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Ensemble Learning for Charging Load Forecasting of Electric Vehicle Charging Stations

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***Abstract*—Electric vehicles (EVs) can help reduce the dependency on fossil oil and increasing concerns on environmental pollution problems. However, due to the complex charging behaviors and the large charging demand, EV charging has imposed a large burden on the power system. The forecasting of electric vehicle charging loads can help address the above issues by providing power systems with the future load as a reference for energy dispatching. Machine learning methods have demonstrated their effectiveness for short-term load forecasting. Different from previous works, this paper proposes a novel ensemble learning-based forecasting model by combining three base learners including the artificial neural network (ANN), recurrent neural network (RNN), and long short-term memory (LSTM) algorithms. Specifically, a linear regression (LR) algorithm is used to learn the weight of each base learner. The feasibility and advantage of our proposed model are demonstrated by experiments conducted on a real-world dataset and comparisons with the other four baselines.**

***Index Terms*—load forecasting, electric vehicle charging station, ensemble learning**

I. Introduction

Traditional vehicles with internal combustion engines are highly dependent on fossil energy and have brought serious environmental issues. To reduce such dependency and further reduce greenhouse gas emissions, traditional vehicles are gradually replaced by electric vehicles (EVs) which are more environmentally friendly. However, the prevalence of electric vehicles has also brought in new challenges to modern power systems, such as larger charging fluctuations and higher load peaks [1], [2]. The charging load forecasting of electric vehicle stations, therefore, plays a crucial role in economical power distributions of the power grid [3], assisting alleviate the impact of fluctuations in charging peaks and valleys caused by disordered charging behavior.

In recent years, several solutions have been proposed for EV charging load forecasting. These studies formulate the load forecasting as time series problems. There are mainly two types of methods: statistical methods and machine learning methods. For the former approach, autoregressive moving average model (ARMA) model [4], autoregressive integral moving average model (ARIMA) model [5], Kalman filtering [6], and Monte Carlo Simulation method [7] are widely adopted for charging load forecasting. However, the randomness of drivers' behavior has a huge impact on the accuracy and robustness of the prediction accuracy. Furthermore, these methods fail to obtain satisfactory prediction accuracy given the increasing number of influencing factors.

Machine learning technology has shown its strong ability in short-term load forecasting [8], [9]. Some machine learning-based methods have already been applied to tackle charging load forecasting related problems. For instance, Qiming Sun et al. [10] employed Support Vector Regression (SVR) to make one-day ahead forecasting for the charging load. Furthermore, Mahmoud et al. [11] established a model for short term load forecasting by combining the Artificial Neural Network (ANN) algorithm with fuzzy systems. As deep learning technique gradually showed its impressive potential in many research area such as natural language processing [12], computer vision [13], etc., some researchers adopted the Long Short-Term Memory (LSTM) [14], an improved Recurrent Neural Network (RNN) algorithm, to solve load forecasting issues [15] [16] [17] [18]. Reinforcement Learning has also been exploited by previous research to predict the charging load of plug-in hybrid electric vehicles (PHEVs) [19].

However, most of the existing works are focused on using only one type of machine learning model for short-term charging load forecasting [20]. Ensemble learning [21], a technique to exploit the benefit of combining more than one machine learning model, has not been well studied for EV charging load forecasting problems. In this paper, we propose a novel ensemble learning-based method for charging load forecasting of EV charging stations. The solution can serve as an assisting tool for energy dispatching of power grids and facilitate the operational efficiency of EV charging [9].

The remaining of this paper is organized as follows. Section II introduces the basic technical background of ANN, RNN, and LSTM. The framework and algorithm of the proposed ensemble learning-based forecasting model are presented in Section III, followed by Section IV which gives the detailed implementation and experimental results. Lastly, Section V presents the conclusions.

II. Technical Background

This section presents a short introduction for the three models utilized in this paper i.e., ANN, RNN, and LSTM.

