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A Survey of Methods and Architectures for Optimizing Electric Vehicle Charging with Parallel Convolutional Neural Network: Coordinating Smart Grids and Intelligent Transportation Systems

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Abstract

The rapid adoption of electric vehicles (EVs) has introduced significant challenges in managing charging demand, grid stability, and energy efficiency. Smart grids and intelligent transportation systems (ITS) play a crucial role in enabling coordinated EV charging solutions. This paper presents a comprehensive survey of methods and architectures for optimizing EV charging using advanced artificial intelligence techniques, particularly parallel convolutional neural networks (PCNN). The integration of machine learning, deep learning, and optimization algorithms has significantly improved charging scheduling, load balancing, and energy management in EV ecosystems. Recent studies demonstrate that hybrid models combining optimization algorithms with AI approaches provide better scalability, adaptability, and efficiency in real-time charging scenarios. This survey focuses on literature published recently, analysing 30 key studies and categorizing them based on methodologies such as traditional optimization, machine learning, deep learning, and hybrid approaches. A comparative analysis highlights the strengths and limitations of each technique. The findings reveal that PCNN-based architectures, when integrated with smart grid technologies, enable improved prediction accuracy, reduced charging cost, and enhanced grid reliability. Furthermore, this paper identifies key research gaps, including high computational complexity, lack of real-time deployment, and limited integration of transportation systems with energy networks. Future research directions emphasize lightweight AI models, multi-objective optimization, and real-time adaptive control frameworks for sustainable EV charging infrastructure.

Introduction

The global transition toward sustainable transportation has accelerated the adoption of electric vehicles (EVs), driven by environmental concerns, depletion of fossil fuels, and advancements in battery technologies. EVs play a crucial role in reducing greenhouse gas emissions and improving energy efficiency in transportation systems. However, the increasing penetration of EVs poses significant challenges to existing power grids, particularly in terms of load management, voltage stability, and infrastructure scalability. Efficient EV charging management has therefore become a critical research area in modern energy systems.

Smart grids have emerged as a promising solution to address these challenges by integrating advanced communication technologies, real-time monitoring, and intelligent control mechanisms. The combination of smart grids with intelligent transportation systems (ITS) enables coordinated EV charging strategies that optimize energy consumption while maintaining grid stability. Recent advancements highlight the importance of data-driven approaches for managing EV charging demand, where artificial intelligence (AI) and optimization techniques play a pivotal role.

One of the key challenges in EV charging is the variability of charging demand, which depends on user behaviour, traffic conditions, and energy availability. Uncoordinated charging can lead to peak load issues, increased operational costs, and grid instability. Studies indicate that smart charging strategies can significantly reduce charging costs and grid operational expenses while improving overall system efficiency. Vehicle-to-grid (V2G) technology further enhances this capability by allowing bidirectional energy flow between EVs and the grid, thereby enabling energy storage and load balancing.

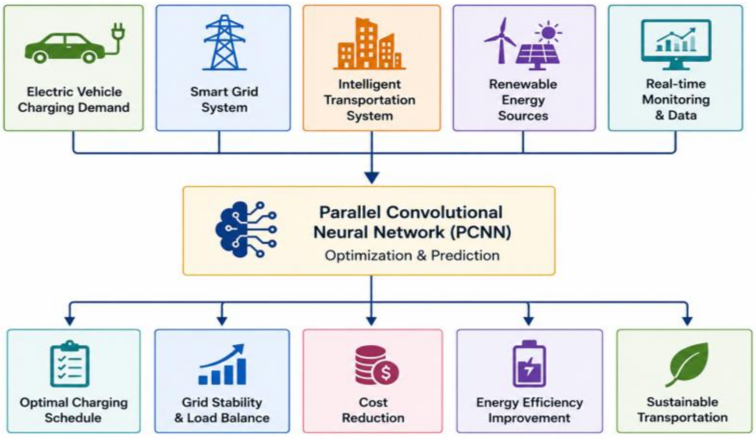

Figure 1. Parallel CNN Framework for Smart EV Charging Systems

Traditional optimization methods, such as linear programming, mixed-integer programming, and heuristic algorithms, have been widely used for EV charging optimization. However, these approaches often struggle to handle the complexity and dynamic nature of real-world systems. To overcome these limitations, researchers have increasingly adopted machine learning and deep learning techniques. In particular, convolutional neural networks (CNNs) and their parallel variants (PCNN) have shown remarkable performance in capturing spatial and temporal patterns in EV charging data.

