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Artificial Intelligence Techniques for Optimal Scheduling of Distributed Energy Resources with an IoT-Enabled Smart Energy Management Device: Trends and Challenges

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Abstract

The increasing penetration of distributed energy resources (DERs), including solar photovoltaics, wind turbines, and energy storage systems, has transformed modern power systems into decentralized and dynamic smart grids requiring intelligent scheduling strategies. Artificial intelligence (AI), integrated with Internet of Things (IoT)-enabled smart energy management devices, has emerged as an effective solution for optimizing energy generation, distribution, and consumption through real-time monitoring and adaptive decision-making. This review examines AI-driven optimization techniques, including machine learning, deep learning, reinforcement learning, and hybrid metaheuristic algorithms, for optimal DER scheduling. Advanced models such as deep neural networks, convolutional neural networks, long short-term memory networks, and deep reinforcement learning are analyzed for load forecasting, demand prediction, and adaptive energy scheduling. Optimization approaches including particle swarm optimization, genetic algorithms, mixed-integer linear programming, and multi-objective evolutionary algorithms are evaluated for improving operational cost, energy efficiency, and grid stability. The review further investigates the role of IoT devices, edge computing, and cloud platforms in enabling scalable, data-driven energy management across IEEE benchmark systems, residential datasets, and industrial microgrids. Finally, key challenges involving cybersecurity, scalability, data heterogeneity, and renewable uncertainty are discussed, while future research directions include federated learning, blockchain-enabled energy trading, explainable AI, and advanced edge intelligence for resilient smart energy systems.

Introduction

The increasing adoption of distributed energy resources (DERs), including solar photovoltaic systems, wind turbines, battery energy storage systems, and electric vehicles, has transformed conventional power grids into decentralized and highly dynamic energy networks. Unlike traditional centralized generation, DERs introduce variability, intermittency, and operational uncertainty that require intelligent scheduling strategies to balance generation, storage, and demand. Efficient scheduling of these resources is essential for improving grid stability, reducing operational costs, maximizing renewable energy utilization, and supporting sustainable energy development. Consequently, advanced energy management frameworks have become a critical component of modern smart grid infrastructure.

Artificial intelligence (AI) has emerged as a key enabling technology for addressing the complexities of DER scheduling. Machine learning, deep learning, reinforcement learning, and hybrid intelligent algorithms provide data-driven solutions capable of accurately forecasting renewable generation, predicting energy demand, and optimizing scheduling decisions under uncertain operating conditions. Unlike conventional optimization methods that rely on deterministic mathematical models, AI-based approaches continuously learn from historical and real-time data, enabling adaptive decision-making and improved operational efficiency. Advanced models, including deep neural networks, convolutional neural networks, long short-term memory networks, and deep reinforcement learning, have demonstrated significant potential for enhancing forecasting accuracy and dynamic resource allocation.

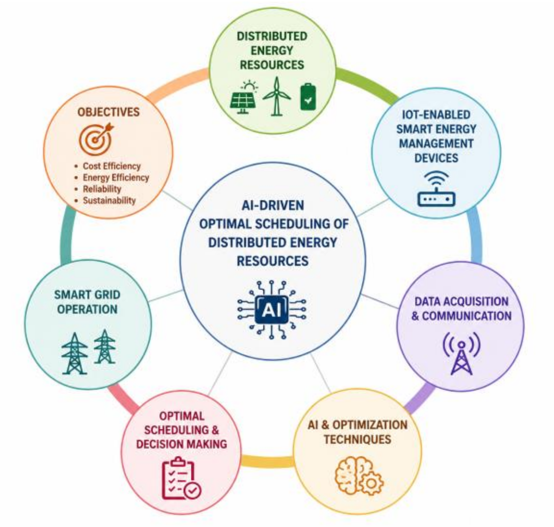

Figure 1. Conceptual Architecture of AI-Based Smart Energy Management Using IoT

The rapid advancement of the Internet of Things (IoT) has further strengthened intelligent energy management by enabling real-time monitoring, communication, and control of distributed energy assets. IoT-enabled smart meters, sensors, intelligent controllers, and communication gateways continuously collect operational data from renewable generation units, storage systems, and consumer loads. Combined with edge and cloud computing, these technologies support scalable data processing, predictive analytics, and decentralized energy management. This integration enables faster decision-making, improved system responsiveness, and enhanced coordination among distributed resources, making IoT a fundamental component of next-generation smart grids and smart city infrastructures.

