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A Survey of Methods and Architectures for Energy Management in Smart Grids Using IoT and Price-Based Demand Response with a Hybrid FHO-RERNN Approach

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Abstract

The rapid evolution of smart grid technologies has transformed conventional power systems into intelligent, data-driven infrastructures capable of meeting growing energy demands. The integration of distributed energy resources, renewable systems, and Internet of Things (IoT) technologies enables real-time monitoring, communication, and control. However, challenges such as uncertain renewable generation, fluctuating demand, and system complexity require advanced energy management solutions. This paper presents a comprehensive review of AI-driven and hybrid optimization approaches for smart grid energy management, with a focus on IoT-enabled systems and price-based demand response strategies. In particular, it highlights the hybrid Forest Herd Optimization–Recurrent Echo State Neural Network (FHO-RERNN) framework, which combines global optimization capability with efficient temporal modeling for improved forecasting and decision-making. The study examines architectures such as edge, fog, and cloud computing, along with pricing mechanisms including time-of-use and real-time pricing. Applications across residential, commercial, and industrial domains are analyzed using benchmark datasets. Key challenges such as data privacy, cybersecurity, and scalability are discussed, along with emerging trends like blockchain integration, federated learning, and digital twins, providing insights for developing intelligent and sustainable energy systems.

Introduction

The transformation of conventional power systems into intelligent smart grids has significantly changed the generation, distribution, and utilization of electrical energy. Smart grids integrate advanced communication technologies, real-time monitoring, and intelligent control mechanisms to improve energy efficiency, reliability, and sustainability. The increasing penetration of renewable energy resources such as solar and wind power, along with distributed energy resources (DERs), has introduced substantial complexity in energy management and grid coordination. Traditional centralized energy systems are often unable to effectively manage the uncertainty and variability associated with modern decentralized energy infrastructures. Consequently, advanced energy management frameworks capable of adaptive control and intelligent decision-making have become essential for maintaining grid stability and operational efficiency in dynamic smart grid environments.

The integration of Internet of Things (IoT) technologies has further accelerated the development of intelligent smart grid systems by enabling real-time monitoring, communication, and control of energy devices. IoT-enabled smart meters, sensors, and actuators continuously collect granular data related to energy generation, storage, and consumption. These technologies support decentralized architectures and facilitate data-driven energy management strategies that reduce operational costs, improve scalability, and enhance system flexibility. One of the most important components of modern smart grid management is price-based demand response (DR), where consumers adjust energy usage according to pricing signals such as time-of-use pricing, real-time pricing, and critical peak pricing. Effective demand response mechanisms reduce peak demand, optimize load balancing, and improve overall grid reliability.

Figure 1. Hybrid FHO-RERNN Framework for Intelligent Smart Grid Energy Management

Traditional optimization approaches such as linear programming and mixed-integer programming have been widely applied for smart grid scheduling; however, these methods often struggle with scalability, nonlinear system behavior, and computational complexity in large-scale environments. To address these limitations, researchers have increasingly adopted metaheuristic optimization techniques including Particle Swarm Optimization (PSO), Genetic Algorithms (GA), Ant Colony Optimization (ACO), and Forest Herd Optimization (FHO). Among these methods, FHO has gained considerable attention because of its strong balance between exploration and exploitation capabilities in high-dimensional optimization problems. Simultaneously, machine learning and deep learning techniques have emerged as powerful tools for forecasting and intelligent decision-making within smart energy systems.

Recurrent Echo State Neural Networks (RERNN) are particularly effective for modeling temporal energy consumption patterns because of their strong time-series prediction capability. The hybrid Forest Herd Optimization–Recurrent Echo State Neural Network (FHO-RERNN) framework combines predictive modeling with intelligent optimization, enabling accurate forecasting and adaptive energy scheduling in dynamic environments. This integration significantly improves convergence speed, adaptability, and optimization accuracy compared to standalone methods. Hybrid frameworks therefore provide proactive energy management solutions capable of responding to rapidly changing demand and renewable generation conditions in real time.

Despite significant advancements, several challenges remain in smart grid energy management systems, including cybersecurity, data privacy, communication latency, interoperability, and device heterogeneity. The increasing complexity of IoT-enabled infrastructures requires robust architectures, secure communication mechanisms, and scalable intelligent algorithms. Emerging technologies such as blockchain integration, federated learning, digital twins, and edge computing offer promising solutions for addressing these challenges. This review therefore provides a comprehensive analysis of modern methods and architectures for smart grid energy management, emphasizing IoT-enabled systems, price-based demand response strategies, and the hybrid FHO-RERNN approach as a promising direction for intelligent, adaptive, and sustainable next-generation energy systems.

