Smart Charging System for Electric Vehicles: Connectivity, Federated Intelligence and Secure Blockchain Transactions

Ramdhan Nugraha, Soo Young Shin*

Kumoh National Institute of Technology.

ramdhan@kumoh.ac.kr, wdragon@kumoh.ac.kr

Abstract

This study proposes a decentralized smart charging system for electric vehicles (EVs) that integrates federated learning and blockchain technology to enhance efficiency, privacy, and security throughout the entire charging process. The system enables EVs to request, schedule, and complete charging sessions autonomously while preserving user data privacy through federated learning, which allows each vehicle to locally train predictive models for optimal charging time and location without sharing raw data. A smart contract deployed on a blockchain network handles booking validation and secure, automated payments between EV users and charging station operators, ensuring transparency and tamper-proof transactions. Simulation results demonstrate the system's ability to reduce communication overhead, protect sensitive data, and optimize charging slot allocation under limited connectivity scenarios. This architecture provides a scalable and privacy-preserving solution for future intelligent transportation and energy systems.

Ⅰ. Introduction

The widespread adoption of electric vehicles (EVs) has brought forward critical demands on the scalability, security, and efficiency of charging infrastructures. As millions of EVs increasingly rely on public and semi-public charging stations, existing centralized systems encounter significant limitations, including load imbalance, data privacy concerns, and high dependency on uninterrupted network connectivity. Addressing these challenges requires an intelligent, decentralized, and secure ecosystem that supports autonomous coordination between EV users and charging station operators.

Recent research efforts have explored decentralized energy management solutions, such as predictive load balancing [1], vehicle-to-grid (V2G) systems [2], and secure EV routing. However, these approaches often require centralized data aggregation, which raises concerns regarding privacy leakage and single points of failure. Federated Learning (FL), introduced by Google [3], offers a promising alternative by enabling collaborative model training across distributed devices without sharing raw data. FL is especially suitable for EV applications where usage patterns are sensitive and vary greatly among individual users.

In parallel, blockchain technology has emerged as a transformative tool for enhancing trust, transparency, and automation in digital transactions. Its decentralized and tamper-proof nature makes it an ideal platform for implementing secure, contract-based payment systems for charging services [4]. Smart contracts deployed on blockchain platforms like Ethereum allow automatic execution of service agreements without intermediaries, reducing operational costs and eliminating fraudulent behavior. This paper presents a novel architecture that integrates federated learning and blockchain smart contracts into a decentralized EV charging system. The proposed framework allows EVs to schedule, execute, and pay for charging sessions while preserving user privacy and ensuring secure payments. The key contributions of this work are: (i) a decentralized federated learning pipeline for EV charging behavior prediction, (ii) a smart contract for secure booking and payment.

Ⅱ. System Model and Methods

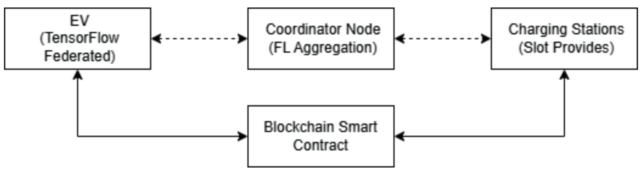

Fig 1. System Model of Digital Twin Blockchain

We consider a system composed of three interacting entities: EV clients, charging station operators (CSOs), and a blockchain-based coordination layer. Each EV acts as a local agent equipped with computational capability and a digital wallet. The CSOs manage a set of charging slots and interact with both EV clients and the blockchain, as shown in Fig. 1.

EV Clients: Each EV is modeled as an edge device that maintains its local usage data (e.g., battery levels, driving history, location preferences) and uses this data to train a local prediction model. These models are periodically shared with a central coordinator for federated averaging.

Coordinator Node: This entity does not access raw data but is responsible for aggregating model updates from multiple EVs using secure and privacy-preserving protocols. The global model is then distributed back to the clients to enhance local predictions.

Charging Station Operators (CSOs): CSOs publish slot availability to the blockchain and respond to confirmed bookings. Once a charging session is completed, smart contracts automatically trigger fund transfers based on predefined terms.

Blockchain Layer: A smart contract is deployed to handle slot reservation, conflict resolution, and payment processing. The contract ensures that transactions are transparent, immutable, and executed without central control.

The interaction among these components is assumed to occur over a partially connected network, where intermittent connectivity is tolerated through asynchronous updates. Time is divided into discrete rounds corresponding to federated learning and charging schedule intervals.

Ⅲ. Result of Simulation and Conclusion

In this section, a private blockchain network is simulated on a system equipped with an Intel(R) Core i5-8500 processor, an NVIDIA GeForce GTX 1050 GPU, and 8 GB of RAM. The simulation explores blockchain performance under three configurations, focusing on two consensus mechanisms: Proof of Work (PoW) and Proof of Authority (PoA). For the PoW scenario, the initial difficulty is set to 0x4000, while in the PoA setup, the block generation period is configured to one second.

Fig 2. Mined Block Time Comparison

Figure 2 emphasizes the graph compares the block generation time between PoW and PoA consensus mechanisms. As the number of blocks increases from 100 to 500, PoW consistently requires more time than PoA. This indicates that PoA offers faster block processing and better scalability for higher block counts, making it more suitable for time-sensitive blockchain applications.

In the simulation for charging estimation location, an EV travels along a linear route from coordinate 0 to 100, covering a total distance of 100 km. The EV consumes battery power at a rate of 1% per kilometer under normal driving conditions. The energy consumption rate increases to 2% per kilometer. Initiate charging only when its battery level falls below 30%.

Different traffic congestion scenarios are tested by designating specific segments of the route as congested. These settings allow for evaluation of battery depletion behavior and identification of optimal charging locations based on traffic conditions and energy consumption patterns.

Table 1. Result of the simulation.

Scenario	charging_points	total_time_minutes
Jam from 0 to 20	[50]	135.5
Jam from 20 to 40	[50]	135.5
Jam from 40 to 60	[55]	136
Jam from 60 to 80	[65]	136
Jam from 80 to 100	[70]	135.5

The simulation result shows in Table 1, that the EV requires one full recharge in each scenario, with the charging location shifting based on the position of traffic congestion. When congestion occurs earlier, the EV charges later (around km 50), while later congestion prompts earlier charging (around km 65-70). Total travel time remains consistent across scenarios (135.5-136 minutes), indicating that congestion placement affects charging behavior more than overall trip duration. This highlights the need for traffic-aware energy management in EV routing.

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REFERENCES

[1] C. Diaz, F. Ruiz and D. Patino, "Smart Charge of an Electric Vehicles Station: A Model Predictive Control Approach," 2018 IEEE Conference on Control Technology and Applications (CCTA), Copenhagen, Denmark, 2018, pp. 54-59, doi: 10.1109/CCTA.2018.8511498.

[2] Mastoi. et al. (2023). A study of charging-dispatch strategies and vehicle-to-grid technologies for electric vehicles in distribution networks. Energy Reports. Volume 9, December 2023, pp. 1777-1806. doi.org/10.1016/j.egyr.2022.12.139.

[3] Banabilah. et al. (2022). Federated learning review: Fundamentals, enabling technologies, and future applications. Information Processing & Management. Volume 59, Issue 6, November 2022, 103061.

[4] Mengelkamp, E. et al. (2018). A blockchain-based smart grid: Towards sustainable local energy markets. Computer Science - Research and Development. 33. 1-8. 10.1007/s00450-017-0360-9.