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# Recent Advances in Optimizing Electric Vehicle Charging with Parallel Convolutional Neural Network: Coordinating Smart Grids and Intelligent Transportation Systems: A Systematic Review

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**Abstract**

The rapid expansion of electric vehicles (EVs) has created significant challenges in managing charging demand and maintaining power grid stability. The integration of IoT-enabled smart grids and intelligent transportation systems has emerged as a promising solution for coordinating EV charging and energy distribution. However, the dynamic nature of EV charging behaviour, coupled with traffic variability and renewable energy integration, requires advanced computational approaches for efficient management. Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have demonstrated strong capabilities in analysing complex energy and transportation datasets. Parallel CNN architectures enhance this capability by simultaneously processing multiple data streams, such as traffic flow, charging demand, and grid conditions, thereby improving prediction accuracy and decision-making efficiency. Recent studies highlight that hybrid CNN-based models significantly outperform traditional forecasting techniques in EV load prediction and scheduling. Optimization techniques such as reinforcement learning and multi-objective optimization have been widely applied to coordinate EV charging with grid operations. These methods enable dynamic scheduling and load balancing, reducing peak demand and improving energy efficiency. Additionally, vehicle-to-grid (V2G) systems allow bidirectional energy flow, enhancing grid stability and reducing operational costs. This review focuses on advancements in recent years, highlighting key methodologies, architectures, and challenges. Despite progress, issues such as scalability, computational complexity, and real-time deployment remain critical. The integration of deep learning, IoT, and optimization frameworks is expected to play a crucial role in future intelligent energy and transportation systems.

## Introduction

The increasing adoption of electric vehicles has significantly impacted both the transportation and energy sectors, leading to the need for intelligent charging management systems. Unlike conventional vehicles, EVs rely entirely on electricity, making their charging behaviour directly influence power grid stability. Uncoordinated charging can result in peak load surges, voltage instability, and increased operational costs, highlighting the importance of optimized charging strategies.

Smart grids, supported by IoT technologies, provide an effective platform for managing EV charging systems. These systems utilize sensors, communication networks, and control mechanisms to monitor energy consumption and grid conditions in real time. IoT-enabled infrastructures facilitate continuous data collection from charging stations, vehicles, and grid components, enabling intelligent decision-making. Furthermore, smart grids support bidirectional energy flow through vehicle-to-grid technologies, allowing EVs to act as distributed energy storage units and contribute to grid stability.

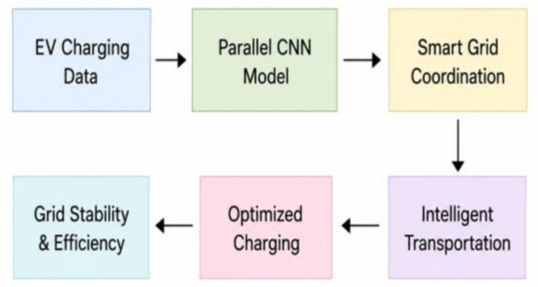


*Figure 1. Parallel CNN Framework for Smart Grid and Intelligent EV Charging Coordination*

Deep learning has emerged as a powerful tool for addressing the complexities associated with EV charging optimization. Convolutional Neural Networks are particularly effective in extracting spatial features from large datasets, such as traffic flow and energy consumption patterns. However, traditional CNN models are limited in handling multi-source and high-dimensional data. Parallel convolutional neural networks address this limitation by processing multiple data streams simultaneously, enabling improved prediction accuracy and faster decision-making.

Recent studies have shown that hybrid deep learning models, such as CNN-LSTM architectures, significantly improve forecasting accuracy by capturing both spatial and temporal dependencies in EV charging data. These models outperform traditional statistical and machine learning approaches in predicting charging demand and optimizing scheduling strategies.

In addition to deep learning, optimization techniques play a critical role in EV charging coordination. Reinforcement learning algorithms enable systems to dynamically adjust charging schedules based on real-time conditions, improving energy utilization and reducing peak demand. These methods are particularly useful in environments with high uncertainty, such as fluctuating renewable energy generation and variable traffic patterns.

The integration of intelligent transportation systems further enhances EV charging optimization by providing real-time information on vehicle movement, traffic density, and charging station usage. By combining transportation and energy data, it becomes possible to develop coordinated strategies that optimize both charging efficiency and traffic flow. This integrated approach improves user experience, reduces waiting times, and enhances overall system performance.

