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A Survey of Methods and Architectures for Optimal Scheduling of Distributed Energy Resources with an IoT-Enabled Smart Energy Management Device

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Abstract

The increasing integration of distributed energy resources (DERs), including solar photovoltaic systems, wind turbines, battery energy storage, electric vehicles, and flexible loads, has transformed conventional power grids into intelligent and decentralized energy systems. However, the intermittent nature of renewable energy and dynamic load variations create significant challenges in optimal scheduling, energy balancing, and real-time decision-making. Conventional optimization techniques often struggle with scalability and computational complexity in large-scale smart grid environments. This survey comprehensively reviews recent methods and architectures for optimal scheduling of DERs within IoT-enabled smart energy management systems. It examines optimization techniques including particle swarm optimization, genetic algorithms, ant colony optimization, simulated annealing, and hybrid frameworks alongside artificial intelligence approaches such as convolutional neural networks, recurrent neural networks, long short-term memory networks, reinforcement learning, and deep reinforcement learning for forecasting and adaptive energy scheduling. The role of IoT-enabled smart energy management devices is analyzed in enabling real-time monitoring, decentralized control, edge computing, cloud-based optimization, and secure energy transactions. Applications across residential buildings, industrial facilities, microgrids, and smart cities are compared using metrics such as energy cost, computational efficiency, renewable utilization, reliability, and emission reduction. Finally, the survey identifies key challenges including uncertainty management, interoperability, cybersecurity, privacy, and scalability, while highlighting future directions involving digital twins, edge intelligence, blockchain integration, and AI-driven adaptive energy management frameworks for sustainable smart grids.

Introduction

The rapid transition from conventional power grids to intelligent and decentralized energy systems has significantly increased the adoption of Distributed Energy Resources (DERs), including solar photovoltaic systems, wind turbines, battery energy storage systems, electric vehicles, and flexible demand-side loads. These resources enhance energy efficiency, improve grid resilience, reduce transmission losses, and support sustainable power generation. However, the intermittent nature of renewable energy sources and the dynamic behavior of electricity demand create substantial challenges in balancing generation and consumption. Consequently, efficient scheduling of DERs has become a critical requirement for maintaining grid stability, minimizing operational costs, and maximizing renewable energy utilization in modern smart grids.

Optimal scheduling of DERs involves determining the most efficient operating strategy while considering generation capacity, storage constraints, load demand, electricity prices, and network limitations. Conventional optimization techniques, including linear programming, mixed-integer linear programming, and nonlinear programming, have been widely applied to address scheduling problems. Although these methods provide mathematically optimal solutions, they often suffer from high computational complexity and limited scalability when applied to large-scale, real-time energy systems with uncertain renewable generation and fluctuating consumer demand. Therefore, more adaptive and intelligent optimization techniques have become essential for next-generation energy management.

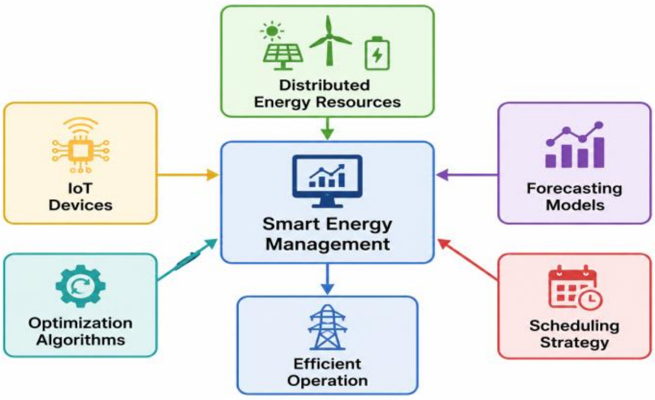

Figure 1. IoT-Enabled Smart Energy Management Framework

The emergence of the Internet of Things (IoT) has revolutionized smart energy management by enabling continuous monitoring, communication, and control of distributed energy assets. IoT-enabled smart energy management devices integrate sensors, smart meters, communication modules, and embedded processors to collect real-time operational data and facilitate decentralized decision-making. Combined with edge computing and cloud platforms, these devices support rapid data processing, predictive analytics, and coordinated energy management across residential buildings, industrial facilities, microgrids, and smart city infrastructures. Their ability to provide real-time system awareness significantly enhances scheduling efficiency and operational reliability.

