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A Method of Prediction of Charging Time Based on LSTM Neural Network

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Abstract. *With the extensive application of electric vehicles, the charging time has become an important problem that car owners are currently concerned about. Therefore, a method of prediction of electric vehicle charging time based on Long-Short Term Memory (LSTM) is proposed. This method combines the sliding window technology and employs the total voltage, current, average temperature, average cell voltage, initial charging state of charge (SOC), required charging energy, and battery capacity of the electric vehicle as the input vector, and the charging time as the output vector to establish an electric vehicle charging time prediction model based on LSTM. According to experimental results, this method is effective for the predication of the charging time of electric vehicles.*

Keywords: Electric Vehicle, Charging Time, LSTM, Sliding Window Technology, Battery.

1. **Introduction.** In recent years, with the development and maturity of electric vehicle technology, electric vehicles have been widely applied [1, 2]. In comparison with fuel vehicles, which can be filled up in a short period of time and the drivers do not need to wait for too long, an electric vehicle with a battery as power source needs to wait tens of minutes or even one or two hours to be completely charged. The charging time of electric vehicles has been an object of great concern to the drivers [3, 4].

Regarding the research of charging time prediction, numerous scholars have conducted in-depth studies [5-7]. Hu et al. [8] proposed a dual-objective optimal charging strategy based on the battery equivalent circuit model, which completely considers the impact of the battery's maximum voltage, maximum current, and charging time on the charging strategy. Meanwhile, the charging time and charging loss of the battery are Optimized. Subsequently, the influence of LiNMC and LiFePO4 battery charging voltage threshold, temperature and health status on the charging results are analyzed. Based on the quasi-two-dimensional model (P2D) of the battery, with temperature and voltage as constraints, Torchio et al. [9] proposed a secondary dynamic matrix control (QDMC) method to minimize the charging time in order to achieve the desired state of charge. Based on simulation experiments, it can be known that the use of this method can significantly reduce the charging time of the battery while the experimental process is limited to simulation verification, and there is no corresponding actual experimental verification. Abdollahi et al. [10] proposed a closed-form solution to the optimal charging of lithium-ion batteries. The charging time, energy loss, and temperature rise index are used as the objective function. At the same time, the Constant Current–Constant Voltage charging process is optimized. Finally, the optimization of the objective function can be realized.

At present, most of the researches on the prediction of charging time stay on the single battery. In this paper, the research object is electric vehicle batteries, and it is carried out directly using the charging process data of electric vehicles instead of using a single lithium battery. Then, an electric vehicle charging time prediction model based on LSTM is proposed in the present study. The voltage, current, temperature and other variables generated during the charging process of electric vehicles are used as input, and the charging time is employed as an output to establish an electric vehicle charging time prediction model based on LSTM. The experimental results prove that the LSTM-based charging time prediction model for electric vehicles is practical and effective.

2. **Related work.**

2.1. **LSTM.** LSTM is a special RNN. Figure 1 shows the internal structure of LSTM [11-13]. The most important thing in LSTM is the cell state. As presented in Figure 1, C represents the cell state. LSTM can add or delete information to the cell state that is controlled by a structure called "gate" [14, 15]. There are three gating units inside the LSTM model, respectively, forget gate, input gate, and output gate. The function of the forget gate determines which part of the cell state information needs to be discarded [16, 17].

