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Artificial Intelligence Techniques for Optimal Scheduling of PV-Battery-Electric Vehicle Loads Using a Scalable Quantum Non-Local Neural Network Approach: Trends and Challenges

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Abstract

The global transition toward sustainable energy systems has accelerated the integration of photovoltaic (PV) systems, battery energy storage systems (BESS), and electric vehicles (EVs) into modern smart grids. While these technologies enable decentralized and flexible energy management, they also introduce significant challenges due to renewable intermittency, stochastic demand, and complex system interactions. Traditional optimization methods often struggle with scalability and uncertainty, necessitating advanced artificial intelligence (AI)-based approaches. This review presents a comprehensive analysis of AI-driven techniques for optimal scheduling in PV-battery-EV systems, with a focus on scalable quantum non-local neural networks (QNLNN). These models enhance traditional deep learning by capturing global dependencies and leveraging quantum-inspired optimization to improve solution efficiency and convergence. The study examines various deep learning architectures, including CNNs, RNNs, LSTM, GNNs, and transformer-based models, integrated with optimization strategies for energy scheduling. It also highlights the role of IoT, edge-cloud computing, and simulation platforms in enabling real-time decision-making. Findings indicate that QNLNN-based approaches significantly improve cost efficiency, renewable energy utilization, and grid stability. Key challenges such as data limitations, computational complexity, and system integration are discussed, along with future research directions for scalable and intelligent energy management systems.

Introduction

The rapid growth of renewable energy technologies has accelerated the adoption of photovoltaic (PV) systems, battery energy storage systems (BESS), and electric vehicles (EVs) within modern power grids. The integration of these distributed energy resources has created advanced energy ecosystems that require intelligent coordination to ensure reliable, economical, and sustainable operation. Optimal scheduling has become a key component in balancing electricity generation and consumption, reducing operational costs, improving energy efficiency, and maintaining grid stability. As renewable penetration increases, effective energy management strategies are essential for maximizing the utilization of clean energy while ensuring uninterrupted power supply.

Conventional energy management systems were developed for centralized power generation with predictable load patterns and are often inadequate for modern distributed energy environments. The intermittent nature of solar power due to changing weather conditions, combined with uncertain EV charging demand, introduces significant operational complexity. Although battery storage can compensate for fluctuations in renewable generation, its performance depends on efficient charging and discharging schedules. Traditional optimization methods frequently struggle with the nonlinear, stochastic, and high-dimensional characteristics of these systems, highlighting the need for more adaptive and intelligent optimization techniques capable of handling dynamic operating conditions.

