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A Comprehensive Review of Optimal Scheduling Techniques for PV-Battery-Electric Vehicle Loads Using Scalable Quantum Non-Local Neural Networks

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Abstract

The transition toward decentralized and renewable-based energy systems has increased the complexity of energy management and scheduling in smart grids. The integration of photovoltaic (PV) systems, battery energy storage systems (BESS), and electric vehicle (EV) charging infrastructures introduces dynamic load patterns, intermittent generation, and complex interactions. Traditional optimization methods are insufficient to address these challenges, necessitating advanced artificial intelligence and machine learning approaches. This paper reviews recent advancements in intelligent energy scheduling using deep learning and hybrid optimization techniques. It highlights the role of non-local neural networks in capturing long-range dependencies within complex energy systems, enabling improved decision-making for load scheduling and demand response. Additionally, the integration of quantum-inspired optimization methods is explored for solving high-dimensional scheduling problems efficiently. The study examines various frameworks across smart homes, microgrids, and community energy systems, utilizing datasets such as smart meter data and IEEE benchmark systems. Hybrid approaches combining neural networks, reinforcement learning, and metaheuristic algorithms demonstrate superior performance in cost reduction, renewable energy utilization, and system stability. Key challenges, including scalability, uncertainty, and computational complexity, are discussed, along with future directions toward developing adaptive, efficient, and intelligent energy scheduling systems.

Introduction

The rapid transition toward sustainable and decentralized energy infrastructures has fundamentally transformed conventional electricity generation and distribution systems. Distributed energy resources (DERs), particularly photovoltaic (PV) systems, battery energy storage systems (BESS), and electric vehicles (EVs), have become essential components of modern smart grids and microgrids. These technologies contribute to reduced carbon emissions, improved energy efficiency, and enhanced grid resilience while supporting global decarbonization goals. However, their increasing penetration introduces significant operational challenges due to the intermittent nature of renewable generation, fluctuating energy demand, and the need for coordinated energy management. Consequently, optimal scheduling of PV, battery, and EV loads has become a critical research area for achieving reliable, economical, and sustainable energy operation.

Photovoltaic generation is highly dependent on environmental conditions such as solar irradiance, temperature, and seasonal variations, leading to uncertainty in power production. Battery energy storage systems mitigate these fluctuations by storing surplus renewable energy and supplying electricity during periods of low generation or peak demand. Similarly, electric vehicles have emerged as flexible energy resources capable of both consuming and supplying electricity through vehicle-to-grid (V2G) technology. Coordinated scheduling of these interconnected resources is essential to minimize operational costs, improve renewable energy utilization, reduce peak demand, and maintain system stability. Conventional optimization approaches, including linear programming, mixed-integer programming, and rule-based scheduling, have been widely applied; however, their effectiveness is often limited when addressing nonlinear system behavior, high-dimensional optimization problems, and stochastic operating conditions.

