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RESEARCH ON SPATIOTEMPORAL DYNAMIC LOAD PREDICTION OF SMART GRID ELECTRIC VEHICLES BASED ON DEEP LEARNING

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Abstract: Electric vehicles have strong spatiotemporal randomness during the charging process, which increases the difficulty of power grid control and affects the quality of electric energy. This article proposes a deep learning based spatiotemporal dynamic load prediction method for electric vehicles to address this challenge. A quantile regression model based on air dynamic causal convolutional neural network is established to accurately predict the charging load. This model uses neural network algorithms to enhance network learning ability, preprocesses data based on factors such as changes in peak morning and evening passenger flow, holidays, and unexpected situations during the charging process of electric vehicles, and improves prediction accuracy. And compared with the QRLSTM and QRNN models through experiments, the experimental results show the scientificity of the model.
Keywords: Deep learning; Load forecasting; Smart grid

1 INTRODUCTION

A smart grid is a system that synchronously transmits information and energy, and is an important means of achieving power automation. According to the development trend of automobiles, electric vehicles are the mainstream of development. With the large-scale integration of electric vehicles into the grid in the future, the load distribution it brings has uncertain characteristics such as intermittency, volatility, and randomness in time and space [1], which will change the power load curve [2] and have an undeniable impact on the operation, planning, and control of the entire power grid [3]. Therefore, it is necessary for us to accurately predict the charging load of electric vehicles in advance, in order to better guide the power system's power generation, distribution, scheduling and other work, and to eliminate and protect harmonic pollution problems that pose a threat to the power grid [4-5]. Generally speaking, the establishment of electric vehicle load forecasting models is relatively complex and is influenced by factors such as user usage habits, transportation infrastructure conditions, equipment characteristics, the number of electric vehicles, and the distribution of charging pile infrastructure. With the steady increase in the penetration rate of electric vehicles, more accurate load forecasting of electric vehicles is needed. However, the prediction methods and model selection mentioned in the above literature have many shortcomings, such as: the establishment of prediction models is relatively idealized, resulting in poor universality; Without a large amount of charging data as support, its prediction parameters are difficult to determine, and there is a significant deviation in the accuracy of the prediction. Therefore, it is necessary to study a new algorithm model, which is a self-learning model that uses deep learning algorithm technology to fit its distribution on the basis of data. The key technologies include optimizing the structure of deep learning models and researching training algorithms for deep learning.

2 RESEARCH STATUS

At present, electric vehicle load forecasting can be mainly divided into two categories. One is to use mathematical models to simulate the charging behavior of electric vehicles and obtain the predicted value of electric vehicle load. The other is to use statistical learning models based on historical data for forecasting.

2.1 A Monte Carlo based Mathematical Model for Load Prediction of Charging Stations

The Monte Carlo method is a method based on the theory of probability and statistics, which treats the problem to be solved as a probability of a random event. After determining the probability model of the problem, a computer is used to take a random number from the probability model to obtain an approximate solution to the problem. The data mainly refers to some basic parameters obtained from studying the influencing factors of charging for various purposes of electric vehicles, including vehicle types (taxis, buses, private cars), distribution of starting charging capacity and starting time during charging periods, etc. Firstly, these data types are classified and processed to determine the probability model of vehicle owners' traffic habits, including charging habits and formal habits, Establish a mathematical model with random probability characteristics. Then, Monte Carlo principles are used to predict the charging location/time and load demand of the car in the future period. Reference [6] proposes a method for predicting the charging load of electric vehicles based on the travel chain of electric vehicles and considering the charging frequency. Based on the survey and statistical data of household vehicle travel, the purpose of household vehicle travel is divided into five categories. Simple and complex travel chains are constructed, and factors such as temperature, traffic conditions, and holidays are comprehensively considered. The distribution of electric vehicle travel is classified and modeled, and the results of electric vehicle load prediction are obtained.

