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Study on prediction of type-2 fuzzy logic power system based on reconstruction phase space

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ABSTRACT

Power load forecasting is the foundation of power system in full consideration of the characteristics and the natural, social conditions, using the effective method, based on historical data to determine the technology in the future when the load value. Short term power load forecast is the sun, week load. As an important basis for ensuring network security, economic operation, power short-term load forecasting accuracy is arranged on, the plan (including the units start and stop, hydro thermal coordination, tie line power, economic load distribution, reservoir operation and equipment maintenance etc.) the premise and the foundation, can improve the electric power enterprise economic, social benefits. According to the power load is difficult to predict accurately the problem, this paper introduces the interval type-2 fuzzy logic method to reduce the prediction error, presents an interval type-2 fuzzy logic model for the time series of one hour of power load forecasting, and adopted the first modeling process model structure, and then use back propagation algorithm to adjust the model parameters are determined by simulation. The results show that, the model has higher prediction accuracy and practical value to a certain extent, the performance is better than that of the corresponding type fuzzy logic model, proved more efficient processing idea uncertainty of type-2 fuzzy logic method.

KEYWORDS

Type-2 fuzzy sets; Prediction; Reconstruction; Forecasting.

INTRODUCTION

The power load is an unsteady stochastic process, affected by many natural, social factors, difficult to accurately predict[1]. The classical forecasting methods such as consumption, trend extrapolation method, elastic coefficient method, the method of linear regression and time series prediction method has many shortcomings, it is often difficult to get an ideal prediction effect[2]. Therefore, people give their attention to the gray system, artificial neural network, wavelet theory and fuzzy logic in artificial intelligence methods, including type-2 fuzzy logic has the extraordinary ability of dealing with uncertainty, in the time series prediction has advantage over the artificial neural network method, and provides a new idea for forecasting of power load. Power load forecasting is based on historical load data as a basis for determining a series of work in the future when the load value[3]. As an important basis for the reasonable planning and economic operation of power system, accurate power load forecasting can improve the electric power enterprise economic benefit and social benefit, plays an important role in promoting the healthy development of the electric power industry[4].

Power load forecasting is based on historical load data as a basis for determining a series of work in the future when the load value[5]. As an important basis for the reasonable planning and economic operation of power system, accurate power load forecasting can improve the electric power enterprise economic benefit and social benefit, plays an important role in promoting the healthy development of the electric power industry[6]. Power the load fluctuation has strong nonlinear characteristics, can be regarded as an unsteady stochastic process, the accurate prediction of the difficulty is very big. The prediction method of the classical (such as linear regression method, the state space method and time series method) have many shortcomings, it is often difficult to get an ideal prediction effect[7]. Therefore, people look into some artificial intelligence methods (such as artificial neural network, genetic algorithm, fuzzy logic), of which two type fuzzy logic can effectively for uncertainty modeling, the original data with time-varying, uncertain noise can directly used to train the parameters of the system, capacity is better than the artificial neural network method for the prediction in time series, therefore it is suitable for electric power load forecasting[8,9].

The main disadvantage of fuzzy logic is the existence of redundancy problem of fuzzy rule base. For a fuzzy system, have proposed a variety of rule base simplification methods, but most of these methods can only remove the redundant fuzzy rules, and can not effectively remove the redundant fuzzy sets, fuzzy similarity in this respect shows unique advantages. Streamline problem type-2 fuzzy system rule base is few. Liang and Men-del first proposed to optimum seeking methods of interval type-2 fuzzy rules with the SVD method, obtained better result, but also can effectively eliminate the redundancy in the adverse effect of fuzzy set. In order to improve the accuracy of power load forecasting, this paper introduced the interval type-2 fuzzy logic, the establishment of interval type two non single valued two type Mamdani fuzzy model is applied to the time series of short-term power load forecasting, and proposed a kind of SVD-SM-BP hybrid iterative algorithm, can effectively simplify the redundant fuzzy sets and fuzzy rules, in order to eliminate its adverse effects, to improve the prediction accuracy of the model, make up the shortage of SVD method.