In Figure 1, S_{t-1} is the output of the upper layer hidden unit, x_t is the current input, S_t is the output of the current layer hidden unit, C_{t-1} is the last cell state, C_t is the cell state updated in the current layer, f_t is the forget gate, i_t is the input gate, o_t is the output gate and σ is the sigmoid function. The update calculations of the LSTM model are expressed in formula 1 to 7:

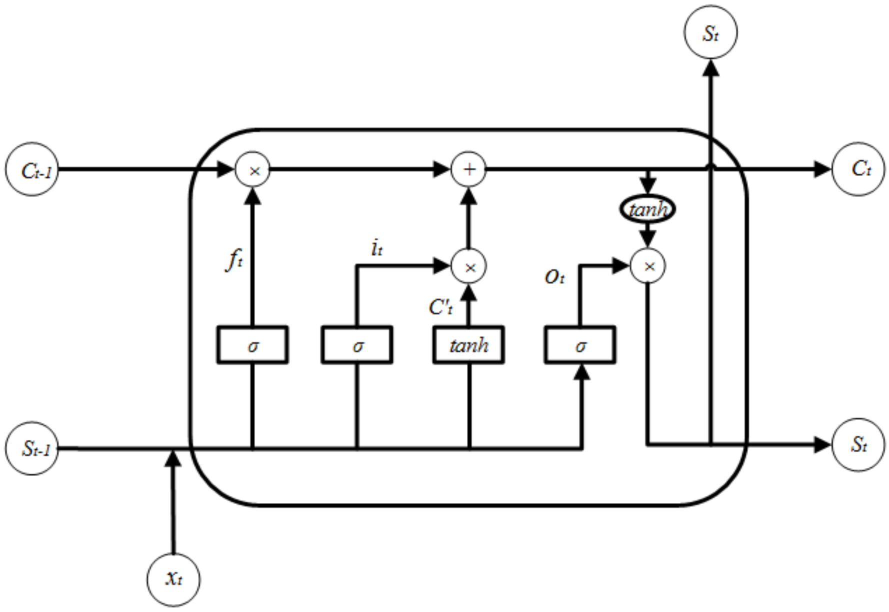


FIGURE 1. LSTM structure

$$f_t = \sigma(w_f S_{t-1} + u_f x_t + b_f) \quad (1)$$
$$i_t = \sigma(w_i S_{t-1} + u_i x_t + b_i) \quad (2)$$
$$C'_t = tanh(w_c S_{t-1} + u_c x_t + b_c) \quad (3)$$
$$g_t = i_t \cdot C'_t \quad (4)$$
$$C_t = f_t C_{t-1} + g_t \quad (5)$$
$$o_t = \sigma(w_o S_{t-1} + u_o x_t + b_o) \quad (6)$$
$$S_t = o_t \cdot tahn(c_t) \quad (7)$$

where w_f, w_i, w_c, w_o, u_f, u_i, u_c, u_o is the weight, b_f, b_i, b_c, b_o is the bias weights.

2.2. **Sliding window technology.** For the LSTM neural network model, in order to enable the training process to remember more information than before, the sliding window technology is used to process the data in the current study. Figure 2 illustrates how to use the sliding window technology to prepare sample data [18]. The value in the Figure 2 denotes the series data, the window size refers to the length of the input data and the prediction window signifies the length of the prediction data. Figure 2 shows that using sequence data {1,5,4} to predict {6} and then sliding 1 step based on {5,4,6} to predict {3}.

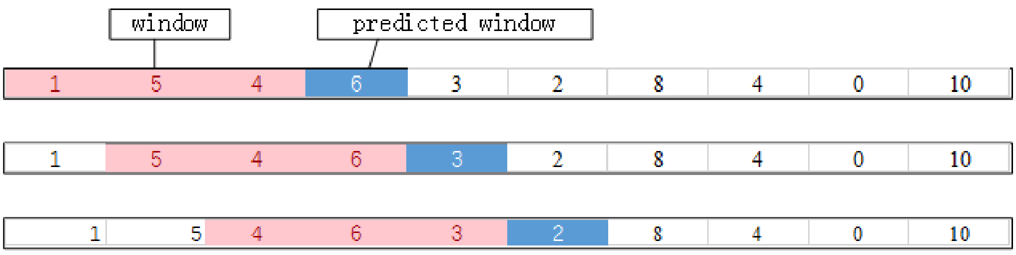


FIGURE 2. Sliding window

2.3. **Pearson correlation coefficient.** The Pearson correlation coefficient (PCC) is a method to measure the correlation between two variables. PCC was developed based on a related idea proposed by Francis Galton in the 1880s [19, 20] and is widely used in scientific research. Its value is between 1 and −1, where 1/−1 is a positive/negative linear correlation, and 0 has no correlation. In Pearson's correlation analysis, when the correlation coefficient of two parameters is less than 0.2, it indicates that the correlation between the two parameters is extremely weak. The calculation of PCC is expressed in formula 8:

