Predicting Electric Vehicle Charging Stations Occupancy: A Federated Deep Learning Framework

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***Abstract*—Electric vehicles (EVs) have long been recognized as a solution to the shortage of fossil fuels and the environmental problems associated with increasing CO2 emissions. However, charging an electric vehicle can take significant time at certain charging stations. Additionally, the limited deployment of charging stations is a significant barrier to the widespread adoption of electric mobility (e-mobility). In fact, many drivers struggle to locate a convenient charging station before their vehicle's battery runs out. This study introduces a novel approach to addressing the issue of congestion at public charging stations and reducing the amount of time drivers spend waiting in line by predicting their occupancy. Previous research has relied on traditional Deep Learning (DL) techniques for prediction, which require centralized data collection. Nevertheless, each Charging Station Operator (CSO) holds sensitive data about its charging stations and users that cannot be shared with external parties. To address these privacy concerns, we propose a Federated Deep Learning approach where each CSO trains a DL model locally and then sends the model updates (or parameters) to a server for aggregation. Experiments on a real-world dataset demonstrate that predicting occupancy using the Federated Deep Learning approach achieves promising results (86,21% of accuracy and 91,49% of f1-score), guarantees privacy, minimizes data transfer costs over the network, and allows individual CSOs to benefit from the rich datasets of others without sharing their sensitive data.**

***Index Terms*—Charging Stations, Federated Learning, Deep Learning, Data Privacy, Data Sharing, Communication Cost**

I. Introduction

With higher expectations to meet the Paris climate agreement, recent years have seen considerable progress in transitioning to electric vehicles (EVs) to achieve the goal of 100% emission-free transportation in the future. For instance, in 2019, there were over 2.1 million electric car sales in the world, and the number of Battery Electric Vehicles (BEVs) in Europe reached (1,125,484) in 2020 [1]. Nevertheless, the poor density of charging infrastructure and accessible charging networks is one of the reasons for limited electric vehicle adoption in some countries. Accordingly, EV drivers often experience delays due to the lack of available charging stations and long wait times. In the European Union (EU), charging points with a capacity of 22kW or less are dominant. Only one in nine fast chargers (with a total of more than 22kW) represents a fraction of 11% of the European infrastructure network. Charging an electric vehicle using one of these low-tech power can take several hours [2]. Therefore, planning the next charging session or forecasting charging point occupancy is crucial to optimally manage this modern transportation system. Significantly, this will help drivers better plan their charging processes and thus convince people to go electric by making the charging process as simple as refuelling is today. Predicting occupancy will also facilitate scheduling maintenance of charging points during periods of low usage [3] and allows Charging Station Operators (CSOs) to manage the available grid resource better.

In recent years, with the emerging Artificial Intelligence (AI) technology, several centralized deep learning (DL) models have been proposed to forecast EV charging stations occupancy [4–6]. However, centralized training can raise privacy concerns because of data sharing with a central server or entity. To bypass this shortcoming, we propose a Federated Deep Learning framework to predict charging station occupancy. The framework allows CSOs to collaborate in a learning system without sharing their data.

The main contributions of this article can be summarized as follows:

- An efficient Deep Federated Learning based architecture for EVs charging stations prediction is proposed. This allows CSOs to contribute to the learning process without revealing sensitive data about their charging station usage. Only the learning parameters of the model are shared with a centralized server.
- Three federated deep learning models based on Long Short-Term Memory (LSTM), Bidirectional LSTM (BiLSTM), and ConvLSTM have been investigated in this study to predict EV charging stations occupancy. This choice is motivated by the capability of these models to efficiently model and handle time dependencies in time-series data [7–9].
- This is the first study introducing a decentralized approach for EVs charging stations occupancy prediction as an alternative to centralized systems that are prone to single points of failure and do not provide private data protection. Our proposed Federated Learning (FL) architecture includes relevant e-mobility actors, with each CSO serving as an FL client that trains the model locally without sharing their data with others.
- The effectiveness of the proposed approach was thor-

oughly tested using a real-world dataset from the City of Dundee and compared to centralized and local methods using different metrics.

The remainder of the paper is organized as follows. Section II discusses the related literature on predicting EV charging stations occupancy, while Section III presents our proposed system architecture, which is based on FL and DL models. In Section IV, we describe the experimental framework and analyze the results obtained from training various models. Section V concludes the paper and highlights potential future works.