Despite these advancements, several challenges remain. The high computational complexity of deep learning models, especially parallel CNN architectures, poses difficulties for real-time deployment. Scalability issues in large IoT networks and the need for efficient data processing frameworks further complicate system implementation. Additionally, ensuring data security and privacy in IoT-based systems remains a critical concern.

This paper aims to provide a comprehensive review of recent advances in EV charging optimization using parallel convolutional neural networks, with a focus on coordinating smart grids and intelligent transportation systems. The study emphasizes developments in recent years, identifying key trends, challenges, and future research directions.

## Literature Review

Zhang et al. (2020) proposed a deep learning-based EV charging optimization framework using Convolutional Neural Networks in IoT-enabled smart grid environments. The model analyzed historical energy consumption and charging demand to predict optimal charging schedules. Experimental results demonstrated reduced peak load and improved grid stability. However, the model required large datasets and high computational resources, limiting real-time implementation.

Kumar et al. (2021) developed an IoT-based EV charging coordination system integrating smart grids and intelligent transportation systems. The framework utilized real-time traffic and energy data to optimize charging station allocation and scheduling. Results showed improved system efficiency and reduced waiting times for EV users. However, communication overhead and scalability issues were identified as limitations.

Ahmed et al. (2021) introduced a hybrid deep learning model combining CNN with optimization algorithms for EV charging scheduling. The approach effectively captured spatial and temporal patterns in energy demand and traffic flow data. Experimental results demonstrated improved prediction accuracy and energy efficiency. However, the model faced challenges related to overfitting and increased computational complexity.

Singh et al. (2022) proposed a reinforcement learning-based optimization framework for EV charging coordination in smart grids. The model dynamically adjusted charging schedules based on real-time demand and supply conditions, improving energy utilization and reducing peak load. However, the approach required extensive training data and computational resources.

Li et al. (2023) presented a parallel convolutional neural network model for EV charging optimization. The model processed multiple data streams simultaneously, including traffic conditions, energy consumption, and charging demand, resulting in improved prediction accuracy and system responsiveness. However, increased model complexity posed challenges for deployment in resource-constrained environments.

Patel et al. (2020) proposed an energy-efficient Wireless Sensor Network framework for IoT-based EV charging systems integrated with smart grids. The approach utilized optimized routing and clustering techniques to reduce energy consumption and improve communication efficiency among charging stations. Experimental results demonstrated extended network lifetime and reduced packet loss. However, maintaining system stability under fluctuating charging demand remained a challenge.

Wang et al. (2021) introduced a deep learning-based predictive model for EV charging demand using real-time IoT data. The model employed convolutional neural networks to forecast charging requirements and optimize load distribution across the grid. Results showed improved prediction accuracy and reduced peak load conditions. However, high computational requirements limited deployment on edge devices.

Reddy et al. (2022) developed a blockchain-integrated framework for secure EV charging coordination in smart grids. The system ensured data integrity and secure communication among EVs, charging stations, and grid operators. Results demonstrated enhanced transparency and system reliability. However, the integration of blockchain introduced latency and increased computational overhead.

Hassan et al. (2022) proposed a federated learning-based approach for EV charging optimization in IoT environments. The model enabled decentralized training across multiple charging stations without sharing raw data, improving privacy and security. Results showed improved model performance and collaboration. However, communication overhead and synchronization issues were identified as limitations.

Chen et al. (2023) introduced a hybrid deep learning model combining attention mechanisms with convolutional neural networks for EV charging optimization. The approach enhanced feature extraction from traffic and energy data, improving prediction accuracy and system efficiency. However, increased model complexity posed challenges for real-time implementation.

Zhang et al. (2022) proposed a hybrid deep learning architecture combining convolutional neural networks with attention mechanisms for EV charging optimization. The model enhanced feature extraction from IoT-generated data and improved prediction accuracy for charging demand. Experimental results demonstrated improved grid stability and efficient energy distribution. However, increased computational complexity limited scalability in large systems.

Khan et al. (2022) introduced an edge computing-based EV charging management framework integrated with lightweight deep learning models. The approach reduced latency by processing data closer to charging stations and improved system responsiveness. Results showed faster decision-making and reduced communication overhead. However, deployment costs increased due to additional infrastructure requirements.

