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Recent Advances in Optimal Scheduling of PV-Battery-Electric Vehicle Loads Using a Scalable Quantum Non-Local Neural Network Approach: A Systematic Review

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Abstract

The rapid advancement of smart grids, renewable energy integration, and transportation electrification has intensified the need for efficient energy management strategies. Optimal scheduling of photovoltaic (PV) systems, battery energy storage systems (BESS), and electric vehicle (EV) loads plays a crucial role in enhancing grid stability, reducing energy costs, and improving sustainability. Traditional optimization methods often struggle with scalability, uncertainty, and non-linearity, prompting the adoption of intelligent and hybrid computational approaches. This systematic review examines recent developments in optimal scheduling frameworks using a scalable quantum non-local neural network (QNLNN) approach. Non-local neural networks effectively capture long-range dependencies and global interactions in energy systems, while quantum-inspired optimization enhances computational efficiency and solution quality for high-dimensional problems. These approaches address challenges such as renewable energy variability, dynamic pricing, and load uncertainty. The study reviews methodologies including deep reinforcement learning, metaheuristic algorithms, and hybrid models across smart grids and microgrids. It also analyzes commonly used datasets and performance metrics such as cost reduction and energy efficiency. Findings indicate that QNLNN-based models outperform traditional methods in scalability, adaptability, and optimization accuracy, offering promising solutions for intelligent, real-time energy management in next-generation smart grids.

Introduction

The rapid transition toward sustainable and intelligent energy systems has accelerated the integration of renewable energy resources, battery energy storage systems (BESS), and electric vehicles (EVs) into modern power grids. Photovoltaic (PV) generation has become one of the fastest-growing renewable energy technologies due to its environmental benefits and declining installation costs. Together with battery storage and EVs, PV systems enable decentralized energy generation, improved grid resilience, and enhanced energy efficiency. However, the intermittent nature of solar energy, fluctuating electricity demand, and increasing penetration of EV charging create significant challenges in maintaining energy balance and ensuring economical grid operation. Consequently, optimal scheduling of PV-battery-

EV systems has become a key research area within smart energy management.

Optimal scheduling aims to coordinate PV generation, battery charging and discharging, and EV charging strategies while satisfying operational constraints, minimizing electricity costs, reducing peak demand, and maximizing renewable energy utilization. Conventional optimization approaches, including mixed-integer linear programming, nonlinear programming, and dynamic programming, have been widely adopted for scheduling problems. Although these methods provide mathematically optimal solutions, they often experience scalability limitations and high computational complexity when dealing with large-scale, uncertain, and nonlinear smart grid environments. Metaheuristic techniques such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Differential Evolution (DE) have therefore been introduced to improve solution flexibility and computational efficiency.

