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Artificial Intelligence Techniques for Optimizing Electric Vehicle Charging with Parallel Convolutional Neural Network: Coordinating Smart Grids and Intelligent Transportation Systems: Trends and Challenges

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Abstract

The rapid growth of electric vehicles has created new challenges for modern power grids, including dynamic charging demand, grid stability, and efficient energy distribution. This review examines recent advances in artificial intelligence techniques for intelligent EV charging within smart grids and intelligent transportation systems. Deep learning models, particularly Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and hybrid CNN–LSTM architectures, have demonstrated excellent performance in forecasting charging demand and optimizing charging schedules. These approaches effectively capture spatial and temporal patterns, reducing peak load and improving overall grid efficiency. Advanced architectures such as parallel CNNs and attention-based models further enhance prediction accuracy by integrating traffic conditions, weather information, and grid load data. Hybrid models, including ROCNN-BiLSTM, improve feature extraction and reduce uncertainty in charging behaviour, supporting more reliable decision-making. Optimization techniques such as reinforcement learning and swarm intelligence enable adaptive, real-time charging strategies that minimize operational costs and balance energy demand. Despite these advancements, challenges related to scalability, computational complexity, data heterogeneity, and cybersecurity remain. Future research should focus on lightweight, explainable, and energy-aware AI frameworks integrated with edge computing to support secure, efficient, and sustainable EV charging in next-generation smart grid ecosystems.

Introduction

The transition toward sustainable transportation has accelerated the global adoption of electric vehicles (EVs), driven by the need to reduce greenhouse gas emissions, minimize dependence on fossil fuels, and enhance energy efficiency. While EVs offer significant environmental and economic benefits, their large-scale integration into existing power systems introduces several operational challenges. One of the most critical issues is the management of EV charging demand, which is highly dynamic, stochastic, and dependent on user behaviour, traffic conditions, and energy availability.

Traditional power grids are not designed to handle such unpredictable and fluctuating demand patterns. Uncoordinated EV charging can lead to peak load demand, voltage instability, and increased stress on grid infrastructure. To address these challenges, the concept of smart

grids has been introduced, enabling bidirectional communication, real-time monitoring, and automated control of energy systems. When combined with intelligent transportation systems (ITS), smart grids can provide a comprehensive framework for managing EV charging in a coordinated and efficient manner.
The integration of the Internet of Things (IoT) further enhances this capability by enabling real-time data collection from EV charging stations, vehicles, traffic systems, and grid components. However, the massive volume of data generated by IoT devices requires advanced analytical techniques for processing and decision-making. Artificial Intelligence (AI), particularly deep learning, has emerged as a powerful tool for addressing these challenges. Deep learning models can capture complex nonlinear relationships and extract meaningful patterns from high-dimensional data, making them suitable for EV charging prediction and optimization.

