Federated Learning with XGBoost and LSTM for Electric Vehicle Energy Demand Prediction

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Abstract: **The growing popularity of electric vehicles (EVs) is driven by their advantages over traditional gas-powered cars, but integrating them into the power grid poses challenges like increased energy demand and peak loads. To address this, we propose a blockchain-based federated learning approach for predicting EV energy demands using linear regression algorithms. Data from EVs is securely stored on the blockchain, accessible only by authorized users. Each EV trains a machine learning model using federated learning, and the resulting model parameters are shared on the blockchain. Our approach also tackles communication delays and overheads within the blockchain-federated learning (BCFL) framework, optimizing system performance. Results demonstrate the efficiency of our method in predicting EV energy needs accurately.**

Keywords: **Electric Vehicles (EVs), Blockchain, Federated Learning, Energy Demand Prediction, Blockchain-Federated Learning (BCFL), Linear Regression, Power Grid, Machine Learning Model**

INTRODUCTION

The rapid growth of electric vehicles (EVs) is driving the evolution of intelligent transportation systems, which play a crucial role in reducing greenhouse gas emissions. With the increasing number of EVs on the road, accurately predicting their charging demand has become essential to prevent excessive strain on power grids and reduce operational costs. Reliable forecasts of EV charging requirements, considering factors like mileage and usage patterns, help both service providers and consumers optimize charging strategies. Consumers can plan ahead, anticipate travel distances, and select alternative charging stations before battery depletion. Federated Learning (FL), a decentralized machine learning approach, enables multiple devices to collaboratively train models while safeguarding data privacy. This method is particularly valuable in sectors like healthcare, finance, and energy. In the energy sector, FL offers promising potential for improving EV energy demand predictions, enabling more efficient energy management and contributing to sustainable transportation networks.

LITERATURE SURVEY

1. McMahan et al. (2016) - Federated Averaging Algorithm
   - This study introduced the Federated Averaging Algorithm (FedAvg), which serves as a foundational technique for federated learning.
   - FedAvg enables decentralized training across multiple devices without sharing raw data, ensuring user privacy.
   - However, it suffers from high communication overhead, which can slow down model convergence.
2. Dedeoglu et al. (2022) - Deep Reinforcement Learning with Federated Learning for EV Demand Reshaping
   - This research applied deep reinforcement learning to reshape EV charging demand using federated learning.
   - The model decentralized the learning process to preserve privacy while optimizing charging schedules.
   - A limitation is that the study does not fully address the communication latency introduced by federated learning.
3. Saputra et al. (2019) - Federated Learning for Energy Demand Prediction in EV Networks
   - The study explored federated learning as a method for predicting EV energy demand while protecting data privacy.
   - Federated learning allowed multiple EV stations to collaboratively improve forecasting without exposing sensitive data.
   - The approach required high computational resources, limiting its deployment in resource-constrained environments.

4. Wang et al. (2022) - Blockchain-Based Privacy-Preserving Federated Learning for IoV
    - This research introduced a blockchain-based federated learning approach for energy forecasting in the Internet of Vehicles (IoV).
    - The integration of blockchain technology ensured secure model aggregation and prevented data tampering.
    - However, it did not fully optimize communication latency, leading to delays in real-time forecasting.
5. Mengelkamp et al. (2018) - Blockchain-Based Energy Trading
    - This study proposed a decentralized blockchain-powered system for local energy trading.
    - The model allowed secure and transparent energy transactions between participants, improving trust and efficiency.
    - Regulatory challenges and adoption barriers remain significant obstacles to large-scale implementation.

PROBLEM STATEMENT

Integrating EVs into the grid introduces energy demand peaks, leading to potential overloads. Current prediction methods lack efficiency and security. A blockchain-based federated learning approach is needed to improve energy forecasting and reduce communication delays.

PROPOSED METHOD

Author of this paper employing Machine Learning algorithms to forecast Energy Demand for Charging Stations and these models will get trained and perform predictions on data obtained from individual Electric Vehicles.

