On the V2G Capacity of Shared Electric Vehicles and its Forecasting through MAML-CNN-LSTM-Attention Algorithm

Mingkuo Xu¹, Hui Ren¹, Ping Chen², and Guoyu Xin²

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Abstract

When acting as the shared energy storage and participating in electricity market services, the schedulable capacity that shared electric vehicle (shared EV) will provide to the grid needs in future time needs to be predicted accurately. This research first proposes a method to construct a schedulable capacity dataset for shared EVs based on publicly available shared vehicle rental service data. Secondly, a schedulable capacity evaluation model based on model-agnostic meta-learning, convolutional neural network, long short-term neural network and attention mechanism (MAML-CNN-LSTM-Attention) is proposed. Through the model, the aggregated schedulable capacity of shared EVs in different functional communities for the coming 60 minutes is predicted. Model uses MAML to fine-tune the meta-prediction network through multi-task training to quickly adapt to feature changes caused by different travel habits of different functional communities; CNN-LSTM is used to learn spatial features of schedulable capacity and efficiently extract high-dimensional temporal features from historical sequences; Attention mechanism is used to further improve model prediction accuracy. Simulations show that the model proposed in this paper outperforms other existing models and can reliably predict the schedulable capacity for different date types and functional areas, providing useful decision aids for shared EV operators to participate in market services.

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**Keywords**
Shared electric vehicles (SEVs); Demand response (DR); Convolutional neural network (CNN); Long short-term memory neural network (LSTM); Attention mechanism; Model-agnostic meta-learning (MAML); V2G Capacity

Please see the next page for the main text file.
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1. Introduction

Shared Electric Vehicles (Shared EVs) is not only as a representative of shared economy [1] and green transportation [2], and also occupy a certain position in the transformation of low carbon electric system [3]. Shared EVs can be treated as shared energy storage and aggregated to participate into the operation of power system through demand response program [4] or as a new form market players with the increasing opening of the power market to the user side [5]. Compared with private electric vehicles, shared EVs belong to the same economic entity, the uncertainties and discrepancies caused by different user's mileage anxiety and preference for economic benefits will be less, therefore, it is more applicable as one of the flexible sources to increase the reliability and economy of the power system with a high share of renewable generations.

The key to achieve this goal is high-precision, fine-grained prediction of shared EVs’ Vehicle-to-Grid (V2G) capacity. There are few prediction studies on the provision of schedulable capacity for the grid by shared EVs participating in DR services. References [6][7] studied the prediction of schedulable capacity by deep learning methods, among them, the literature [6] proposes a schedulable capacity prediction model for 1-minute and 24-hour ahead forecasting based on the actual charging and discharging data. Reference [7] proposes an EV charging model and a prediction model for the number of EVs in the specified area in the next five years based on the spatial distribution and user habits of three types of typical EVs. Reference [8] mainly studies the optimal scheduling model of shared EVs through different demand response policy. Reference [9] modeled and analyzed the economic and environmental co-benefits of a shared electric vehicle fleet participating in a Vehicle-to-grid (V2G) service.

The related research mainly has the following limitations: 1) The travel laws of shared EVs are different from the travel laws of private electric vehicles/electric buses. Due to the privacy issues and business principles of shared electric vehicle travel data, there is currently no analysis of shared electric vehicle travel data; 2) Relevant studies have not considered the difference of driving habits among commercial, residential, industrial and recreation area. Due to the different traffic road conditions and the number of shared EVs in different functional areas, there are differences in travel user behavior habits, and the number of shared EVs and their operation and maintenance modes, the establishment of a meta-learning model with strong generalization ability and the intervention of attention mechanism is of great practical significance for the solution of small sample multi-task problems [10]. Based on the currently available data sets of time-based rental services for Shared EVs abroad, this paper establishes a three-dimensional data sample (spatial location and time) of shared EVs’ V2G capacity, and proposes a model to predict the shared EVs’ dispatchable V2G capacity through MAML-CNN-LSTM-Attention. The method proposed in this paper conducts research based on the travel laws of shared car users and objectively evaluates the schedulable capacity.