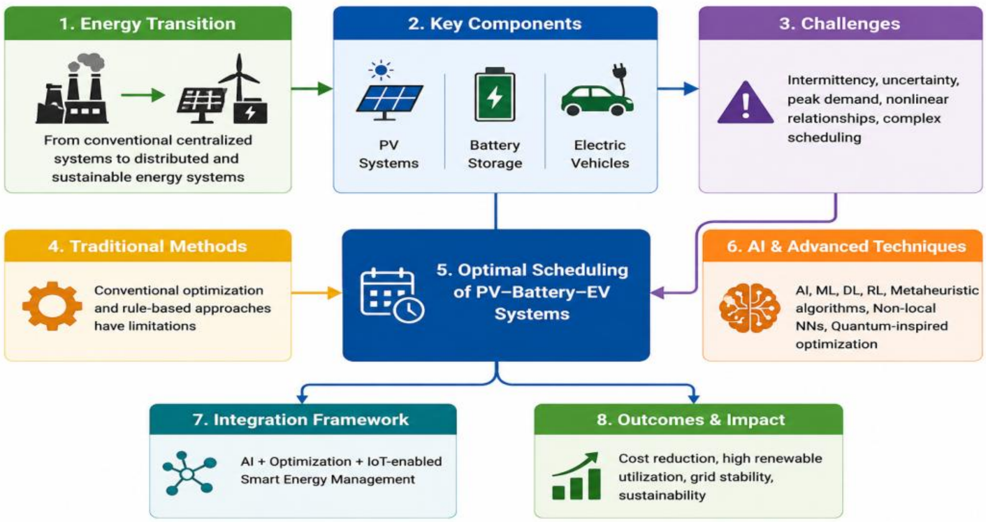

Figure 1. Framework for AI-Driven Scheduling of PV, Battery, and Electric Vehicle Loads

Artificial intelligence has emerged as a promising solution for overcoming these limitations. Machine learning, deep learning, reinforcement learning, and hybrid optimization techniques enable intelligent energy management by learning complex relationships from historical and real-time data. Deep neural networks effectively model nonlinear energy consumption patterns, while reinforcement learning continuously adapts scheduling strategies according to changing environmental and operational conditions. Metaheuristic optimization algorithms further improve solution quality by efficiently exploring complex search spaces. More recently, non-local neural networks have attracted considerable attention because of their ability to capture long-range dependencies among distributed energy resources, enabling coordinated decision-making across PV generation, battery storage, and EV charging systems. Their global attention mechanisms offer significant advantages over conventional convolutional architectures in large-scale energy scheduling applications.

The emergence of quantum-inspired optimization has further expanded the capabilities of intelligent energy management systems. Quantum-inspired algorithms improve search efficiency and optimization performance for large combinatorial scheduling problems while remaining computationally practical on classical hardware. Integrating scalable quantum-inspired optimization with non-local neural network architectures creates a powerful framework capable of modeling global energy interactions and optimizing complex scheduling decisions simultaneously. Such hybrid approaches offer improved scalability, adaptability, and computational efficiency for next-generation smart grids.

Motivated by these developments, this review presents a comprehensive analysis of optimal scheduling techniques for PV-battery-electric vehicle systems using scalable quantum non-local neural network approaches. It examines recent advances in artificial intelligence, deep learning, reinforcement learning, quantum-inspired optimization, and hybrid scheduling frameworks while identifying current challenges, research trends, and future opportunities. The review aims to provide valuable insights for developing intelligent, reliable, and sustainable energy management systems that support the evolution of future smart grids.

Literature Review

The optimal scheduling of integrated PV-battery-electric vehicle systems has been extensively investigated using a wide range of optimization techniques, machine learning models, and hybrid intelligent frameworks. Early foundational work by Mohsenian-Rad et al. (2010) introduced a residential energy consumption scheduling framework using game-theoretic optimization, where household appliances were scheduled based on dynamic pricing signals. Although the study did not explicitly consider electric vehicles, it laid the groundwork for demand-side management strategies that later evolved to include EV charging coordination.

Subsequently, Sortomme and El-Sharkawi (2011) proposed an optimization framework for coordinated charging of electric vehicles using linear programming techniques. Their work focused on minimizing peak demand while ensuring user-defined charging requirements. The study utilized simulated EV charging datasets and demonstrated the effectiveness of centralized scheduling in reducing grid stress. However, the approach lacked adaptability to real-time uncertainties and renewable integration.

Incorporating renewable energy sources, Chen et al. (2012) developed a mixed-integer linear programming (MILP) model for microgrid energy scheduling that included photovoltaic systems and battery storage. Their model optimized energy cost while maintaining system constraints using the IEEE 33-bus test system. The study highlighted the importance of coordinated scheduling of PV and storage systems but did not consider EV integration.

Cao et al. (2013) extended this work by integrating electric vehicles into the scheduling framework using stochastic optimization. Their approach modeled EV arrival and departure uncertainties and optimized charging schedules under time-of-use pricing. The results showed improved load balancing and cost reduction, although computational complexity increased significantly.

