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International Journal of Recent Advances in Engineering and Technology

ISSN: 2347 - 2812

Volume 13 Issue 02, 2024

A Survey of Methods and Architectures for Optimal Scheduling of PV-Battery-Electric Vehicle Loads Using a Scalable Quantum Non-Local Neural Network Approach

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Peer Review Information

Submission: 12 July 2024

Revision: 23 July 2024

Acceptance: 10 Aug 2024

Keywords

Optimal energy scheduling, photovoltaic systems, battery energy storage, electric vehicles, quantum neural networks, deep reinforcement learning

Abstract

The transformation of modern power systems into decentralized and sustainable smart grids has increased the complexity of energy management, particularly in the optimal scheduling of photovoltaic (PV) systems, battery energy storage systems (BESS), and electric vehicle (EV) loads. These systems introduce challenges due to renewable intermittency, stochastic demand, and nonlinear interactions, making traditional optimization methods insufficient for large-scale and dynamic environments. This review examines advanced artificial intelligence (AI) and optimization techniques for energy scheduling, with a focus on scalable quantum non-local neural networks (QNLNN). These models combine quantum-inspired computational principles with non-local learning mechanisms to capture global dependencies and enhance optimization performance.

The study explores various methodologies, including deep learning, reinforcement learning, and hybrid metaheuristic approaches, applied across smart grids and microgrids. It also highlights advanced architectures such as graph neural networks and transformer models for handling complex energy interactions. Datasets such as IEEE benchmark systems, smart meter data, and EV charging profiles are analyzed alongside simulation platforms. Findings indicate that QNLNN-based approaches improve scalability, convergence speed, and adaptability. Key challenges include computational complexity and integration issues, while future directions emphasize scalable, intelligent, and sustainable energy management solutions.

Introduction

The global transition toward sustainable energy systems has accelerated the adoption of renewable energy technologies, particularly photovoltaic (PV) systems, as well as the electrification of transportation through electric vehicles (EVs). These developments are central to reducing greenhouse gas emissions and achieving energy sustainability goals. However, the integration of PV generation and EV charging into existing power grids introduces significant operational challenges due to the intermittent nature of solar energy and the stochastic demand patterns of EV users. Battery energy storage systems (BESS) have emerged as a critical component in mitigating these challenges by enabling energy buffering, load shifting, and improved grid reliability. The combined operation of PV, battery storage, and EV loads forms a complex cyber-physical system that requires advanced scheduling and optimization strategies.

Traditional power systems were designed for centralized generation and unidirectional power flow. In contrast, modern smart grids are characterized by distributed energy resources (DERs), bidirectional power flows, and real-time communication capabilities. This transformation necessitates the development of intelligent energy management systems (EMS) capable of handling high levels of uncertainty, variability, and complexity. Optimal scheduling in such systems involves determining the best operational strategy for PV generation, battery charging/discharging, and EV charging/discharging over a given time horizon, while satisfying various constraints such as power balance, battery capacity limits, and user preferences.

Conventional optimization techniques, including linear programming, nonlinear programming, and mixed-integer programming, have been widely used for energy scheduling problems. While these methods provide mathematically rigorous solutions, they often suffer from scalability issues when applied to large-scale systems with numerous variables and constraints. Moreover, they require accurate system models and may not effectively capture the nonlinear and stochastic behavior of renewable energy sources and EV demand. Heuristic and metaheuristic algorithms such as genetic algorithms, particle swarm optimization, and simulated annealing have been proposed to address these limitations. Although these methods offer flexibility and adaptability, they may exhibit slow convergence and lack guarantees of optimality.

In recent years, artificial intelligence (AI) and machine learning (ML) techniques have gained significant attention in the field of energy management. Deep learning models, including convolutional neural networks and recurrent neural networks, have demonstrated strong capabilities in modeling complex nonlinear relationships and temporal dependencies. Reinforcement learning, particularly deep reinforcement learning (DRL), has been widely applied to sequential decision-making problems in energy scheduling, enabling systems to learn optimal policies through interaction with the environment. These approaches have shown promising results in handling uncertainty and adapting to dynamic conditions.

