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ADVANCED TECHNIQUES FOR ELECTRIC VEHICLE CHARGING LOAD FORECASTING UNDER EMERGENCY CONDITIONS

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Abstract:
Experiments play a crucial role in high school physics education, providing a solid foundation for establishing concepts and discovering laws in physics. Experimental teaching is an essential component of the physics curriculum, as it aids students in understanding fundamental principles, developing basic skills, and cultivating scientific thinking. Relying solely on textbook knowledge and teacher lectures is insufficient for students to thoroughly grasp and comprehend physics concepts. By incorporating physics experiments, students can effectively integrate theoretical knowledge with practical exploration, facilitating the transformation of textbook knowledge into personal understanding. This article presents a specific simulated apparatus for high school physics velocity experiments, aiming to improve the accuracy and convenience of simulating physics velocity experiments through equipment enhancements.

Keywords: deep learning; long short-term memory artificial neural network; short term load prediction; K-means clustering algorithm

1. Introduction

The power industry is a crucial industry of carbon emissions, and the power system is an essential platform for new energy consumption. Therefore, constructing a new power system with new energy as the main body is a critical way to achieve the dual carbon goal [1]. The development of clean energy has become an inevitable trend. China has made it clear that during the 14th Five-Year Plan period, it will promote the clean, low-carbon, safe and efficient energy use. Electric vehicles (EV) not only inject new solid drivers into economic growth but also help achieve the goal of "carbon peak and carbon neutrality".

However, large-scale electric vehicle charging station access brings an impact on the security [2-3] and stability [4] of power grid operation. The distribution characteristics of large-scale EVs and the effective prediction of charging load are helpful in reducing this negative impact and promote mutual benefit between EVs and the power grid.

In this paper, a period of data regularly recorded in the past is integrated into a period series to forecast the future, which belongs to the problem of forecasting the time series. There are two main methods to solve the problem of time series prediction: statistical methods and deep learning-based methods. The most commonly used statistical methods include exponential smoothing (ES), auto-regressive moving average (ARMA), and empirical mode decomposition (EMD), etc.[5-6] These methods have high requirements on the stability of power load in order to obtain the proper function of the fitting result, which is suitable for the situation with few influencing factors and weak fluctuation of the load curve. However, the power load is affected by holidays, weather, and special events [7], and the randomness of load variation is enormous.

Therefore, deep learning-based methods have been widely used in power load forecasting in recent years. Literature [8] proposed a short-term power load prediction method based on the GRU-NN model, which has higher prediction accuracy and faster prediction speed. This method deals with different types of load influencing factors, and introduces a gated cyclic unit (GRU) network to process the historical load sequence with temporal characteristics. It also models and learns the internal dynamic change law of load data, analyzes the internal relationship between factors and load change as a whole, and finally completes load prediction. Literature [9] used the improved K-means algorithm to process power load data and used the training samples obtained after clustering to construct recurrent neural networks (RNN). The optimal weights were input into the RNN recurrent neural network model to achieve short-term power load prediction. It can improve the efficiency of forecasting and the accuracy of short-term load forecasting. Literature [10] puts forward a hybrid prediction model of the GRU and Catboost based on the Attention mechanism. Vector features of input data are extracted by the CNN model. The two-layer GRU model is used to learn input features and master their feature laws. The self-attention mechanism is used to mine input feature information fully. Finally, the load value is predicted to improve the accuracy of region-level load prediction, through the study of the characteristics of power load data. Literature [11] proposed a short-term power load forecasting model of LSSVM optimized by the Beetle Antennae Search Algorithm（BAS）. The Monte Carlo rule of the simulated annealing algorithm is introduced to enhances the optimization algorithm, which improves the algorithm's stability. The LSSVM model optimized by the improved BAS algorithm is applied to short-term power load forecasting. Wavelet threshold denoising is used to process power load data, which reduces the influence of some uncertain factors on load prediction and improves prediction accuracy.

However, none of the literatures above considered the impact of emergency events on load. RNN often has the problems of gradient disappearance and gradient explosion [12] and it is not accurate enough when dealing with time series problems.The large-scale access of EV's distributed power supply further increases the volatility and randomness of the power load [13]. Considering the dependence of load forecasting on timing and the impact of emergencies, this paper uses the long short term memory (LSTM) to construct load forecasting model. On this basis, the prediction model is improved by introducing the vector representing the impact of emergencies. Using real EV load data for training, the prediction results show that the proposed prediction method is better than Baseline algorithm in accuracy.