II. Related Work

There have been several studies in the literature on issues related to electric vehicle charging systems. Some researchers proposed methods to predict the energy demand of electric vehicles, analyzing electric vehicle behavior among households or recommending charging stations to reduce waiting time. However, there is a paucity of literature on forecasting the availability of charging points. Related work in EV charging stations can be divided into two categories: (i) statistical methods and (ii) artificial intelligent algorithms. The first category considers methods based on the theory of probability and statistics. For example, in [10], a Monte Carlo simulation based on probability distributions to forecast the charging load of plug-in electric vehicles (PEVs) in China is presented. Lee et al. [11] used Gaussian mixture models to understand user behavior and predict each charging session's duration and energy demand. In [12], a different method is presented, where Markov chains are used to model EV charging stations' occupation. The model considers factors such as the distribution of vehicles in charging stations, average plug time, and amount of energy withdrawn to predict the availability of a single charging station and its consumption profile. The second category focused on predicting occupancy for each charging outlet using artificial intelligence methods. For instance, a deep learning approach has been conducted recently [6] to predict availability by taking advantage of both dynamic (e.g., daytime and weekday) and static information (e.g., mean occupation for a given time of day). The goal is to accurately predict the future occupancy of a charging point for a given period, such as 10 minutes to several hours. The model can only make predictions for each charging point individually. Authors in [13] discussed features' importance and the characteristics of charging stations that can influence the predictability of occupancy; they applied logistic regression models. Similarly, Soldan et al. [14] developed a big data streaming architecture that receives real-time data from charging stations and provides the occupancy probability in the next 15 minutes. Hybrid LSTM neural networks were proposed in [5]; they combined historical charging occupancy sequence data and charging occupancy rate and then trained a hybrid LSTM neural network. The results show higher performance for short-term (10 minutes) and long-term predictions (2 hours).

Note that all the studies mentioned above focused on forecasting EV charging station availability using centralized training methods, where the data is collected and stored in a central server. Nevertheless, these methods may raise concerns about confidentiality due to the sensitive nature of the collected data. For instance, this data may include details about charging sessions, such as duration, energy dispensed, current and voltage, and data about the drivers using the stations. This information could be valuable to competitors or used to track vehicles and predict drivers' habits. To comply with GDPR[1], we propose an FL [15] framework that involves training DL models using multiple datasets distributed across various Charging Station Operators. The only information that is transmitted between CSOs and the central server is model weights.

III. Federated Deep Learning Framework Description

In this section, we introduce federated learning and describe our solution's architecture and the learning process.

Federated Learning is a collaborative approach for training machine learning models across multiple independent devices, referred to as clients. Clients use their locally collected data to conduct a training process. The updates from all clients are then aggregated by a centralized server to build a new global model, which is then distributed back to the clients for further training. The cloud server aggregates client updates using an aggregation algorithm, such as Fed-Avg [16].

Fig. 1 shows the most relevant subsystems of the electric mobility ecosystem:

- CSO: is responsible for installing and managing the charging points, as well as maintaining the EV supply equipment (charging connectors). Therefore, CSO managers own all data related to the usage of their charging stations.
- e-MSP: e-Mobility Service Provider offers EV charging services, including access to charging stations and payment facilitation, by signing agreements with one or more CSOs.
- EV Users: are individuals who operate electric vehicles.

As shown in Fig. 2, the data for charging stations in a given geographical area (e.g., a city) is held by different CSOs. We propose a collaborative DL architecture to protect this data from leakage and reduce communication costs. This approach allows each CSO to train a local model using data from their charging stations, while a cloud server orchestrates the learning by aggregating the local models to create a globally trained model. This globally trained model can then be used to predict the availability of charging stations, providing valuable insights to users and stakeholders. Local models are trained by each CSO using data from their charging stations generated locally. A cloud server that may belong, for example, to a public authority orchestrates the learning by aggregating the

[1] General Data Protection Regulation https://gdpr-info.eu/

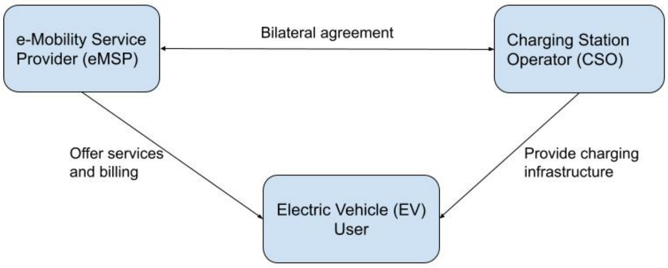

Fig. 1: Stakeholders (or actors) involved in an e-mobility system inspired by [17].

