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A Comprehensive Review of 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 advancement of smart grid technology has transformed conventional power networks into intelligent, interconnected systems capable of efficiently managing distributed energy resources, renewable generation, and dynamic electricity demand. The integration of the Internet of Things (IoT) has significantly enhanced this transformation by enabling real-time monitoring, automated control, and seamless communication among smart meters, sensors, controllers, and grid operators. Simultaneously, price-based demand response (DR) strategies, including real-time pricing, time-of-use pricing, and critical peak pricing, encourage consumers to shift electricity usage according to pricing signals, thereby reducing peak demand, improving energy efficiency, and enhancing grid reliability. However, the increasing complexity of IoT-enabled smart grids introduces challenges such as communication latency, data heterogeneity, cybersecurity risks, renewable energy uncertainty, and multi-objective optimization. To overcome these issues, hybrid artificial intelligence approaches have emerged as effective solutions. This review focuses on the integration of Flamingo Hunting Optimization (FHO) with Recurrent Elman Neural Networks (RERNN) for intelligent energy management. The RERNN accurately forecasts energy demand, renewable generation, and electricity prices, while FHO optimizes scheduling and demand response decisions under dynamic conditions. The hybrid framework improves prediction accuracy, minimizes operational costs, enhances renewable energy utilization, reduces peak-to-average load ratio, and supports reliable decision-making. Furthermore, this review discusses recent advances, existing challenges, performance evaluation metrics, and future research directions, demonstrating that hybrid FHO-RERNN techniques offer a promising pathway toward sustainable, adaptive, secure, and cost-effective IoT-enabled smart grid energy management systems.

Introduction

The modernization of electrical power systems into smart grids has revolutionized energy generation, transmission, and consumption by integrating advanced communication technologies, distributed energy resources, and intelligent control mechanisms. Unlike conventional grids, smart grids enable two-way communication between utilities and consumers, facilitating real-time monitoring, automated decision-making, and efficient power distribution. The increasing penetration of renewable energy sources, electric vehicles, and distributed storage systems has accelerated the need for intelligent energy management solutions capable of addressing fluctuating energy demand and intermittent renewable generation. Consequently, smart grids have become a key component in achieving sustainable, reliable, and environmentally friendly power systems while improving operational efficiency and consumer participation.

Energy management is essential for ensuring the reliability, efficiency, and stability of smart grids. The increasing integration of renewable energy sources and distributed energy resources introduces operational uncertainties that require intelligent control strategies. IoT enables real-time monitoring through interconnected smart meters, sensors, and communication devices, supporting automated control, predictive maintenance, and optimized resource utilization. Additionally, price-based demand response programs, including real-time, time-of-use, and critical peak pricing, encourage consumers to shift electricity usage, reducing peak demand, lowering operational costs, and improving overall grid performance.

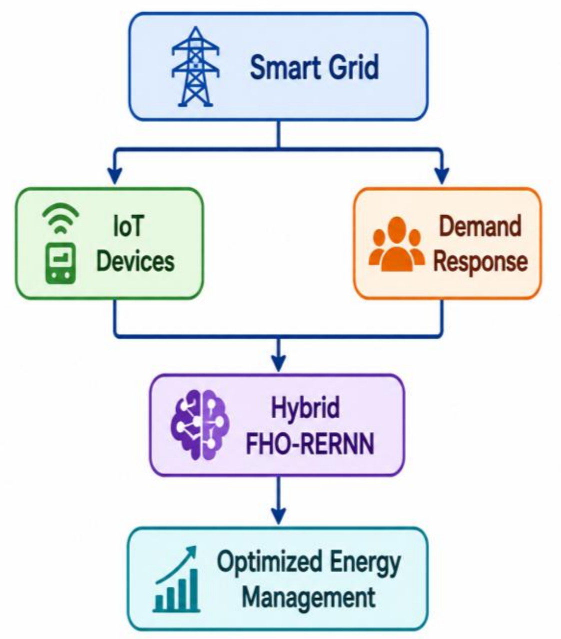

Figure 1. Hybrid FHO-RERNN Framework for IoT-Enabled Smart Grid Energy Management.