A. Artificial Neural Network

Artificial Neural Networks imitate the operation mechanism of the human brain neurons. ANN is composed of multiple neurons (nodes) connections, each of which is represented by different weights ω_{ij}. Besides, each neuron contains an activation function σ, which can be used to process the information from other neurons [22]. The output of each neuron can be calculated as:

$$a_j^l = \sigma_j^l \left(\sum_{i=0}^{n_{l-1}} \left(a_i^{l-1} \omega_{ij} \right) + b_j^l \right) \tag{1}$$

where a_j^l represents the output of jth node in layer l. a_i^{l-1} represents the output of ith node in layer $l-1$. σ_j^l is the activation function. ω_{ij} and b_j^l are weight and bias.

As shown in Fig. 1, we utilize the ANN model with 1 input layer, 3 hidden layers, and 1 output layer. The activation function is selected as the ReLU function.

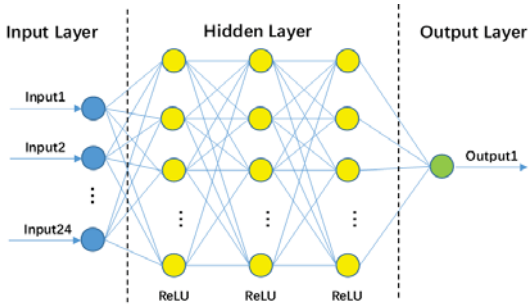

Fig. 1. ANN structure.

B. Recurrent Neural Network

To take the temporal relationship between input sequences into account, the Recurrent Neural Networks introduces a directional graph to show dynamic temporal behavior. RNN could not only receive the current information but also consider the information saved in previous memory. Given the above characteristics, RNN provides an effective method to solve time series forecasting issues. The structure of the RNN adopted in our study is presented in Fig. 2.

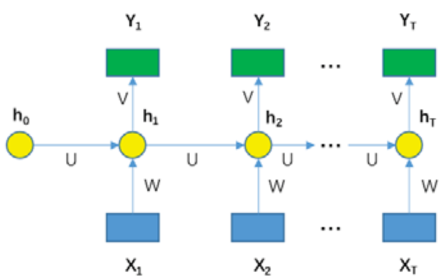

Fig. 2. RNN structure.

The calculation process of RNN is as follows:

$$h_T = f\left(U h_{T-1} + W x_T + b\right) \tag{2}$$

$$y_T = g\left(V h_T + c\right) \tag{3}$$

where h_T and h_{T-1} denote the state of the hidden layer at time T and time $T-1$. x_T and y_T are the input and output at time T. U, W, and V are the weight matrices. b and c are the biases. f and g denote the activation functions.

C. Long Short-Term Memory

Traditional standard RNN always suffers from the problems of vanishing gradient and exploding gradient [23]. To address these problems, LSTM, a kind of technique that employs a gating mechanism to control the addition and discarding of information, is proposed. This paper also utilizes LSTM, whose structure is shown in Fig. 3, as one of the base learners.

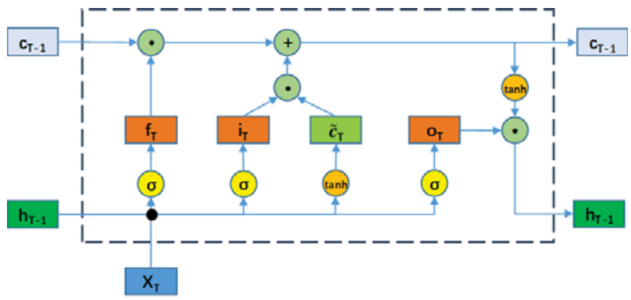

Fig. 3. LSTM structure.

Compared with RNN, the neuron of LSTM adds input gate i_T, forget gate f_T, output gate o_T, and internal memory unit c_T. The updating of parameters and cell states can be obtained by the following equations:

$$\begin{bmatrix} i_T \\ f_T \\ o_T \\ \tilde{c}_T \end{bmatrix} = \begin{bmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{bmatrix} \left(W \begin{bmatrix} x_T \\ h_{T-1} \end{bmatrix} + b \right) \tag{4}$$

$$c_T = f_T * c_{T-1} + i_T * \tilde{c}_T \tag{5}$$

$$h_T = o_T * \tanh\left(c_T\right) \tag{6}$$

where σ and $\tanh$ are the activation functions. W and b are weight and bias. x_T and h_T denote the input and state of hidden layer at time T.