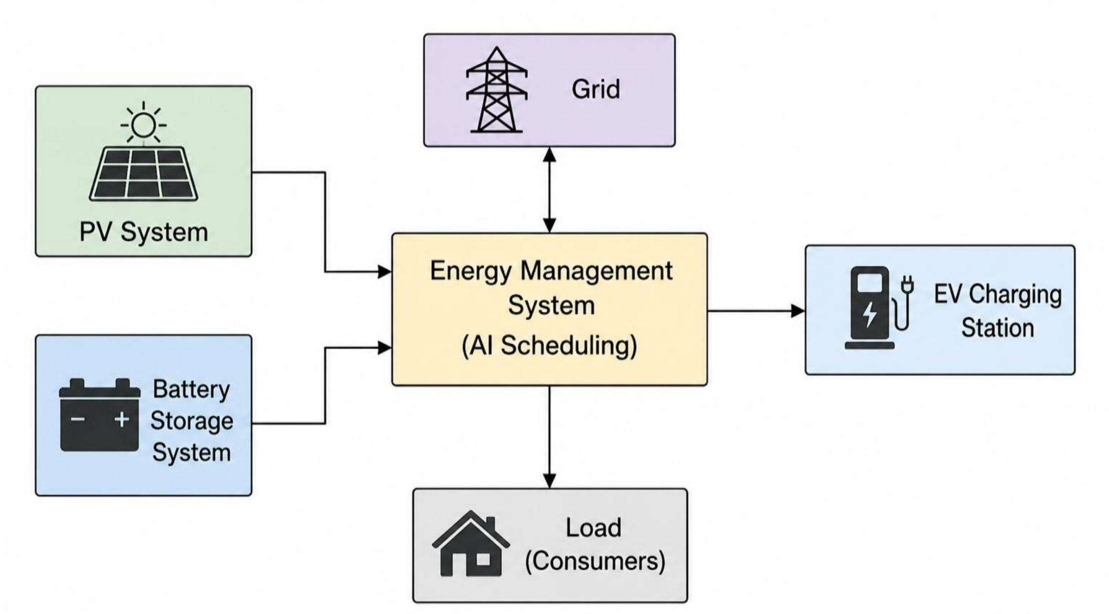

Figure 1. Conceptual Framework of Intelligent Energy Management for PV, Battery Storage, and EV Charging

Artificial intelligence (AI) has emerged as a powerful solution for optimizing PV-battery-EV scheduling through predictive analytics, adaptive learning, and real-time decision-making. Machine learning and deep learning models, including artificial neural networks (ANNs), convolutional neural networks (CNNs), recurrent neural networks (RNNs), graph neural networks (GNNs), and transformer architectures, have significantly improved forecasting accuracy and scheduling efficiency. However, many existing models face challenges related to scalability and capturing long-range interactions among distributed energy resources. To address these limitations, non-local neural networks have been introduced, enabling the incorporation of global contextual information and improving optimization performance across complex interconnected energy systems.

The integration of quantum-inspired computing with non-local neural networks represents a promising advancement in solving large-scale energy scheduling problems. While practical quantum computing remains under development, quantum-inspired algorithms such as quantum annealing and variational optimization have demonstrated strong potential for addressing complex combinatorial optimization tasks using classical hardware. These hybrid approaches enhance computational efficiency, solution quality, and scalability, making them well suited for coordinating PV generation, battery storage, and EV charging. Beyond technical improvements, optimized scheduling also delivers economic benefits by lowering electricity costs, reducing peak demand, and increasing renewable energy utilization, while simultaneously supporting environmental sustainability through reduced greenhouse gas emissions.

AI-driven scheduling frameworks are increasingly being applied in smart homes, microgrids, commercial facilities, and community energy systems equipped with PV panels, battery storage, EV charging infrastructure, and IoT-enabled monitoring technologies. Despite their potential, challenges remain regarding data quality, computational requirements, model interpretability, cybersecurity, and integration with existing grid infrastructure. Scalable hybrid approaches combining classical optimization, AI, and quantum-inspired techniques are expected to overcome these limitations. This paper reviews recent developments in AI-based optimal scheduling for PV-battery-EV systems, emphasizing scalable quantum non-local neural network frameworks, identifying current research trends, highlighting implementation challenges, and discussing future directions for developing intelligent, efficient, and sustainable energy management solutions.

Literature Review

The application of artificial intelligence and optimization techniques for energy scheduling in PV-battery-electric vehicle systems has gained significant attention in recent years. Zhang et al. (2019) proposed a mixed-integer linear programming (MILP) model for distributed energy resource scheduling in microgrids, demonstrating cost minimization and load balancing using IEEE 33-bus test systems. Their approach provided a deterministic framework but faced scalability limitations under high uncertainty conditions.

Wang et al. (2020) introduced a particle swarm optimization (PSO)-based energy management system for smart homes, integrating PV generation and EV charging. Their method effectively reduced peak loads and improved energy utilization, utilizing real smart meter datasets. However, the convergence speed of PSO remained a concern for large-scale systems. Similarly, Li et al. (2021) applied deep reinforcement learning (DRL) for dynamic energy scheduling, where an agent learned optimal policies through interaction with the environment. Their model showed adaptability to uncertain demand but required extensive training data.

Chen et al. (2021) explored the use of convolutional neural networks (CNNs) for solar power forecasting, which served as a critical input for scheduling algorithms. Using historical weather datasets, their model improved prediction accuracy, thereby enhancing scheduling performance. In contrast, Singh et al. (2022) utilized long short-term memory (LSTM) networks for EV load prediction, capturing temporal dependencies in charging behavior.