RELATED THEORY

Logic theory of type-2 fuzzy sets

A type of fuzzy set compared with traditional, capability of type-2 fuzzy sets processing has more uncertainty, but its structure is also more complex[10]. Defined on a continuous domain on X type-2 fuzzy set A can be expressed as:

$$\overline{A} = \int_{x\in X} \int_{u\in J_x} \mu_{\overline{A}}(x,u)/(x,u) \tag{1}$$

In the formula: $\mu_{\overline{A}}(x,u) \in [0,1]$ is the membership function; $u \in J_x$ is the main membership values; Jx Union called the uncertainty of the trace; FOU, the corresponding lower limit set, membership function; formula in the discrete domain, to replace the formula by Σ.

$$\overline{A} = \int_{x\in X} \int_{u\in J_x} 1/(x,u) \tag{2}$$

$\mu_{\overline{A}}(x,u) = 1$, so the interval type-2 fuzzy sets, pay, and fill operations are greatly simplified. Interval type two interval valued fuzzy sets of type-2 fuzzy logic is the mainstream application based on[11].

Fuzzy similarity is the measure of fuzziness of a very wide range of applications, represents a fuzzy set and another fuzzy set similarity. This paper adopts axiomatic definition of the following interval type-2 fuzzy similarity, and puts forward the calculation formula based on the.

$$N(\overline{A},\overline{B}) = \frac{1}{2}\left(\frac{\int_{x\in X} \min\left\{\overline{\mu}_A(x), \overline{\mu}_B(x)\right\} dx}{\int_{x\in X} \max\left\{\overline{\mu}_A(x), \overline{\mu}_B(x)\right\} dx} \right) \tag{3}$$

Interval type-2 fuzzy logic

A definition in the X domain of the two type fuzzy set is as follows:

$$\tilde{A} = \int_{x\in X} [\int_{u\in J_x} \mu_{\tilde{A}}(x)] / x$$
$$= \int_{x\in X} [\int_{u\in J_x} f_x(\mathrm{u}) / u] / x \quad \textbf{(4)}$$

Where: u is the element of the X main membership values, Fx (U) is a membership value, the range of Jx u and the uncertainty of a trace (FOU), FOU, respectively, lower limit of the corresponding membership function.

Visible, two types of fuzzy membership function is three-dimensional, more than one type of fuzzy membership function of fuzzy set multiple one-dimensional, degree of enhancement, but also increase the complexity of the set and its complement, intersection, so the computational complexity.

The time interval of type-2 fuzzy set membership values are 1, as shown in the following formula:

$$\tilde{A} = \int_{x\in X} [\int_{u\in J_x} 1/u] / x \quad \textbf{(5)}$$

The fuzzy set of interval type two is a simplified version of the type-2 fuzzy sets, avoids the choice of membership functions, and the pay, compensation, and calculation are greatly simplified, so it has practical value.

The shortcomings of the existing type-2 fuzzy theory

Starting from the late ninety's, people gradually realized the limitations of a type of fuzzy set in the description of multiple fuzzy uncertainty, makes some students study a type of fuzzy sets have turned to type-2 fuzzy sets. The J. M. Mendel, et al America University of Southern California professor of type-2 fuzzy sets are vigorously promote the improvement and application of the theoretically, and the two type fuzzy system has been successfully used in the nonlinear and time varying channel homogenization. Since then, two types of fuzzy set theory in the communication, biology, finance, automation control and many other fields have been successfully applied. The successful application reflects with nonlinear fuzzy uncertainty information of complex giant system modeling and analysis of application potential[12].