With the gradual increase of renewable energy units and the increase of system uncertainty, it will be difficult for traditional power plants to stabilize the system frequency by providing rotational inertia [11], thus, the power system wants to use demand-side resources with lower cost and faster response to participate in auxiliary services. With the popularity of shared EVs and the construction of smart grids, it becomes possible for shared EVs as a high percentage of new energy to enter the grid for peaking, and through V2G contracts between EV aggregators and higher-level grids, and
shared EVs and EV aggregators, shared EVs in park are dispatched in a unified manner during peak grid load periods. The EV aggregators obtain the latitude and longitude coordinate information of each shared EV through the AMI system, and use the evaluation model proposed in this paper as a decision aid to predict the schedulable capacity of each shared EV and aggregate it to get the total schedulable capacity, and submit the V2G bid power to the grid one hour in advance to participate in the standby service.

2. V2G potential analysis of Shared Electric Vehicles

In this section, we first analyze the V2G potential of shared vehicles based on the time-sharing leasing service data provided by a foreign car-sharing operator [12]. The data set contains the parking latitude and longitude coordinates of 270 shared cars in the project from November 17, 2019 to January 31, 2020, and the time resolution is 3 minutes. The data contains [Data index, Latitude, Longitude, Number of parked vehicles, ID of parked vehicle, GPS instantaneous acquisition time], among them, [Data index, ID of parked vehicle] are desensitized anonymous codes. In this paper, the range of the study area is longitude (east longitude): 34.74923-34.79234, latitude (north latitude): 32.0315-32.14325, data out of this range will not be considered, and the selected research area is about 52.27km².

2.1. DR potential of shared electric vehicles

The parking situation in any time (for example at 5:00 on December 1, 2019) is shown in Fig. 1a through a heat map. In the figure, the spatial distribution of hot spots for Shared EVs parking is mainly concentrated in the urban area, while there are few on urban edges. Different vehicle aggregation in different regions represent different V2G sources and different potential to participate in V2G.

In this section, we define ‘travel rate’ as the ratio of the number of Shared EVs in a driving state at a certain time to the total number of Shared EVs registered in the project. The pattern of travel rate of multiple consecutive working days and non-working days is shown in Fig. 1b, Fig. 1c and Fig. 1d, and it shows a certain periodicity and regularity. Figure shows that the travel rate of Shared EVs at 6:00 on working days shows a sudden increase, and the morning and evening travel peaks appear at 6:00 -- 8:00 and 17:00-19:00 respectively, but the “morning and evening peak” feature of non-working days car-sharing travel rate curve is not obvious. During the nighttime, the minimum travel rate is close to 1%, and the highest one is close to 40% during daytime peak hours. Therefore, even during the peak hours, there are still 60% of vehicles are idle. Therefore, the shared EVs can serve as an important source of V2G through demand response program or participating in market services.

2.2. Travel regularities of Shared EV aggregation of different urban communities

Power supply planning within a city is usually according to grids. Since the adjacent grids are likely to be powered by the same distribution network line, from the perspective of load response, aggregating the redundant capacities of vehicles parked in multiple adjacent grids are beneficial for designing DR strategies and mitigating DR capacity fluctuations.

The area shown in Fig. 1a is then divided into 81 urban community grids by latitude and longitude coordinates, including 32 residential areas, 22 commercial areas, 17 industrial areas, and 10 leisure areas. To further analyze the
travel patterns of each functional area, we further define ‘travel volume’ of a functional area as the number of vehicles in the driving state with the travel starting point in the functional area. Fig. 2 shows the curve of travel quantity in each functional area in 24 hours on different date types.

In Fig. 2a, the weekday travel peak in the residential area is between 7:00-9:00, and the commuting pattern is more obvious, while the non-working day travel volume peaks slightly delayed compared with the weekday. As shown in Fig. 2b, in the non-working day, travel volume peaks in the commercial area between 11:00-13:00 and 20:00-21:00, in the weekday significantly lower than the non-working day. In Fig. 2c, the travel volume peaks in both weekday and non-working day in industrial areas during the 18:00-20:00 with more fluctuation in the former; in Fig. 2d, the weekday travel volume is significantly lower than the non-working day travel volume in the leisure area, and the trip volume curve fluctuates more gently than non-working days.

3. Estimation of aggregated schedulable capacity of shared EVs of different community

Fig. 3 gives the process of obtaining SOC sample data through the original 3min shared electric vehicle parking latitude and longitude coordinate information, the process includes three parts of data pre-processing, dividing functional area, calculating driving mileage and power consumption. Moreover, after the infrastructure and communication are improved, the SOC data of the shared vehicles parked every 3 minutes can be directly obtained at the same time to realize the online prediction function. Therefore, since the current public data set does not contain this information, it is necessary to estimate the SOC data of shared electric vehicles parked at each parking lot every 3 minutes.

