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Using Bayesian Deep Learning for Electric Vehicle Charging Station Load Forecasting

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Abstract: In recent years, replacing internal combustion engine vehicles with electric vehicles has been a significant option for supporting reducing carbon emissions because of fossil fuel shortage and environmental contamination. However, the rapid growth of electric vehicles (EVs) can bring new and uncertain load conditions to the electric network. Precise load forecasting for EV charging stations becomes vital to reduce the negative influence on the grid. To this end, a novel day-ahead load forecasting method is proposed to forecast loads of EV charging stations with Bayesian deep learning techniques. The proposed methodological framework applies long short-term memory (LSTM) network combined with Bayesian probability theory to capture uncertainty in forecasting. Based on the actual operational data of the EV charging station collected on the Caltech campus, the experiment results show the superior performance of the proposed method compared with other methods, indicating significant potential for practical applications.

Keywords: electric vehicle charging station; load forecasting; Bayesian deep learning; long short-term memory (LSTM) network; capture uncertainty

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1. Introduction

1.1. Background

With the rapid economic and social development, climate warming, energy shortage, environmental pollution and other issues are becoming more and more serious and have received continuous attention from governments and scholars worldwide [1,2]. Energy use and pollution emissions from the transportation industry are one of the main factors contributing to the escalation of these problems. With the continuous maturity of technology and the policy support of various governments, the number of electric vehicles (EVs) has been increasing rapidly in recent years [3] because of EVs' low carbon and environmental friendliness characteristics. Meanwhile, global decarbonization has boosted the rapid development of electric vehicles (EVs). In the past few decades, quantities of EVs charging stations have been built to meet EV owners' increasing demand. Nevertheless, some significant adverse effects may be brought to the existing power systems because of the high penetration of EVs, which include unstable voltage and frequency, massive harmonic injection, power losses and the instability of the power system [4]. With the widespread use of EVs, the large-scale implementation of peer-to-peer energy transactions is promoted, and the safe operation of the power grid is also affected [5]. Therefore, for the efficiency and safety of distribution grid operation with EV charging stations, it is essential to develop a useful and accurate forecasting model for EV charging load, which is not merely vital for the economic and optimal operation of the distribution network, but also the further development of the EVs [6].

1.2. Motivation

With the increasing number of EVs and EV charging stations, some significant adverse effects may be brought to the existing power systems because of the high penetration of EVs, and the uncertainty and difficulty of load forecasting of electric vehicle charging stations are also increasing. In order to solve the problem that less attention is paid to the impact of uncertainty on load forecasting in the current load forecasting research of electric vehicle charging stations, this paper will develop a novel method that combines Bayesian theory and the LSTM network to explore the impact of uncertainty on load forecasting for an EV charging station.

1.3. Related Work

In the literature, load forecasting has been widely and extensively studied for EV charging stations. Owing to the lack of actual charging data, many scholars have paid particular attention to building mathematical models to forecast charging load in the past decades, including the state-of-charge (SOC) model [7], energy consumption model [8] and so on. Ref. [7] calculated the probabilistic day-ahead charging load of the workplace, which proposed a combined methodology based on state-of-charge (SOC). Ref. [8] employed a mathematical consumption modeling to predict the load demand of PHEVs. An inverse load flow technology and a regional charging time-shift method are explored to predict daytime and midnight energy transfer, respectively. In [9], a systematic method was explored to predict the additional loads in the mid-and-long period generated by EV charging, including probabilistic models which describe the EV charging profiles and predictive models to forecast EV ownership in the future. Although the studies above have contributed much to exploring useful methods to forecast EVs charging load, the performance and accuracy are unsatisfactory. Meanwhile, the Monte Carlo method has attracted much attention because of its great performance. In [10,11], the Monte Carlo method was employed to calculate EVs charging load. A Monte Carlo-based simulation in [11] was employed to forecast the EV energy consumption, which was uncontrolled. Ref. [10] proposed a forecasting model considering the impact of various vehicles, which predicted and analyzed the number of EVs and used Monte Carlo to compute the charging load of EVs. In [11], a novel model Monte Carlo-based simulation was proposed to predict EV charging load demand. In [12], an optimal parameter forecasting method was proposed to forecast the charging demand of EVs, which effectively reduce forecasting errors of EVs. Although these studies have contributed much to solving the charging load forecasting, these methods fail to receive satisfactory forecasting accuracy because many factors could influence the model performance, including the EV owner behaviors, traffic flow and weather conditions. These mathematical models established in the above studies are complicated, and the process of calculation is difficult.

In recent years, machine learning techniques have revealed perfect performance in short-term load forecasting [13–16] because of its black model. For example, a load forecasting model in the short term for EV charging stations was proposed in [17], where particle swarm optimization (PSO) was applied for optimizing the parameters of the support vector machine (SVM), and great performance was achieved. Ref. [18] developed a support vector regression (SVR)-based algorithm for charging load forecasting. Ref. [19] proposed a novel forecasting method for different charging scenarios, which used the Q-learning technique and obtained great performance in load forecasting for the plug-in hybrid EV charging. The authors explored some single machine learning methods with different datasets to compare the performance of different machine learning models. Ref. [20] employed four different machine learning technologies to forecast the EVs charging load based on two different datasets. In order to obtain better performance in load forecasting, ensemble learning combines multiple machine learning models and has received much attention. For instance, Ref. [21] proposed an ensemble learning method to forecast the EVs charging station load, which combined three fundamental learners, including the artificial neural network, recurrent neural network (RNN) and LSTM. In [22], four machine learning models were combined to predict EV charging load for different geographic regions, including gradient boosted regression trees, quantile regression forests and quantile regression neural networks.

