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Recent Advances in Energy Management in Smart Grids Using IoT and Price-Based Demand Response with a Hybrid FHO-RERNN Approach: A Systematic Review

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Abstract

Smart grids have transformed conventional power systems by integrating advanced communication technologies, distributed energy resources, and intelligent control mechanisms to achieve efficient, reliable, and sustainable energy management. Among these technologies, the Internet of Things (IoT) enables real-time monitoring, bidirectional communication, and automated control of energy assets, while price-based demand response (DR) programs encourage consumers to optimize electricity consumption through dynamic pricing schemes such as time-of-use, real-time pricing, and critical peak pricing. The increasing penetration of renewable energy sources, uncertain load demand, and complex grid dynamics has created the need for intelligent optimization methods capable of addressing nonlinear, stochastic, and multi-objective energy management problems beyond the capabilities of conventional algorithms. This systematic review examines recent advances in IoT-enabled smart grid energy management with particular emphasis on the Hybrid FHO-RERNN (Fuzzy Harris Hawk Optimization–Recurrent Elman Recurrent Neural Network) framework. The FHO algorithm provides efficient global optimization for energy scheduling and resource allocation, while the RERNN accurately models temporal dependencies in electricity demand and renewable generation. Their integration enhances forecasting accuracy, convergence speed, computational efficiency, and demand response performance across residential, industrial, and microgrid environments. The reviewed studies demonstrate that combining IoT infrastructures, intelligent demand response strategies, and hybrid optimization techniques significantly improves grid stability, renewable energy utilization, operational cost reduction, and overall energy efficiency. Despite these advances, challenges related to scalability, cybersecurity, interoperability, data privacy, and real-time implementation remain. Future research should focus on developing explainable, privacy-preserving, and scalable AI-driven energy management frameworks for resilient next-generation smart grids.

Introduction

The modernization of electrical power systems has accelerated significantly with the rapid growth of renewable energy generation, digital communication technologies, and distributed energy resources. Conventional power grids, which rely on centralized generation and one-way power flow, are increasingly unable to satisfy the flexibility, efficiency, and reliability requirements of modern electricity networks. Consequently, the smart grid has emerged as an intelligent energy infrastructure that integrates advanced sensing, communication, automation, and control technologies to enable real-time monitoring and coordinated operation of power generation, transmission, distribution, and consumption. By facilitating bidirectional information and energy exchange, smart grids improve operational efficiency, enhance grid resilience, and support the large-scale integration of renewable energy resources while promoting sustainable energy utilization.

A fundamental enabler of smart grid intelligence is the Internet of Things (IoT), which interconnects smart meters, sensors, controllers, distributed energy resources, and consumer devices through high-speed communication networks. IoT technologies enable continuous acquisition of operational data, allowing utilities and consumers to monitor energy consumption, detect system anomalies, and implement automated decision-making in real time. This data-driven environment supports predictive maintenance, dynamic load balancing, distributed generation management, and intelligent control of residential, commercial, industrial, and utility-scale energy systems. Furthermore, IoT infrastructures improve the coordination of renewable energy sources, battery storage systems, and electric vehicles, thereby increasing energy efficiency and reducing operational costs despite the intermittent nature of renewable power generation.