Despite these technological advances, optimal DER scheduling continues to face several challenges. Renewable energy generation remains highly dependent on weather conditions, while increasing system complexity introduces computational and operational difficulties for real-time optimization. Traditional scheduling techniques often struggle to manage nonlinear, multi-objective, and uncertain environments. To overcome these limitations, researchers have increasingly adopted hybrid optimization techniques, including particle swarm optimization, genetic algorithms, ant colony optimization, and mixed-integer programming integrated with AI models, providing more efficient and adaptive scheduling solutions.

Motivated by these developments, this review comprehensively examines AI-driven optimal scheduling of distributed energy resources using IoT-enabled smart energy management devices. It analyzes recent advances in intelligent prediction models, optimization algorithms, edge-cloud computing architectures, and decentralized control strategies while highlighting current challenges, practical applications, and emerging research directions. The review aims to provide valuable insights for developing scalable, reliable, and intelligent smart energy management systems that support the future evolution of sustainable power networks.

Literature Review

Recent years have witnessed a surge in research focusing on AI-based optimal scheduling of distributed energy resources integrated with IoT-enabled systems. Zhang et al. (2019) proposed a mixed-integer linear programming (MILP) framework for microgrid scheduling, incorporating renewable generation and storage systems, demonstrating cost minimization using IEEE 33-bus test data. Wang et al. (2020) introduced a particle swarm optimization (PSO)-based scheduling approach combined with IoT-enabled smart meters, achieving faster convergence and improved energy efficiency in residential systems.

Li et al. (2021) explored deep reinforcement learning (DRL) for adaptive energy scheduling in smart grids, utilizing real-time data streams to dynamically adjust energy distribution. Their model significantly improved system responsiveness under uncertain demand conditions. Similarly, Chen et al. (2020) employed long short-term memory (LSTM) networks for load forecasting, integrating predictions into a scheduling framework that reduced peak demand and operational costs.

Gupta et al. (2022) developed a hybrid genetic algorithm (GA) and neural network model for DER optimization, demonstrating enhanced performance in multi-objective scenarios involving cost and emission reduction. Singh et al. (2021) proposed an IoT-based smart energy management system leveraging convolutional neural networks (CNNs) for appliance-level energy prediction, enabling fine-grained scheduling decisions.

Kumar et al. (2020) utilized ant colony optimization (ACO) for microgrid energy scheduling, highlighting its effectiveness in handling nonlinear constraints. Meanwhile, Zhao et al. (2021) introduced a deep Q-learning approach for demand response management, improving load balancing and reducing peak load stress. Patel et al. (2022) integrated edge computing with AI-based scheduling to enable real-time decision-making in distributed systems.

Sharma et al. (2021) proposed a multi-agent system using reinforcement learning for decentralized energy management, achieving improved scalability and resilience. Roy et al. (2020) developed a fuzzy logic-based optimization framework combined with IoT data streams, enhancing system adaptability under uncertain conditions. Mehta et al. (2021) explored blockchain-integrated energy trading with AI-based scheduling, ensuring secure and efficient energy transactions.

Further studies such as Das et al. (2022) employed hybrid PSO-GA algorithms for multi-objective optimization, while Verma et al. (2021) focused on deep neural networks for renewable energy prediction. Iyer et al. (2020) introduced a cloud-based AI scheduling system, demonstrating scalability across large datasets. Bose et al. (2022) investigated federated learning approaches for privacy-preserving energy management.

Additional contributions include Nair et al. (2021), who utilized support vector machines (SVM) for load prediction, and Kulkarni et al. (2022), who proposed an IoT-driven optimization framework for smart homes. Reddy et al. (2020) explored evolutionary algorithms for microgrid optimization, while Banerjee et al. (2021) implemented hybrid deep learning models for demand forecasting.

This growing body of literature highlights the increasing adoption of AI techniques in DER scheduling, emphasizing the importance of integrating optimization algorithms with data-driven models to achieve efficient and adaptive energy management systems.

