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Short-Term Power Load Forecasting Based on Artificial Recurrent Neural Networks

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Abstract: An artificial recurrent neural network for short-term power load forecasting is given, which is based on BP network and constructs an artificial neural network structure with dynamic implied layer recurrent transfer, and adopts a fixed number of implied layers in the single smooth interval of the grid load, and adopts a dynamic number of implied layers in the extreme interval, so as to improve the accuracy of the grid load forecasting.

Keywords: Artificial recurrent neural network; Electricity load; Short-term forecasting; Sliding window sequence

1. Introductory

Accurate short-term load forecasting is very important for the power supply and demand departments to carry out the combination of economic dispatch of units in the coming days, and also has a high reference value for the development of power market operation [1]. The short-term load sequence is characterized by periodicity and volatility, and the time series regression forecasting method considering the periodicity as well as the forecasting method of support vector machine have better forecasting effect. However, facing the shortcomings of intelligent algorithms, the problems of premature convergence, narrow application surface and low adaptability still need to be solved in the field of load forecasting, and there is still much room for improvement in the parameters and structure of the forecasting model.

In this paper, a method of artificial recurrent neural network for short-term power load forecasting is given, which is based on BP network and constructs an artificial neural network structure with dynamic implied layer recurrent transfer, and adopts a fixed number of implied layers in the single smooth interval of the grid load and a dynamic number of implied layers in the extreme interval, so as to improve the accuracy of the grid load forecasting.

2. Artificial Recurrent Neural Network

Artificial neural networks are bionic to the complex and efficient human brain nervous system, with neurons as the unit structural body, adding dendrites, axons and other units, and a network model composed of multiple nodes connected. In this, the transmission medium connecting each node can be given different parameters to solve the mapping relationship between inputs and outputs, and Fig. 1 shows the computational structure with feedback mechanism [2-3].

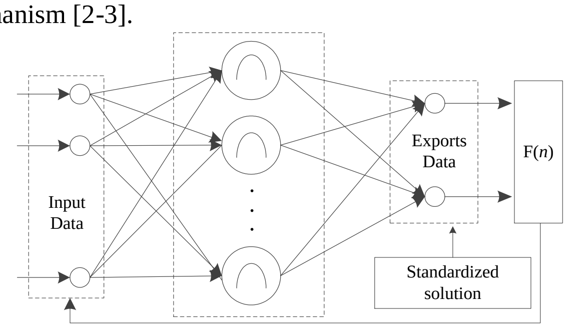

Fig. 1 Neural network structure with feedback mechanism

For general nonlinear functions that do not contain integral and differential relations, the mapping relations can be easily searched using the computational structure above [4-6]. The steps of the prediction problem can be summarized as

1) Input known information, normalized input value $u(x)$, linear transformation of input layer to implicit layer $x^k \to F^k$ as

$$F^k(x^k) = \left[W_{ij}^k\right]\left[x^k\right] + \left[b_j^k\right] \tag{1}$$

In Eq. (1), $\left[W_{ij}^k\right], \left[b_j^k\right]$ are the weight matrix and bias matrix, which change with adaptation.

2) Input the nonlinear activation function tanh or Sigmoid to transform the function $F^k(x^k)$ nonlinearly to a fixed interval value.

$$N^k(x^k) = \varphi\left(F^k(x^k)\right) \tag{2}$$

3) Similarly, for a single implicit layer structure, the computational flow from the implicit layer to the output layer is the same as 1) and 2), namely

$$L^l\left(\left[N^k(x^k)\right]\right) = \psi\left(\left[W_{ij}^l\right]\left[N^k(x^k)\right] + b_j^l\right) \tag{3}$$

4) The output is L^l the grid load forecast value in the target interval, which generally has a large deviation from the correct solution, and the loss function R needs to be introduced at this time.

$$R = \frac{1}{N_D}\sum_{i=1}^{N}\left|L^l(x_i^l) - u(x_i^k)\right|^2 \tag{4}$$

The loss function R is the nonlinear combination of the residuals of multiple prediction sequences, the literature shows that for the residual problem, a suitable non-convex optimization algorithm can be chosen to optimize the loss function, and the weight matrix and bias matrix can be changed by back-propagation, this paper builds the structure of the implicit layer for different time intervals on the basis of this paper, and based on the loading data law obtained from the training set, the number of nodes of the implicit layer is 15 when it is in the smoothing time interval, and the number of nodes of the implicit layer is 15 when it is in the When in the extreme time interval, the number of implied layer nodes M is

$$M_n = M_{n-1} + \left\lceil \frac{R_{n-1} - 0.05}{\max(R_{n-1}, 0.05)} \right\rceil \tag{5}$$

In Eq. (5), R_{n-1} is the loss function for n-1 predictions in the extreme value interval, when the loss function is greater than 5%, the fraction is positive at this time, rounded upward to 1, and the value of M is increased by 1. When the loss function is less than 5%, the fraction is negative at this time, rounded upward to 0, and the number of nodes M is unchanged, and the results can be output.

