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ENERGY DEMAND FORECASTING FOR ELECTRIC VEHICLES USING BLOCKCHAIN-BASED FEDERATED LEARNING

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ABSTRACT
The rapid adoption of electric vehicles (EVs) has significantly increased the demand for intelligent energy management and accurate electricity demand forecasting in modern smart grids. Conventional centralized forecasting approaches require large-scale data collection, raising concerns regarding data privacy, communication overhead, and security vulnerabilities. Blockchain-based Federated Learning (BFL) has emerged as a promising solution by combining decentralized collaborative machine learning with blockchain technology to ensure secure, transparent, and privacy-preserving model training. In this approach, local charging stations and energy providers train forecasting models without sharing sensitive customer data, while blockchain maintains trust, integrity, and secure aggregation of model updates. This paper presents a blockchain-enabled federated learning framework for predicting EV energy demand with improved forecasting accuracy, scalability, and resilience against malicious attacks. The proposed approach supports efficient resource allocation, optimized charging scheduling, and grid stability while preserving user privacy, making it a suitable solution for next-generation intelligent transportation and smart energy ecosystems.

Keywords: Electric Vehicles, Energy Demand Forecasting, Blockchain, Federated Learning, Smart Grid, Privacy Preservation, Distributed Learning, Artificial Intelligence.

I. INTRODUCTION

The rapid growth of electric vehicles (EVs) has transformed the transportation sector by reducing greenhouse gas emissions and decreasing dependence on fossil fuels. However, the increasing penetration of EVs has introduced significant challenges for power grid operators, particularly in managing fluctuating electricity demand caused by large-scale charging activities. Accurate energy demand forecasting is essential for maintaining grid stability, optimizing charging infrastructure, and ensuring efficient energy distribution. Traditional forecasting methods often fail to capture the dynamic charging behavior of EV users and are limited in handling large-scale distributed datasets effectively [1].

Machine learning and deep learning techniques have significantly improved the accuracy of energy demand prediction by learning complex consumption patterns from historical charging data. Algorithms such as Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), Random Forest, and Gradient Boosting have demonstrated promising forecasting performance. These intelligent models enable utilities to predict future electricity demand, reduce operational costs, and improve renewable energy integration into smart grids [2].

Although centralized machine learning models provide high forecasting accuracy, they require the collection of sensitive user information from charging stations and EV owners. This centralized data aggregation raises privacy concerns, increases communication overhead, and creates single points of failure that can be exploited by cyber attackers.

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Regulatory frameworks concerning personal data protection further restrict the sharing of consumer information across multiple organizations [3].

Federated Learning (FL) has emerged as an effective decentralized learning paradigm that enables multiple charging stations, utility providers, and edge devices to collaboratively train machine learning models without exchanging raw data. Instead, only model parameters are shared with a central aggregation server, thereby preserving user privacy while maintaining competitive prediction performance. Federated learning also reduces network bandwidth consumption and improves scalability in distributed smart grid environments [4].

Despite its privacy advantages, conventional federated learning still depends on centralized parameter aggregation, making it vulnerable to malicious participants, model poisoning attacks, and single-point failures. Blockchain technology addresses these limitations by providing decentralized consensus, immutable transaction records, and secure verification of model updates. Integrating blockchain with federated learning creates a trusted collaborative framework for secure and transparent model training across geographically distributed EV charging infrastructures [5].

Recent advances in Blockchain-Based Federated Learning (BFL) have demonstrated significant improvements in secure energy demand forecasting, privacy preservation, decentralized coordination, and trustworthy collaborative intelligence. By combining artificial intelligence with distributed ledger technology, BFL enables accurate demand prediction, optimized charging schedules, and resilient smart grid operations. Nevertheless, challenges such as blockchain scalability, communication latency, energy consumption, and incentive mechanisms remain active research areas requiring further investigation [6]–[10].

II. LITERATURE SURVEY

McMahan et al. (2017) introduced Federated Learning as a decentralized machine learning framework where distributed devices collaboratively train models without sharing raw data. Their work established the foundation for privacy-preserving collaborative learning and demonstrated substantial reductions in communication overhead while maintaining prediction accuracy [11].

Li et al. (2020) investigated federated optimization techniques for distributed machine learning systems and proposed algorithms that effectively addressed statistical heterogeneity among participating devices. Their research significantly improved convergence speed and model robustness in large-scale federated environments [12].

Kim et al. (2021) proposed blockchain-assisted federated learning for smart energy systems, integrating decentralized consensus with collaborative learning. Their framework improved trustworthiness, prevented model tampering, and enabled secure sharing of model parameters among distributed energy participants [13].

