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Short-Term Electric Vehicle Charging Demand Prediction: A Deep Learning Approach

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Abstract

Short-term prediction of the Electric Vehicle (EV) charging demand is of great importance to the operation of EV fleets and charging stations. This paper develops a Long Short-Term Memory (LSTM) neural network to predict the EV charging demand at the station level for the next few hours (e.g., 1-5 hours), using a unique trajectory dataset containing over 76,000 private EVs in Beijing in January 2018. To explore the performance of the LSTM model, we set up four scenarios by 1) comparing LSTM against two typical time series prediction models, i.e., the Auto-Regressive Moving Average model (ARIMA), and the Multiple Layer Perceptron model (MLP), 2) and investigating how different input data structures, sample sizes, and time spans and intervals would influence model accuracy. The results suggest that the LSTM model outperformed the ARIMA, and MLP models, and their $MAPE_1$ values are 6.83%, 21.58%, and 18.31%, respectively. In addition, we find that the time span and interval tend to be more influential to the LSTM model's prediction accuracy than input data structures, and sample sizes. In general, the LSTM model with a shorter time span or interval (e.g., 1 hour) would perform better.

Keywords: Electric vehicle; Charging demand prediction; Long short-term memory neural network; Trajectory data

1 Introduction

Nowadays, vehicle emissions such as fine particulate matter (PM2.5) are becoming a major source of air pollution, particularly in highly populated areas (Tie et al., 2013). The United Nations' World Urbanization Prospects 2018 reported that more than half of the world's population lived in cities, where they were frequently exposed to high concentrations of pollution released by vehicles (Yang et al., 2019). Vehicle emissions have negative health impacts, including cardiovascular illness, lung damage, and cancer (Wu et al., 2017). In addition, vehicle emissions could give rise to several environmental issues, such as acid rain and global climate change (Geller et al., 2006). To solve the above problems, electrifying transportation has been commonly viewed as a potential strategy for decarbonizing the transport sector, integrating renewable energy (e.g., solar and wind energy) and reducing local vehicular emissions. The rapid growth in the popularity of Electric Vehicles (EVs) has led to an increase in charging demand. However, it remains challenging to well accommodate charging demand with the existing charging infrastructure.

This paper will be focused on the short-term prediction of the Electric Vehicle (EV) charging demand at the station level. This is of great importance to the operation of EV fleets and charging stations, and would be helpful for several EV-related stakeholders in their decision making, including EV users, grid companies, and operators of charging stations. Specifically, EV users may wish to know the number of

EVs at those charging stations around their trip destinations in the next few hours to better plan their journeys and charging events. Specifically, they can choose suitable charging stations with a shorter waiting time or book a charging station in advance based on the predicted charging demand in the near future (Aluisio et al., 2017), so that they could well manage charging events and reduce charging costs. For electricity companies, they would also be interested in the geographic distribution of EV charging demand at the station level in the short term, so that they could take actions to accommodate the EV charging demand, which may vary over time and offset the potential negative effects of EV charging on the grid. For example, with the future charging demand information, electricity companies could develop strategies or actions (e.g., instant smart load management, peak shaving, and frequency regulation) to schedule EV charging events more flexibly, so as to reduce excessive grid load and enhance grid stability and security (Buzna et al., 2021; Zhu et al., 2019).

In addition, for the operator of charging stations, they would want to know the number of EVs that may arrive at each charging station in the next few hours (e.g., 1-5 hours) so that they could take measures to accommodate the charging demand. Specifically, the operators could develop efficiently coordinated management strategies (e.g., dynamic pricing strategy, charging reservation, the designed publish/subscribe communication framework) based on the predicted charging demand information (Cao et al., 2017). This can help shift charging demand from peak periods to off-peak periods, so as to maintain high charging facility utilization rates and avoid charging congestion and queuing to a large extent (Hu et al., 2019). Especially for the scenarios in which EV users are not able to charge as planned due to traffic congestion, the operators can dynamically provide EV users with new charging plans (e.g., recommending new suitable charging stations or adjusting time slots allocated) based on the predicted charging demand (Qin et al., 2022).

Moreover, deep learning approaches, such as Long Short-Term Memory (LSTM) neural networks, have been widely used in many different types of short-term demand prediction in both transport and electricity sectors, such as online taxi-hailing demand (Zhou et al., 2021), bus passenger demand (Monje et al., 2022), taxi passenger demand (Hu et al. 2018; Yu et al., 2019; Zhang et al., 2020), private car passenger demand (Ke et al., 2017), residential electricity demand (Saeed et al., 2021), and electric load demand (Zheng et al., 2017; Bouktif et al., 2019; Zhu et al., 2019). However, it remains unclear whether such deep learning approaches would also be useful in the short-term EV charging demand prediction, and if yes, how their performance would be. This is a research gap in both the studies of EVs and deep learning approaches.

To fill the research gap, this paper developed a Long Short-Term Memory (LSTM) neural network to predict the EV charging demand at the station level for the next few hours, using a unique trajectory dataset containing over 76,000 private EVs in Beijing in January 2018. The dataset contained a large number of charging events at over 1,000 charging stations, which would be a perfect dataset for training the LSTM model. To summarize, the main contributions of this paper are twofold: first, we proposed a large-scale station-level EV charging demand prediction model based on a deep learning approach, which had been seldom developed in previous studies; Second, we fully examined the model's applicability and performance within different scenarios, considering the potential influences of input data structures, sample sizes, and time span and interval. This would be particularly helpful for the applications of this model in other real-world scenarios.

2 Literature Review

2.1 Charging demand of electric vehicles (EVs)

Charging demand estimation and prediction is an important research area in EV studies. Previous studies have investigated charging demand at both macro and micro levels, using various data sources (e.g., emerging big data and traditional survey data). The estimation/prediction results could be used for infrastructure development, policy making, and real-time operation of EV fleets and charging facilities.

(1) Macroscopic charging demand estimation

At the macro-level, previous studies tended to analyze and model EV charging demand at the traffic zone, district- or city- levels, generally from a long-term perspective. Such charging demand estimation could be useful for infrastructure planning and policy making. For example, Zhou et al. (2014) proposed an improved Monte Carlo probability simulation method to estimate charging demand for multiple EV types (including buses, taxis, public service vehicles, and private vehicles) and different sectors (e.g., industrial , commercial, and residential sectors). The result indicated that the EV charging demand could significantly influence the power grid system, especially during peak periods, and the demand was greater on workdays than non-workdays. Hardinghaus et al. (2019) presented a four-step approach to estimating public EV charging demand in Berlin, Germany at the traffic zone level. The results found that a large fraction of public charging demand was from carsharing, and the demand was concentrated in the city center (though carsharing was available citywide). Using the historical real traffic data (conventional vehicles) in South Korea, Arias et al. (2016) applied decision tree and cluster analysis methods to predict the EV charging demand at the city level. The result showed that the EV charging demand was high on the residential sites on weekends and on the commercial sites during non-operational hours.

(2) Microscopic charging demand estimation

At the micro-level, previous studies tended to estimate EV charging demand at the station level. Micro-simulation models have been one of the most-used approaches in these studies. For example, Bae et al. (2012) developed a fluid dynamic traffic model to forecast the EV charging demand for a fast charging station. The results showed that the model could mine the spatio-temporal features of the EV charging demand at the charging station. Based on the real-world charging scenario at the University of California, Los Angeles, Majidpour et al. (2016) applied the Historical Average (HA), k-Nearest Neighbor (kNN) , and weighted kNN models to predict EV charging demand (referred to the charging load) at the charging outlet level. They found that the kNN (k = 1) was more accurate. Lu et al. (2018) applied the Regression Tree and the Random Forest (RF) algorithm to predict the EV charging demand at the single-station level with a time interval of 15 min. The prediction model had a Mean Absolute

Percentage Error (MAPE) of 9.76%, and the accuracy was reliable and practical.

(3) Short-term charging demand prediction

Short-term charging demand prediction is of great importance to the operation of EV fleets and charging facilities, but only a few attempts have been made to predict charging demand in the short term at the station level. For example, Yi et al. (2021) applied the Sequence to Sequence (Seq2Seq) model, which is a deep learning approach to predict the monthly commercial EV charging demand. The Seq2Seq model had an acceptable prediction accuracy for one-month charging demand, but its short-term predictability (for example, for the next few hours) remained unclear. Some attempts have been made to predict the EV charging occupancy patterns of chargers (Pantelidis et al., 2021). For example, Gruoss et al. (2020) constructed a Markov chain model to investigate the occupancy state of 40 public charging stations. However, the study only compared the predicted and the observed data values with no report on prediction accuracy. Soldan et al.(2021) developed a logistic regression model to predict the charging station occupancy using historical occupancy information as input. However, the study only explored the occupancy probability prediction over the next 15 minutes. The model's applicability and performance for those scenarios with a longer time interval (e.g., 1 hour or even longer) remained unclear.