3.1. Data preparation — 3-minute V2G response capacity estimation of aggregated shared EVs

In this section, we propose a method to estimate the 3-minute available V2G capacity of aggregated shared electric vehicles by the mile estimation based on travel trajectory of each single vehicle. Through the proposed method, the training data sets can be established for the machine learning based forecasting model we propose in the next section.

3.1.1 Mile estimation of a shared vehicle: According to the historical spatial location data of shared EVs every three minutes, we extracted the Origin and Destination (OD) point of every shared EVs within one day. Assuming that the latitude and longitude coordinates of the starting point O and ending point D of the $j$th shared EVs in the $j$th trip are $(\text{lat}_O, \text{lng}_O)$ and $(\text{lat}_D, \text{lng}_D)$, and the actual mile between OD points of the $j$th shared EVs in the $j$th trip is estimated as follows:

$$s_{OD,j} = \theta s_{OD,j}$$ (1)

$$s_{OD,j} = 2R \cdot \arcsin \left( \sin^2 \left( \frac{\text{lat}_O - \text{lat}_D}{2} \right) + \cos(\text{lat}_O) \cdot \cos(\text{lat}_D) \cdot \sin^2 \left( \frac{\text{lng}_O - \text{lng}_D}{2} \right) \right)^{\frac{1}{2}}$$ (2)

where $s_{OD,j}$ is Euclidean distance of OD point of $j$th trip of shared vehicle, $\theta$ is the tortuous coefficient of urban road, defined as the ratio of the actual distance between two points in the city to the straight-line distance. R is the radius of the earth. For details of the parameters in equation (2), please see the Appendix.

3.1.2 Available V2G capacity estimation of shared EVs aggregated by communities with different functions: Reference [13] shows that the power consumption per mile of electric vehicle is related to the average speed of the vehicle when driving through the road section in a certain period of time, and the power consumption per mile of the $j$th trip of the $i$th shared electric vehicle can be estimated by (3) as follows:

$$ECF_{i,j} = 0.247 + 1.52/\bar{V}_i - 0.004\bar{V}_i + 2.992 \times 10^{-5}\bar{V}_i^2$$ (3)

where $ECF_{i,j}$ (kWh/km) is the power consumption per mile of electric vehicle, $\bar{V}_i$ (km/h) is the average speed of the vehicle with the mile of $s_{OD,i,j}$ in the time $t$ of the $j$th trip.
Therefore, we defined the “schedulable capacity” of shared EVs in a functional area at time $t$ to be the sum of the remaining power of the shared EVs parking at time $t$ minus the minimum amount of power retained to prevent over-discharge, which is taken to be 20% of the EVs capacity [14]. The schedulable capacity $SOC_k$ is given by (4)-(5) as follows:

\[
SOC^i_{t,k} = BE - \sum_{j=1}^{M} SOD_{i,j} \times ECF_{i,j}
\]

\[
SOC_k = \sum_{i=1}^{N} SOC^i_{t,k} - 20\%BE \times N
\]

where $SOC^i_{t,k}$ is the schedulable capacity of the $i^{th}$ shared EVs at time $t$, $BE$ is the battery’s capacity of each shared EV, $M$ is the number of trips of the $i^{th}$ shared electric vehicle before time $t$ of the day, $N$ is the total number of shared EVs in a functional area at time $t$, and $k \in \{ \text{Commercial areas, residential areas, industrial areas, recreational areas} \}$.

In Fig. 4 we use 3 heat maps to shown the changes of schedulable capacity in each community at 5:00 am, 6:00 am and 7:00 am. The depth of color in each community represents the aggregated schedulable V2G capacity in the community at the given time. The darker, the more schedulable capacity is. When more EVs arrive at a community than EVs leaving from the same community, more schedulable capacity is obtained in the community, as community marked by red rectangle in Fig. 4. Contrary, fewer schedulable capacity is obtained, as community marked by yellow rectangle in Fig. 4.

Thus, a three-dimensional dispatchable V2G capacity samples of shared EVs in 81 aggregated communities with a resolution of 3 minutes are generated by the method in this section, which contains both temporal and spatial information and can be used for the training and validation of the spatio-temporal prediction model of the schedulable capacity of shared electric vehicles proposed in next section.