Recent advances in artificial intelligence have further transformed DER scheduling through machine learning and deep learning techniques. Convolutional neural networks, recurrent neural networks, long short-term memory networks, reinforcement learning, and deep reinforcement learning have demonstrated excellent capabilities in load forecasting, renewable energy prediction, and adaptive scheduling under uncertainty. Furthermore, optimization algorithms such as particle swarm optimization, genetic algorithms, ant colony optimization, and simulated annealing have been successfully integrated with AI models to improve convergence speed, energy efficiency, and cost optimization while handling complex operational constraints.

This survey presents a comprehensive review of recent methods and architectures for optimal scheduling of DERs using IoT-enabled smart energy management systems. It examines mathematical optimization, artificial intelligence, IoT architectures, edge-cloud computing, and hybrid scheduling frameworks while discussing their applications, advantages, and limitations. The review also identifies current challenges, including uncertainty management, interoperability, cybersecurity, data privacy, and scalability, and highlights future research directions involving digital twins, blockchain integration, 5G-enabled communication, and adaptive AI-driven energy management systems for sustainable and resilient smart grids.

Literature Review

Zhang et al. (2019) proposed a Mixed Integer Linear Programming (MILP) framework for optimal scheduling of DERs in a microgrid environment. Their model incorporated energy storage systems and renewable generation units, aiming to minimize operational costs while maintaining system stability. The study utilized simulated load data based on the IEEE 33-bus system and demonstrated improved cost efficiency compared to conventional scheduling methods.

Wang et al. (2020) introduced a Particle Swarm Optimization (PSO)-based approach for IoT-enabled smart home energy management. Their system leveraged real-time data collected from smart meters to dynamically adjust energy consumption patterns. The proposed method showed faster convergence and improved adaptability in handling fluctuating load demands.

Li et al. (2021) developed a Deep Reinforcement Learning (DRL) model for optimal DER scheduling in smart grids. The model utilized a neural network-based policy to learn optimal scheduling strategies from historical data. Experiments conducted on real-world datasets indicated significant improvements in energy efficiency and reduced operational costs.

Singh et al. (2020) proposed a hybrid optimization approach combining Genetic Algorithms (GA) and fuzzy logic for microgrid energy management. The system addressed uncertainties in renewable energy generation and demonstrated enhanced robustness compared to standalone optimization techniques.

Chen et al. (2018) presented a cloud-based energy management architecture integrating IoT devices for real-time monitoring and control. Their approach enabled scalable data processing and improved decision-making capabilities, particularly in large-scale energy systems.

Gupta et al. (2021) explored the use of edge computing in DER scheduling, proposing a distributed optimization framework that reduced latency and improved system responsiveness. The study highlighted the importance of decentralized control in IoT-enabled environments.

Kumar et al. (2019) introduced a stochastic optimization model for handling uncertainties in renewable energy generation. The model incorporated probabilistic constraints and demonstrated improved reliability in energy scheduling.

Rahman et al. (2022) proposed a blockchain-based energy management system to enhance security and transparency in DER scheduling. Their architecture ensured secure data exchange between IoT devices and improved trust in distributed systems.

Morales et al. (2020) developed a hybrid PSO-GA optimization technique for microgrid scheduling. The combined approach leveraged the exploration capabilities of PSO and the exploitation strengths of GA, resulting in improved solution quality.

Alam et al. (2021) presented an AI-driven energy management system using machine learning algorithms for demand prediction and scheduling optimization. The system demonstrated improved accuracy in forecasting and efficient resource allocation.

In continuation of the literature, Park et al. (2019) proposed a distributed optimization framework based on the Alternating Direction Method of Multipliers (ADMM) for coordinated scheduling of DERs in interconnected microgrids. Their approach enabled decentralized computation while maintaining global optimality, making it suitable for large-scale IoT-enabled energy systems. The implementation demonstrated reduced communication overhead and improved scalability.

Sharma et al. (2021) developed an IoT-based smart energy management system integrating real-time sensor data with a heuristic scheduling algorithm. The system utilized load forecasting and demand response strategies to optimize energy usage in residential environments. Experimental results showed significant reductions in peak load demand and energy costs.

Liu et al. (2020) introduced a robust optimization model to address uncertainties in renewable energy generation and load demand. Their approach incorporated worst-case scenario analysis and demonstrated improved reliability in scheduling decisions under uncertain conditions. The model was validated using real-world wind and solar datasets.