Data obtained from Electric Vehicles may put vehicle owner security as risk as this data contains owner location and other financial values. To provide security to Vehicle owner's data, author employing Blockchain based Federated Learning which will allow each vehicle to train a local model and then report all those local model parameters to Blockchain server. Charging stations may ask Blockchain to aggregate all local models to generate Global model by taking average of all local model weights.

For accurate forecasting author employing different machine learning algorithms such as Lasso, Ridge, MLP, Random Forest and Decision Tree. Each algorithm performance is evaluated in terms of R2Score, MSE (mean square error), MAE (mean absolute error) and RMSE (root mean square error). Among all algorithms Random Forest got high R2score (accuracy) and less MSE error. MSE, MAE or RMSE refers to difference between true values and forecasted values so the lower the difference the better is the algorithm.

METHODOLOGY

Data Collection:
Data is obtained from the Boulder Colorado EV Charging Dataset, which includes variables such as charging times, energy demand, and vehicle-specific data.

Data Preprocessing:
The data undergoes preprocessing steps such as normalization, date conversion, and correlation analysis. The dataset is split into 80% training and 20% testing.

Blockchain Integration:
Smart contracts are designed using Solidity to handle data retrieval and storage securely. Blockchain enables decentralized storage of model parameters and guarantees tamper-proof data aggregation.

Model Training:
Several machine learning models, including Random Forest, Decision Tree, Lasso, and Ridge, are trained on the preprocessed data. XGBoost is later introduced as an extended model due to its superior performance.

Federated Learning Implementation:
Each EV trains a local model, and the local model parameters are stored on the blockchain. The global model aggregates the local parameters to forecast energy demand without requiring raw data.

Machine Learning Models for Forecasting
Various machine learning algorithms are tested to forecast energy demand based on EV data. Each model is evaluated based on its accuracy, using performance metrics such as R2 Score, MSE, MAE, and RMSE.
XGBoost for Enhanced Accuracy
As an extension to the project, XGBoost is introduced as a superior forecasting model due to its use of

multiple estimators and decision trees. XGBoost helps refine the accuracy of the global model in the federated learning framework.

XGBoost Features:

1. High Accuracy:

XGBoost achieves an R2 Score of 99.99%, outperforming all previous models in terms of accuracy, precision, and reliability for energy demand forecasting.

Blockchain and Federated Learning

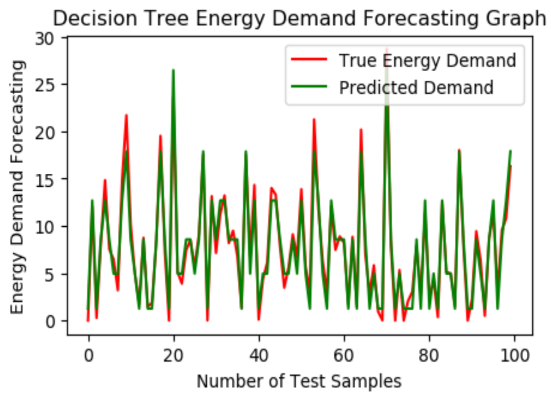
Blockchain and Federated Learning ensure data privacy and secure model aggregation. The system enables each EV to train its local model without exposing raw data, while blockchain securely stores and aggregates these models.

Blockchain Integration:

1. Smart Contracts:
   - Smart contracts written in Solidity manage the storage and retrieval of model parameters on the blockchain. These contracts ensure the integrity and security of the data.
2. Tamper-Proof Storage:
   - Blockchain's decentralized structure ensures that data is tamper-proof, preventing unauthorized access or modification of sensitive EV data.

RESULTS

#function to load and display dataset values and selecting only those features from dataset selected by author



#training Lasso algorithm using training features and then evaluate performnace on test features

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 demand; with Random Forest algorithm yielding superior MSE and MAE performance results . The maximum R2 was achieved by this model as well, indicating excellent prediction accuracy. Although R2 values above 0.91 were found for all models, the MLP Neural Network performed poorly. The results emphasize the BCFL framework's potential for enhancing smart grid management and promote the growth of EV infrastructure, showcasing the benefits of integrating blockchain technology for secure and reliable energy usage predictions.

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