

Privacy-Aware Energy Consumption Modeling of Connected Battery Electric Vehicles using Federated Learning

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Abstract— Battery Electric Vehicles (BEVs) are increasingly significant in modern cities due to their potential to reduce air pollution. Precise and real-time estimation of energy consumption for them is imperative for effective itinerary planning and optimizing vehicle systems, which can reduce driving range anxiety and decrease energy costs. As public awareness of data privacy increases, adopting approaches that safeguard data privacy in the context of BEV energy consumption modeling is crucial. Federated Learning (FL) is a promising solution mitigating the risk of exposing sensitive information to third parties by allowing local data to remain on devices and only sharing model updates with a central server. Our work investigates the potential of using FL methods, such as FedAvg, and FedPer, to improve BEV energy consumption prediction while maintaining user privacy. We conducted experiments using data from 10 BEVs under simulated real-world driving conditions. Our results demonstrate that the FedAvg-LSTM model achieved a reduction of up to 67.84% in the MAE value of the prediction results. Furthermore, we explored various real-world scenarios and discussed how FL methods can be employed in those cases. Our findings show that FL methods can effectively improve the performance of BEV energy consumption prediction while maintaining user privacy.

Index Terms—Federated Learning, Electric Vehicles, Energy Consumption Modelling, Edge-Cloud Computing, Digital Twin, Privacy Awareness

LIST OF ABBREVIATIONS & ACRONYMS

ANN	Artificial Neural Networks
BEV	Battery Electric Vehicle
CNN	Convolutional Neural Networks
EV	Electric Vehicle
FedAvg	Federated Averaging
FedPer	Federated Personalization
FedProx	Federated Proximal
FedRep	Federated Representation Learning
FedSGD	Federated Stochastic Gradient Descent
FL	Federated Learning
GRU	Gated Recurrent Unit
ITR	Iterations

Manuscript received May 6, 2023; revised July 28, 2023 and October 20, 2023; accepted December 4, 2023. This work was supported by Science Foundation Ireland 21/FFP-P/10266 and 12/RC/2289_P2 at Insight the SFI Research Centre for Data Analytics at Dublin City University. The dataset is now available on GitHub and can be accessed via <https://github.com/SFIEssential/FedBEV>. (Corresponding authors: Ji Li; Mingming Liu.)

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LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
ML	Machine Learning
RF	Random Forest
TS	Time Step
VED	Vehicle Energy Dataset
XGB	eXtreme Gradient Boosting

I. INTRODUCTION

The transition from conventional internal combustion engine vehicles to Electric Vehicle (EV) has emerged as a major global initiative due to increasing concerns related to the environment and public health. Governments worldwide are introducing policies, laws, and regulations to promote EVs. For instance, the Members of the European Parliament recently approved regulations to encourage the production of zero- and low-emission vehicles, such as EVs and plug-in hybrids¹. In Ireland, the Zero Emission Vehicles Ireland office has been established with a goal of switching an expected 30% of the private car fleet to electric by 2030². Furthermore, numerous studies have indicated a significant reduction in air pollution, noise pollution, and dependence on fossil fuels [1]–[3] resulting from the adoption of EVs.

Energy modeling is essential for policymakers to assess the impact on the grid, identify necessary infrastructure requirements based on vehicle-to-grid technology, and inform energy policy to support the transition to clean transportation to enhance the overall driving experience while mitigating transportation's environmental impact [4], [5]. It is beneficial to automakers and companies in understanding the performance of EVs and optimizing the energy usage patterns, leading to improved battery management and energy efficiency [6], [7]. Besides, accurate predictions of energy consumption can enable drivers to make informed decisions regarding trip planning, route selection, and charging strategies [8], [9].

To this end, various methods have been applied in this research field, ranging from system dynamics models to statistical and data-driven models [10]–[16]. However, with the increasing volume of data generated by connected vehicles, conventional energy modeling methods often lack the capacity to efficiently manage the produced data. Specifically, these methods often require data collection from various sources to create and train a centralized model. This centralized

¹<https://www.europarl.europa.eu/news/en/press-room/20230210IPR74715/fit-for-55-zero-co2-emissions-for-new-cars-and-vans-in-2035>

²<https://www.gov.ie/en/campaigns/18b95-zero-emission-vehicles-ireland/>

approach can introduce challenges in data management, such as data transfer and the risk of data leakage. Instead, Federated Learning (FL) offers a promising solution that enables vehicles to share local models rather than raw data [17] in a decentralized manner for better data privacy, security and scalability. While FL-based methods may demand increased computational resources and more robust communication infrastructure [18], their superior learning capabilities can generally lead to improved model performance in accuracy, precision, and generalizability for many real-world applications [19]–[25].

In our preliminary study [26], FL methods show great potential to deal with privacy issues of connected vehicles. Edge-cloud computing is believed to be the key to meeting all challenges in big transportation data [27]–[30]. Based on these foundations, our research aims to achieve energy consumption modeling for EVs based on FL methods and investigates the effectiveness of models together with edge-cloud computing techniques. By evaluating and comparing the performance of different models for Battery Electric Vehicle (BEV) energy consumption prediction with various configurations, we provide recommendations for their practical implementation in different real-world scenarios. The main contributions of our work are outlined below:

- An extensive review of existing methods employed in previous research focusing on energy consumption modeling for EVs.
- A comparative study is conducted on five local model candidates and five FL algorithms to identify the optimal combination for BEV energy consumption modeling.
- The performances are evaluated for the models with different setups, including the number of iterations, data splitting ratio, and input data size.
- By leveraging distributed data sources and federated learning, the proposed method offers the potential to overcome data privacy concerns and enhance the accuracy and efficiency of EV energy modeling.
- The proposed method is discussed in two centralized and decentralized edge-cloud computing structures for BEV energy consumption modeling. This enables more accurate predictions of EV energy consumption in various real-world scenarios.

The structure of this paper is as follows. In Section II, we provide a review of the relevant literature on EV energy consumption modeling and FL algorithms and their applications. The research question and object are explained in detail in Section III. Section IV describes the methodology employed in our work, and Section V provides the description and analysis of our dataset. Section VI presents the experiment setups and corresponding results, and relevant discussions and analysis are included in Section VII. Finally, we conclude our work in Section VIII and discuss future plans and potential improvements.

II. LITERATURE REVIEW

In this section, a comprehensive overview of the literature on energy consumption modeling for EVs is provided at first.

Secondly, an introduction to FL algorithms is presented with some applications. The unique advantage of FL algorithms in addressing privacy concerns is discussed at the end.

A. Energy Consumption Modeling

The literature on estimating EV energy consumption models has used three distinct categories of methods: white box, grey box, and black box. This section aims to provide a brief introduction to white and grey box methods while focusing primarily on black box methods.