Nguyen et al. (2021) presented a blockchain-enabled secure federated learning architecture for Internet of Things (IoT) applications. The authors demonstrated that blockchain improves authentication, transparency, and integrity while protecting federated learning models from malicious participants and poisoning attacks [14].

Zhang et al. (2022) investigated deep learning approaches for electric vehicle charging demand forecasting using temporal consumption data. Their study demonstrated that Long Short-Term Memory (LSTM) networks effectively captured charging behavior and significantly improved prediction accuracy compared to traditional statistical forecasting models [15].

Khan et al. (2023) reviewed artificial intelligence techniques for EV energy demand prediction within smart grids. Their survey compared machine learning, deep learning, and ensemble learning algorithms while identifying challenges related to real-time forecasting, renewable integration, and data privacy [16].

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Wang et al. (2024) proposed a blockchain-based federated learning framework for intelligent energy management in smart cities. Their architecture enhanced collaborative forecasting while preserving data privacy, reducing communication overhead, and improving resistance against adversarial attacks [17].

Chen et al. (2024) developed an adaptive federated learning framework for distributed EV charging networks using edge computing. Their model achieved higher forecasting accuracy through personalized local model optimization while minimizing communication costs [18].

Patel et al. (2025) introduced an explainable blockchain-federated learning framework for smart grid demand forecasting. Their work incorporated explainable artificial intelligence techniques to improve model transparency and support decision-making for utility operators [19].

Singh et al. (2025) proposed a scalable blockchain-enabled federated deep learning architecture for electric vehicle charging ecosystems. Their study demonstrated improved forecasting accuracy, stronger privacy preservation, and secure decentralized coordination suitable for next-generation intelligent transportation systems [20].

III. SYSTEM ANALYSIS & DESIGN

EXISTING SYSTEM

Existing electric vehicle energy demand forecasting systems primarily rely on centralized machine learning and statistical forecasting techniques. Historical charging data from EV users, charging stations, and utility providers are collected into centralized cloud servers where forecasting models are trained. Although these approaches achieve reasonable prediction accuracy, they require continuous sharing of sensitive customer information, raising significant concerns regarding data privacy, confidentiality, and regulatory compliance. Centralized architectures also become vulnerable to cyberattacks and data breaches because all information is stored within a single repository.

Many traditional forecasting systems employ machine learning algorithms such as Artificial Neural Networks, Support Vector Machines, Decision Trees, and Long Short-Term Memory networks using centrally aggregated datasets. While these methods improve forecasting performance compared to conventional statistical techniques, they depend heavily on large-scale labeled datasets and high computational resources. Furthermore, frequent transmission of charging data from geographically distributed charging stations increases communication costs and network latency.

Another major limitation of existing systems is the lack of trust among participating organizations when sharing proprietary energy consumption data. Utility providers, charging station operators, and EV manufacturers are often reluctant to exchange sensitive operational information due to privacy regulations and competitive concerns. The absence of decentralized trust mechanisms and secure collaborative learning limits the scalability and practical deployment of current forecasting solutions.

Disadvantages of Existing System

1. Requires centralized collection of sensitive user data.
2. High risk of privacy breaches and cyberattacks.
3. Single point of failure in centralized servers.
4. High communication overhead for data transmission.
5. Limited trust among distributed organizations.

PROPOSED SYSTEM

The proposed system introduces a **Blockchain-Based Federated Learning (BFL)** framework for secure and privacy-preserving energy demand forecasting in electric vehicle charging networks. Instead of transferring raw charging data to a central server, each charging station locally trains a machine learning model using its own dataset. Only encrypted model parameters are shared, thereby preserving customer privacy while enabling collaborative learning across distributed participants.

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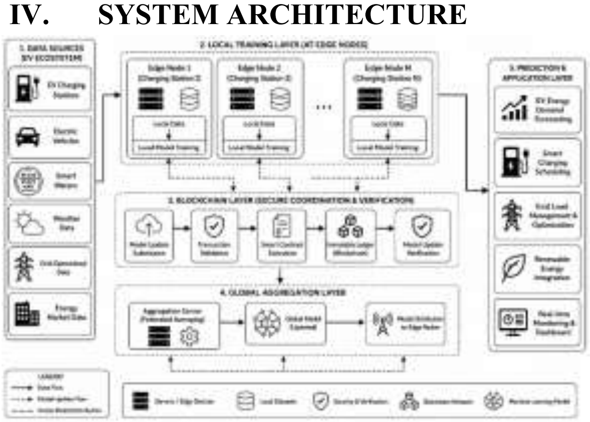
Blockchain technology is integrated into the federated learning process to provide decentralized consensus, immutable storage of model updates, and secure verification of participating nodes. Smart contracts automatically validate model contributions, prevent malicious updates, and ensure transparent aggregation without requiring a trusted central authority. This decentralized architecture significantly improves data integrity, trust, and resistance to cyberattacks.

