Study on Ultra Short Term Prediction of Residential Power Load

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Abstract. Because of the increasing demand of modern residents for electric energy, the power supply load of electric power enterprises also increases. Under this condition, affected by the randomness of electricity consumption behavior of different residents, the electricity load generated by each resident will fluctuate greatly, which directly leads to the decline of power safety level. Under this condition, as the power manager, the power enterprise must guarantee the operation safety of the system and scheduling is the main means to achieve the goal. However, if the dispatching work is not carried out in time, it cannot completely eliminate the impact of residential power load. At this time, modern scholars put forward a super short-term forecasting technology of residential power load based on long-term and short-term memory cyclic neural network. The implementation of this technology can provide strong support for the power dispatching work, make the dispatching work more real-time, thus avoiding the negative residential power consumption the impact of the lotus. This paper mainly studies the ultra-short term forecasting of residential power load, expounds the basic concept and model building method of this method, and verifies its effectiveness through simulation and examples.

Keywords: Residents, Electricity Load, Ultra Short Term Forecast

1. Introduction

The super short-term forecasting method of residential power load mainly uses a memory model to mine all residential power load data and obtain the correlation among all data, thus generating a long-term and short-term memory type recurrent neural network. Based on the network structure, the forecasting model can be obtained, and the super short-term forecasting purpose can be achieved according to the data association in the network [1].

At present, the ultra short term prediction of residential power load the lack of traditional smart meter data acquisition devices makes short-term prediction of residential power load difficult in the power industry, but its role has been verified in many experiments, so it has the value of promotion.

The purpose of this paper is to let more electric power workers understand the realization method and significance of ultra short term prediction of residential power load.
2. Basic Concept of Ultra-Short Term Prediction of Residential Power Load

The recurrent neural network is similar to the common artificial neural network, but there are substantial differences, that is, both the recurrent neural network and the artificial neural network complete the output of results according to the time step order, while the former will consider the impact of the previous step order before entering each time step order, so that the recurrent neural network has the memory ability [2-3]. In the operation of cyclic neural network, the data will be modeled according to the sequence, and the data results generated in each time step can be obtained according to the modeling. These data results will be saved (memorized) as historical information and listed in the output calculation P4 [7]. There are many nodes in the structure of recurrent neural network. Each node represents a neuron node in a single time step. There is an input connection relationship between nodes. The weight of input connection is W1, the weight of self-linked structure is W2, and the weight of neuron output is W3. At this time, data input connection can be realized by means of the input sequence x(t), x(t−1), x(t−2),------ in the structure, the time steps in the input process are x1, X2, X3, so that the weight of each time step entering the network will be used repeatedly, and each time step will be saved for the next step[5].

In addition, the operation flow of the input layer of the recurrent neural network is: input sequence x at time t, X contains the neurons of each input layer I.H hidden layer neurons and k output layer neurons. According to the operation process, the value of input layer neuron I at time t can be expressed as XTi; the input of neuron J at time t and the activation value of neuron J at time t can be expressed as AJT and BJT; the weight between nodes I and J can be expressed as Wij. In addition, Wij satisfies formula (1) [6].

\[
\begin{align*}
  a^j_h &= \sum_{i=1}^{l} \omega_{h^i b^j_h} b^{i-1}_h \\
  b^i_h &= \theta_h(a^i_h)
\end{align*}
\]

Because the information of the last time step in the operation of the recurrent neural network needs to be read by the next step, the next step must have the ability of reverse calculation. Formula(2) is the reverse calculation method of cyclic neural network.

\[
\begin{align*}
  \delta^h_i &= \theta'(a^h_i) \left( \sum_{k=1}^{K} \delta^k_j \omega_{hk} + \sum_{h=1}^{H} \delta^h_{i+1} \omega_{hh} \right) \\
  \delta^j_i &= \frac{\partial L}{\partial a^j_i} \\
  \frac{\partial L}{\partial \omega_{ij}} &= \sum_{t=1}^{T} \frac{\partial L}{\partial a^j_i} \frac{\partial a^j_i}{\partial \omega_{ij}} = \sum_{t=1}^{T} \delta^j_i b^j_i
\end{align*}
\]

3. Construction Method of Ultra-Short Term Forecasting Model for Residential Power Load

3.1 Memory Model

The memory model is the core model of the recurrent neural network, which can avoid the problem of gradient disappearance in the training of the recurrent neural network model. That is to say, the existence of the memory model can make the neurons of the recurrent neural network have input gate, output gate and forgetting gate, which can play the role of information acquisition. As long as these gates are controlled manually, the relevance of a certain time step can be captured, which is based on the neural network model of time steps[7]. In addition, the memory model in the recurrent neural network also has long and short memory function, so the model can be called long and short memory
neuron structure.