$$p_{(X,Y)} = \frac{Cov(X,Y)}{\sqrt{D(X)}\sqrt{D(Y)}} = \frac{E((X-E(X))(Y-E(Y)))}{\sqrt{D(X)}\sqrt{D(Y)}} \tag{8}$$

where E is the mathematical expectation or mean, D is the variance and $\sqrt{D}$ is the standard deviation. $E((X-E(X))(Y-E(Y)))$ is called the covariance of the random variable X and Y.

2.4. **Evaluation.** In this article, three indicators are used to evaluate the prediction results of the model, namely, MSE, MAE and maximum error (MAX_ERROR). The calculation of MSE, MAE and MAX_ERROR are shown in formula 9 to 11:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \tag{9}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i| \tag{10}$$

$$MAX\_ERROR = max(|\hat{y}_i - y_i|), i = 1, 2, ..., n \tag{11}$$

where n is the number of data, $\hat{y}_i$ is the predicted value of the model and y_i is the actual charging time value.

3. **Method.** Since the data generated during the charging process of electric vehicles are time series data, an electric vehicle charging time prediction model based on LSTM is proposed. Firstly, the data set is preprocessed and normalized, and then divided into three parts, respectively, the training set, the validation set and the test set. Then, processed and normalized training set data are imported into LSTM to build the electric vehicle charging time prediction model. The specific steps are shown in Figure 3.

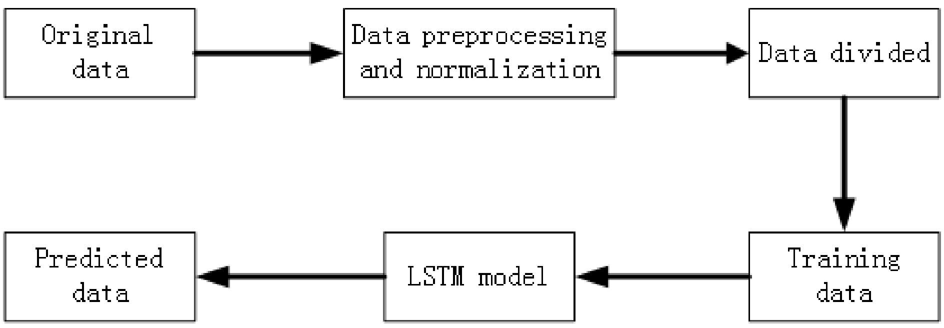


FIGURE 3. Steps of electric vehicle charging time prediction model

3.1. **Data information.** In this article, in order to investigate the charging time of electric vehicles, the charging data of 10 electric vehicles are selected for performing the analysis. Among the 10 selected electric vehicles, according to the vehicle information, they can be divided into 5 types. Table 1 shows the specific information of these 5 types electric vehicle. It can be observed from Table 1 that the battery types and battery capacities of these 5 types electric vehicles are different. The battery type of electric vehicles of type 1 is Li2Mn2O4, and the rest are LiFePO4. The battery capacities of various types of electric vehicles are respectively 93kWh, 99kWh, 180kWh, 295kWh, and 221kWh.