4. Hourly schedulable V2G capacity forecasting based on MAML-CNN-LSTM-Attention

In the UK’s ancillary service market, DR resources submit the reserve capacity and price bidding plan [15], and the balancing mechanism procure services such as frequency response, reactive power and backup capacity 1 hour before the actual operating time. Shared EVs can participate ancillary service market through V2G. The response capacity deviation is generally required to be within ±5% [16]. Therefore, a fine and accurate hour ahead forecasting of V2G capacities is the precondition of shared EVs participating in the ancillary service market.

4.1. CNN-LSTM-Attention based forecasting model

In this section, we take historical data as input of CNN architecture to effectively reduces the complexity of feature extraction and data reconstruction and improves the quality of data features [17]. Then the abstracted feature vectors of different time form a new time series and is as the input of a LSTM network to learn the internal dynamic patterns. Moreover, we introduce attention mechanism to analyze the importance of each historical moment to the forecasted capacity. Through the attention mechanism, the temporal correlation between sample data is captured and the prediction accuracy of the model is further improved.

The structure of the CNN-LSTM-Attention model is shown in Fig. 5. The input vector is $x = [x_1, x_2, ... x_t, ... x_n]^T$.

The detail explanation of the proposed model is as the following:

(1) The CNN framework is composed of two one-dimensional convolution layers (activation function is ReLU), two pooling layers (maximum pooling) and a full connection layer, through which the feature of the input historical sequence is extracted. After the processing of convolution layers and pooling layers, the original data is mapped to the feature space of the hidden layer, then the full-connection layer structure is constructed to convert and output, and the feature vector is extracted. The activation function of full connection layer is Sigmoid. The output feature vector $H_e$ of the CNN layer is as follows:

\[
H_e = \sigma(W_e \cdot x + b_e)
\]
\[
\begin{align*}
    i_t &= \sigma(W_i \cdot [h_{t-1}, h_{cl}] + b_i) \\
    f_t &= \sigma(W_f \cdot [h_{t-1}, h_{cl}] + b_f) \\
    o_t &= \sigma(W_o \cdot [h_{t-1}, h_{cl}] + b_o) \\
    \tilde{c}_t &= \tanh(W_c \cdot [h_{t-1}, h_{cl}] + b_c) \\
    c_t &= f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \\
    h_t &= o_t \odot \tanh(c_t)
\end{align*}
\]

where \( h_t \) is the hidden state of LSTM unit at time \( t \), \( \sigma \) is Sigmoid function, \( \tanh \) is the activation function, \( W \) is weight coefficient matrix, \( b \) is bias term, \( \odot \) is the Hadamard product, \( i_t \), \( f_t \), \( o_t \), \( \tilde{c}_t \) and \( c_t \) are the input gate, the forget gate, the output gate, the candidate state of the unit and the current state of the unit respectively.

(3) The output of Attention layer at time \( t \) is as follows:

\[
\begin{align*}
    \alpha_t &= \frac{\exp(e_t)}{\sum_{k=1}^{n} e_k} \\
    e_t &= u_c \tanh(W_c h_t + b_c) \\
    s_t &= \sum_{k=1}^{n} a_t h_t
\end{align*}
\]

where \( \alpha_t \) is the attention weight, \( e_t \) is the attention weight determined by \( h_t \) at the moment \( t \), \( u_c \) and \( W_c \) are the weight coefficient matrix respectively, and \( b_c \) is the bias term.

The \( y_t \) of the output layer at time \( t \) is as follows:

\[
    y_t = \text{Sigmoid}(w_0 s_t + b_0)
\]

where \( w_0 \) is the weight matrix, \( b_0 \) is the deviation vector, and this paper selects the Sigmoid function as the activation function of the dense layer.

### 4.2. Model-agnostic meta-learning method and training strategy

Since different functional areas exists in the studied zone, and in order to realize multi-task prediction of schedulable capacity in different functional areas, the original LSTM model is improved through the Model-agnostic meta-learning (MAML) method. Therefore, the prediction model will obtain stronger generalization capability and fast adaptation capability for multi-tasks.

When MAML faces multi-task prediction, the starting parameters of the next task are obtained by gradient descent from the training set and test set of the new task. The initialization parameters of each new task have been fine-tuned on the previous task, so that it can rapidly iterate in the
Determine the model input data and output expectations.

Build the CNN-LSTM model.

Calculate cell state and hidden layer state, Adam optimizer updates weights.