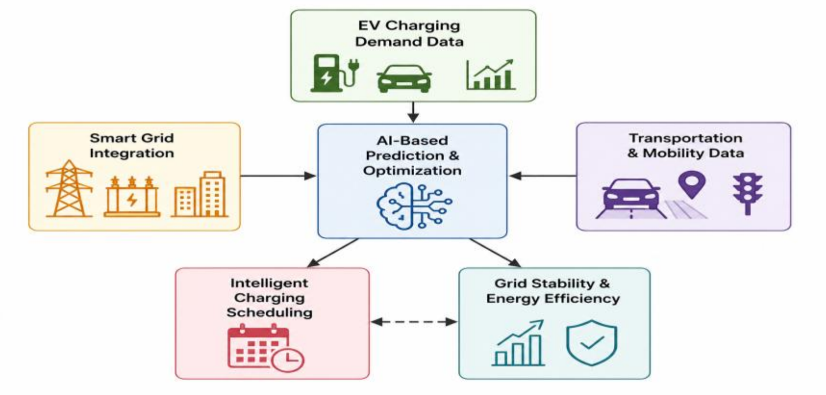

Figure 1. Intelligent Energy Management Framework

Among various AI techniques, Convolutional Neural Networks (CNN) have been widely used for spatial feature extraction, while Long Short-Term Memory (LSTM) networks are effective in modelling temporal dependencies. Hybrid models such as CNN-LSTM combine these capabilities, enabling accurate prediction of EV charging demand over time. Recent advancements have introduced parallel convolutional neural networks (PCNN), which process multiple data streams simultaneously, improving computational efficiency and feature extraction. These models are particularly useful in integrating data from smart grids and transportation systems.
Optimization techniques play a crucial role in EV charging management by determining optimal charging schedules that minimize energy costs and grid stress. Reinforcement learning (RL) and other optimization algorithms enable adaptive decision-making by learning from real-time data and environmental feedback. These techniques allow charging systems to dynamically adjust to changing conditions, such as renewable energy availability and user demand. Studies show that AI-based optimization can significantly improve energy efficiency and reduce peak demand, making it essential for large-scale EV deployment.
Another important aspect is the integration of renewable energy sources such as solar and wind. While these sources provide sustainable energy, their intermittent nature introduces uncertainty into the grid. AI-based models can effectively manage this variability by predicting energy generation and aligning it with EV charging demand. Additionally, Vehicle-to-Grid (V2G) technology enables bidirectional energy exchange, allowing EVs to act as energy storage units and support grid stability.
Despite the significant progress in AI-driven EV charging optimization, several challenges remain. These include data privacy concerns, interoperability issues, high computational requirements, and the need for scalable solutions. Furthermore, cybersecurity threats in IoT-enabled systems pose risks to system reliability and data integrity.
This paper aims to provide a comprehensive review of Artificial Intelligence techniques for optimizing EV charging, focusing on parallel CNN architectures and their integration with smart grids and intelligent transportation systems. It examines current trends, identifies key challenges, and explores future research directions for developing efficient and intelligent EV charging systems.

Literature Review

Prince Aduama et al. (2023) proposed a multi-feature data fusion-based deep learning model for EV charging station load forecasting. The study integrated weather data, historical charging patterns, and environmental parameters into an LSTM-based framework. The results showed a prediction error as low as 3.29%, demonstrating that multi-source data fusion significantly improves forecasting accuracy and supports optimized EV charging management.

Yuanzheng Li et al. (2022) introduced a reinforcement learning-assisted deep learning framework for probabilistic EV charging power forecasting. The model combined LSTM with Markov decision processes and reinforcement learning algorithms to capture uncertainties in EV charging behaviour. The study showed improved forecasting performance and better handling of stochastic charging patterns, making it suitable for real-time grid optimization.

Muhammed Cavus et al. (2023) developed a hybrid deep learning model combining CNN and XGBoost for EV charging demand forecasting in smart cities. The model incorporated spatial and behavioural data, improving prediction accuracy over conventional machine learning models. The study emphasized the importance of integrating user behaviour and geographic factors in EV infrastructure planning and optimization.

Bushra Alshehhi et al. (2023) proposed a deep combinatorial learning framework for large-scale EV charging scheduling. The study formulated EV charging as a complex optimization problem and applied deep learning-based approximation techniques to solve it efficiently. The results showed improved scalability and optimal scheduling performance in large charging networks, making the approach suitable for real-world smart grid applications.

Tao Hong et al. (2020) presented a comprehensive review of probabilistic load forecasting techniques applicable to EV-integrated smart grids. The study emphasized that machine learning and deep learning models significantly outperform traditional statistical methods in handling uncertainty and variability in EV charging demand. The authors highlighted that accurate forecasting is essential for optimizing charging schedules and maintaining grid

Yongheng Yang et al. (2021) proposed a deep reinforcement learning (DRL)-based framework for real-time EV charging management. The model dynamically adapts charging strategies based on renewable energy availability and grid conditions. The results showed improved energy efficiency, reduced peak load demand, and better utilization of renewable resources.