Despite these advancements, existing AI-based methods face challenges related to scalability, generalization, and computational efficiency. As the size and complexity of smart grid systems increase, there is a need for more advanced architectures that can efficiently process large-scale data and capture long-range dependencies among distributed components. This has led to the exploration of quantum-inspired neural networks and non-local learning mechanisms. Quantum neural networks leverage concepts from quantum computing, such as superposition and entanglement, to enhance the expressive power of neural models. Although practical quantum hardware is still in its early stages, quantum-inspired algorithms can be implemented on classical hardware to achieve improved performance.

Non-local neural networks, originally developed for computer vision tasks, introduce a mechanism for capturing global dependencies by computing relationships between all pairs of positions in the input space. When applied to energy systems, non-local operations enable the model to consider interactions among geographically distributed energy resources, leading to more coordinated and efficient scheduling decisions. The integration of quantum-inspired techniques with non-local neural architectures results in scalable quantum non-local neural networks (QNLNN), which offer a powerful framework for addressing high-dimensional optimization problems in smart grids.

The application of QNLNN to PV-battery-EV scheduling is particularly promising due to the complex interdependencies among these components. For example, the charging schedule of EVs can be optimized based on PV generation forecasts and battery state-of-charge, while also considering electricity pricing and user preferences. Similarly, battery storage can be strategically utilized to store excess solar energy during peak generation periods and discharge during high-demand periods. These interactions require models that can simultaneously handle temporal dynamics, spatial correlations, and uncertainty.

Real-world applications of optimal scheduling in PV-battery-EV systems include residential energy management, commercial microgrids, and utility-scale smart grids. In residential settings, homeowners can benefit from reduced electricity bills and increased energy independence. In commercial and industrial environments, efficient energy scheduling can lead to significant cost savings and improved operational efficiency. At the utility level, coordinated management of distributed resources can enhance grid stability, reduce peak demand, and support the integration of renewable energy.

The increasing availability of high-resolution data from smart meters, IoT devices, and EV charging stations has further enabled the development of data-driven approaches for energy scheduling. However, challenges related to data quality, privacy, and interoperability remain significant barriers. Additionally, the deployment of advanced AI models in real-world systems requires careful consideration of computational constraints, reliability, and regulatory requirements.

This paper aims to provide a comprehensive survey of methods and architectures for optimal scheduling of PV-battery-electric vehicle loads, with a focus on scalable quantum non-local neural network approaches. By analyzing existing literature, identifying key trends, and highlighting research gaps, this work seeks to contribute to the advancement of intelligent energy management systems. The subsequent sections present an extensive literature review, comparative analysis, and discussion of current challenges and future directions in this rapidly evolving field.

Literature Review

The problem of optimal scheduling in PV-battery-electric vehicle systems has been extensively studied using a variety of optimization and machine learning techniques. Early research primarily relied on mathematical optimization frameworks. For instance, Zhang et al. (2019) proposed a mixed-integer linear programming (MILP) model for distributed energy resource scheduling in a microgrid environment, utilizing an IEEE 33-bus system with simulated load and generation data. Their work demonstrated effective cost minimization under deterministic conditions but highlighted limitations in handling uncertainty and scalability [1].

Wang et al. (2020) introduced a particle swarm optimization (PSO)-based approach for smart home energy management systems integrating PV and EV loads. Using real smart meter datasets, the study achieved significant peak load reduction and improved load balancing. However, the convergence speed of PSO was observed to be sensitive to parameter tuning, limiting its robustness in dynamic environments [2]. Similarly, Li et al. (2021) applied deep reinforcement learning (DRL) to develop an adaptive energy scheduler capable of learning optimal charging policies for EVs in residential microgrids. Their approach leveraged temporal patterns in electricity pricing and PV generation, achieving improved cost savings compared to rule-based systems [3].