Beyond the above studies mainly based on classical methodology or machine learning technology, deep learning, one of the advanced technologies, has performed very well in a series of fields and received widespread attention in recent years. In [23], a load forecasting method for EV charging combining Extreme Gradient Boosting (XGBoost) and LSTM was proposed, and the data of a charging station was used to check the calculation example. Ref. [24] divided EV charging modes into three types and established three categories of a day-by-day load forecasting model to predict load for an EV charging station. Ref. [25] predicted the EV charging station loads by employing four featured deep learning approaches and comparing their performance. Ref. [26] employed a combined load forecasting methodology considering the elastic charging and discharging of EVs, which used a deep neural network (DNN) and time series method to forecast the load data. Ref. [27] employed LSTM to forecast EV charging station load and used an imputation method to handle missing EV charging data to improve accuracy. Ref. [28] proposed a novel method to forecast EV charging load, which combined CNN and a novel queuing model.

Although existing studies have successfully demonstrated the superior performance of deep learning on prediction tasks, most studies are actually based on deterministic models and lack the ability to capture uncertainty.

1.4. Contribution and Organization of the Paper

Bayesian deep learning (BDL), a novel probabilistic deep learning model, has been more and more prevalent in recommender systems [29], natural language processing [30], computer vision [31], autonomous driving [32] and health care [33–36]. In this paper, a novel load forecasting framework for EV charging stations is proposed on the strength of BDL, which aims at capturing uncertainty and great forecast performance. We experiment with using actual operation data collected on the Caltech campus. Compared with other deep learning methods, the proposed method performs better. In general, the major contributions of this paper are as the following:

(1) A novel load forecasting methodology is proposed to capture uncertainties in forecasting for EV charging stations, combining Bayesian probability theory and the LSTM neural network framework. The proposed model shows great performance not only for handling time series but also for capturing uncertainty.

(2) To capture uncertainty in forecasting, place a prior distribution upon the network weights and bias parameters of LSTMs and then apply variational inference to infer a posterior distribution over the given data. The results of Pinball and Winkler validate the ability of the model to capture uncertainty.

(3) The proposed methodology is compared with a series of popular benchmark methods by using Caltech's public EV charging dataset. Numerical results are presented, which demonstrate the superiority and effectiveness of the proposed method. Compared with other methods, the proposed model's deterministic and probabilistic forecasting results are significantly improved.

The following of this paper is arranged as below. Section 2 identifies the main challenges of EVs station load forecasting. Section 3 describes the BDL network and variational inference. Section 4 describes the proposed load forecasting framework for EV charging stations. Section 5 performs comprehensive digital experiments to prove the superb performance of the proposed model. Section 6 arrives at the conclusions.

2. Primary Challenges

The wide employment of EVs and its stochastic nature lead to failure in increasing the predictability of the charging station load significantly. In this part, the primary challenges existing in the process of forecasting are summarized as follows:

(1) Extensive stochastic uncertainty: For the EV charging stations load, uncertainty includes the load uncertainty and EV uncertainty. In this paper, stochastic uncertainty is employed to denote the uncertainty within the charging station load injected from various sources such as climate change, the behavior of EV owners, and the initial state-of-charge (SOC) of the EV battery. During the last years, although many probabilistic prediction methods have been developed to capture these abundant uncertainties, in the EV load or EV charging station load, the majority of the existing means can merely offer the prediction interval, which fails to provide detailed information about the prediction distribution of each single time step.

(2) Uncertainty in the model: Model uncertainty includes the uncertainty of model structure and model parameters. Apart from stochastic uncertainty, model uncertainty is also very vital for the task of EV charging load forecasting. Among an abundance of potential model parameters and structures, it is vital to understand the extent to which the selected combinations can accurately predict the EV charging station load under different conditions, such as climate, the behavior of EV owners and traffic flow.

Because of the above challenges, investigating and developing a deep learning model to address extensive uncertainty in the load is crucial. Thus, this paper selects the BDL model to predict EV charging station load because of its perfect performance in handling uncertainty.

3. Methodology

EV charging station load forecasting is a challenging problem because of numerous uncertainties mentioned in Section 2. To address this challenge, a novel short-term load forecasting framework for the EV charging station is introduced in this section, shown in Figure 1. The proposed framework includes two stages: (1) the data preprocessing stage; (2) the forecasting stage.

