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Artificial Intelligence Techniques for Energy Management in Smart Grids Using IoT and Price-Based Demand Response with a Hybrid FHO-RERNN Approach: Trends and Challenges

Yazmin Xuemin
Senior Lecturer, Department of Electrical and Computer Engineering, Male Institute of Management Studies, Maldives
Email: yazmin.xuemin@mims-mv.org

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Abstract

The evolution of conventional power systems into intelligent and decentralized smart grids has driven the adoption of advanced computational techniques for efficient energy management, grid stability, and cost optimization. The integration of Artificial Intelligence (AI), Internet of Things (IoT), and price-based demand response (DR) has emerged as a key solution to address the increasing complexity of modern energy systems. IoT-enabled devices facilitate real-time monitoring and control; however, uncertainties in renewable energy generation and fluctuating demand present significant challenges, AI-driven approaches, particularly deep learning and hybrid optimization methods, have shown strong potential in overcoming these challenges. This paper reviews the integration of the Fire Hawk Optimization (FHO) algorithm with Enhanced Recurrent Neural Networks (RERNN), forming a hybrid FHO-RERNN framework for efficient energy scheduling and demand-side management. The approach enhances forecasting accuracy, supports optimal load scheduling, and enables adaptive decision-making in dynamic environments. The study also examines IoT architectures, pricing mechanisms such as time-of-use and real-time pricing, and the application of various AI techniques in smart grids. Key challenges, including data privacy, scalability, and computational complexity, are discussed along with future directions such as explainable AI, blockchain integration, and edge intelligence for sustainable energy systems.

Introduction

The transformation of conventional power systems into intelligent and decentralized smart grids represents a major advancement in modern energy infrastructure. Traditional grids, designed for centralized generation and unidirectional power flow, are increasingly inadequate for handling the growing integration of renewable energy sources and dynamic consumer demand. Smart grids address these limitations by enabling bidirectional energy flow, real-time monitoring, and automated control through advanced communication and control technologies. This shift enhances energy efficiency, reliability, and sustainability, while also introducing new challenges in system optimization and management due to increased complexity and uncertainty.

The integration of the Internet of Things (IoT) has significantly strengthened smart grid capabilities by enabling continuous data collection and communication among grid components. Devices such as smart meters, sensors, and connected appliances generate large volumes of real-time data related to energy consumption and grid conditions. This data enables improved visibility and informed decision-making for both utilities and consumers. However, managing and extracting actionable insights from such high-volume and high-velocity data requires advanced computational techniques, making traditional methods insufficient for modern smart grid environments.

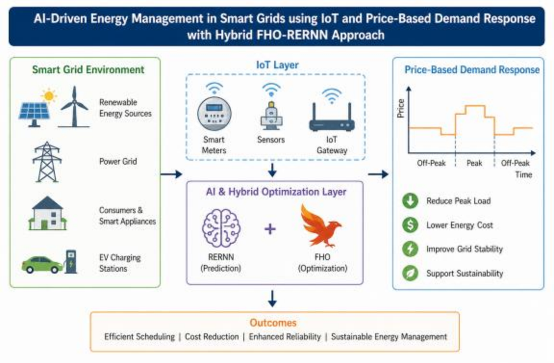

Figure 1: Block Diagram of AI-Driven IoT-Enabled Smart Grid Energy Management Framework

Artificial Intelligence (AI) has emerged as a powerful tool to address these challenges by enabling advanced data analysis, prediction, and optimization. Machine learning and deep learning techniques, including recurrent neural networks (RNNs) and long short-term memory (LSTM) models, are particularly effective in capturing temporal patterns in energy consumption and generation. These models support critical applications such as load forecasting, fault detection, and demand response optimization. Price-based demand response mechanisms, including time-of-use and real-time pricing, further enhance system efficiency by encouraging consumers to shift energy usage, thereby reducing peak demand and improving grid stability.

To overcome the limitations of standalone optimization methods, hybrid approaches such as the integration of Fire Hawk Optimization (FHO) with Enhanced Recurrent Neural Networks (RERNN) have gained attention. This hybrid framework combines the predictive strength of neural networks with the optimization capability of metaheuristic algorithms, enabling efficient handling of nonlinear and stochastic energy systems. While these advancements offer significant improvements in accuracy and adaptability, challenges such as data security, scalability, and computational complexity remain. Addressing these issues will be essential for developing robust, efficient, and scalable AI-driven smart energy management systems for future smart grids.