Table 1. Information on 5 types of pure electric vehicles

Parameter	Type 1	Type 2	Type 3	Type 4	Type 5
Curb quality (in kg)	8150	8800	11700	17000	12200
Wheelbase (in mm)	4500	5300	5100	5600	5600
Maximum speed (in km/h)	69	69	69	69	69
Motor rated power (in kW)	80	100	100	100	100
recharge mileage (in km)	201	261	281	520	420
Battery Type	Li2Mn2O4	LiFePO4	LiFePO4	LiFePO4	LiFePO4
battery capacity (in kWh)	93	99	180	295	221
Number of single cell	384	162	156	384	192
working voltage of single cell (in V)	2.5-4.0	2.5-4.0	2.5-4.0	2.5-4.0	2.5-4.0
Number of temperature measuring points	96	54	52	96	36

The actual data of the electric vehicle are collected by the on-board terminal T-box, and then the T-box is connected to the electric vehicle big data platform through network communication. The sampling time of the data set is 10 seconds.

3.2. **Data information.** In the data, the dimensions of the various characteristic parameters are inconsistent, and some values are extremely large, even reaching more than one hundred. However, some are very small with only single digits. Therefore, the data need to be normalized. The main function of data normalization is to ensure the independence of data, and thus the data are distributed in a uniform interval to meet the model's requirements. Data normalization is calculated by formula 12, where x_{max} refers to the maximum value and x_{min} denotes the minimum value. After data normalization, the data can be compressed between [0,1].

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{12}$$

3.3. **Charging time prediction model.** In this paper, the charging data of electric vehicles are used as the training data, validation data and test data of the charging time prediction model. Additionally, the relationship between input and output is established through LSTM mapping. The structure of the LSTM-based prediction model for the charging time of electric vehicles is presented in Figure 4, where $(X_{1,1}, X_{2,1}, X_{3,1})$, $(X_{1,2}, X_{2,2}, X_{3,2})$, ... , $(X_{1,n}, X_{2,n}, X_{3,n})$ are the input feature vector, and T_{l1}, T_{l2}, ... , T_{ln} are the output feature vector.

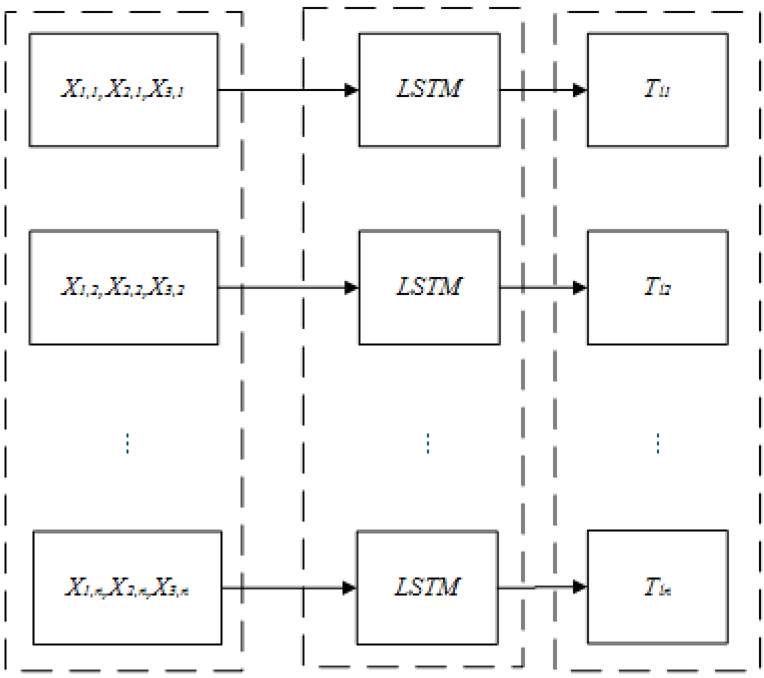


FIGURE 4. Structure of the charging time prediction model based on LSTM

4. **Experiment and result.** According to the electric vehicles involved in the present study, the data of 9 electric vehicles are selected randomly to build the model. During the 9 vehicles, 10% of charging processes of each vehicle are selected as the first test data set, and charging processes of another electric vehicle which does not participate in the establishment of the model, are selected as the second test data set. Testing using the charging starting point data of the first test data set is called the internal test experiment, and using the charging starting point data of the second test data set is called the external testing experiment.