(4) Data sources for charging demand estimation and prediction

Emerging big data have become a promising data source for EV charging demand estimation or prediction, as they contain rich travel, and charging information. For example, Cai et al. (2014) analyzed a large-scale one-month dataset containing 11,880 taxis (not battery EVs) in Beijing to explore the influence of travel patterns on public charging infrastructure demand. Arias et al. (2016) utilized real-time historical traffic data in South Korea in 2014, including hourly traffic flow and vehicle miles traveled, to develop the EV charging demand prediction model. Kontou et al. (2019) explored the association between charging demand and people's daily activities with private vehicles, using three GPS travel survey datasets from different metropolitan areas (e.g., the Puget Sound area, the Atlanta metropolitan area and California). However, the above studies used CV data with the assumption that EVs and CVs have the same travel patterns. To overcome this limitation, real-world EV data have been used in some studies. For example, Lee et al. (2019) released a dynamic publicly-available dataset to learn and predict EV user behavior. This dataset contains over 30,000 charging sessions which were generated at two workplace-based charging stations in California. The key information including the start and end times of a charging event, the amount of energy consumed, and charger type and location. However, such charging session datasets do not contain travel or trip information of EV users. Sun et al. (2021a) used a real-world shared EV dataset to estimate charging demand and further explore the potential contribution of EVs to the smart grid through vehicle-to-grid technology. The dataset contained moving trajectories of 967 EVs in Beijing in January 2019. Yang et al. (2021) and Wang et al. (2021) used GPS trajectory datasets to figure out spatiotemporal patterns of charging demand and further deploy battery swap stations for shared EVs and freight electric vehicles, respectively.

2.2 Applications of Long Short-Term Memory (LSTM) model in demand prediction

Deep learning approaches have been widely used in many fields for prediction purposes. There are several typical deep learning approaches, such as Feed forward neural networks (FF), Deep belief networks (DBN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN). For example, Jovanovic et al. (2015) used the FF model to predict heating energy consumption on a university campus. Huang et al. (2014) applied DBN to predict traffic flow. Topić et al. (2019) applied the Multiple Layer Perceptron model (MLP) and CNN model to predict the fuel consumption and battery state of charge of EVs at the trip destination. Li et al. (2021) applied deep neural networks (DNN) to predict vehicle speed and passenger numbers, and estimate the future energy demand of hybrid electric buses (HEB).

The Long Short-Term Memory (LSTM) model is one of the most-used deep learning approaches (Wang et al., 2022). It has been applied in many research fields to predict different demand types and tackle other time series-related problems, such as traffic demand, passenger demand, and energy demand. In the transport studies, Zhao et al. (2017) developed an LSTM network to forecast short-term traffic flow, and further compared it against other representative forecast models, including the Auto-Regressive Moving Average model (ARIMA), SVM, RBF, and RNN. The findings showed that the LSTM network had a better performance. In the environmental studies, Zhao et al. (2019) combined the LSTM and the Fully connected neural network to predict the PM 2.5 concentration. The results showed that the proposed model outperformed the artificial neural network (ANN) in terms of prediction accuracy. In response to urban flooding, Zhang et al. (2018) used an LSTM model to simulate and predict the water level. The results showed that the simulation accuracy of the proposed LSTM-based model is higher than that of ARIMA, SVM, and Back Propagation (BP) Neuron Network. Poornima et al. (2019) used intensified LSTM model to predict rainfall in comparison with other typical prediction models, including Holt-Winters, Extreme Learning Machine (ELM), ARIMA, and RNN. The results showed that the intensified LSTM model had a better performance. In the energy sector, Wang et al. (2020) proposed an LSTM-based model to predict periodic energy consumption. The experimental results showed that the proposed model performed better than the ARMA, Autoregressive fractional integrated moving average model (ARFIMA), and Back Propagation Neural Network (BPNN). Peng et al. (2018) used LSTM to predict electricity prices. The results showed that LSTM outperformed existing forecasting models, such as ARIMA, ANN, and BPNN.

2.3 Comments on previous work

As reviewed above, EV charging demand estimation and prediction has been a hot topic in EV studies. However, short-term EV charging demand prediction tended to receive much less attention, especially at the station level. On the other hand, deep learning approaches, such as LSTM, have been widely used in predicting various demand types, but their capability to predict the short-term station-level charging demand remains unclear.

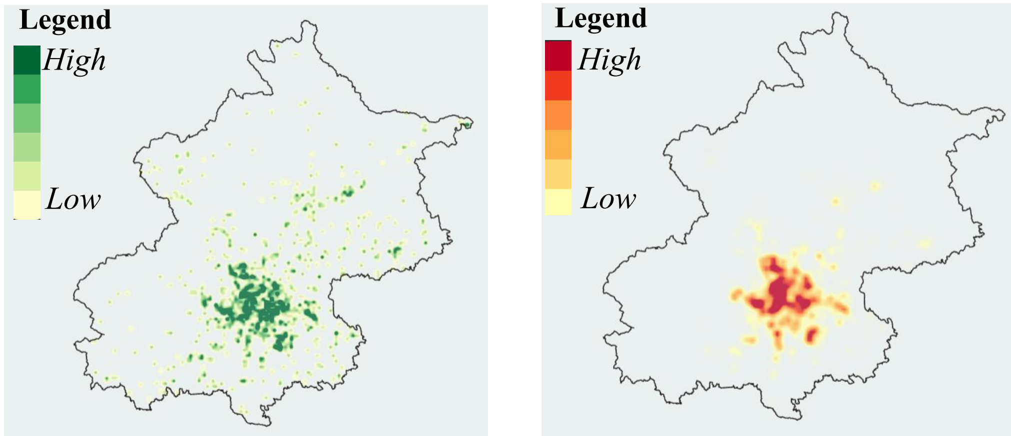
In response, this study will develop a LSTM model for the short-term station-level charging demand prediction. In particular, we will extract EV charging demand at over 1000 charging stations from a unique trajectory dataset, which contains trajectories of over 76,000 private EVs in Beijing in January 2018, through spatial big data analysis. Such historical station-level charging events from a perfect dataset for training and validating the LSTM model. The LSTM model is expected to benefit various EV stakeholders, including operators of charging stations, EV users, and power grid companies, as discussed before.

3 Study Area and Data Sources

We used Beijing as a case study. Beijing's auto ownership has exceeded 6 million, with private cars accounting for 78.14% (BMBS & NBSSO, 2020). Beijing has become the largest EV market in China, with 507,000 EVs and over 1,000 charging stations in 2018. Furthermore, the Beijing government aims to have 2 million EVs by 2025 with very supportive EV policies. For example, Beijing has a license plate lottery policy under which potential EV purchasers could have a much higher probability of getting a license plate (Zhuge et al., 2020).

The essential input data for the LSTM model to be developed is the EV charging session data. Such datasets should essentially contain the start and end times of a charging session (or event) and the location where the charging event occurs. There are two general ways for us to prepare the input data: first, we have sensors attached to charging posts, which can be used to monitor the charging status. The charging session data can be automatically generated (Helmus et al., 2020; Powell et al., 2022;

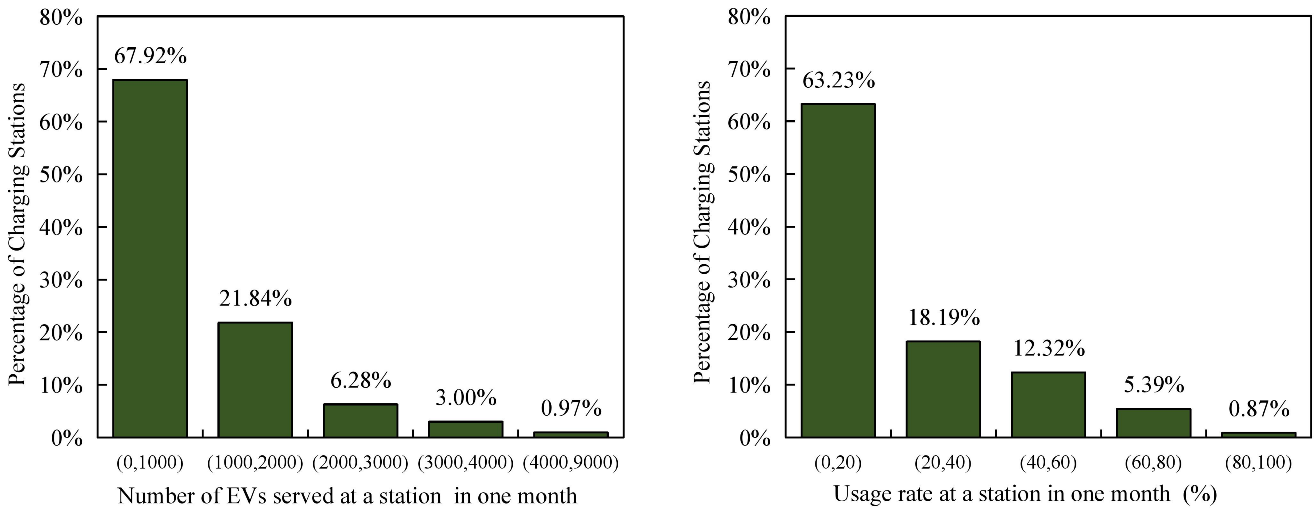
Wolbertus et al., 2018). Second, we can also extract charging events/sessions from the EV trajectory data, which contains rich travel, parking, and charging information of EV users (Cui et al., 2022; Sun et al., 2021a; Yang et al., 2022). We prepared the input data with the second method and used a one-month GPS trajectory dataset containing moving trajectories of 76,774 private EVs in January 2018 (Sun et al., 2021b), from which we extracted EV charging session data. The reason why we chose this dataset was because it contained charging events generated on a large-scale scenario with over 1,000 charging stations, and this allows us to fully test whether the model could also perform well in megacities like Beijing. Each trajectory record contains several key fields, including time, location, state of charge, and speed. The dataset was first processed through an EV trajectory data analytical framework proposed by Sun et al. (2021b) to extract travel, parking, and charging events of EVs, which were further converted to the EV charging demand at each charging station. Here, the EV charging demand at a station is defined as the number of EVs served at a station in a specific period (e.g., 1 hour). Finally, we extracted EV charging demand for 1,128 charging stations (see Figure 1-(a)). Most of the charging stations are located in the central districts and central areas of the outer districts of Beijing; while most of the charging demand were generated at the central districts (see Figure 1-(b)).