Chen et al. (2020) explored a hybrid genetic algorithm (GA) combined with fuzzy logic for PV-battery scheduling. The model incorporated uncertainty in solar irradiance and user demand, demonstrating improved flexibility over traditional deterministic approaches. The study utilized MATLAB-based simulations with synthetic datasets, showing enhanced energy utilization efficiency [4]. In another study, Singh et al. (2022) proposed a deep Q-network (DQN)-based scheduling framework for EV charging, integrating battery storage and renewable sources. Their model was evaluated using real EV charging datasets and showed improved adaptability to stochastic demand patterns [5].

The application of neural networks has also gained traction in this domain. Kim et al. (2021) employed a convolutional neural network (CNN) for forecasting PV generation and integrating it with a scheduling optimizer. Their approach improved prediction accuracy and enabled better scheduling decisions in a microgrid testbed using real-world solar datasets [6]. Meanwhile, Liu et al. (2022) proposed a long short-term memory (LSTM)-based model for time-series prediction of energy demand and PV output, achieving superior performance in capturing temporal dependencies [7].

Graph-based approaches have also been explored to model distributed energy systems. Zhao et al. (2023) introduced a graph neural network (GNN) for energy scheduling across interconnected microgrids. The model captured spatial dependencies among distributed nodes and improved coordination in energy sharing, evaluated on IEEE 118-bus systems [8]. Similarly, Huang et al. (2022) utilized a graph attention network (GAT) to enhance decision-making in EV charging networks, demonstrating improved scalability and performance in large-scale systems [9].

Reinforcement learning continues to dominate recent research trends. Mnih et al. (2015) laid the foundation for deep reinforcement learning, which has since been adapted for energy systems. Building on this, Zhang et al. (2022) developed a multi-agent reinforcement learning (MARL) framework for coordinated scheduling of PV, battery, and EV systems. Their approach enabled decentralized decision-making while maintaining global optimization objectives, using GridLAB-D simulations [10]. Similarly, Yang et al. (2023) proposed a proximal policy optimization (PPO)-based scheduler for real-time energy management, achieving faster convergence and improved stability [11].

Hybrid optimization approaches have also shown promising results. Kumar et al. (2021) combined PSO with neural networks to optimize energy scheduling in smart grids. Their hybrid model leveraged the exploration capability of PSO and the learning capability of neural networks, resulting in improved performance metrics such as cost reduction and energy efficiency [12]. In another study, Patel et al. (2022) integrated genetic algorithms with LSTM models for predictive scheduling, achieving enhanced forecasting accuracy and optimized load management [13].

The emergence of quantum-inspired computing has opened new avenues for solving complex optimization problems. Schuld et al. (2020) introduced quantum neural networks (QNNs) capable of representing high-dimensional data using quantum states. Although implemented on classical hardware, these models demonstrated improved expressiveness and optimization capabilities [14]. Building on this concept, Li et al. (2023) proposed a quantum-inspired deep learning model for energy scheduling, achieving faster convergence compared to classical neural networks [15].

Non-local neural networks have been increasingly adopted for capturing global dependencies. Wang et al. (2018) introduced the concept of non-local operations in neural networks, which has since been applied to energy systems. Chen et al. (2023) utilized non-local neural networks for coordinated scheduling in distributed energy systems, demonstrating improved performance in capturing long-range interactions [16]. Furthermore, Zhang et al. (2024) combined quantum-inspired learning with non-local architectures to develop scalable quantum non-local neural networks (QNLNN) for smart grid applications, achieving significant improvements in computational efficiency and scalability [17].

Transformer-based architectures have also been explored for energy scheduling. Vaswani et al. (2017) introduced the transformer model, which has been adapted for time-series forecasting in energy systems. Liu et al. (2023) applied transformers for PV and load forecasting, enabling improved scheduling decisions in smart grids [18]. Additionally, hybrid transformer-RL frameworks have been proposed to enhance decision-making in dynamic environments.

Recent studies have also focused on real-world implementation and deployment. Gupta et al. (2022) developed an IoT-based energy management system integrating PV, battery, and EV loads, using real-time data from smart sensors. Their system demonstrated improved operational efficiency and user satisfaction [19]. Similarly, Ahmed et al. (2023) implemented a cloud-based energy scheduling platform using DRL, enabling scalable and real-time optimization [20].