For type-2 fuzzy sets high computation complexity of the problem, Mendel et al. Further put forward the concept of interval type-2 fuzzy sets, namely the type-2 fuzzy set of two order membership function is defined as the degree of membership for the "1" of the interval valued fuzzy sets. This concept was proposed to simplify operation type-2 fuzzy sets, to enhance the ability of type-2 fuzzy systems for real-time applications in engineering, to promote application of type-2 fuzzy sets theory. Since then, most applications of type-2 fuzzy sets theory based on the interval type-2 fuzzy sets.

SHORT TERM POWER LOAD FORECASTING BASED ON INTERVAL

Interval type-2 fuzzy forecasting model

The interval SVD-SM-BP hybrid iterative algorithm of two non single valued Mamdani type-2 fuzzy prediction model is established based on the process is: first to identify the model input and rules, the number of pieces before after collection of shapes and rules, then use BP algorithm to adjust the parameters of the model, and then use the interval type-2 fuzzy similarity to streamline the redundant rules in the library collection, and finally to the selection of rule by SVD method.

(a) Fuzzy controller

Fuzzy controller will enter the exact values into intervals of type-2 fuzzy set, in order to fully process the load has a strong uncertainty. Interval two main membership function of fuzzy set selection variance of uncertainty the Gauss function, membership function, as shown in the following formula. The model has 3 input, 1 output, that is, with the first 3 moments of the load values to predict values after a moment.

$$\bar{\mu}_{X_k}(x_k) = \exp\left[-\frac{1}{2}\left(\frac{x_k - x_k^*}{\bar{\sigma}_k}\right)^2\right] \underline{\mu}_{X_k}(x_k) = \exp\left[-\frac{1}{2}\left(\frac{x_k - x_k^*}{\underline{\sigma}_k}\right)^2\right] \quad \textbf{(6)}$$

Where: x^*_k is the exact input values, $\left[\underline{\sigma}_k, \bar{\sigma}_k\right]$ is variation range of variance; K =1,... p, is the input dimension, p =3.

(b) The rule library

In this model, the form of the rule is as follows. Rule before, after parts are selected interval type-2 fuzzy sets, membership function is the main function of mean Gauss, uncertain, membership functions such as type (7), type (8) are shown. Each of the front parts of the input space consists of three sets, so the rule base containing M complete =3 * 3 * 3 =27 rule. Due to the adoption of Center - of - sets drop type, it can be set after the piece with (interval set) instead, as shown in eq.:

$$\bar{\mu}_{F\xi}(x_k) = \begin{cases} \exp\left[-\frac{1}{2}\left(\frac{x_k - \underline{m}_k^l}{\sigma_k^l}\right)^2\right], & x \le \underline{m}_k^l, \\ 1, & \underline{m}_k^l \le x \le \underline{m}_k^l, \\ \exp\left[-\frac{1}{2}\left(\frac{x_k - \bar{m}_k^l}{\sigma_k^l}\right)^2\right], & x > \bar{m}_k^l, \end{cases} \tag{7}$$

$$\underline{\mu}_{F\xi}(x_k) = \begin{cases} \exp\left[-\frac{1}{2}\left(\frac{x_k - \bar{m}_k^l}{\sigma_k^l}\right)^2\right], & x \le \frac{\underline{m}_k^l + \bar{m}_k^l}{2}, \\ \exp\left[-\frac{1}{2}\left(\frac{x_k - \underline{m}_k^l}{\sigma_k^l}\right)^2\right], & x > \frac{\underline{m}_k^l + \bar{m}_k^l}{2}, \end{cases} \tag{8}$$

(c) Reasoning machine

For the two type of interval Mamdani fuzzy model, the reasoning process is as follows, in the calculation is set, membership function.

$$\mu_{\tilde{G}^l}(y) = \int_{b^l \in \left[\underline{f}^{l*}\underline{\mu}\tilde{G}l(y),\, \bar{f}^{l*}\bar{\mu}\tilde{G}l(y)\right]} \frac{1}{b^l} \qquad y \in Y \tag{9}$$

Type: * is the t- norm, the minimal operator; $\underline{\mu}_{\tilde{G}l}(y)$, $\bar{\mu}_{\tilde{G}l}(y)$ is respectively after piece is set, membership function; $\bar{f}^l$, $\underline{f}^l$ are active set, membership function.