2. The LSTM

2.1 The RNNs

A neural network is composed of multiple artificial neurons, where input variables are transformed to obtain output values. In the problem of time series prediction, there will be a specific relationship between the data before and after, so people introduced the RNNs. Its structure is shown in Figure 1.

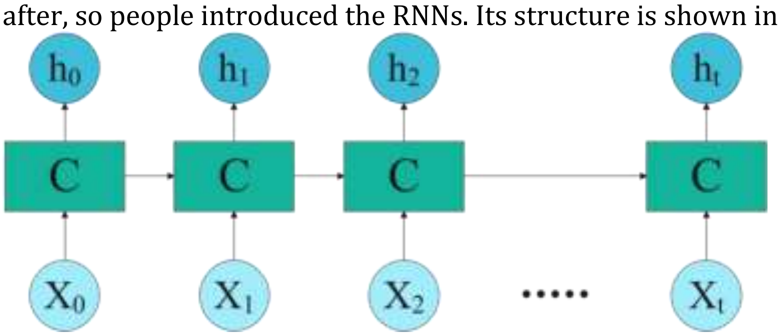

Figure 1: Structure diagram of RNNs

In Figure 1: x_t represents the input at each moment;h_t represents the output at each moment; C represents the processing part of the model.

Unlike traditional neural networks, each neuron in RNNs will pass information to the next neuron, thus solving the problem of long-term dependence well. However, as the time is lengthened, the model will forget the previous input information, which affects the final accuracy.

2.2 The structure of LSTM

LSTM is improved based on RNNs. LSTM introduces memory units into each neuron in the hidden layer and uses three gating units, namely the forget gate, input gate, and output gate to control the state of memory units. The network structure of LSTM is shown in Figure 2.

LSTM solves the problem of gradient disappearance and gradient explosion in RNN when processing a large amount of data [14]. It is more commonly used in time series prediction. The memory unit and the hidden state together remember the historical information of the sequence. The information in the memory unit is controlled by three gating units: the forget gate, and input gate and output gate.

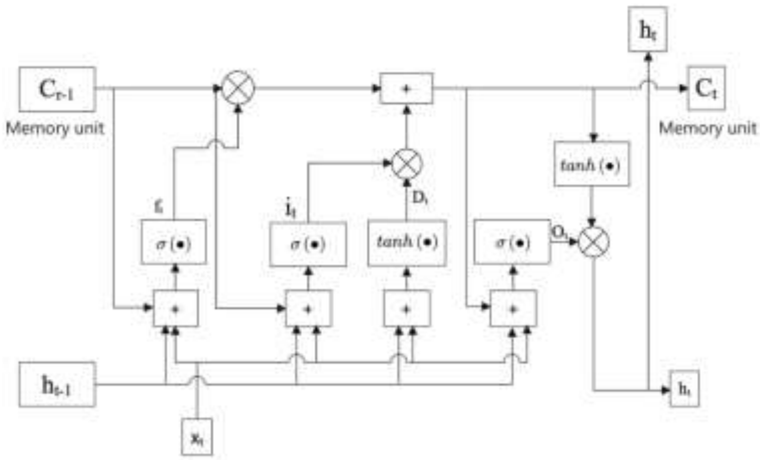

Figure 2: LSTM structure diagram

The input gate inputs new information into the memory unit according to h_{t-1} and $_t$. As shown in equations (1) and (2).

$i_t = \sigma(W_{ri}[h_{t-1}\ x_t]) + b_{ri}$ (1)

$D_t = \tanh(W_{ri}0[h_{t-1}\ x_t]) + b_{ri}$ (2)

Where: i_t is the information to be memorized; D_t is the candidate memory unit; W_{ri} and W_{rd} is the weight of each connection layer of the input gate; b_{ri} and b_{rd} is the input gate bias; σ(·) is the sigmoid activation function; tanh(·) is hyperbolic tangent function; x_t is the input of time t; h_{t-1} is the hidden state at the time t − 1.

The information that the forget gate deletes from the memory unit according to h_{t-1} and $_t$. As shown in equation (3).

$f_t = (W_f[h_{t-1}\ x_t]) + b_f$

(3) Where:$_f$ is the weight of the forget gate; b_f is the forget gate bias.

