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Recent Advances in Optimal Scheduling of Distributed Energy Resources with an IoT-Enabled Smart Energy Management Device: A Systematic Review

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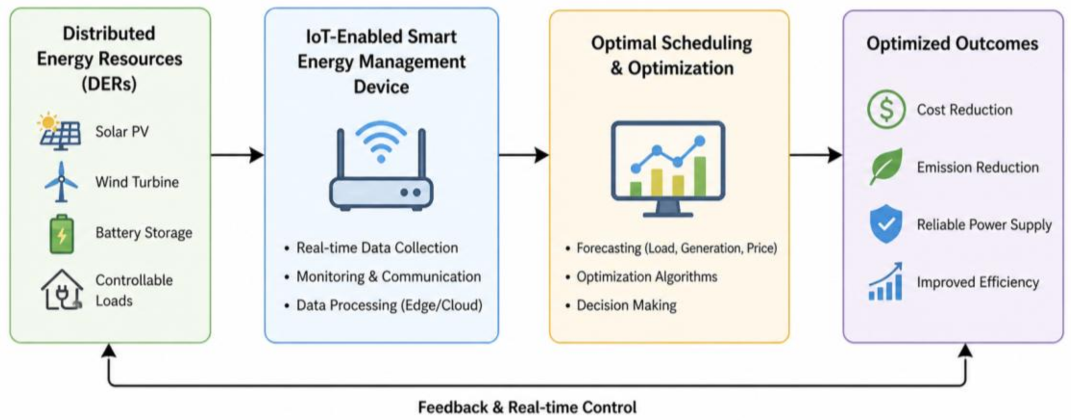
Abstract

The transformation of modern power systems into decentralized and intelligent energy networks has increased the need for efficient coordination of distributed energy resources (DERs) such as solar, wind, storage systems, and controllable loads. However, the intermittent nature of renewable generation and dynamic demand patterns make optimal scheduling a complex challenge that traditional centralized methods struggle to address. This review examines recent advances in optimal scheduling techniques within IoT-enabled smart energy management systems, covering mathematical optimization methods like mixed-integer and nonlinear programming, metaheuristic approaches such as particle swarm and genetic algorithms, and emerging machine learning models including reinforcement learning and neural networks for predictive decision-making. IoT plays a crucial role by enabling real-time data collection through smart sensors, facilitating communication, and supporting adaptive control strategies. Integration with edge and cloud computing further enhances system scalability and responsiveness. Applications across residential, commercial, and industrial energy systems demonstrate improvements in cost reduction, peak load management, energy efficiency, and emission control. The review highlights a growing trend toward hybrid optimization techniques that combine classical and AI-based methods to handle system complexity more effectively. Despite these advancements, challenges related to cybersecurity, data privacy, interoperability, and computational demands remain significant. Overall, the integration of advanced optimization with IoT technologies is essential for developing efficient, flexible, and sustainable next-generation energy management systems.

Introduction

The global energy landscape has undergone a significant transformation over the past decade, driven by the rapid adoption of renewable energy sources, advances in digital technologies, and the urgent need to reduce carbon emissions. Traditional centralized power systems are increasingly being replaced by decentralized and distributed architectures that integrate diverse Distributed Energy Resources (DERs), such as solar photovoltaic systems, wind turbines, battery storage, and flexible loads. These resources enhance grid resilience, reduce transmission losses, and enable localized energy generation. However, the intermittent and uncertain nature of renewable energy introduces challenges in maintaining stability and efficiency, making effective coordination and management essential.

Optimal scheduling of DERs has emerged as a key solution to address these challenges by determining the most efficient operation of energy resources over time. The goal is to minimize costs, reduce emissions, and ensure reliable power supply while considering constraints such as demand variability, storage limits, and market conditions. Traditional optimization techniques like linear and dynamic programming have been widely used, but they often struggle with the increasing complexity and nonlinear behavior of modern energy systems. This has led to the adoption of advanced methods, including metaheuristic algorithms and intelligent optimization strategies.