The integration of uncertainty modeling has also been a key research focus. Robust optimization techniques have been applied to handle variability in renewable generation and load demand. For example, Bertsimas et al. (2018) proposed a robust optimization framework for energy systems, ensuring reliable operation under uncertain conditions [21]. Stochastic programming approaches have also been widely used, as demonstrated by Morales et al. (2014), who developed a two-stage stochastic model for renewable energy scheduling [22].

Overall, the literature demonstrates a clear transition from traditional optimization methods to advanced AI-driven approaches. The integration of quantum-inspired and non-local neural architectures represents a significant advancement in addressing the complexity of modern energy systems. However, challenges related to scalability, data requirements, and real-world deployment remain open research issues.

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 smart home	Smart meter data	Peak reduction
Li et al.	2021	DRL	RL-based scheduler	Residential microgrid	Real EV data	Adaptive scheduling
Chen et al.	2020	GA + Fuzzy	Hybrid controller	MATLAB simulation	Synthetic	Uncertainty handling
Singh et al.	2022	DQN	EV scheduling model	Smart grid	EV dataset	Demand adaptation
Kim et al.	2021	CNN	Forecasting + scheduling	Microgrid	Solar data	Improved prediction

Liu et al.	2022	LSTM	Time-series model	Smart grid	Load/PV data	Temporal modeling
Zhao et al.	2023	GNN	Distributed scheduling	IEEE 118-bus	Simulated	Spatial modeling
Huang et al.	2022	GAT	EV network model	Large-scale grid	Charging data	Scalability
Zhang et al.	2022	MARL	Multi-agent system	GridLAB-D	Synthetic	Decentralized control
Yang et al.	2023	PPO	RL scheduler	Real-time EMS	Real data	Stability
Kumar et al.	2021	PSO + NN	Hybrid optimizer	Smart grid	Mixed	Efficiency
Patel et al.	2022	GA + LSTM	Predictive model	Microgrid	Time-series	Forecast + optimize
Schuld et al.	2020	QNN	Quantum model	Classical sim	Synthetic	High-dimensional learning
Li et al.	2023	Quantum DL	Hybrid QNN	Smart grid	Simulated	Faster convergence
Chen et al.	2023	Non-local NN	Global dependency model	Distributed grid	Real data	Long-range interaction
Zhang et al.	2024	QNLNN	Quantum + non-local	Smart grid	Mixed	Scalability
Liu et al.	2023	Transformer	Forecasting model	Smart grid	Real data	Accuracy
Gupta et al.	2022	IoT + ML	EMS platform	IoT grid	Sensor data	Real-time control
Ahmed et al.	2023	DRL + Cloud	Scalable EMS	Cloud platform	Real data	Deployment

Comparative Analysis

The comparative analysis of the reviewed studies reveals several important trends in the field of optimal scheduling for PV-battery-electric vehicle systems. A significant shift can be observed from traditional optimization techniques such as MILP and heuristic algorithms toward advanced AI-based methods, particularly deep learning and reinforcement learning. While classical methods provide reliable baseline solutions, their scalability limitations and inability to handle uncertainty have driven the adoption of intelligent approaches.

Reinforcement learning, especially deep reinforcement learning, has emerged as one of the most widely used techniques due to its ability to handle sequential decision-making problems in dynamic environments. Multi-agent reinforcement learning frameworks further enhance scalability by enabling decentralized control, which is essential for large-scale smart grids. Hybrid approaches combining metaheuristic algorithms with neural networks have also demonstrated improved performance by leveraging the strengths of both paradigms.

Another notable trend is the increasing use of advanced neural architectures such as graph neural networks and transformers. These models are particularly effective in capturing spatial and temporal dependencies, respectively, which are critical in distributed energy systems. The integration of IoT and cloud computing platforms has further enabled real-time data processing and scalable deployment of energy management systems.

The emergence of quantum-inspired neural networks and non-local architectures represents a significant advancement in addressing the complexity of modern energy systems. These approaches offer improved scalability, faster convergence, and enhanced capability to model high-dimensional interactions. However, their practical implementation remains challenging due to computational requirements and the need for large datasets.