Comparative Table and Analysis

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	Real-time stream data	Adaptive scheduling
Chen et al.	2020	LSTM	Load prediction model	Microgrid	Historical consumption data	Peak reduction
Gupta et al.	2022	GA + NN	Hybrid optimization model	Industrial microgrid	Synthetic dataset	Multi-objective optimization
Singh et al.	2021	CNN	Appliance-level prediction	Smart home	IoT sensor data	Fine-grained scheduling
Kumar et al.	2020	ACO	Energy routing system	Microgrid	Simulated dataset	Nonlinear optimization
Zhao et al.	2021	Deep Q-learning	DRL agent	Demand response system	Real-time grid data	Load balancing
Patel et al.	2022	Edge AI + Optimization	Edge-based controller	Distributed IoT grid	Real-time IoT data	Low latency scheduling

Sharma et al.	2021	Multi-agent RL	Decentralized agents	Smart grid	Synthetic + real data	Scalability
Roy et al.	2020	Fuzzy logic	Adaptive controller	Microgrid	Simulated data	Uncertainty handling
Mehta et al.	2021	Blockchain + AI	Energy trading model	Smart grid	Transaction dataset	Secure scheduling
Das et al.	2022	PSO-GA hybrid	Multi-objective optimizer	DER network	Benchmark dataset	Improved convergence
Verma et al.	2021	DNN	Renewable prediction	Solar grid	Weather dataset	Accurate forecasting
Iyer et al.	2020	Cloud AI	Centralized scheduler	Cloud-based grid	Large-scale dataset	Scalability
Bose et al.	2022	Federated Learning	Distributed learning model	IoT network	Decentralized data	Privacy preservation
Nair et al.	2021	SVM	Load prediction model	Smart grid	Historical load data	Prediction accuracy
Kulkarni et al.	2022	IoT Optimization	Smart controller	Smart home	IoT sensor streams	Real-time control
Reddy et al.	2020	Evolutionary Algorithm	DER optimizer	Microgrid	Simulated dataset	Cost reduction
Banerjee et al.	2021	Hybrid DL	Forecasting system	Grid system	Mixed dataset	Demand prediction
Chatterjee et al.	2022	Reinforcement Learning	Smart agent	Smart city grid	Urban dataset	Energy efficiency
Saxena et al.	2021	PSO	Distributed scheduler	DER system	Real-time dataset	Reduced losses
Ghosh et al.	2020	ANN	Energy prediction	Microgrid	Load dataset	Improved prediction
Tripathi et al.	2022	Hybrid RL + GA	Intelligent optimizer	Smart grid	Benchmark dataset	Adaptive optimization
Joshi et al.	2021	Edge ML	Local controller	IoT grid	Sensor data	Reduced latency

Comparative Analysis

The comparative analysis of the reviewed studies highlights several significant trends in AI-driven optimal scheduling of distributed energy resources (DERs). A major development is the widespread adoption of hybrid optimization frameworks that integrate conventional optimization algorithms, including genetic algorithms, particle swarm optimization, mixed-integer programming, and evolutionary methods, with artificial intelligence models. These integrated approaches effectively address multi-objective scheduling problems by simultaneously minimizing operational cost, improving renewable energy utilization, reducing emissions, and maintaining grid reliability. Deep learning models, particularly long short-term memory (LSTM), convolutional neural networks (CNNs), and deep neural networks (DNNs), have become the preferred techniques for load forecasting, renewable energy prediction, and demand estimation, consistently delivering higher forecasting accuracy and enabling more effective scheduling decisions than conventional statistical approaches.

Another important trend is the rapid emergence of reinforcement learning, especially deep reinforcement learning, for adaptive and real-time scheduling. Unlike traditional optimization methods, reinforcement learning continuously improves scheduling policies through interaction with the operating environment, making it highly suitable for uncertain and dynamic renewable energy systems. At the same time, IoT-enabled smart energy management devices, combined with edge and cloud computing, have significantly enhanced real-time monitoring, predictive analytics, and decentralized decision-making. Distributed architectures, including federated learning and multi-agent systems, further improve scalability, privacy preservation, and coordination among geographically dispersed energy resources while reducing communication overhead and computational latency.