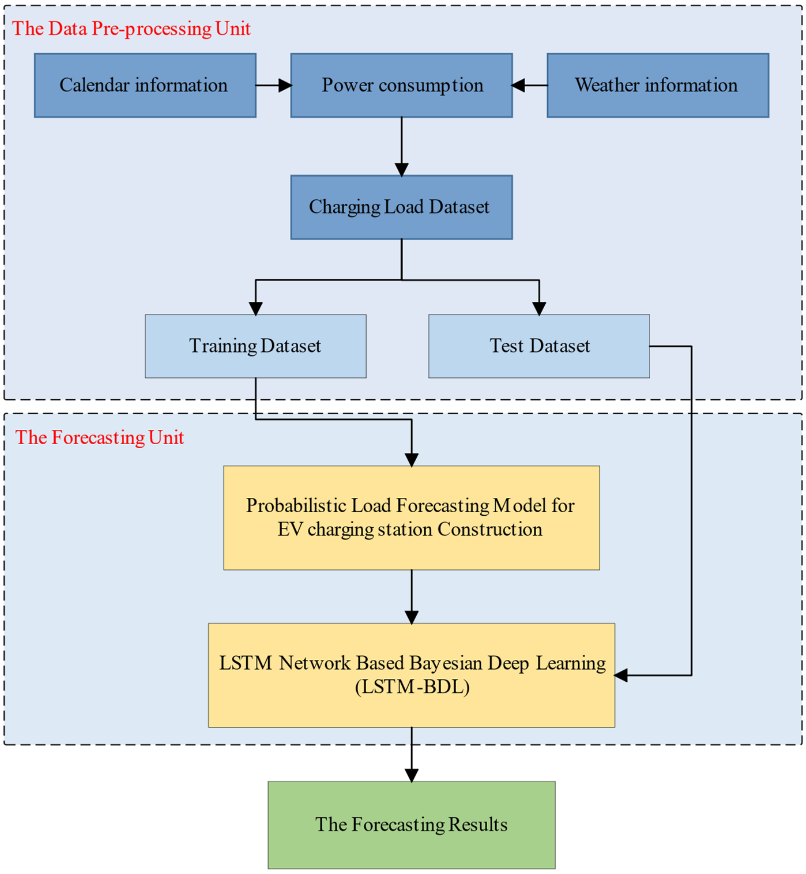


Figure 1. Overall framework of the method.

(1) Data preprocessing stage: Given the EV charging load dataset, compile a temporal series of power consumption and construct a group of potentially related predictors.

(2) Forecasting stage: Bayesian deep learning model for load forecasting is built and trained using the temporal series of power consumption. This procedure is iterated until the model performance is stable. Charging load forecasting is performed on the test dataset, and the forecasting performance is assessed through the evaluation criteria.

The proposed framework is described in the following subsections.

3.1. Bayesian Deep Learning Model

LSTM network, an especial RNN architecture, has proved to have great performance in many fields in the literature, such as load forecasting [37]. Firstly, we describe the structure of LSTM cell, shown in Figure 2, so we can introduce the fundamental architecture of the proposed BDL network. LSTM cell consists of the following parts, including the internal hidden state h_t, it controls the information flow by an independent hidden memory cell c_t and three types of gating cells during the whole learning process. A group of five vectors in $\mathbb{R}^d$ are employed to represent the states of the LSTM units at each time step t, including the forget gate f_t, the input gate i_t, the output gate o_t, the memory cell c_t, and the hidden state h_t. d denotes the amount of the LSTM cells. The computation functions of LSTM [28] are:

$$\begin{bmatrix} \widetilde{\mathrm{c}}_t \\ \mathrm{o}_t \\ \mathrm{i}_t \\ \mathrm{f}_t \end{bmatrix} = \begin{bmatrix} \tanh \\ \sigma \\ \sigma \\ \sigma \end{bmatrix} \left(\mathrm{W} \begin{bmatrix} \mathrm{x}_t \\ \mathrm{h}_{t-1} \end{bmatrix} + \mathrm{b} \right) \tag{1}$$

$$\mathrm{c}_t = \widetilde{\mathrm{c}}_t \cdot \mathrm{i}_t + \mathrm{c}_{t-1} \cdot \mathrm{f}_t \tag{2}$$

$$\mathrm{h}_t = \mathrm{o}_t \cdot \tanh(\mathrm{c}_t) \tag{3}$$

in which $\mathrm{x}_t \in \mathbb{R}^m$ is the present input, σ denotes the logistic sigmoid function, $\mathrm{W} \in \mathbb{R}^{4h\times(d+m)}$ and $\mathrm{b} \in \mathbb{R}^{4h}$ represent weights and bias of LSTM, respectively. The forget gate will selectively delete unnecessary information from the memory cell, the input gate will add fresh information into the cell, and the output gate will expose the interior memory state. The memory cell c_t could handle long-period dependencies in the sequences better by updating, deleting, and forgetting interior information selectively via these three types of gates. Because of the serial nature of the onefold LSTM layer, we can employ a random number of LSTM layers to construct a deep neural network. Unlike the common LSTM, the LSTM network combined with Bayesian theory (LSTM-BDL) replaces the weights and bias by actual number with a group of random variables, as shown in Figure 3.

In general terms, a prior distribution, such as $\mathcal{N}(0, I)$, is employed to denote W. Nevertheless, BNN's prior distributions ought to denote the prior belief concerning the neural network parameters distribution, including weights and bias, that are difficult to be determined due to the unclear physical meaning of these parameters. According to References [32,38,39], one of the most effective solutions is employing standard parametric distributions when prior belief is difficult to determine. As a result, the prior distribution is denoted as the standard normal distribution $p(W) \sim \mathcal{N}(0, 1)$.

