Prediction Model of Short-term Load in Power System Based on Interval Type-2 Fuzzy Logic

Yun-Peng Li, Jie-Sheng Wang *, and Ming-Wei Wang

Abstract—**The operation schedule system in electric power system needs to predict the short-term load on-line in that its prediction accuracy has great influence on the technique and economic performance index. A prediction model on short-term load of power system was put forward based on the interval type-2 fuzzy logic system (IT2FLS). Firstly, IT2FLS and the corresponding prediction model are discussed in details. Then interval type-1 fuzzy sets (IT1FSs) and IT2FLS based forecasting algorithms are adopted to realize the prediction of the chaotic time series and short-term load in electric power system. Simulation results show the effectiveness of proposed prediction method with higher prediction accuracy.**

Index Terms—**power system, short-term load, interval type-2 fuzzy logic, prediction**

I. Introduction

THE operation schedule system in electric power system needs to predict the short-term load on-line. The business plan includes a series of decision processes, and the prediction accuracy of short-term load has great influence on the technique and economic performance index in the power system [1]. The prediction of the short-term load is vital important in the power system, which can directly affect the management, planning, design, safety and other aspects of power system. The short-term load forecasting (STLF) can predict electric load from an hour to a week, and has been successfully applied in many domains, such as thermal power and geothermal power [2]. The prediction methods of power mainly includes two kinds: classic prediction algorithms and intelligent algorithms. The former classical prediction algorithms contains gray system, time series analysis, extrapolation method and regression algorithm [3]. The classic prediction methods have the solid theory foundation mature theoretical basis But these kind of methods can not handle the nonlinear prediction problems due to the limitation in theory. So their applications are usually simple and the prediction accuracy can not meet expectations in general. So more and more intelligent prediction algorithms have widely been applied in the field of power system load forecasting, such as genetic programming, integration method, spectral analysis method, rough set method, and so on.

Fuzzy theory is the basic concept or continuous membership function of fuzzy sets. A fuzzy method with the combined structure was adopted to realize the prediction of power short-term load, which uses fuzzy reasoning and learns parameters from the historical load modes [4]. An adaptive network was adopted to identify system parameters and fuzzy inference system is adopted to set up the no-linear relationship between input data and power load data [5]. With decrease for power data acquisition cost and the interconnection of large power system, the data types available in power network are more and more abundant. A short-term load prediction method for power system was proposed by using the back propagation (BP) artificial neural network optimized by particle swarm optimization (PSO) algorithm [6]. Aiming at increasing the prediction accuracy, the fuzzy analytic hierarchy (AHP) strategy was adopted to predict power load based on its features and inherent uncertainty [7]. An improved fuzzy AHP method was proposed to realize the medium and long load prediction, where the triangular fuzzy number was introduced into the model to represent the expert's judgment, and AHP method was adopted to determine the optimal parameters of different prediction schemes [8]. A novel fuzzy system optimized by evolutionary algorithm was established to forecast the power load [9]. In this paper, a prediction model of short-term load in power system based on interval type-2 fuzzy logic (IT2FLS) was set up, and its effectiveness was verified by simulation experiment results. The paper mainly includes the following sections. In section 2, the principle of IT2FLS is introduced in Section 2. In Section 3, the design of IT2FLS prediction model was discussed in details. Then the short-load prediction experiments were carried out and discussed. The conclusion was obtained in the end of paper.

II. Interval Type-2 Fuzzy Logic

A. Basic Theory of Fuzzy Set

The basic theory of fuzzy set was proposed by Zadeh to establish a kind of satisfactory performance method system to handle uncertainties information firstly [10]. However, IT1FSs can partially deal with uncertainties, while applications in the real world usually have many characteristics, such as strong uncertainty and fuzziness. Therefore, more appropriate fuzzy logic forms have been proposed, such as IT2FLS shown in Fig.1 [11-12].

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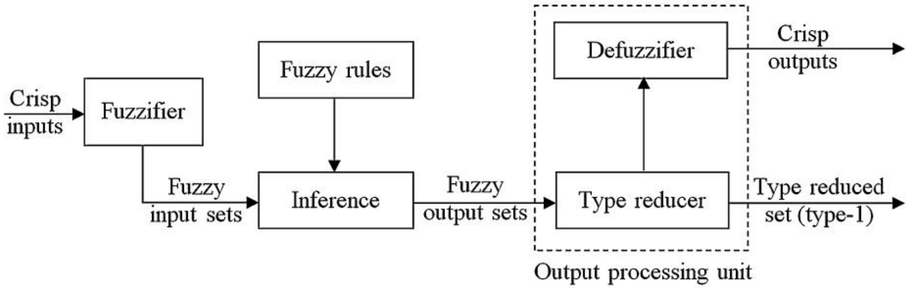


Fig. 1. Structure of IT2FLS system.