III. The Ensemble Learning-Based Charging Load Forecasting Model

Ensemble learning aims to combine different base machine learning models to improve model performance. This paper presents a novel ensemble learning method that exploits three base learning techniques, that is, ANN, RNN, and LSTM, using a weighted averaging approach. Specifically, considering simplicity and robustness, a linear regression (LR) algorithm is trained to learn the weights for different base learners.

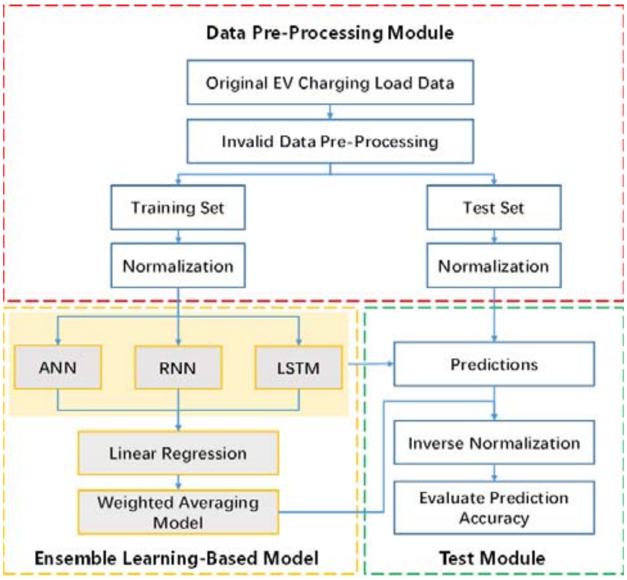

Fig. 4. Forecasting framework of the ensemble learning-based model.

A. Framework

The framework of the proposed ensemble learning-based forecasting model is presented in Fig. 4. As we can see, the original electric vehicle charging load dataset is first pre-processed to obtain proper data for experiments. The original data is composed of random transactions, which means that we need to first convert the energy consumption into real-time charging power according to the charging time, and then set the time window to one hour to obtain the average charging load of the charging stations per hour. To prevent some invalid data from impacting the prediction accuracy, we pre-process the dataset by replacing defective data with the average charging load of the same time before the day and after the day.

For experimental purposes, the charging load related data is divided into two subsets – training set and test set, according to a ratio of 0.7/0.3. The training set is used for model training. The test set is used for final function evaluation. Further, considering that three different neural networks are used to learn from the charging load data, the data scale has a great impact on the training and prediction of neural networks. Thus, the input data for the forecasting model is normalized with min-max scaling to scale data to a fixed range (0 to 1).

$$X' = \frac{X - x_{\min}}{x_{\max} - x_{\min}} \tag{7}$$

In the training phase, the training set is utilized to train the three base learners – ANN, RNN, and LSTM. After the final training epoch, predictions on the training data are generated based on the trained base learners. Next, the predictions and the true labels of training data are set as the features and labels for the training of the LR, which is adopted to learn the weight of each base learner.

In the test phase, predictions on test data are made using the trained base learners. Subsequently, the learned weighted averaging model is tested based on the predictions generated by base learners. Then, by inverting normalization, the final results are obtained and the prediction accuracy can be calculated based on the test labels and final results.

B. Algorithm

Algorithm. 1 illustrates the pseudo code of the proposed ensemble learning algorithm. The three base learners are first trained using training data and then make their predictions for training data. Next, the predicted values are concatenated as the features and labels of training data are used as the labels for the training of LR. Finally, the LR algorithm is tested based on the concatenated predictions generated by base learners using test data.