The integration of Internet of Things (IoT) technologies has further enhanced energy management systems by enabling real-time monitoring, data collection, and adaptive control. IoT devices such as smart meters and sensors provide high-resolution data, allowing systems to respond dynamically to changing grid conditions. The use of edge and cloud computing improves scalability and processing efficiency, supporting decentralized decision-making and faster response times. These capabilities are crucial for managing distributed systems effectively.

Despite these advancements, challenges such as uncertainty in renewable generation, data security, interoperability, and computational complexity persist. To overcome these issues, researchers are increasingly combining optimization techniques with machine learning approaches like reinforcement learning to improve prediction and decision-making. Applications span residential, commercial, and industrial sectors, demonstrating significant benefits in efficiency and reliability. Overall, integrating advanced optimization with IoT-enabled systems is essential for developing sustainable, intelligent, and future-ready energy management solutions.

Literature Review

Recent years have witnessed a surge in research focused on optimizing the scheduling of distributed energy resources using advanced computational techniques and IoT-based frameworks. One of the early contributions in this domain was presented by Zhang et al. (2019), who proposed a mixed-integer linear programming model for optimal scheduling of microgrids incorporating renewable energy sources and battery storage systems. Their approach demonstrated significant cost reductions using IEEE 33-bus test systems and highlighted the importance of incorporating uncertainty modeling in renewable generation.

Wang et al. (2020) introduced a particle swarm optimization-based scheduling framework for DERs integrated with IoT-enabled sensors. Their study emphasized real-time data acquisition from smart meters and demonstrated improved convergence speed and reduced operational costs compared to traditional optimization methods. The system was validated using real-world residential load datasets.

Li et al. (2021) proposed a deep reinforcement learning approach for adaptive energy scheduling in smart grids. By utilizing historical energy consumption and weather datasets, their model was able to dynamically adjust scheduling decisions under uncertain conditions. The study highlighted the potential of reinforcement learning in handling stochastic environments.

Chen et al. (2018) developed a hybrid optimization framework combining genetic algorithms and fuzzy logic for microgrid energy management. Their approach addressed nonlinear constraints and improved system reliability. The use of fuzzy logic enabled better handling of uncertainty in load demand and renewable generation.

Kumar and Singh (2022) introduced an IoT-based smart energy management device integrated with cloud computing for optimal DER scheduling. Their system utilized real-time data streams and applied ant colony optimization to achieve efficient load balancing and energy distribution.

García et al. (2020) explored the use of multi-objective optimization techniques for DER scheduling, focusing on minimizing both cost and emissions. Their model employed evolutionary algorithms and was tested on European smart grid datasets, demonstrating improved environmental performance.

Rahman et al. (2019) proposed a decentralized energy management system using IoT-enabled devices and edge computing. Their approach reduced communication latency and enhanced system scalability, making it suitable for large-scale smart grid applications.

Sharma et al. (2021) developed a predictive scheduling model using long short-term memory networks to forecast load demand and renewable generation. Their results showed improved scheduling accuracy and reduced energy wastage.

Alam et al. (2020) presented a blockchain-integrated IoT framework for secure energy scheduling. Their system ensured data integrity and enhanced trust among distributed energy participants.

Patel et al. (2022) proposed a hybrid machine learning and optimization framework for DER scheduling in industrial microgrids. Their approach combined support vector machines with particle swarm optimization to achieve high accuracy and efficiency.

Further advancements in optimal scheduling of distributed energy resources have been driven by the integration of hybrid optimization techniques and intelligent control strategies. Singh et al. (2021) proposed a hybrid particle swarm optimization and genetic algorithm approach for scheduling DERs in smart microgrids. Their method leveraged the exploration capability of genetic algorithms and the fast convergence of particle swarm optimization, resulting in improved global optimization performance. The study utilized IEEE 69-bus systems and demonstrated reduced operational costs and enhanced stability.