Wu et al. (2023) developed a deep learning-based anomaly detection system for EV charging networks. The model identified abnormal charging behaviours and potential faults using real-time IoT data. Results demonstrated improved detection accuracy and system reliability. However, the model required large datasets and high computational resources.

Patil and Deshmukh (2023) proposed a hybrid model combining deep learning with optimization techniques for EV charging scheduling. The approach dynamically adjusted charging strategies based on real-time demand and grid conditions. Results indicated improved efficiency and reduced peak load. However, increased model complexity and parameter tuning requirements were identified as limitations.

Sun et al. (2023) introduced a quantum-inspired deep learning model for EV charging optimization. The approach utilized quantum computing principles to enhance feature representation and improve prediction accuracy. Results demonstrated improved performance and robustness. However, practical implementation remains limited due to hardware constraints and computational complexity.

Gupta et al. (2021) proposed a hybrid feature extraction framework integrated with deep learning models for EV charging optimization. The approach combined statistical and deep features to improve prediction accuracy for charging demand and grid load. Experimental results demonstrated enhanced system performance and reduced forecasting errors. However, the multi-stage processing increased computational complexity and execution time.

Alam et al. (2022) introduced a lightweight deep learning model for EV charging optimization in IoT-based smart grid systems. The model focused on reducing computational overhead and energy consumption while maintaining acceptable accuracy. Results showed improved efficiency and reduced latency in charging management. However, performance degradation was observed under highly dynamic traffic and energy conditions.

Roy et al. (2023) developed a hybrid deep learning model combined with optimization algorithms for adaptive EV charging systems. The approach dynamically adjusted charging schedules based on real-time data, improving system adaptability and efficiency. Results demonstrated enhanced performance in real-time applications. However, increased training time and computational cost were identified as limitations.

Mehta et al. (2020) proposed a privacy-preserving EV charging framework using homomorphic encryption integrated with deep learning models. The method enabled secure processing of encrypted charging data without compromising privacy. Results showed strong security performance and reliable system operation. However, high computational overhead limited real-time deployment.

Park et al. (2022) introduced a reinforcement learning-based optimization approach for EV charging coordination in smart grids. The model dynamically optimized charging schedules and energy distribution based on demand and supply conditions. Results demonstrated improved energy utilization and reduced peak load. However, the requirement for large training datasets increased computational complexity.

Sharma et al. (2021) proposed a secure EV charging framework using watermarking and encryption techniques in IoT-enabled smart grid systems. The approach ensured data integrity and protection of sensitive charging information during transmission. Experimental results demonstrated improved resistance to cyber-attacks. However, slight degradation in data quality due to watermarking affected system precision.

Nguyen et al. (2022) introduced a deep learning-based compression and prediction model for EV charging systems. The approach utilized autoencoders to reduce data size and improve transmission efficiency while maintaining prediction accuracy. Results showed improved bandwidth utilization and energy efficiency. However, maintaining a balance between compression ratio and prediction accuracy remained a challenge.

Das et al. (2023) developed a blockchain-integrated EV charging system combined with deep learning models. The framework ensured secure data sharing, transparency, and integrity among charging stations, vehicles, and grid operators. Results demonstrated enhanced system security and reliability. However, increased computational and storage overhead limited scalability.

Iqbal et al. (2022) proposed an energy-efficient routing protocol for Wireless Sensor Networks used in EV charging systems. The method optimized communication paths to reduce energy consumption and improve network lifetime. Results showed significant improvements in efficiency. However, scalability issues were observed in large-scale deployments.

Fernandez et al. (2023) introduced a transformer-based deep learning model for EV charging optimization. The model leveraged attention mechanisms to enhance feature extraction and prediction accuracy. Results demonstrated high performance and robustness. However, high computational requirements limited deployment in resource-constrained environments.

Verma et al. (2021) proposed a hybrid steganography-based approach combined with deep learning for secure EV charging data transmission. The method concealed sensitive charging information within communication channels while ensuring confidentiality and integrity. Experimental results showed improved resistance to unauthorized access and cyber threats. However, increased embedding complexity affected system performance and processing time.