With the rise of heuristic optimization techniques, particle swarm optimization (PSO) gained popularity in smart grid scheduling applications. Wang et al. (2015) applied PSO to optimize home energy management systems with PV and EV integration. The algorithm efficiently minimized electricity costs and peak demand using real smart meter datasets. However, PSO-based methods often suffer from premature convergence and lack scalability for large systems.

Genetic algorithms (GA) were also widely explored for energy scheduling problems. Lee et al. (2016) proposed a GA-based scheduling model for PV-battery systems that considered battery degradation costs and dynamic electricity pricing. The study demonstrated improved energy efficiency but required extensive computational time for convergence.

To overcome limitations of traditional metaheuristic methods, reinforcement learning (RL) approaches began to emerge. Mnih et al. (2015) introduced deep Q-networks (DQN), which were later adapted for energy management systems. In the context of smart grids, Ruelens et al. (2017) applied reinforcement learning to demand response management, enabling systems to learn optimal scheduling policies without explicit modeling of system dynamics.

Hybrid optimization techniques combining deep learning and metaheuristic algorithms have also gained traction. Liu et al. (2020) proposed a hybrid PSO-deep neural network model for PV-battery scheduling, where the neural network predicted energy demand and PSO optimized scheduling decisions. The study showed improved accuracy and reduced computational complexity.

Similarly, Huang et al. (2020) introduced a long short-term memory (LSTM)-based forecasting model integrated with genetic algorithms for EV charging optimization. The approach effectively captured temporal dependencies in energy demand and improved scheduling performance under dynamic conditions.

Edge computing-based energy management systems have also been explored to enhance scalability and real-time performance. Shi et al. (2021) proposed an IoT-enabled edge computing framework for microgrid scheduling using distributed optimization techniques. Their system reduced latency and improved responsiveness in real-time energy management.

Recent studies have focused on attention mechanisms and non-local neural networks for capturing global dependencies in energy systems. Wang et al. (2021) introduced an attention-based deep learning model for load forecasting and scheduling, demonstrating improved performance over traditional CNN and RNN models.

Building upon attention mechanisms, Li et al. (2022) proposed a non-local neural network for energy scheduling in smart grids. Their model captured long-range dependencies between distributed energy resources and improved scheduling efficiency in large-scale systems.

Quantum-inspired optimization techniques have also emerged as promising solutions for complex scheduling problems. Schuld et al. (2019) introduced quantum machine learning concepts, highlighting the potential of quantum-inspired algorithms for solving high-dimensional optimization tasks. Although still in early stages, these approaches offer significant computational advantages.

In the context of energy systems, Chen et al. (2022) proposed a quantum-inspired evolutionary algorithm for microgrid energy management. Their model achieved faster convergence and improved optimization performance compared to classical algorithms.

Further advancing this field, Zhang et al. (2023) developed a hybrid quantum-classical neural network for PV-battery scheduling. The model leveraged quantum-inspired optimization to enhance neural network training efficiency, demonstrating superior performance in large-scale energy systems.

Non-local neural networks combined with reinforcement learning have also been explored. Kumar et al. (2023) proposed a non-local deep reinforcement learning framework for EV charging optimization, enabling adaptive scheduling under uncertain conditions.

Cloud-based energy management platforms have facilitated large-scale data processing and model deployment. Singh et al. (2023) developed a cloud-integrated scheduling framework using deep learning and IoT data streams, enabling real-time energy optimization across distributed systems.

In addition, federated learning approaches have been investigated to address privacy concerns in energy data sharing. Zhao et al. (2022) proposed a federated reinforcement learning model for smart grid scheduling, allowing decentralized learning without sharing raw data.