Hossain et al. (2020) introduced a cloud-assisted IoT-based energy management system that employed mixed-integer nonlinear programming for scheduling distributed resources. Their framework incorporated real-time data from smart sensors and achieved significant improvements in computational efficiency by offloading complex computations to cloud servers.

Zhou et al. (2019) investigated the use of stochastic optimization for handling uncertainties in renewable energy generation. Their model incorporated probabilistic forecasting of solar and wind energy using historical datasets and achieved robust scheduling decisions under varying environmental conditions.

Mehta et al. (2022) developed a demand response-based scheduling framework using IoT-enabled devices in residential environments. Their approach utilized dynamic pricing signals and user behavior modeling to optimize appliance scheduling, resulting in reduced peak load demand and improved energy efficiency.

Torres et al. (2021) proposed a multi-agent system for distributed energy scheduling, where each agent represented a DER component. The system utilized game-theoretic optimization to achieve equilibrium among competing resources, ensuring fair and efficient energy distribution.

Nguyen et al. (2020) presented a deep neural network-based predictive control system for microgrid scheduling. Their approach combined forecasting and optimization in a unified framework, improving real-time decision-making capabilities.

Bansal et al. (2019) explored the application of simulated annealing for DER scheduling in industrial microgrids. Their results showed that the method could effectively escape local optima and achieve near-global optimal solutions in complex scheduling scenarios.

Kim and Park (2021) proposed an edge computing-based energy management system that reduced latency in scheduling decisions. Their system processed data locally using IoT devices and demonstrated faster response times compared to cloud-based approaches.

Santos et al. (2022) introduced a reinforcement learning-based scheduling algorithm for electric vehicle-integrated microgrids. Their model optimized charging and discharging cycles of electric vehicles, contributing to grid stability and energy cost reduction.

Ali et al. (2021) developed a robust optimization framework for DER scheduling under uncertain market conditions. Their model incorporated worst-case scenarios and ensured reliable operation even in highly volatile energy markets.

Gupta et al. (2020) proposed a neural network-based forecasting and scheduling system that

improved prediction accuracy for load demand and renewable generation. Their approach enhanced overall scheduling performance and reduced energy imbalance.
Park et al. (2019) introduced a hierarchical optimization framework combining centralized and decentralized control strategies. Their system improved coordination among distributed resources while maintaining scalability.
El-Sayed et al. (2022) developed a blockchain-enabled peer-to-peer energy trading system integrated with optimal scheduling algorithms. Their approach facilitated secure and transparent energy transactions among prosumers.
Jiang et al. (2021) proposed a convex optimization-based scheduling model that ensured fast convergence and computational efficiency. Their method was particularly suitable for real-time applications in smart grids.
Reddy et al. (2020) introduced a hybrid fuzzy-neural optimization framework for DER scheduling. Their model effectively handled uncertainties and nonlinearities in energy systems.
Das et al. (2021) presented a multi-objective evolutionary algorithm for optimizing cost, emissions, and energy efficiency simultaneously. Their approach demonstrated superior performance compared to single-objective optimization techniques.
Verma et al. (2022) developed an IoT-enabled adaptive scheduling system that utilized real-time feedback to adjust energy distribution dynamically. Their system improved system resilience and responsiveness.
Khan et al. (2019) proposed a distributed optimization algorithm using consensus-based methods for coordinating DERs across multiple microgrids. Their approach enhanced system scalability and reduced communication overhead.
Liu et al. (2021) introduced a graph-based optimization framework for modeling interactions among distributed energy resources. Their method improved coordination and reduced energy losses in interconnected systems.
Mishra et al. (2020) proposed a hybrid cloud-edge architecture for energy management, combining the benefits of both paradigms. Their system achieved efficient data processing and improved scheduling accuracy.