1) *White Box Methods*: Methods that integrate physical constraints into their modeling process, known as white box methods, are invariably built upon theories of vehicle dynamics. These approaches typically estimate energy consumption by employing vehicle dynamics principles with data obtained from a single vehicle. For instance, [31] explores power relationships with velocity, acceleration, and road grade for EVs through statistical analysis and an analytical model based on vehicle dynamics principles. The data used in this study, including battery status, speed, acceleration, and position, was collected from a single test vehicle. For readers interested in further exploration of this topic, we recommend referring to the studies in [32]–[38].

2) *Grey Box Methods*: Researchers have applied grey box methods to estimate EV energy consumption by combining physical knowledge with data fitting techniques. These methods, capable of handling larger datasets through data fitting techniques, primarily focus on the input and output of models using data collected from individual vehicles. For example, the authors of [39] investigated energy consumption modeling for EVs using data collected from a custom-designed EV. Their approach blends physics-based equations with empirical data, resulting in a hybrid power model that offers improved power consumption estimations and addresses range anxiety concerns. Furthermore, statistical techniques such as the Monte Carlo method [40], multinomial logistic regression [41], and Gaussian process regression [42] have been utilized for similar purposes. For those interested in further exploring this topic, we recommend referring to the studies mentioned in [43]–[46].

3) *Black Box Methods*: Instead of physical knowledge, black box methods use data fitting techniques, such as Machine Learning (ML) models, due to their capacity to make predictions and analyses of datasets. Some classic ML models, such as Support Vector Machine [14], Decision Tree and Random Forest (RF) [12], have been applied and estimated in previous relevant work. Furthermore, deep learning methods such as Artificial Neural Networks (ANN) [13] and Convolutional Neural Networks (CNN) have also been employed to solve the same problem. Methods mentioned above are widely used to estimate EV energy consumption based on clustered data collected from multiple vehicles. For instance, in [10], the authors employed eXtreme Gradient Boosting (XGB) to forecast energy consumption based on the real-world data collected from 55 electric taxis from 2017 to 2018 in Beijing, China. The method demonstrated an impressive performance with a Root Mean Squared Error of 0.159 kWh. For further

information, we refer interested readers to the explanations included in [10]–[16].

B. Privacy-Aware in Transportation Data

The utilization of transportation data has gained significant traction in both research and industry applications. However, the integration of transportation data without due consideration for privacy can give rise to various risks and consequences. Recent scholarly investigations [27]–[30] have elucidated and examined the potential risks associated with the usage of big transportation data, including privacy infringement, data breaches, misuse, and the erosion of user trust. For instance, direct usage of source data may expose sensitive information. [30] highlighted how the divulgence of origin-destination information of individual users can compromise their privacy, allowing malevolent actors to deduce their residential or workplace locations. Another pertinent issue related to big transportation data exists in open datasets. As outlined in [27], by cross-referencing publicly available datasets from the New York City Taxi and Limousine Commission, the cash tips paid by celebrities could be discovered and released easily. The perception of data vulnerability and the potential for misuse or privacy breaches can undermine user trust, resulting in a hesitancy to share data or participate in related research endeavours.

Simultaneously, the studies referenced above have also highlighted the advantages of incorporating privacy-aware methodologies in the context of transportation data. These benefits can be summarized as follows:

- From the users’ perspective, the implementation of privacy-aware approaches is paramount to safeguarding user data, ensuring that sensitive information such as personal identities, location data, and behavioral patterns are adequately protected. By prioritizing privacy, users can have greater confidence in sharing their data and engaging in various services and platforms.
- From the operators’ standpoint, adopting privacy-conscious practices is instrumental in building trust and cultivating a positive reputation among users. This, in turn, can foster increased user participation, collaboration, and support for initiatives that prioritize privacy protection. Operators who prioritize user privacy are more likely to attract and retain a loyal user base.
- In terms of privacy regulations and ethical considerations, adhering to privacy-aware practices is crucial for organizations to comply with relevant privacy laws and regulations. By implementing robust privacy measures, organizations demonstrate their commitment to respecting individuals’ rights to privacy and autonomy. Aligning with ethical principles promotes a responsible and trustworthy environment for data collection and usage.

C. Federated Learning

To reduce the computational complexity and enhance the privacy preservation of the centralized approach, FL was developed and recently it has received considerable attention

due to its ability to enable multiple data holders, such as EVs, to collaboratively train models without the need to share their underlying data, thereby providing a natural safeguard against data privacy breaches [47]. As a subfield of ML, FL methods bring revolutionary changes to the conventional system identification process. Instead of processing the data which is previously collected from a single vehicle or clustered from multiple vehicles, FL methods enable each EV to collect data and train the individual model locally without raw data sharing, so it is unnecessary to anonymize the data as what conventional methods did. Besides, the capability of FL methods to deal with large-scale data make it possible to update the trained model and make the decision in time rather than optimize the system performance after another round of data clustering, processing and model training.

In the seminal paper [48], the Federated Stochastic Gradient Descent (FedSGD) and Federated Averaging (FedAvg) algorithms were first proposed. A recent study [49] employed CNN and bidirectional Long Short-Term Memory (LSTM) networks as local models and implemented FedAvg for global optimization. The study revealed that the performance of the model improved compared to the original local model. In another study [50], the authors proposed the Federated Proximal (FedProx) framework, which aims to address the challenges posed by statistical and system heterogeneity in the context of FL.

The domain of EVs is characterized by significant variability in data distribution across different devices. Recent research has proposed novel approaches such as Federated Personalization (FedPer) [51] and Federated Representation Learning (FedRep) [52] to address the challenges arising from this statistical heterogeneity. These methods introduce the concept of dividing the model into standardized layers, which perform weight sharing across the devices, and personalized layers, which are responsible for generating the final personalized output based on the local data of each device. These methods represent a promising strategy for mitigating the negative impacts of statistical heterogeneity in FL for EVs. Several survey papers, including [53] and [54], have listed various comparative experiments where different FL approaches (e.g., FedAvg and FedPer) with diverse local models, such as LSTM and Gated Recurrent Unit (GRU), have been implemented and compared.

Among the five FL algorithms previously discussed, i.e., FedSGD, FedAvg, FedProx, FedPer, and FedRep, each exhibits unique strengths within this domain. While some studies have compared specific pairs of these algorithms, a comprehensive comparison of all five is still warranted to offer a more thorough understanding of their respective advantages and limitations.

III. SYSTEM MODEL

In this section, we present our research object in terms of the research problem statement, the specification of vehicles, and the introduction of energy consumption calculation. The problem statement part provides a comprehensive overview

of the research objectives, while the vehicle specification outlines the parameters of the vehicles used in the experiment. Additionally, the last part talks about the benchmark for calculating the energy consumed in transit.

A. System Setup

We consider a scenario where a BEV company wishes to improve its customers' satisfaction and convenience in the aspect of battery capacity management by enhancing the performance of its energy consumption prediction model while respecting the customers' privacy (e.g., without sharing their trip detail data such as location, time, speed, or the status of the remaining charge of the vehicle battery). Thus, the aim of our research is to implement and improve the energy consumption prediction by keeping the collected private dataset locally but updating the ML models globally with the help of different FL methods. To do this, we assume that each BEV in the system is equipped with an onboard computing/communication unit, which is connected to our sensor group including various sensors capturing different trip attributes (e.g., velocity, trip distance, temperature and road slope) and is able to process the data collected, train a local machine-learning model accordingly and communicate and transfer data with other sections.