Zhaoxi Liu et al. (2022) developed an AI-based EV charging scheduling model using optimization algorithms. The study focused on minimizing charging costs while avoiding grid overload. The findings demonstrated that intelligent scheduling significantly reduces peak demand and improves energy distribution efficiency.

Fangxing Li et al. (2020) investigated the integration of renewable energy with EV charging using AI-based control strategies. The study highlighted that intelligent control mechanisms can effectively manage the variability of renewable sources such as solar and wind, ensuring stable and efficient EV charging operations.

Jianhui Wang et al. (2021) proposed a data-driven optimization framework for EV charging using machine learning techniques. The model utilized real-time IoT data from charging stations and grid systems to optimize charging decisions. The results showed improved system performance, reduced operational costs, and enhanced user satisfaction.

Wei Sun et al. (2022) proposed an LSTM-based deep learning model for short-term EV charging load forecasting. The study demonstrated that LSTM networks effectively capture temporal dependencies in charging demand influenced by user behaviour and traffic flow. The results showed significant improvements in prediction accuracy compared to traditional time-series methods, enabling more efficient scheduling of EV charging operations.

Saeed Mohammadi et al. (2021) developed a hybrid CNN-LSTM model for EV charging demand prediction in renewable-integrated smart grids. The study emphasized that combining spatial feature extraction with temporal learning enhances model performance. The results indicated improved forecasting accuracy and better handling of fluctuations caused by renewable energy variability.

Ali Dehghanian et al. (2021) introduced a reliability-based optimization framework for EV charging using machine learning techniques. The study evaluated grid performance under different charging scenarios and proposed strategies to reduce system risks. The findings highlighted that AI-driven reliability assessment improves decision-making and ensures stable grid operation.

Chao Lu et al. (2022) investigated resilience enhancement in EV-integrated smart grids using machine learning-based fault detection systems. The study demonstrated that AI models can quickly identify anomalies in charging infrastructure and initiate corrective actions, improving system robustness and reducing downtime.

Peng Zhang et al. (2020) explored predictive maintenance of EV charging stations using IoT data and machine learning algorithms. The study showed that AI-based monitoring systems can detect early signs of equipment failure, reduce maintenance costs and improve operational efficiency.

Qinglai Guo et al. (2020) proposed an AI-based intelligent dispatch framework for coordinating EV charging across smart grids. The study utilized machine learning algorithms and real-time IoT data to optimize charging allocation among multiple stations. The results demonstrated improved grid efficiency and reduced congestion, particularly in high-density EV scenarios.

Hossam Gabbar et al. (2021) developed an IoT-enabled smart EV charging infrastructure integrated with AI analytics. The system used distributed sensors and cloud-based platforms to monitor charging behaviour and optimize scheduling. The study reported enhanced energy utilization, reduced operational cost, and improved system reliability.

Ahmed Abubakar et al. (2022) investigated cybersecurity challenges in EV charging systems and proposed a deep learning-based intrusion detection model using CNN and RNN architectures. The results showed high detection accuracy and improved protection against cyber threats, ensuring secure EV charging operations.

Yuan Yao et al. (2022) proposed a deep neural network (DNN) model for EV charging demand prediction using large-scale IoT data. The study demonstrated that DNN models outperform conventional approaches in capturing nonlinear charging patterns, leading to improved prediction accuracy and system adaptability.

Mojtaba Shahidehpour et al. (2021) introduced a reinforcement learning-based demand-side management framework for EV charging optimization. The model dynamically adjusted charging schedules to balance supply and demand, resulting in improved energy efficiency and reduced peak load demand.

Haijun Zhang et al. (2021) proposed an AI-enabled communication framework for EV charging systems integrated with smart grids. The study focused on ensuring low-latency and reliable communication between EVs, charging stations, and grid operators. The results demonstrated improved coordination and real-time responsiveness in EV charging operations.