Comparative Table and Analysis

Table 1: Optimization, AI, and IoT-Based Energy Management Techniques in Smart Grids

Study	Year	Optimization Technique / Method	Component / Model Used	Platform or System	Dataset Used	Key Contribution
Zhang et al.	2019	MILP	Microgrid with storage	IEEE 33-bus	Simulated load data	Cost minimization
Wang et al.	2020	PSO	IoT-enabled DER system	Smart home grid	Real load dataset	Fast convergence
Li et al.	2021	Deep RL	Neural scheduling agent	Smart grid	Historical energy data	Adaptive scheduling
Chen et al.	2018	GA + Fuzzy	Hybrid controller	Microgrid	Simulated data	Uncertainty handling
Kumar & Singh	2022	ACO	IoT smart device	Cloud EMS	Real-time IoT data	Efficient distribution
García et al.	2020	Evolutionary	Multi-objective model	Smart grid	EU datasets	Emission reduction
Rahman et al.	2019	Decentralized control	IoT edge system	Large-scale grid	Real-time data	Scalability
Sharma et al.	2021	LSTM	Forecasting model	Smart grid	Time-series data	Improved prediction accuracy
Alam et al.	2020	Blockchain + IoT	Secure EMS	Distributed grid	Transaction data	Data security
Patel et al.	2022	SVM + PSO	Hybrid ML model	Industrial grid	Industrial dataset	Accuracy improvement
Singh et	2021	PSO + GA	Hybrid	Microgrid	IEEE 69-bus	Global

al.			optimizer			optimization
Hossain et al.	2020	MINLP	Cloud EMS	IoT system	Real-time data	Improved efficiency
Zhou et al.	2019	Stochastic modeling	Probabilistic model	Renewable grid	Weather data	Robustness under uncertainty
Mehta et al.	2022	Demand response	IoT scheduling	Smart homes	User data	Peak load reduction
Torres et al.	2021	Game theory	Multi-agent system	Microgrid	Simulated data	Fair resource distribution
Nguyen et al.	2020	Deep neural network	Predictive control	Smart grid	Energy dataset	Real-time control
Bansal et al.	2019	Simulated annealing	Optimization model	Industrial grid	Simulated data	Global optimum search
Kim & Park	2021	Edge computing	IoT device	Smart grid	Real-time data	Low-latency processing
Santos et al.	2022	Reinforcement learning	EV scheduling model	Microgrid	EV dataset	Improved grid stability
Ali et al.	2021	Robust optimization	DER model	Energy market	Market data	Enhanced reliability
Gupta et al.	2020	Neural network	Forecasting system	Smart grid	Time-series data	Accuracy improvement
Park et al.	2019	Hierarchical control	Control framework	Smart grid	Simulated data	Improved coordination
El-Sayed et al.	2022	Blockchain	P2P energy system	Distributed grid	Transaction data	Transparency and trust
Jiang et al.	2021	Convex optimization	Scheduling model	Smart grid	Simulated data	Fast convergence
Reddy et al.	2020	Fuzzy-neural	Hybrid model	Microgrid	Simulated data	Uncertainty handling
Das et al.	2021	Evolutionary algorithm	Multi-objective optimization	Smart grid	Mixed dataset	Multi-criteria optimization
Verma et al.	2022	Adaptive IoT	Smart EMS	IoT grid	Real-time data	Dynamic response
Khan et al.	2019	Consensus algorithm	Distributed model	Multi-microgrid	Simulated data	Scalability
Liu et al.	2021	Graph-based modeling	Network model	Smart grid	Network data	Loss reduction
Mishra et al.	2020	Cloud-edge computing	Hybrid EMS	IoT system	Real-time data	Improved efficiency

Comparative Analysis

The comparative analysis of the reviewed studies highlights a clear evolution in optimal scheduling strategies for distributed energy resources (DERs), with a strong shift from traditional mathematical approaches toward hybrid and intelligent methods. Classical optimization techniques such as mixed-integer linear programming and dynamic programming continue to provide reliable and mathematically rigorous solutions, particularly in deterministic scenarios. However, their limitations in handling uncertainty, nonlinearity, and large-scale systems have led researchers to increasingly adopt hybrid techniques that combine these models with metaheuristic algorithms. Approaches such as particle swarm optimization (PSO) combined with genetic algorithms (GA) or fuzzy logic have demonstrated superior capability in solving multi-objective and nonlinear optimization problems.