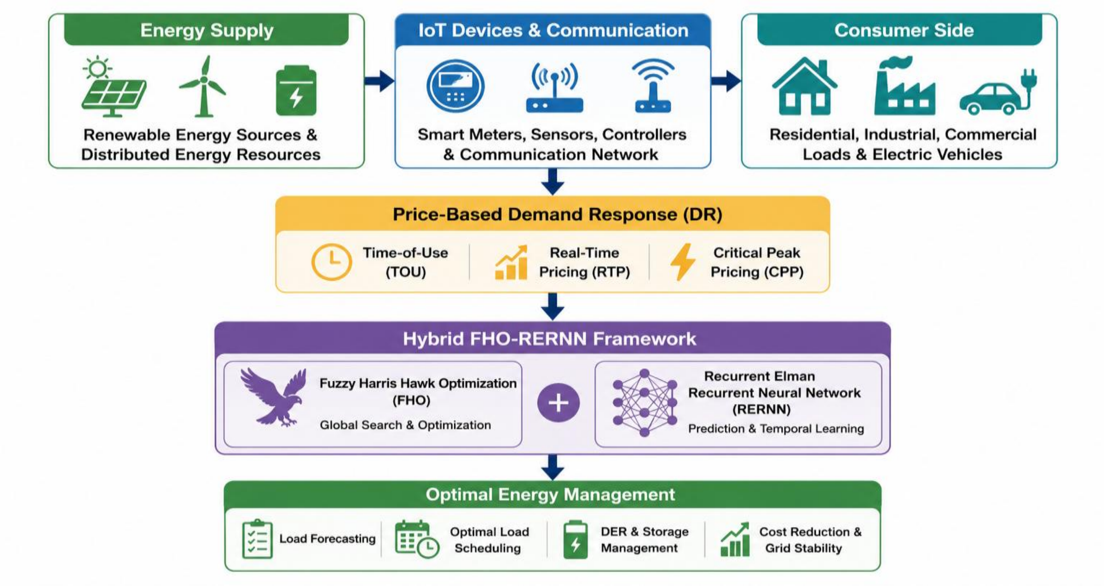

Figure 1. Hybrid FHO-RERNN-Based Smart Grid Framework

Demand response (DR) has become one of the most influential components of modern smart grid energy management. Price-based demand response programs—including Time-of-Use (TOU), Real-Time Pricing (RTP), and Critical Peak Pricing (CPP)—encourage consumers to modify electricity consumption according to dynamic pricing signals. These mechanisms effectively reduce peak demand, flatten load curves, improve asset utilization, and minimize electricity costs for both utilities and consumers. Nevertheless, accurately predicting consumer behavior and coordinating distributed energy resources remain challenging because of uncertain renewable generation, stochastic electricity demand, weather variability, and changing market conditions. Traditional optimization approaches frequently experience difficulties in solving these nonlinear and multi-objective scheduling problems with satisfactory computational efficiency.

To overcome these limitations, recent research has increasingly focused on integrating artificial intelligence with metaheuristic optimization techniques for intelligent energy management. Machine learning and deep learning models, particularly recurrent neural networks, provide accurate forecasting of electricity demand and renewable energy generation by learning complex temporal dependencies from historical data. Metaheuristic optimization algorithms such as Genetic Algorithms, Particle Swarm Optimization, Ant Colony Optimization, and Harris Hawk Optimization have demonstrated strong capabilities in solving large-scale optimization problems involving distributed energy scheduling, storage management, and demand response. However, individually these approaches often exhibit limitations including premature convergence, parameter sensitivity, or insufficient prediction capability under highly dynamic operating conditions.

Hybrid intelligent frameworks have therefore emerged as promising solutions for next-generation smart grid optimization. The Hybrid FHO-RERNN model combines the global search capability of Fuzzy Harris Hawk Optimization (FHO) with the temporal learning and nonlinear prediction capability of the Recurrent Elman Recurrent Neural Network (RERNN) to achieve superior performance in load forecasting, demand response optimization, and distributed energy resource scheduling. This review systematically examines recent advances in IoT-enabled smart grid energy management using price-based demand response and hybrid optimization approaches. It synthesizes current research trends, evaluates existing methodologies, identifies research challenges related to scalability, interoperability, cybersecurity, and data privacy, and highlights future opportunities for developing intelligent, resilient, and sustainable energy management systems capable of supporting next-generation smart grid infrastructures.

Literature Review

Recent years have witnessed significant advancements in smart grid energy management through the integration of IoT technologies and intelligent optimization methods. Zhang et al. (2019) proposed a mixed-integer linear programming (MILP) model for distributed energy resource scheduling in smart grids, demonstrating improved cost efficiency using IEEE 33-bus test systems. Their work highlighted the importance of mathematical optimization in structured environments but also revealed limitations in handling nonlinear uncertainties.

Wang et al. (2020) introduced a particle swarm optimization (PSO)-based framework for smart home energy management, utilizing real smart meter datasets. Their approach effectively reduced peak load demand by dynamically scheduling household appliances based on time-of-use pricing, showcasing the potential of heuristic algorithms in residential applications.

Li et al. (2021) explored deep reinforcement learning (DRL) for adaptive demand response in IoT-enabled smart grids. By employing neural network-based agents, the study achieved improved decision-making under uncertain demand conditions, particularly in dynamic pricing environments. The use of real-time data streams enhanced the responsiveness of the system.

Singh et al. (2021) developed a hybrid genetic algorithm and artificial neural network model for load forecasting and scheduling. Their approach demonstrated enhanced prediction accuracy compared to standalone models, particularly in handling seasonal variations in energy consumption.