Similar to the model setup presented in our previous work [26], we now formulate the BEV energy consumption prediction as follows. Let N be the number of BEVs in our system and $\mathbb{N} := \{1, 2, 3, \dots, N\}$ be the set for indexing these BEVs. For a vehicle $i \in \mathbb{N}$, we assume the number of its trip records is K and denote its j^{th} trip by $\mathbb{T}_{i,j}$ where $j \in \{1, 2, \dots, K\}$. If our sensor group capture the trip features M times in trip $\mathbb{T}_{i,j}$, the trip features will be divided into M sets accordingly. Thus, at a given sampling moment $t \in \{1, 2, \dots, M\}$, the feature set is represented by $f_{i,j}^t$ and consequently, the trip $\mathbb{T}_{i,j}$ could be defined based on its feature sets as:

$$\mathbb{T}_{i,j} = [f_{i,j}^1, f_{i,j}^2, \dots, f_{i,j}^M] \quad (1)$$

Assuming that the length of the trip feature set is L , we could denote the feature set at the sampling moment t in the trip $\mathbb{T}_{i,j}$ by:

$$f_{i,j}^t = [f_{i,j}^t(1), f_{i,j}^t(2), \dots, f_{i,j}^t(L)] \quad (2)$$

where each $f_{i,j}^t(k)$ represents the k^{th} feature in the feature set $f_{i,j}^t$, so accordingly, all the K historical trip records of the vehicle i could be defined as a collection of all trips during the day as:

$$\mathbb{D}^i = [\mathbb{T}_{i,1}, \mathbb{T}_{i,2}, \dots, \mathbb{T}_{i,K}] := [\mathbb{D}^i(1), \mathbb{D}^i(2), \dots, \mathbb{D}^i(L)] \quad (3)$$

where $\mathbb{D}^i(k)$ is a column vector of \mathbb{D}^i where only the k^{th} feature of the trip data is included. Assuming that the last feature, i.e., $\mathbb{D}^i(L)$, represents the energy consumption data E^i of the vehicle i , we could use the other columns in \mathbb{D}^i as the input feature F^i for training the local model for the vehicle i , which could be defined as:

$$F^i := [\mathbb{D}^i(1), \mathbb{D}^i(2), \dots, \mathbb{D}^i(L-1)] \quad (4)$$

and output label data, i.e., the energy consumption data of the vehicle i (E^i), could be defined as:

$$E^i := \mathbb{D}^i(L) \quad (5)$$

Finally, for a given time t , we define the past m observations from the input and output sets as $F_{t-m+1:t}^i$ and $E_{t-m+1:t}^i$, respectively. The output vector has a dimension of m , representing the energy consumption, while the input matrix has a dimension of $m \times (L-1)$, representing the feature set at each given time point with the past m steps in standard time units. Here, we consider the overall energy consumption data during the m steps instead of the point-wise data of the vector, so we define the overall energy consumption within the past m observations as:

$$\hat{E}_{t-m+1:t}^i := \mathbf{1}^T \cdot E_{t-m+1:t}^i \quad \forall t \in \mathbb{K} \quad (6)$$

where $\mathbf{1} \in \mathbb{R}^m$ is the column vector with all entries equal to 1, and $\mathbb{K} := \{m, m+1, \dots\}$ is a feasible indexing set.

Given the notation above, a local model training process for vehicle i can be defined to find a local hypothesis function $\mathbf{H}_i(\cdot)$ which is able to address the following problem:

$$\begin{aligned} \min_{\mathbf{H}_i} \sum_{t \in \mathbb{K}} \left| \hat{E}_{t-m+1:t}^i - \tilde{E}_{t-m+1:t}^i \right| \\ \text{s.t. } \tilde{E}_{t-m+1:t}^i = \mathbf{H}_i(F_{t-m+1:t}^i) \end{aligned} \quad (7)$$

B. Research Object

The studied vehicles are considered the same type of passenger BEVs as shown in Fig. 1. It is equipped with an electric motor of a maximum of 102 kW at 3000 rpm and a battery pack with $120s5p$ cells for a total usable energy of 45 kWh and a maximum power of 160 kW. In order to maximize reliability, vehicle models are constructed through the industrial development software AVL Cruise M.

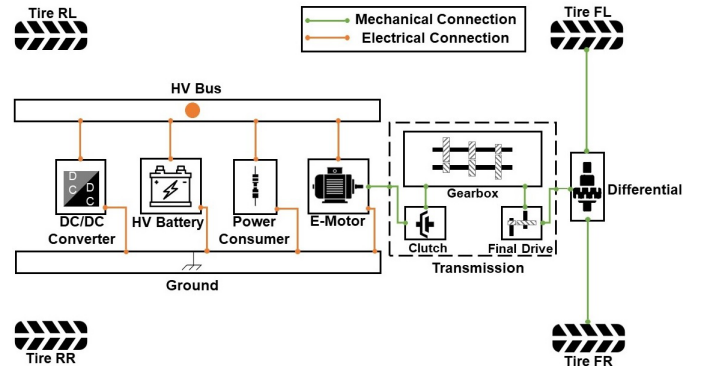


Fig. 1. Vehicle architecture.

In this model, battery management and electric motor control systems are involved to ensure that the vehicle works under safe conditions, i.e., the power limitation of the battery pack and a current limit for the e-motor to match the battery

limitation. The most used functionalities of velocity-dependent regenerative braking, electrical-mechanic parallel braking and battery current limitation are also represented. By modifying the cockpit output signals, the electric drive control calculates the e-motor load signal in both traction and recuperation conditions. If the braking effect of the electric motor torque is below the driver's request in terms of equivalent brake pressure, then the service brakes are supplied with pressure.

C. Energy Consumption Calculation

The model setup has been introduced in the previous sections, while here we present the method used to calculate energy consumption as the benchmark of our work based on the introduction in our previous work in [55]. The energy consumption of the studied EV is all generated from its battery pack. In the model of the battery pack, battery cell current and voltage are applied in iterative calculations to simulate the battery cell dynamics. Starting from each iteration, the battery cell current I_{bc} needs to be calculated firstly by the following formula:

$$I_{bc} = \frac{P_{bp}}{n_{bc} \cdot V_{bc}} \quad (8)$$

where P_{bp} is the power of the battery pack, n_{bc} is the number of battery cells and V_{bc} is the terminal voltage of the battery cell. Here, a standard Resistor-Capacitor equivalent battery model is employed to expose the current-voltage dynamics of a lithium-ion battery cell. The battery's voltage dynamics must obey:

$$\begin{cases} V_{bc} = V_{oc}(SoC) - V_{p1} - R_0(SoC)I_{bc} \\ C_{p1}(SoC) \cdot \frac{dV_{p1}}{dt} = I_{bc} - \frac{V_{p1}}{R_{p1}(SoC)} \end{cases} \quad (9)$$

where V_{oc} is open circuit voltage, which is a function of the battery cell's State of Charge SoC ; V_{p1} represents the transient voltage; R_0 and R_{p1} indicate the effective series resistance and the transient resistance; and each of them is a function of the battery cell's SoC ; C_{p1} indicates the transient capacity, which is a function of the SoC as well. The SoC of the battery cell is calculated by:

$$SoC = SoC_0 - \int_0^t \frac{I_{bc}}{Q_{bc}} dt \quad (10)$$

where SoC_0 is the initial SoC of battery cells and Q_{bc} is quantity of electric charge of battery cells. The battery cell data and calibrated model parameters are sourced from AVL Cruise M.