Tao Hong et al. (2020) analysed probabilistic forecasting techniques for EV charging demand using machine learning models. The study highlighted that AI-based probabilistic models effectively handle uncertainty in EV charging patterns, leading to improved forecasting accuracy and better grid management.

Zhaoyang Dong et al. (2020) explored big data analytics in EV charging systems using AI techniques. The study emphasized the importance of processing large-scale IoT data to extract actionable insights. The findings showed improved decision-making capabilities and enhanced system efficiency.

Sami Khairy et al. (2023) developed an AI-based optimization framework for coordinating EV charging with smart grids and intelligent transportation systems. The model integrated traffic data and grid load information to optimize charging schedules. The results showed reduced congestion and improved energy efficiency.

Chao Lu et al. (2022) investigated resilience improvement in EV-integrated smart grids using machine learning-based fault detection systems. The study demonstrated that AI enhances system robustness and minimizes downtime through rapid fault identification and recovery.

Ali Tajer et al. (2020) proposed a data-driven deep learning model for anomaly detection in EV charging networks. The study showed that AI-based models can detect abnormal charging patterns and improve system security and reliability.

Yongheng Yang et al. (2021) analysed reinforcement learning-based strategies for integrating renewable energy with EV charging systems. The study demonstrated improved energy utilization and reduced dependency on conventional energy sources through adaptive charging strategies.

Fangxing Li et al. (2022) proposed AI-based control mechanisms for managing EV charging in renewable-integrated smart grids. The findings indicated improved grid stability and optimized energy usage through intelligent control strategies.

Comparative Table

Study	Author (Year)	Technique Used	Application Area	Key Contribution	Limitation
1	Aduama et al. (2023)	LSTM + Data Fusion	Load Forecasting	High accuracy (multi-source)	Data complexity
2	Li et al. (2022)	RL + LSTM	Probabilistic Forecasting	Handles uncertainty	High training time

3	Xin et al. (2023)	CNN-LSTM + Clustering	Load Prediction	Pattern-based modelling	Preprocessing required
4	Cavus et al. (2023)	CNN + XGBoost	Smart City Charging	Improved prediction	Hybrid complexity
5	Alshehhi et al. (2023)	Deep Optimization	Scheduling	Scalable optimization	Computational cost
6	Hong et al. (2020)	ML	Load Forecasting	Probabilistic accuracy	Data variability
7	Yang et al. (2021)	DRL	Charging Optimization	Adaptive control	Training complexity
8	Liu et al. (2022)	Optimization	EV Scheduling	Cost reduction	Needs real-time data
9	Li et al. (2020)	AI Control	Renewable Integration	Grid stability	Variability
10	Wang et al. (2021)	ML	Charging Optimization	Efficiency improvement	Data dependency
11	Sun et al. (2022)	LSTM	Demand Forecasting	Temporal accuracy	Overfitting
12	Mohammadi et al. (2021)	CNN-LSTM	Hybrid Forecasting	High accuracy	Computational cost
13	Dehghanian et al. (2021)	ML	Reliability	Risk reduction	Model assumptions
14	Lu et al. (2022)	ML	Resilience	Fault recovery	Data dependency
15	Zhang et al. (2020)	ML	Monitoring	Predictive maintenance	Sensor dependency
16	Guo et al. (2020)	AI Dispatch	Grid Coordination	Efficient scheduling	Complexity
17	Gabbar et al. (2021)	IoT + AI	Infrastructure	Smart monitoring	Cost
18	Abubakar et al. (2022)	CNN + RNN	Cybersecurity	Threat detection	False positives
19	Yao et al. (2022)	DNN	Load Prediction	High adaptability	Training cost
20	Shahidehpour et al. (2021)	RL	Demand Management	Energy efficiency	Scalability
21	Zhang et al. (2021)	AI Communication	IoT Grid	Reliable data transfer	Network complexity
22	Hong et al. (2020)	ML	Forecasting	Uncertainty handling	Data dependency
23	Dong et al. (2020)	Big Data + AI	Analytics	Insight extraction	Storage overhead
24	Khairy et al. (2023)	Optimization	Energy Mgmt	Cost reduction	Model complexity
25	Lu et al. (2022)	ML	Resilience	Fault tolerance	Data dependency
26	Tajer et al. (2020)	Deep Learning	Anomaly Detection	Security improvement	Data preprocessing