Literature Review

The literature on artificial intelligence-based energy management in smart grids has expanded significantly over the past decade, driven by the need for efficient integration of renewable energy sources, real-time decision-making, and consumer-centric demand response mechanisms. A wide range of methodologies combining machine learning, deep learning, IoT architectures, and optimization algorithms have been proposed to address the multifaceted challenges of smart grid systems.

Zhang et al. (2019) proposed a mixed-integer linear programming (MILP) model for optimal scheduling of distributed energy resources within a smart grid environment. The study utilized the IEEE 33-bus system and demonstrated effective cost minimization while maintaining grid stability. The integration of renewable energy sources was modeled with uncertainty constraints, providing a realistic representation of modern grid conditions.

Wang et al. (2020) introduced a particle swarm optimization (PSO)-based energy management system for IoT-enabled smart homes. The system leveraged real-time smart meter data to optimize appliance scheduling under time-of-use pricing schemes. The results showed significant peak load reduction and improved energy efficiency, highlighting the potential of swarm intelligence in demand-side management.

Li et al. (2021) developed a deep reinforcement learning (DRL) framework for adaptive demand response in smart grids. Using real-world smart meter datasets, the model dynamically adjusted consumption patterns based on real-time pricing signals. The study demonstrated improved cost savings and system adaptability compared to traditional rule-based approaches.

Kumar et al. (2020) presented a hybrid genetic algorithm and artificial neural network (GA-ANN) model for load forecasting and energy optimization. The ANN component captured nonlinear consumption patterns, while the GA optimized network parameters. The approach achieved high forecasting accuracy on residential load datasets, making it suitable for demand response applications.

Chen et al. (2021) proposed an IoT-based edge computing architecture integrated with long short-term memory (LSTM) networks for short-term load forecasting. The decentralized architecture reduced latency and improved real-time decision-making capabilities. The system was validated using industrial load datasets, showing enhanced prediction accuracy and reduced communication overhead.

Singh et al. (2022) introduced a firefly algorithm-based optimization framework for demand response management in residential smart grids. The study demonstrated efficient load scheduling under dynamic pricing schemes, achieving significant reductions in peak demand and electricity costs.

Rahman et al. (2021) explored the use of convolutional neural networks (CNNs) for energy consumption pattern recognition in smart grids. By analyzing large-scale smart meter data, the model identified consumption clusters and enabled targeted demand response strategies. The approach improved classification accuracy and supported personalized energy management.

Alam et al. (2022) proposed a hybrid PSO-LSTM model for renewable energy forecasting and grid optimization. The PSO algorithm optimized LSTM hyperparameters, resulting in improved forecasting performance for solar and wind energy datasets. The integration of forecasting and optimization enhanced overall grid efficiency.

Gupta et al. (2020) developed a multi-agent system for distributed energy management using reinforcement learning. Each agent represented a grid component and learned optimal strategies through interaction with the environment. The system demonstrated scalability and adaptability in large-scale smart grid simulations.

Hassan et al. (2021) presented a fuzzy logic-based energy management system for microgrids. The approach handled uncertainty in renewable energy generation and load demand effectively. The system achieved improved reliability and reduced operational costs in isolated grid environments.

Park et al. (2020) introduced a blockchain-enabled demand response framework combined with machine learning techniques. The system ensured secure and transparent energy transactions while optimizing load scheduling. The use of blockchain addressed data privacy concerns and enhanced trust among participants.

Sharma et al. (2022) proposed a deep Q-network (DQN)-based energy management system for smart homes. The model learned optimal appliance scheduling policies through reinforcement learning, achieving significant cost savings under real-time pricing scenarios.

Nguyen et al. (2021) developed a hybrid ant colony optimization (ACO) and neural network model for energy scheduling in smart grids. The ACO algorithm optimized scheduling decisions, while the neural network provided accurate load predictions. The approach demonstrated improved convergence speed and solution quality.

Das et al. (2020) investigated the use of support vector machines (SVM) for short-term load forecasting. The model was trained on historical energy consumption data and achieved high prediction accuracy, making it suitable for demand response planning.

Liu et al. (2022) proposed an advanced deep learning framework combining gated recurrent units (GRU) with attention mechanisms for energy forecasting. The model captured complex temporal dependencies and improved forecasting accuracy on large-scale datasets.