SVD-SM-BP hybrid iterative algorithm

For a collection of highly overlapping, can be used to identify the fuzzy similarity, combined to produce a public collection, and then use the public collection to replace these overlapping set.

$$\bar{m}_k^{lq} = \lambda_1 \bar{m}_k^l + (1-\lambda_1)\bar{m}_k^q \tag{10}$$

$$\underline{m}_k^{lq} = \lambda_2 \underline{m}_k^l + (1-\lambda_2)\underline{m}_k^q \tag{11}$$

$$\sigma_k^{lq} = \lambda_3 \sigma_k^l + (1-\lambda_3)\sigma_k^q \tag{12}$$

If there are two similar interval type-2 fuzzy sets, $\left[\underline{m}_k^l, \bar{m}_k^l\right] = [59, 63]$ respectively $\left[\underline{m}_k^q, \bar{m}_k^q\right] = [65, 70]$, the mean variance respectively $\underline{m}_k^{lq} = \frac{\underline{m}_k^l}{2} + \frac{\underline{m}_k^q}{2} = 62$, the replacement ensemble FOU mean is shown in Figure 1.

The front piece equivalent if rule in the rule base obtained by means of merger, delete set in, then only need to keep one, the consequent parameters and determine the retention rules.

SVD-SM-BP hybrid iterative algorithm is proposed in this paper takes three threshold α, β, ρ, the flow chart shown in Figure 2.

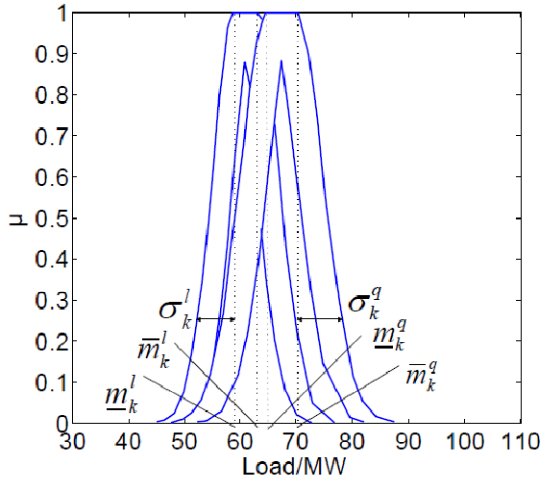


Figure 1: (a) FOUs of interval type two fuzzy sets $\tilde{F}_k^l$ and $\tilde{F}_k^q$