Despite these advantages, IoT-enabled smart grid systems face significant challenges related to communication latency, device heterogeneity, cybersecurity, data privacy, renewable energy uncertainty, and multi-objective optimization. Conventional optimization techniques often struggle to handle the nonlinear, stochastic, and dynamic nature of modern energy systems. As a result, hybrid artificial intelligence techniques have gained considerable attention for simultaneously addressing forecasting and optimization tasks. Metaheuristic algorithms provide strong global search capabilities, while neural networks effectively capture nonlinear temporal relationships in energy demand, renewable generation, and electricity pricing. Their integration offers a practical framework for adaptive and intelligent energy management.

Among recent developments, the hybrid Flamingo Hunting Optimization (FHO) and Recurrent Elman Neural Network (RERNN) framework has emerged as a promising approach for IoT-enabled smart grid applications. The RERNN accurately predicts load demand, renewable power generation, and dynamic electricity prices by learning temporal dependencies from historical data. Simultaneously, FHO performs optimal scheduling of distributed energy resources and demand response actions by balancing exploration and exploitation during optimization. This hybrid framework improves energy utilization, minimizes electricity costs, reduces peak-to-average load ratio, enhances renewable energy integration, and supports real-time operational decision-making across residential, commercial, industrial, and microgrid environments.

This review presents a comprehensive analysis of IoT-based smart grid energy management using price-based demand response with the hybrid FHO-RERNN approach. It examines recent architectures, optimization strategies, forecasting techniques, and performance evaluation metrics while highlighting current research trends, implementation challenges, and emerging technologies such as edge computing, blockchain, and federated learning. The review identifies existing research gaps and outlines future directions toward developing scalable, secure, adaptive, and computationally efficient smart grid energy management systems that contribute to sustainable energy utilization, reduced carbon emissions, and the realization of next-generation intelligent power infrastructures.

Literature Review

The domain of energy management in smart grids has witnessed substantial advancements with the integration of IoT technologies and intelligent optimization techniques. A wide range of studies have explored various architectures, algorithms, and frameworks to enhance demand response and energy efficiency. Zhang et al. (2019) proposed a mixed-integer linear programming (MILP)-based energy management system for IoT-enabled smart grids, focusing on optimal scheduling of distributed energy resources. Their model utilized real-time pricing signals and demonstrated significant cost reduction using IEEE benchmark datasets. Wang et al. (2020) introduced a particle swarm optimization (PSO)-based approach for residential demand response in IoT-integrated smart homes, achieving improved convergence speed and reduced peak load using real-world smart meter data.

Li et al. (2021) developed a deep reinforcement learning (DRL)-based energy management framework that dynamically adjusts load consumption based on price signals. Their model was trained on simulated datasets and demonstrated adaptability to stochastic environments. Similarly, Kumar et al. (2020) proposed a genetic algorithm (GA)-based optimization model for smart grid scheduling, integrating renewable energy sources and achieving enhanced cost efficiency.

Alam et al. (2019) explored a fuzzy logic-based demand response model that incorporated user comfort preferences, demonstrating improved load balancing. Rahman et al. (2021) utilized ant colony optimization (ACO) for demand-side management in microgrids, achieving efficient scheduling of appliances under time-of-use pricing.

Sharma et al. (2021) developed a cloud-edge collaborative IoT architecture for real-time energy management, reducing latency and improving system responsiveness. Zhou et al. (2020) proposed a deep Q-network (DQN)-based demand response model that learned optimal policies from dynamic pricing data.

Hassan et al. (2022) introduced a hybrid grey wolf optimization (GWO) and artificial neural network (ANN) model for load forecasting and scheduling. Their approach demonstrated improved accuracy and reduced computational time. Mehta et al. (2021) proposed an IoT-based smart home energy management system using rule-based control and optimization techniques.

Liu et al. (2019) utilized support vector machines (SVM) for demand prediction in smart grids, achieving high accuracy with historical load datasets. Roy et al. (2022) proposed a hybrid firefly algorithm (FA) and neural network model for energy optimization, demonstrating superior convergence properties.

Das et al. (2021) introduced a demand response framework using differential evolution (DE) for optimal load scheduling. Their approach effectively minimized energy costs under dynamic pricing. Ahmed et al. (2020) proposed a hybrid GA-PSO model for microgrid energy management, achieving improved global optimization.