When the suitable prior was determined, the likelihood of the model $p(Y_{train}|h_W(X_{train}))$ is defined as a normal distribution $\mathcal{N}(h_W(X_{train}), \sigma^2)$ which has a steady noise level σ, where $h_W(X_{train})$ denotes the target of LSTM about X_{train} and model parameters W. Based on Bayes' theorem, the model parameter's posterior distribution is acquired as

$$p(W|X_{train}, Y_{train}) = \frac{p(Y_{train}|X_{train}, W) \cdot p(W)}{p(Y_{train}|X_{train})} \tag{4}$$

Based on $p(W|X_{train}, Y_{train})$, we could predict the new output $\hat{y}$ that is defined as a random variable when setting a new input point $\hat{x}$, and can be formulated as below:

$$p(\hat{y}|\hat{x}, X_{train}, Y_{train}) = \int p(\hat{y}|\hat{x}, W) p(W|X_{train}, Y_{train}) dW \tag{5}$$

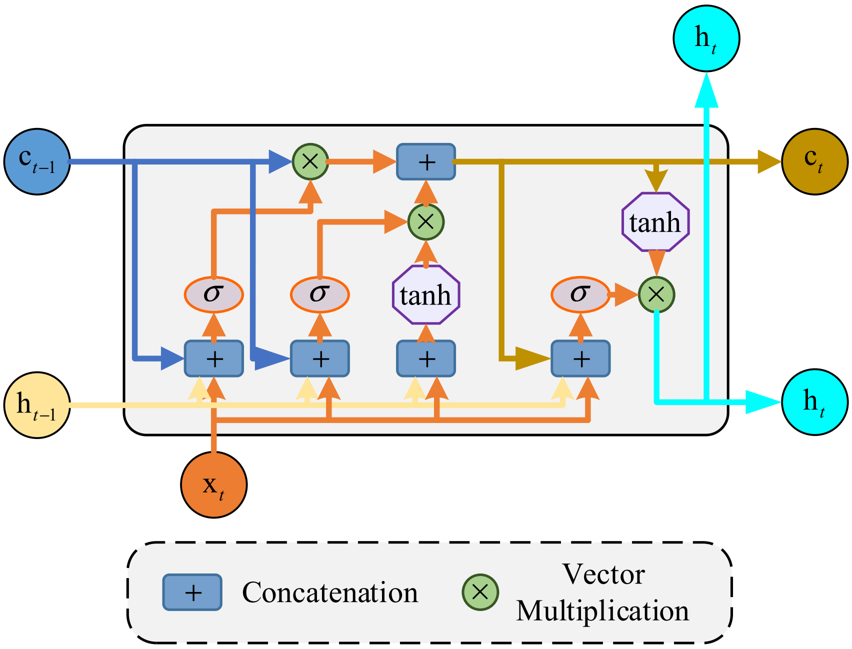


Figure 2. Structure of LSTM cell.

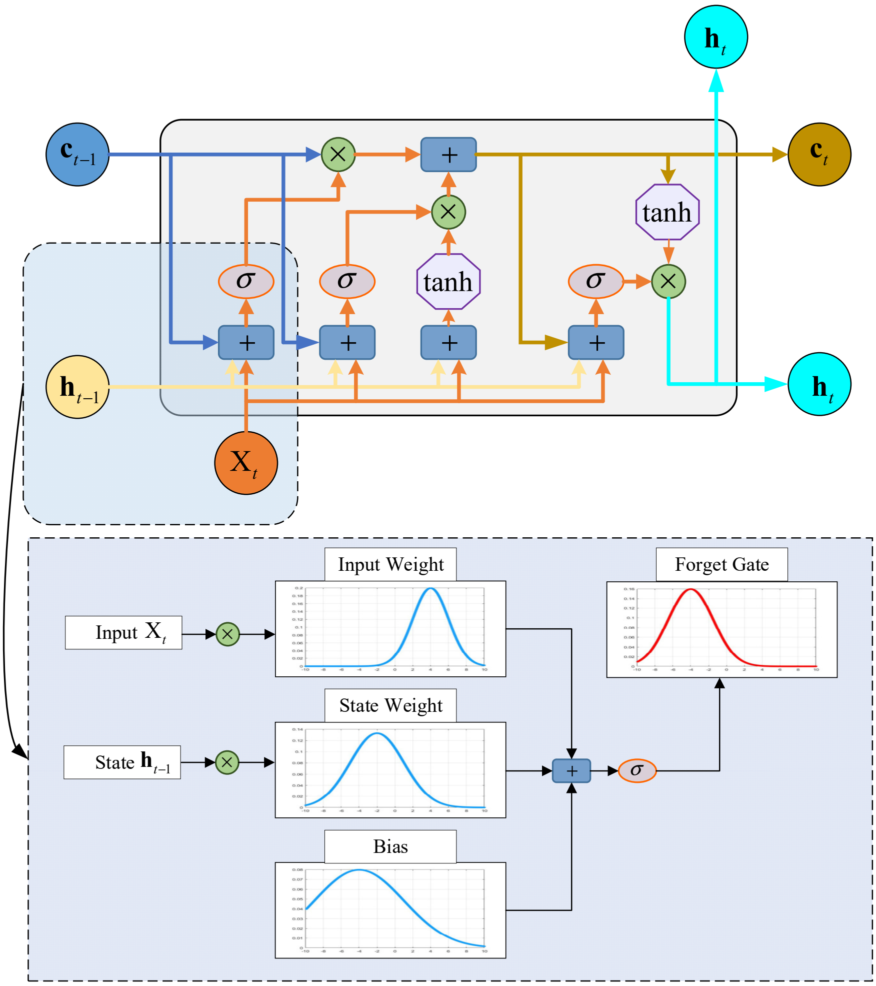


Figure 3. A proposed example of the LSTM-BDL network with an enlarged image of the forget gate.

Nevertheless, it is difficult to calculate the true posterior, especially for complex models. Therefore, different inference techniques are proposed to approximate posterior, including variational inference (VI) and Markov chain Monte Carlo (MCMC). The introduction of the VI-based method is below.