After calculating forget gate and input gate, the cell memory unit is updated by equation (4).

$C_t = f_t \circ C_{t-1} + i_t \circ D_t$ (4) Type:∘ is the product of Hadamard.

The output gate is then determined by equations (5) and (6).

$o_t = (W_o[h_{t-1}\ x_t]) + b_o$ (5)

$h_t = o_t \circ tanhC_t$ (6) Where: W_o is the output gate weight; b_o is the output gate bias.

3. Load forecasting model based on LSTM

The training process of the prediction model includes three stages: data pre-processing, model training, and model evaluation.

3.1 Data Pre-processing

Firstly, the daily EV load and time curve observations from December 12， 2019 to February 1, 2020 were plotted, as shown in Figure 3. It can be seen that due to the impact of the epidemic, the charging load began to decrease significantly. The influence of sub-emergencies was introduced, and the data was divided into three groups by using the K-means clustering algorithm, namely, "not affected by the epidemic", "just affected by the epidemic", and "affected by the epidemic". Variable Q was introduced, and the value of Q in each group was determined according to the daily average power load. At this point, the impact of the emergency on the power load was quantificated.

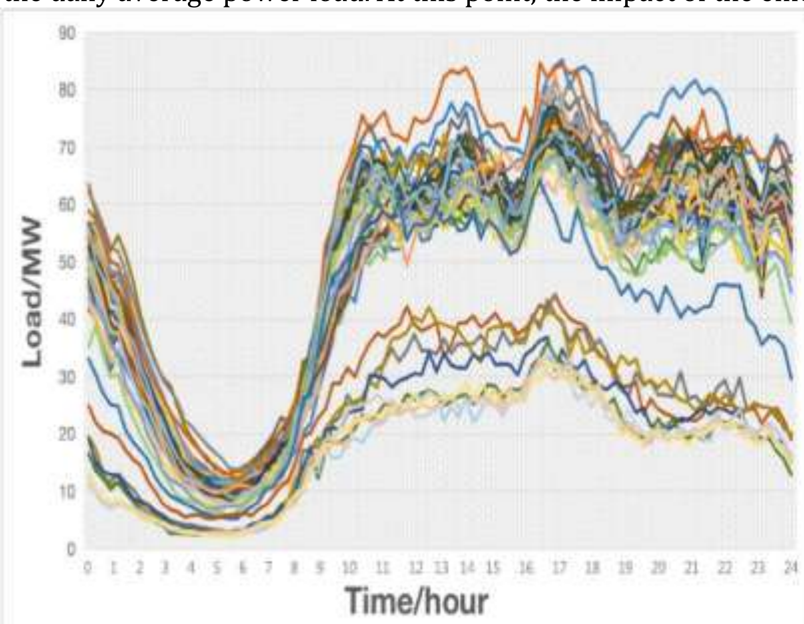

Figure 3: Daily load curve Neural networks are based on linear algebraic theory and cannot be trained directly on raw data, which needs to be converted into vectors before training [15].

Neural networks use the Back Propagation to find the optimal parameter configuration. Too large or too small data will increase the difficulty of finding the optimal solution. Therefore, equation (7) is adopted in this paper to convert all the input data into the numbers [0,1][15].

$$X_n = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (7)$$

Where: X_n is the normalized data; X is the original data; X_{max} is the maximum value in the original data; X_{min} is the minimum value in the original data.

3.2 Model training

There are two mainstream training methods: Back Propagation through time (BPTT) and Real Time Recurrent learning (RTRL).[16].In this paper, BPTT is used to train the neural network. Figure 4 is the training flow chart.

$y = \frac{(y_{pre} - y_{true})^2}{2}$ (8) $w_a = w_b \ \alpha \nabla w$ (9)

Where: y_{pre} is the predicted value; y_{true} is the true value; y is the loss function; w_a is the updated weight; w_b is the weight before the update; α is the learning rate; ∇w is the gradient of the loss function to the weight. Equation (8) is the expression of the loss function, and equation (9) is the expression of weight update among each neural unit.

