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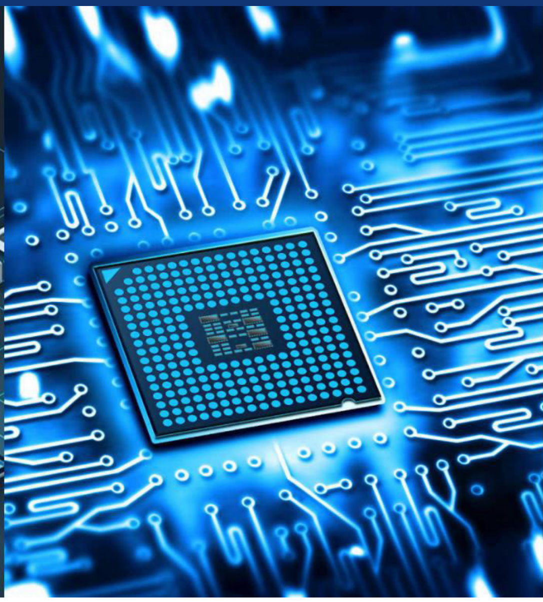


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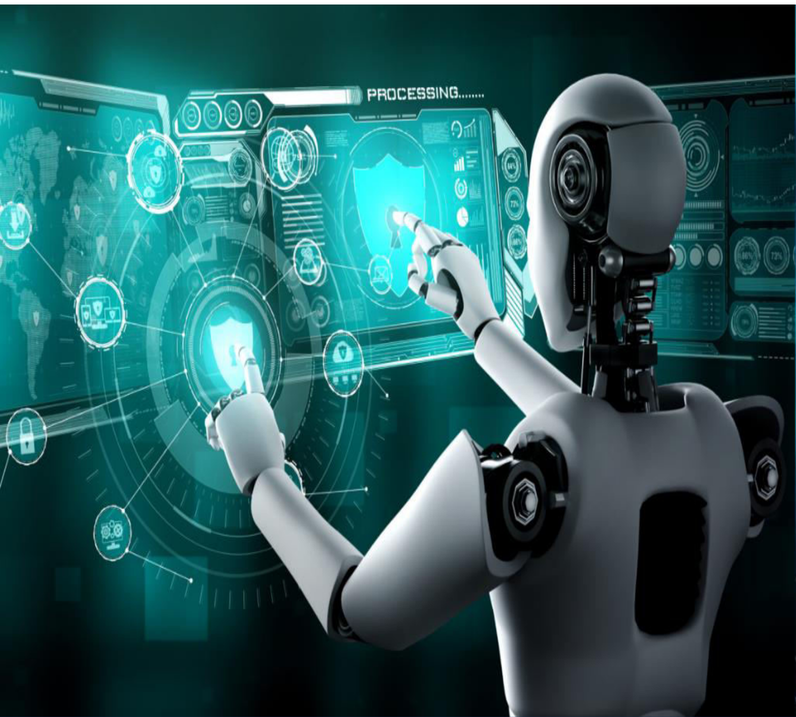