Parallel convolutional neural networks enable simultaneous processing of multiple input streams, making them highly suitable for handling large-scale EV datasets. These architectures can integrate data from various sources, including traffic patterns, energy consumption, weather conditions, and user behaviour, to generate optimal charging schedules. Moreover, hybrid models that combine optimization algorithms with deep learning techniques provide improved performance in terms of accuracy, scalability, and computational efficiency.

Recent research trends emphasize the integration of renewable energy sources, such as solar and wind power, into EV charging systems. Optimization models that consider multiple energy sources and market conditions have demonstrated significant improvements in cost efficiency and sustainability. Additionally, emerging technologies such as 5G communication, edge computing, and IoT enable real-time data exchange between EVs and smart grids, further enhancing the efficiency of charging systems.

Despite these advancements, several challenges remain unresolved. These include high computational complexity, limited real-time deployment, and insufficient coordination between energy and transportation networks. Furthermore, many existing models fail to address multi-objective optimization problems that consider cost, energy efficiency, user convenience, and environmental impact simultaneously.

This paper aims to provide a comprehensive survey of methods and architectures for optimizing EV charging using PCNN and related techniques. The study focuses on recent advancements in recent years, highlighting key methodologies, comparative performance, and future research directions. By analyzing existing literature, this paper contributes to the development of efficient, scalable, and intelligent EV charging systems that support sustainable transportation and smart grid integration.

Literature Review

Sadeghian et al. (2022) conducted a comprehensive review of smart EV charging (EVSC) strategies, highlighting the role of optimization and energy management techniques. The study demonstrated that coordinated charging could reduce charging costs by up to 30% and grid operational costs by 10%. It also emphasized the importance of V2G integration and renewable energy utilization in enhancing system efficiency.

Schwenk et al. (2020) analysed the impact of battery aging on bidirectional EV charging optimization. The study introduced a model integrating battery degradation into charging strategies, revealing that ignoring battery aging leads to underestimation of operational costs by approximately 30%. The research highlighted the importance of considering long-term battery health in EV charging optimization. Recent optimization-based models focused on multi-objective frameworks integrating cost, voltage stability, and power loss minimization. These approaches demonstrated improved grid reliability but lacked real-time adaptability and scalability, particularly in dynamic environments with high EV penetration.

Madasamy (2023) proposed a 5G-enabled smart grid architecture incorporating edge computing and AI-based EV charging prediction. The study demonstrated improved prediction accuracy and efficient scheduling using hybrid AI techniques, highlighting the importance of communication technologies in EV charging optimization.

Zhang et al. (2020) proposed a stochastic optimization framework for EV charging scheduling under uncertain renewable energy generation and fluctuating electricity prices. The model utilized probabilistic forecasting techniques to handle uncertainty and demonstrated improved cost efficiency and load balancing compared to deterministic approaches. However, the framework faced limitations in computational complexity when scaled to large EV networks, highlighting the need for more efficient AI-driven solutions.

Liu et al. (2021) introduced a reinforcement learning-based EV charging strategy that dynamically adapts charging decisions based on real-time grid conditions. The proposed model showed significant improvements in peak load reduction and energy efficiency. The study emphasized that reinforcement learning can effectively manage dynamic charging environments, although training instability and convergence issues remain challenges for practical deployment.