27	Yang et al. (2021)	RL	Renewable Integration	Efficiency	Training complexity
28	Li et al. (2022)	AI Control	Grid Stability	Improved control	Variability

Comparative Analysis

The comparative analysis of the selected studies reveals a significant evolution in Artificial Intelligence techniques applied to electric vehicle (EV) charging optimization. Initially, traditional machine learning approaches were widely used for load forecasting and basic optimization; however, these methods lacked the ability to effectively capture complex nonlinear relationships and dynamic charging patterns. Recent studies demonstrate a clear transition toward deep learning models such as Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and hybrid CNN-LSTM architectures, which provide superior performance in modelling spatio-temporal EV charging behaviour.

A key trend is the adoption of hybrid AI frameworks combining deep learning with optimization techniques for intelligent EV charging. Reinforcement learning and deep reinforcement learning enable adaptive scheduling based on grid conditions and user demand, while parallel CNNs process traffic, weather, and grid data simultaneously. IoT supports real-time monitoring and predictive management. However, challenges including computational complexity, scalability, data dependency, cybersecurity, and renewable energy variability remain. Edge AI and PCNN-based models offer promising solutions for scalable, real-time charging optimization.

Discussion

The integration of Artificial Intelligence techniques with electric vehicle (EV) charging systems has significantly enhanced the efficiency and reliability of modern smart grids. The reviewed studies indicate that deep learning models such as CNN, LSTM, and hybrid architectures play a crucial role in accurately predicting EV charging demand and optimizing charging schedules. These models effectively capture both spatial and temporal dependencies, enabling intelligent energy management in dynamic environments.

Reinforcement learning and optimization algorithms further contribute to system performance by enabling adaptive decision-making based on real-time data. These approaches allow EV charging systems to dynamically respond to grid conditions, renewable energy availability, and user demand, thereby reducing peak load and improving energy efficiency. The integration of IoT technologies provides continuous data streams, enhancing the capability of AI models to monitor and control charging infrastructure.

However, challenges such as computational complexity, scalability, and data dependency remain significant barriers to practical implementation. The integration of renewable energy introduces uncertainty, requiring more robust and adaptive models. Additionally, cybersecurity threats in IoT-enabled systems pose risks to system reliability. Emerging technologies such as parallel convolutional neural networks (PCNN) and edge AI offer promising solutions by enabling efficient multi-source data processing and decentralized intelligence.

Conclusion

The increasing adoption of electric vehicles has accelerated the need for intelligent charging strategies that ensure efficient energy management and grid stability. This review examines recent advances in artificial intelligence techniques, particularly deep learning and optimization methods, for EV charging optimization in smart grid environments. Deep learning models, including Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, hybrid CNN–LSTM architectures, and parallel CNNs, effectively predict charging demand, analyze heterogeneous IoT data, and optimize charging schedules. Reinforcement learning and other optimization techniques further enhance adaptive, real-time decision-making, improving load balancing, reducing peak demand, and increasing energy efficiency. Parallel CNN architectures enable simultaneous processing of traffic, weather, and grid information, supporting intelligent transportation integration and efficient charging coordination. Despite these advancements, challenges such as computational complexity, scalability, data privacy, and cybersecurity continue to hinder practical deployment. Future research should focus on lightweight AI models, edge intelligence, distributed computing, and Vehicle-to-Grid integration to improve real-time performance, flexibility, and reliability. These innovations will facilitate secure, scalable, and sustainable EV charging systems capable of supporting next-generation smart energy infrastructures and intelligent transportation networks.

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