It is effective for VI to calculate various learning and inference problems in BDL, which has been demonstrated. The advantage of VI is that it transforms calculating posterior into approximating intractable distributions in machine learning. Calculating $p(W|X_{train}, Y_{train})$ is the main difficulty of BDL, especially when network structures are complex and data is multidimensional. To overcome this difficulty, approximating the posterior distribution via a variational distribution becomes VI's key idea, which is a probability distribution assessing for further inference easily. Two procedures will generally be taken to implement. First, we choose an approximative variational distribution $q_\tau(W)$ as the variational distribution family, which is parameterized by τ. In the second place, we minimize the Kullback–Leibler (KL) divergence between $q_\tau(W)$ and $p(W|X_{train}, Y_{train})$ in regard to τ, then find an optimal variational distribution. Here, the definition of the KL divergence between these two distributions is

$$\begin{aligned} &KL(q_\tau(W)||p(W|X_{train}, Y_{train})) \\ &= \int q_\tau(W) \log \frac{q_\tau(W)}{p(W|X_{train}, Y_{train})} dW \end{aligned} \tag{6}$$

Nevertheless, analytically solving the optimization problem is intractable. As a result, the target is transformed into maximizing Evidence Lower Bound (ELBO). In [32], a detailed mathematical derivation of VI is given.

3.2. Framework of Model

3.2.1. Data Pre-Processing Unit

We compile a temporal series of power consumption and a group of potentially related predictors from the dataset.

(1) Compilation of temporal series

A temporal series is defined as a group of observations representing a particular time, and the time difference is equal for all observations between two consecutive observations [40]. We extract the temporal series power consumption from the dataset with an observation per hour. We calculate the load consumed during one hour in a charging session according to the charging start and end time and the load used in each charging session. Then according to the sequence of sampling time, the charging load is sorted into the temporal series.

(2) Preparation of predictors.

There are two main types of ectogenous predictors in the forecasting models, including weather predictors and calendar predictors.

Weather conditions, such as temperature and humidity, can influence EV mileage. In order to handle possible intrinsic connections between EV charging patterns and weather, historical weather data for the area are included. Because the chosen charging station is located on the California Institute of Technology campus, the weather data for Pasadena, Caltech's location, is chosen as the weather predictor.

As a type of input in load forecasting, calendar predictors are typical. The author considers calendar predictors as important factors in [22], because of close connection with the social behavior of the EV users. For instance, EV users' social behavior may change during holidays or weekdays, even during different periods of the day. In this paper, 0 represents a working day, and 1 denotes a nonworking day.

3.2.2. Forecasting Unit

A novel BDL method is proposed in the Forecasting Unit, which is the basic core of the entire model. As shown in Section 3, Bayesian probability theory and the LSTM network are combined in LSTM-BDL to catch uncertainty in the forecasting process.

For the prepared load dataset, the proposed LSTM-BDL network is trained on the strength of the constructed features X^{Train} and the target labels Y^{Train}. The network parameters are built using a standard normal distribution as the prior, including the network's weights and bias, when the LSTM-BDL network is initialized. When finishing the training step, applying the test dataset X^{Test} to the trained model, the final outputs are the predicted EV charging station load.

4. Basic Setup of Experiments

4.1. Data Sources

The ACN-Data [41] is a dataset collected from EV charging sessions in the workplace, which Caltech has provided to the researchers for studying EV charging. The dataset contains more than 30,000 charging sessions collected from two workplace charging sites in California, located on the Caltech campus and Jet Propulsion Laboratory. In this paper, we use charging data collected from the charging site located on the Caltech campus as our experimental data. The adaptive charging network (ACN) on the Caltech campus has 54 EV supply equipment along with a 50 kW DC fast charger, which is open to the public and often used by non-drivers. The dataset has collected detailed information about each charging session in the ACN framework. Each charging session contains detailed information, such as "connectionTime", "doneChargingTime", "disconnectTime", "kWhDelivered", "sessionID", "stationID" and so on. Table 1 introduces the corresponding data fields of the dataset.

Table 1. Part of data fields in ACN-Data.

Field	Description
connectionTime	Time when the user plugs in.
doneChargingTime	Time of the last non-zero charging rate.
disconnectTime	Time when the user unplugs.
kWhDelivered	Measured Energy Delivered.
sessionID	Unique identifier for the session.
stationID	Unique identifier of the EV Supply Equipment.

This article applies the charging load data from 26 April 2018 to 29 February 2020 to train and test the model.

4.2. Experimental Setup

To evaluate the proposed forecasting model's superior performance, a series of advanced regression methods are used for comparison, which have been applied extensively and proven in the literature to have great performance. More specifically, point forecasting techniques, including multiple linear regression (MLR) and LSTM, SVR and probabilistic model, and quantile regression (QR), are applied to test forecasting performance compared with LSTM-BDL. All the tested models were carried out using Python with scikit-learn [42], Tensorflow [43] and Edward2 [44]. All algorithms were run on a laptop with the Windows 11 operating system, AMD Ryzen 7 5800 H CPU, 16 GB DDR4 RAM, and Nvidia GeForce RTX 3060 graphics processing unit.

4.3. Evaluation Criteria

The root mean square error (RMSE), the mean absolute error (MAE) and the R^2 score (R^2) are applied to assess the forecasting performance of the examined methods, which are typical evaluation criteria. Given the actual load of the EV charging station L^{test} and the predicted load of the EV charging station $\hat{L}^{test}$, the definition of the above-mentioned metrics is formulated as below.