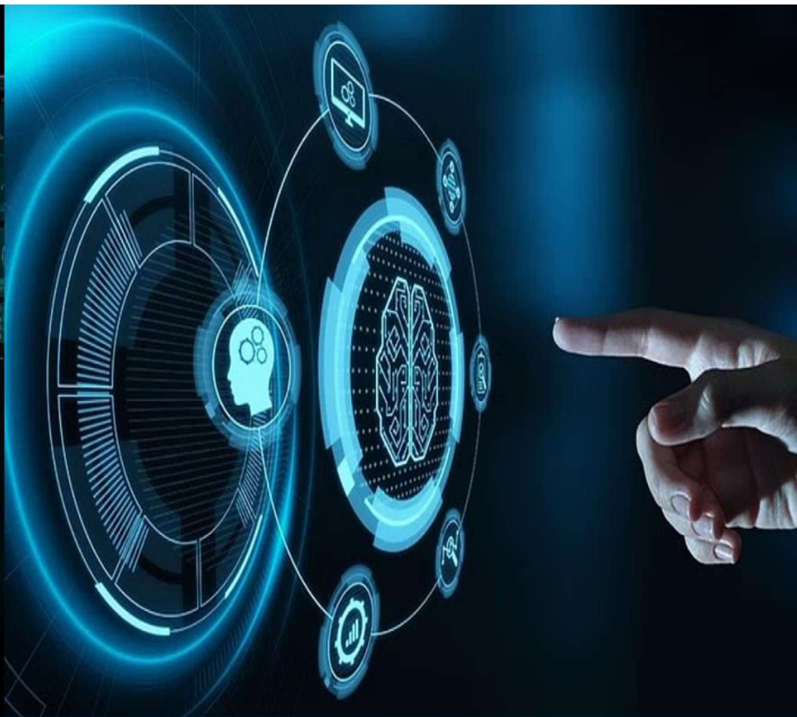

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Energy Demand Forecasting for Electric Vehicles Using Block chain-Based Federated Learning

Mr. Dr. G. Mohan Ram[1], Kairamkonda Preetham[2], Kuruva Surendra[3], Golipally Pradeep Reddy[4]

Guide, Department of Computer Science and Engineering, Malla Reddy University, Hyderabad, India[1]

Department of Computer Science and Engineering, Malla Reddy University, Hyderabad, India[2-4]

ABSTRACT: The widespread adoption of electric cars (EVs) can be attributed to their many advantages over conventional gas- powered automobiles. However, there may be difficulties in incorporating EVs into the grid due to increased Energy demand and peak load. We propose a blockchainbased federated learning scheme using different linear regression algorithms for energy demand prediction for EVs. The information gathered from EVs is stored on the blockchain network. Only those with the proper credentials can decrypt the data from its encrypted storage. Data from EVs is utilized to train a machine learning model with the use of a federated learning algorithm. Each EV is used to train a model, and then the models' parameters are distributed throughout the blockchain. Our approach is innovative in analyzing of BCFL communications overhead and latency issues, while delving deeper into its dynamics to measure and reduce communication delays to maximize system efficiency. The implementation results verify the effectiveness of our system in anticipating EVs' energy requirements. For the training of the BCFL model, a huge real-world dataset was used from over 60,000 transactions at EV charging stations in Boulder city, Colorado. The results show that the framework is reliable, since all the models have R2 values above 0.91, which indicates a high degree of accuracy in predicting energy use.

I. INTRODUCTION

The rapid expansion and widespread adoption of electric vehicles are key factors in the development of intelligent transportation networks, which help to reduce harmful greenhouse gas emissions. As the number of EVs on the road has risen in recent years, so has the need to meet their charging requirements. Because of this, it is crucial to accurately forecast the demand for charging electric vehicles in order to lessen the strain on power systems and save money. Predicting the charging demand for electric vehicles is important because of the rising demand for electrical power and the growing number of EV installations; this provides both the company and its customers with valuable insight into the charging requirements of their vehicles based on factors like mileage and usage patterns. Consumers could anticipate their travel distances and choose alternative charging stations before their battery runs out thanks to the EV charging demand prediction Federated Learning (FL) is a decentralized machine learning technique in which multiple nodes or devices collaborate to train a shared model without sharing private data with each other. This method has become widely adopted due to its ability to protect users' privacy and produce accurate forecasts, making FL an excellent way for applications in sectors like healthcare, banking and energy. There have also been various contemporary applications of Federated Learning throughout recent history. One promising application of FL in the energy sector is in predicting energy demand for electric vehicles (EVs) using charging stations as participating nodes. This method provides more accurate energy forecasts while protectinguser privacy while lowering energy use and data transfer costs to a centralized server. FL also can reduce data storage offers a secure and decentralized data-sharing platform, has also been suggested as a method to facilitate FL in theenergy industry. To implement this approach, participating charging stations communicate their local model to the blockchain network, which then compiles all models into one unified global model to protect confidentiality among connected nodes and prevent attempts at hacking. The primary motivation for this study comes from the difficulty of integrating electric vehicles into the grid, particularly the need to control increasing energy demands and peak loads, store this data safely using blockchain technology, and use machine learning to make more accurate predictions about the relationships between energy supply and demand. The optimization of BCFL communication overhead/latency is used to improve the model's efficiency, which is part of a larger effort to progress EV Charging Solutions while ensuring efficiency and security. Following are the contributions of this paper: • Application of machine learning techniques with particular attention paid to Blockchain-Based Federated Learning (BCFL), to predict energy consumption in electric vehicle (EV) charging stations.