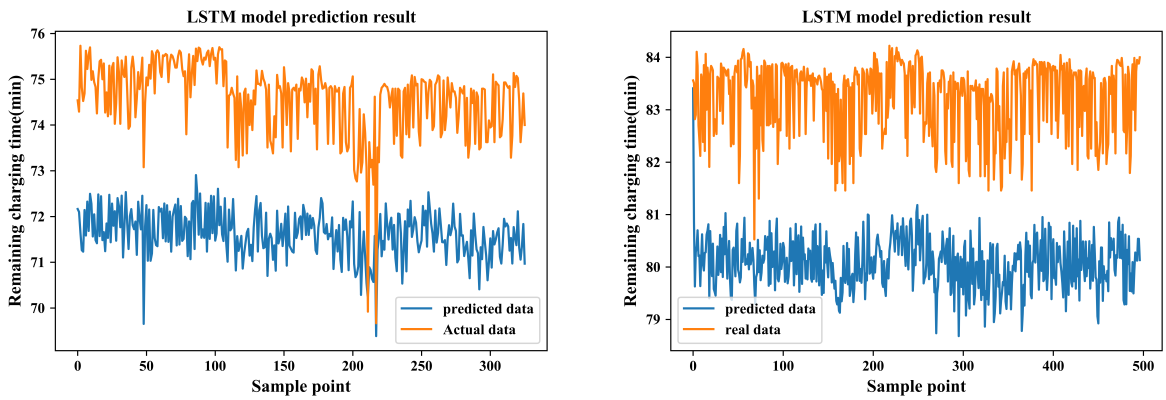
4.1. **Feature analysis.** In this paper, the total voltage, current, average temperature, average cell voltage, initial charging SOC, and required energy of electric vehicle batteries are selected as the main factors which can affect the charging time. In the meanwhile, the PCC is used to analyze the above factors. The PCC results are displayed in Table 2. It can be seen from the Table 2 that the correlation between the above factors and the charging time is greater than 0.2, indicating that the above factors exert a certain influence on the charging time. Considering that charging data of 10 electric vehicles are used to build the prediction model, the charging time of electric vehicles varies with its battery capacity. The final characteristic parameters are determined as follows: total voltage, current, average temperature, average cell voltage, initial SOC, required energy, and battery capacity.

TABLE 2. The correlation analysis results of charging time

Parameter	Total voltage	Current	Average temperature	Average cell voltage	Initial charging SOC	Required energy
Coefficient value	0.6830	0.2520	−0.5143	−0.8366	−0.2030	0.9792

4.2. **Parameters.** In the LSTM neural network model, the numbers of hidden layer, the batch size, the number of neurons, the selection of the optimizer, and the size of the window generate a great influence on the forecast of the model. Based on the established electric vehicle charging time prediction model and the selection of characteristic parameters, a set of parameters of the model is set as follows: LSTM layer = 1, number of neurons = 50, batch size = 128, windows size = 9, predicted window size = 1 and optimizer = SGD.

According to the above model parameters, the internal and the external test are carried out. The experimental results are shown in Figure 5 and Table 3. As can be seen from Figure 5, whether it is internal test experiment or external test experiment, there exists a certain gap between the model prediction results and the actual results. The MSE and MAE of the internal and external test experiment are greater than 9 and 2.5, respectively, indicating that the model prediction results and the actual results are low in anastomosis. According to the experimental results of internal and external test, it can be judged that it is feasible to predict the charging time of electric vehicles based on the LSTM model. However, the model based on the above parameters has poor predictive ability.