This work simplifies the battery package computational complexity by not considering the unbalance between cells in the battery pack as their overall EV range will not be affected. So far, the energy consumption of each cell J used in the studied EV can be calculated as:

$$J = \int_0^t (V_{oc}(SoC) \cdot I_{bc}) dt \quad (11)$$

IV. RESEARCH METHODOLOGY

In this section, we briefly introduce centralized and decentralized FL structures, specify the ML models used as our local model candidates and provide a comprehensive overview of some FL optimization algorithms which have been widely employed in a variety of domains.

A. Federated Learning Structures

In general, FL methods can be implemented in both centralized and decentralized structures, which are tailored to various real-world conditions. Specifically, a centralized FL implementation is illustrated in Fig. 2, where each local model is trained on private data collected from a BEV and transmits the requisite information to the centralized server. After calculating and updating the global model, the unique information is sent back to each BEV to update its local model. In this scenario, a powerful centralized server is indispensable, and the requirement for BEV computing units is relatively low.

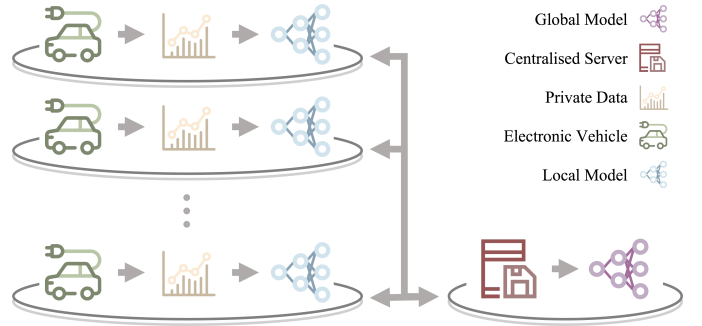


Fig. 2. Centralized FL architecture.

In contrast, for a decentralized FL structure, as demonstrated in Fig. 3, BEVs share essential information and perform local model calculation and updating independently instead of relying on a server. In this case, the requirement for BEV computing units is greater, but the need for a centralized server is eliminated.

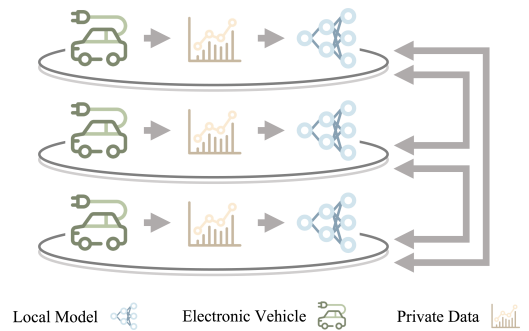


Fig. 3. Decentralized FL architecture.

B. Local Model Selection

Several basic ML algorithms are adopted and compared to obtain the best candidate as our local model. As discussed in Section II, we selected traditional ML algorithms, e.g., RF and XGB, and deep learning algorithms, e.g., GRU and LSTM. The implementation of these models and their performance are provided in the following sections.

C. Federated Learning Algorithms

We apply different FL optimization algorithms in our prediction model section and compare their results to find the best-performing algorithm as our basic design together with the local candidate model. As introduced in Section II, FedSGD, FedAvg, FedProx, FedRep and FedPer are widely used in similar systems, so these federated methods are adopted and their definitions are introduced in this part.

FedSGD: the direct transposition of stochastic gradient descent to the federated setting. The gradients are averaged by the server proportionally to the number of training samples on each node and used to make a gradient descent step. The pseudocode for the FedSGD algorithm is shown in Algorithm 1.

Algorithm 1 FedSGD for BEVs

Notations:

The V BEVs are indexed by v ; the initial global gradient is g_0 , the global gradient in the t^{th} round is g_t and the local gradient for vehicle v in the t^{th} round is g_t^v , the number of data points on vehicle v is n_v , the total number of data points is n , the loss function is $\mathbf{Loss}(\cdot)$, and the local learning rate is η .

Server executes:

```

initialize  $g_0$ 
for each round  $t = 1, 2, \dots$  do
  for each BEV  $v \in V$  in parallel do
     $g_{t+1}^v \leftarrow \text{SgdOpt}(v, g_t)$ 
  end for
   $g_{t+1} \leftarrow g_t - \eta \sum_{v=1}^V \frac{n_v}{n} \cdot g_{t+1}^v$ 
end for

```

SgdOpt(v, g):

```

// run on vehicle  $v$ 
 $g \leftarrow \nabla \text{Loss}(g)$ 
return  $g$ 

```

FedAvg: a generalization of FedSGD, which enables local nodes to perform more than one batch update on local data and exchanges the updated weights rather than the gradients. The pseudocode for the FedAvg algorithm is shown in Algorithm 2.

FedProx: a modified algorithm based on FedAvg, characterized by two modifications. Firstly, partial models that have not been fully trained are allowed, and all partial models participating in the training are integrated regardless of their accuracy. Secondly, the objective function of the local model is composed of the loss function plus the proximal term. The pseudocode for the FedProx algorithm is shown in Algorithm 2.

FedPer: a federated learning optimization method based on SGD which requires activating all clients and aggregating only the base layer parameters into individual personalized models. The pseudocode for the FedPer algorithm is shown in Algorithm 3.

Algorithm 2 FedAvg and FedProx for BEVs

Notations:

The V BEVs are indexed by v ; the initial global weight is w_0 , the global weight in the t^{th} round is w_t and the local weight for vehicle v in the t^{th} round is w_t^v , the number of data points on vehicle v is n_v , the total number of data points is n , the loss function is $\mathbf{Loss}(\cdot)$, the local data of vehicle v is D_v , the local minibatch size is B , the number of local epochs is E , and the local learning rate is η .