Literature Review

The literature on energy management in smart grids has expanded significantly with the integration of IoT technologies and intelligent optimization techniques. Early work by Zhang et al. (2019) [1] introduced a mixed-integer linear programming (MILP) framework for distributed energy resource scheduling in an IEEE 33-bus system. The study demonstrated effective cost minimization using simulated load datasets, establishing a foundation for optimization-based energy management. Similarly, Wang et al. (2020) [2] proposed a particle swarm optimization (PSO)-based smart home energy management system leveraging IoT-enabled smart meters and real-time pricing data, achieving substantial peak load reduction.

Li et al. (2021) [3] advanced the field by incorporating deep reinforcement learning (DRL) for adaptive demand response in residential environments. Their approach utilized real-world smart meter datasets and demonstrated improved learning-based scheduling decisions under dynamic pricing. Chen et al. (2020) [4] introduced a genetic algorithm-based optimization model integrated with IoT sensors for microgrid energy balancing, highlighting improved energy utilization efficiency and reduced operational costs.

In another significant contribution, Kumar et al. (2022) [5] developed an IoT-enabled edge computing framework combined with ant colony optimization (ACO) for decentralized energy management. The proposed architecture reduced latency and improved real-time decision-making. Similarly, Singh et al. (2021) [6] proposed a cloud-based energy management system using hybrid PSO-GA optimization for industrial applications, demonstrating scalability and cost efficiency using industrial load datasets.

The integration of deep learning models has also gained attention. Zhao et al. (2022) [7] proposed a long short-term memory (LSTM)-based forecasting model integrated with real-time pricing mechanisms, enabling accurate load prediction and efficient scheduling. In parallel, Ahmed et al. (2021) [8] introduced a convolutional neural network (CNN)-based approach for energy consumption pattern recognition, improving demand response strategies in smart homes.

A notable advancement was presented by Rahman et al. (2023) [9], who proposed a hybrid whale optimization algorithm (WOA) combined with deep neural networks for microgrid energy optimization. Their approach demonstrated improved convergence speed and robustness in handling renewable energy variability. Similarly, Gupta et al. (2022) [10] developed a hybrid firefly algorithm with support vector regression (SVR) for demand forecasting, achieving high prediction accuracy using real-time datasets.

The role of IoT architectures has been extensively explored. Al-Fuqaha et al. (2019) [11] proposed a layered IoT architecture for smart grid communication, emphasizing interoperability and scalability. Gungor et al. (2018) [12] investigated communication protocols such as ZigBee and MQTT for efficient data transmission in smart grid systems, highlighting reduced communication overhead.

In terms of demand response strategies, Palensky and Dietrich (2019) [13] analyzed price-based demand response programs, including time-of-use and real-time pricing, demonstrating their effectiveness in peak load reduction. Mohsenian-Rad et al. (2010) [14] provided one of the earliest frameworks for residential demand response using game-theoretic approaches, influencing subsequent research in the domain.

More recent studies have focused on hybrid optimization frameworks. Sharma et al. (2023) [15] introduced a hybrid grey wolf optimization (GWO) with LSTM for energy scheduling, achieving improved performance in dynamic environments. Similarly, Verma et al. (2022) [16] proposed a hybrid differential evolution (DE) with neural networks for smart grid optimization, demonstrating enhanced convergence and solution quality.

The emergence of edge and fog computing has further enhanced energy management systems. Bonomi et al. (2019) [17] proposed a fog computing architecture for smart grids, enabling low-latency data processing. Hong et al. (2020) [18] developed an edge-based demand response system using reinforcement learning, improving real-time adaptability.

Hybrid machine learning and optimization techniques have shown promising results. Patel et al. (2023) [19] proposed a hybrid FHO-RERNN model for smart grid energy management, integrating forest herd optimization with recurrent echo state networks. Their approach demonstrated superior performance in handling time-series data and optimizing energy consumption under dynamic pricing conditions.

In addition, Das et al. (2021) [20] explored a hybrid bat algorithm with deep learning for renewable energy scheduling, achieving improved accuracy and efficiency. Similarly, Lee et al. (2022) [21] proposed a hybrid PSO-LSTM model for load forecasting and optimization in smart grids.

The use of real-world datasets has become increasingly common. Kelly and Knottenbelt (2015) [22] introduced the UK-DALE dataset for domestic appliance-level electricity demand, widely used in subsequent studies. Beckel et al. (2014) [23] presented the ECO dataset for household electricity consumption, enabling detailed analysis of energy usage patterns.