Because IT2FLS can provide the additional freedom, which might be more suitable to dispose the uncertainty problem. The adopted membership function (MF) in IT2FLS is a kind of fuzzy set, rather than a clear value [13]. The crisp inputs are firstly fuzzified as type-2 fuzzy set. Due to simplicity of single point fuzzy method, it is easy to be implemented in the embedded processor and real time application, so it is often used in the FLS applications. The inputs are fed into the type-2 fuzzy set inference module based on fuzzy rules in order to generate fuzzy output sets. Then they are disposed by the output processing unit (type reducer and defuzifier) to obtain the crisp outputs. In this paper, the set type reducer is adopted because its computational complexity is located between the center type reducer with high time consummation and the type reduced method to revise heights. After the reduction of the type, the exact value output is obtained by using its mean value. Because the IT2FLS can dispose high uncertainty, it has been applied in more and more engineering fields, such as optimization control [14], back propagation neural networks [15], clustering [16], edge-detection [17], evaluating cardiac health [18], autonomous underwater vehicles [19], etc.

B. Type-2 Fuzzy Set (T2FS)

Definition 1: A T2FS A on domain X can be expressed as:

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

In Eq.(1), the constraint is $0\le u_A(x)\le 1$, $u\in J_x\subseteq[0,1]$ meets the type-1 fuzzy membership, $u_{\tilde{A}}(x, u)$ is the type-2 fuzzy membership function, $\iint$ represents all possible combination of x and u. For the discrete domain, $\sum$ can substitute $\int$.

Definition 2: One point $x = x'$ in the theoretical domains of T2FS $\tilde{A}$. The intersection $u_{\tilde{A}}(x', u)$ of MF $u_{\tilde{A}}(x, u)$ and plane x=x' is named as the sub-membership function, which is shown in Eq. (2).

$$u_{\tilde{A}}(x=x', u)=u_{\tilde{A}}(x')=\int_{u\in J_x} f_X(u)/u \tag{2}$$

where, $u\in J_x\subseteq[0,1]$, $0\le f_{x'}(u)\le 1$.

$\tilde{A}$ can be represented as the sum of all sub-membership functions shown in Eq. (3).

$$\tilde{A}=\int_{x\in X} u_{\tilde{A}}(x)/x=\int_{x\in X}\left[\int_{u\in J_x} f_x(u)/u\right]/x \tag{3}$$

where, $x\in X$, $u\in J_x\subseteq[0,1]$, $0\le f_x(u)\le 1$.

The sub-MF is used in T2FS. Suppose it adopts Gaussian function, the set will be named as Gaussian T2FS.

Definition 3: Main membership is the domain of sub-MF of T2FS $\tilde{A}$. It can be seen from Eq. (2) that $J_{x'}\subseteq[0,1]$ represents the membership degree belonging to a certain point x', and value of the main membership degree is u.

Definition 4: The trace of uncertainty is the sum of all the main membership degrees J_x of the T2FS $\tilde{A}$, which can be represented as:

$$FOU(\tilde{A})=\bigcup_{x\in X} J_x \tag{4}$$

The concept FOU directly reflects the uncertainty of the scope, which is the sub-membership of supporting the type-2 membership function.

C. Type-2 Fuzzy System

Type-2 fuzzy system was established by adopting T2FS, which contains five parts (Fuzzifier, Defuzzifier, Type-reducer, Rules and Inference). For T1FS, "Type-1" is the set of inference engine output and "type-0" is the exact value of the defuzzifier output. But for the T2FS, "Type 2" is a set of reasoning inference output, "Type-0" is not directly obtained precise value through the defuzzifier process. The type reducer link is imperative from "Type-2" to "Type-1".

(1) Fuzzifier

The input's precise value can be fuzzied into T1FS and T2FS. Suppose T2FS has p dimension input X=(x_1, $x_2 ... x_p$), $x_1\in X_1$, $x_2\in X_2 ... x_p\in X_p$, and $\tilde{A}_1$, $\tilde{A}_2 \cdots \tilde{A}_p$ is the type-2 fuzzy set in domain, then the input membership function can be described by Eq. (5).

$$\begin{aligned} u_{\tilde{A}}(X) &= u_{\tilde{A}_1\times\tilde{A}_2\times ... \tilde{A}_p}(x_1, x_2, ... x_p) \\ &= u_{\tilde{A}_1}(x_1)\cap u_{\tilde{A}_2}(x_2)\cap ... \cap u_{\tilde{A}_p}(x_p) \\ &= \bigcap_{k=1}^{p} u_{\tilde{A}_k}(x_k) \end{aligned} \tag{5}$$

In Eq. (5), p is the inputs' dimension.