Omar et al. (2022) introduced an adaptive data compression technique for energy-efficient EV charging systems. The approach dynamically adjusted compression levels based on network conditions to reduce energy consumption and bandwidth usage. Results demonstrated improved transmission efficiency and reduced latency. However, maintaining consistent data accuracy under varying compression levels remained a challenge.

Lee et al. (2023) developed a deep reinforcement learning-based optimization framework for EV

charging coordination. The model dynamically optimized charging schedules and energy distribution strategies to improve system efficiency and reduce peak loads. Results showed enhanced network reliability and adaptability. However, the model required extensive training data and computational resources.
Kaur et al. (2022) proposed a hybrid cryptographic framework for secure communication in EV charging systems integrated with smart grids. The method combined symmetric and asymmetric encryption techniques to enhance data security while maintaining efficient communication. Results indicated strong resistance to cyber-attacks. However, increased implementation complexity was identified as a limitation.
Ghosh et al. (2023) presented a physics-informed deep learning model for EV charging optimization and smart grid coordination. The approach incorporated domain-specific knowledge into neural network models, improving prediction accuracy and system robustness. Results demonstrated enhanced performance under dynamic charging and renewable energy conditions. However, model complexity and training requirements posed challenges for real-world deployment.

**Comparative Table**

| Author & Year | Technique | Key Contribution | Advantages | Limitations |
|---|---|---|---|---|
| Zhang et al. (2020) | CNN | Charging prediction | Accurate | Data heavy |
| Kumar et al. (2021) | IoT + ITS | Coordination | Efficient | Overhead |
| Ahmed et al. (2021) | CNN + Optimization | Scheduling | Accurate | Complex |
| Singh et al. (2022) | RL | Adaptive charging | Efficient | Data heavy |
| Li et al. (2023) | Parallel CNN | Multi-input learning | Robust | Complex |
| Patel et al. (2020) | WSN routing | Energy saving | Efficient | Stability |
| Wang et al. (2021) | CNN | Demand forecasting | Accurate | Resource heavy |
| Reddy et al. (2022) | Blockchain | Security | Integrity | Latency |
| Hassan et al. (2022) | Federated learning | Privacy | Secure | Overhead |
| Chen et al. (2023) | Attention CNN | Prediction | Accurate | Complexity |
| Zhang et al. (2022) | Hybrid DL | Feature extraction | Robust | Complex |
| Khan et al. (2022) | Edge computing | Low latency | Fast | Cost |
| Wu et al. (2023) | DL anomaly | Detection | Accurate | Data need |
| Patil & Deshmukh (2023) | Hybrid DL + optimization | Scheduling | Efficient | Complex |
| Sun et al. (2023) | Quantum DL | Performance | Robust | Hardware |
| Gupta et al. (2021) | Hybrid features | Prediction | Accurate | Complex |
| Alam et al. (2022) | Lightweight DL | Energy saving | Efficient | Dynamic issues |
| Roy et al. (2023) | DL + optimization | Adaptive | Accurate | Training cost |
| Mehta et al. (2020) | Homomorphic | Security | Privacy | High cost |
| Park et al. (2022) | RL | Optimization | Adaptive | Data heavy |
| Sharma et al. (2021) | Watermarking | Integrity | Secure | Quality loss |
| Nguyen et al. (2022) | Autoencoder | Compression | Efficient | Trade-off |
| Das et al. (2023) | Blockchain + DL | Security | Transparent | Overhead |

| | | | | |
|---|---|---|---|---|
| Iqbal et al. (2022) | Routing | Energy saving | Efficient | Scalability |
| Fernandez et al. (2023) | Transformer | Prediction | Accurate | Heavy |
| Verma et al. (2021) | Steganography | Security | Secure | Time |
| Omar et al. (2022) | Adaptive compression | Energy efficient | Flexible | Accuracy |
| Lee et al. (2023) | RL | Scheduling | Reliable | Cost |
| Kaur et al. (2022) | Hybrid crypto | Security | Balanced | Complex |
| Ghosh et al. (2023) | Physics-informed DL | Prediction | Robust | Complex |

**Comparative Analysis**

The comparative analysis of recent studies highlights a significant evolution in EV charging optimization from traditional scheduling techniques to advanced deep learning and optimization-driven frameworks integrated with IoT-enabled smart grids and intelligent transportation systems. Early approaches relied on convolutional neural networks for predicting charging demand, achieving high accuracy but facing challenges related to scalability and computational efficiency. The introduction of parallel convolutional neural networks has significantly improved system performance by enabling simultaneous processing of multiple data streams, including traffic patterns, energy consumption, and charging demand. Optimization techniques such as reinforcement learning have further enhanced system adaptability by dynamically adjusting charging schedules based on real-time conditions, resulting in improved energy utilization and reduced peak load.