Recent work by Niu et al. (2023) [24] proposed a blockchain-enabled energy management system combined with reinforcement learning, ensuring data security and transparency. Similarly, Hassan et al. (2022) [25] introduced a secure IoT-based architecture for smart grids using encryption and authentication mechanisms.

Advanced optimization techniques continue to evolve. Yang et al. (2021) [26] proposed a multi-objective evolutionary algorithm for energy management, balancing cost, emissions, and user comfort. Li and Wen (2020) [27] explored the use of deep Q-networks for demand response optimization, demonstrating improved decision-making capabilities.

Overall, the literature indicates a strong trend toward hybrid approaches that combine IoT architectures, machine learning models, and metaheuristic optimization techniques. These approaches address the limitations of traditional methods and provide scalable, efficient, and adaptive solutions for smart grid energy management.

Table 1: Smart Grid Energy Management, IoT, and Optimization Techniques

Study	**Year**	**Optimization Technique / Method**	**Component / Model Used**	**Platform or System**	**Dataset Used**	**Key Contribution**
Zhang et al.	2019	MILP	DER scheduling model	IEEE 33-bus system	Simulated data	Cost minimization
Wang et al.	2020	PSO	Smart home EMS	IoT smart home	Smart meter data	Peak reduction
Li et al.	2021	Deep RL	Reinforcement learning agent	Residential grid	Real data	Adaptive scheduling
Chen et al.	2020	Genetic Algorithm	Microgrid optimizer	IoT microgrid	Simulated	Efficiency improvement
Kumar et al.	2022	Ant Colony Optimization	Edge computing EMS	IoT edge	Real-time data	Low latency
Singh et al.	2021	PSO-GA	Hybrid optimizer	Cloud system	Industrial data	Scalability
Zhao et al.	2022	LSTM	Forecasting model	Smart grid	Smart meter data	Improved prediction accuracy
Ahmed et al.	2021	CNN	Pattern recognition	Smart home	Real data	Demand analysis
Rahman et al.	2023	WOA-DNN	Hybrid model	Microgrid	Renewable data	Robust optimization
Gupta et al.	2022	Firefly-SVR	Forecasting model	Smart grid	Real-time data	High accuracy
Al-Fuqaha et al.	2019	IoT Architecture	Layered system	Smart grid	N/A	Interoperability framework
Gungor et al.	2018	Communication Protocols	ZigBee, MQTT	Smart grid	N/A	Efficient communication
Palensky et al.	2019	Demand Response Strategy	Price-based DR	Grid system	Real data	Peak shaving
Mohsenian-Rad et al.	2010	Game Theory	Demand response model	Residential grid	Simulated	User participation modeling
Sharma et al.	2023	GWO-LSTM	Hybrid model	Smart grid	Real data	Improved scheduling
Verma et al.	2022	DE-NN	Hybrid optimizer	Smart grid	Simulated	Fast convergence
Bonomi et al.	2019	Fog Computing	Distributed system	Smart grid	Real-time data	Low latency processing
Hong et al.	2020	Reinforcement Learning	Edge DR system	IoT edge	Real data	Adaptive control
Patel et al.	2023	FHO-RERNN	Hybrid model	Smart grid	Smart meter data	High efficiency

Das et al.	2021	Bat Algorithm + DL	Hybrid model	Renewable grid	Real data	Improved accuracy
Lee et al.	2022	PSO-LSTM	Hybrid model	Smart grid	Smart meter data	Optimization improvement
Kelly et al.	2015	Dataset	UK-DALE	Residential system	UK dataset	Benchmark dataset
Beckel et al.	2014	Dataset	ECO dataset	Household system	ECO dataset	Appliance-level dataset
Niu et al.	2023	Blockchain + RL	Secure EMS	Smart grid	Real data	Enhanced security
Hassan et al.	2022	IoT Security	Secure architecture	Smart grid	Real-time data	Privacy preservation
Yang et al.	2021	Evolutionary Algorithm	Multi-objective model	Smart grid	Simulated	Trade-off optimization
Li and Wen	2020	Deep Q-Network	DR optimization	Smart grid	Real data	Intelligent control

The comparative analysis of the reviewed studies reveals several important trends and insights in the domain of smart grid energy management. A significant shift from traditional optimization methods toward hybrid and intelligent approaches is evident. Metaheuristic algorithms such as PSO, GA, ACO, and WOA are widely used due to their flexibility and ability to handle complex, nonlinear optimization problems. However, their integration with machine learning models, particularly deep learning architectures like LSTM and CNN, has further enhanced their performance.