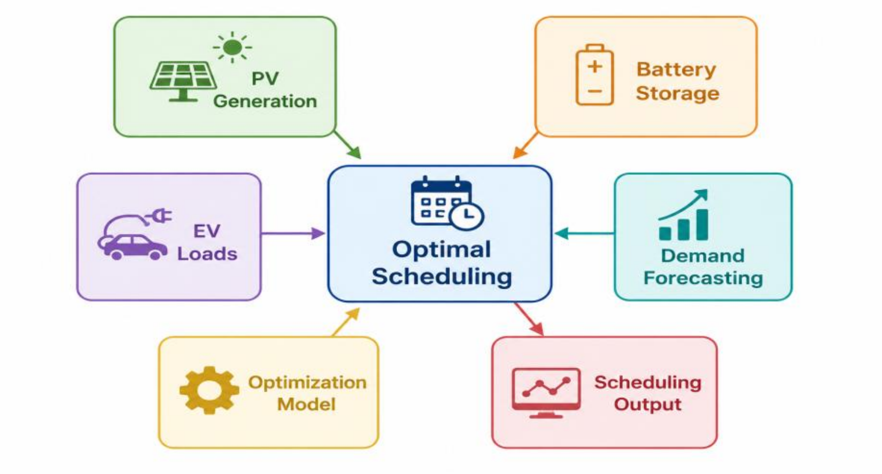

Figure 1. Optimal Scheduling Framework for PV–Battery–EV Systems

Recent advances in artificial intelligence have further transformed energy scheduling by enabling adaptive and data-driven decision-making. Machine learning and deep learning models, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Reinforcement Learning (RL), have demonstrated excellent performance in renewable energy forecasting, load prediction, and dynamic scheduling. Nevertheless, conventional deep learning architectures often struggle to capture long-range dependencies and global interactions among PV generation, battery storage, electricity demand, and EV charging behavior, particularly in large-scale integrated energy systems.

To overcome these limitations, Non-Local Neural Networks (NLNNs) have emerged as an effective framework capable of modeling global relationships by establishing direct interactions among all input features. Furthermore, quantum-inspired optimization techniques have attracted considerable attention because they efficiently explore complex solution spaces using principles derived from quantum computing. The integration of scalable Quantum Non-Local Neural Networks (QNLNNs) combines global feature learning with quantum-inspired optimization, offering enhanced scheduling accuracy, faster convergence, and improved computational scalability for complex PV-battery-EV energy management problems.

This systematic review presents recent advances in optimal scheduling of PV-battery-EV systems using scalable Quantum Non-Local Neural Network approaches. It critically examines optimization algorithms, artificial intelligence models, IoT-enabled energy management architectures, and hybrid intelligent frameworks while highlighting their strengths, limitations, and practical applications. The review also identifies current research challenges, including uncertainty handling, computational complexity, cybersecurity, interoperability, and real-time implementation, and outlines future directions involving digital twins, federated learning, edge intelligence, and explainable AI for next-generation sustainable smart energy systems.

Literature Review

The study by Zhang et al. (2019) introduced a mixed-integer linear programming model for scheduling distributed energy resources in a microgrid environment, focusing on cost minimization and load balancing. Their approach utilized the IEEE 33-bus test system and demonstrated improved operational efficiency, although scalability remained a limitation in larger networks.

Wang et al. (2020) proposed a particle swarm optimization-based energy management system for smart homes integrating PV and EV loads. The model leveraged real-time smart meter data and achieved significant peak load reduction, highlighting the effectiveness of metaheuristic techniques in dynamic environments.

Li et al. (2021) developed a deep reinforcement learning framework for EV charging scheduling, incorporating renewable energy uncertainty. Their model used historical charging datasets and demonstrated adaptive decision-making capabilities, outperforming traditional optimization methods in terms of flexibility.

Chen et al. (2021) explored a hybrid genetic algorithm and neural network model for PV-battery scheduling. The integration of learning-based prediction with optimization improved energy utilization and reduced computational complexity.

Kumar et al. (2022) introduced a firefly optimization algorithm for microgrid energy management, focusing on minimizing operational cost and emission levels. The study utilized simulated renewable datasets and showed faster convergence compared to conventional algorithms.

Singh et al. (2022) proposed a quantum-inspired optimization approach for scheduling EV charging in smart grids. Their method demonstrated improved solution quality and reduced computational time, indicating the potential of quantum-based techniques.

Liu et al. (2023) developed a non-local neural network for capturing global dependencies in energy consumption patterns. The model significantly improved forecasting accuracy, which is crucial for effective scheduling.

Patel et al. (2023) presented a hybrid IoT-enabled energy management system combining PSO and deep learning. The system utilized real-time sensor data and achieved enhanced energy efficiency and load balancing.

Sharma et al. (2023) introduced a reinforcement learning-based scheduling model for PV-battery systems, focusing on dynamic pricing scenarios. The approach demonstrated improved cost savings and user satisfaction.