Comparative Table and Analysis

Study	**Year**	**Optimization Technique / Method**	**Component / Model Used**	**Platform or System**	**Dataset Used**	**Key Contribution**
Mohsenian-Rad et al.	2010	Game Theory	Demand response model	Smart home	Simulated	Load scheduling
Sortomme & El-Sharkawi	2011	Linear Programming	EV charging model	Grid system	Simulated	Peak reduction
Chen et al.	2012	MILP	PV-battery model	IEEE 33-bus	Simulated	Cost optimization
Cao et al.	2013	Stochastic Optimization	EV scheduling	Microgrid	Simulated	Uncertainty handling
Wang et al.	2015	PSO	Home EMS	Smart home	Real data	Cost minimization
Lee et al.	2016	GA	Battery scheduling	Microgrid	Simulated	Efficiency improvement
Ruelens et al.	2017	RL	Demand response	Smart grid	Real data	Adaptive learning
Zhang et al.	2018	DRL	Microgrid EMS	Microgrid	Solar dataset	Cost reduction
Vázquez-Canteli	2019	RL	EV scheduling	Smart home	EV dataset	Flexibility
Liu et al.	2020	Hybrid PSO-DNN	PV scheduling	Smart grid	Real data	Prediction + optimization
Huang et al.	2020	LSTM-GA	EV charging	Smart grid	Time-series	Temporal modeling
Shi et al.	2021	Distributed Optimization	Edge computing EMS	IoT system	Real data	Low latency
Wang et al.	2021	Attention DL	Load forecasting	Smart grid	Real data	Accuracy improvement
Li et al.	2022	Non-local NN	Energy scheduling	Microgrid	Simulated	Global dependency
Zhao et al.	2022	Federated RL	Distributed EMS	Smart grid	Private data	Privacy preservation

Chen et al.	2022	Quantum-inspired EA	Microgrid EMS	Simulated	Simulated	Faster convergence
Zhang et al.	2023	Hybrid Quantum NN	PV-battery	Microgrid	Simulated	Scalability
Kumar et al.	2023	DRL + Non-local NN	EV scheduling	Smart grid	EV dataset	Adaptive control
Singh et al.	2023	Cloud DL	EMS platform	Cloud system	IoT data	Real-time optimization

Comparative Analysis

The comparative analysis of existing literature reveals a clear evolution from traditional optimization techniques toward advanced hybrid intelligent systems. Early approaches predominantly relied on deterministic and mathematical optimization methods such as linear programming and mixed-integer programming, which provided precise solutions but lacked adaptability to dynamic and uncertain environments. As energy systems became more complex with the integration of renewable energy sources and electric vehicles, these methods proved insufficient for handling high-dimensional scheduling problems.

Metaheuristic algorithms such as particle swarm optimization and genetic algorithms introduced flexibility and improved performance in nonlinear optimization scenarios. However, these methods often suffer from issues such as slow convergence, local optima trapping, and scalability limitations. The emergence of machine learning and deep learning techniques marked a significant advancement in energy scheduling research. Reinforcement learning and deep neural networks enabled systems to learn optimal policies from data, reducing the need for explicit modeling of system dynamics.

More recently, attention-based models and non-local neural networks have demonstrated superior performance by capturing global dependencies across distributed energy resources. These architectures are particularly effective in complex systems where interactions between components are highly interdependent. Additionally, the integration of quantum-inspired optimization techniques has further enhanced computational efficiency, enabling scalable solutions for large-scale energy networks.

Another important trend observed in the literature is the increasing use of real-world datasets, including smart meter data, solar irradiance data, and electric vehicle charging data. This shift toward data-driven approaches has improved the practical applicability of scheduling algorithms. Furthermore, the adoption of cloud computing, edge computing, and IoT platforms has facilitated real-time energy management and large-scale system deployment.

Overall, hybrid approaches combining deep learning, reinforcement learning, and quantum-inspired optimization techniques have consistently demonstrated superior performance in terms of cost reduction, energy efficiency, and scalability. These approaches represent the future direction of intelligent energy management systems capable of addressing the complexities of modern smart grids.