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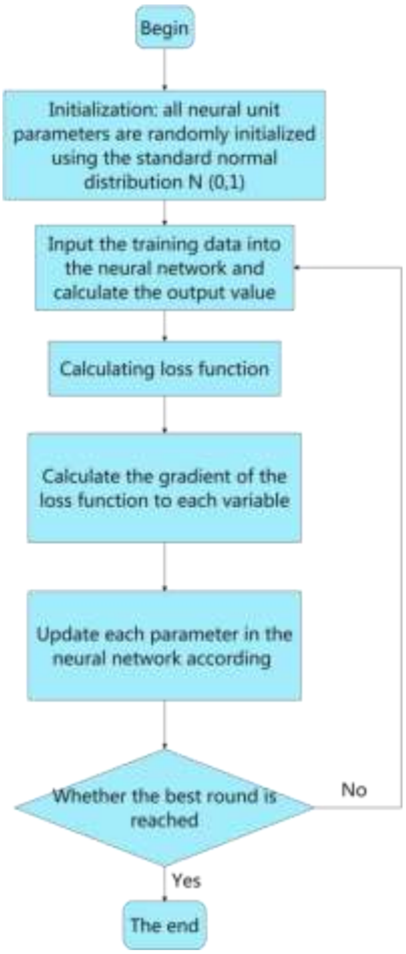

Figure 4: Training flow chart

After training the neural network with the training set for 1 round each time, the validation set is used to find the loss function, and the model parameters with the minimum loss function are reserved for the input of the test set. Figure 5 shows the flow chart of the optimal round determination[17].

3.3 Evaluation of the model

Predictions are usually judged by several criteria: mean absolute error (MAE), mean square error (MSE), and root mean squared error (RMSE). But above three criteria cannot be used to compare the prediction results between different time series. To be able to compare forecasts at a different time and spatial scales, Mean absolute percentage Error (MAPE) should be used. Equation (10) is the calculation formula of MAPE.

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \qquad (10)$$

Where: y_i is the true value; $\hat{y}_i$ is the predicted value.

The value range of MAPE is [0,+∞), where a MAPE of 0% indicates a perfect model, and a MAPE greater than 100% indicates a poor model. A smaller MAPE means a better accuracy of the prediction model.

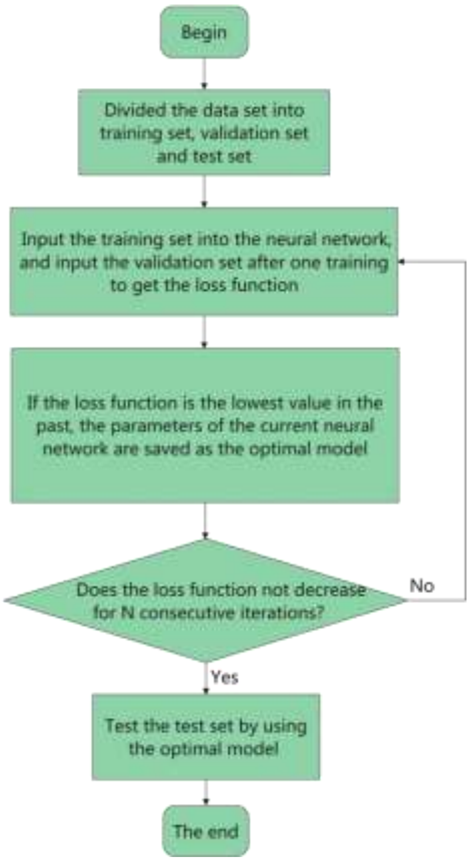

Figure 5: Flow chart of optimal turn determination

4. Example analysis

4.1 Experimental data processing and parameter setting

The short-term charging load of an EV charging station in Beijing was predicted, and the charging load data from December 12, 2019 to February 1, 2020 was used as the historical data set. The last day of the historical data set was used as the test set, and the rest were divided into the training set and the validation set according to 7:3.

The input data of each training was set to 36, and the learning rate was 0.001. The impact of the emergency on power load was quantificated as Q, and the historical load and the one-to-one corresponding Q were merged into vectors and used as the input layer of the neural network.The number of neural units in each layer of the hidden layer is set to increase from 5 to 30. The number of hidden layers was set as 1,2,3, and MAPE was used as the evaluation standard. According to the LSTM model established above, the model optimizer selected the random optimizer Adam, and the loss function adopted the mean square deviation. After ten iterations of training with the data of the first 35 days, the trained model was obtained, and its loss function was shown in Figure 6.