Dataset usage patterns indicate a mix of simulated and real-world data, with increasing emphasis on real datasets from smart meters, EV charging stations, and renewable energy sources. Performance improvements across studies are typically measured in terms of cost reduction, peak load minimization, and energy efficiency, with AI-based methods consistently outperforming traditional approaches.

Overall, the literature highlights the growing importance of scalable, data-driven, and intelligent optimization techniques in the field of energy management. The integration of quantum-inspired and non-local neural networks is expected to play a crucial role in the future development of smart grid technologies.

The integration of photovoltaic systems, battery energy storage, and electric vehicle loads within modern smart grids represents a transformative shift in how energy systems are designed, operated, and optimized. The reviewed literature clearly indicates that optimal scheduling in such systems is no longer a purely deterministic or static optimization problem, but rather a dynamic, multi-dimensional, and data-driven challenge. The incorporation of artificial intelligence techniques, particularly deep learning and reinforcement learning, has significantly enhanced the capability of energy management systems to adapt to real-time conditions, forecast uncertainties, and optimize decision-making processes across multiple time horizons.

One of the most important implications of this research field is the transition from centralized control architectures to distributed and decentralized frameworks. Multi-agent reinforcement learning and graph-based neural networks have enabled the modeling of distributed energy resources as interconnected agents that can collaboratively optimize energy usage. This paradigm shift is particularly relevant for large-scale smart grids where centralized optimization becomes computationally infeasible. The ability of these methods to capture both local and global interactions among PV systems, batteries, and EV loads contributes to improved system-wide efficiency and resilience.

The effectiveness of the reviewed methods is evident in their ability to address key challenges such as uncertainty in renewable generation, variability in load demand, and the stochastic behavior of EV charging patterns. Deep reinforcement learning approaches, for example, have demonstrated strong performance in learning optimal policies under uncertain environments without requiring explicit mathematical models. Similarly, hybrid approaches that combine metaheuristic algorithms with neural networks provide a balance between exploration and exploitation, leading to improved convergence and solution quality. Quantum-inspired neural networks further extend these capabilities by offering enhanced representational power, enabling the modeling of complex, high-dimensional relationships that are difficult to capture باستخدام classical methods.

Despite these advancements, several limitations remain. One of the primary challenges is the high computational complexity associated with advanced AI models, particularly quantum-inspired and non-local neural networks. These models often require significant computational resources and large volumes of training data, which may not always be available in real-world scenarios. Additionally, the interpretability of AI-based models remains a concern, especially in critical infrastructure systems such as power grids where transparency and reliability are essential. The “black-box” nature of deep learning models can hinder their acceptance in industry applications.

Another limitation is the dependency on high-quality and high-resolution datasets. While the availability of smart meter data and IoT-enabled devices has improved data accessibility, issues related to data privacy, security, and standardization persist. Furthermore, many studies rely on simulated datasets or simplified system models, which may not fully capture the complexities of real-world environments. This gap between simulation and practical deployment highlights the need for more real-world validation and pilot implementations.

The importance of optimization techniques in this domain cannot be overstated. Efficient scheduling directly impacts energy cost savings, grid stability, and environmental sustainability. The reviewed literature demonstrates that advanced optimization techniques can significantly reduce peak demand, improve load balancing, and enhance the utilization of renewable energy. Moreover, the integration of pricing mechanisms and demand response strategies within optimization frameworks enables more economically efficient operation of energy systems.

From a practical perspective, the deployment of intelligent energy management systems has significant implications for residential, commercial, and utility-scale applications. In residential settings, optimal scheduling can reduce electricity bills and improve energy independence through better utilization of rooftop PV and home battery systems. In commercial and industrial environments, these techniques can enhance operational efficiency and reduce energy costs. At the grid level, coordinated scheduling of distributed energy resources can improve grid reliability, reduce congestion, and support the integration of renewable energy at scale.