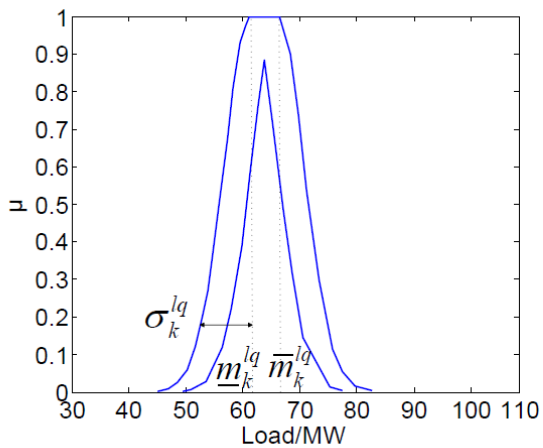


Figure 1: (b) FOU of Alternative set $\tilde{F}_k^{lq}$

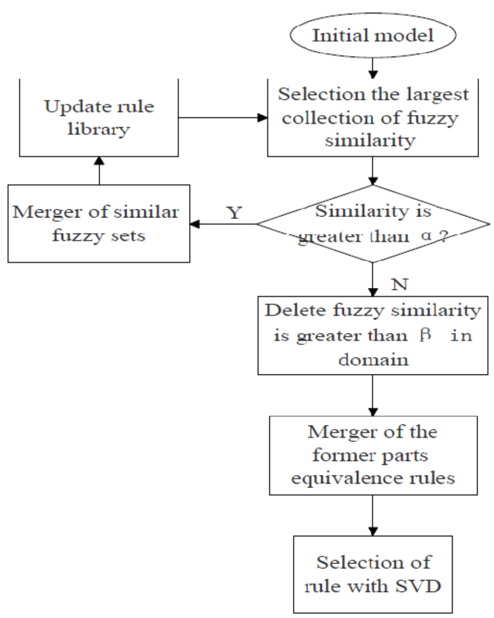


Figure 2: The initial model by BP algorithm to regulate the parameters of the model

Figure 2 is the initial model by BP algorithm to regulate the parameters of the model. Assume that after parameter adjustment interval type-2 fuzzy system rule base with M rule R = {R_1,…, R_M}, α (0, 1) and the β (0, 1).

Type-2 fuzzy logic system

Type-2 fuzzy logic system based on type two fuzzy sets, generally includes the fuzzifier, rule base, the inference engine, drop type device and the defuzzification part five, as shown in Figure 3, a type of fuzzy logic system of more than one drop type links.

Compared with the first type fuzzy logic systems, type-2 fuzzy logic system in construction and reasoning mode of the system and there is no significant change, but it is to type-2 fuzzy sets as a basis, the adjustable parameter increased, increasing the number of degrees of freedom can be adjusted, so as to obtain the better ability of handling uncertainty. Ordinary the two type of fuzzy logic system, realize the difficult and complicated calculation, application of interval type-2 fuzzy logic system can reduce the amount of calculation, and simplifies the reasoning process.

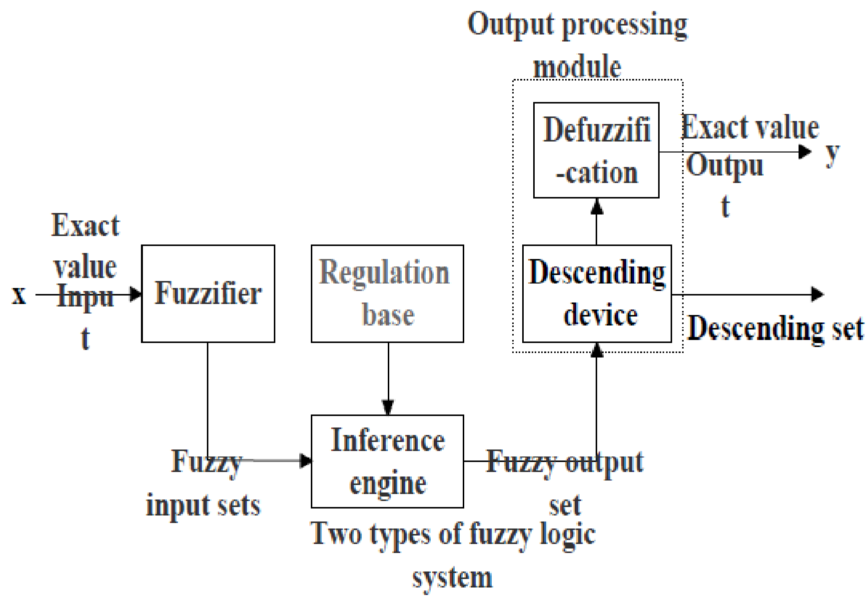


Figure 3: The inference engine, drop type device and the defuzzification

Adjusting the prediction model parameters

According to the way of input-output data to establish a fuzzy logic system has 2 kinds: one kind is the first by the input and output data to generate fuzzy rules, then select the fuzzy inference machine, fuzzy controller and fuzzy solution is to construct the system; another is the first to identify the structure of fuzzy logic system, part or all of the free parameters change in the structure of the system, and then through some parameter learning algorithm (such as the back-propagation algorithm) to determine these free parameters.