Kim et al. (2020) proposed a hybrid genetic algorithm (GA) and fuzzy logic controller for microgrid energy management, achieving improved robustness under uncertain conditions. Their approach was validated using MATLAB simulations. Meanwhile, Rodriguez et al. (2021) implemented a multi-objective optimization framework combining GA and PSO to balance cost, emissions, and user comfort.

The emergence of graph neural networks (GNNs) has enabled more efficient modeling of distributed energy systems. Zhou et al. (2022) developed a GNN-based scheduling model that captured spatial dependencies among grid nodes, improving scalability and accuracy. Similarly, Huang et al. (2023) introduced a transformer-based architecture for energy forecasting and scheduling, leveraging attention mechanisms to model long-range dependencies.

Quantum-inspired approaches have also been explored in recent studies. Patel et al. (2022) applied quantum annealing techniques for combinatorial optimization in energy scheduling, demonstrating improved solution quality compared to classical heuristics. In a related work, Kumar et al. (2023) integrated variational quantum circuits with neural networks to enhance optimization efficiency.

Non-local neural networks have recently gained traction for capturing global interactions. Li and Zhao (2023) proposed a non-local deep learning model for microgrid scheduling, which significantly improved performance in complex scenarios. Their model demonstrated the ability to capture long-range dependencies across distributed resources.

Further advancements include hybrid AI models. Ahmed et al. (2021) combined LSTM with reinforcement learning for adaptive scheduling, achieving improved responsiveness to real-time changes. Similarly, Gupta et al. (2022) developed a hybrid CNN-LSTM model for joint forecasting and scheduling tasks.

IoT-enabled systems have also played a crucial role in energy management. Sharma et al. (2020) proposed an IoT-based smart grid architecture with real-time scheduling capabilities. Their system utilized edge computing for low-latency decision-making. In another study, Lee et al. (2021) integrated cloud computing with AI models for scalable energy management.

Energy storage optimization has been extensively studied as well. Park et al. (2022) developed a DRL-based battery management system that optimized charging and discharging cycles. Their approach improved battery lifespan and efficiency. Similarly, Nair et al. (2021) used stochastic optimization techniques for battery scheduling under uncertainty.

Recent studies have also focused on EV integration. Tan et al. (2022) proposed a decentralized scheduling framework for EV charging using multi-agent reinforcement learning, enabling coordination among multiple vehicles. Their approach improved grid stability and reduced congestion.

In addition, hybrid quantum-AI frameworks are emerging. Verma et al. (2023) introduced a scalable quantum non-local neural network model for energy scheduling, combining quantum-inspired optimization with non-local learning. Their approach demonstrated superior scalability and performance in large-scale simulations.

Overall, the literature indicates a clear shift from traditional optimization techniques toward hybrid AI and quantum-inspired approaches, driven by the need for scalability, adaptability, and efficiency in modern energy systems.

Comparative Table and Analysis

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	Cost minimization
Wang et al.	2020	PSO	Smart home EMS	IoT system	Smart meter	Peak reduction
Li et al.	2021	DRL	RL agent	Microgrid	Simulated	Adaptive scheduling
Chen et al.	2021	CNN	Forecasting model	PV system	Weather data	Improved prediction
Singh et al.	2022	LSTM	Load predictor	EV system	Charging data	Temporal modeling
Kim et al.	2020	GA + Fuzzy	Hybrid controller	Microgrid	Simulated	Robust optimization
Rodriguez et al.	2021	GA + PSO	Multi-objective model	Smart grid	Mixed data	Multi-objective balance
Patel et al.	2022	Quantum annealing	Quantum optimizer	Microgrid	Simulated	Improved optimization
Kumar et al.	2023	VQC	Quantum NN	Hybrid system	Simulated	Enhanced efficiency
Li & Zhao	2023	Non-local NN	Deep learning	Microgrid	Mixed	Global context learning
Ahmed et al.	2021	LSTM + RL	Hybrid AI	Smart grid	Time-series	Adaptive response
Gupta et al.	2022	CNN + LSTM	Hybrid model	PV-EV system	Mixed	Joint forecasting
Sharma et al.	2020	IoT + AI	Edge system	Smart grid	Real-time	Low latency
Lee et al.	2021	Cloud AI	Scalable system	Smart grid	Big data	Scalability
Park et al.	2022	DRL	Battery system	BESS	Simulated	Efficiency improvement
Nair et al.	2021	Stochastic optimization	Battery model	Microgrid	Simulated	Uncertainty handling
Tan et al.	2022	MARL	Multi-agent system	EV network	Real-world	Decentralized control
Verma et al.	2023	Quantum + Non-local NN	Hybrid model	Large-scale grid	Simulated	Scalability