The RMSE measures the errors between the real and the forecasting values, which can be formulated as below:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{T}\left(L_t^{test} - \hat{L}_t^{test}\right)^2}{T}} \tag{7}$$

where L^{test} is the real load value and $\hat{L}^{test}$ is the predictive load value at time step t.

In order to take measures of the absolute difference between the real and the forecasting EV charging station load, the MAE and the MAPE are calculated in W and percent % separately and are denoted as below:

$$MAE = \frac{1}{T}\sum_{t=1}^{T}\left|L_t^{test} - \hat{L}_t^{test}\right| \tag{8}$$

$$R^2 = 1 - \frac{\sum_{t=1}^{T}\left(\hat{L}_t^{test} - L_t^{test}\right)^2}{\sum_{t=1}^{T}\left(\overline{L}_t^{test} - L_t^{test}\right)^2} \tag{9}$$

where $\overline{L}_t^{test}$ is the average value of the L^{test}, at time step t.

Pinball and Winkler are typical evaluation metrics to evaluate the performance of the probabilistic forecasting methods. Pinball could evaluate the reliability and sharpness of the model, and Winkler could indicate the coverage and interval width. Pinball and Winkler are denoted as below:

$$Pinball = \begin{cases} q(L_t^{test} - \hat{L}_{t,q}^{test}) & L_t^{test} \geq \hat{L}_{t,q}^{test} \\ (1-q)(\hat{L}_{t,q}^{test} - L_t^{test}) & L_t^{test} < \hat{L}_{t,q}^{test} \end{cases} \tag{10}$$

$$Winkler = \begin{cases} \delta + \frac{2(M_t - L_t^{test})}{\alpha} & L_t^{test} > M_t \\ \delta + \frac{2(m_t - L_t^{test})}{\alpha} & L_t^{test} < m_t \\ \delta & m_t \leq L_t^{test} \leq M_t \end{cases} \tag{11}$$

where $\hat{L}_{t,q}^{test}$ represents the predictive load at the qth quantile, at time step t, M_t and m_t denote the upper and lower prediction interval bounds, respectively. It is notable that $q = 0.5$ for Pinball and $\alpha = 0.1$ for Winkler in this case.

5. Results and Discussion

In this section, we apply the test dataset to predict the charging load for 480 time steps in the future to compare the predictive performance between the proposed LSTM-BDL network and other advanced forecasting methods, including the point and probabilistic forecasting results. Notably, the 50th percentile values for QR and LSTM-BDL models are applied to evaluate their deterministic forecasting results.

In Figure 4, the predictive results of the RMSE, the MAE and the R^2 score in kWh are shown. For three evaluation metrics, a lower value of RMSE and MAE corresponds to the better performance of the forecasting model, and a higher value of R^2 score represents the better performance of the forecasting model. The results in Figure 4 show that the proposed LSTM-BDL takes the lead in the predictive performance, as shown by the approximately 39.3%, 42.4% lower RMSE, MAE and 17.9% higher R^2 score when we made a comparison with the benchmark method of support vector regression. Moreover, the performance of the LSTM-BDL also takes the lead when compared with the probability forecasting method, quantile regression, with approximately 32.2%, 40.2% and 16.0% improvements in the three evaluation metrics. The value of RMSE, MAE and R^2 score shows that capturing uncertainty in load forecasting for an EV charging station is significant. Due to the ability of the proposed model to capture uncertainty, its predictive performance is the best among all methods.

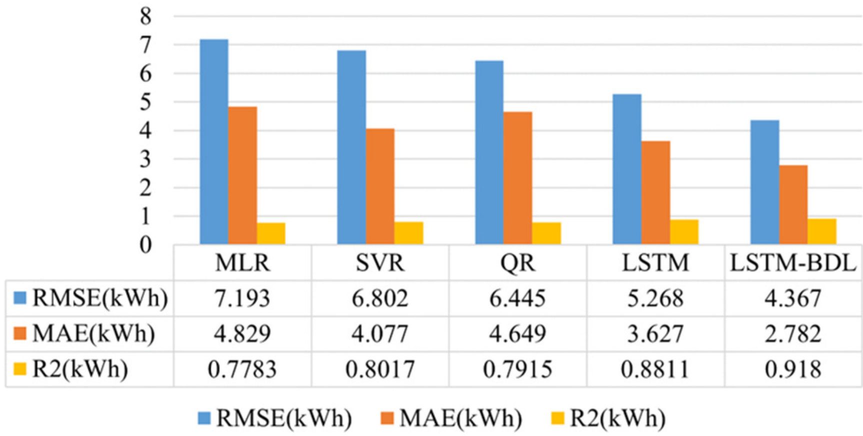


Figure 4. Forecasting results for different methods.

Additionally, Figure 5 shows the predictive outcomes of the 10 test days achieved through the LSTM-BDL model and QR model. It is notable that the blue line expresses the real charging load during the tested time, the predictive load of QR is represented by the red line and the predictive load of LSTM-BDL is represented by the green line. Figure 5 shows that QR cannot forecast the peak demand well, and some unexpected results are less than zero. It should be emphasized that the proposed LSTM-BDL model can well forecast the charging loads during peak periods which is a key factor for the safe operation of an EV charging station. In other words, the result reveals the ability of the proposed LSTM-BDL model to catch uncertainty is better than the QR method.