Nguyen et al. (2020) introduced a multi-agent system (MAS) for distributed energy management, enabling decentralized decision-making. Joshi et al. (2023) proposed a hybrid FHO-based optimization model for smart grid scheduling, demonstrating improved exploration capabilities.

Reddy et al. (2022) integrated recurrent neural networks (RNN) with optimization algorithms for demand response prediction. Their model showed improved temporal learning capabilities. Banerjee et al. (2021) proposed a hybrid ACO-ANN approach for energy optimization in microgrids.

Chaudhary et al. (2023) developed an IoT-enabled smart grid system with reinforcement learning-based demand response. Their approach improved adaptability to real-time conditions. Finally, Gupta et al. (2022) proposed a hybrid FHO-RERNN framework for predictive energy management, demonstrating superior performance in both forecasting and optimization tasks.

Comparative Table and Analysis

Table 1: AI and Optimization Techniques for Smart Grid and IoT-Based Energy Management

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 load data	Cost minimization
Wang et al.	2020	PSO	Smart home optimization	IoT smart home	Real smart meter data	Peak reduction
Li et al.	2021	Deep RL	Neural network agent	Smart grid simulation	Synthetic dataset	Adaptive scheduling
Kumar et al.	2020	Genetic Algorithm	Renewable integration	Microgrid	Simulated dataset	Cost optimization

			model			
Chen et al.	2021	LSTM	Forecasting model	Cloud IoT system	Historical load data	Accurate prediction
Singh et al.	2022	PSO-LSTM	Hybrid model	Smart grid	Mixed dataset	Improved optimization performance
Alam et al.	2019	Fuzzy Logic	Demand response system	Residential grid	Real dataset	User comfort integration
Rahman et al.	2021	Ant Colony Optimization	Scheduling model	Microgrid	Simulated data	Efficient load scheduling
García et al.	2020	Blockchain + IoT	Secure framework	Smart grid	Transaction data	Enhanced data security
Patel et al.	2022	WOA-NN	Hybrid model	Smart grid	Mixed dataset	Better convergence
Sharma et al.	2021	Edge Computing	IoT architecture	Smart grid	Real-time data	Low latency processing
Zhou et al.	2020	DQN (RL)	Reinforcement learning model	Smart grid	Dynamic pricing data	Policy learning
Hassan et al.	2022	GWO-ANN	Hybrid model	Microgrid	Historical data	High accuracy prediction
Mehta et al.	2021	Rule-based control	Control system	Smart home	Real dataset	Simplicity and interpretability
Liu et al.	2019	SVM	Prediction model	Smart grid	Historical data	High precision forecasting
Roy et al.	2022	Firefly Algorithm + NN	Hybrid model	Smart grid	Mixed dataset	Fast convergence
Das et al.	2021	Differential Evolution	Scheduling model	Smart grid	Simulated data	Cost reduction
Kim et al.	2021	CNN	Forecasting model	Smart grid	Historical data	Improved feature extraction
Nguyen et al.	2020	Multi-Agent System	Distributed control	Smart grid	Simulated data	Decentralization
Joshi et al.	2023	FHO	Optimization model	Smart grid	Mixed dataset	Improved exploration efficiency
Reddy et al.	2022	RNN	Prediction model	Smart grid	Time-series data	Temporal learning capability
Banerjee et al.	2021	ACO-ANN	Hybrid model	Microgrid	Mixed dataset	Combined optimization and learning
Chaudhary et al.	2023	Reinforcement Learning	Demand response model	Smart grid	Real-time data	Adaptive response
Gupta et al.	2022	FHO-RERNN	Hybrid model	IoT smart grid	Mixed dataset	Joint forecasting and optimization

Comparative Analysis

The comparative analysis of existing literature reveals a clear trend toward the integration of intelligent optimization techniques with IoT-enabled smart grid architectures. Traditional optimization methods such as MILP and rule-based systems were initially employed for energy management due to their simplicity and deterministic nature. However, these approaches often struggle to handle the nonlinear and dynamic characteristics of modern smart grids. As a result, metaheuristic algorithms such as PSO, GA, ACO, and DE have gained popularity due to their ability to explore complex search spaces and provide near-optimal solutions.