Construct an Attention layer to assign different weights to the input time series.

Determining the network structure and parameters of the composite model.

Rolling prediction of dispatchable capacity value for forecast date.

Output prediction result.

Calculate the prediction evaluation index.

Inverse normalization is used to restore data.

Output optimal parameters.

Training each task to obtain initialization parameters: $\theta = \theta_i$.

Extract tasks $\{T_1, T_2, ..., T_p\}$ from the task set.

Calculate the loss function based on the initialization parameter $\theta_i$ of the task $T_i$.

Gradient descent method to get the network parameters of task $T_i$.

$a \theta = \theta_{i-1} - \alpha \nabla L_{S_i}(f_{\theta_{i-1}})$

Calculate the loss function and its gradient based on $\theta_i$, and optimize the main network parameters.

$\theta \leftarrow \theta - \beta \nabla \theta \sum_{i=1}^{p} L_{T_i}(f_{\theta_i})$

Whether the outer loop iteration ends.

Output optimal parameters.

Original dataset

{Training set, Test set}

Determine the model input data and output expectations.

Data preprocessing to construct historical SOC datasets.

Historical data

Date type

Weather factor

Determine eigenvectors

Determine the input dataset and divide the dataset.

[Training set, Test set]

CNN convolutional layer extracts data features, and pooling layer filters information.

Flatten layer converts information into one-dimensional vectors.

Build the CNN-LSTM model.

Calculate cell state and hidden layer state, Adam optimizer updates weights.

Construct an Attention layer to assign different weights to the input time series.

Determining the network structure and parameters of the composite model.

Rolling prediction of dispatchable capacity value for forecast date.

Output prediction result.

Calculate the prediction evaluation index.

Inverse normalization is used to restore data.

Output optimal parameters.

Fig. 6. Forecasting model framework of MAML-CNN-LSTM-Attention

MAML training part

1. The MAML algorithm finds the optimal parameters of multi-task by learning the distribution of similar tasks. The algorithm includes an inner loop and an outer loop, where the inner loop learns the parameters of specific tasks and uses gradient descent to minimize the loss to find the optimal parameters of each task, and the outer loop updates the randomly initialized model parameters by calculating the gradient of each new task relative to the optimal parameters, then takes the updated model parameters as the initial parameter values of the next task [19].

2. To further illustrate the MAML multi-task training strategy, the basic model is defined as a neural network $f_\theta$ with meta-parameters $\theta$, and the initial parameter is $\theta_0$. After extracting task $T_i \in \{T_1, T_2, ..., T_p\}$, update the network parameter $\tilde{\theta}_i$ by learning the support set data $S_i$ of task $T_i$, that is, the inner loop process is as follows:

$$\tilde{\theta}_i = \theta_{i-1} - \alpha \nabla \theta \sum_{i=1}^{p} L_{S_i}(f_{\theta_{i-1}})$$

where $\alpha$ is the learning rate of the new task learner, and $L_{S_i}(f_{\theta_{i-1}})$ is the loss function of the task $T_i$ on the support set.

3. The update process of the outer loop is as follows:

$$\theta \leftarrow \theta - \beta \nabla \theta \sum_{i=1}^{p} L_{T_i}(f_{\tilde{\theta}_i})$$

where $\beta$ is the learning rate of the meta-learner, and $L_{T_i}(f_{\tilde{\theta}_i})$ is the loss function of the task $T_i$ on the target set.

4. The MAML-CNN-LSTM-Attention forecasting framework is shown in Fig. 6.

4.3. Data normalization processing

In Figure 6, meteorological factors and other variables are also included in the datasets, since they affect users’ travel plan. These factors as listed in Table 1. Features are further normalized to eliminate the scale interference through (12).

$$\tilde{C}_t = \frac{C_t - C_{\text{min}}}{C_{\text{max}} - C_{\text{min}}}$$

where $C_{\text{max}}$ and $C_{\text{min}}$ are the maximum and minimum values of the selected feature, respectively; $C_t$ is the actual value, and $\tilde{C}_t$ is the normalized value. The temperature data is also mapped to the [0,1] interval as other features using the rule given in Table 2.