Looking forward, the development of scalable and efficient architectures remains a critical research direction. The integration of quantum-inspired computing with non-local neural networks offers a promising pathway for addressing the scalability challenges of large-scale energy systems. Additionally, the combination of AI techniques with emerging technologies such as edge computing, blockchain, and digital twins could further enhance the efficiency, security, and transparency of energy management systems.

Conclusion

The rapid evolution of smart grid technologies and the increasing integration of renewable energy sources and electric vehicles have fundamentally transformed the landscape of modern energy systems. This review has provided a comprehensive survey of methods and architectures for optimal scheduling of photovoltaic-battery-electric vehicle loads, with a particular emphasis on scalable quantum non-local neural network approaches. The findings of this study highlight the critical importance of intelligent, adaptive, and scalable optimization techniques in managing the complexity and uncertainty inherent in such systems.

One of the key insights from the literature is the clear transition from traditional optimization methods to advanced artificial intelligence-based approaches. While classical techniques such as mixed-integer linear programming and heuristic algorithms have laid the foundation for energy scheduling, their limitations in handling large-scale, nonlinear, and stochastic problems have necessitated the adoption of more sophisticated methods. Deep learning, reinforcement learning, and hybrid optimization techniques have emerged as powerful tools for addressing these challenges, offering improved performance, adaptability, and scalability.

The integration of advanced neural architectures, including convolutional neural networks, recurrent neural networks, graph neural networks, and transformer models, has significantly enhanced the ability of energy management systems to model complex relationships and temporal dynamics. These models have demonstrated strong capabilities in forecasting, decision-making, and optimization, enabling more efficient and reliable operation of PV-battery-EV systems. Furthermore, the incorporation of multi-agent systems and decentralized control frameworks has facilitated scalable solutions for large and distributed energy networks.

A particularly noteworthy development in this field is the emergence of quantum-inspired neural networks and non-local learning mechanisms. These approaches represent a significant advancement in the ability to model high-dimensional interactions and capture long-range dependencies among distributed energy resources. Scalable quantum non-local neural networks combine the strengths of quantum-inspired computation and non-local operations, providing a powerful framework for solving complex optimization problems in smart grids. The reviewed studies indicate that these models offer advantages such as faster convergence, improved scalability, and enhanced robustness to uncertainty.

However, the adoption of these advanced techniques is not without challenges. Computational complexity remains a major concern, particularly for large-scale implementations. The need for high-quality datasets and the difficulty of obtaining real-world data pose additional challenges. Moreover, issues related to model interpretability, reliability, and integration with existing grid infrastructure must be addressed to ensure practical deployment. Regulatory and standardization challenges also play a crucial role in determining the feasibility of implementing these technologies in real-world systems.

Another important observation from the literature is the increasing role of real-time data and IoT-enabled systems in energy management. The availability of high-resolution data from smart meters, sensors, and EV charging stations has enabled the development of data-driven approaches that can adapt to dynamic conditions and improve decision-making. The integration of cloud computing and edge computing technologies further enhances the scalability and responsiveness of energy management systems.

In terms of future research directions, several promising avenues can be identified. The development of more efficient and scalable quantum-inspired algorithms is a key area of interest, particularly as quantum computing technologies continue to advance. The integration of explainable AI techniques could address concerns related to model interpretability and trustworthiness. Additionally, the use of digital twins and simulation-based optimization could enable more accurate modeling and validation of energy systems.

The combination of AI with other emerging technologies such as blockchain could also enhance the security and transparency of energy transactions. Furthermore, the exploration of federated learning approaches could enable collaborative model training while preserving data privacy, addressing one of the major challenges in data-driven energy management. The development of standardized datasets and benchmarking frameworks would also facilitate more consistent evaluation and comparison of different methods.

In conclusion, the optimal scheduling of PV-battery-electric vehicle loads is a critical component of modern smart grid systems. The integration of advanced AI techniques, particularly scalable quantum non-local neural networks, offers a promising pathway for addressing the complexity and uncertainty of these systems. While significant progress has been made, further research is needed to overcome existing challenges and fully realize the potential of these technologies. The continued advancement of intelligent energy management systems will play a crucial role in enabling sustainable, efficient, and resilient energy systems for the future.

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