Server executes:

```

initialize  $w_0$ 
for each round  $t = 1, 2, \dots$  do
   $V_t \leftarrow$  (Full or partial set of  $V$  BEVs)
  for each BEV  $v \in V_t$  in parallel do
     $w_{t+1}^v \leftarrow \text{AvgOpt}(v, w_t)$  or  $\text{ProxOpt}(v, w_t, w_{t-1})$ 
  end for
   $w_{t+1} \leftarrow \sum_{v=1}^V \frac{n_v}{n} \cdot w_{t+1}^v$ 
end for

```

AvgOpt(v, w):

```

// run on vehicle  $v$ 
 $\mathbb{B} \leftarrow$  (split  $D_v$  into batches of size  $B$ )
for each local epoch  $e$  from 1 to  $E$  do
  for batch  $b \in \mathbb{B}$  do
     $w \leftarrow w - \eta \nabla \text{Loss}(w; b)$ 
  end for
end for
return  $w$ 

```

ProxOpt(v, w^t, w^{t-1}):

```

// run on vehicle  $v$ ;  $\mu$  is the proximal term coefficient
 $\mathbb{B} \leftarrow$  (split  $D_v$  into batches of size  $B$ )
for each local epoch  $e$  from 1 to  $E$  do
  for batch  $b \in \mathbb{B}$  do
     $w^t \leftarrow w^t - \eta \nabla (\text{Loss}(w; b) + \frac{\mu}{2} \|w^t - w^{t-1}\|^2)$ 
  end for
end for
return  $w_t$ 

```

FedRep: a federated learning optimization method based on SGD which requires activating all clients and focuses on learning a shared representation of the data, rather than learning individual models for each device. The pseudocode for the FedRep algorithm is shown in Algorithm 3.

V. DATA & DATASET

This section presents the data in our dataset with both text descriptions and figure visualizations, followed by explanations of data pre-processing and feature selection in detail.

A. Description & Analysis

The dataset used in our work is generated based on Vehicle Energy Dataset (VED), a real-world dataset collected in

Algorithm 3 FedPer and FedRep for BEVs

Notations:

The V BEVs are indexed by v ; the initial standardized layer weight matrix for vehicle v is $W_S^{v,0}$, the standardized layer weight matrix for vehicle v in the t^{th} round is $W_S^{v,t}$, the initial personalized layer weight matrix for vehicle v is $W_P^{v,0}$, the personalized layer weight matrix for vehicle v in the t^{th} round is $W_P^{v,t}$, the number of data points on vehicle v is n_v , the total number of data points is n , the loss function is $\mathbf{Loss}(\cdot)$, and the local learning rate is η .

Server executes:

```
// for FedPer:  $W_S$  are base layers,  $W_P$  are head layers;
// for FedRep:  $W_S$  are head layers,  $W_P$  are base layers.
initialize  $W_S^0 := \{W_S^{1,0}, W_S^{2,0}, \dots\}$ 
initialize  $W_P^{1,0}, W_P^{2,0}, \dots$ 
for each round  $t = 1, 2, \dots$  do
  for each BEV  $v \in V$  in parallel do
     $(W_S^{v,t+1}, W_P^{v,t+1}) \leftarrow \text{Opt}(v, W_S^{v,t}, W_P^{v,t})$ 
  end for
   $W_S^{t+1} \leftarrow \sum_{v=1}^V \frac{n_v}{n} \cdot W_S^{v,t+1}$ 
end for
```

Opt(v, W_S^v, W_P^v):

```
// run on vehicle  $v$ 
 $(W_S^v, W_P^v) \leftarrow (W_S^v, W_P^v) - \eta \nabla \text{Loss}((W_S^v, W_P^v))$ 
return  $(W_S^v, W_P^v)$ 
```

Michigan, USA [56]. We filtered 10 trips from VED with a duration longer than 1,800 seconds. We then extracted their GPS coordinates and the altitude data as the input for our vehicle model introduced in Section III, with the speed data set as the desired velocity of our vehicle model. The output, consisting of multiple trip attributes such as temperature, actual speed and trip distance, is then used as our dataset. In other words, our dataset is a collection of 10 tables of trip information for all 10 vehicles. Each table includes 1,800 rows and 12 columns, representing different attributes respectively.

We have explored the data for 10 vehicles and have discovered a correlation between their average speed and the total amount of energy consumed during a 60-second interval. For example, the relationship between average speed and energy consumption for Vehicle 1 is shown in Fig. 4. It is evident that there is a slight delay in the change of the average speed relative to the energy usage. Following our analysis, we have determined that this delay is approximately 23 seconds.

The energy consumption values in 60-second intervals have a wide range from a minimum of -28.15 Wh to a maximum of 283.38 Wh. The data analysis results revealed the distinct statistical features of individual vehicles, which suggests that they have been exposed to different road conditions and other circumstances in the 1,800 seconds of observation. Additionally, Fig. 5 indicates that there are a number of outliers in the data of Vehicle 1 and Vehicle 5, all of which are valid and

cannot be disregarded.

B. Pre-processing

As introduced above, we found a strong connection between energy consumption and the average speed in a certain Time Step (TS), which makes it highly possible to predict energy consumption based on other features. Thus, we divide the data in each 60-second interval I^i as follows:

$$I^i := \{F_{t-59}^i, F_{t-58}^i, \dots, F_{t-1}^i, F_t^i\} = F_{t-59:t}^i \quad (12)$$

where F_t^i is the set of trip features at time t for Vehicle i . With a full length of 1,800 seconds, the trip record data of one vehicle is divided into 1741 intervals.

Moreover, standardization of the data is implemented to shift the distribution such that the mean is zero and the standard deviation is one. This preserves the essential information regarding the outliers, making the algorithm less susceptible to them, in comparison to Min-Max normalization.

C. Feature Selection

As discussed in Section II, most researchers working on similar research problems used speed, distance, acceleration and altitude as their features. Accordingly, we adopted these trip attributes and employed Principal Component Analysis and RF Regression to select features generated by mathematical transformations (e.g., square, logarithm, and exponent), and based on the results, we selected acceleration a , speed v , the square root of speed \sqrt{v} , the cube of speed v^3 and the square root of the distance moved in each second $\sqrt{\Delta d}$ as the features for model training.

VI. EXPERIMENT & RESULTS

This section outlines our experimental cases, which encompass various experimental settings along with their corresponding results. By default, we assumed an input of the data from all vehicles would result in the best performance.

Case 1: Local Model Comparison

Setups: In this section, we applied various ML models and compared their performance as the candidates of our local model deployed on each BEV. Here we implemented and evaluated RF, XGB, ANN, GRU and LSTM models.

Machine Learning Models: We initially applied the RF and XGB to implement the BEV energy consumption prediction on decentralized datasets, which were separately split into a training set and a test set with a ratio of 3 : 1. In the setup of the RF model, 16 estimators were applied with a maximum tree depth of 9 to run 16 jobs in parallel, while for the XGB model, the regressor from the XGB library with a gradient-boosted tree booster was used to run 50 jobs in parallel.