Algorithm 1 Ensemble Learning for Charging Load Forecasting

Input: Training data $D_T = \{(X_1, Y_1), (X_2, Y_2), \ldots\}$; Test data $D_t = \{(x_1, y_1), (x_2, y_2), \ldots\}$; Base learner B_i, where i = 1, 2, 3; Linear Regression L
Output: Ensemble learning model h_L; $RMSE$; MAE

while not at the end of this algorithm **do**
  for $i = 1, 2, 3$ **do**
    for $iteration = 1, 2, \ldots$ **do**
      $h_i \leftarrow B_i(D_T)$
    end for
    $P_T^i \leftarrow h_i(X)$
    $P_t^i \leftarrow h_i(x)$
  end for
  $P_T \leftarrow [P_T^1, P_T^2, P_T^3]$
  $h_L \leftarrow L(P_T, Y)$
  $P_t \leftarrow [P_t^1, P_t^2, P_t^3]$
  $P_l \leftarrow h_L(P_t)$
  Calculate $RMSE(P_l, y)$ and $MAE(P_l, y)$
end while

IV. Experiments

A. Experimental Setting

To verify the effectiveness and feasibility of the proposed method, the experiment under a real-world dataset [24] is conducted by comparing the ensemble learning method for charging load forecasting with 4 baselines including LR, ANN, RNN, and LSTM. Specifically, when LR works as the baseline, it utilizes the previous charging loads as the independent variables, while it adopts the prediction results of the three base learners as the independent variables when functions in the ensemble learning algorithm.

In this paper, we utilize a dataset of electric vehicle charging loads from 1 January 2018 to 31 July 2020 of all city-owned electric vehicle charging stations in Boulder, Colorado. Specifically, this dataset includes an overview of 20,562 random transactions. Even though there are several data types in the original dataset, we only use the transaction start time, charging time, and energy consumption as the data selected to be pre-processed.

To train the proposed model, we take one hour as the length for the time step and set timestep = 24 for look-back, that is to say, the base learner utilizes the information from the previous 24 hours as the input and subsequently output the information at the current moment. Furthermore, mean squared error (MSE) is used as the loss function for all models:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(y_i^{\mathrm{p}} - y_i\right)^2 \tag{8}$$

where N denotes the number of samples. y_i^{p} and y_i are the prediction and true label, respectively.

After the comparison of several optimizers, Adam is adopted for ANN and LSTM, and RMSProp is employed for RNN. In order to evaluate the prediction accuracy of the forecasting models, two common metrics including mean absolute error (MAE) and root mean squared error (RMSE) are used as the evaluation indexes. MAE is formulated as:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|y_i^{\mathrm{p}} - y_i\right| \tag{9}$$

RMSE is formulated as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i^{\mathrm{p}} - y_i\right)^2} \tag{10}$$

B. Experimental Results

The predicted values with different algorithms and the ground truth for one sample data are presented in Fig. 5. It can be seen that the forecasting curve of all algorithms can follow the trend of the real charging load curve. It is obvious that the charging load in the morning (from 0:00 to 8:00) is close to zero, while the peak charging load comes at noon (from 10:00 to 14:00). After that, the charging load fluctuates and finally declines at night. It can also be seen from Fig. 6 that the proposed ensemble learning-based forecasting model generates lower prediction errors thus better fit the real charging load curve, which verifies its effectiveness and advantages compared with other algorithms.

Fig. 7 shows the charging load forecasting results for one week (October 25, 2019, to October 31, 2019). We can see that the daily charging load curve has a certain periodicity. The load peak this week appears at noon every day while there are almost no electric vehicles charging in the early morning.

The forecasting performance on test set is presented in Table. I. As we can see, ANN, RNN, and LSTM algorithms obtain lower RMSE and MAE than LR, which proves the advantage of the deep learning technique. Further, the proposed ensemble learning model achieves the lowest prediction errors, with RMSE of 3.83 and MAE of 2.42. We can conclude that the ensemble learning-based model improves the prediction accuracy by 1.79%, 0.26%, 1.83%, and 1.57% compared with LR, ANN, RNN, and LSTM, respectively

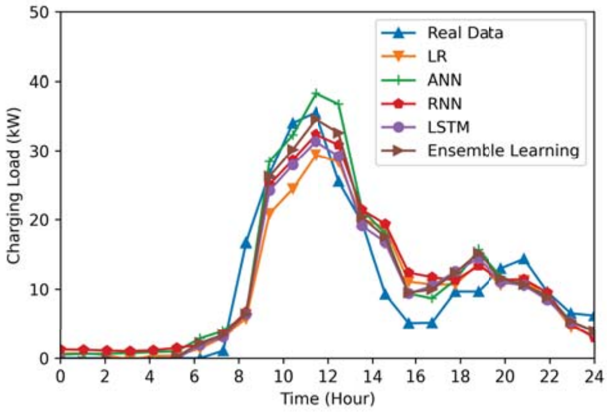

Fig. 5. One-day charging load forecasting results of different models.