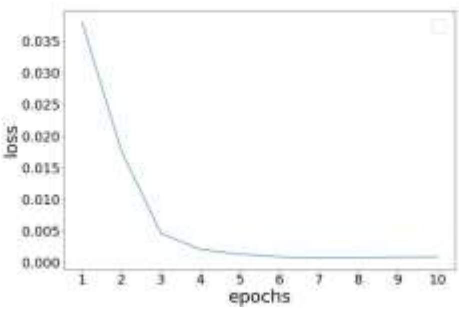

Figure 6: Curve of LSTM iterative loss value

4.2 Experimental results and analysis

Finally, the optimal model was obtained as the number of hidden layers was 2, and the number of neural units in each layer was 23. At this time, the lowest MAPE was 4.17%. To highlight the accuracy of the LSTM model in time series prediction, the RNN model and the CNN model were used to predict the load of the last one day based on the above data, and the MAPE was 10.72% and 7.07%, respectively, as shown in Table 1.

Table 1: Comparison of results of different models

Prediction model	LSTM	RNN	CNN
MAPE/%	4.17	10.72	7.07

Figure 7, Figure 8, and Figure 9 respectively show the comparison between the predicted results of the LSTM model, the RNN model, and the CNN model and the real value. In this paper, the load of an EV charging station in Beijing is trained and predicted. The data of the previous 51 days in this area is used for training and verification, and the load of the 52nd day is predicted. The above three figures show the prediction results of each model. It can be seen that the error of prediction results using the LSTM model is significantly lower than RNN and CNN, among which MAPE reduced by 6.55% and 2.9%, respectively. The reduction of the MAPE index indicates that the LSTM model used in this paper has a higher overall prediction accuracy when considering the impact of emergencies on power load.

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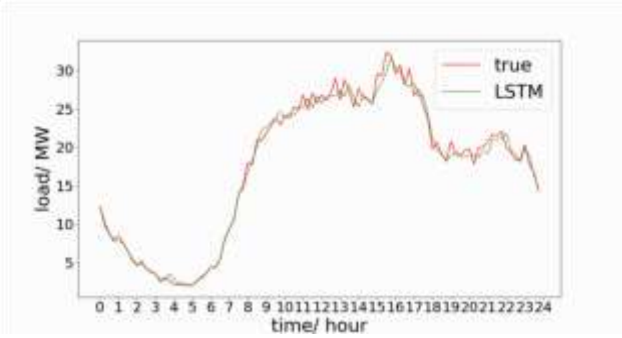

Figure 7: LSTM prediction results

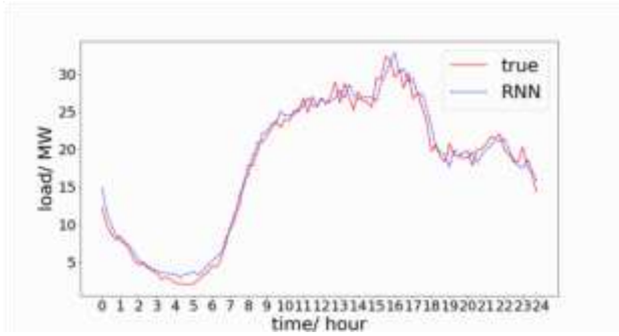

Figure 8: RNN prediction results

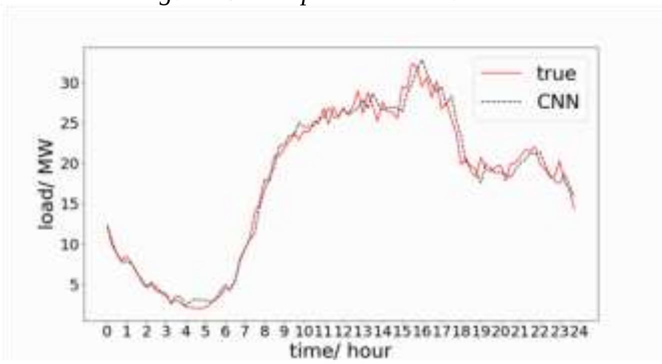

Figure 9: CNN prediction results

5. Conclusion

In this paper, the LSTM is used to construct a load prediction model which takes advantage of its ability to learn long-distance temporal dependence and considers the impact of emergencies on power load. The true load data is used to verify the model. Compared with the RNN and the CNN, the results show that this method improves the accuracy of load prediction, and the prediction performance is stable. In the future, EV charging load prediction in more complex environments considering weather, holidays and other influencing factors can be studied and combined with other load prediction methods to further improve the universality of the prediction model and the ability to process data.

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