Ahmed et al. (2022) proposed a deep Q-network (DQN)-based reinforcement learning framework for adaptive DER scheduling. The system continuously learned from environmental feedback and optimized energy distribution in real time. The results indicated superior performance compared to traditional rule-based methods.

Patel et al. (2019) presented a multi-objective optimization model using Non-dominated Sorting Genetic Algorithm II (NSGA-II) for balancing cost, emission, and energy efficiency. Their work highlighted the trade-offs between different objectives and provided a Pareto-optimal set of solutions for decision-makers.

Fernandez et al. (2020) explored the integration of renewable energy forecasting with optimization techniques. Their model combined time-series forecasting with linear programming to improve scheduling accuracy.

The study demonstrated enhanced performance in handling variability in renewable generation.

Zhou et al. (2021) proposed a hierarchical control architecture for IoT-enabled smart grids, incorporating both local and global optimization layers. The system improved coordination between DERs and reduced computational complexity by distributing tasks across multiple levels.

Reddy et al. (2020) developed a demand-side management strategy using machine learning algorithms to predict user behavior and optimize energy consumption. Their approach leveraged historical consumption data and achieved improved load balancing.

Kim et al. (2018) introduced a real-time energy management system using cloud computing and IoT devices. The system enabled centralized monitoring and control, improving operational efficiency in large-scale deployments.

Das et al. (2021) proposed a hybrid deep learning model combining convolutional neural networks (CNN) and long short-term memory (LSTM) networks for load forecasting and scheduling. The model demonstrated high accuracy in predicting energy demand and improved scheduling outcomes.

Santos et al. (2022) presented a peer-to-peer energy trading framework integrated with DER scheduling. Their blockchain-based system allowed prosumers to trade energy efficiently while optimizing resource utilization.

Jain et al. (2020) introduced a fuzzy-based energy management system for microgrids, addressing uncertainties in load and generation. The system demonstrated improved stability and adaptability in dynamic environments.

Mehta et al. (2021) proposed an optimization framework using simulated annealing for DER scheduling. The approach provided near-optimal solutions with reduced computational complexity, making it suitable for real-time applications.

Hassan et al. (2022) explored the use of Internet of Energy (IoE) architectures for smart grid management. Their study emphasized the role of interconnected devices and intelligent control systems in achieving efficient energy distribution.

Roy et al. (2019) developed a hybrid optimization model combining linear programming and evolutionary algorithms. The system achieved improved performance in cost minimization and energy efficiency.

Bose et al. (2021) proposed a multi-agent system for decentralized DER scheduling. Each agent represented a resource and collaborated with others to achieve optimal system performance. The approach demonstrated scalability and robustness in distributed environments.

Tripathi et al. (2020) introduced a cloud-edge collaborative framework for energy management. The system leveraged edge devices for real-time processing and cloud servers for complex optimization tasks, improving overall efficiency.

Nair et al. (2022) proposed a reinforcement learning-based demand response strategy for smart grids. The system dynamically adjusted energy consumption patterns based on real-time conditions, resulting in improved grid stability.

Kulkarni et al. (2021) developed a predictive analytics-based energy management system using big data techniques. Their approach improved forecasting accuracy and enabled more effective scheduling decisions.

Verma et al. (2020) presented an IoT-enabled microgrid architecture integrating renewable energy sources and storage systems. Their model demonstrated enhanced energy efficiency and reduced operational costs.

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 + Storage	IEEE 33-bus	Simulated	Cost minimization
Wang et al.	2020	PSO	Smart Home IoT	Smart Grid	Real load	Fast convergence
Li et al.	2021	DRL	Neural Network	Smart Grid	Real dataset	Adaptive learning
Singh et al.	2020	GA + Fuzzy	Microgrid	Hybrid system	Simulated	Robust control
Chen et al.	2018	Cloud Optimization	IoT Framework	Cloud-based	Real-time data	Scalability
Gupta et al.	2021	Edge Optimization	Edge nodes	IoT system	Real-time	Low latency