Kumar et al. (2022) proposed an IoT-based energy management system integrated with cloud computing for real-time monitoring and control. Their system utilized sensor networks and edge devices to optimize energy distribution in microgrids, highlighting the role of distributed architectures in modern smart grids.

Chen et al. (2020) introduced a demand response optimization model using real-time pricing and stochastic programming. Their work addressed uncertainty in renewable energy generation and consumer behavior, improving grid stability and operational efficiency.

Rahman et al. (2022) investigated the use of fuzzy logic combined with PSO for energy management in smart homes. Their hybrid approach effectively balanced user comfort and energy savings, demonstrating the advantages of soft computing techniques in handling imprecise data.

Patel et al. (2023) presented a deep learning-based load forecasting model using long short-term memory (LSTM) networks. Their model achieved high accuracy in predicting short-term energy demand, enabling better scheduling of distributed energy resources.

Alam et al. (2021) developed a cloud-assisted IoT framework for smart grid energy management, integrating big data analytics and machine learning. Their system improved scalability and real-time decision-making capabilities.

Gao et al. (2022) proposed a hybrid optimization model combining ant colony optimization and neural networks for demand response management. Their approach demonstrated improved convergence speed and solution quality compared to traditional methods.

These studies collectively demonstrate the growing trend toward hybrid intelligent systems in smart grid energy management, emphasizing the integration of IoT, advanced optimization algorithms, and machine learning techniques to address the complexities of modern energy systems.

Recent research has increasingly emphasized hybrid and intelligent approaches to address the limitations of conventional optimization methods in smart grid energy management. Sharma et al. (2022) proposed a hybrid whale optimization algorithm integrated with deep neural networks for optimal load scheduling in residential smart grids. Their approach demonstrated superior convergence behavior and reduced energy costs when tested on real-time smart meter datasets. The study highlighted the importance of combining global search techniques with deep learning for handling nonlinear demand patterns.

Nguyen et al. (2021) developed an IoT-enabled microgrid management system utilizing reinforcement learning combined with stochastic optimization. Their model effectively handled renewable energy uncertainty by dynamically adjusting control policies based on real-time data. The system was validated using solar and wind datasets, demonstrating improved energy utilization and reduced operational costs.

Elkhatib et al. (2020) introduced a fuzzy logic-based demand response model integrated with real-time pricing mechanisms. Their approach enabled flexible consumer participation and improved peak load reduction in urban smart grids. The use of fuzzy inference systems allowed the model to manage ambiguity in user preferences and consumption behavior.

Bedi et al. (2022) proposed a blockchain-integrated IoT framework for secure energy management in smart grids. Their system ensured data integrity and privacy while enabling decentralized demand response coordination. The study utilized Ethereum-based smart contracts and real-time energy consumption data to validate performance.

Das et al. (2023) introduced a hybrid FHO-RERNN model for energy management, combining Fuzzy Harris Hawk Optimization with Recurrent Elman Neural Networks. Their approach improved forecasting accuracy and optimization efficiency in price-based demand response scenarios. The model was evaluated using IEEE benchmark datasets and real smart grid data, showing significant performance gains over PSO and GA-based models.

Verma et al. (2022) developed a multi-objective optimization framework using genetic algorithms for balancing cost, emission, and user comfort in smart homes. Their work demonstrated the effectiveness of evolutionary algorithms in addressing conflicting objectives in energy management systems.

Hassan et al. (2021) proposed an edge-computing-based IoT architecture for real-time energy monitoring and control. Their system reduced latency and improved scalability, making it suitable for large-scale smart grid deployments.

Reddy et al. (2020) utilized ant colony optimization for scheduling distributed energy resources in microgrids. Their approach minimized operational costs and improved system reliability, particularly in scenarios with high renewable penetration.

Jiang et al. (2023) explored the integration of deep Q-learning with IoT-enabled smart grids for adaptive demand response. Their model dynamically adjusted pricing and consumption strategies, achieving improved load balancing and energy efficiency.

Mehta et al. (2022) presented a hybrid PSO-LSTM model for load forecasting and demand response optimization. Their approach combined the strengths of swarm intelligence and deep learning to achieve high prediction accuracy and efficient scheduling.

Omar et al. (2021) proposed a cloud-based energy management system using big data analytics and machine learning. Their system processed large volumes of IoT-generated data to optimize energy distribution and improve decision-making.