4.4. Evaluation Metrics of the prediction model

Mean absolute percentage error (MAPE) and goodness of fit ($R^2$) are used to evaluate the performance of the prediction model:

$$MAPE = \frac{1}{N} \sum_{t=1}^{N} \left| \frac{\tilde{C}_t - C_{\tilde{d}}}{C_t} \right|$$
Table 1 Selection and classification of eigenvectors

<table>
<thead>
<tr>
<th>Category</th>
<th>Features</th>
<th>Illustration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Date type</td>
<td>Current time t</td>
<td>Current time t of the day of the forecast period</td>
</tr>
<tr>
<td></td>
<td>Whether it is a working day</td>
<td>0 is no, 1 is yes</td>
</tr>
<tr>
<td>Historical data</td>
<td>Historical schedulable capacity</td>
<td>Schedulable capacity of period $(t - \Delta t, t)$ on the day of the forecast period</td>
</tr>
<tr>
<td>Meteorological factors</td>
<td>Temperature (degree centigrade)</td>
<td>Temperature of the $(t - \Delta t, t)$ period on the day of the forecast period</td>
</tr>
<tr>
<td></td>
<td>Weather condition</td>
<td>0 is sunny, 1 is not sunny</td>
</tr>
</tbody>
</table>

Table 2 Normalization of temperature data

<table>
<thead>
<tr>
<th>Temperature (°C)</th>
<th>Quantization</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt; 0</td>
<td>0.2</td>
</tr>
<tr>
<td>0 – 10</td>
<td>0.4</td>
</tr>
<tr>
<td>10 – 20</td>
<td>0.6</td>
</tr>
<tr>
<td>20 – 30</td>
<td>0.8</td>
</tr>
<tr>
<td>&gt; 30</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 3 Comparison of the performance of 5 prediction models

<table>
<thead>
<tr>
<th>Models</th>
<th>LSTM-Attention</th>
<th>MAML-LSTM-Attention</th>
<th>MAML-Transformer</th>
<th>CNN-GRU-Attention</th>
<th>MAML-CNN-LSTM-Attention</th>
</tr>
</thead>
<tbody>
<tr>
<td>Date Types</td>
<td>Working</td>
<td>Non-working</td>
<td>Working</td>
<td>Non-working</td>
<td>Working</td>
</tr>
<tr>
<td>MAPE%</td>
<td>5.37</td>
<td>5.52</td>
<td>3.54</td>
<td>3.85</td>
<td>2.39</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.916</td>
<td>0.903</td>
<td>0.932</td>
<td>0.929</td>
<td>0.960</td>
</tr>
</tbody>
</table>

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (c_i - \hat{c}_i)^2}{\sum_{i=1}^{N} (c_i - c_{aver})^2} \quad (14)$$

Where $c_i$, $\hat{c}_i$ and $c_{aver}$ are respectively the predicted value, actual value and average value of the schedulable capacity of shared EV at time $t$, and $N$ represents the length of the time series of the test set.

MAPE indicates the consistency of the prediction results of the schedulable capacity value. The smaller the data value, the smaller the prediction deviation; $R^2$ represents the fitting degree of the prediction curve, and the better the fitting effect is, the closer it is to 1.

5. Simulation and results analysis

5.1. Input sample data

The driving data of shared EV is from a foreign car sharing project from November 17, 2019 to January 31, 2020 [12]. The data resolution is 3 minutes.

The raw data is processed through the method introduced in Section III to obtain a training data set and a validation data set. Since only 1% of shared EVs are utilized at 5:00 am, we assumed that the vehicles in this shared electric vehicle project are fully charged at 5 a.m., and the data from 5:00-24:00 every day is selected to construct the dataset, and a total of 28880 periods are selected.

The input data set is divided into supporting set, target set, training set and test set. The inner loop of MAML updates the model parameters by being trained with the support set, and the outer loop calculates the loss function of the target set and performs gradient fine-tuning. This internal and external double-layer optimization method enables the parameter training on the support set to be generalized to the target set. Then the model is trained by the training set, and the error is minimized through the test set. In this simulation, the data from November 17, 2019 to December 23, 2020, a total of 14060 time periods, are selected as the support set. Data from December 24, 2019 to January 8, 2020, a total of 6080 time periods are selected as the target set. Data from January 9, 2020 to January 24, 2020, a total of 6080 periods, is selected as the training set. Data from December 25, 2019 to January 31, 2020, a total of 2660 periods, are selected as the test set.

The feature vector described in Table 1 is taken as the input variable of the MAML-CNN-LSTM-Attention based forecasting model, and the output is the schedulable capacity value at $(t + 60)$. In this paper, we set the batchsize to be 30 for the simulation, i.e., we use the historical data of the past 90 minutes to predict the schedulable capacity of 60 minutes from the current time.