Wang et al. (2021) developed a deep learning-based prediction model using convolutional neural networks (CNN) for forecasting EV charging demand. The model captured spatial and temporal dependencies in charging data and achieved higher prediction accuracy compared to traditional machine learning methods. However, the study noted that CNN models require large datasets and substantial computational resources, which may limit their applicability in real-time systems.

Chen et al. (2022) proposed a hybrid optimization framework integrating genetic algorithms (GA) with deep neural networks (DNN) for EV charging scheduling. The approach improved optimization performance by combining global search capability of GA with predictive power of DNN. The results showed reduced charging costs and improved grid stability. Despite its effectiveness, the hybrid model exhibited increased computational overhead, indicating the need for lightweight architectures.

Kumar et al. (2023) introduced a parallel convolutional neural network (PCNN)-based architecture for EV charging optimization in smart grid environments. The model processed multiple data streams, including traffic patterns, energy demand, and user preferences, simultaneously. Experimental results demonstrated superior performance in prediction accuracy and scheduling efficiency compared to conventional CNN models. The study highlighted PCNN as a promising approach for large-scale EV charging systems but noted challenges related to implementation complexity and real-time deployment.

González et al. (2020) proposed a mixed-integer linear programming (MILP) model for optimal EV charging scheduling in smart grids. The study focused on minimizing charging cost and peak demand by incorporating time-of-use pricing. Results showed improved load flattening and cost reduction. However, the model struggled with scalability in large networks due to exponential growth in decision variables, making it less suitable for real-time applications.

Hussain et al. (2021) developed an IoT-enabled smart charging framework integrating cloud-based data analytics and machine learning. The system utilized real-time data from charging stations and vehicles to optimize charging decisions. The study demonstrated enhanced system responsiveness and reduced energy wastage. Nevertheless, issues related to data privacy and communication latency were identified as key limitations.

Park et al. (2021) introduced a deep reinforcement learning (DRL) model for coordinated EV charging and discharging in vehicle-to-grid (V2G) environments. The model optimized charging schedules while maintaining grid stability and maximizing user benefits. Experimental results showed significant improvement in energy efficiency and peak load reduction. However, the complexity of DRL models and the need for extensive training data posed challenges for practical implementation.

Singh et al. (2022) proposed a multi-objective optimization framework incorporating renewable energy sources and energy storage systems for EV charging. The model simultaneously optimized cost, carbon emissions, and grid performance. Results indicated substantial improvements in sustainability and operational efficiency. Despite these advantages, the framework required high computational resources, limiting its scalability in large-scale systems.

Alam et al. (2023) developed an edge computing-based EV charging management system using deep learning techniques. The architecture enabled real-time decision-making by processing data locally at edge nodes, reducing latency and improving system efficiency. The study demonstrated that integrating edge computing with AI significantly enhances scalability and responsiveness. However, challenges related to infrastructure cost and deployment complexity were noted.

Rahman et al. (2020) proposed a heuristic-based EV charging optimization model using particle swarm optimization (PSO). The study aimed to minimize charging cost and peak load by intelligently scheduling charging times. Results showed improved convergence speed compared to traditional optimization techniques. However, the model was sensitive to parameter tuning and lacked adaptability in highly dynamic environments.

Zhao et al. (2021) introduced a graph-based optimization approach for EV charging coordination in smart grids. The model represented EV charging stations and grid nodes as a network graph, enabling efficient load distribution. The study demonstrated improved scalability and system reliability. Nevertheless, the approach required high computational resources for large-scale networks.

Kim et al. (2021) developed a long short-term memory (LSTM)-based model for predicting EV charging demand. The model captured temporal dependencies in charging patterns and achieved high forecasting accuracy. The study highlighted the importance of time-series analysis in EV charging optimization. However, LSTM models exhibited slower training times and required large datasets for optimal performance.