3. Instance Validation

The data used in the paper comes from Annex 1 of the Chinese Electrical Engineering Society Cup Mathematical Modeling Competition A. The sampling points are sampled at 15min intervals, i.e., there are 96 load sampling points in a day, and the time corresponding to the sampling points is taken as the dimension to transform the data of a day into a 96-dimensional input load matrix, and the date is taken as the time-series value, and the load data from December 02 to December 10 in region A are used in this paper As a training set, the length of a training dimension of the time series is 9, the first sliding window of December 11 is used as a validation set, and other data are used as a test set, and the prediction process adopts a sliding window strategy with a dimension of 15 (225 min) in the smoothing interval, in order to intuitively represent the sensitivity of different methods for the training set and the test set, the sliding window of the first test set in the paper adopts the value of the validation set sliding window, and the value of the validation set sliding window is used. The step size is set to 6 dimensions (90min).

By using the root mean square error (RMSE) function as the fitness function, the test uses the mean absolute percentage error (MAPE) as the fitness output [7-10], which is calculated with the expression

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Z_{ip} - Z_{it}}{Z_{it}}\right| \times 100\% \tag{6}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Z_{ip} - Z_{it}\right)^2} \tag{7}$$

Eq. (6) and (7), Z_{ip} is predicted values and Z_{it} is actual values.

Figure 2 gives the effect of different model prediction, in which the deviation value is more obvious in the "peak" and "valley" position, the prediction accuracy of GM-BP in the peak position is not high, and there is an obvious delay effect; the computational cost of GM-RBF is lower, and the structure of GM-RBF is more accurate. GM-RBF has low computational cost, simple structure and fast operation speed, but the prediction accuracy of deviation value and fluctuation region is not high; the artificial recurrent neural network in this paper has obvious advantages over other algorithms in time series region through the parameter optimization of sliding window strategy.

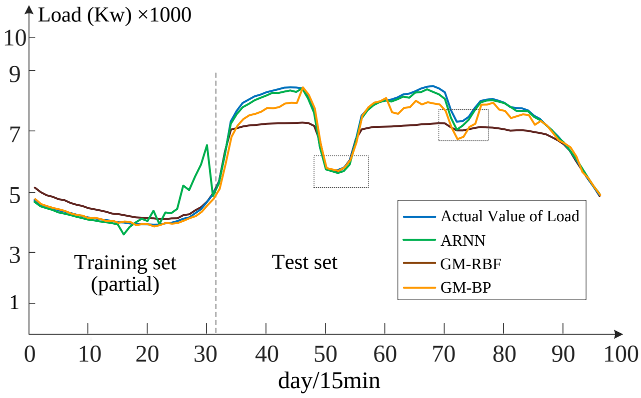

Fig.2 Artificial recurrent neural network model predicts effect

Table 1 gives the comparative effects of the prediction methods used in some literatures with the three indexes of MAPE, MAE and RMSE of this paper's method, and this paper's method has obvious advantages in prediction accuracy compared with GM-RBF and GM-BP algorithms, and it is more advantageous in the aspects of sequence length selection and spatial robustness, and it optimizes the traditional prediction model from multidimensional aspects.

Table 1 Comparison of the prediction effect of QBABP-RMNN model and LSTM model

Predictive algorithms	Time(s)	RMSE	MAE	MAPE(%)
ARNN	<200	283.183	192.163	2.4288
GM-BPNN	Long	505.889	326.122	5.6176
GM-RBFNN	<10	518.091	452.523	6.5423

4. Conclusion

In this paper, a method based on artificial recurrent neural network for short-term power load forecasting is given, which optimizes the search space of parameter nodes in AI forecasting, improves the global and rapidity of forecasting, and has a new reference value for the problem of accurate forecasting.

The prediction model in this paper can provide reference significance and use value for the method of short-term power load forecasting, and at the same time, it can be a good reference value for the study of other forecasting problems in the field of power system, such as wind power grid and energy utilization forecasting. However, in the actual power load application, the data factors are generally complex coupling relationship, that is, the power load time series has a composite characteristic. At the same time, the relationship between other factors such as temperature, humidity, rainfall and customer density and load data characteristics, as well as the impact on the model prediction effect are also elements that need in-depth attention. Therefore, the next step will be to try to use convolutional neural network (CNN) and random forest to extract the pairs of load-related feature factors, in the hope of further improving the accuracy of the parallel swarm optimization load forecasting method.

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