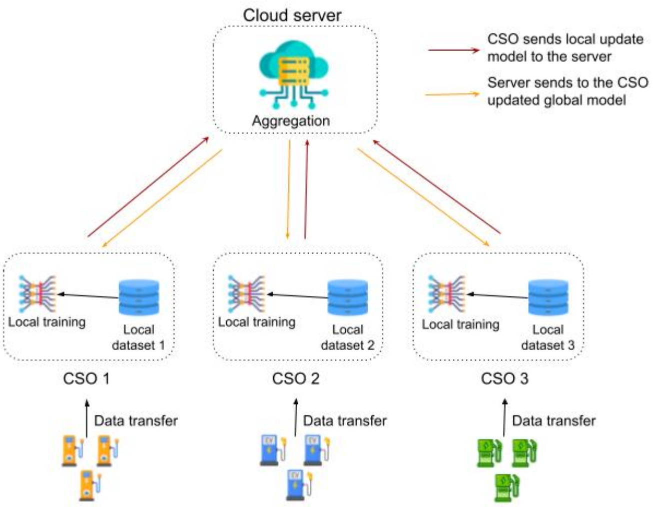

Fig. 2: EV charging stations prediction: FL Architecture.

local models to get a globally trained model. The federated learning process typically follows these steps in each iteration:

- *Step 1:* The cloud server randomly initializes a DL model M^i and sends it, along with characterizing hyperparameters, to all participating Charging Station Operators (CSOs).
- *Step 2:* Each CSO k trains the received model using their locally-stored data D_k and sends the weights of the local model M_k^i back to the centralized server.
- *Step 3:* The server calculates new weights from the weights received from all clients using the Fed-Avg algorithm, resulting in a new global model, M^{i+1}.
- *Step 4:* The server sends the updated model M^{i+1} to all clients for another round of training.

The training process ends when the loss function reaches convergence.

IV. Experiments and Results Analysis

This section aims to provide an overview of the real-world dataset and the pre-processing steps for creating time-series data. It also outlines the selection process for FL architecture parameters and hyperparameters. Finally, the proposed FL framework is evaluated.

A. Data description

In this paper, we consider a real-world dataset from the open data portal of Dundee City, UK[2], containing 8870 charging sessions from July 01, 2018, to August 01, 2018. The dataset includes three types of charging stations based on power capacity: slow stations (7kW), fast stations (22kW), and rapid stations ($\geq$ 43kW) [5]. In this study, 53.9% of sessions were recorded using slow chargers, 28.4% at rapid chargers, and 17.7% at fast chargers. Outliers with abnormal charging duration patterns were removed from the dataset, including sessions with charging times longer than 20 hours or shorter than 10 minutes. These outliers may indicate errors in recording or a fully charged vehicle occupying a charger. The EV charging stations occupancy prediction is influenced by various factors, including charger usage on weekdays/weekends, charging power, energy supplied, charging demand, EV battery capacity, and others. To enhance the dataset's limited features, the following features were generated:

In this study, we aim to predict the occupancy of charging stations in the future (e.g., from 10 minutes to 2 hours). We denote S the set of charging stations and $T = \{1, 2, \ldots, 144\}$ the set of discrete time index obtained by dividing a day of 24 hours into 144 intervals of 10 minutes based on the work done by [5].

- **Day of the week (d):** Charging time and duration patterns differ with respect to the weekday. We represent the weekday via label encoding (Sanday = 0, Monday = 1, ..., Saturday = 6).
- **Time of day (t):** Charging patterns are influenced by the time of the day. The time of the day is represented by a number from 1 to 144, where the number corresponds to a time interval $t \in T$.
- **Charging occupation (O_t^s):** A binary flag called "charging occupation" indicates whether a charging station $s \in S$ is in use at a specific time $t \in T$.