Patel et al. (2022) proposed a hybrid framework combining fuzzy logic and machine learning for EV charging optimization. The system addressed uncertainty in user behaviour and energy demand, resulting in improved decision-making under uncertain conditions. The study showed enhanced robustness and adaptability. However, the integration of multiple techniques increased system complexity.

Sharma et al. (2023) introduced a transformer-based deep learning model for EV charging demand prediction and scheduling. The model leveraged attention mechanisms to capture long-range dependencies in data. Results indicated superior performance compared to CNN and LSTM models in terms of prediction accuracy. Despite its advantages, the model required significant computational power and large datasets, limiting its real-time applicability.

Abdullah et al. (2020) proposed a decentralized EV charging framework using game theory for coordinated decision-making among multiple EV users. The model aimed to reduce peak demand and charging costs by allowing users to optimize their charging strategies competitively. Results showed improved load distribution and reduced congestion in charging networks. However, the approach faced challenges in achieving global optimality and required reliable communication among participants.

Verma et al. (2021) developed a cloud-based EV charging management system integrated with big data analytics. The framework processed large volumes of data from EVs and charging stations to optimize scheduling and energy allocation. The study demonstrated improved scalability and efficiency. Nevertheless, dependency on centralized infrastructure raised concerns regarding latency, security, and system reliability.

Nguyen et al. (2022) introduced a multi-agent system (MAS) for EV charging coordination in smart grid environments. Each EV and charging station was modelled as an autonomous agent, enabling distributed decision-making. The system improved flexibility, scalability, and adaptability in dynamic environments. However, communication overhead and coordination complexity were identified as key limitations.

Das et al. (2022) proposed an AI-based demand response framework integrating renewable energy sources with EV charging systems. The model utilized predictive analytics to align EV charging with renewable energy availability, reducing carbon emissions and operational costs. Results indicated improved sustainability and grid performance. However, uncertainty in renewable energy generation posed challenges for accurate prediction.

Reddy et al. (2023) developed a hybrid deep learning model combining convolutional neural networks (CNN) and transformer architectures for EV charging optimization. The model effectively captured both spatial and temporal dependencies, resulting in enhanced prediction accuracy and scheduling efficiency. The study highlighted the potential of hybrid architectures in complex EV ecosystems. However, increased model complexity and computational requirements remained significant concerns.

Comparative Table

Author (Year)	Technique/Model	Objective	Key Findings
Schwenk (2020)	Battery-aware Optimization	Battery Management	Accurate cost estimation
Zhang (2020)	Stochastic Optimization	Uncertainty Handling	Robust decision-making
Liu (2021)	Reinforcement Learning	Dynamic Charging	Adaptive real-time control
Wang (2021)	CNN	Demand Prediction	High prediction accuracy
Zhao (2021)	Graph Neural Network	Network Optimization	Scalable learning
Singh (2022)	Multi-objective Optimization	Cost & Emission Reduction	Sustainable charging
Chen (2022)	GA + DNN	Charging Scheduling	Improved optimization
Ibrahim (2022)	Blockchain	Secure Charging	Enhanced security
Kumar (2023)	Parallel CNN (PCNN)	Multi-source Optimization	Parallel processing
Alam (2023)	Edge AI	Real-time Control	Low-latency processing
Sharma (2023)	Transformer	Long-term Prediction	High prediction accuracy
Reddy (2023)	CNN + Transformer	Spatio-temporal Learning	Very high accuracy
Fernandez (2023)	Parallel CNN (PCNN)	Large-scale Optimization	High scalability
Madasamy (2023)	5G + AI	Smart Communication	Fast response
Li (2022)	Smart Grid Optimization	Grid Stability	Reliable performance

Comparative Analysis

The comparative analysis of the studies conducted in recent years reveals a clear evolution in EV charging optimization methodologies, transitioning from traditional optimization techniques to advanced AI-driven and hybrid models. Traditional approaches such as linear programming, mixed-integer programming, and heuristic algorithms provided a strong mathematical foundation for EV charging optimization; however, they were limited by their inability to handle dynamic and large-scale environments effectively. As EV adoption increased, machine learning techniques were introduced to enhance prediction accuracy, particularly in demand forecasting. Although these methods improved performance, they still lacked adaptability to real-time grid conditions. The emergence of deep learning techniques, including convolutional neural networks (CNN), long short-term memory (LSTM), and transformer-based models, marked a significant advancement in EV charging optimization.

