms of computational complexity and coordination bottlenecks. The growing adoption of artificial intelligence and data-driven methodologies offers potential for adaptive, robust, and predictive control, but simultaneously raises critical concerns regarding model transparency, reliability, and cyber-physical security. The interplay between energy, market, and cyber domains is increasingly recognized as a defining feature of modern DPS, necessitating holistic approaches that bridge technical, economic, and regulatory objectives.

The findings of this review bear important implications for both academic research and practical deployment. For researchers, the persistent challenges of scalability, privacy preservation, and model interpretability call for the development of hybrid approaches that balance mathematical rigor with data-driven adaptivity. Advancements in federated learning, edge-cloud architectures, and resilient optimization algorithms indicate promising directions for overcoming current limitations. For practitioners, the gap between simulation-based validation and field deployment remains a significant hurdle. Real-world implementation demands not only algorithmic excellence, but also attention to interoperability, standardization, and ongoing system monitoring. The increasing presence of distributed energy resources, flexible loads, and cyber vulnerabilities underscores the necessity of multidisciplinary design, where engineering, information science, and regulatory compliance converge.

Looking ahead, the trajectory of optimization-based energy management in distributed power systems is set to be shaped by deeper integration of computational intelligence, enhanced cyber-physical resilience, and greater automation of operational processes. The transition toward autonomous, self-healing, and market-responsive DPS will require innovative solutions that are both theoretically robust and practically viable. Sustainable success in this domain will depend on collaborative progress across academia, industry, and policy-making spheres. The ongoing convergence of optimization theory, artificial intelligence, and engineering practice offers both unprecedented opportunities and formidable challenges, marking a new chapter in the evolution of distributed energy systems.

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