Addressing rising energy demands while protecting user security and maintaining user privacy. • Utilization of methods including

Decision Tree, LASSO Regression, Random Forest, Ridge Regression and MLP Neural Network can accurately estimate energy consumption; all algorithms being thoroughly tested using publicly available datasets. Thorough investigation of communication overhead and latency within BCFL frameworks for energy demand prediction at electric vehicle charging stations. We explore its complex dynamics, with particular attention paid to quantifying and mitigating communication delays which impact system efficiency; our nove approach stands out as offering key insight into optimizing BCFL frameworks for real world applications in energy sector thus creating more resilient yet efficient predictive models. The rest

of the paper is organized as follows. Section-II discusses the related work, section-III provides the background information about the blockchain and smart contracts. Section-IV presents

II. LITERATURE SURVEY

[1]Z.TeimooriandA.Yassine https://www.mdpi.com/2071-1050/14/21/14100 2022
A Review on Intelligent Energy Management Systems for Future Electric Vehicle Transportation This review analyses existing challenges and solutions in Electric Vehicle (EV) energy management, focusing on theintegration of EVs with the Smart Grid, AI techniques, privacy preservation, Federated Learning (FL), and blockchaintechnology. The review identifies key challenges in EV energy management, emphasizing the need for improvedcharging/discharging coordination. Federated Learning and blockchain technologies are highlighted as promising solutions for addressing security and privacy concerns.

[2] S.Aslam,H.Herodotou,S.M.Mohsin,N.Javaid,N.Ashraf,andS.Aslamhttps://www.sciencedirect.com/science/article/abs/pii/S1 364032121002847?via%3Dihub 2021 A survey on deep learning methods for power load and renewable energy forecasting in Smart microgridsThis surveyprovides a comprehensive review of deep learning (DL) methods for forecasting power generation from renewable energy sources (RESs) like wind and solar, as well as energy load forecasting in smart microgrids. The survey compares various deep learning approaches for forecasting energy generation and demand, highlighting the significance of large datasets. It identifies open research problems, offering insights for future advancements in renewable energy forecasting.

[3] Y. L. Tun, K. Thar, C. M.Thwal, and C. S. Hong https://ieeexplore.ieee.org/document/93 73194 2021 Federated Learning based Energy Demand Prediction with Clustered Aggregation
The paper proposes a federated learning-based energy demand prediction system using recurrent neural networks. Clients' model updates are clustered based on attributes, speeding The proposed method improves the convergence speed of the global model by clustering clients with similar attributes. It effectively predicts energy demand while utilizing federated learning,

[4] E.Mengelkam p, B. Notheisen, C. Beer, D.Dauer, and C.Weinhardt https://ieeexplore.ieee.org/document/9013587 2019
Energy Demand Prediction with Federated Learning for Electric Vehicle Networks
The paper introduces Federated Energy Demand Learning (FEDL) for electric vehicle networks, using federated learning to protect privacy and reduce communication overhead. A clustering-based approach further enhances prediction accuracy and efficiency. the proposed scheme, section-V discusses the performance evaluation of the proposed scheme and section-VI concludes the paper.
methods improve energy demand prediction accuracy by 24.63% and reduce communication overhead by 83.4% compared to traditional machine learning approaches, demonstrating effective privacy protection and resource efficiency in EV networks.

[5] E.Mengelkamp, B.Notheisen,C. Beer, D.Dauer, and C.Weinhardt https://link.springer.com/article/10.1007/s00450017-0360-9 2017
A blockchainbased smart grid: towards sustainable local energy markets
The paper proposes a blockchain-based decentralized local energy market design for 100 households. It uses a private blockchain for secure, peer-to-peer energy trading, eliminating central intermediaries and enabling local energy consumption and generation balancing. The proposed blockchain-based market design allows energy prosumers and

consumers to trade locally produced energy securely. The study presents a promising framework for decentralized energy markets but requires further technological and economic evaluations.