(a) A heat map for charging stations (b) A heat map for charging demands

Figure 1 Spatial distributions of charging stations and charging demand in Beijing

Figure 2 shows the usage pattern of charging stations using two indicators, namely the average number of EVs served at a station in one month (see Figure 2-(a)), and the average usage rate of charging stations over one month (see Figure 2-(b)). For the 1,128 charging stations in the study area, the maximum number of EVs served at a station was 8687, and the average number of EVs served at a station was 786.35 in one month (i.e., around 25 EVs per day). The maximum usage rate of charging stations was 92%, and the average usage rate of charging stations was 18%. Also, it is worth noting that some stations have a high charging demand. However, some stations were not used at all (i.e., no EV served) over this one month.



(a) The number of EVs served pattern at a station

(b) The usage rate pattern at a station

Figure 2 Usage patterns of the charging stations in Beijing

4 Methodology

Table 1 summarizes the terminology used in this paper.

Table 1 Terminology

Terminology	**Explanation**
Abbreviation	
ARIMA	Auto-Regressive Moving Average model
EV charging	The number of EVs served at a charging station during a specific time

demand	interval (e.g., 1-5 hours)
LSTM	Long Short-Term Memory Neural Network
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
$MAPE_1$(%)	MAPE only for those samples higher or equal to 1
MLP	Multiple Layer Perceptron model
RMSE	Root Mean Square Error

Nomenclature

n	The number of points/records indexed in time order
x_t	The number of EVs served at a charging station in the t-th time interval.
m	The number of past time intervals
p	The number of future time intervals
$f(.)$	The objective of an EV charging demand prediction model
Y_t	The output of the model

4.1 Problem statement

The short-term EV charging demand prediction is formulated as a mathematical problem below:

In a study area with a set of charging stations, each charging station may have one or more charging posts. Given the historical data on EV charging demand at the station level, we aim to develop a deep learning model to predict charging demand over a short period (e.g., 1-5 hours). Here, the EV charging demand refers to the number of EVs served at a charging station during a specific time interval (e.g., 1-5 hours). Thus, for each station, the charging demand can be converted into time-series data $(x_1, x_2, ...x_t, ...)$, $t = (1, 2, ..., n)$, n is the number of points/records indexed in time order. x_t is the number of EVs served at a charging station in the t-th time interval.

Given a sequence of EV charging demand over the m-past time intervals, i.e., $(x_{t-m-1}, ..., x_{t\text{-}1}, x_t)$ before t. The deep learning model is used to predict the number of EVs served at each charging station for future p time intervals $(x_{t+1}, ..., x_{t+p})$. Therefore, the EV charging demand prediction problem can be formulated by Equation (1).

$$[x_{t-m+1}, \ldots, x_t] \xrightarrow{f(\cdot)} [x_{t+1}, \ldots, x_{t+p}] , \tag{1}$$

where $0 < m < n$, $0 < t + m \text{-} 1 < n$, $0 < p < t + p \leq n$. Essentially, the EV charging demand prediction model aims to learn a function $f(.)$ that can well predict the EV charging demand for the next p steps based on the information extracted from the previous m steps.

4.2 Modelling and testing procedure

As shown in Fig. 3, the procedure of implementing the LSTM-based EV charging demand model is composed of three steps: Step 1 is data preparation. After we clean the EV trajectory dataset, we further extract charging events from the dataset, and organize them as input data, i.e., charging demand time-series data. Step 2 is to develop the LSTM-based prediction model. After we construct the model structure, we further train and validate the model with the input data. Specifically, as mentioned in section 4.1, we need to learn a function that can well predict the EV charging demand for the next steps. Here, we use a typical deep learning approach, i.e., Long Short-Term Memory Neural Network (LSTM), to extract temporal characteristics of the EV charging demand for prediction. Step 3 is to further test the prediction performance of the LSTM model within four scenarios designed from different perspectives. Specifically, Scenario A is used for evaluating the performance of the LSTM model by comparing it against ARIMA and MLP (see Section 4.4.1); Scenario B is to evaluate the LSTM model performance under different input data structures (see Section 4.4.2); Scenario C is used to test the LSTM model with different sub-datasets, which contained the top 5%, 10%, 20%, 30%, and 50% charging stations sorted by the number of EVs served and the usage rate of charging stations (see Section 4.4.3); Scenario D is to evaluate model performance with different time spans and different time intervals (see Section 4.4.4).

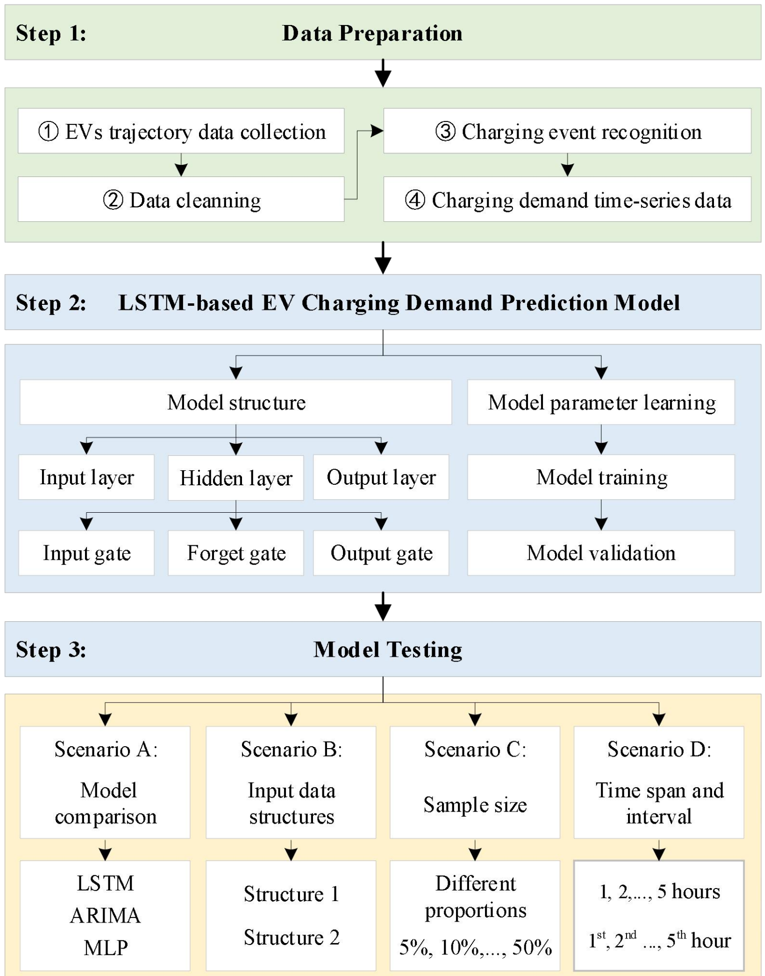


Figure 3 Flowchart for the procedure of implementing the LSTM-based EV charging demand prediction model

4.3 EV charging demand prediction model: Long Short-Term Memory Neural Network (LSTM)

4.3.1 The LSTM-based EV charging demand prediction model

We use the Long Short-Term Memory Neural Network (LSTM), which is a typical deep learning neural network, to predict the EV charging demand at the station level, as LSTM generally has the better capability of mining the long-time dependency, compared to other classical machine learning algorithms, such as ARIMA, SVM, and MLP. It is noted that there are many variants of LSTM (Schmidhuber et al., 2007; Jozefowicz et al., 2015). However, as suggested by Greff et al. (2017), the most commonly used LSTM architecture (i.e., vanilla LSTM) performs reasonably better with various data sets. Therefore, we will base our EV charging demand prediction model on the commonly used LSTM architecture.