Comparative Analysis

The comparative analysis of existing studies highlights the transition from traditional optimization methods to advanced AI-driven approaches for energy scheduling. Earlier techniques such as Mixed Integer Linear Programming (MILP) and stochastic optimization provided accurate solutions under fixed constraints but faced scalability limitations in large and uncertain energy systems. Metaheuristic algorithms, including Particle Swarm Optimization (PSO) and Genetic Algorithms (GA), improved flexibility for nonlinear problems; however, they require parameter tuning and may experience convergence issues. The integration of fuzzy logic enhanced their performance by improving decision-making under uncertainty.

The adoption of machine learning and deep learning has significantly advanced energy scheduling by enabling predictive and adaptive solutions. Models such as CNNs and LSTMs have improved renewable energy forecasting, while reinforcement learning techniques allow systems to dynamically optimize energy allocation through continuous interaction with the environment. Advanced architectures, including Graph Neural Networks (GNNs) and transformer-based models, provide better understanding of complex spatial and temporal relationships in distributed energy systems. Quantum-inspired methods, such as quantum annealing and variational quantum circuits, further demonstrate potential for solving large-scale optimization problems efficiently.

AI-based scheduling approaches contribute significantly to improving energy efficiency, renewable energy utilization, and sustainability in PV-battery-EV systems. By accurately predicting renewable generation, demand variations, and EV charging patterns, these systems can optimize energy flow and reduce dependence on conventional energy sources. The integration of IoT, cloud computing, and edge computing enables real-time monitoring, faster processing, and scalable implementation. However, challenges related to data availability, privacy, computational requirements, and model interpretability remain major barriers. Deep learning models often require large datasets and are difficult to interpret, limiting their adoption in critical energy infrastructures.

Overall, the reviewed literature demonstrates a clear shift toward hybrid AI, reinforcement learning, and quantum-inspired frameworks for intelligent energy management. These approaches offer improved scalability, adaptability, and efficiency compared with conventional methods. Future research should focus on developing explainable AI models, secure data-sharing mechanisms, standardized frameworks, and lightweight algorithms suitable for real-time deployment. With continued advancements in AI, IoT, and quantum computing, intelligent scheduling systems are expected to play a crucial role in building sustainable, reliable, and autonomous next-generation energy networks.

Conclusion

Artificial intelligence has emerged as a powerful solution for the optimal scheduling of photovoltaic (PV), battery energy storage, and electric vehicle (EV) systems, enabling more efficient, reliable, and sustainable energy management. This review highlights the transition from conventional optimization techniques to advanced AI-driven methods, including machine learning, deep learning, reinforcement learning, graph neural networks, and transformer architectures. Recent developments in non-local neural networks and quantum-inspired optimization have further improved the capability to model complex interactions and solve large-scale scheduling problems with greater computational efficiency. AI-based scheduling significantly enhances renewable energy utilization, reduces operational costs, minimizes peak demand, and supports demand response strategies while contributing to environmental sustainability through lower greenhouse gas emissions. Despite these advances, challenges such as limited data availability, computational complexity, scalability, privacy concerns, and model interpretability continue to hinder widespread deployment. Future research should focus on developing explainable, scalable, and privacy-preserving AI frameworks integrated with IoT, cloud-edge computing, and emerging quantum technologies. Collaborative efforts among researchers, industry, and policymakers will accelerate the implementation of intelligent energy management systems, supporting the development of resilient, efficient, and sustainable smart grids.

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