III. PROPOSED SCHEME

This paper proposes a Blockchain-based Federated Learning (BCFL) scheme by using different linear regression algorithms to predict the energy demand at electric vehicle (EV) charging stations. The overview of the proposed BCFL architecture is shown in Figure 3. The network model consists of electric vehicle charging points at different charging stations. Each charging station receives electricity from the electrical grid in order to power EVs. Each charging station collects itslocal dataset consisting of features such as the station's name, the start time of charging, the effective charging time, energy consumed, and other details. In a corresponding log file, the charging history of all electric vehicles at a particular charging station can be viewed. Transactions and model updates in the BCFL system are recorded securely and transparently using a blockchain network. Charging stations, which are nodes in the network, contribute to the training of a global machine learning model using the information they collect, without sharing any of that information with anyone else. The global model is iteratively updated by an algorithm–likely a form of distributed gradient descent–that aggregates the gradient updates (local model changes) given by nodes. These gradients are computed by each node using its own local data and then used collectively to refine the global model. Verifiability and immutability of blockchain records of model updates guarantees reliability in model training procedures, while its ability to aggregate data and reach consensus on model upgrades bolsters federated learning processes. Furthermore, each station maintains a log file which provides comprehensive history on all EVs charged there; this record supports BCFL predictive analytics while simultaneously helping operators of charging stations manage resources more effectively while offering superior service to EV drivers by analyzing energy usage trends with data from this log file.

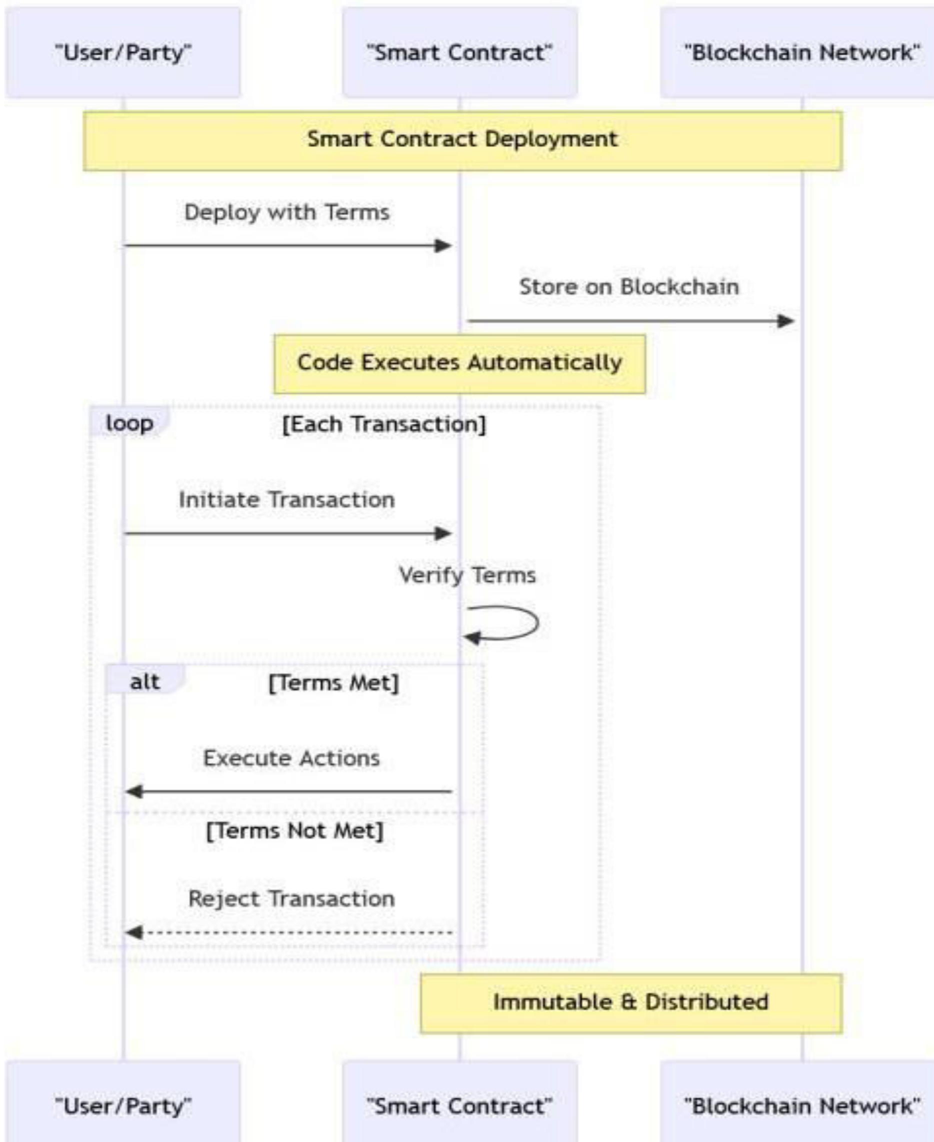

FIGURE 2. Smart contract execution process in blockchain.