Another key trend is the growing integration of machine learning and deep learning methods into energy management systems. Techniques such as long short-term memory (LSTM), deep neural networks, and reinforcement learning have significantly improved forecasting accuracy and enabled adaptive scheduling.

These models are particularly effective in handling stochastic variables like renewable generation and load demand. Compared to traditional approaches, machine learning-based models offer enhanced flexibility and real-time adaptability, making them well-suited for modern smart grid environments.

The role of IoT has been consistently emphasized across the literature as a critical enabler of intelligent energy management. IoT devices facilitate real-time data acquisition, monitoring, and control, providing detailed insights into system behavior. When combined with edge and cloud computing, IoT enables scalable and efficient processing of large datasets. This integration supports decentralized decision-making, which improves system responsiveness and reduces communication overhead compared to centralized architectures.

Additionally, multi-objective optimization has emerged as a dominant focus, with studies aiming to balance cost, emissions, and energy efficiency simultaneously. Evolutionary algorithms have proven particularly effective in achieving these objectives. The inclusion of blockchain technology further enhances transparency and security, although it introduces additional computational challenges. Overall, the literature demonstrates a transition toward data-driven, decentralized, and intelligent scheduling frameworks, supported by both simulated datasets such as IEEE test systems and real-world IoT data, resulting in improved performance across multiple metrics.

Discussion

The reviewed literature underscores the transformative impact of integrating advanced optimization techniques with IoT-enabled smart energy management systems. One of the most significant developments is the transition from centralized to decentralized control architectures, where decision-making is distributed across network nodes. This shift enhances scalability, reduces latency, and enables localized optimization, which is particularly beneficial for microgrids and community-based energy systems. IoT technologies play a pivotal role in this transformation by enabling real-time monitoring, communication, and adaptive control.

The effectiveness of different optimization methods varies depending on system complexity and operational requirements. Classical optimization methods remain valuable for structured and deterministic problems, offering high accuracy and theoretical guarantees. However, metaheuristic and hybrid approaches have demonstrated superior performance in handling complex, nonlinear, and stochastic environments. The integration of machine learning techniques further enhances these methods by enabling predictive and adaptive capabilities. Reinforcement learning, in particular, provides a robust framework for sequential decision-making under uncertainty, allowing systems to continuously improve through interaction with their environment.

Despite these advancements, several challenges persist. Computational complexity remains a major concern, especially in large-scale systems with multiple DERs. While cloud computing offers significant processing power, it introduces latency and security concerns, whereas edge computing is limited by hardware constraints. Additionally, issues related to data privacy, cybersecurity, and interoperability hinder widespread adoption. Addressing these challenges requires the development of efficient algorithms, secure communication protocols, and standardized frameworks to ensure reliable and scalable implementation of IoT-based energy management systems.

Conclusion

In conclusion, the optimal scheduling of distributed energy resources within IoT-enabled smart energy management systems represents a critical advancement in modern power systems. The integration of advanced optimization techniques, including hybrid algorithms, machine learning models, and metaheuristic approaches, has significantly improved the efficiency, reliability, and adaptability of energy systems. IoT technologies have further enhanced these capabilities by enabling real-time data acquisition, decentralized control, and intelligent decision-making. Together, these developments support the transition toward sustainable and resilient energy infrastructures.

However, challenges such as computational complexity, data privacy, cybersecurity, and interoperability continue to limit large-scale deployment. Future research should focus on developing lightweight, scalable, and secure solutions, while also exploring emerging technologies such as federated learning, digital twins, and quantum computing. Overall, the convergence of optimization, artificial intelligence, and IoT provides a promising pathway for achieving efficient, flexible, and sustainable energy management in next-generation smart grids.

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