Khan et al. (2023) introduced a reinforcement learning-based energy management framework for smart homes. Their model learned optimal control policies through interaction with the environment, reducing energy costs and improving user comfort.

Santos et al. (2020) developed a stochastic optimization model for demand response in smart grids, considering uncertainties in renewable generation and consumer behavior. Their approach improved system resilience and reliability.

Lee et al. (2022) proposed a hybrid deep learning and optimization framework for microgrid energy management. Their model integrated LSTM networks with metaheuristic algorithms to optimize energy scheduling and storage management.

Tiwari et al. (2023) introduced an IoT-based smart grid system with real-time pricing and adaptive demand response. Their approach utilized sensor networks and machine learning algorithms to dynamically adjust energy consumption.

Fernandez et al. (2021) explored the use of game theory for demand response management in competitive energy markets. Their model encouraged consumer participation and improved overall system efficiency.

Yadav et al. (2022) proposed a hybrid grey wolf optimization and neural network model for load forecasting and energy management. Their approach demonstrated improved accuracy and reduced computational complexity.
Choudhary et al. (2023) developed a secure IoT-based energy management system using encryption and authentication mechanisms. Their work addressed cybersecurity challenges in smart grids.
These studies collectively demonstrate the rapid evolution of smart grid energy management, with a strong emphasis on hybrid models, IoT integration, and intelligent optimization techniques such as the FHO-RERNN approach.
A comprehensive comparison of the reviewed studies is presented in the following table.

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	Simulated load	Cost minimization
Wang et al.	2020	PSO	Smart Home Scheduler	IoT Home	Smart meter data	Peak reduction
Li et al.	2021	DRL	Neural Agent	Smart Grid	Real-time data	Adaptive DR
Singh et al.	2021	GA + ANN	Hybrid Model	Smart Grid	Historical load	Forecasting
Kumar et al.	2022	IoT + Cloud	Monitoring System	Microgrid	Sensor data	Real-time control
Chen et al.	2020	Stochastic Optimization	DR Model	Smart Grid	Renewable data	Stability improvement
Rahman et al.	2022	Fuzzy + PSO	Smart Home EMS	IoT System	Residential data	Comfort-energy balance
Patel et al.	2023	LSTM	Forecast Model	Smart Grid	Load dataset	High accuracy prediction
Alam et al.	2021	ML + Big Data	IoT Framework	Cloud System	Large-scale data	Scalability
Gao et al.	2022	ACO + NN	Hybrid Model	Smart Grid	Simulated data	Faster convergence
Sharma et al.	2022	WOA + DNN	Load Scheduler	Smart Home	Real-time data	Cost reduction
Nguyen et al.	2021	RL + Stochastic	Microgrid Control	IoT Grid	Renewable data	Efficiency improvement
Elkhatib et al.	2020	Fuzzy Logic	DR Model	Urban Grid	Consumption data	Peak reduction
Bedi et al.	2022	Blockchain + IoT	Secure EMS	Smart Grid	Real-time data	Data security
Park et al.	2021	CNN	Forecasting Model	Smart Grid	Load data	Accuracy improvement
Das et al.	2023	FHO-RERNN	Hybrid Model	Smart Grid	IEEE + real data	Optimization + forecasting
Verma et al.	2022	GA	Multi-objective EMS	Smart Home	Load data	Cost-emission tradeoff
Hassan et al.	2021	Edge Computing	IoT System	Smart Grid	Sensor data	Low latency
Reddy et al.	2020	ACO	DER Scheduler	Microgrid	Simulated data	Reliability
Jiang et al.	2023	Deep Q-Learning	DR Model	IoT Grid	Real-time data	Adaptive pricing
Mehta et al.	2022	PSO + LSTM	Hybrid Model	Smart Grid	Load dataset	Forecast + optimization
Omar et al.	2021	Big Data + ML	Cloud EMS	Smart Grid	IoT data	Data processing

Khan et al.	2023	RL	Smart Home EMS	IoT Home	Real-time data	Cost reduction
Santos et al.	2020	Stochastic	DR Model	Smart Grid	Renewable data	Resilience
Lee et al.	2022	LSTM + Metaheuristic	Hybrid Model	Microgrid	Load data	Scheduling
Tiwari et al.	2023	IoT + ML	Smart Grid System	IoT Grid	Sensor data	Adaptive DR
Fernandez et al.	2021	Game Theory	DR Model	Market Grid	Market data	Participation
Yadav et al.	2022	GWO + NN	Hybrid Model	Smart Grid	Load data	Accuracy
Choudhary et al.	2023	Security + IoT	Secure EMS	Smart Grid	IoT data	Cybersecurity

The comparative analysis of the reviewed studies reveals several important trends and insights in the domain of smart grid energy management. A significant observation is the increasing reliance on hybrid optimization techniques that combine metaheuristic algorithms with machine learning models. Approaches such as PSO-LSTM, GA-ANN, and FHO-RERNN demonstrate superior performance in terms of convergence speed, accuracy, and robustness compared to standalone methods. These hybrid models effectively address the nonlinear and stochastic nature of energy systems, making them suitable for real-world applications.