global machine learning model using the information they collect, without sharing any of that information with anyone else. The global model is iteratively updated by an algorithm–likely a form of distributed gradient descent–that aggregates the gradient updates (local model changes) given by nodes. These gradients are computed by each node using its own local data and then used collectively to refine the global model. Verifiability and immutability of blockchain records of model updates guarantees reliability in model training procedures, while its ability to aggregate data and reach consensus on model upgrades bolsters federated learning processes. Furthermore, each station maintains a log file which provides comprehensive history on all EVs charged there; this record supports BCFL predictive analytics while simultaneously helping operators of charging stations manage resources more effectively while offering superior service to EV drivers by analyzing energy usage trends with data from this log file.

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Each charging station trains the model on its local dataset. The training process involves minimizing the mean squared error (MSE) loss function: where y is the true energy demand, y' is the predicted energy demand, and n is the number of samples. Each charging station submits its locally trained model to the blockchain network. The global model parameters are generated by taking the weighted average of the local models. where wi is the weight assigned to the local model and ai is the model parameters of local model i. The weights can be proportional to the size of the local dataset, or other criteria such as the local model's performance. The federated learning process iterates between local model training and global model aggregation until a predefined number of communication rounds is reached or convergence is achieved. After each round, the global model is distributed back to the charging stations for further local fine-tuning. This federated learning algorithm allows for decentralized training, preserving the privacy of the local datasets, and utilizing the power of the blockchain network to aggregate and distribute the global model among the participating nodes. Algorithm 1 represents the pseudocode of the smart contract used for uploading the global model to blockchain and Figure 4 shows the flowchart of the proposed algorithm. FederatedLearning smart contract handles registering nodes (participants), collecting local model updates from them, combining them into a global model, and then sending

Variables:
model_parameters: Array registered_nodes: List local_updates: Map[Node⇒Update] global_update_flag: Boolean

Initialize:
model_parameters = Empty Array registered_nodes = Empty List
local_updates = Empty Map global_update_flag = False **Function** registerNode(Node node):
if node NOT in registered_nodes **then**
Add node to registered_nodes

end if
Function submitUpdate(Node node, Update update): **if** node in registered_nodes **then** local_updates[node] = update
end if
Function aggregateUpdates():
if Count of local_updates EQUALS Count of registered_ nodes **then**
for each update in local_updates **do** Aggregate update into model_parameters **end for**
global_update_flag = True
else
Display ''Waiting for all nodes to submit updates''
end if
Function retrieveModel(Node node):
if global_update_flag **then return** model_parameters **else**
Display ''Global model is not ready yet''
end if

the parameters from the global model back to the nodes. It begins with a flag indicating that the global model is ready and an empty set of data structures for storing model parameters, registered nodes, and their local changes. Participating nodes must register via a registerNode function and provide model parameter updates on a per-node basis. An aggregation function then incorporates all of the nodes' updates into a unified global model. Nodes can get the new model parameters once the aggregation has been completed and the global update flag has been set. This protects the federated learning process within the blockchain architecture by ensuring a synchronised and secure update mechanism across the network.
processing, and game playing, among others. The model parameters of NN are: Hidden Layers: Layers between the input and output layers. A neural network can have any number of hidden layers, and each hidden layer can have any number of neurons. The presence of multiple hidden layers makes the network ''deep,'' leading to the term ''Deep Learning.''