In the construction of a fuzzy logical system, if the selection of the singleton fuzzifier, Max product composition, product definition and highly defuzzifier, can be used to describe the system type:

$$y(x) = f_s(x) = \frac{\sum_{l=1}^{M} \bar{y}^l \prod_{k=1}^{p} \mu_{F_k^l}(x_k)}{\sum_{l=1}^{M} \prod_{k=1}^{p} \mu_{F_k^l}(x_k)} = \sum_{l=1}^{M} \bar{y}^l \varphi_l(x) \tag{13}$$

Visible, a type of fuzzy logic system can be seen as the fuzzy basis function expansion, the fuzzy basis function and fuzzy rules are in correspondence.

EXPERIMENTAL RESULTS

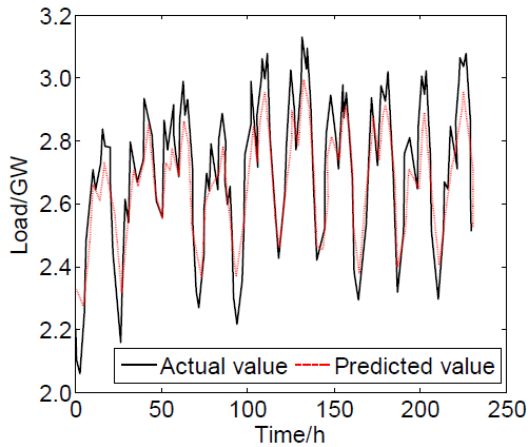
The simulation and verification

Selects the city in August 1, 2013 to August 31st a hourly load data as time series prediction, a total of 744 data, of which the first 504 data (21 days before the data) is used to adjust the parameters, 240 months after the data (after 10 days of data) used to test results.

The prediction accuracy of the two models with the average relative error is shown in the formula to evaluate the absolute value:

$$E = \frac{1}{N}\sum_{i=1}^{N}\frac{\left| f(x^{(k)}) - s(k+1) \right|}{s(k+1)} \quad \textbf{(14)}$$

Type: s (K + 1) is the actual data, f (x (k)) is a model to predict the data, is the model input data.
The prediction results of the two models are shown in Figure 4.



Prediction results of the non single value type Mamdani fuzzy logic model

Figure 4: The prediction results of the two models

From the modeling process and the prediction results can be known, non single valued type Mamdani fuzzy logic model with 3*3*3 = 27 rules, a total of 1*3 + 2*3* 27 + 1*27 = 192 design parameters, including input set variance sigma K, before rule set of mean m_{lk} and variance sigma L_K, consequent of a rule set center of mass Y_L, and the error between the true value of the predictive value of 3.67%. in the same number of rules, interval type non single valued design parameters of two type Mamdani fuzzy logic model has a total of 2*3 + 3* 3*27 + 2*27 = 303, including input set variance sigma K, before rule set M - L_K and M - mean L and variance sigma L_K, the consequents of the rules set Y - L and Y - the center of mass L, more adjustable parameters means more adjustable degree of freedom therefore, the prediction performance is improved, the error decreased to 3.18%.

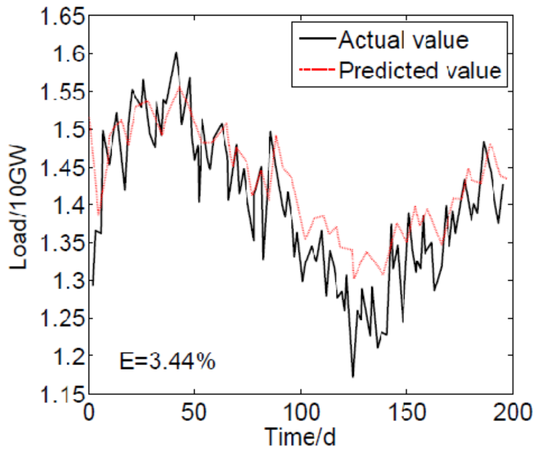
From Figure 4 can be seen, the prediction curves of the two models are better to track actual load curve, and the interval of a non single valued type two The prediction value of Mamdani fuzzy logic model is close to the actual value, especially has higher precision in near the peak, indicating that the prediction model has certain practical value in the field of electric power load