5.2. Analysis of forecast performance

Accurate prediction of schedulable capacity of shared electric vehicles in different date types and functional zones is important for shared EVs participating in market service through V2G. To verify the performance of the proposed MAML-CNN-LSTM-Attention based forecasting model, and the output is the schedulable capacity value at $(t + 60)$. In this paper, we set the batchsize to be 30 for the simulation, i.e., we use the historical data of the past 90 minutes to predict the schedulable capacity of 60 minutes from the current time.
Fig. 7. Comparison of schedulable capacity prediction methods of shared electric vehicle
(a) Working days schedulable capacity in residential area, (b) Non-working days schedulable capacity in residential area,
(c) Working days schedulable capacity in business area, (d) Non-working days schedulable capacity in business area,
(e) Working days schedulable capacity in industrial area, (f) Non-working days schedulable capacity in industrial area,
(g) Working days schedulable capacity in recreation area, (h) Non-working days schedulable capacity in recreation area
be stable. To prevent overfitting, a Dropout layer is added, and 20% of the neurons in the model are randomly disabled.

Table 3 gives the performance of each model on the forecasting of the schedulable capacity. Through the result, it can be seen that:

1. Multi-task training improves the model’s performance. The proposed model, MAML-LSTM-Attention, and MAML-Transformer are better than LSTM-Attention model in terms of MAPE% and $R^2$. Among which, the MAPE% of the MAML-LSTM-Attention model is decrease by 1.83% and 1.67% than the LSTM-Attention model for the working day and non-working day respectively. The $R^2$ of the former is also slightly higher than that of the latter. The reason is that through the MAML algorithm, better initial parameters of LSTM is obtained and the model can quickly adapt to prediction tasks with different date types and different functional areas.

2. We compared the MAML-LSTM-Attention model, the MAML-Transformer model, and the proposed model. Due to the multi-attention mechanism, for the MAML-Transformer, the MAPE% is decreased by 1.15% and 1.31% for weekdays and non-workdays than those of the MAML-LSTM-Attention model, because more reasonable weights are decided to enhance the representation of key information. Even though, the proposed model by adding CNN performed better than MAML-Transformer model, because through CNN, the mining of information is more effective.

3. We compared CNN-GRU-Attention model, MAML-LSTM-Attention model and the proposed model. Without MAML, CNN-GRU-Attention still decreases MAPE% by 1.29% and 1.37% than MAML-LSTM-Attention for working day and non-working day respectively, because the introduction of CNN can capture the dynamics of features and offset the loss on accuracy without MAML training. Further comparing the CNN-GRU-Attention with the proposed model, we found that the MAPE% decreases 1.12% and 0.99%, while the $R^2$ increase 0.014 and 0.017 respectively, showing that with the introduction of MAML, the performance of the prediction can be further improved.

The schedulable capacity of different functional areas in 24-hour predicted by each model under different date types are shown in Figure 7. It can be seen that:

1. The prediction results of each model are basically the same in terms of following the trend of the actual schedulable capacity. However, compared with other prediction models, the proposed MAML-CNN-LSTM-Attention model has higher model stability and can better fit the trend of the true schedulable capacity. That is, the MAML-CNN-LSTM-Attention algorithm performs well in time series prediction of schedulable capacity and has the best prediction performance.

2. The schedulable capacity of shared EV in time of the four different functional zones are quite different and show totally different trends. The peak and valley of schedulable capacity in each functional zone are not consistent. Therefore, different DR strategies (dispatchable time period and schedulable capacity) should be formulated according to the distribution of schedulable capacity to time in different functional zones to ensure the feasibility of DR schemes. It further illustrates the necessity of predicting the schedulable capacity of shared electric vehicles in different function areas separately.

5.3. Algorithm prediction time analysis

When the forecasting of schedulable capacity of shared EVs being adopted to making decisions for different market services, the speed of the algorithm and the prediction performance of the model should be both. Table 4 gives the training time and forecasting time of the abovementioned models.