Deep Learning Models: We adopt a similar structure for all the deep learning models in our work (i.e., ANN, GRU and LSTM) and replace the hidden layers with specific modules (i.e., dense layers, GRU layers and LSTM layers respectively). The deep learning model was set up based on three hidden

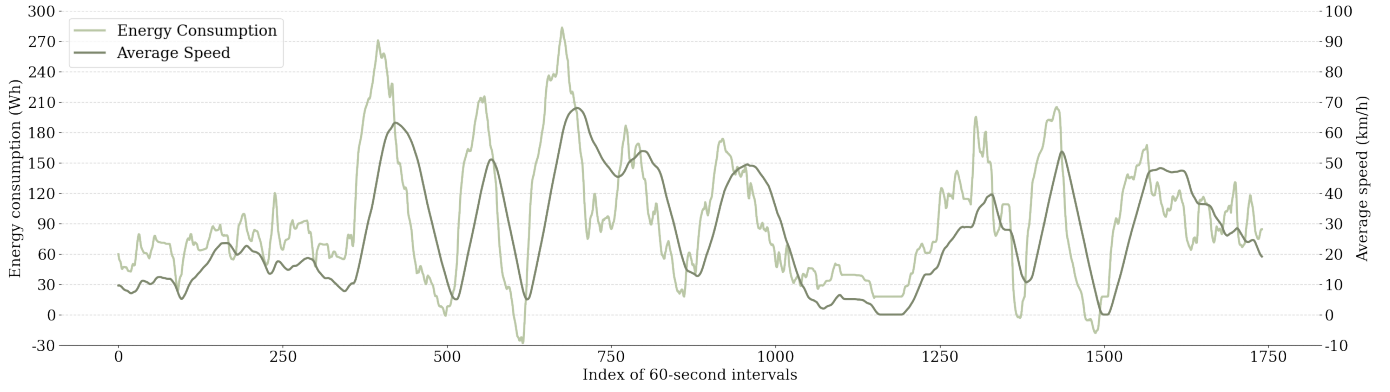


Fig. 4. Effect of average speed on energy consumption in Vehicle 1.

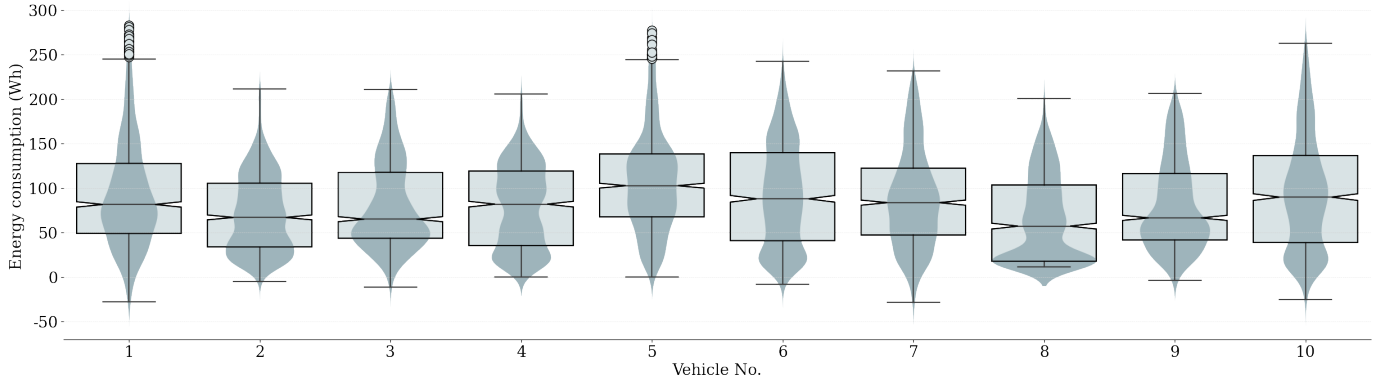


Fig. 5. Box and violin plot of energy consumption for each vehicle.

layers containing 40, 32 and 16 neurons respectively with hyperbolic tangent as the activation function and the dropout layer was applied with a rate of 0.10 and 0.20 between the first and second and the second and third hidden layers separately. Coming from a dense layer, the model output of the model is a single value that by default captures the vehicle’s overall energy consumption over the past 60 seconds. The loss function was chosen as the Mean Absolute Error (MAE) which represents the average difference between the actual energy consumption of a BEV during a trip and the energy consumption predicted by the model. A lower MAE indicates that the model is better at predicting energy consumption and that the vehicle is likely to be more efficient, which can lead to reduced driving range anxiety and lower energy costs. The model was optimized by the Adam optimizer with the default learning rate, i.e., $1e^{-3}$. Each local dataset was split into batches with a size of 70 with 65 epochs.

Results: In Table I, a comparative analysis of the credible and competitive results of these models is presented. The value in each row of this table represents the average value of the MAE for the model trained on the corresponding vehicle’s training set and tested on all vehicles’ test sets.

Evaluations: As observed in Table I, the LSTM model demonstrates the best performance in terms of MAE. It is noteworthy, however, that different datasets with varying attributes may result in different best-performing models. As such, in our study, we selected the LSTM model as the local

TABLE I
LOCAL MODEL PERFORMANCE (MAE) ON EACH VEHICLE (WH).

ID	RF	XGB	ANN	GRU	LSTM
V1	9.5375	9.0951	6.9207	5.3355	5.1759
V2	10.4122	9.7776	8.3997	6.8031	6.7997
V3	10.1580	9.4953	7.2892	6.3033	4.4117
V4	8.9370	8.6519	7.8394	6.6888	4.6765
V5	10.7788	10.6958	8.6680	5.6422	6.1466
V6	9.2424	8.8490	8.2999	4.9306	5.8707
V7	11.5519	10.5905	7.0247	5.3347	4.9729
V8	8.9563	9.0859	9.0698	7.5178	5.7530
V9	12.1133	11.5608	11.0439	10.7237	8.6670
V10	9.0282	8.8239	11.7233	7.1755	8.1254

model for our FL framework. Nonetheless, we acknowledge the need for adjusting the selection of the local model based on the prevailing conditions and characteristics of the dataset in future applications.

Case 2: Federated Learning Algorithm Comparison

Setups: As reviewed in Section IV, five algorithms, i.e., FedSGD, FedAvg, FedProx, FedPer and FedRep, were implemented and evaluated at this stage. It is evident that these algorithms share a similar structure and basic logic, with the exception of FedSGD, which calculates the gradient rather than weights, and FedPer and FedRep, which employ an additional parameter, namely the number of personalized layers.

The performances of the different local model candidates, as shown in Table I, led to the selection of LSTM due to its lowest MAE scores. Given the low complexity of the model, only one personalized LSTM unit was set, with the other layers being standardized.

Results: The comparative analysis of different FL algorithms is presented in Table II. The value in each row of this table represents the average value of the MAE for the model trained on the corresponding vehicle’s training set and tested on all vehicles’ test sets.

TABLE II
FL METHOD PERFORMANCE (MAE) ON EACH VEHICLE (WH).