(a) internal test (b) external test

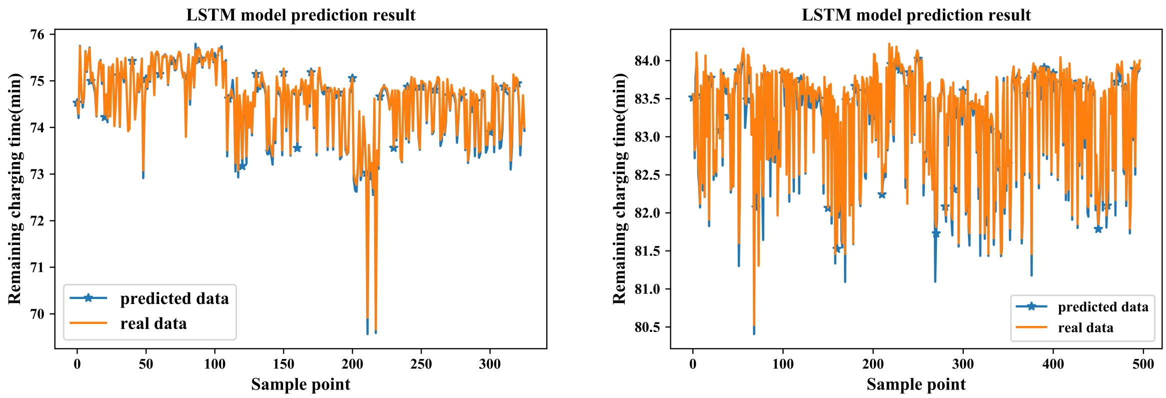
FIGURE 5. Model prediction results

TABLE 3. Evaluation indicators of test results

test	MSE	MAE	MAX_ERROR(in minute)
internal	9.2531	2.9828	4.4
external	10.3362	3.1584	4.3

4.3. **Analysis.** In order to enhance the predictive ability of the charging time prediction model, an experimental analysis on the parameters of the LSTM model is conducted. The analysis is started inside of the LSTM model. Therefore, the influence of different hidden layers and the number of neurons on the prediction effect of the model are discussed firstly. Then, it analyzes the impact of batch size and window size on the model during model training. Finally, the impact of using different optimizations is conducted. The specific parameters are set as follows: hidden layer = [1,2,3], neuron= [25,50,75,100], batch size= [8,16,32,64,128,256,512], window size = [3,6,9,12,15,18] (representing half a minute, one minute, 1.5 minutes, 2 minutes, 2.5 minutes, 3 minutes) and optimizer = [RMSprop, Adagrad, Adadelta, Adam, SGD].

According to the results of corresponding parameter analysis, it is finally determined that the best LSTM model parameters in this paper include: layer = 1, neuron = 100, batch size = 16, window size = 9 and optimizer = Adam. Based on the best model parameters, the internal and external test experiment were performed. The results of the experiment are shown in Figure 6 and Table 4. It can be observed from Figure 6 that the predicted results based on the best model parameters are highly consistent with the actual charging time. The MSE of the model predicted results is less than 0.02, the MAE is less than 0.1, and the MAX_ERROR is within 1 minute.



(a) internal test (b) external test

Figure 6. Model prediction results

Table 4. Evaluation indicators of test results

test	MSE	MAE	MAX_ERROR(in minute)
internal	0.0070	0.0649	0.4
external	0.0168	0.0902	0.9

4.4. **Result.** Based on the parameter analysis results of the above-mentioned electric vehicle charging time prediction model, electric vehicle charging time prediction model based on CNN [21] and RNN [22] is established as a comparison. Table 5 and Table 6 are the experimental results of using the CNN, RNN, and LSTM models to conduct internal and external test.