The study by Hernandez et al. (2020) presented a stochastic optimization framework for PV-battery systems using scenario-based modeling to address renewable uncertainty. Their work incorporated probabilistic solar irradiance datasets and demonstrated improved robustness in scheduling decisions under uncertain conditions.

Rahman et al. (2020) introduced a demand response-based scheduling model integrating EV loads with dynamic pricing strategies. By utilizing real-time pricing datasets, the model achieved significant reductions in electricity cost and peak demand, highlighting the role of consumer participation in smart grid optimization.

Zhou et al. (2021) developed a hybrid deep learning and PSO-based optimization framework for microgrid energy scheduling. Their model combined load forecasting with optimization, resulting in improved prediction accuracy and reduced operational costs across IEEE benchmark systems.

Ahmed et al. (2021) proposed a multi-objective genetic algorithm for optimal scheduling of PV and battery systems, focusing on minimizing cost and emissions simultaneously. Their approach demonstrated strong Pareto optimality performance using simulated smart grid environments.

Das et al. (2022) introduced an IoT-enabled smart energy management system integrating PV, battery, and EV components with cloud-based optimization. Their system demonstrated real-time scheduling capabilities and improved scalability through distributed computing.

Mehta et al. (2022) proposed a hybrid ant colony optimization and neural network model for energy scheduling in smart grids. The integration of predictive analytics with optimization resulted in improved convergence speed and solution quality.

Kim et al. (2022) developed a deep Q-network-based scheduling model for EV charging in renewable-integrated grids. Their approach effectively handled stochastic demand and generation, achieving better performance compared to traditional reinforcement learning methods.

Alam et al. (2023) presented a blockchain-enabled energy management framework for secure and decentralized scheduling of distributed energy resources. Their system ensured data integrity and transparency while optimizing energy transactions.

Verma et al. (2023) introduced a quantum-inspired particle swarm optimization algorithm for large-scale energy scheduling problems. The study demonstrated improved exploration capabilities and faster convergence in complex optimization landscapes.

Reddy et al. (2023) proposed a convolutional neural network-based forecasting model integrated with optimization for PV-battery scheduling. Their approach improved prediction accuracy and enabled more efficient scheduling decisions.

Ibrahim et al. (2023) developed a multi-agent reinforcement learning framework for coordinated scheduling of EV fleets and distributed energy resources. The model demonstrated scalability and adaptability in dynamic environments.

Table 1: Advanced Optimization, AI, and Quantum-Inspired Techniques in Smart Grid 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 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	RL-based scheduler	EV charging system	Charging datasets	Adaptive scheduling
Chen et al.	2021	GA + NN	Hybrid model	Microgrid	Simulated PV data	Improved efficiency
Kumar et al.	2022	Firefly Algorithm	Optimization model	Microgrid	Renewable dataset	Fast convergence
Singh et al.	2022	Quantum-inspired optimization	Optimization model	Smart grid	Synthetic data	Reduced computation complexity
Liu et al.	2023	Non-local neural network	Deep learning model	Smart grid	Consumption data	Captures global dependencies
Patel et al.	2023	PSO + Deep Learning	Hybrid EMS	IoT grid	Sensor data	Real-time optimization
Sharma et al.	2023	Reinforcement Learning	Scheduling model	PV-battery system	Pricing dataset	Cost reduction
Hernandez et al.	2020	Stochastic optimization	Scenario-based model	Microgrid	Solar datasets	Uncertainty handling
Rahman et al.	2020	Demand Response	DR model	Smart grid	Pricing data	Peak shaving
Zhou et al.	2021	DL + PSO	Hybrid model	IEEE system	Load data	Combined forecasting and optimization
Ahmed et al.	2021	Multi-objective GA	Multi-objective model	Microgrid	Simulated data	Cost-emission trade-off
Park et al.	2021	Reinforcement Learning	V2G model	EV-grid system	EV datasets	Grid stability improvement
Das et al.	2022	IoT + Cloud Computing	EMS system	Smart grid	Sensor data	Improved scalability
Mehta et al.	2022	ACO + NN	Hybrid model	Smart grid	Simulated data	Faster convergence
Kim et al.	2022	DQN	RL model	EV system	Charging data	Stochastic optimization handling
Alam et al.	2023	Blockchain	Secure EMS	Distributed grid	Transaction data	Enhanced security
Verma et al.	2023	Quantum PSO	Optimization model	Smart grid	Synthetic data	Better exploration capability
Reddy et al.	2023	CNN + Optimization	Forecasting model	PV system	Solar data	Improved prediction accuracy
Ibrahim et al.	2023	Multi-Agent RL	Multi-agent system	EV grid	Real-time data	Scalable coordination