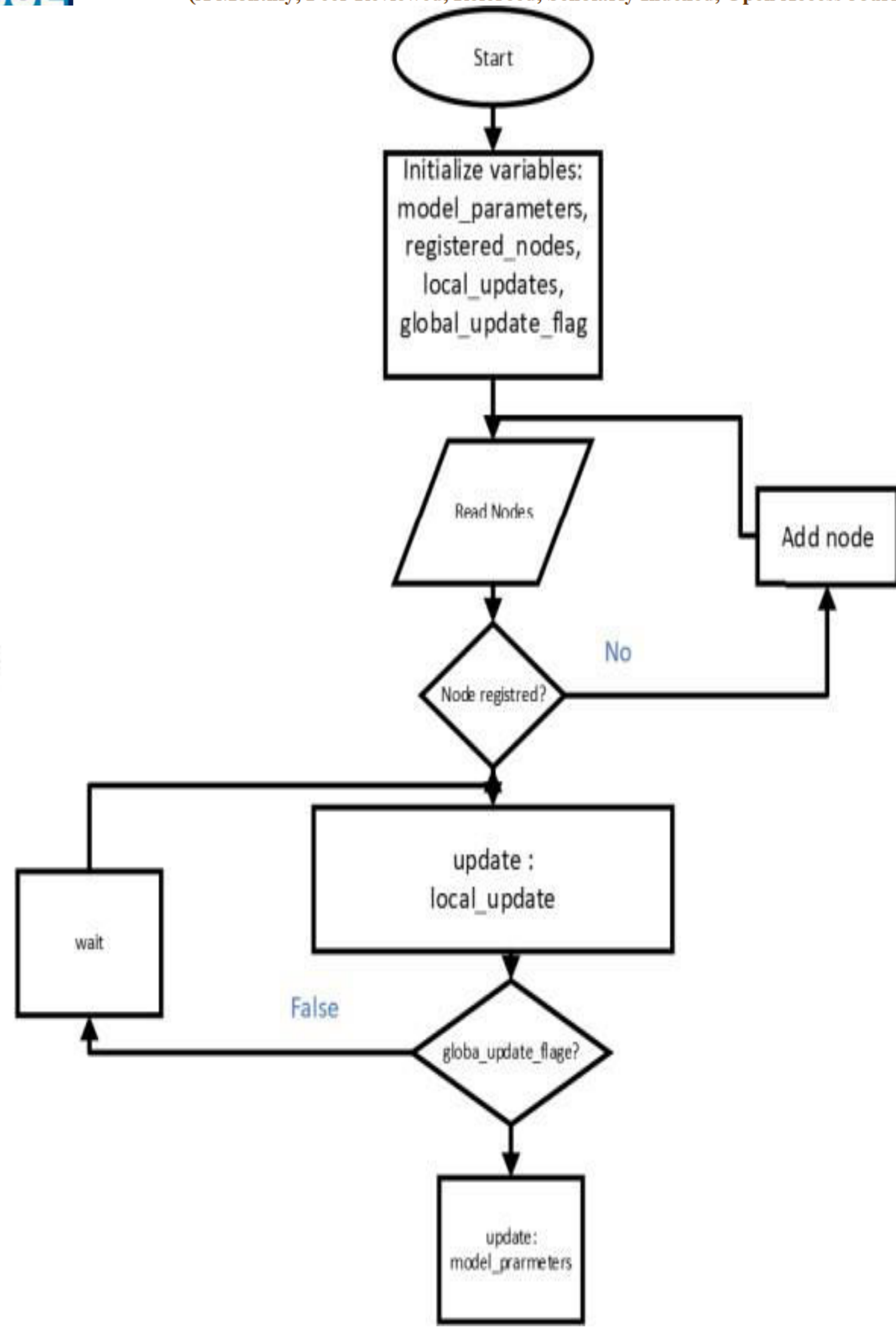

FIGURE 4. A flowchart of blockchain-based federated learning.

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1. BLOCKCHAIN

Distributed ledger technology (DLT) and blockchain have been all the rage recently because to the widespread belief that they can usher in a level of digital innovation not witnessed since the Internet's inception. There has been a dramatic change from the old, centralized model of transactions to the new, decentralized one, and blockchain technology is making it possible. Blockchain is a distributed ledger system that improves security, makes it easier to trace transactions, and increases transparency [18]. In a peer-topeer (P2P) network, the individual computers that make up a blockchain are known as nodes. The blockchain database is accessible from any node in the network. These nodes possess the ability to produce new blocks that are to be appended to the blockchain, as well as initiate, receive, or verify transactions. Public blockchains and private blockchains are the two main varieties of blockchain technology. Hybrid and Consortium blockchains are two further options. Since public blockchains do not require special uthorization, anyone with an internet- connected computer can join the network and contribute to it as a node. These nodes are capable of adding blocks to the blockchain and verifying transactions. Platforms like Ethereum and Bitcoin are examples of public blockchains. Nodes in a private blockchain network must first obtain authorization to join the network, making it private and restricted. In these blockchains, the data is controlled by a single entity or organization that wants to keep it private and not share it with everyone. Hyperledge Fabric and Ripple are two examples of private blockchains. Every node in a blockchain network, whether public or private, has access to the same ledger, may validate transactions, and add new blocks as needed. Blocks are used to store data on the blockchain.