These methods all use mathematical formulas to simulate charging behavior for charging station load prediction. Reference [7] considers establishing a dynamic fluid dynamics model based on transportation to predict the charging load of charging stations in the context of fast charging stations at high-speed exits. The experiment shows that the model can effectively predict the dynamic charging demand of fast charging stations on highways in terms of space and time. Reference [8] used the BCMP queuing network model to predict the charging demand of plug-in electric vehicles, and the model was validated with traffic flow data from New York, achieving good prediction results. Reference [9] proposes a method based on Monte Carlo method to predict charging load, using Monte Carlo to randomly simulate the selected starting state of charging, charging method, starting point of charging battery, etc. Then calculate the actual charging time to obtain the charging load. Finally, it is predicted that electric vehicles in China will have a significant impact on the power grid by 2030. Based on a large amount of data, reference [10] establishes a model for the behavior habits of electric vehicles, including driving trajectories, charging habits, etc., and calculates the total load of electric vehicles based on the road network structure ball. Reference [11] proposes an electric vehicle load forecasting method based on energy equivalence, which converts the fuel sales of gas stations into electric vehicle charging loads through the energy equivalence method, taking into account two modes of charging facilities: decentralized and centralized. Finally, obtain the maximum load for both modes.

2.2 Statistical Learning Method for Charging Station Load Prediction Based on Historical Data Background

The traditional load forecasting methods for electric vehicle charging based on power load forecasting include regression analysis, similar day method, etc; Modern prediction methods include wavelet analysis based prediction, neural network-based prediction, and Support Vector Machine (SVM) prediction. SVR [12-14] (Support Vector Regression), Grey Model, and Wavelet Neural Network [15], etc. The Monte Carlo model method is a method based on probability and statistics. Reference [16] used a Monte Carlo model to simulate the charging process of electric vehicles and derived a mathematical relationship for the optimal usage conditions. The SVR model based on GA-PSO adopted in reference [17] has a good effect on the charging load of electric vehicles. However, the kernel function in SVR cannot be applicable to all situations, and selecting the appropriate kernel function requires some experience. Reference [18] used three models, namely grayscale model, RBF (radial basis function) neural network, and BP neural network, to predict the charging load of electric vehicles, and compared the prediction results. The grey model is widely used in power load prediction, and the GM (1, 1) prediction model is the most commonly used grey model based on first-order differential equations. This model requires a small amount of data and is easy to calculate, but it is difficult to achieve the desired prediction results for more complex data. The short-term prediction performance of RBF neural network and BP neural network models for electric vehicle charging load is similar. For medium - and long-term predictions, RBF neural networks are generally more accurate. Reference [19] proposes a big data based method for predicting the charging load of electric vehicles. Using big data technology to introduce electric vehicle charging demand prediction models and real-world traffic distribution data and weather data. Specifically, the prediction model is based on big data technology that integrates collection, storage, and management, where the data is based on historical traffic distribution data and weather data from South Korea. Analyze through the following steps: (1) Cluster historical traffic allocation data with high similarity into clusters using clustering analysis; (2) Identify the impact of weather data on traffic patterns using correlation analysis; (3) Develop classification criteria for the relationship between traffic clusters and weather influencing factors using decision trees. Finally, use this classification standard to establish a predictive model for predicting the charging load of electric vehicles. Reference [20] mentions a short-term charging station load prediction model based on time series distance measurement method, which predicts the charging load based on the distance measurement between the load series and time series.

The past statistical learning methods for predicting the charging load of electric vehicles only considered the time dimension. However, the charging load of electric vehicles also includes complex spatiality. Only by comprehensively considering the dual dynamic changes of load time and space can better spatiotemporal dynamic prediction be made. Therefore, it is necessary to study and establish a deep learning model for high-precision prediction of spatiotemporal dynamic loads of electric vehicles based on historical data.

3 DESIGN OF DEEP LEARNING MODELS

3.1 Selection of Factors Affecting the Operation Status Of Charging Stations

With the rapid development of the electric vehicle industry, the impact of charging loads during the charging process on the power grid will become increasingly significant. The factors that affect the charging and discharging status of charging piles have complex characteristics, such as regional development differences, population density differences, differences in the number of electric vehicles owned, user schedules and charging and discharging habits, holidays, etc. Therefore, this article selects characteristic variables from three aspects to characterize the influencing factors of the operating status of charging stations: a) Power parameters of charging stations, which are the most intuitive parameters for expressing the network, obtained through information perception; b) Spatial factors require quantitative transformation of qualitative descriptions and merging them into the input feature vectors of the model; c) The time factor highlights factors such as changes in peak morning and evening flow, holidays, and unexpected situations. Due to different feature data and different dimensions, it is necessary to preprocess the data based on empirical knowledge, mainly including correlation analysis, data noise cleaning, and input data normalization.

