Chaos-GA-BP Neural Network Power Load Forecasting Based on Rough Set Theory

Dianwen Li¹, Xiu Ji²* and Xin Tian¹

¹ School of electrical and electronic engineering, Changchun University of Technology, Changchun, Jilin, JL431, China
² School of electrical and information engineering, Changchun Institute of Technology, Changchun, Jilin, JL431, China

*Corresponding author’s e-mail: jixiu523@ccit.edu.cn

Abstract. In order to accurately grasp the trend of power load changes and provide guidance for stable and efficient operation of the power system, this paper proposes a Chaos-GA-BP power load forecasting model based on rough sets. First, screen the main factors that affect power load changes, remove redundant data, and optimize the input of the prediction model; Second, rely on the BP neural network prediction model to adjust its topology, optimize weights and thresholds, and build a rough set-based Chaos-GA-BP power load forecasting model; Finally, considering the impact of severe power load fluctuations on the forecast results, rough set theory is introduced to perform forecast compensation when the slope on both sides of the peak is large. Applying the above method to a one-month power load forecast in a certain area in Northeast China, the change trend of the forecast curve closely follows the actual load curve. Compared with the traditional method, the average absolute error percentage is reduced by 2.67%. The experiment shows that this method has certain practicability.

1. Introduction

The trend of power load change has the characteristics of randomness and volatility, which brings great challenges to the forecast of power load trend [1]. The accuracy of power load forecasting is easily affected by various uncertain factors such as meteorological factors and human factors. This is also the main reason that has affected the forecasting accuracy for many years [2]. The basis of evaluating the predictive ability of the model lies in overcoming the randomness of power load changes, that is, the predictive accuracy [3].

At present, with the development of computer science, artificial intelligence algorithms have been rapidly developed in the field of power load forecasting with superior performance. Commonly used forecasting algorithms include artificial neural networks, support vector machine regression and other methods [4]. The LSTM model described in the literature [5] is one of the neural networks, and the paper verifies the superiority of its long-term dependence on learning ability. Literature [6] proposed an integrated algorithm based on a new load decomposition method, and finally used the support vector machine (SVM) method to predict. The key technology of the literature [7-10] is the reduction of power load forecasting factors, but short-term power load changes have strong randomness and uncertainty. With the increase of test samples, the error of the forecasting model will also increase. In the literature [11], composite forecasting models are used. Compared with a single forecasting model, more external factors are considered and the forecasting accuracy is higher.
In this paper, the method of combining genetic algorithm and chaotic BP neural network is proposed to build the CHAOS-GA-BP neural network prediction model, and then the rough set theory is applied to correct the prediction results, to solve the problem that the prediction results are caused by the fluctuation of the power grid error, showing a good effectiveness.

2. Forecasting method based on Chaos-GA-BP

2.1. Rough Set-Chaos-GA-BP Forecasting Process

The idea of the power load forecasting method based on rough set-Chaos-GA-BP proposed in this paper is shown in Figure 1. The load data is preprocessed by the method of attribute reduction, and the processed data is normalized, and then input into the Chaos-GA-BP power load forecasting model. Finally, the rough set theory is used to progressively compensate the forecast error.

![Figure 1](image)

Figure 1: Rough set-Chaos-GA-BP power load forecasting model execution structure

As shown in Figure 1, the compound forecasting model combines genetic algorithm and rough set theory on the basis of the BP neural network chaotic time series forecasting model to form a new load forecasting model. The specific steps are as follows:

Step 1: Using chaos theory, phase space reconstruction of variables is carried out to calculate the optimal embedding dimension \( m \), which is taken as the number of input nodes of BP neural network, and then the topological structure of BP neural network is determined.

Step 2: Genetic algorithm is used to optimize the weight and threshold of BP neural network prediction model and build CHAOS-GA-BP neural network prediction model.

Step 3: The rough set theory is introduced to correct the prediction error, especially to compensate and correct the unnecessary error caused by the curve convergence in advance when the curve slope is large.

2.2. Chaos-BP neural network prediction model

In the evolution of genetic algorithm, the weights and thresholds corresponding to the optimal individuals are the optimal weights and thresholds required in the article [12]. The steps of the genetic algorithm to optimize the BP neural network prediction algorithm are as follows:

1. The initial population, set the population size to \( P \) and the individual \( Q_i = (q_1, q_2, \cdots, q_5) \)
2. Determine the individual evaluation function. The fitness value \( H \) and the average fitness value \( \bar{H} \) are defined as:
\[ H_i = \sum_{j=1}^{M} (\hat{y}_j - y_j)^2 (i = 1, 2, \ldots, P) \]
\[ \bar{H} = \frac{\sum_{i=1}^{P} H_i}{P} \]

(3) Selection operator. The probability of selection is:
\[ p_i = \frac{G_i}{\sum_{i=1}^{P} G_i} (i = 1, 2, \ldots, P) \]
\[ G_i = \frac{1}{H_i} \]

(4) Cross operation
\[ q_{kg} = q_{kg} (1 - b) + q_{pb} b \]
\[ q_{p} = q_{pb} (1 - b) + q_{kg} b \]

(5) Mutation operation
\[ q_{p} = q_{\min} + \beta (q_{\max} - q_{\min}) \]

\( \beta \) is a uniformly distributed random number in [0, 1].

(6) Solve the optimal connection weights and thresholds in the sample.

3. ROUGH SET THEORY

3.1. Basic overview of rough set theory
Rough set theory is usually used to deal with incomplete and uncertain knowledge expressions. This theory can quantitatively analyze and process information and knowledge in nonlinear systems, dig out hidden relationships, and reveal potential laws [23].