The design of the prediction modelvia type-2 fuzzy logic

We can see from the process of modeling and simulation results: a model with 3 * 3 * 3 = 27 rules, a total of 1 * 3 + 2 * 3 * 27 + 1 * 27 =192 design parameters, including input set variance parameter K, before rule set mean parameter m_{lk} and mean variance parameters sigma L_K, gauge after pieces of centroid parameters of YL set, the predictive value and the actual value of the average relative error between the absolute value of 3.44%.

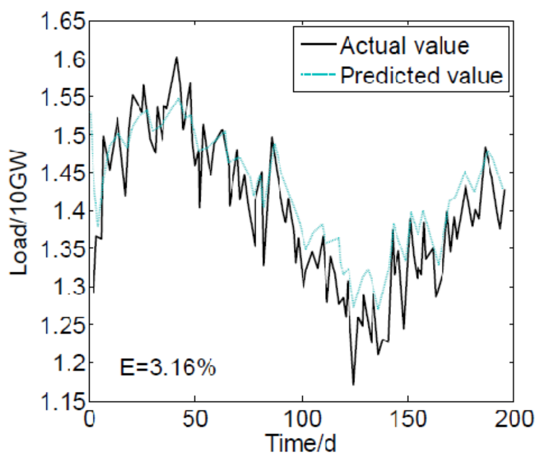
With the same number of rules, model two design parameters than the model a more, a total of 2 x 3 +3 x 3 x 27 +2 x 27 = 303, including input set variance parameter K, before rule set mean parameter m_{lk} and the mean variance parameter L_K, rule consequent matter cardiac parameters of Y_L set, this means that the model two has more adjustable degree of freedom, and thus improve the prediction accuracy, the prediction error is down to 3.16%; the model three with SVD method in model two is based on rejecting the bad rules, further improve the prediction accuracy, only 12 rules, which makes the prediction error is reduced to 2.98%.

The model of three phase ratio, model four first makes use of similarity and eliminates the redundant rules in the library collection in the merger process, redundant set, produced the same rules of the former parts, the merger will reduce the number of rules, and then on this basis, using the method of SVD selected the most important rules for rule base, further "downsizing", and improve the prediction accuracy, only with 8 rules, so that the prediction error is reduced to 2.80%. Figure 5 and Figure 6 in the simulation curve is also verified the above analysis, to the 4 model can be used to track the actual load curve, but the model two prediction curve than the model closer to the actual load curve fitting, model three better performance than the model two, and model fitting performance of four of the best.



Prediction results of model first

Figure 5: The actual value of the average relative error value of 3.44%



Prediction results of model second

Figure 6: The actual value of the average relative error value of 3.16%

CONCLUSIONS

Power load SVD-SM-BP hybrid iterative algorithm based on model prediction, it has higher forecast precision, better able to track the actual load curve in electric power load forecasting, the field has a good application prospect. Compared with the SVD-BP hybrid iterative algorithm, SVD-SM-BP hybrid iterative algorithm much streamlining the process redundancy of set, so it has the disadvantage of large amount of calculation, but it took the lean capacity stronger, not only reduced the redundancy in the model set, improve the rules of interpretation, but also a greater degree of reduced the number of rules, and thus a greater extent reduces the adverse effects of redundancy and improving the accuracy of approximation model. Fuzzy similarity is an important measure of the degree of similarity between two fuzzy sets, using the fuzzy similarity to simplify fuzzy system rule base, has the advantages of simple and easy to understand, accord with human thinking. In the system modeling, BP algorithm is sensitive to initial value, improper initial value will affect the precision of the model, to get the optimal initial value is an urgent problem to be solved.

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