ID	FedSGD	FedAvg	FedProx	FedPer	FedRep
V1	5.4300	4.0245	4.9574	3.8197	4.4066
V2	6.3252	4.8791	6.8512	4.8160	5.6075
V3	4.3714	3.8117	4.4467	3.6836	4.1196
V4	4.2921	3.4877	4.4171	3.3153	3.9459
V5	4.9364	4.5298	6.4715	4.6095	5.5250
V6	5.1704	3.7653	5.5837	3.8582	4.3317
V7	4.5819	4.1943	5.2512	4.3598	4.9148
V8	5.1873	4.3449	6.0334	4.1380	5.1330
V9	7.5800	7.4539	9.9346	7.5819	9.5547
V10	8.9892	7.5734	7.7679	7.6032	7.5043

Evaluations: As observed in Table II, FedAvg and FedPer exhibit comparable performances on the dataset utilized in the study. As discussed in Section II, the efficacy of personalized FL approaches is highly reliant on the personalized layers selected. Hence, the reason for FedPer and FedRep failing to surpass the performance of FedAvg could be attributed to the relatively low complexity of the local models employed in the study. Notwithstanding the comparable performances of FedAvg and FedPer, the time cost associated with both methods must be carefully considered. Taking into account the time required to complete 15 Iterations (ITR) of FedAvg and FedPer, i.e., around 49 and 58 minutes respectively, we ultimately decided to adopt FedAvg as the global FL method for the subsequent experiments.

Case 3: Impact of Iteration

Setups: To investigate the impact of iteration numbers, the performances of the models with ITR of 15, 30, 45 and 60 were examined based on the LSTM-FedAvg structure. These results were compared to the performance of the local models (i.e., with 0 ITR), which served as the baselines.

Results: Table III presents the impact of iteration on the model performance. The value in each row of this table represents the MAE value of the model trained and tested on the corresponding vehicle’s training and test sets.

Evaluations: As demonstrated in Table III, an increase in the number of ITR is accompanied by a decrease in the MAE for half of the objects (Vehicles 3, 5, 7, 8, and 9), indicating an improved model performance. However, for four objects (Vehicles 2, 4, 6, and 10), the best model performance occurred after 45 ITR. Vehicle 1 had the lowest MAE after 30 ITR.

TABLE III
ITR ON MODEL PERFORMANCE (WH).

ID	LSTM	15 ITR	30 ITR	45 ITR	60 ITR
V1	2.0949	1.0118	0.6384	0.7127	0.6771
V2	1.4466	0.7181	0.5268	0.3533	0.3961
V3	1.5723	0.5057	0.5268	0.5463	0.3087
V4	1.6571	0.8222	0.8466	0.4838	0.6151
V5	1.1317	0.5640	0.5039	0.5823	0.2765
V6	2.2842	0.9905	0.6548	0.5882	0.8435
V7	1.4967	0.7576	0.5935	0.4758	0.4244
V8	1.7994	0.8203	0.8849	0.6794	0.4169
V9	1.3155	0.6690	0.5529	0.3905	0.2754
V10	2.2864	0.9877	0.7184	0.5738	0.7174

This trend can be attributed to the unique nature of the local data. Furthermore, while the model performance improved for some vehicles, the training process’s time requirements increased. Specifically, executing 15, 30, 45, and 60 ITR required approximately 49, 98, 148, and 197 minutes, respectively, which implies that each iteration took about 49 minutes. After careful consideration of both model performance and time requirements, we chose to execute 15 ITR for this study.

Case 4: Impact of Data Split Ratio

Setups: Based on the LSTM-FedAvg structure, we conducted a comparative analysis of model performance across varying train-validation-test splitting ratios, i.e., 4:1:5, 5:1:4, 6:1:3, 7:1:2, and 8:1:1 to investigate the impact of data split ratio.

Results: The impact of data-splitting ratios on model performance is reported in Table IV. The value in each row of this table represents the MAE value of the model trained and tested on the corresponding vehicle’s training and test sets.

TABLE IV
IMPACT OF SPLITTING RATIO ON MODEL PERFORMANCE (WH).

ID	4:1:5	5:1:4	6:1:3	7:1:2	8:1:1
V1	1.3546	1.3068	1.0626	0.7437	1.0118
V2	0.7424	0.6625	0.8641	0.6374	0.7181
V3	1.0652	0.9029	0.7644	0.7448	0.5057
V4	1.2096	1.0056	1.0278	0.7597	0.8222
V5	0.9935	0.7111	0.6575	0.7352	0.5640
V6	1.2573	1.4778	1.1662	1.1626	0.9905
V7	1.0656	0.9155	0.6053	0.5805	0.7576
V8	1.2109	1.0480	1.0135	0.9522	0.8203
V9	0.7191	1.1471	0.9642	0.7911	0.6690
V10	1.6850	1.2798	1.6003	1.0928	0.9877

Evaluations: Based on the results presented in the table, it can be observed that a data splitting ratio of 7:1:2 or 8:1:1 tends to yield the best performance on our dataset compared to the other ratios. In particular, a ratio of 8:1:1 demonstrates superior performance across all metrics. This indicates that an increase in the quantity of training data facilitates enhanced learning from the input under our experimental conditions.

Consequently, in this work, we have selected a data splitting ratio of 8:1:1 due to its superior overall performance.

Case 5: Impact of Input Data Size

Setups: Concerning the input data sizes, we utilized data inputs with varying TS of 60, 90, 120, 150, and 180 timestamps to train the model based on LSTM-FedAvg, with the subsequent performance evaluation.

Results: The results of the experiments are presented in Table V. The value in each row of this table represents the MAE value of the model trained and tested on the corresponding vehicle’s training and test sets.

TABLE V
IMPACT OF INPUT DATA SIZE (TS) ON MODEL PERFORMANCE (WH).

ID	60 TS	90 TS	120 TS	150 TS	180 TS
V1	1.0118	2.0234	2.4310	3.4794	7.2946
V2	0.7181	1.0923	1.2904	1.7201	3.9600
V3	0.5057	1.5067	1.6543	2.4812	3.4214
V4	0.8222	1.5299	2.0712	2.9217	3.2603
V5	0.5640	1.1884	1.4450	2.1414	2.4692
V6	0.9905	1.5533	1.7502	2.6796	3.7042
V7	0.7576	1.1970	1.6349	1.7855	2.5312
V8	0.8203	1.6027	1.7615	2.6084	3.5714
V9	0.6690	0.9991	0.9454	1.5623	1.6180
V10	0.9877	2.0208	2.2899	3.8614	8.7896

Evaluations: As can be seen in the table, the increase in input data size is typically associated with an increase in MAE, indicating poorer model performance. This result may be attributed to the decrease in the number of windows due to the increase in window size, resulting in a reduction of training data and consequent degradation of model performance.

Case 6: Decentralized Approaches

Setups: In order to incorporate various real-world scenarios, experiments were conducted based on the chosen FL approach in a decentralized setup. Using results from LSTM-based local models, we selected Vehicles 3, 4, and 6 as the top three performers (G), and Vehicles 2, 9, and 10 as the three weakest performers (W) to investigate the performance of decentralized FL approaches. From these 6 models, different test groups were formed based on the number of weaker performers as below:

- Three weak performers (0G+3W)
- One good performer with two weak performers (1G+2W)
- Two good performers with one weak performer (2G+1W)
- Three good performers (3G+0W)

Results: The findings are presented in Table VI.