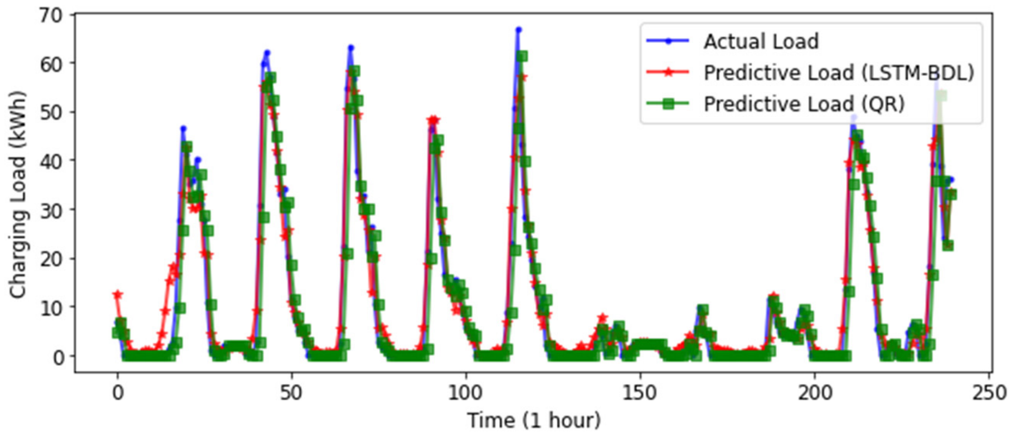


Figure 5. Probabilistic EV charging station load forecasting result.

Additionally, we separately predict the charging load on working days and nonworking days to investigate the probabilistic forecasting performance across different types of days. Figure 6 presents the average pinball loss values and the bar plots for QR and LSTM-BDL. As shown, although the amount of relative improvement varies across working days and nonworking days, the proposed model consistently outperforms QR.

Additionally, the overall probabilistic evaluation metric values of LSTM-BDL and QR are listed in Figure 7 to prove the superior performance of the proposed model. The results show that all probabilistic evaluation metrics of the proposed model are significantly better than QR. It indicates that QR focuses only on the uncertainty in the charging load data and performs poorly in forecasting.

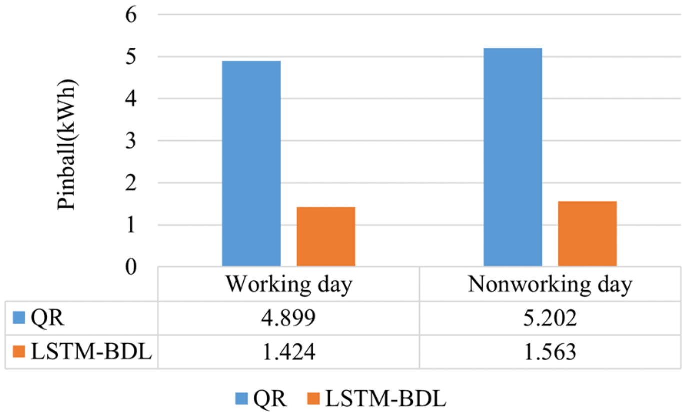


Figure 6. The average pinball loss across working days and nonworking days.

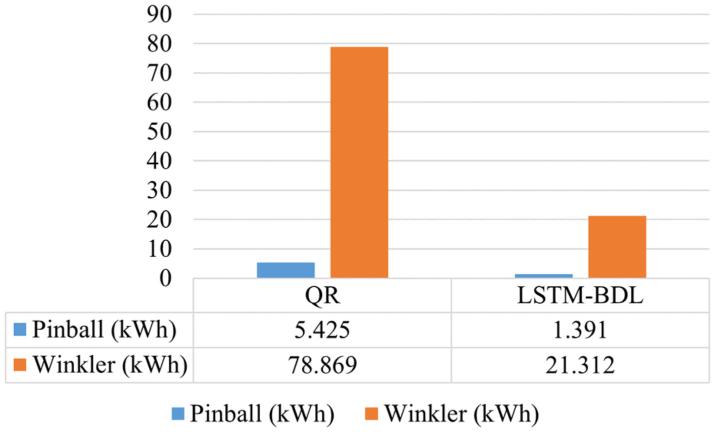
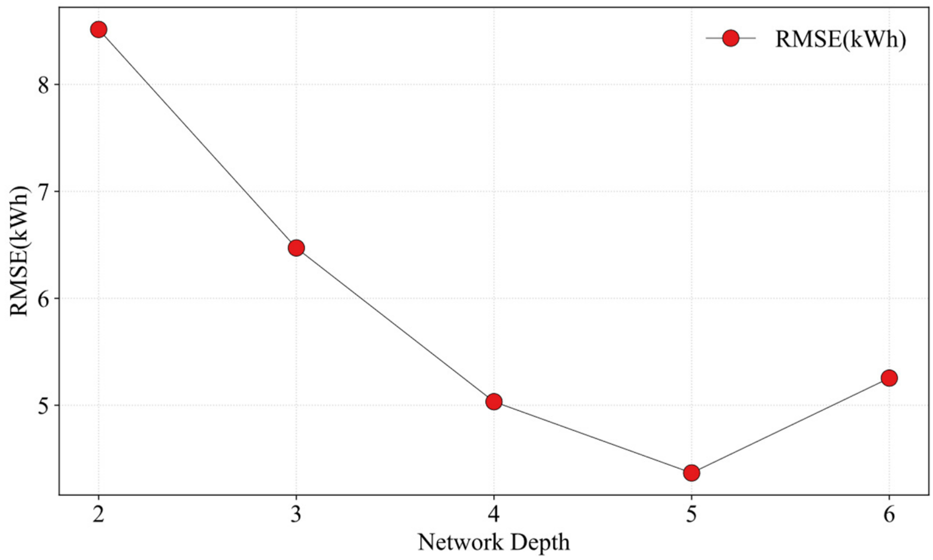


Figure 7. Probabilistic forecasting results for LSTM-BDL and QR.