The power load trend change is affected by many factors such as historical data, temperature, humidity and wind speed. The knowledge reduction of rough set theory is used to preprocess the experimental data, to screen the main factors affecting the power load change, and to remove redundant data, discover the key attributes, and reduce the amount of calculation without affecting the prediction accuracy.

![Figure 2](image_url)

Figure 2 Rough set-Chaos-GA-BP power load forecasting model structure

The power load trend changes are characterized by random fluctuations. If the power load fluctuates greatly in a short period of time, when using traditional load forecasting models to predict it, the predicted value curve is difficult to follow the actual value change trend closely. The fundamental reason is that when the slope on both sides of the peak point is too large, the prediction curve enters the saturated state ahead of time, and the prediction curve converges in advance, which leads to a certain gap with the actual curve. This paper proposes that when the power load fluctuates sharply, the rough set theory is
used to the predicted value of the load forecasting model is revised and compensated, and the structure is shown in Figure 2.

3.2. Compensation and Correction of Power Load Forecast Value Based on Rough Set Theory

The algorithm is based on the BP neural network power load forecast value, and the correction formula is as follows.

\[
\begin{align*}
Y_{i+1} &= Y_{i+1} + \mu |k_{i+1} - k_i| \\
k_{i+1} &= Y_{i+2} - Y_{i+1} \\
k_i &= Y_{i+1} - Y_i
\end{align*}
\]

(5)

In the formula, decision attribute sets \( L = \{d\} \) and \( d \) are the scale factor \( \mu \), defined as \( C = \{a, b, c\} \), then

\[
\begin{align*}
a &= \frac{|k_{i+1} - k_i|}{y_i''} \\
b &= \text{sgn}(k_{i+1} - k_i) \\
c &= \frac{Y_i}{\max_{i} Y_i''}
\end{align*}
\]

(6)

Where, \( Y_i'' \) is the predicted value of electricity consumption per unit time of \( i \).

4. Case analysis

According to the above analysis to establish the prediction model, the test using a certain area in northeast China on March 1, 2013 to June 1, 2013 change of power load sequence as the historical data sample to predict the power system load in March 2015 and sample With an interval of 1 hour, the data relies on raw data such as electricity, temperature, humidity, wind speed, and air pressure. First verify the BP neural network prediction model based on chaotic time series. In the experiment, the structure of the BP neural network is m-5-1 three-layer structure, m is the embedding dimension, and the result is shown in Figure 3.

![Figure 3](image)

Figure 3 Comparison of BP forecasting model's forecast results and real load.

As shown in Figure 4, given the experimental results with a training sample of 2000 and a predicted sample of 100. As the time of forecasting data increases, the error gradually increases. In order to solve the above problems, the GA-BP neural network prediction model based on chaotic time series was rebuilt. In the experiment, the BP neural network structure selected the M-5-1 three-layer structure, the population size was set as 30, the number of evolution was 100, the crossover probability was 0.3, and the mutation probability was 0.1. The experimental results are shown in Fig. 4.
The convergence speed of the BP neural network prediction model optimized by the genetic algorithm is significantly accelerated, the prediction leading and lagging phenomena are significantly improved, the trend of the prediction can effectively reflect the real situation, and the average absolute error is reduced by 0.277. The relative error is reduced by 0.347, and this method has a certain effect. But there is still a lot of room for modification. In the case of large fluctuations in sample data, the predicted value can only reflect the changing trend of the real situation. The peak-point curve with too large slope on both sides will enter the saturation state in advance, resulting in a large kurtosis error. In order to solve this problem, rough set is proposed to compensate and correct the error. The prediction result of Chaos-GA-BP prediction model based on rough set is shown in Figure 5.

The prediction curve compensated by rough set theory follows closely. In order to compare the accuracy of these prediction models, average error and average absolute error percentage are selected as evaluation criteria. After a lot of calculation, the prediction results of common prediction models in the set are obtained, and their MAE and MAPE values are shown in Table 1 below.

| Prediction model | ORB   | AKAZE |
|------------------|-------|-------|
| BP               | 101.734 | 6.12  |
| RBF              | 117.93 | 7.23  |
| Chaos-GA-BP      | 47.28  | 4.48  |
| The rough set-Chaos-GA-BP | 35.12 | 3.45  |

Compared with the traditional BP neural network prediction model, the average absolute error percentage of the optimized load prediction model is reduced by 2.67%. The experiment shows that the composite prediction model has obvious effect on improving the accuracy of load prediction.
5. Conclusion
In summary, this paper proposes a new composite model for power load forecasting. Firstly, the article analyzes the main factors that affect the accuracy of load forecasting, and uses the knowledge reduction of rough set theory to reduce the redundancy of the original data, making the selection of parameters for the forecasting model more targeted. Secondly, construct a power load forecasting model based on BP neural network, and optimize the forecasting model according to the problems exposed by the experimental results. Then, the structure of the prediction model is adjusted through the input and output parameters of the chaotic time series algorithm, and the weights and thresholds of the BP neural network are modified according to the parameters corresponding to the best individual sought by the genetic algorithm, and then the rough set theory is introduced to modify the load peak forecast. For the problem of large errors, a new Chaos-GA-BP neural network power load forecasting model based on rough set theory is constructed. A set of data from Northeast China was introduced for model verification. Through comparison and demonstration, the composite forecast model reduced data redundancy to a certain extent and improved forecast accuracy.

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