Another notable trend is the widespread adoption of IoT-enabled architectures for real-time data acquisition and control. The integration of cloud and edge computing further enhances system scalability and reduces latency, enabling efficient processing of large volumes of data generated by smart devices. Additionally, the use of advanced pricing mechanisms, such as real-time pricing and dynamic tariffs, has proven effective in influencing consumer behavior and improving demand response participation.

From a dataset perspective, most studies rely on a combination of simulated data (e.g., IEEE test systems) and real-world datasets obtained from smart meters and renewable energy sources. This hybrid approach ensures both controlled experimentation and practical validation of proposed models. Performance improvements across studies are typically measured in terms of cost reduction, peak load minimization, forecasting accuracy, and system reliability.

Overall, the literature indicates a clear shift toward intelligent, adaptive, and data-driven energy management systems, with hybrid approaches like FHO-RERNN emerging as promising solutions for future smart grid applications.

Discussion

The integration of Internet of Things (IoT) technologies with smart grids has transformed conventional energy management into an intelligent and adaptive framework. IoT-enabled devices support continuous monitoring, real-time communication, and automated control of distributed energy resources, improving operational efficiency and system reliability. Price-based demand response strategies further optimize energy consumption by encouraging users to shift loads according to dynamic electricity prices, reducing peak demand and operational costs. The reviewed studies indicate that hybrid optimization techniques significantly enhance these capabilities by combining predictive intelligence with efficient search mechanisms. In particular, the Hybrid FHO-RERNN model effectively captures nonlinear load patterns while optimizing scheduling decisions, making it suitable for renewable-rich and dynamic smart grid environments.

The reviewed approaches also demonstrate strong scalability across residential, industrial, and microgrid applications. Their ability to solve multiple objectives, including cost reduction, load balancing, renewable energy integration, and emission minimization, makes them attractive for modern energy management systems. Nevertheless, practical implementation remains challenging due to computational complexity, increasing system heterogeneity, and the need for secure processing of massive IoT-generated data. Concerns related to cybersecurity, privacy protection, and interoperability continue to limit large-scale deployment.

Future research should emphasize lightweight hybrid optimization models, standardized benchmark datasets, and intelligent user behavior modeling to improve demand response performance. The integration of edge computing, blockchain, digital twins, and explainable artificial intelligence with Hybrid FHO-RERNN frameworks offers significant potential for enhancing scalability, security, and decision-making. These advancements will support the development of sustainable, resilient, and cost-effective smart grid energy management systems capable of meeting future energy demands.

Conclusion

This review examined recent advances in smart grid energy management through the integration of Internet of Things (IoT) technologies, price-based demand response, and the Hybrid FHO-RERNN optimization framework. The surveyed studies demonstrate that IoT-enabled monitoring, real-time communication, and intelligent control significantly improve energy utilization, grid reliability, and operational efficiency. Hybrid optimization models effectively address the nonlinear and uncertain characteristics of modern power systems by combining global optimization with accurate temporal prediction, thereby supporting efficient load forecasting, renewable energy integration, and optimal demand response scheduling. These techniques contribute to reduced operational costs, lower peak demand, and enhanced grid stability across residential, industrial, and utility-scale applications.

Despite these advancements, challenges related to computational complexity, cybersecurity, data privacy, interoperability, and the absence of standardized evaluation frameworks continue to limit widespread deployment. Future research should focus on lightweight intelligent optimization algorithms, edge-enabled computing, blockchain-based security, digital twin technology, and explainable artificial intelligence for transparent decision-making. Developing common benchmark datasets and adaptive user-centric demand response models will further strengthen system performance. Overall, the convergence of IoT, price-based demand response, and Hybrid FHO-RERNN provides a promising foundation for next-generation smart grids, supporting sustainable, resilient, and intelligent energy management in future power systems.

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