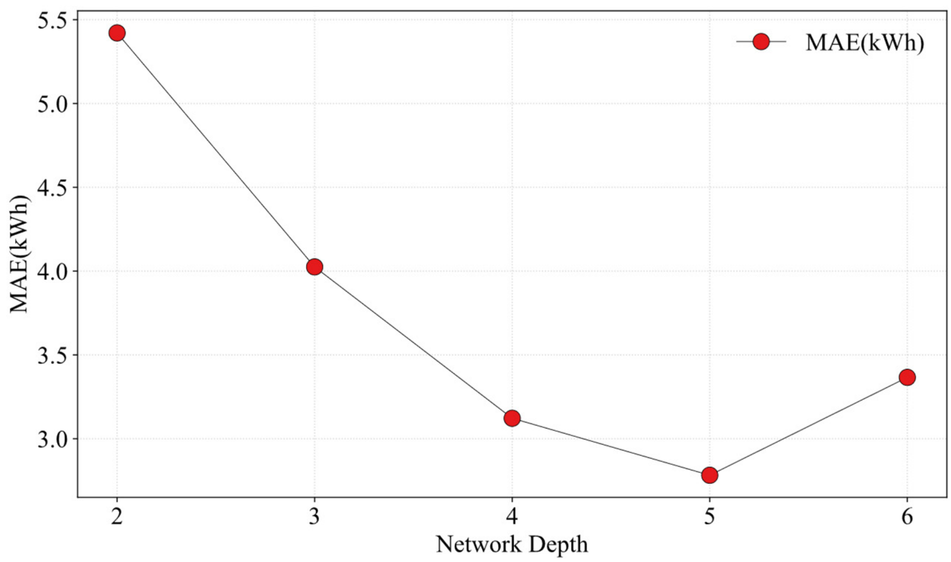
Additionally, we test the forecasting performance compared with different network depths. Figure 8 presents the results of RMSE and MAE for applying the prepared dataset when the layers increased from two to six. It indicates that the optimum performance will be obtained when the proposed LSTM-BDL model has five layers. When increasing the network depth from two to five, the RMSE and MAE results get smaller, and the forecasting performance improves. It indicates that appropriately increasing the network depth and parameters can significantly improve the forecasting performance. As the depth of the network increases, it can lead to overfitting and performance loss due to increased parameter redundancy and decreased data diversity. Table 2 lists the training time required for different layers of LSTM-BDL. As the number of layers increases, the parameters that need to be optimized for training continue to increase, so the required time also increases. However, when the number of layers increases further, it does not obtain a better forecasting performance and causes a time loss.

Table 2. Training time for different layers of LSTM-BDL.

Layer of LSTM-BDL	CPU Time (s)
2	507.28
3	857.43
4	1392.57
5	1985.63
6	2284.89



(**a**) RMSE versus different network layers



(**b**) MAE versus different network layers

Figure 8. The result of RMSE (**a**) and MAE (**b**) for the LSTM-BDL model with the changes in the network depth.

Furthermore, to test the proposed model's performance in practical use, we use a sub-dataset of ACN-Data collected from JPL to verify the prediction effect of the proposed model and compare it with QR. Table 3 lists the validation results. It can be seen from the results that the evaluation indicators of the proposed model are better than QR, which indicates the excellent performance of the model proposed in this paper.

Table 3. Forecasting results for LSTM-BDL and QR.

	LSTM-BDL	**QR**
RMSE	5.033	8.695
MAE	3.366	6.349
Pinball	2.851	6.782
Winkler	23.217	81.864

6. Conclusions

The research for improving the precision of load forecasting for EV charging stations is significant, which can not only provide guidance for power system economic dispatch but also promote the development of EVs. This paper proposes a Bayesian deep learning technique for load forecasting of electric vehicle charging stations with many uncertainties. In the proposed method, the data preprocessing unit is mainly used to process the original dataset, compile time series data and add necessary features to the forecast data. In the forecasting unit, we combine Bayesian theory with the LSTM neural network, change the LSTM parameters to the prior distribution, and use variational inference to approximate the posterior distribution during prediction. The prediction results show that this Bayesian deep learning technique can effectively solve the uncertainty problem in the load prediction process of electric vehicle charging stations. Further, the superior performance of the proposed method is demonstrated by comparison with a series of prediction methods. From the point forecasting results, the proposed model is approximately 39.3%, 42.4% lower RMSE, MAE and 17.9% higher than the benchmark method of support vector regression. When compared with QR, the proposed model is 74.4%, 73.0% lower than Pinball and Winkler. The excellent performance on different datasets shows that the proposed method could be applied to load forecasting for EV charging stations in real life.

In the future, we will further optimize the proposed probabilistic forecasting method and improve its prediction performance. Accurate load forecasting results of EV charging stations will have guiding significance for implementing the orderly charging strategy of electric vehicles. They also have important significance for optimizing the allocation of distribution network resources, reducing the peak-to-valley difference in electricity consumption. We will continue to apply the proposed model to more EV charging datasets and forecast the load consumed from various types of charging piles, such as AC, DC or higher power. Meanwhile, we will also try to apply the proposed method to more fields, such as distributed grid load forecasting, wind power forecasting, and so on.

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