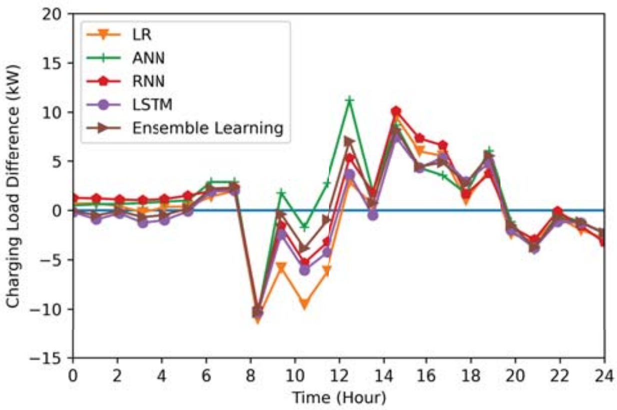

Fig. 6. One-day charging load forecasting errors of different models.

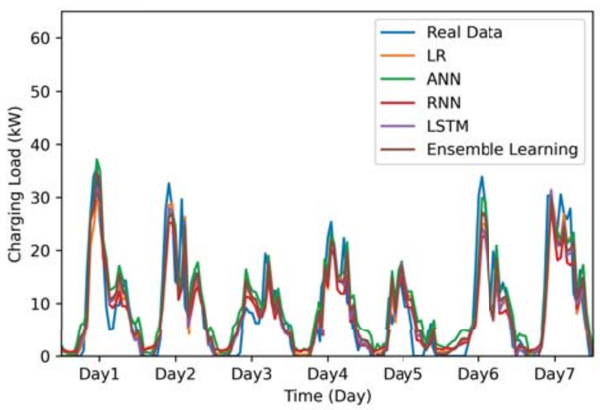

Fig. 7. One-week charging load forecasting results of different models.

when using RMSE as the prediction error. When MAE is adopted, the ensemble learning-based model improves the prediction accuracy by 5.79%, 2.48%, and 0.83% compared with LR, ANN, and RNN, respectively, while generating the same MAE score as LSTM.

TABLE I
PERFORMANCE COMPARISON OF DIFFERENT FORECASTING MODELS WHEN LOOK-BACK IS 24

Model	LR	ANN	RNN	LSTM	Ensemble Learning
RMSE	3.90	3.84	3.90	3.89	**3.83**
MAE	2.56	2.48	2.44	**2.42**	**2.42**

To verify the effectiveness of our proposed model under different look-back values, Table. II summarizes the prediction performance of different forecasting models when the look-back value is 12. As we can see, the ensemble learning-based model still achieves the lowest prediction errors in both RMSE and MAE. However, every model obtains higher prediction errors compared with the corresponding model with a look-back value of 24.

TABLE II
PERFORMANCE COMPARISON OF DIFFERENT FORECASTING MODELS WHEN LOOK-BACK IS 12

Model	LR	ANN	RNN	LSTM	Ensemble Learning
RMSE	4.24	4.06	4.22	4.13	**4.00**
MAE	2.96	2.80	2.96	2.83	**2.57**

V. CONCLUSION

In this paper, a novel ensemble learning-based forecasting model is proposed to predict the charging load of electric vehicle charging stations. Three base learners including ANN, RNN, and LSTM are employed in the ensemble learning algorithm. In order to fully exploit the advantages of the base learners, the weighted average technique is used by training an LR algorithm to learn the proper weights for different base learners. The comparisons with four baselines on a real-world dataset show that the ensemble learning-based model can achieve the lowest prediction error, which demonstrates the effectiveness of our proposed method. However, only limited data is used and one-step ahead forecasting is considered in this paper. We plan to further explore more possibilities with a wider range of data and multi-step forecasting methods in future research.

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