Specifically, the proposed LSTM-based EV charging demand model comprises an input layer, a hidden layer, and an output layer (Greff et al., 2017). The input layer is composed of multiple EV charging demand time-series records. The input time-series data is defined as $\boldsymbol{X}=(\boldsymbol{X}_1, \boldsymbol{X}_2, ..., \boldsymbol{X}_t)$, where, $X_t = (x_{t+m-1}, x_{t-m}, ..., x_{t-1}, x_t)$, $0 < m < n$, $0 < t + m - 1 < n$. m is the time step, meaning that the input vector of the LSTM model contains the m -step historical EV charging demand data backward t. The output layer is composed of the EV charging demand in the next time interval. The output layer is defined as $\boldsymbol{Y}=(\boldsymbol{Y}_1, \boldsymbol{Y}_2, ..., \boldsymbol{Y}_t)$, corresponding to the input layer X_t ; where, $Y_t = (x_{t+1}, x_{t+2}, ..., x_{t+p})$, $0 \le p < n$, $0 < t + p \le n$, means to predict the EV charging demand in the future k-step time interval. The hidden layer, different from the traditional RNN neural network, is composed of a set of memory blocks. The memory block is the central idea of the LSTM structure (Greff et al. 2017), which is composed of different self-connected memory cells, the input gate, the output gate, and the forget gate (Fig. 4). The memory cells are used to memorize the historical information of EV charging demand in the long and short term. For example, for a short-term time-series input data such as 1 hour, the memory cells not only memorize the information of short-term information such as the past 1 hour, but also can memorize the long-term information needed from the past two weeks or even two months, which is difficult for RNN. The calculation procedure of the LSTM memory block is given in Appendix.

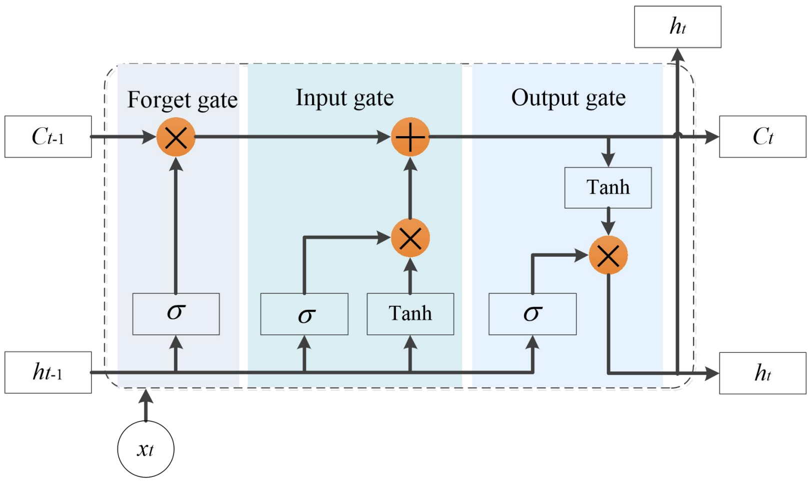


Figure 4 Architecture of the LSTM memory block (Source: Ma et al. 2015)

In addition, for the structure of the LSTM-based EV charging demand prediction model, we use one LSTM layer to mine the EV charging demand feature, one dropout layer for regularization to overcome the over-fitting (Srivastava et al., 2014), and one fully connected dense layer to control the dimension of output. The weights of the LSTM model are learned through the Back Propagation Through Time (BPTT) to minimize the loss function (Wu et al., 2021). The loss function applied is the mean squared error which is used to estimate the difference between the predicted value and the observed value. The Adam optimizer is applied to the BPTT to minimize the training error and avoid local minimal points, and the learning rate is set to 0.01 (Wu et al., 2021).

4.3.2 Model evaluation metrics

We will use three typical evaluation metrics (Lyu et al., 2022), namely Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE), to evaluate model performance by comparing the difference between the predicted and observed charging demands (denoted as $\hat{y}_t$ and y_t, respectively) from different perspectives.

(a) Mean Absolute Error (MAE)

The MAE can quantify the error between the predicted and observed EV charging demands. The MAE is calculated by Eq. (2).

$$\mathrm{MAE} = \frac{1}{n}\sum_{t=1}^{n}\left|\hat{y}_t - y_t\right| \tag{2}$$

where n is the number of records used for evaluation.

(b) Root Mean Square Error (RMSE)

The RMSE index is sensitive to outliers. The RMSE will be relatively large if the difference between the predicted and observed data is large. Therefore, a larger RMSE indicates a worse performance of the model. The RMSE is calculated by Eq (3).

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(\hat{y}_t - y_t)^2} \tag{3}$$

(c) Mean Absolute Percentage Error (MAPE)

MAPE is a conventional metric in the field of statistics to measure the accuracy of prediction. A smaller MAPE indicates a smaller error between the predicted and observed data. The MAPE is calculated by Eq (4).

$$\mathrm{MAPE} = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{\hat{y}_t - y_t}{y_t} \right| \tag{4}$$

Since MAPE is unsuitable for those cases where the observed value is zero, we calculate MAPE only for those samples with EV charging demand (i.e., the number of EVs served) higher or equal to 1, denoted by MAPE_1(%).

4.4 Testing the LSTM model within different scenarios

We set up four scenarios to explore the performance of the LSTM model by comparing it against other typical machine learning algorithms (Scenario A), and investigating how different input data structures (Scenario B), sample sizes (Scenario C), and time spans and intervals (Scenario D) would influence model accuracy.

4.4.1 Scenario A: Model comparison

Scenario A is to evaluate the performance of the LSTM model by comparing it against two typical models, namely ARIMA, and MLP.

Auto-Regressive Moving Average model (ARIMA) is a traditional statistical technique used to analyze the linear part of the time-series prediction problem. In this study, the future charging demand is assumed to be a linear function of several past observations and random errors (Zhang, 2003). In other words, the ARIMA model makes a prediction with the assumption that the fitted curve will continue inertially with the existing pattern over the future period (Aasim et al., 2019). ARIMA needs to fit three key parameters, i.e., Difference (D) for data stability, Autoregressive (AR) for historical information regression, and Moving-Average (MA) for error linear regression. A more detailed introduction to ARIMA can be found in work by Ning et al. (2022). ARIMA generally performs well for those stationary datasets whose mean and variance remain relatively constant on the entire domain. Therefore, we have to first convert the non-stationary time series to a stationary time series before fitting a regression to the stationary time series (Yuan et al., 2016).

Multiple Layer Perceptron (MLP) model is a kind of traditional feedforward artificial neural network. Because of its excellent self-adaptation and self-learning abilities, it can tackle non-linear and high-dimensional problems well (Szoplik et al., 2015; Orhan et al., 2022). MLP consists of three layers, i.e., an input layer, a hidden layer, and an output layer. An input and output layer are connected by a hidden layer. Besides the input layer, the other layers are composed of neurons with non-linear activation functions (Liu et al., 2022). An algorithm based on supervised back-propagation is used to learn each neuron's parameters (i.e., weights, and bias) in this network (Riazi et al., 2022).

In the model comparison, we used a dataset containing the first 2/3 of the time-series records of all charging stations for model training, and another dataset containing the remaining time-series records of all charging stations for model evaluation.

4.4.2 Scenario B: Input data structures

Scenario B is to evaluate how different input data structures would influence model performance. As aforementioned, Data Structure 1 (which is used in Scenario A) uses the first 2/3 of the time series records of all charging stations for model training, and the remaining 1/3 of the records for model validation. While in Scenario B (or Data Structure 2), we use the time series records of 2/3 of the charging stations for model training, and use the time series records of the remaining 1/3 of the charging stations for model testing. Schematic diagram of data structures 1 and 2 are shown in Fig. 5.