Crypto graphichash algorithms sequentially chain these blocks. Figure 1 shows the architecture of the blockchain, which consists of m blocks labeled $B1, B2, \ldots, Bn{-}1, Bn, Bn{+}1, \ldots, Bm$. A hash of the preceding block is included in the header of each block, and each block also contains transactions. The transaction memory pool is updated whenever new data or events occur. Adding a block header and selecting the transaction from the memory pool generate a new block. The cryptographic hash of the preceding block is added in the header of the current block which are computed on the block header to identify each block in the blockchain uniquely. Since the hash of the previous block is contained in each block header and is required to compute the hash of the current block, all blocks in a blockchain are linked chronologically. Due to its distributed and secure nature, blockchain technology has the opportunity to revolutionize various industries by enhancing reliability, efficiency, and transparency across a wide range of operations. Smart grids can benefit from blockchain technology's increased security and transparency in energy transactions, which can improve energy distribution efficiency and boost renewable energy usage. Improved patient care and privacy can result from its use in healthcare by ensuring the integrity and privacy of medical records and easing the movement of such data between different healthcare providers. If blockchain technology can provide an Weights & Biases:

These are the parameters of the neural network that are adjusted during training. Each connection between neurons has a weight, and each neuron has a biasimmutable and transparent ledger of all goods and transactions, it might revolutionize supply chain management. As a result, supply chain efficiency may be improved, product authenticity can be guaranteed, and fraudulent behaviors can be decreased. By enhancing transparency in the supply chain for automotive components, facilitating secure communication and transactions between vehicles, and enabling innovative business models like peer-to-peer car sharing, blockchain technology has the potential to revolutionize the automotive sector. These sectors can benefit from increased confidence in their operations, efficiency, and security thanks to blockchain technology, which in turn encourages the creation of novel solutions and stronger systems.

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A. SMART CONTRACT

The use of block chain technology in smart contracts represents a fundamental change how agreements are executed