Compared with the CNN and RNN electric vehicle charging time prediction models built under the same experimental conditions, in the experimental results of the internal and external test, the RNN and LSTM based on time series have obvious advantages. The MSE of the CNN model prediction result is greater than 2.7, and the MAE is greater

Table 5. Evaluation index of internal test results

model	MSE	MAE	MAX_ERROR(in minute)
CNN	2.7476	1.2852	5.6
RNN	0.8794	0.7094	3.2
Our	0.0070	0.0649	0.4

Table 6. Evaluation index of external test result

model	MSE	MAE	MAX_ERROR(in minute)
CNN	4.5422	1.6957	7.0
RNN	1.2572	0.8724	6.0
Our	0.0168	0.0902	0.9

than 1.2, while the model based on the time series has a MSE less than 1.5 and MAE less than 0.9. There is such a gap between the prediction results of CNN and the time series model. The main reason refers to that CNN is based on convolution and pooling calculation, while the time series model is based on time changes. In the meanwhile, for the prediction results of the RNN and LSTM models, in the internal and external test experiment, whether it is MSE, MAE or the MAX_ERROR, the prediction results of the LSTM model are obviously better. The MSE of the internal test result based on LSTM is 0.0070, MAE is 0.0649, and the MAX_ERROR is 0.4 minute. The MSE of the external test result based on LSTM is 0.0168, MAE is 0.0902, and the MAX_ERROR is 0.9 minute.

5. **Conclusions.** In this paper, an electric vehicle charging time prediction model is established based on LSTM. First, PCC analysis is performed to determine the characteristic parameters of the model. Second, the sliding window technology is employed to prepare data for the model. Then, the best model parameters are determined through LSTM model parameter analysis experiments. Finally, CNN and RNN models are established as comparative experiments. The experimental results demonstrate that the MSE of internal test experiment based on LSTM model is 0.0070, the MAE is 0.0649 and the MAX_ERROR is 0.4 minutes. The MSE of external test experiment based on LSTM model is 0.0168, and the MAE is 0.0902. The MAX_ERROR is 0.9 minutes. The results indicate that the LSTM-based electric vehicle charging time prediction model has better advantages.

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REFERENCES

[1] F. Q. Zhang, T. Y. Wu, Y. Wang, R. Xiong, G. Y. Ding, P. Mei and L.Y. Liu, Application of Quantum Genetic Optimization of LVQ Neural Network in Smart City Traffic Network Prediction, *IEEE Access*, vol. 8, pp. 104555-104564, 2020.

[2] Z. Dong, C. Liu, Y. Li, J. Bao, Y. Gu and T. He, REC: Predictable Charging Scheduling for Electric Taxi Fleets, *2017 IEEE Real-Time Systems Symposium (RTSS)*, Paris, France, pp. 287-296, 2017.

[3] H. Li, J. Lv, W. Chen and X. Zeng, Orderly Charging Model of Private Electric Vehicle based on Double Sequence Valley Period, *2018 China International Conference on Electricity Distribution (CICED)*, Tianjin, China, pp.2961-2965, 2018

[4] Y. Zhang, Q. F. Ma, X. Zhang, M. H. Gao, P. H. Yang, H. He, H. Hu, and B. Aliya, Integrated Route and Charging Planning for Electric Vehicles Considering Nonlinear Charging Functions, *2018 IEEE 22nd International Conference on Computer Supported Cooperative Work in Design (CSCWD)*, Nanjing, China, pp. 660-665, 2018.

[5] T. Nazghelichi, F. Torabi, and V. Esfahanian, Reducing the charging time of a lead–acid cell in the sense of linear stability analysis, *Journal of Energy Storage*, vol. 36, 102369, 2021.

[6] M. H. Amini, A. Kargarian and O. Karabasoglu, ARIMA-based decoupled time series forecasting of electric vehicle charging demand for stochastic power system operation, *Electric Power Systems Research*, vol. 140, pp. 378-390, 2016.