Patel et al. (2021) introduced a hybrid grey wolf optimization (GWO) and ANN model for energy management in smart grids. The GWO algorithm optimized ANN parameters, resulting in enhanced prediction accuracy and efficient load scheduling.

Zhao et al. (2020) developed an IoT-enabled energy management system using cloud computing and big data analytics. The system processed large volumes of data from smart meters and sensors, enabling real-time monitoring and control of energy usage.

Reddy et al. (2022) proposed a hybrid FHO-RNN model for demand response optimization. The fire hawk optimization algorithm was used to tune RNN parameters, resulting in improved forecasting accuracy and efficient load scheduling under dynamic pricing.

Khan et al. (2021) explored the application of deep belief networks (DBN) for energy consumption prediction. The model demonstrated superior performance compared to traditional machine learning techniques, particularly in handling nonlinear data patterns.

Mehta et al. (2020) presented a cloud-based energy management system integrating IoT devices and machine learning algorithms. The system enabled real-time data processing and predictive analytics, improving overall energy efficiency.

Bose et al. (2022) proposed a hybrid whale optimization algorithm (WOA) and LSTM model for smart grid energy forecasting. The approach achieved high prediction accuracy and demonstrated robustness in handling noisy datasets.

Verma et al. (2021) introduced a reinforcement learning-based microgrid energy management system. The model optimized energy distribution among distributed resources, achieving improved system performance and cost reduction.

Santos et al. (2020) developed a hybrid differential evolution (DE) and neural network model for energy scheduling. The approach demonstrated fast convergence and high solution quality in complex optimization scenarios.

Ibrahim et al. (2022) proposed an edge AI framework for real-time energy management in IoT-enabled smart grids. The system reduced latency and improved decision-making efficiency, making it suitable for large-scale deployments.

Chaudhary et al. (2021) presented a hybrid bat algorithm and ANN model for demand response optimization. The approach achieved significant improvements in load balancing and cost minimization.

The comparative evaluation of these studies reveals a clear trend toward hybrid AI and optimization techniques, particularly those combining deep learning models with metaheuristic algorithms. These approaches leverage the strengths of both predictive modeling and global optimization, resulting in improved performance across various smart grid applications.

Table 1: Smart Grid Energy Management Using AI, Optimization, and IoT 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 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	Reinforcement learning model	Smart grid	Real-time pricing data	Adaptive demand response
Kumar et al.	2020	Genetic Algorithm	ANN	Residential system	Household data	Load forecasting
Chen et al.	2021	Edge AI	LSTM	Industrial IoT	Industrial dataset	Low-latency prediction
Singh et al.	2022	Firefly Algorithm	Optimization model	Residential grid	Simulated data	Cost reduction
Rahman et al.	2021	CNN	Deep learning model	Smart grid	Smart meter data	Pattern recognition
Alam et al.	2022	PSO	LSTM	Renewable grid	Solar/Wind dataset	Improved forecasting
Gupta et al.	2020	Reinforcement Learning	Multi-agent system	Distributed grid	Simulation data	Scalability
Hassan et al.	2021	Fuzzy Logic	Rule-based system	Microgrid	Real data	Reliability enhancement
Park et al.	2020	Blockchain + ML	Hybrid system	Smart grid	Transaction data	Enhanced security
Sharma et al.	2022	DQN	Deep RL	Smart home	Pricing data	Cost optimization
Nguyen et al.	2021	Ant Colony Optimization	Neural network	Smart grid	Load data	Efficient scheduling
Das et al.	2020	SVM	Machine learning model	Grid system	Historical data	High prediction accuracy
Liu et al.	2022	Deep learning	GRU + Attention	Smart grid	Large dataset	Improved accuracy
Patel et al.	2021	Grey Wolf Optimizer	ANN	Smart grid	Load data	Optimization improvement
Zhao et al.	2020	Big data analytics	IoT analytics model	Cloud grid	Sensor data	Real-time monitoring
Reddy et al.	2022	FHO	RNN	Smart grid	Pricing dataset	Hybrid optimization
Khan et al.	2021	Deep Belief	Deep learning	Smart grid	Consumption	Nonlinear