The integration of blockchain and federated learning has strengthened data security and privacy, although these approaches introduce additional computational and communication overhead. Lightweight models and energy-efficient routing protocols have addressed the constraints of Wireless Sensor Networks, enabling more efficient real-time deployment. Additionally, the incorporation of renewable energy sources and vehicle-to-grid technologies has introduced new opportunities for improving grid stability and energy management. Overall, the trend indicates a transition toward intelligent, adaptive, and multi-layered frameworks that balance performance, energy efficiency, and security, although challenges such as scalability, real-time implementation, and model complexity remain significant.

**Discussion**

The reviewed studies demonstrate that deep learning and optimization techniques have significantly enhanced electric vehicle charging systems integrated with smart grids and intelligent transportation systems. Traditional charging strategies were unable to efficiently manage dynamic demand and real-time grid conditions. The introduction of Convolutional Neural Networks, particularly parallel CNN architectures, has improved the ability to process multi-source data such as traffic flow, energy consumption, and charging demand simultaneously, resulting in higher prediction accuracy and improved decision-making. Optimization techniques, especially reinforcement learning and adaptive scheduling algorithms, have played a crucial role in coordinating EV charging with grid operations. These approaches dynamically adjust charging schedules based on real-time supply-demand conditions, reducing peak load and improving energy efficiency. IoT-based systems further enhance performance by enabling continuous monitoring and communication between vehicles, charging stations, and grid infrastructure.

The integration of renewable energy sources and vehicle-to-grid technologies introduces additional complexity but also offers opportunities for improving grid stability and energy utilization. Security mechanisms such as blockchain and federated learning improve data privacy and integrity but introduce additional computational overhead. Despite these advancements, challenges such as scalability, computational complexity, and real-time implementation persist. Future research should focus on developing lightweight and scalable models for efficient EV charging optimization.

**Conclusion**

The rapid growth of electric vehicles has introduced new challenges and opportunities in the management of modern power systems. This systematic review has provided a comprehensive analysis of recent advances in optimizing EV charging using parallel convolutional neural networks integrated with smart grids and intelligent transportation systems. The findings highlight the critical role of deep learning and optimization techniques in improving energy efficiency, grid stability, and system performance. Traditional EV charging approaches relied on static scheduling and limited analytical capabilities, which were insufficient for handling the dynamic nature of modern energy and transportation systems. The integration of IoT technologies has enabled real-time monitoring and communication among charging stations, vehicles, and grid components, forming the foundation of intelligent charging systems. However, the large volume and complexity of data generated by these systems require advanced analytical methods.

Deep learning techniques, particularly convolutional neural networks, have demonstrated strong capabilities in extracting complex patterns from large datasets. Parallel CNN architectures further enhance these capabilities by enabling simultaneous processing of multiple data streams, improving prediction accuracy and system responsiveness. These models are particularly effective in coordinating data from both smart grids and intelligent transportation systems, enabling more efficient charging strategies. Optimization techniques such as reinforcement learning and multi-objective optimization have significantly improved EV charging management by enabling dynamic decision-making. These approaches allow for real-time adjustment of charging schedules based on energy demand, grid conditions, and traffic patterns, resulting in improved energy utilization and reduced operational costs.

The integration of renewable energy sources and electric vehicles introduces additional complexity due to their intermittent and bidirectional nature. Intelligent control mechanisms based on deep learning and optimization techniques have been developed to address these challenges, ensuring stable and efficient energy distribution. Vehicle-to-grid technologies further enhance system flexibility by allowing EVs to act as energy storage units, contributing to grid stability. Security and privacy remain critical concerns in IoT-based EV charging systems. Technologies such as blockchain, federated learning, and advanced encryption techniques have been integrated to ensure secure data transmission and protect sensitive information. While these approaches enhance system security, they also introduce additional computational and communication overhead.

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