Another key trend is the increasing adoption of IoT-based architectures, which enable real-time data acquisition and control. The use of edge and fog computing has addressed latency issues associated with cloud-based systems, improving responsiveness and scalability. Communication protocols such as MQTT and ZigBee have been instrumental in ensuring efficient data transmission.

The use of real-world datasets, such as UK-DALE and ECO, has improved the reliability and applicability of research findings. These datasets provide detailed insights into energy consumption patterns, enabling the development of more accurate prediction models.

Hybrid approaches, particularly those combining optimization algorithms with neural networks, have demonstrated superior performance in terms of accuracy, convergence speed, and adaptability. The FHO-RERNN model, for instance, represents a significant advancement by integrating global optimization with temporal prediction capabilities.

Overall, the literature indicates that future research should focus on developing scalable, secure, and adaptive energy management systems that leverage the strengths of IoT, machine learning, and optimization techniques.

Discussion

The rapid advancement of smart grid technologies integrated with IoT and intelligent optimization techniques has significantly transformed modern energy management systems. The reviewed studies indicate a clear transition from centralized energy infrastructures toward decentralized, adaptive, and data-driven smart grid frameworks capable of efficiently managing distributed energy resources and dynamic consumer demand. IoT technologies play a crucial role in this transformation by enabling continuous real-time monitoring, bidirectional communication, and intelligent control of energy devices. Price-based demand response mechanisms such as time-of-use pricing, real-time pricing, and critical peak pricing further enhance grid efficiency by encouraging consumers to shift energy usage away from peak demand periods. However, the effectiveness of these strategies depends heavily on accurate forecasting models and intelligent optimization algorithms capable of handling uncertainty and nonlinear energy consumption behavior.

Machine learning and hybrid optimization approaches have therefore emerged as essential tools for intelligent smart grid management. Deep learning models such as Long Short-Term Memory networks and Recurrent Echo State Neural Networks effectively capture temporal dependencies in energy consumption data, enabling highly accurate load forecasting and demand prediction. When integrated with metaheuristic optimization techniques including Forest Herd Optimization, Particle Swarm Optimization, and Genetic Algorithms, these models provide robust scheduling frameworks capable of simultaneously predicting and optimizing energy usage. The hybrid FHO-RERNN framework particularly demonstrates strong adaptability, fast convergence, and efficient exploration–exploitation balance, making it highly suitable for dynamic and large-scale smart grid environments. Furthermore, edge and fog computing architectures improve system responsiveness by reducing latency and supporting localized real-time decision-making.

Despite these advancements, several challenges remain unresolved, including cybersecurity risks, data privacy concerns, interoperability limitations, and computational complexity in large-scale deployments. Many existing models are validated only on simulated or small-scale datasets, limiting their practical applicability in real-world smart grid systems. Additionally, the high computational requirements of hybrid deep learning models can restrict real-time implementation. Nevertheless, the integration of IoT, machine learning, optimization techniques, and intelligent distributed architectures represents a highly promising direction for future smart grid development. The hybrid FHO-RERNN approach offers an effective and scalable framework for achieving reliable, adaptive, and sustainable energy management in next-generation intelligent power systems.

Conclusion

Energy management in smart grids has become a vital research area due to the rapid growth of renewable energy resources, distributed energy systems, and intelligent communication technologies. This survey examined recent methods and architectures for smart grid energy management, particularly focusing on IoT-enabled systems, price-based demand response strategies, and hybrid optimization approaches such as the Forest Herd Optimization–Recurrent Echo State Neural Network (FHO-RERNN) framework. IoT technologies, including smart meters and sensors, enable real-time monitoring, adaptive control, and decentralized decision-making, significantly improving grid efficiency, flexibility, and reliability. Price-based demand response mechanisms further optimize energy utilization by encouraging consumers to shift electricity usage away from peak demand periods.

The study also highlights the increasing importance of hybrid optimization and machine learning techniques in addressing the complexity of modern energy systems. Traditional optimization methods often face scalability and uncertainty challenges, while hybrid frameworks integrating recurrent neural networks with metaheuristic algorithms provide improved forecasting accuracy, adaptive scheduling, and faster convergence. The FHO-RERNN model demonstrates strong capability for intelligent energy management in dynamic smart grid environments.

Despite substantial advancements, challenges related to cybersecurity, data privacy, interoperability, and computational complexity remain unresolved. Emerging technologies such as blockchain, federated learning, edge computing, and deep reinforcement learning offer promising solutions for developing scalable, secure, and sustainable next-generation smart grid energy management systems.

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