To make the training phase of Federated DL models converge faster, we first scale all the values to a range of 0 to 1. Next, we split the entire dataset into a training set (70% of the dataset) and a test set (30% of the dataset). The training set is further partitioned based on the number of clients (i.e., CSOs) participating in the federated learning training. Since we do not have information about the charging station operators in Dundee City, we have assumed that there are four CSOs and have divided the station data into four randomly chosen subsets.

B. Occupancy state prediction models

Given a sequence of historical charging occupancy $(y_{t-1}, y_{t-2}, \ldots)$ before the time $t \in T$, we aim to predict the charging occupancy for a station $s \in S$ in $t+1, t+2, t+3, \ldots$. To accomplish this, we create charging sequences using a sliding window over the time-series with 12 past charging occupancy states (i.e., 2 hours) and 6 steps ahead (1 hour).

[2]https://data.dundeecity.gov.uk/dataset/ev-charging-data

This choice was made based on experiments with various time window sizes.

In this experiment, three DL models were implemented to predict the occupancy of EV charging stations. These models were designed to analyze the available data and predict the charging stations' usage. The models included:

- *Long Short-Term Memory (LSTM)*[9]: is a type of recurrent neural network (RNN) that can capture long-term dependencies in times-series data by using gating mechanisms to control the flow of information through the network.
- *Bidirectional LSTM (BiLSTM)*[7]: is a type of LSTM that processes input sequences in both forward and backward directions. This allows the model to capture both the past and future context of each word, which can lead to better predictions.
- *Convolutional LSTM (ConvLSTM)*[8]: a model that integrates conventional filters into the LSTM layers. The input sequences are passed to a 2D ConvLSTM cell and then flattened and connected by a fully connected layer to handle the time-series.

We use the binary cross entropy (BCE) loss function to evaluate the performance of our model. This function is used to measure the difference between the predicted and actual outcomes of our model and is defined in (1):

$$BCE = \frac{-1}{k}\sum_{j=1}^{k} y_j . \log \hat{y}_j + (1 - y_j) . \log(1 - \hat{y}_j) \tag{1}$$

Where y_j is the real value at time j, and $\hat{y}_j$ is the predicted value. After manually tuning, we chose hyperparameters based on the proposed models. Table I reports the retrained hyperparameters. To evaluate the model's performance, we utilize metrics such as accuracy, precision, recall, and F1-score [3].

TABLE I: Hyperparameter settings of the model.

Hyperparameter	**Value**
Activation function	Tanh = $\frac{1}{1+\exp(-2x)}$
Optimizer	Adam
Regularization	0.2
Batch size	128
Epochs	20
Learning rate	0.001
Number of FL iterations	10

C. Results Analysis

Within our system, there are four local CSOs, each training an LSTM model on their respective datasets. Once the training phase concludes, each CSO sends only their model's learned parameters to a central server, which aggregates all the received parameters using the Fed-Avg algorithm. We used Fed-Avg for aggregation after conducting experiments with different algorithms and finding that it performed the best.

Fig. 3 displays all tested models' accuracy, precision, recall, and f1-score using federated, centralized and local training.

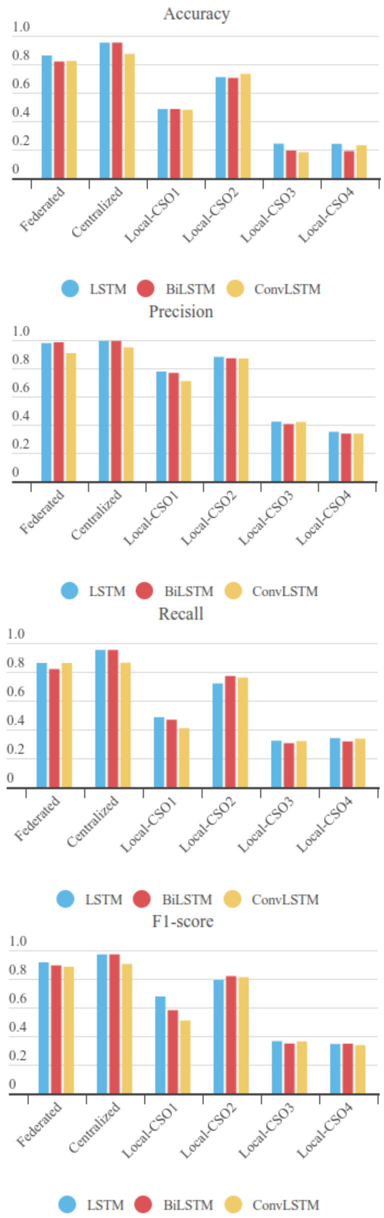

Fig. 3: EV charging stations prediction results.