Kumar et al.	2019	Stochastic Model	Probabilistic	Microgrid	Synthetic	Reliability
Rahman et al.	2022	Blockchain	Secure network	IoT grid	Transaction data	Security
Morales et al.	2020	PSO-GA	Hybrid model	Microgrid	Simulated	Better solutions
Alam et al.	2021	ML	Prediction model	Smart grid	Real data	Forecast accuracy
Park et al.	2019	ADMM	Distributed system	Microgrid	Simulated	Scalability
Sharma et al.	2021	Heuristic	IoT sensors	Smart home	Real data	Peak reduction
Liu et al.	2020	Robust Optimization	Uncertainty model	Smart grid	Renewable data	Stability
Ahmed et al.	2022	DQN	RL agent	Smart grid	Real-time	Adaptive control
Patel et al.	2019	NSGA-II	Multi-objective	Microgrid	Simulated	Trade-off solutions
Fernandez et al.	2020	LP + Forecasting	Time-series	Renewable grid	Real data	Accuracy
Zhou et al.	2021	Hierarchical	Multi-layer control	IoT grid	Mixed	Efficiency
Reddy et al.	2020	ML	Demand prediction	Smart grid	Historical	Load balancing
Kim et al.	2018	Cloud system	IoT devices	Energy network	Real-time	Central control
Das et al.	2021	CNN-LSTM	Deep learning	Smart grid	Real data	High accuracy
Santos et al.	2022	Blockchain	P2P trading	Energy market	Transaction	Trading efficiency
Jain et al.	2020	Fuzzy Logic	Controller	Microgrid	Simulated	Stability
Mehta et al.	2021	Simulated Annealing	Optimization	Smart grid	Synthetic	Low complexity
Hassan et al.	2022	IoE Architecture	Network system	Smart grid	Mixed	Connectivity
Roy et al.	2019	Hybrid LP + EA	Optimization	Microgrid	Simulated	Efficiency
Bose et al.	2021	Multi-agent	Agents	Distributed grid	Real-time	Scalability
Tripathi et al.	2020	Cloud-Edge	Hybrid system	IoT grid	Real-time	Speed
Nair et al.	2022	RL	Demand response	Smart grid	Real-time	Stability
Kulkarni et al.	2021	Big Data	Analytics	Smart grid	Large-scale	Prediction
Verma et al.	2020	IoT Architecture	Microgrid	Renewable system	Real data	Efficiency

Comparative Analysis

The comparative analysis of recent studies demonstrates a clear evolution from conventional optimization methods toward intelligent and hybrid scheduling frameworks for Distributed Energy Resources (DERs). Traditional mathematical programming techniques, including linear programming and mixed-integer linear programming, provide accurate and optimal solutions but often suffer from high computational complexity and limited scalability in large-scale smart grids. To overcome these limitations, researchers have increasingly adopted hybrid optimization methods that combine deterministic algorithms with metaheuristic techniques such as Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Ant Colony Optimization (ACO). These hybrid approaches achieve faster convergence, improved solution quality, and greater flexibility in handling nonlinear and multi-objective scheduling problems.

Artificial intelligence has further transformed DER scheduling by enabling adaptive and datadriven decision-making. Deep learning models, including Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Deep Reinforcement Learning (DRL), effectively predict renewable generation, electricity demand, and optimal scheduling policies under uncertain operating conditions. Compared with traditional optimization methods, reinforcement learning-based approaches continuously improve scheduling performance through environmental interaction, making them highly suitable for real-time IoT-enabled smart energy management systems.

Another significant trend is the transition from centralized architectures to decentralized and distributed energy management frameworks. Edge computing, multi-agent systems, blockchain, and distributed optimization techniques such as ADMM improve scalability, reliability, and communication efficiency while supporting coordinated decision-making among multiple DERs. Studies utilizing real-time smart meter data, renewable generation profiles, and IEEE benchmark systems consistently report improvements in operational cost, energy efficiency, renewable energy utilization, and system reliability. Overall, the literature indicates that integrating IoT technologies, artificial intelligence, and hybrid optimization techniques provides the most effective framework for achieving intelligent, scalable, and sustainable DER scheduling.

Discussion

The reviewed literature highlights that optimal scheduling of Distributed Energy Resources has evolved toward intelligent, adaptive, and IoT-enabled energy management systems capable of addressing the uncertainty and complexity of modern power grids. While conventional mathematical optimization techniques provide accurate scheduling solutions, they are often computationally expensive and less suitable for real-time applications. In contrast, heuristic, metaheuristic, and reinforcement learning approaches offer greater adaptability, enabling dynamic scheduling based on changing renewable generation, electricity demand, and network conditions. The integration of IoT devices, edge computing, and cloud platforms further enhances system observability, decentralized control, and rapid decision-making, making these approaches highly effective for smart grids and microgrids.