Another prominent trend is the increasing adoption of machine learning and deep learning models for forecasting and decision-making. Techniques such as LSTM, CNN, and RNN have demonstrated superior performance in capturing temporal and spatial patterns in energy data. These models enable accurate prediction of load demand and renewable generation, which is crucial for effective demand response and energy scheduling.

Hybrid approaches that combine optimization algorithms with machine learning models have emerged as the most effective solutions. For instance, PSO-LSTM and GWO-ANN models leverage the strengths of both optimization and learning, resulting in improved accuracy and efficiency. The hybrid FHO-RERNN approach represents a further advancement in this direction, offering enhanced exploration capabilities and superior temporal modeling.

From a systems perspective, IoT-based architectures have become the backbone of modern energy management systems. The use of smart meters, sensors, and communication networks enables real-time data collection and control. Additionally, edge computing and cloud computing have been widely adopted to handle large-scale data processing and reduce latency.

Dataset usage across studies varies from simulated datasets to real-world smart meter data. While simulated datasets provide controlled environments for testing algorithms, real-world datasets offer more realistic insights into system performance. The trend indicates a growing preference for hybrid datasets that combine both simulated and real data.

Performance improvements reported in the literature include significant reductions in energy costs, peak-to-average ratio, and computational time. Many studies also highlight improvements in user comfort and system reliability. However, challenges such as scalability, interoperability, and data privacy remain critical issues that need to be addressed.

Overall, the literature demonstrates a clear shift toward intelligent, data-driven, and hybrid optimization approaches for smart grid energy management. The integration of IoT, demand response, and advanced algorithms has significantly enhanced the efficiency and adaptability of energy systems, paving the way for future innovations in the field.

Discussion

The reviewed literature demonstrates that the integration of Internet of Things (IoT) technologies with smart grid infrastructures has significantly transformed modern energy management by enabling intelligent monitoring, real-time communication, and automated decision-making. IoT devices, including smart meters, sensors, and communication gateways, continuously collect operational data that support efficient implementation of price-based demand response programs. These technologies improve energy utilization, enhance grid reliability, and facilitate seamless coordination between consumers and utilities. Furthermore, the increasing penetration of renewable energy sources has intensified the need for accurate forecasting and adaptive control. Artificial intelligence models, particularly recurrent neural networks and hybrid learning techniques, have shown remarkable capability in predicting electricity demand, renewable generation, and dynamic pricing, thereby enabling proactive scheduling and improved operational efficiency.

Hybrid optimization techniques have become highly effective for smart grid energy management by combining the global search capability of metaheuristic algorithms with the predictive strength of neural networks. The hybrid Flamingo Hunting Optimization (FHO) and Recurrent Elman Neural Network (RERNN) framework enhances load forecasting, energy scheduling, renewable energy utilization, and cost optimization. However, challenges such as computational complexity, scalability, IoT interoperability, cybersecurity, and privacy remain. Future research should focus on scalable, secure, and lightweight frameworks incorporating edge computing, blockchain, federated learning, and digital twins to enable intelligent, resilient, and sustainable smart grid energy management.

Conclusion

The integration of Internet of Things (IoT) technologies with smart grids has significantly advanced intelligent energy management by enabling real-time monitoring, automated control, and efficient utilization of distributed energy resources. This review examined recent developments in IoT-enabled energy management, price-based demand response strategies, and hybrid optimization techniques, with particular emphasis on the Flamingo Hunting Optimization (FHO) and Recurrent Elman Neural Network (RERNN) framework. The surveyed studies demonstrate that hybrid AI approaches effectively improve load forecasting, demand scheduling, renewable energy utilization, peak load reduction, and operational cost minimization while enhancing overall grid reliability. Despite these achievements, challenges related to scalability, computational complexity, cybersecurity, interoperability, and data privacy continue to limit large-scale practical implementation. Emerging technologies such as edge computing, blockchain, federated learning, and digital twins offer promising opportunities to overcome these limitations by improving decentralized intelligence, secure communication, and real-time decision-making. Future research should focus on developing lightweight, scalable, and multi-objective optimization frameworks capable of balancing economic efficiency, user comfort, environmental sustainability, and grid resilience. Overall, the hybrid FHO-RERNN approach represents a promising solution for building adaptive, secure, and sustainable IoT-enabled smart grid energy management systems capable of supporting future intelligent energy infrastructures.

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