The results of federated training show that LSTM performed well with 86.21% accuracy and 91.49% F1-score after ten iterations for all FL clients. This is compared to BiLSTM and ConvLSTM, which achieved 81.99% and 82.23% accuracy, respectively. For comparison, we also implemented a centralized architecture and trained the same models (LSTM, BiLSTM and ConvLSTM). Centralized training showed that LSTM and BiLSTM performed similarly, with LSTM achieving 95.16% accuracy and BiLSTM achieving 94.67% accuracy. In contrast, LSTM performed better than ConvLSTM, which had an accuracy of 87.33%.

The results obtained by training the models locally by each CSO indicate that some local models have low accuracy. This is due to the fact that clients (or CSOs) perform local training on their smaller subset of data. In contrast, when we combine these local models using FL, the global model performs well. The confusion matrices when predicting 6 time steps are shown in Fig. 4.

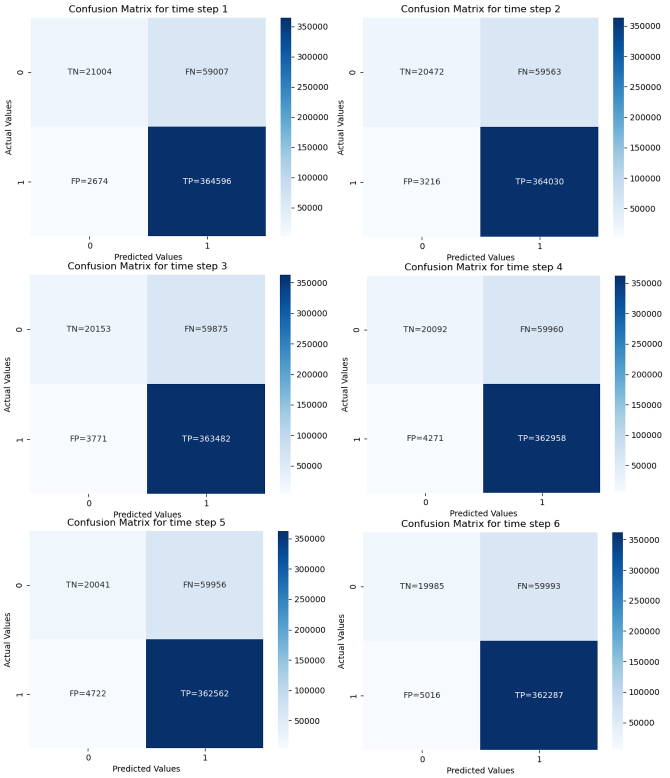

Fig. 4: Confusion matrices on the test dataset for multiple time steps ahead.

These experimental results show that the performance of the proposed Federated LSTM is comparable to centralized LSTM. Even though centralized LSTM outperforms Federated LSTM in terms of accuracy and f1-score, the centralized approach leads to privacy concerns as CSOs need to upload their data to a central server. Furthermore, our FL framework allows for a reduction in data transfer because only 576 kilobytes of data need to be transferred (the size of parameters), compared to the 194 megabytes of data that would need to be transferred to a central server in a traditional centralized approach.

V. Conclusion

In this paper, we addressed the problem of EV charging stations occupancy prediction. Specifically, by regarding each CSO as an FL client, we developed a Federated Deep Learning framework that allows CSOs to collaborate in training a deep neural network without sharing their data; they exchange only model parameters with a central server that belongs to a local authority in a given city. It aggregates the gradient uploaded by all locally trained models by CSOs using the Fed-Avg algorithm and constructs a global model to predict the availability of charging stations.

FL has already proven its worth in most fields, allowing devices or organizations to collaborate without revealing their own individual data. In doing so, we reduce data communication costs and allow CSOs with limited or small datasets to benefit from models trained by other CSOs. We evaluate the performance of the proposed framework on a real-world dataset collected from Dundee City and compare results with a centralized approach which compromises data privacy while forecasting charging occupancy. Results show that the performance of our FL framework is comparable to a centralized approach. We plan to extend this framework for a public EV charging stations recommendation system or real-time EV charging scheduling for future work.

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