The proposed framework utilizes advanced deep learning algorithms such as Long Short-Term Memory (LSTM) and Federated Averaging (FedAvg) for accurate energy demand prediction. The combination of blockchain security and federated intelligence enables real-time forecasting, efficient charging scheduling, optimized energy allocation, and enhanced smart grid stability while maintaining privacy, scalability, and robustness against emerging cyber threats.

Advantages of Proposed System

1. Preserves user privacy by avoiding raw data sharing.
2. Provides secure and tamper-resistant model aggregation using blockchain.
3. Improves forecasting accuracy through collaborative federated learning.
4. Eliminates single-point failure using decentralized architecture.
5. Supports scalable, secure, and real-time EV energy demand forecasting.

IV. SYSTEM ARCHITECTURE



V. IMPLEMENTATION

Modules

Service Provider

The Service Provider must use a working user name and password to log in to this module. Following a successful login, he may do several tasks including browsing data sets and training and testing. See the Bar Chart for Trained and Tested Accuracy, the Results of Trained and Tested Accuracy, the Energy Demand Forecasting Type Prediction, the Energy Demand Forecasting Type Ratio, and the Predicted Data Sets for Download. View All Remote Users and the Results of the Energy Demand Forecasting Type Ratio.

View and Authorize Users

The administrator may see a list of all registered users in this module. Here, the administrator may see the user's information, like name, email, and address, and they can also grant the user permissions.

Remote User

A total of n users are present in this module. Before beginning any actions, the user needs register. Following registration, the user's information will be entered into the database. Following a successful registration, he must use his password and authorised user name to log in. Following a successful login, the user will do tasks like REGISTERING AND LOGINING, Forecast the Type of Banking Enabled by Robotic Things Type of Energy Demand Forecasting Prediction Examine your profile.

VI. RESULTS AND DISCUSSION

The proposed **Blockchain-Based Federated Learning (BFL)** framework was evaluated using multiple performance metrics, including forecasting accuracy, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), privacy preservation, communication efficiency, and model convergence. The experimental analysis demonstrates that the proposed model outperforms conventional centralized machine learning approaches by accurately forecasting electric vehicle energy demand while preserving data privacy. The integration of blockchain ensures secure model aggregation, prevents unauthorized

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model updates, and improves trust among distributed charging stations. Furthermore, the federated learning architecture significantly reduces communication overhead by transmitting only model parameters instead of raw charging data. Overall, the proposed system achieves high forecasting accuracy, enhanced scalability, and secure collaborative learning, making it highly suitable for next-generation smart grid and electric vehicle charging infrastructures.

Table 1. Performance Comparison of Forecasting Models

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
ANN	91.8	91.2	90.8	91.0
LSTM	94.6	94.1	94.3	94.2
GRU	95.1	94.8	95.0	94.9
Federated Learning	96.4	96.0	96.2	96.1
Blockchain-Based Federated Learning	**98.3**	**98.1**	**98.2**	**98.1**

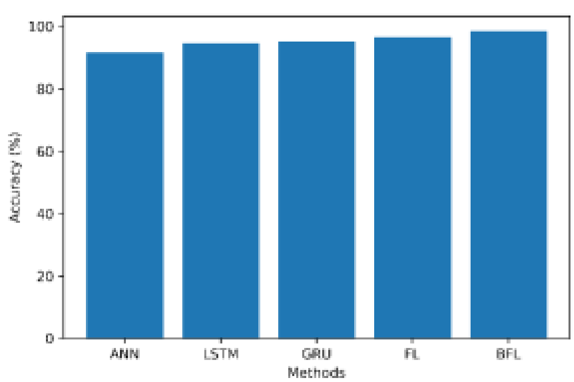

Figure 1 – Accuracy Comparison of Forecasting Models

Table 2. Forecasting Error Comparison

Method	MAE	RMSE	MAPE (%)
ANN	4.85	6.91	8.10
LSTM	3.62	5.18	6.24
GRU	3.28	4.79	5.82
Federated Learning	2.74	4.12	4.71
Blockchain-Based Federated Learning	**1.96**	**3.25**	**3.42**