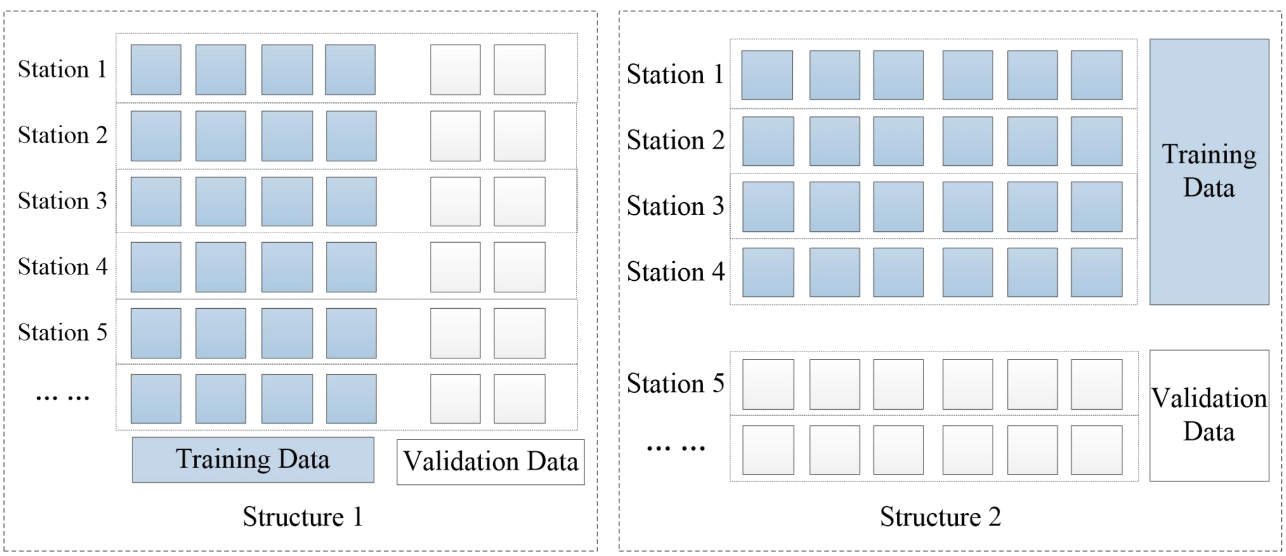


Figure 5 Schematic diagram of data structures 1 and 2

4.4.3 Scenario C: Sample size

Scenario C is to investigate how different sample sizes would influence model performance. We first sorted charging stations by the charging demand (i.e., the number of EVs served) at a station or the usage rate of a station, and then used the top k% (k=5, 10, 20, 30, 40, and 50) of charging stations for model training and validation, as illustrated with an example in Fig. 6.

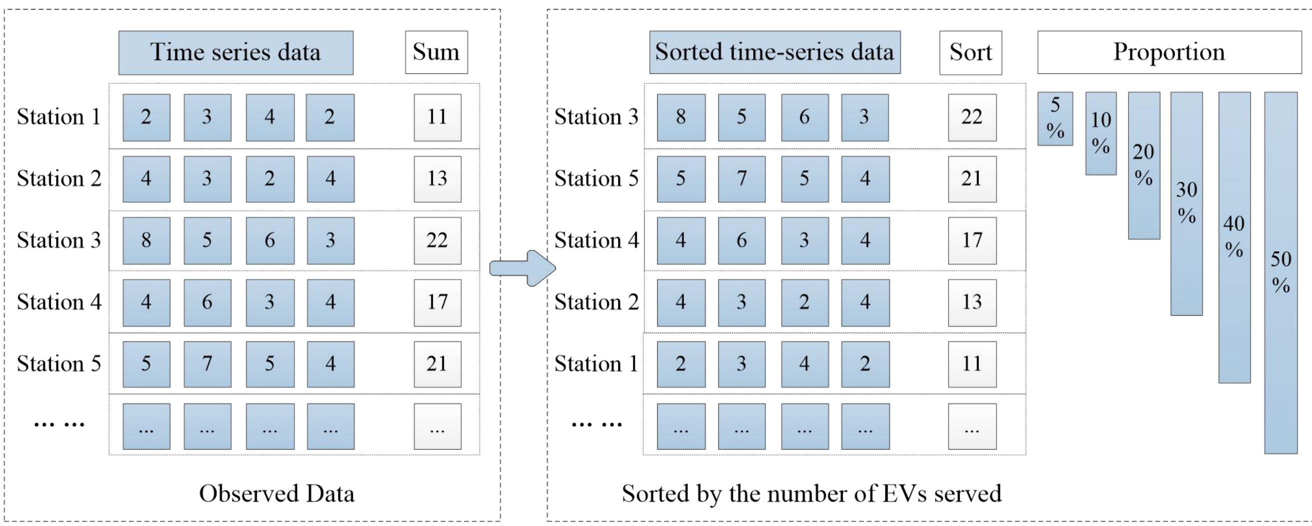


Figure 6 Schematic diagram of sorting charging stations

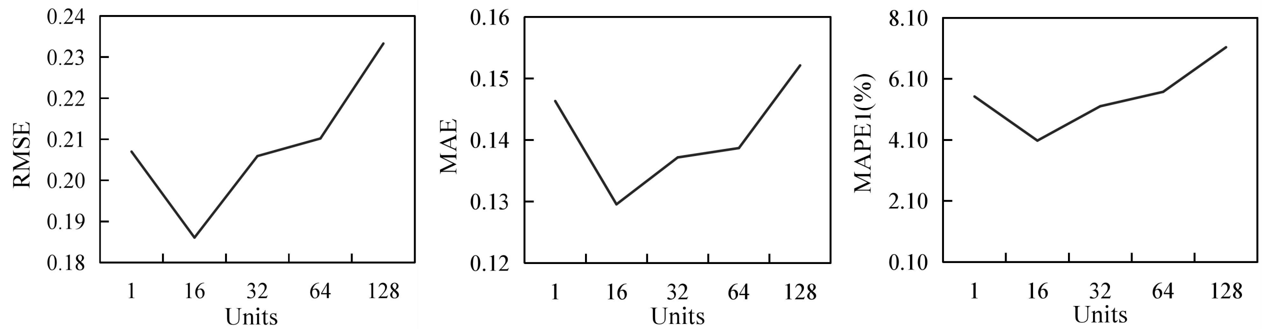
4.4.4 Scenario D: Time span and interval

Scenario D is to evaluate model performance with different time spans and different time intervals. Specifically, in the scenarios with different time spans, the LTSM model will predict the EV charging demand over the next 1-5 hours with a one-hour interval used in model training. In the scenarios with different time intervals, the LSTM model will predict charging demand over the next 1 hour, 2 hours, 3 hours, 4 hours, and 5 hours with 1-hour, 2-hour, 3-hour, 4-hour and 5-hour intervals used in model training, respectively.

5 Results

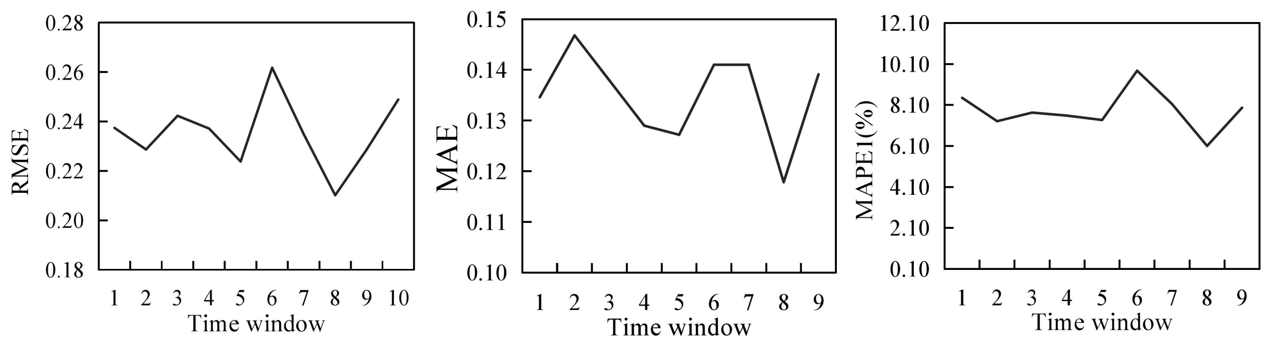
5.1 Model hyperparameters

To develop the LSTM-based EV charging demand prediction model, we utilize the Python package Keras (Grattarola et al., 2020), which is based on TensorFlow (Martí et al., 2016). The key model parameters were set as follows: To prevent overfitting, we used the dropout layer and early stopping with a rate of 0.02. The batch size was set to 50. In attention, a set of hyperparameters need to be first set: the numbers of hidden units and the time windows. The model performance under the different numbers of hidden units and time windows is shown in Fig. 7 and Fig. 8, respectively. We can see from Fig. 7 that a better model result could be obtained when the number of units was set to 16. Meanwhile, according to the results in Fig. 8, it can be found that the LSTM model worked better when the time window was set to 8. For the two baseline models, the parameters of ARIMA and MLP were determined by the trial-and-error method. In ARIMA, Difference (D), Autoregressive (AR), and Moving-Average (MA) were set to 1, 5, and 4, respectively. For MLP, the hidden layer, the batch_size, and learning rate were set to 64, 50, and 0.01, respectively. Furthermore, the early stopping was used for overfitting.



(a) RMSE (b) MAE (c) $MAPE_1$(%)

Figure 7 Model performance with different numbers of hidden units



(a) RMSE (b) MAE (c) $MAPE_1$(%)

Figure 8 Model performance with different numbers of time windows

5.2 Scenario A: Model comparison

We compared LSTM against the other two baseline models within Scenario A in terms of their prediction performance. In general, the performance of a deep learning method (e.g., LSTM) is primarily associated with characteristics of the data used for model training (e.g., temporal characteristics of EV charging data in this paper) and model structure. Since Scenarios B and C examined the influence of input data structures, sample sizes, time spans, and intervals, and did not change neither the charging pattern/temporal characteristics of the datasets used nor the model structures, there is no need to further examine the performance of the baseline models within these two scenarios.