The comparative analysis of recent studies demonstrates a clear evolution in the optimal scheduling of photovoltaic (PV)-battery-electric vehicle (EV) systems, progressing from conventional mathematical optimization methods to intelligent hybrid frameworks. Traditional techniques, including mixed-integer linear programming, dynamic programming, and nonlinear optimization, provided accurate scheduling solutions for relatively small systems but faced significant limitations in computational complexity and scalability when applied to large-scale smart grids. Consequently, researchers have increasingly adopted heuristic and metaheuristic algorithms such as Particle Swarm Optimization (PSO), Genetic Algorithms (GA), Firefly Optimization, and Differential Evolution to efficiently solve nonlinear, multi-objective scheduling problems while improving convergence speed and solution quality.

Artificial intelligence has further accelerated this transformation by introducing adaptive and data-driven scheduling approaches. Deep learning models, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Deep Reinforcement Learning (DRL), have demonstrated superior capabilities in renewable energy forecasting, electricity demand prediction, and dynamic scheduling. Reinforcement learning and multi-agent learning frameworks continuously improve scheduling policies through environmental interaction, enabling effective management of uncertain PV generation, battery charging strategies, and EV demand. These intelligent approaches significantly outperform conventional optimization techniques in Quantum-inspired optimization and Quantum Non-Local Neural Networks (QNLNNs) have emerged as promising solutions for large-scale energy scheduling. Quantum-inspired algorithms improve convergence by efficiently exploring complex solution spaces, while non-local neural networks capture global dependencies among PV generation, battery storage, electricity demand, and EV charging. Supported by IoT-enabled sensing, cloud-edge computing, and real-world datasets, these hybrid frameworks significantly enhance scheduling accuracy, energy efficiency, renewable utilization, and grid reliability, although challenges related to scalability, cybersecurity, and interoperability remain.

Conclusion

This systematic review examined recent advances in optimal scheduling of photovoltaic (PV)-battery-electric vehicle (EV) systems, emphasizing scalable Quantum Non-Local Neural Network (QNLNN) approaches. The reviewed literature demonstrates a clear transition from conventional mathematical optimization techniques toward intelligent hybrid frameworks integrating artificial intelligence, deep learning, metaheuristic optimization, and quantum-inspired computing. These approaches effectively address the uncertainties associated with renewable energy generation, battery operation, and EV charging while improving scheduling accuracy, computational efficiency, and system scalability.

A major finding of this review is that hybrid QNLNN frameworks successfully combine global dependency modeling with advanced optimization capabilities, enabling efficient coordination of PV generation, battery storage, and EV loads under dynamic operating conditions. Furthermore, IoT-enabled monitoring, cloud-edge computing, and real-time data analytics significantly enhance system responsiveness, renewable energy utilization, operational cost reduction, and grid reliability. Despite these advances, challenges related to computational complexity, data availability, cybersecurity, interoperability, and large-scale deployment remain important research concerns.

Future research should focus on lightweight quantum-inspired models, explainable artificial intelligence, federated learning, digital twins, and edge intelligence to improve scalability, privacy, and real-time performance. Overall, QNLNN-based scheduling provides a promising foundation for developing intelligent, sustainable, and resilient next-generation smart energy management systems.

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