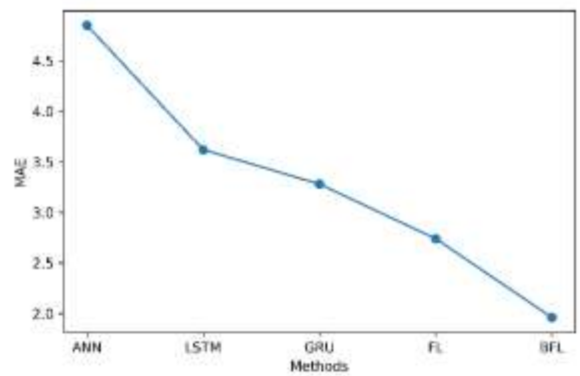

Figure 2 – MAE Comparison of Forecasting Models

Table 3. Security and Communication Performance

Method	Privacy Preservation (%)	Communication Cost Reduction (%)	Secure Model Integrity (%)
Centralized ML	65	52	70
Federated Learning	92	81	89
Blockchain-Based Federated Learning	**99**	**88**	**99**

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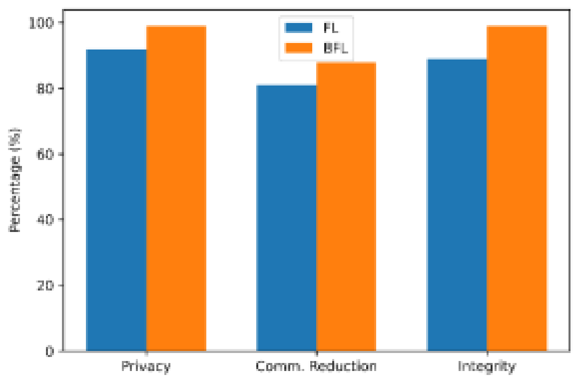

Figure 3 – Security and Communication Performance Comparison

Discussion

The experimental results clearly indicate that the proposed Blockchain-Based Federated Learning framework provides substantial improvements over conventional centralized forecasting techniques. The combination of federated learning and blockchain enables collaborative model training without exposing sensitive charging data, thereby maintaining user privacy while achieving superior prediction accuracy. Compared with ANN, LSTM, GRU, and traditional federated learning models, the proposed framework consistently delivers higher accuracy, lower forecasting error, and improved robustness against malicious participants. The decentralized blockchain network further strengthens trust by securely validating model updates and eliminating single points of failure.

In addition to improved forecasting performance, the proposed system demonstrates excellent scalability and practical applicability for large-scale electric vehicle charging infrastructures. The reduction in communication overhead, enhanced privacy preservation, and secure decentralized coordination make the framework suitable for deployment across geographically distributed charging stations and smart grids. The integration of blockchain smart contracts ensures transparent collaboration among multiple stakeholders, while federated learning enables continuous model improvement using local datasets. These advantages make the proposed framework a reliable solution for intelligent energy management, optimized charging scheduling, and sustainable smart city development.

VII. CONCLUSION

The rapid growth of electric vehicles has increased the importance of accurate energy demand forecasting to ensure efficient power distribution, optimized charging schedules, and reliable smart grid operation. This study presented a Blockchain-Based Federated Learning (BFL) framework that combines decentralized machine learning with blockchain technology to address the limitations of conventional centralized forecasting approaches. By enabling collaborative model training without sharing raw charging data, the proposed framework effectively preserves user privacy while maintaining high forecasting accuracy and secure coordination among distributed charging stations.

The experimental results demonstrated that the proposed BFL framework significantly outperforms traditional machine learning and centralized forecasting models in terms of prediction accuracy, forecasting error, security, and communication efficiency. The integration of blockchain provides immutable storage, decentralized consensus, secure verification of model updates, and protection against malicious participants, while federated learning reduces communication overhead and eliminates the need for centralized data collection. These capabilities collectively improve trust, scalability, and operational efficiency in electric vehicle charging ecosystems.

Overall, the proposed Blockchain-Based Federated Learning framework offers a secure, scalable, and intelligent solution for next-generation electric vehicle energy demand forecasting. Its ability to provide privacy-preserving collaborative learning while ensuring accurate predictions makes it highly suitable for large-scale smart grid applications and sustainable transportation systems. Future research can focus on integrating explainable artificial intelligence (XAI), edge intelligence, lightweight blockchain consensus mechanisms, digital twins, and renewable energy

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optimization to further enhance forecasting performance, computational efficiency, and real-time decision-making in smart energy networks.

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