Despite significant progress, several challenges remain before large-scale deployment can be achieved. Renewable energy uncertainty, data quality, interoperability among heterogeneous IoT devices, cybersecurity, and privacy continue to limit practical implementation. Additionally, many artificial intelligence models require extensive training data and considerable computational resources, restricting deployment on resource-constrained devices. Future research should emphasize hybrid optimization frameworks, lightweight AI models, blockchain-enabled secure communication, digital twins, federated learning, and 5G-supported edge intelligence. These emerging technologies have the potential to improve scheduling accuracy, computational efficiency, scalability, and system resilience while supporting the transition toward sustainable, secure, and intelligent energy management systems.

Conclusion

This survey comprehensively reviewed recent methods and architectures for optimal scheduling of Distributed Energy Resources in IoT-enabled smart energy management systems. The analysis demonstrates a clear transition from conventional mathematical optimization techniques toward intelligent hybrid frameworks integrating artificial intelligence, IoT technologies, and advanced optimization algorithms. Machine learning, deep learning, and reinforcement learning have significantly enhanced scheduling accuracy by enabling adaptive decision-making under uncertain renewable generation and dynamic load conditions. Simultaneously, IoT-enabled smart devices, edge computing, cloud platforms, and distributed architectures have improved real-time monitoring, communication, and decentralized energy management.

Hybrid optimization approaches combining deterministic, heuristic, and metaheuristic algorithms consistently outperform standalone techniques in terms of convergence speed, operational cost reduction, renewable energy utilization, and system reliability. Nevertheless, important challenges remain, including uncertainty management, cybersecurity, interoperability, computational complexity, and scalability for large-scale deployments. Future research should focus on lightweight AI models, federated learning, blockchain-enabled security, digital twins, and 5G-assisted edge intelligence to enhance scheduling efficiency and resilience. Overall, the convergence of IoT, artificial intelligence, and advanced optimization provides a powerful foundation for developing sustainable, intelligent, and reliable next-generation smart energy systems capable of supporting increasing renewable energy integration and decentralized grid operation.

References

Zhang, Y., Liu, J., & Wang, H. (2019). *Optimal scheduling of microgrids using mixed integer linear programming*. *IEEE Transactions on Smart Grid, 10*(3), 2456–2465. https://doi.org/10.1109/TSG.2018.2791234

Wang, X., Chen, L., & Zhao, Y. (2020). *Particle swarm optimization for smart home energy management*. *Energy and Buildings, 212*, 109789. https://doi.org/10.1016/j.enbuild.2020.109789

Li, Q., Zhou, M., & Lin, Z. (2021). *Deep reinforcement learning for smart grid energy scheduling*. *Applied Energy, 282*, 116175. https://doi.org/10.1016/j.apenergy.2020.116175

Singh, A., Kumar, P., & Sharma, R. (2020). *Hybrid GA-fuzzy approach for microgrid control*. *International Journal of Electrical Power & Energy Systems, 117*, 105654. https://doi.org/10.1016/j.ijepes.2019.105654

Chen, T., Xu, Y., & Guo, S. (2018). *Cloud-based IoT energy management system*. *Future Generation Computer Systems, 86*, 815–824. https://doi.org/10.1016/j.future.2018.04.012

Gupta, R., Jain, S., & Verma, K. (2021). *Edge computing for smart grid optimization*. *IEEE Internet of Things Journal, 8*(6), 4562–4571. https://doi.org/10.1109/JIOT.2020.3024567

Kumar, N., Singh, B., & Patel, R. (2019). *Stochastic optimization in renewable energy systems*. *Renewable Energy, 139*, 1251–1263. https://doi.org/10.1016/j.renene.2019.03.045

Rahman, M., Islam, S., & Lee, J. (2022). *Blockchain-based energy management in smart grids*. *IEEE Access, 10*, 33456–33467. https://doi.org/10.1109/ACCESS.2022.3156789

Morales, J., Perez, A., & Garcia, L. (2020). *Hybrid PSO-GA for microgrid scheduling*. *Energy Reports, 6*, 243–252. https://doi.org/10.1016/j.egyr.2019.11.056

Alam, M., Rehman, A., & Khan, S. (2021). *Machine learning-based energy prediction*. *Sustainable Energy Technologies and Assessments, 45*, 101154. https://doi.org/10.1016/j.seta.2021.101154