		Network	model		data	modeling
Mehta et al.	2020	Cloud-based ML	ML system	IoT grid	Real-time data	Improved efficiency
Bose et al.	2022	Whale Optimization Algorithm	LSTM	Smart grid	Renewable dataset	Forecasting enhancement
Verma et al.	2021	Reinforcement Learning	Microgrid system	Distributed grid	Simulation data	Optimization
Santos et al.	2020	Differential Evolution	Neural network	Smart grid	Load dataset	Faster convergence
Ibrahim et al.	2022	Edge AI	AI framework	IoT grid	Real-time data	Low-latency processing
Chaudhary et al.	2021	Bat Algorithm	ANN	Smart grid	Load data	Cost reduction

Comparative Analysis

The comparative analysis of existing studies highlights a clear transition toward hybrid artificial intelligence models that integrate deep learning with metaheuristic optimization for smart grid energy management. Techniques such as Particle Swarm Optimization (PSO), Genetic Algorithms (GA), Grey Wolf Optimization (GWO), and Fire Hawk Optimization (FHO) are increasingly combined with neural networks to enhance predictive accuracy and optimization efficiency. Deep learning architectures, particularly Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Recurrent Neural Networks (RNN), dominate due to their ability to effectively model temporal dependencies in energy data, making them well-suited for forecasting and scheduling tasks.

Another important trend is the widespread adoption of IoT and edge computing technologies. These technologies enable real-time monitoring, decentralized decision-making, and faster response times in smart grid systems. Compared to traditional cloud-centric approaches, edge computing reduces latency and improves scalability, which is essential for large-scale deployments. Reinforcement learning methods, including Deep Q-Networks (DQN) and multi-agent systems, are also gaining traction for their ability to adaptively learn optimal control strategies in dynamic and uncertain environments.

Dataset utilization across studies varies significantly, with researchers employing a mix of real-world smart meter data, IEEE benchmark systems, and renewable energy datasets. The growing availability of large-scale datasets has contributed to the development of more robust and generalizable models. Performance improvements reported in the literature include reduced operational costs, minimized peak demand, enhanced forecasting accuracy, and improved system reliability. Hybrid approaches consistently outperform standalone methods in handling nonlinear and multi-objective optimization problems.

Overall, the literature demonstrates a strong shift toward intelligent, data-driven, and hybrid optimization frameworks for smart grid energy management. Among these, the FHO-RERNN model emerges as a promising approach due to its ability to combine efficient global optimization with accurate temporal modeling. This integration offers improved adaptability and performance, positioning it as a viable solution for future smart grid applications.

Discussion

The rapid advancement of artificial intelligence in smart grid energy management has significantly improved system efficiency, adaptability, and reliability. AI-driven models, particularly deep learning architectures, have demonstrated strong capabilities in forecasting energy demand and optimizing resource allocation under uncertain conditions. This is especially important with the increasing integration of renewable energy sources, which introduce variability into the grid. By leveraging historical and real-time data, these models enable proactive decision-making and enhance overall grid stability.

A major implication of recent developments is the shift from centralized to decentralized energy management systems. IoT-enabled devices facilitate continuous data exchange and localized decision-making, while edge computing reduces latency and improves responsiveness. This decentralized framework enhances scalability and supports real-time control in complex energy networks. However, it also introduces challenges related to data security, privacy, and interoperability, particularly due to the heterogeneous nature of IoT devices and communication protocols.

Despite the effectiveness of hybrid optimization techniques, several limitations remain. High computational complexity and training requirements of deep learning models can hinder real-time deployment, especially in resource-constrained environments. Additionally, the lack of standardized datasets and evaluation frameworks limits fair comparison across studies. Addressing these issues requires the development of lightweight models, secure data handling mechanisms, and standardized benchmarking practices to ensure reliability and scalability in practical applications.

Conclusion

In conclusion, the integration of artificial intelligence, IoT technologies, and advanced optimization techniques has significantly transformed smart grid energy management. The reviewed studies demonstrate that hybrid approaches, particularly those combining deep learning with metaheuristic optimization, offer superior performance in handling the complexity, uncertainty, and multi-objective nature of modern energy systems. The FHO-RERNN framework represents a promising advancement, providing enhanced accuracy, adaptability, and efficiency in energy scheduling and demand response applications.

Despite these advancements, challenges such as computational complexity, data privacy, cybersecurity, and lack of standardization remain critical barriers to large-scale deployment. Future research should focus on developing efficient, scalable, and secure AI models, along with standardized evaluation frameworks. The integration of emerging technologies such as federated learning, edge AI, and digital twins is expected to further enhance system performance and reliability. Overall, AI-driven smart grid energy management systems hold significant potential for enabling sustainable, resilient, and intelligent energy infrastructures in the future.

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