3.2 Model Design

The concept of deep learning originated from the study of artificial neural networks. The model structure is an LSTM (Long Short Term Memory) neural network proposed by Hochreiter and Schmidhuber in 1997, which can effectively solve the problem of long-term dependencies in sequences. Its main structure is shown in Figure 1, and LSTM can be represented as a chain structure by time expansion. There are four neural network layers in the repeating module of LSTM.

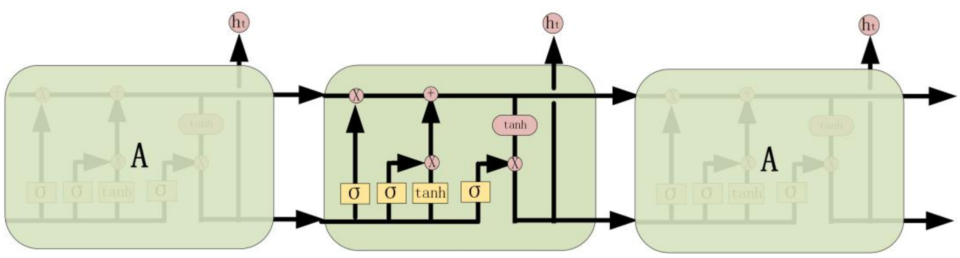


Figure 1 LSTM Structure

Figure 1 is called a cell, and LSTM has four gates. The first layer of neurons is the sigmoid control layer of the forget gate, as shown in Equation (1).

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

The second and third layers are input gates and tanh layers, respectively, as shown in equations (2) and (3). The sigmoid layer of the input gate determines which information to update; The tanh layer creates a new candidate value that may be added to the cellular state.

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (2)$$

$$\tilde{C}_t = \tanh(W_C[h_{t-1}, x_t] + b_C) \quad (3)$$

Update the old state of the cell to, as shown in equation (4).

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (4)$$

Finally, by using an output gate containing a sigmoid layer as shown in equation (5), equation (4) is passed through a tanh layer (such that the output value is between -1 and 1), and then multiplied with the output gate, the forgetting and memory parameters are substituted to the final output.

$$O_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (5)$$

$$h_t = O_t \tanh(C_t) \quad (6)$$

Among them, W_f and b_f Representing forget gate weights and biases; W_i and b_i Represents the weight and bias of the input gate; W_c and b_c Represents the weight and bias of updated values; W_o and b_o Indicates the weight and bias of the output gate; $\sigma(g)$ Representing the sigmoid activation function, $\tanh(g)$ Represents the hyperbolic tangent activation function. $\bullet$ Representing matrix multiplication; $[h_{t-1}, x_t]$ Merge columns representing matrices or vectors with equal rows; * Representative point multiplication.

Faced with massive charging data, data mining techniques are used for classification, organization, and data partitioning. A learning model is designed to automatically discover common features from unlabeled monitoring data to describe the samples. Then, a labeled dataset is trained by manually labeling only a small number of samples (load state determination output) as input to the prediction classifier, ultimately forming a model that can be used for actual prediction. Combining quantile regression with deep learning, a deep learning quantile regression probability density prediction method is proposed, which is the Quantile Regression Dilated Causal Convolution (QRDCC) neural network quantile regression model. The model framework is shown in Figure 2.