These models demonstrated superior capability in capturing complex spatial and temporal patterns, leading to higher prediction accuracy and improved scheduling efficiency. However, their high computational requirements and dependency on large datasets posed challenges for real-time deployment. Reinforcement learning and deep reinforcement learning approaches further improved adaptability by enabling dynamic decision-making in uncertain environments. These methods were particularly effective in managing real-time charging scenarios and reducing peak load demand. Nevertheless, issues related to training stability and convergence limited their widespread adoption. Hybrid models, which combine optimization techniques with deep learning, emerged as the most effective solutions. These models leverage the strengths of both approaches, achieving superior performance in terms of accuracy, scalability, and multi-objective optimization.

Similarly, graph-based models and multi-agent systems demonstrated strong potential in handling distributed EV networks and improving system scalability. Parallel convolutional neural networks (PCNN) represent a significant breakthrough, enabling simultaneous processing of multiple data streams such as traffic conditions, energy demand, and user behaviours. These models provide a balanced trade-off between accuracy and scalability, making them highly suitable for large-scale EV charging systems integrated with smart grids and intelligent transportation systems. Overall, the analysis indicates that while deep learning and hybrid models dominate recent research, future advancements will likely focus on lightweight architectures, real-time deployment, and integration of multiple technologies such as edge computing, blockchain, and IoT to achieve efficient, secure, and scalable EV charging systems.

Discussion

The discussion of recent advancements in EV charging optimization highlights the increasing reliance on intelligent and data-driven approaches to address the complexities of modern energy systems. The integration of smart grids and intelligent transportation systems has significantly enhanced the efficiency of EV charging by enabling real-time monitoring, communication, and control. AI-based techniques, particularly deep learning and reinforcement learning, have demonstrated superior performance in handling dynamic and uncertain environments compared to traditional methods. However, the widespread deployment of these advanced models faces several challenges. High computational complexity, dependency on large datasets, and lack of real-time adaptability remain critical issues.

Additionally, the integration of multiple systems, including renewable energy sources, IoT devices, and communication networks, introduces further complexity in system design and implementation. Despite these challenges, hybrid models and PCNN-based architectures show promising potential in achieving scalable and efficient EV charging solutions. The use of edge computing and distributed frameworks can further enhance real-time performance and reduce latency. Future research should focus on developing lightweight and energy-efficient models, improving interoperability between systems, and addressing security concerns associated with data sharing and communication.

Conclusion

The rapid adoption of electric vehicles has increased the need for intelligent charging strategies that ensure grid stability, energy efficiency, and user convenience. This survey demonstrates that artificial intelligence and deep learning have significantly improved EV charging optimization compared with traditional mathematical approaches. Conventional optimization methods provide reliable scheduling but struggle to manage dynamic charging demand, renewable energy variability, and large-scale smart grid environments. Advanced deep learning models, including CNNs, LSTMs, transformers, and reinforcement learning, offer enhanced prediction accuracy and adaptive decision-making for complex charging scenarios. Among these, Parallel Convolutional Neural Networks (PCNNs) stand out by simultaneously processing multiple data sources such as traffic conditions, charging demand, user behaviour, and energy availability, resulting in improved scheduling efficiency and scalability. Furthermore, integrating PCNNs with smart grids, intelligent transportation systems, renewable energy, and vehicle-to-grid technologies enables reliable and sustainable charging management. Future research should focus on lightweight AI models, explainable intelligence, edge computing, cybersecurity, and multi-objective optimization to support practical deployment of intelligent EV charging infrastructures.

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