Evaluations: The results indicate that after 15 ITR using the FedAvg algorithm, the performance of all local models in each case improved, demonstrating the efficacy of decentralized FL methods in enhancing BEV energy consumption modeling. However, an increase in the number of good performers does not always equate to an improvement in performance. Specifically, the MAE value of Vehicle 10 increased when

TABLE VI
PERFORMANCE (MAE) OF DECENTRALIZED FEDAVG METHOD (WH).

ID	LSTM	0G+3W	1G+2W	2G+1W	3G+0W
V1 (W)	2.0949	0.2403	-	-	-
V2 (G)	1.4466	-	-	-	0.1956
V5 (G)	1.1317	-	0.1929	0.1892	0.2687
V6 (W)	2.2842	0.3488	0.2770	-	-
V9 (G)	1.3155	-	-	0.1413	0.2301
V10 (W)	2.2864	0.2815	0.3700	0.3106	-

interacting with Vehicles 5 and 6 (1G+2W) compared to being aggregated with two weak performers (Vehicles 1 and 6). Conversely, the interaction among good performers does not always result in the most suitable setup for an individual vehicle model. For example, the best model performance for Vehicle 2 occurs when interacting with Vehicles 9 and 10 (2G+1W), but it becomes worse when aggregated with Vehicles 5 and 9 (3G+0W).

VII. DISCUSSIONS

This section presents a comprehensive discussion of the experiment results in terms of the performance of a decentralized structure and FL applications in the real world.

A. Decentralized Aggregation

In the experiments presented in Section VI, it was observed that the aggregation results of models trained on separate private data were not directly affected by the number or percentage of good performers, but rather a suitable group for aggregation is more crucial for individual models. For instance, for two good performers, Vehicle 5 and 9, the results from interacting with Vehicle 10 were significantly better than those with Vehicle 2. This suggests that the similarity and dissimilarity of data attributes are crucial factors, and exploring the similarity of user behaviours and driving patterns is necessary for achieving better aggregation results.

B. Real-World Application

FL methods are well-suited to edge-cloud computing frameworks. We propose the application of our work in a real-world edge-computing-based system, the framework of which is illustrated in Fig. 6. The top layer comprises a cloud data center, the middle layer consists of multiple edge infrastructures and the bottom layer is composed of base stations and BEVs. Different methods of data transmission and calculation have been considered and marked with different colours to accommodate various communication situations and hardware conditions. We now provide details of the four blocks from left to right in this framework:

- The first block in yellow illustrates the classic centralized method, wherein data provided by BEVs is transferred to the edge server through the base station and then passed to and calculated by the cloud server. This approach does not necessitate BEVs to calculate, but they can request the edge server to calculate the weights in local models.

- The subsequent block in red depicts the fully decentralized method, wherein BEVs communicate with each other directly. This necessitates that the data computing and transmission capabilities of BEVs be highly robust and reliable.
- The third block in blue represents cloud computing, wherein data provided by BEVs is sent to the cloud server directly through the base station, without the requirement of edge infrastructures.
- Lastly, the block in green indicates that data is only transmitted to the edge server, thus requiring the edge server to possess a high capability to calculate and deploy the data.

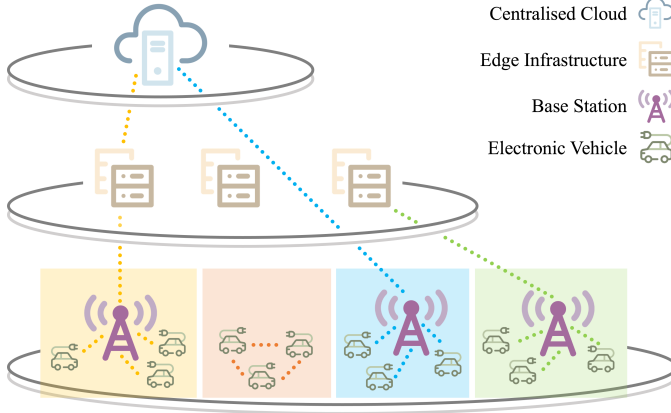


Fig. 6. System framework based on edge computing.

VIII. CONCLUSION & FUTURE WORK

This paper aims to establish a privacy-aware energy consumption modeling framework for connected BEVs. To achieve that, we investigated the performance of various FL algorithms in BEV energy consumption modeling. Based on comparative experimental results and relevant discussions in the previous section, we initially identified the superiority of LSTM and FedAvg as the local model and FL algorithm for our dataset. Subsequently, we examined the impact of ITR, data splitting ratios, and input data sizes on model performance. Through the linear correlation between the number of ITR and time spent, and considering the corresponding model performances, we recommend the application of 15 ITR in our task. Regarding the model performance based on different data splitting ratios, we found that 8:1:1 is a suitable choice for datasets similar to ours. Furthermore, we observed a decrease in model performance corresponding to the increase in input data size, indicating that a TS of 60 timestamps leads to relatively good results. After conducting our experiments, we observed a significant reduction in the MAE of our prediction results. Specifically, we achieved a reduction of up to 67.84% (from 1.5723 to 0.5057 for Vehicle 3) by performing 15 ITR. The average MAE value for all vehicles was around 0.7847, indicating that the mean error for predicting energy consumption within one minute is approximately 0.8 Wh.

In addition, we explored decentralized FL approaches for BEV energy consumption modeling by testing the selected FL

framework on the three best and three worst performers. The results demonstrated the effectiveness of FL methods in this prediction task. Moreover, we provided a detailed description of how to apply FL methods with an edge-cloud computing framework with various setups. We believe that the explorations and relevant analysis we conducted are meaningful and beneficial for future researchers, business operators, and policymakers.

Notwithstanding our extensive experiments and analyses, there are still some potential avenues for improvement. Firstly, the scope of our study could be extended by including a wider range of local model candidates and FL methods. Additionally, in this paper, we made certain assumptions to simplify the presence of cell heterogeneity, which could be addressed by absorbing and analyzing extensive datasets in our future work. Furthermore, augmenting the size of our dataset could help us design better models that enable us to explore personalized FL further. Besides, investigating the performance of models trained on simulated data on a real-world dataset is another aspect that can be explored in future work. Addressing these limitations would contribute to a more comprehensive understanding of FL methods for BEV energy consumption modeling.

ACKNOWLEDGEMENT

The authors would like to thank Rajesh Dande and Samaksh Chandra from Dublin City University for their help with the experiments, and also AVL List GmbH (AVL) for providing access to its advanced simulation technologies and software technical support within the frame of the University Partnership Program. This research was conducted with the financial support of Science Foundation Ireland 21/FFP-P/10266 and 12/RC/2289_P2 at Insight the SFI Research Centre for Data Analytics at Dublin City University.

The VED dataset is available at <https://github.com/gsoh/VED>. Our processed data used for this study is available on GitHub (URL: <https://github.com/SFIessential/FedBEV>).

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