[7] Z. Guo, B. Y. Liaw, X. P. Qiu, L. L. Gao, and C. S. Zhang, Optimal charging method for lithium ion batteries using a universal voltage protocol accommodating aging, *Journal of Power Sources*, vol. 274, pp. 957-964, 2015.

[8] X. S. Hu, S. B. Li, H. Peng, and F. C. Sun, Charging time and loss optimization for LiNMC and LiFePO 4 batteries based on equivalent circuit models, *Journal of Power Sources*, vol. 239, pp. 449-457, 2013.

[9] M. Torchio, N. A. Wolff, D.M. Raimondo, L. Magni, U. Krewer, R. B. Gopaluni, J. A. Paulson and R. D. Braatz, Real-time model predictive control for the optimal charging of a lithium-ion battery, *Proceedings of the American Control Conference*, pp. 4536-4541, 2015.

[10] A. Abdollahi, X. Han, G.V. Avvari, N. Raghunathan, B. Balasingam, K.R. Pattipati and Y. Bar-Shalom, Optimal battery charging, Part I: Minimizing time-to-charge, energy loss, and temperature rise for OCV-resistance battery model, *Journal of Power Sources*, vol. 303, pp. 88-398, 2016.

[11] M. Krishan, S. Jha, J. Das, A. Singh, M. K. Goyal and C. Sekar, Air quality modelling using long short-term memory (LSTM) over NCT-Delhi, India, *Air Quality, Atmosphere and Health*, vol. 12, no. 8, pp. 899–908, 2019.

[12] R. Pascanu, T. Mikolov, and Y. Bengio, On the diffificulty of training recurrent neural networks, *International Conference on Machine Learning*, pp. 1310–1318, 2013.

[13] L. W. Chen, Y. Zhou, S. Huang, W. Lu and S. Akram, UAV decoy method based on LSTM neural network, *Journal of Network Intelligence*, vol. 6, no. 1, pp. 71-82, 2021.

[14] K. Greff, R. K. Srivastava, J. Koutník, B. R. Steunebrink and J. Schmidhuber, LSTM: A Search Space Odyssey, *IEEE Transactions on Neural Networks and Learning Systems*, vol. 28, no. 10, pp. 2222-2232, 2017.

[15] Y. Bengio, P. Simard and P. Frasconi, Learning long-term dependencies with gradient descent is difficult, *IEEE Transactions on Neural Networks*, vol. 5, no. 2, pp. 157-166, 1994.

[16] Z. C. Lipton, J . Berkowitz and C. Elkan, A Critical Review of Recurrent Neural Networks for Sequence Learning, *arXiv preprint*, arXiv:1506.00019, 2015.

[17] S. Hochreiter and J. Schmidhuber, Long short-term memory, *Neural computation,*, vol. 9, no. 8, pp. 1735–1780, 1997.

[18] J. C. Hong, Z. P. Wang, W. Chen and Y. T. Yao, Synchronous multi-parameter prediction of battery systems on electric vehicles using long short-term memory networks, *Applied Energy*, vol. 254, 113648, 2019.

[19] H. M. Zhou, Z. H. Deng, Y. Q. Xia and M. Y. Fu, A new sampling method in particle filter based on Pearson correlation coefficient, *Neuro computing*, vol. 216, pp. 208-215, 2016

[20] H. H. Xu and Y. Deng, Dependent evidence combination based on shearman coefficient and pearson coefficient, *IEEE Access*, vol. 6, pp. 11634-11640, 2017.

[21] Y. Lecun, L. Bottou, Y. Bengio and P. Haffner, Gradient-based learning applied to document recognition, *Proceedings of the IEEE*, vol. 86, no. 11, pp. 2278-2324, 1998.

[22] H. Chaoui and C. C. Ibe-Ekeocha, State of Charge and State of Health Estimation for Lithium Batteries Using Recurrent Neural Networks, *IEEE Transactions on Vehicular Technology*,vol. 66, no. 10, pp. 8773-8783, 2017.