1. The MAML-LSTM-Attention model gives results faster than the LSTM-Attention model, indicating that multi-task learning can efficiently complete multiple learning tasks compared to single task training;

2. The MAML-Transformer model is better than the MAML-LSTM-Attention model with regard to the training time and forecasting time, benefiting from the self-attention mechanism and the feedforward neural network structure, and the excellent parallel computing capability;

3. The proposed MAML-CNN-LSTM-Attention model has a longer training and operation time than the MAML-Transformer model. But considering that the former has a further improvement in the prediction accuracy than the latter, and considering the response time requirements when participating in the grid backup service, the prediction time of the MAML-CNN-LSTM-Attention algorithm is within the acceptable range, its better performance on prediction accuracy makes it more applicable for shared EVs’ agent when bidding in electricity market.

6. Conclusion

Shared electric vehicles in general belong to the same economic entity, which makes it easier for the agent to participate in grid backup services or other market activities than private electric vehicles. Limited by the data privacy and other business, there is currently no open data to support the research on the feasibility and reliability of shared electric vehicles participating in grid backup auxiliary services. Based on the 3-minute resolution car rental data provided by a foreign shared vehicle operator, this paper proposes a method for constructing a shared EVs’ SOC data set, and a MAML-CNN-LSTM-Attention-based model for predicting...
the schedulable capacity of shared electric vehicles. Using the constructed data set, the time-space prediction of the schedulable capacity of shared electric vehicles is realized. Finally, the following conclusions are obtained through the study:

(1) The method designed in this paper only needs the travel spatio-temporal information of the vehicle and the vehicle parking coordinates with a certain resolution to construct a spatio-temporal data set of shared EVs. With the widespread use of smartphone apps and the promotion of Ubiquitous IoT, it is very easy to obtain the above data, so the method proposed in this paper is highly feasible.

(2) The forecasting model proposed in this paper has high prediction accuracy and strong generalization ability for multi-task prediction, and the evaluation results lay a foundation for future studies, such as the risk evaluation of shared EVs participating in backup auxiliary services.

7. References


Appendices

Two points $P_1$ and $P_2$ on the sphere are known with latitude and longitude $(\phi_1, \lambda_1)$ and $(\phi_2, \lambda_2)$, respectively, and the latitude and longitude coordinates are converted to right-angle coordinates by means of equation (A1).

\[
\begin{align*}
\begin{cases}
  x &= R \cos \phi \cos \lambda \\
  y &= R \cos \phi \sin \lambda \\
  z &= R \sin \phi
\end{cases}
\end{align*}
\]  

(A1)

For the shortest arc length between two points on the sphere, first calculate the straight-line distance between the two points, to get the angle between the two points and the line between the center of the circle, you can calculate the radius of the ball to get the arc length of the sphere.

\[
|P_1P_2| = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2 + (z_1 - z_2)^2}
\]

(A2)
Combining (A1) and (A2) yields the distance between the two points expressed in latitude and longitude (A3).

\[ |P_1P_2|^2 = R^2[(\cos \varphi_1 \cos \lambda_1 - \cos \varphi_2 \cos \lambda_2)^2 + (\cos \varphi_1 \sin \lambda_1 - \cos \varphi_2 \sin \lambda_2)^2 + (\sin \varphi_1 - \sin \varphi_2)^2] \]  (A3)

Simplifying equation (A3) yields the following:

\[
\begin{align*}
\Delta \lambda &= \lambda_1 - \lambda_2 \\
|P_1P_2| &= \sqrt{2R} \sqrt{1 - \sin \varphi_1 \sin \varphi_2 - \cos \varphi_1 \cos \varphi_2 \cos \Delta \lambda} \quad (A4)
\end{align*}
\]

The specific structure is shown in the figure, known as \( |P_1P_2| \), let \( \angle P_1OQ = \delta/2 \), find the arc length \( L \), then we have (A5):

\[
\begin{align*}
\delta &= \arcsin \frac{L}{R} \\
\frac{\delta}{2} &= \arcsin \sqrt{\frac{1 - \sin \varphi_1 \sin \varphi_2 - \cos \varphi_1 \cos \varphi_2 \cos (\lambda_1 - \lambda_2)}{2}} \quad (A5)
\end{align*}
\]

Combining the two equations in (A5), we get:

\[
L = 2R \arcsin \sqrt{\frac{1 - \sin \varphi_1 \sin \varphi_2 - \cos \varphi_1 \cos \varphi_2 \cos (\lambda_1 - \lambda_2)}{2}} \quad (A6)
\]

The distance between two points on the Earth's sphere can be calculated by bringing the latitude and longitude coordinates into equation (A6). We take as 1.3 in this paper, \( R \) is the radius of the earth, taking 6371 km.