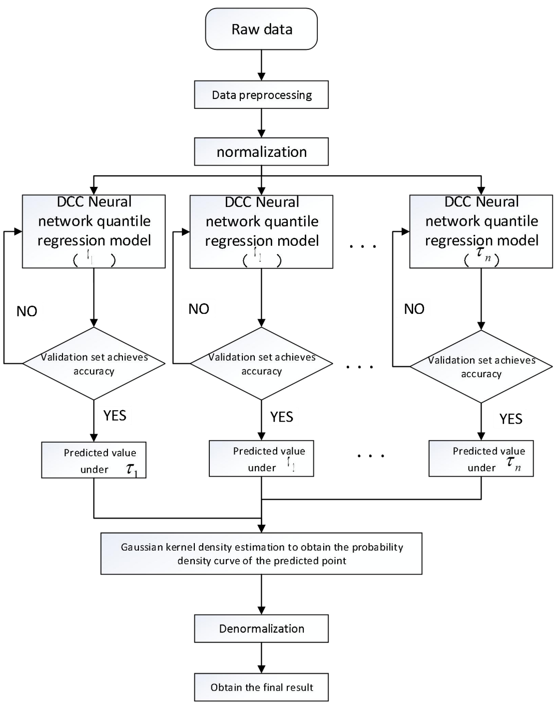


Figure 2 QRDCC program flowchart

4 EXPERIMENTAL SIMULATION AND CONCLUSION

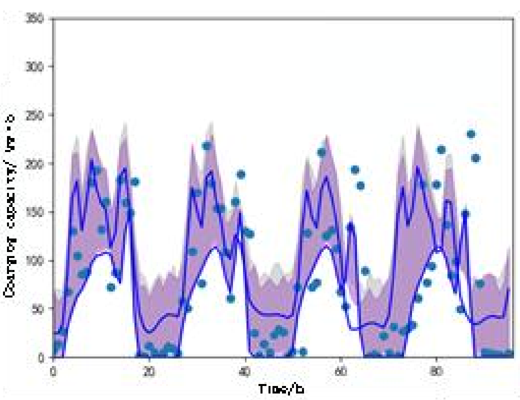
Experimental environment:

CPU: Core i7-7700, Memory: 16GB, GPU: 1080Ti 11GB,

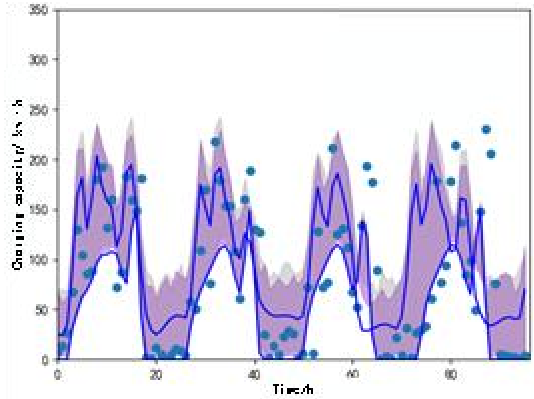
Experimental data: Charging load data of charging piles inside Huazi Charging Station in Changsha City (30 days),

Experimental platform: Keras

The experiment was tested from two aspects. Firstly, the channel for QRDCC charging load prediction under a certain range of built-in reliability was compared, with confidence values of 85% and 80%, respectively. The accuracy of QRDCC regression prediction mode was better than that of QRLSTM and QRNN modes. The prediction results of QRDCC mode were basically consistent with the original data, and the verification results are shown in Figure 3. Secondly, the first test was conducted to predict the probability density of the time point. The QRDCC model test results were generally consistent with the true values, while the QRLSTM test results were significantly higher than the test data values. The experimental results are shown in Figure 4.



a) Comparison of QRDCC charging load prediction intervals at 85% confidence level



b) Comparison of QRDCC charging load prediction intervals at 80% confidence level

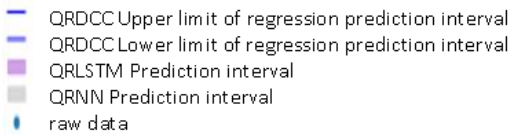


Figure 3 Probability prediction results of electric vehicle load

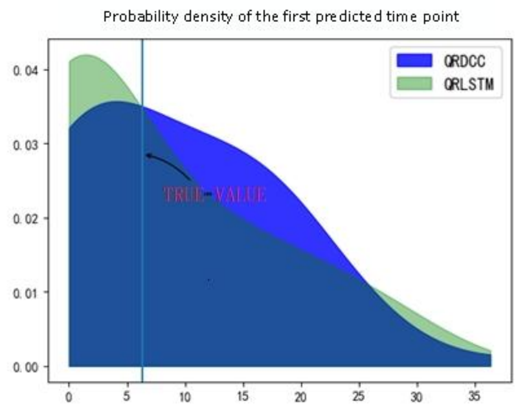


Figure 4 Probability density map of charging load prediction at the first time point

Based on the experimental analysis in Figures 3 and 4, it is evident that the model proposed in this paper outperforms traditional power load prediction models. This is because this model uses non parametric kernel density charging load interval probability prediction models - the air causal convolutional neural network quantile regression model and the LSTM neural network quantile regression model - to estimate the parameters of the air causal convolutional neural network under different quantile conditions, Then, the predicted values under different quantiles are obtained, and the

KDE method is used to predict the probability interval of charging load, which can effectively predict the fluctuation range of charging load within a certain range. According to the structure of the spatiotemporal causal convolutional neural network, it is known that it can learn long-term historical patterns well without significantly increasing parameters. Estimating the charging load prediction interval using Gaussian distribution kernel function resulted in better reliability and sensitivity compared to QRLSTM and QRNN.

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COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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