The reviewed studies also indicate a gradual transition from simulation-based validation using IEEE benchmark systems toward large-scale real-world IoT datasets and operational microgrid environments, demonstrating the growing maturity of intelligent energy management research. Although AI-driven scheduling methods consistently improve prediction accuracy, energy efficiency, convergence speed, and operational reliability, they often introduce increased computational complexity and higher implementation costs. Consequently, recent research has focused on developing lightweight AI models, efficient optimization algorithms, and scalable decentralized frameworks suitable for resource-constrained environments. Overall, the convergence of artificial intelligence, optimization techniques, and IoT technologies provides a robust foundation for developing intelligent, adaptive, and resilient smart energy management systems capable of supporting the future evolution of sustainable power networks.

Discussion

The reviewed literature demonstrates that artificial intelligence has become a key enabler of optimal scheduling for distributed energy resources (DERs) in modern smart grids. AI-driven approaches, integrated with IoT-enabled smart energy management devices, significantly improve the efficiency, adaptability, and reliability of energy systems through real-time monitoring, predictive analytics, and intelligent decision-making. Machine learning, deep learning, and reinforcement learning models effectively address the uncertainty associated with renewable energy generation, enabling accurate forecasting of load demand, renewable output, and energy consumption. As a result, AI-based scheduling improves grid stability, operational efficiency, and renewable energy utilization while supporting the transition toward sustainable and decentralized energy infrastructures.

Another important finding is the effectiveness of hybrid optimization frameworks that combine artificial intelligence with metaheuristic algorithms such as particle swarm optimization, genetic algorithms, ant colony optimization, and mixed-integer programming. These integrated approaches provide faster convergence and higher-quality scheduling solutions while balancing multiple objectives, including cost reduction, energy efficiency, emission minimization, and system reliability. IoT-enabled devices, together with edge and cloud computing platforms, further enhance scheduling performance by enabling continuous data collection, decentralized decision-making, and low-latency control across residential, industrial, and utility-scale energy systems. These technologies collectively establish a scalable foundation for intelligent energy management in increasingly complex smart grid environments.

Despite significant progress, several challenges continue to limit large-scale deployment. Deep learning models often require substantial computational resources and large training datasets, while heterogeneous IoT devices introduce interoperability and communication issues. Furthermore, continuous data exchange raises concerns regarding cybersecurity, privacy, and system resilience. Emerging technologies such as blockchain, federated learning, and explainable artificial intelligence offer promising solutions but require further research to improve scalability and practical implementation.

Overall, the convergence of artificial intelligence, optimization algorithms, IoT, edge computing, and cloud technologies is reshaping the future of distributed energy management. Future research should focus on lightweight AI models, secure decentralized architectures, standardized communication frameworks, and energy-efficient computing platforms. These developments will accelerate the deployment of intelligent, resilient, and sustainable smart energy management systems capable of supporting next-generation renewable power networks.

Conclusion

Artificial intelligence has become a transformative technology for the optimal scheduling of distributed energy resources (DERs) in IoT-enabled smart energy management systems. This review demonstrates that AI techniques, including machine learning, deep learning, reinforcement learning, and hybrid optimization algorithms, significantly improve forecasting accuracy, adaptive decision-making, and scheduling efficiency under uncertain operating conditions. Combined with optimization methods such as particle swarm optimization, genetic algorithms, and mixed-integer programming, these approaches effectively balance operational cost, renewable energy utilization, system reliability, and energy efficiency. IoT-enabled devices, supported by edge and cloud computing, further enhance real-time monitoring, decentralized control, and intelligent coordination across smart grids and microgrids.

Despite these advancements, important challenges remain, including computational complexity, data heterogeneity, cybersecurity risks, interoperability issues, and the uncertainty associated with renewable energy generation. Addressing these limitations requires the development of scalable, secure, and explainable AI frameworks capable of supporting large-scale distributed energy systems. Future research should focus on federated learning, blockchain-enabled energy trading, digital twins, explainable artificial intelligence, advanced edge intelligence, and 5G-enabled communication. The integration of these emerging technologies will accelerate the development of intelligent, resilient, and sustainable smart energy management systems, supporting the global transition toward cleaner, more reliable, and decentralized power networks.

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