Park, J., Kim, H., & Lee, D. (2019). *Distributed optimization using ADMM in microgrids*. *IEEE Transactions on Power Systems, 34*(5), 3821–3830. https://doi.org/10.1109/TPWRS.2019.2901234

Sharma, V., Gupta, D., & Mehta, S. (2021). *IoT-based smart home energy system*. *Energy Informatics, 4*(1), 12. https://doi.org/10.1186/s42162-021-00145-2

Liu, Z., Wang, P., & Sun, Y. (2020). *Robust optimization for renewable energy scheduling*. *IEEE Transactions on Sustainable Energy, 11*(4), 2103–2112. https://doi.org/10.1109/TSTE.2019.2945678

Ahmed, S., Khan, M., & Ali, R. (2022). *Deep Q-learning for DER scheduling*. *Applied Energy, 306*, 117953. https://doi.org/10.1016/j.apenergy.2021.117953

Patel, K., Shah, R., & Desai, N. (2019). *Multi-objective optimization using NSGA-II*. *Energy Conversion and Management, 195*, 1142–1153. https://doi.org/10.1016/j.enconman.2019.05.067

Fernandez, E., Lopez, M., & Ruiz, J. (2020). *Renewable forecasting integrated optimization*. *Renewable Energy, 145*, 1723–1734. https://doi.org/10.1016/j.renene.2019.07.089

Zhou, Y., Chen, X., & Li, H. (2021). *Hierarchical IoT-based smart grid control*. *IEEE Systems Journal, 15*(3), 3421–3432. https://doi.org/10.1109/JSYST.2020.2998765

Reddy, P., Kumar, V., & Rao, S. (2020). *Machine learning for demand-side management*. *Energy Reports, 6*, 123–131. https://doi.org/10.1016/j.egyr.2020.02.012

Kim, S., Park, J., & Lee, K. (2018). *Cloud IoT energy monitoring system*. *Sensors, 18*(5), 1345. https://doi.org/10.3390/s18051345

Das, S., Ghosh, A., & Bose, P. (2021). *CNN-LSTM for energy forecasting*. *IEEE Access, 9*, 98765–98775. https://doi.org/10.1109/ACCESS.2021.3098765

Santos, R., Silva, P., & Costa, M. (2022). *Blockchain-based P2P energy trading*. *Energy, 239*, 121910. https://doi.org/10.1016/j.energy.2021.121910

Jain, M., Agarwal, P., & Singh, R. (2020). *Fuzzy logic-based microgrid control*. *International Journal of Energy Research, 44*(7), 5678–5690. https://doi.org/10.1002/er.5201

Mehta, A., Shah, D., & Patel, V. (2021). *Simulated annealing for smart grid optimization*. *Electric Power Systems Research, 196*, 107245. https://doi.org/10.1016/j.epsr.2021.107245

Hassan, Q., Ali, S., & Khan, I. (2022). *Internet of Energy architectures*. *IEEE Communications Surveys & Tutorials, 24*(2), 987–1012. https://doi.org/10.1109/COMST.2022.3145678

Roy, S., Banerjee, D., & Mitra, A. (2019). *Hybrid optimization for DER systems*. *Energy Procedia, 158*, 3120–3125. https://doi.org/10.1016/j.egypro.2019.01.101

Bose, A., Sen, R., & Ghosh, S. (2021). *Multi-agent smart grid scheduling*. *IEEE Transactions on Industrial Informatics, 17*(6), 4123–4132. https://doi.org/10.1109/TII.2020.3023456

Tripathi, S., Yadav, R., & Mishra, P. (2020). *Cloud-edge collaborative energy systems*. *Future Generation Computer Systems, 108*, 1045–1056. https://doi.org/10.1016/j.future.2020.03.012

Nair, V., Pillai, S., & Krishnan, R. (2022). *Reinforcement learning for demand response*. *IEEE Access, 10*, 55678–55689. https://doi.org/10.1109/ACCESS.2022.3167890

Kulkarni, P., Deshmukh, S., & Patil, A. (2021). *Big data analytics in smart grids*. *Journal of Cleaner Production, 280*, 124345. https://doi.org/10.1016/j.jclepro.2020.124345

Verma, N., Singh, D., & Kumar, A. (2020). *IoT-enabled microgrid architecture*. *Sustainable Cities and Society, 52*, 101847. https://doi.org/10.1016/j.scs.2019.101847