(a) Overall Model Performance

From Table 2, it can be found that the proposed LSTM model outperforms the ARIMA and MLP models, as evident from the three lowest evaluation metrics, namely RMSE, MAE, and $MAPE_1$(%). For the indicator of RMSE, the LSTM model is 0.20, which is 0.39 and 0.30 lower than 0.59 for ARIMA and 0.50 for MLP, respectively, i.e., the RMSE errors are reduced by 66.10% and 60.00%, respectively. For the indicator of MAE, the LSTM model is 0.12, which is 0.16 and 0.09 lower than 0.28 for ARIMA and 0.21 for MLP, respectively (i.e., 57.14% and 42.86% lower). For the indicator of $MAPE_1$(%), the LSTM model is 6.83, which is 14.75 and 11.48 lower than 21.58 for ARIMA and 18.31 for MLP, respectively (i.e., 68.35% and 62.70% lower). It can be found that the prediction accuracy of LSTM is 93.17% (=1- 6.83%), which is 68.35% and 62.70% higher than those of the ARIMA and MLP models, respectively.

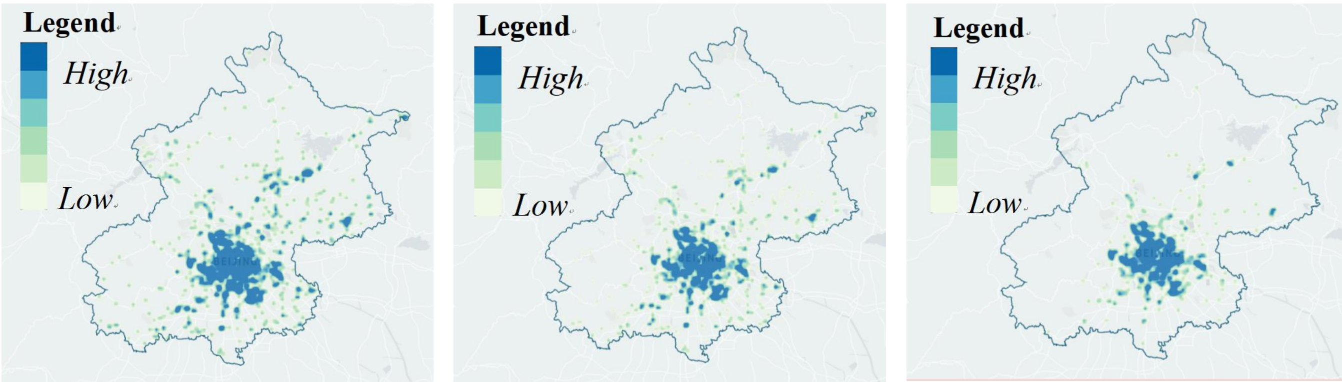
The reason why the LSTM model performed better than the two baseline models is discussed as follows: ARIMA is capable of learning the linear relationship from time-series datasets but is limited in processing the non-linear correlations of EV charging demand. Although MLP has the activation function to learn the non-linear correlations from the time-series datasets, it cannot memorize the historical long-term EV charging information. Compared with ARIMA and MLP, the LSTM structure has the advantage of extracting complex and non-linear time-series characteristics meanwhile memorizing the long-term historical EV charging information. Thus, it could obtain a higher prediction accuracy.

Table 2 Performance of ARIMA, MLP and LSTM

Evaluation	ARIMA	MLP	LSTM
RMSE	0.59	0.50	0.20
MAE	0.28	0.21	0.12
$MAPE_1$(%)	21.57	18.31	**6.83**

(b) Spatial distribution of model errors

We produced a heat map for model errors at each charging station for each of the three models (i.e., LSTM, MLP, and ARIMA), using $MAPE_1$ (%) as an indicator, as shown in Fig. 9. The following spatial patterns can be observed: First, those charging stations located in the central areas of Beijing tended to have a higher MAPE for all of the three models. This may be because the EV charging demand could be influenced by various factors in these central areas generally with a complex built environment. These models could be improved by incorporating more potential influential factors (e.g., the number of different facilities around the station) into the EV charging demand. Second, although LSTM had a much lower $MAPE_1$ (%), its predictability was not good in the central districts or central areas of the outer districts; while for the other two models, their predictability tended to be worse in the central districts than that in central areas of the outer districts.

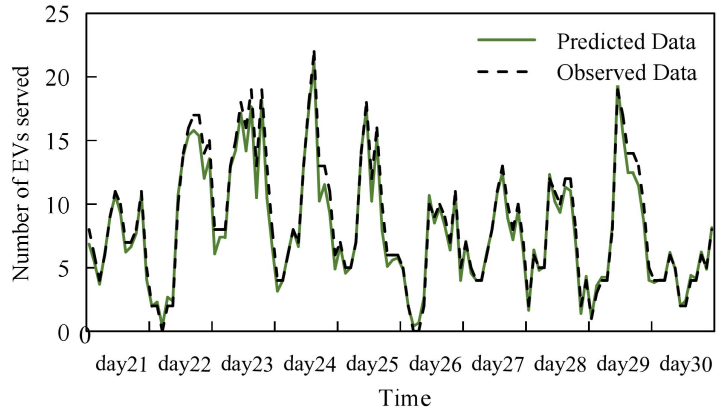


(a) LSTM (b) MLP (c) ARIMA

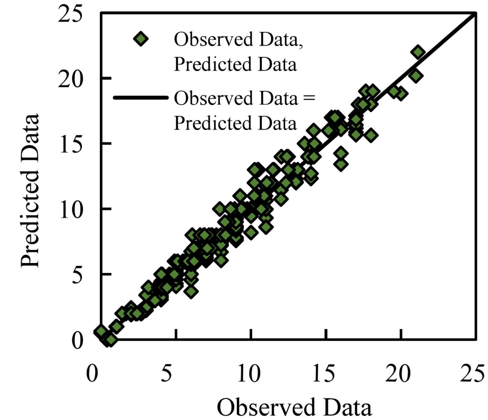
Figure 9 Spatial distribution of $MAPE_1$ (%) at each charging station

(c) Comparison between predicted and observed data

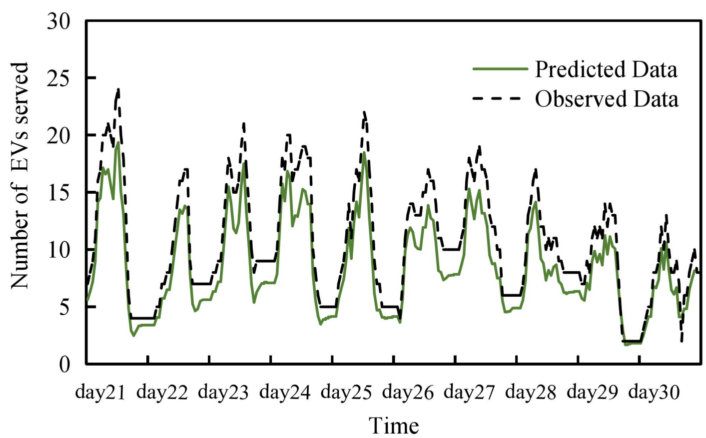
For each of the three models, we choose one station with a MAPE close to the $MAPE_1$(%)of all charging stations to illustrate model performance at the individual level: 21.57% for ARIMA, 18.31% for MLP, and 6.83% for LSTM (see Fig. 10). Essentially, LSTM could much better predict the EV charging demand at the station level over time, with a quite small gap between the predicted and observed data (see Fig. 10-(a1) and (a2)). For ARIMA and MLP, they were able to roughly represent the time-series patterns (see Fig. 10-(b) and (c)), but the differences between the observed and predicted charging demands were large for the majority of points.