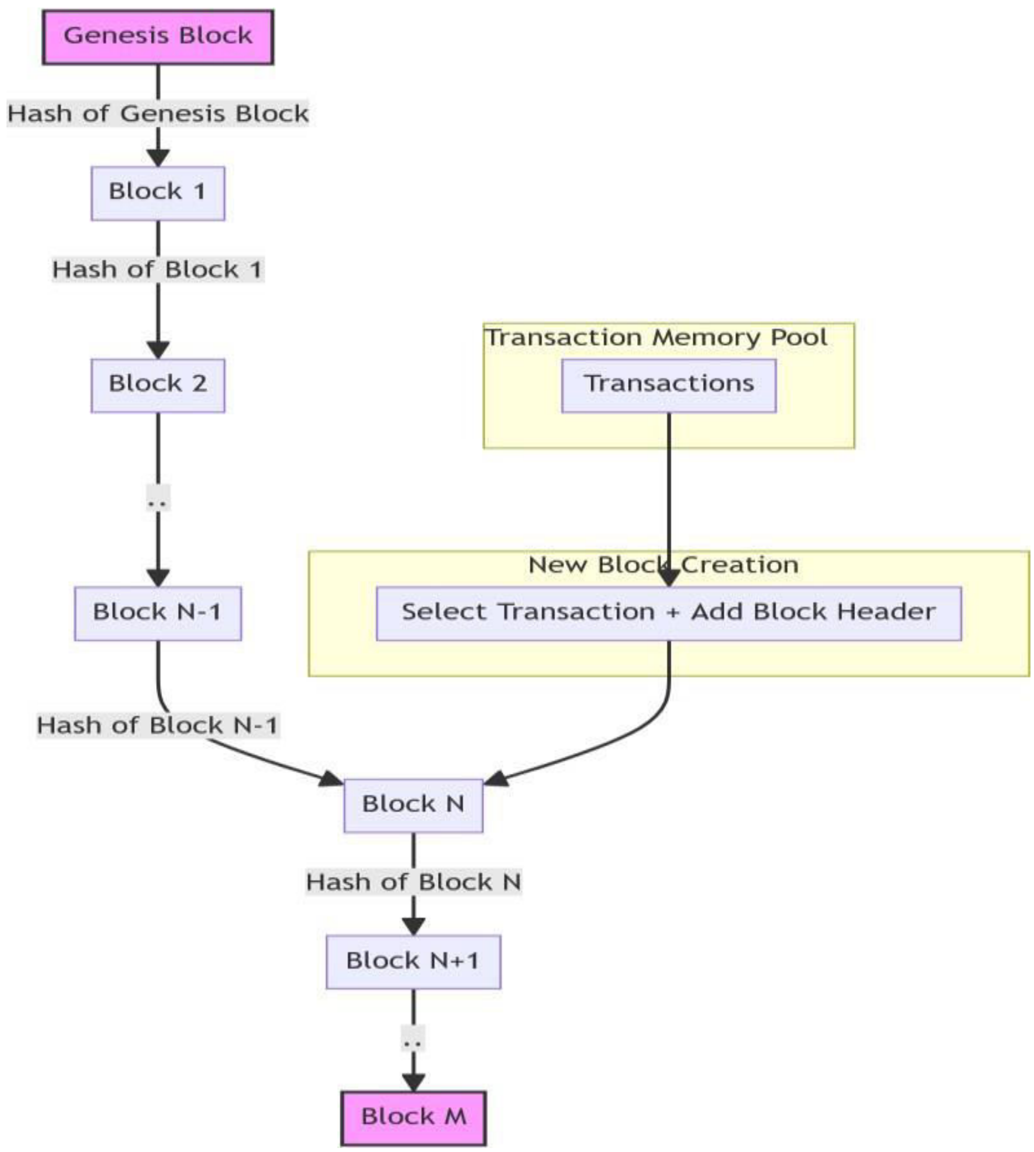

FIGURE 1. Blockchain architecture.

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IV.RESULTS

Energy demand forecasting using blockchain technology is an innovative approach that leverages the decentralized, secure, and transparent nature of blockchain to enhance the accuracy and efficiency of predicting energy consumption. Blockchain provides a tamper-proof record of data, ensuring that energy usage data collected from various sources (such as smart meters, IoT devices, and grid sensors) remains trustworthy and verifiable. This transparency is particularly valuable in energy markets, where trust in data is crucial for decision-making.In this system, smart contracts can be used to automate transactions based on real-time energy demand forecasts. For example, smart grids can adjust energy supply or implement dynamic pricing based on predictive models, ensuring that the supply matches demand without overproduction or waste. By integrating blockchain with AI and machine learning models, energy providers can continuously refine their forecasts using real-time data, leading to more accurate predictions of energy demand, even in the face of changing weather patterns or unexpected consumption spikes.Additionally, blockchain can support decentralized energy markets, such as peer-to-peer (P2P) energy trading platforms, where consumers can buy and sell excess energy. This opens up new opportunities for consumers to participate in energy markets, creating more distributed and resilient energy systems. Blockchain also facilitates the creation of transparent and automated billing and settlement systems, reducing administrative costs and potential disputes. Despite its potential, implementing blockchain in energy demand forecasting faces challenges like scalability, as the system needs to process large volumes of real-time data without compromising performance. Privacy concerns also arise, as individual consumption data could potentially be exposed on a public blockchain, although privacy-preserving techniques like zero-knowledge proofs could be used to address this. Integration with existing grid infrastructure is another hurdle, as energy systems would need to adopt blockchain technology, requiring significant changes in both hardware and software. Nonetheless, as the technology matures, energy demand forecasting using blockchain could significantly improve grid management, energy efficiency, and the sustainability of energy systems.

V. CONCLUSION

This paper investigates how machine learning techniques, with an emphasis on Blockchain-Based Federated Learning (BCFL), can be employed to forecast energy consumption at electric vehicle (EV) charging stations. Our proposed BCFL framework not only addresses increased energy demands but also guarantees data security and user privacy. To evaluate its performance, real world data was utilized. Study participants used Decision Tree, LASSO Regression, Random Forest, Ridge Regression and MLP Neural Network estimation techniques to estimate energy consumption. A thorough examination demonstrated that blockchain-based Federated Learning Architecture accurately predicts EV charging station energy

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