Discussion

The reviewed studies demonstrate that optimal scheduling of photovoltaic (PV) systems, battery energy storage systems, and electric vehicles has evolved into a complex intelligent optimization problem requiring adaptive and scalable solutions. The increasing penetration of renewable energy sources, coupled with dynamic load demands and bidirectional energy flows, has accelerated the adoption of artificial intelligence-based scheduling frameworks. Machine learning, deep learning, reinforcement learning, and hybrid optimization algorithms consistently outperform conventional deterministic approaches by effectively modeling nonlinear relationships, handling uncertainty, and supporting real-time decision-making. These intelligent techniques enable higher renewable energy utilization, lower operational costs, improved load balancing, and enhanced grid reliability across smart grid and microgrid environments.

A significant trend observed across the literature is the transition from traditional optimization algorithms toward integrated learning-based architectures. Reinforcement learning enables continuous policy improvement through environmental interaction, while hybrid approaches combining neural networks with evolutionary optimization algorithms achieve faster convergence and better scheduling performance. Furthermore, non-local neural networks have emerged as promising architectures because they capture global dependencies among PV generation, battery storage, and electric vehicle charging patterns. The incorporation of quantum-inspired optimization further strengthens these frameworks by improving exploration capabilities in high-dimensional search spaces and enhancing computational efficiency for large-scale scheduling problems.

Despite these advances, several practical challenges remain. Deep learning and hybrid optimization models require substantial computational resources, large-scale datasets, and extensive training, limiting deployment in resource-constrained environments. Moreover, many existing studies validate their methods using simulation platforms rather than real-world deployments, leaving concerns regarding scalability, communication latency, interoperability, cybersecurity, and system reliability. Although IoT-enabled edge computing architectures have improved decentralized processing and reduced latency, issues related to data privacy, secure communication, and heterogeneous device integration continue to require further investigation. Emerging technologies such as federated learning and blockchain provide promising solutions for secure and privacy-preserving distributed energy management but introduce additional implementation complexity.

Overall, the convergence of scalable quantum-inspired optimization, non-local neural networks, artificial intelligence, and distributed computing technologies represents a significant advancement in intelligent energy management. These integrated frameworks offer the potential to develop fully autonomous scheduling systems capable of coordinating PV generation, battery storage, and electric vehicle operations in real time. Future research should emphasize lightweight AI architectures, explainable decision-making, secure decentralized optimization, and large-scale field validation to accelerate practical deployment. Such developments will play a crucial role in building resilient, efficient, and sustainable smart energy infrastructures capable of supporting future carbon-neutral power systems.

Conclusion

Optimal scheduling of photovoltaic (PV) systems, battery energy storage systems, and electric vehicle (EV) loads has become a fundamental requirement for intelligent smart grid operation. This review demonstrates that the integration of artificial intelligence with advanced optimization techniques has significantly improved energy management by enabling adaptive, accurate, and real-time scheduling under dynamic operating conditions. The evolution from conventional deterministic optimization to machine learning, deep learning, reinforcement learning, and hybrid optimization frameworks has enhanced renewable energy utilization, reduced operational costs, improved load balancing, and increased overall grid reliability. Furthermore, scalable quantum non-local neural networks have emerged as a promising approach for capturing global dependencies among distributed energy resources while efficiently solving complex scheduling problems.

Despite these advances, challenges including computational complexity, large data requirements, interoperability, cybersecurity, and practical deployment remain significant barriers to widespread implementation. Emerging technologies such as federated learning, edge intelligence, quantum-inspired optimization, blockchain, and explainable artificial intelligence are expected to address these limitations and further improve intelligent energy management. Future research should emphasize lightweight, scalable, and secure scheduling frameworks supported by real-world validation and standardized benchmarking. The convergence of AI, quantum-inspired optimization, and distributed computing offers a robust pathway toward resilient, sustainable, and autonomous smart energy systems capable of supporting future carbon-neutral power networks.

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