3.2 Prediction Model
Prediction model is the scheduling layer of recurrent neural network, which can schedule the data in memory model to achieve ultra short term prediction. The prediction model is mainly built on the memory model. The main function of the model is to predict the trend of each inhabitant's electricity load according to the data given by the memory model according to the data of the memory model. That is to say, according to the data of the memory model, the historical information of every inhabitant in the last step, including the mean time and the mean value of the valley and peak value, and so on. For these historical information, in the current step, the prediction model first judges the current residents' electricity load trend according to the time information, and gives the peak value average value. Secondly, when the residents' load curve exceeds the historical information average value, the prediction model will take the maximum peak value in the residents' historical information as the benchmark to predict for the dispatcher to manage[8]. The construction method of the prediction model is similar to that of the artificial neural network (because the prediction model is built on the basis of the memory model, and does not need the memory function, so it can be built according to the artificial neural network model construction method), that is, all information is listed as the neural node, and then the operation logic of the model is adjusted to "list all the neural nodes as the basic nodes, Analyze the connection between each basic node and other nodes.

4. Simulation and Example Verification

4.1 Simulation Verification
With the help of put in software, this paper tests the method of residential power load in order to verify the accuracy and information of the prediction model. The test will use the traditional double-layer feedforward neural network as a reference to run in the same link with this model, and then compare the results to see the advantages and disadvantages [9]. In the test, firstly, the input and output vector dimensions of the two models are set uniformly, then the load data of one year is taken as the training set of the two models, and then the load results of one month are taken for comparative analysis. Table 1 is the basic data of simulation test. Secondly, the rolling test method is mainly used for ultra short-term prediction. From the results, it can be seen that both prediction models have the function of tracking the change of residential power load data, and the quality of the prediction results are up to standard, but the double-layer feedforward neural network is higher than the actual, and the long-term memory network model is more practical (see Table 2 for the test results).

| Data item                        | Data  |
|----------------------------------|-------|
| Sampling interval of electric load data | 30min |
| Input vector dimension of prediction model | N=8   |

**Table 1.** Basic data of simulation test

| Model                                      | Test value | Actual value |
|--------------------------------------------|------------|--------------|
| Double layer feedforward neural network model | 6001kW     | 5979         |
| Long and short term memory network model    | 5971kW     |              |

**Table 2.** Simulation test results of double layer feedforward neural network and long short memory network model (one month)

At the same time, in order to verify the effectiveness and superiority of the algorithm in the long-term and short-term memory network model, this paper selects two prediction models one day to analyze the relative error value of the prediction results of residential power load[10]. It can be seen from the error value that there are errors between the prediction results of the two models and the actual values, while the overall error value has amplitude, but the amplitude of the error value of the
double-layer feedforward neural network model will change according to the actual value amplitude, which shows that if the actual load fluctuation increases, the prediction error value of the double-layer feedforward neural network model will become larger and larger, and the long-term and short-term memory network model will be reflected, the error value will not change according to the actual value amplitude, and can always remain at the original level, which shows that the algorithm of long-term memory network model is more effective and superior. Table 3 shows the maximum error value data of double-layer feedforward neural network and long-term memory network model.

**Table 3.** Maximum error data of double layer feedforward neural network and long short memory network model

| Model                                           | Maximum error value |
|-------------------------------------------------|---------------------|
| Double layer feedforward neural network model   | 6.8%                |
| Long and short term memory network model        | 2.3%                |

It can be seen from table 3 that compared with the reference model, the model in this paper has more performance in prediction accuracy and stability, which shows that the model in this paper has advantages. In addition, the RMSE and Mae values of the two are compared in the test. See Table 4 for the comparison results. It can be seen that the error value of the overall prediction results of the model in this paper is less than that of the double-layer feedforward neural network model, which represents that the model in this paper has excellent robustness and is conducive to the ultra short term prediction quality.

**Table 4.** Comparison of RMSE and Mae values of the two models

| Model                                           | RMSE | MAE  |
|-------------------------------------------------|------|------|
| Double layer feedforward neural network model   | 314.46 | 239.41 |
| Long and short term memory network model        | 405.72 | 288.54 |

4.2 Example Verification

Under the condition of permission, this paper will take an electric power enterprise as an example to test the model. The test method is: carry out manual power load test and model prediction in three time periods (8-9, 9-10 and 10-11) at the same time in the evening. The accuracy of the model can be confirmed by comparative analysis of the test results. According to the test, the power load of the residents at 8, 9 and 10 in the evening is 545.1kw, 544.3kw and 539.6kw respectively under the condition of manual test; the power load of the residents at 8, 9 and 10 in the evening is 540.3kw, 547.4kw and 540.1kw respectively under the condition of long and short-term memory network model test. It can be seen from the comparison that the prediction results of the long-term memory network model in the actual work have some errors with the manual test, but the error value is not large, basically meeting the requirements of qualification, so the long-term memory network model can be applied in the actual work.

5. Conclusions

To sum up, this paper analyzes the basic concept of ultra short term prediction of residential power load, and expounds the operation mechanism of the cyclic neural network and the construction method of the cyclic neural network model. Through the analysis, the ultra short term prediction function is successfully realized. Theoretically, this function can be used for tracking prediction of residential power load. In addition, in order to verify the validity of the model, simulation verification and example verification are carried out. According to the simulation results, the long-term and short-term memory network model of the cyclic neural network has advantages in stability, accuracy and effectiveness compared with the traditional double-layer feed-forward neural network model, and although there is error with the artificial test conditions, the error value basically meets the
requirements and can be put into operation into the actual work.

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