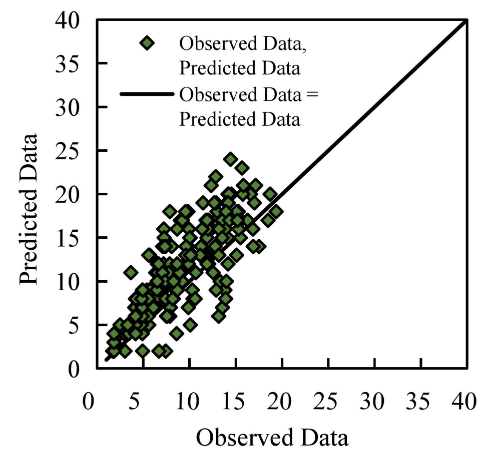
(a) LSTM: predicted VS observed data over time



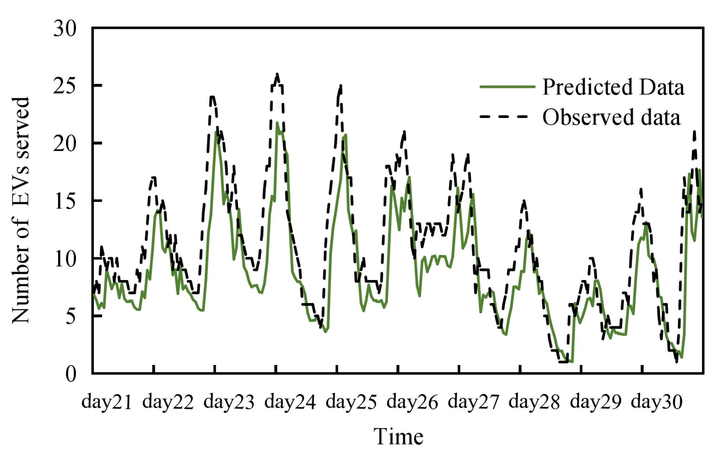
(b) LSTM: predicted VS observed data



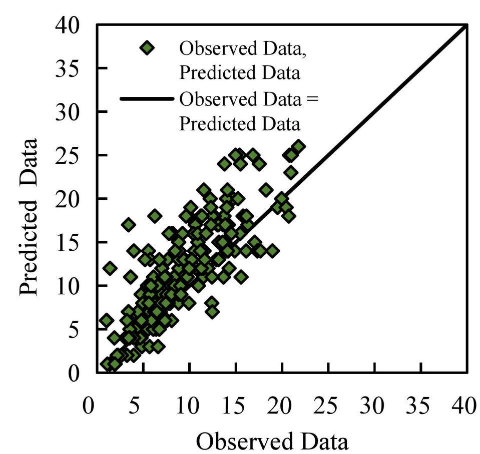
(c) MLP: predicted VS observed data over time



(d) MLP: predicted VS observed data



(e) ARIMA: predicted VS observed data over time



(f) ARIMA: predicted VS observed data

Figure 10 Examples to show the ability of ARIMA, NPL, and LSTM models to predict charging demand at the station level

5.3 Scenario B: Input data structures

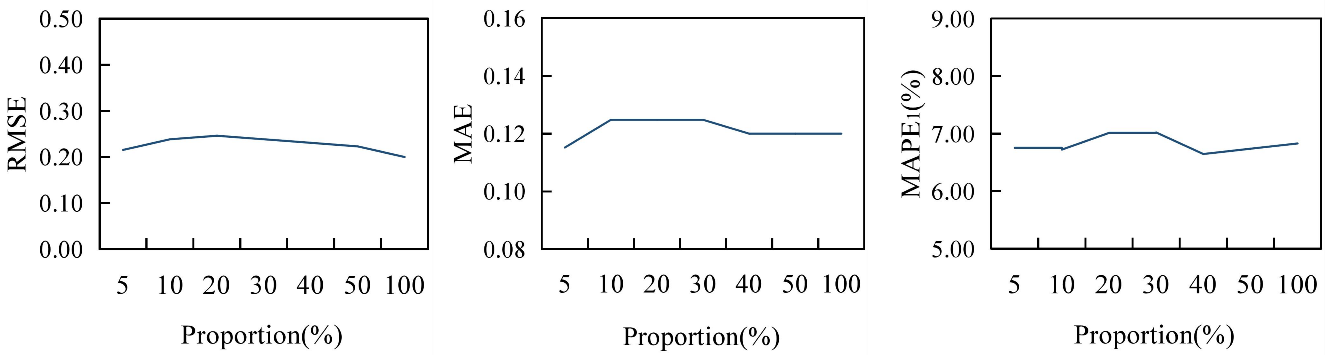
It can be seen from Table 3 that Structure 1 has a better performance than Structure 2, as evident from all of the three evaluation metrics. Specifically, the $MAPE_1$ (%) for Structure 2 is 8.94, which is higher than that of Structure 1 at 6.83. Similarly, the MAE and RMSE for Structure 2 are 0.25 and 0.26, respectively, which are both higher than those of Structure 1 (which are 0.12 and 0.20). This indicates that the proposed LSTM model would work better in those scenarios where charging stations' historical records have been used in model training. However, we can also find that the $MAPE_1$ (%) for Structure 1 is slightly lower than that of Structure 2. This indicates that the trained LSTM model has a satisfactory performance in those scenarios where charging stations' historical records are not used in model training. Therefore, the trained model can be applied, for example, to predict EV charging demand at those newly built charging stations with no (or few) charging records generated or used in model training.

Table 3 Model results of Scenario B

Evaluation	Data Structure 1	Data Structure 2
RMSE	0.20	0.26
MAE	0.12	0.25
$MAPE_1$(%)	**6.83**	8.94

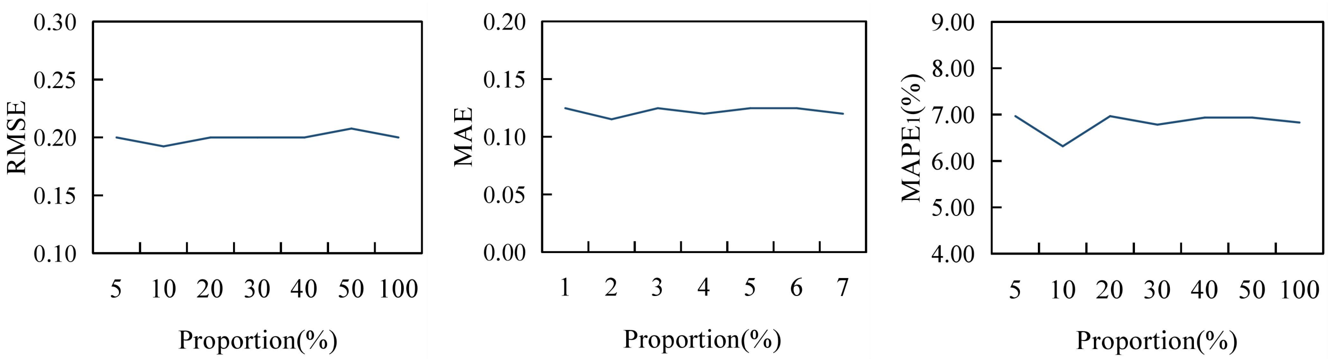
5.4 Scenario C: Sample size

In Scenario C, we trained and validated the LSTM model with different sub-datasets, which contained the top 5%, 10%, 20%, 30%, and 50% charging stations sorted by the number of EVs served- and the usage rate of charging stations. These scenarios were compared with the baseline scenarios where the full sample size (i.e., 100%) is used, so as to provide insights into the influence of sample size on model performance (see Fig. 11). Overall, the sample size has little influence on model performance, because the three indicators, i.e., RMSE, MAE, and MAPE, fluctuate slightly, as more samples are used. In addition, we find the variance of these indicators is also small, as shown in Table 4. These findings would be helpful for the operators of charging stations: since sample size would have little influence on model accuracy, the operators may be just focused on those charging stations with a higher usage rate or the number of EVs served, and use a small sub-dataset (only containing these target stations) for model training and prediction. This would help improve computational efficiency and reduce computing costs.



(a1) RMSE (a2) MAE (a3) $MAPE_1$(%)

(a) Scenarios with charging stations sorted by the number of EVs served



(b1) RMSE (b2) MAE (b3) MAPE1(%)

(b) Scenarios with charging stations sorted by their usage rate

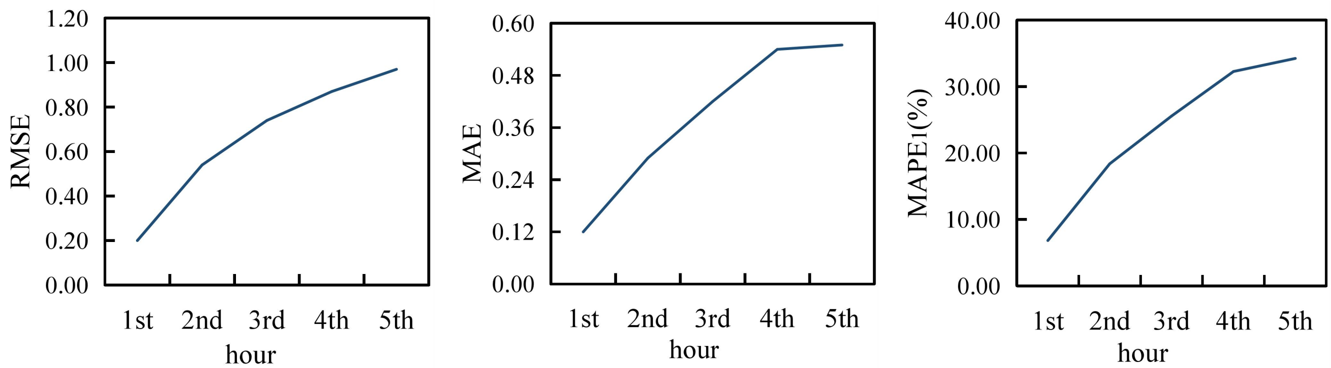
Figure 11 Evaluation results of Scenario C (note: the title of the x-axis, Proportion (%), means the proportion of samples/charging stations used for model training)

Table 4 Statistical description of the evaluation metrics in Scenario C

Indicators	Evaluation	Mean	Variance	Min value	Max value
The number of EVs served	RMSE	0.227	0.002	0.200	0.246
	MAE	0.121	0.000	0.115	0.125
	MAPE1(%)	6.818	0.021	6.647	7.021
Usage rate	RMSE	0.200	0.000	0.192	0.208
	MAE	0.122	0.000	0.115	0.125
	MAPE1(%)	6.820	0.054	6.318	6.968

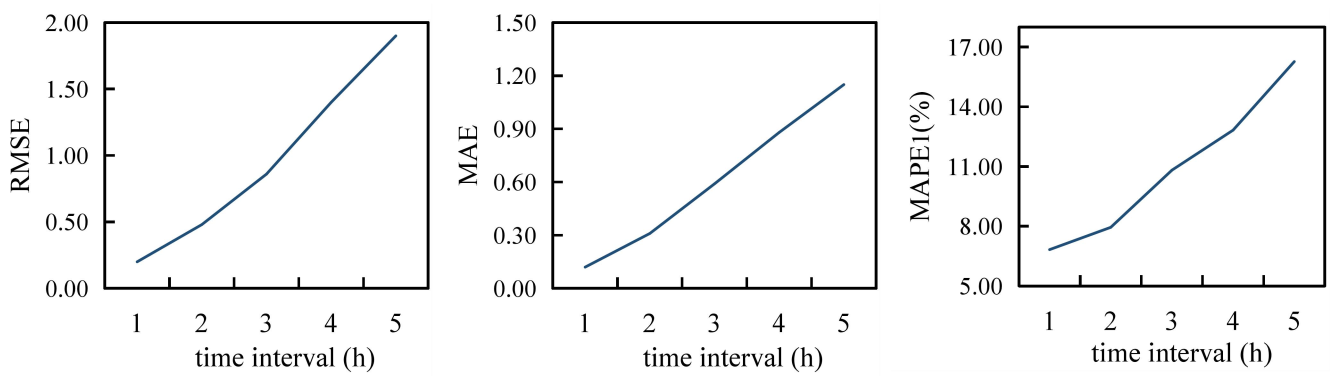
5.5 Scenario D: Time span and interval

Overall, the increase in either time span or time interval would reduce model accuracy. For example, the scenario with a time span of 1 hour has a MAPE of 6.83%, which is much lower than that with a time span of 5 hours (whose MAPE is 34.24%). This indicates that the LSTM model has a higher capability of predicting the EV charging demand in a shorter term (see Fig. 12). The scenarios with different time intervals indicate that a shorter time interval would help improve model performance (see Fig. 13). For example, the scenario with a 1-hour interval has a MAPE of 6.83%, which is much lower than that with a 5-hour interval (whose MAPE is 16.27%). Understanding the influence of time span and interval on model accuracy would be helpful for the operator of charging stations, as they could, for example, encourage or discourage EV users to charge through a dynamic pricing strategy, based on the predicted charging demand at a charging station over the next few hours. According to the findings above, the operator needs to make a trade-off between prediction accuracy and the desired number of hours ahead.



(a) RMSE (b) MAE (c) MAPE1(%)

Figure 12 Performance of the LSTM model in the Scenarios with Different Time Spans



(a) RMSE (b) MAE (c) MAPE1(%)

Figure 13 Performance of the LSTM Model in the Scenarios with Different Time Intervals

6 Conclusions

We developed a Long Short-Term Memory Neural Network (LSTM)-based EV charging demand prediction model, which is capable of predicting the number of EVs served at a charging station over the next few hours (e.g., 1-5 hours). To explore the performance of the LSTM model, we set up four scenarios by comparing it against other typical machine learning algorithms, and investigating how different input data structures, sample sizes, and time spans and intervals would influence model accuracy. The key findings are as follows: First, the LSTM model outperforms the two traditional time series prediction models, namely Auto-Regressive Moving Average model (ARIMA), and Multiple Layer Perceptron model (MLP). Their $MAPE_1$(%) values were 6.83, 21.58, and 18.31, respectively. Second, the time span and interval tended to be much more influential to the LSTM model's prediction accuracy than input data structures, and sample sizes. In general, the LSTM model with a shorter time span or interval would perform better.In summary, the LSTM model performs well in charging demand prediction because of its advantages of memorizing long-term historical information and further extracting complex and non-linear time features. Meanwhile, we also found the LSTM's limitation in extracting the spatial correlations. For example, in our case study, we found that the LSTM model's prediction accuracies at those charging stations in the central districts of Beijing and central areas of the outer districts tended to lower, likely because of the complicated built environment in these areas.

To overcome the LSTM's limitations in charging demand prediction and to further improve the model performance, our future work will try to extend the prediction model by incorporating spatial factors, such as the number of different facilities (e.g., shops and buildings) around a charging station, and the location information of charging stations. In addition, we will explore the geographical transferability of the LSTM model by applying the trained LSTM model to other areas or cities, where no historical EV charging data were used in model training, and further evaluate the model performance by quantifying the extent to which the model can exactly predict charging demand at other places.

Acknowledgments

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Appendix: The calculation procedure of LSTM model

The hidden state of LSTM memory cells is denoted as $H=(h_1, h_2, ..., h_t)$, and the state of the memory cell is defined as $C=(c_1, c_2, ..., c_t)$.

The memory block of LSTM works as follows:

Firstly, the forget gate decides which time-series information of EV charging demand in the history needs to be discarded. Specifically, EV charging time series for the current input layer X_t, the previous output layer of the hidden state h_{t-1}, and the previous state of the memory cell c_{t-1} are used together as the inputs of the current layer's forget gate (f_t), which can be calculated by Eq. (A1) (Greff et al. 2017).

$$f_t = \sigma\left(W_{fx}X_t + W_{fh}h_{t-1} + W_{fc}c_{t-1} + b_f\right) \tag{A1}$$

where W_{fx}, W_{fh}, and W_{fc} are weight matrices of the forget gate, b_f is the bias vector of the forget gate. The weight matrix and bias vector are used to make a connection between the input layer, memory block and output layer. $\sigma()$ is denoted as the standard logistics sigmoid activation function. Where, $\sigma(x) = 1/(1+e^x)$, $\sigma(x) \in (0,\ 1)$. The sigmoid function can nonlinearize the relationship of the forget gate parameters. Further, the non-linear relationship of the EV charging demand time feature can be mined.

Secondly, the input gate decides which time series information of EV charging demand in the history is to be remembered down. The input gate i_t is calculated as shown in Eq. (A2) (Greff et al. 2017).

$$i_t = \sigma\left(W_{ix}X_t + W_{ih}h_{t-1} + W_{ic}c_{t-1} + b_i\right), \tag{A2}$$

where W_{ix}, W_{ih}, and W_{ic} are weight matrices of the input gate, b_i is the bias vector of the input gate.

Finally, the output of the memory block is controlled by the output gate. The output gate o_t is calculated as shown in Eq. (A3) (Greff et al. 2017).

$$o_t = \sigma\left(W_{ox}X_t + W_{oh}h_{t-1} + W_{oc}c_t + b_o\right), \tag{A3}$$

where W_{ox}, W_{oh}, and W_{oc} are weight matrices of the output gate, b_o is the bias vector of the output gate.

The hidden state of memory cells h_t is updated according to the current output gate and the current state of the memory cell, as shown in Eq. (A4) (Greff et al. 2017).

$$h_t = o_t \cdot \tanh(C_t), \tag{A4}$$

The current state of the memory cell c_t is updated according to Eq. (A5) (Greff et al. 2017).

$$c_t = \tanh(W_{cx}X_t + W_{ch}h_{t-1} + b_c), \tag{A5}$$

where W_{cx}, and W_{ch} are weight matrices of the memory cell state, b_c is the bias vector of the memory cell state. $\tanh()$ is the hyperbolic tangent activation function, where $\tanh(x) = (e^x - e^{-x})/(e^x + e^{-x})$, $\tanh(x) \in (-1,\ 1)$.

After the output of the LSTM block, a dropout layer is followed for regularization. Then a fully connected layer is connected to further extract the temporal feature of EV charging demand. The output of the proposed LSTM-based EV charging demand model is the predicted EV charging demand $\hat{y}_t$, which is formulated as Eq. (A6).

$$\hat{y}_t = \sigma(W_{yh}h_t + b_y), \tag{A6}$$

where, W_{yh} and b_y are the weigh matrix and bias vector of the fully connected layer, respectively.