(2) Rule Database

The rules of T2FLS also adopt the "IF-THEN" form, which can be divided into TSK type and traditional Mamdani fuzzy system. The adopted T2FLS can be expressed as.

$$\begin{aligned} &R^1: IF \quad x_1 \quad is \quad \tilde{F}_1 \quad and \quad x_2 \quad is \quad \tilde{F}_2 \quad and... \\ &and \quad x_p \quad is \quad \tilde{F}_p, THEN \quad y \quad is \quad \tilde{G} \end{aligned} \tag{6}$$

where, $\tilde{F}_1$, $\tilde{F}_2$ and $\tilde{F}_p$ are the set of rules preset pieces, $\tilde{G}$ is the set of the rule followed parts, l is the rule number (l =1,2, ... , M).

$$\begin{aligned} &u_R(X,y) = u_{\tilde{F}_1\times\tilde{F}_2\times...\times\tilde{F}_p\to\tilde{G}}(x_1,x_2,x_3,...,x_p,y) \\ &= \left[\bigcap_{k=1}^{p} u_{\tilde{F}_k}(x_k)\right] \cap u_{\tilde{G}}(y) \end{aligned} \tag{7}$$

(3) Inference Machine

The fuzzy inference of T1FS needs Sup-star synthesis to complete. Then the fuzzy inference of T2FS is realized by expanded Sup-star synthesis including two kinds of operations (Join and Meet). A Type-2 output fuzzy set $\tilde{B}$ can be determined by Eq. (8).

$$\begin{aligned} &u_{\tilde{B}}(y) = u_{\tilde{G}}(y) \cap \{\left[\cup_{x_l\in X_1} u_{\tilde{A}_1}(x_1) \cap u_{F_1}(x_1)\right] \cap \\ &\left[\cup_{x_2\in X_2} u_{\tilde{A}_2}(x_2) \cap u_{F_2}(x_2)\right] ... \left[\cup_{x_p\in X_p} u_{\tilde{A}_p}(x_p) \cap u_{F_p}(x_p)\right]\} \end{aligned} \tag{8}$$

For a T2FS in the given region, the upper MF and lower sub-MF of the set are involved in the calculation, and the output of the inference machine is described as follows:

$$u_{\tilde{B}}(y) = \int_{b\in\left[\bar{f}*\bar{u}_{\tilde{G}}(y) f*u_{\tilde{G}}(y)\right]} \frac{1}{b} \quad y \in Y \tag{9}$$

where, $\bar{u}_{\tilde{G}}(y)$ and $u_{\tilde{G}}(y)$ are the upper MF and lower MF of the latter set, $\bar{f}$ and f are the upper MF and lower MF of the activation set.

(4) Type Reducer

The extension of the defuzzifier is the function of type reducer. The calculation of mass center in fuzzy set is to realize defuzzifier. That is to say the weighted average of the discrete points is the center of mass. Let X as the domain of T2FS. The input is gradually transferred into N discrete points, and the membership degree J_i of each point $x_i(i=1,2,...,N)$ is transferred into M_i discrete points. Then the prime membership degree values of x_i and the associated prior membership degree values form a T1FS $\prod_{i=1}^{V} M_i$, which is named as embedded type-1 set. The calculation of the mass center for each T1FS is named as type reducer. Then a new set is formed including all the centers of mass and the produced membership degrees, which is named as type-reduced set. Then a kind of center-of-sets type reducer method is adopted, which is shown in Eq. (10).

$$\begin{aligned} &Y_{\cos}(X) = \int_{d_1\in C_{G^1}} ... \int_{d_M\in C_{G^M}} \int_{e_1\in E_1} ... \int_{e_M\in E_M} \\ &\overset{M}{\underset{i=1}{T}} u_{C_{G^1}}(d_1) * \overset{M}{\underset{i=1}{T}} u_{C_{E_i}}(e_i) \Big/ \frac{\sum_{i=1}^{M} d_i e_i}{\sum_{i=1}^{M} e_i} \end{aligned} \tag{10}$$

where, c_{G^1} is the posterior center of mass, $E_i = \bigcap_{k=1}^{p} u_{F_k^1}(x_k)$ is the activation set, * is the norm function, which usually takes the smallest product sum.

For the IT2FLS, an interval set is obtained by type reducer, which is shown in Eq. (11).

$$\begin{aligned} &Y_{\cos}(X) = [y,\bar{y}] = \int_{y^1\in[y^1,\bar{y}^1]} ... \int_{y^M\in[y^M,\bar{y}^M]} \int_{f^1\in[f^1,\bar{f}^1]} ... \\ &\int_{f^1\in[f^1,\bar{f}^1]} 1 \Big/ \frac{\sum_{i=1}^{M} f^1 y^1}{\sum_{i=1}^{M} f^1} \end{aligned} \tag{11}$$

where, y^1 and $\bar{y}^1$ are the upper and lower bounds of latter set; f^1 and $\bar{f}^1$ are the upper and lower bounds of activation set, and L and R are the thresholds.

(5) Defuzzifier

The basic idea of the defuzzifier for IT2FLS is the same with T1FS.

III. IT2FLS BASED PREDICTION METHOD

(1) Fuzzifier

Strong uncertainty is an important characteristic of the fluctuation of power load. It can be seen that the input is polluted by noises, so the uncertainty must be fully dealt with. IT2FS is to the inputs' fuzzy accurate values. The mean square error Gaussian function containing the uncertainty is the primary membership function, whose upper and lower membership function are shown in Eq. (12) and Eq. (13).

$$\bar{u}_{x_k}(x_k) = \exp\left[-\frac{1}{2}\left(\frac{x_k - x_k^*}{\bar{\sigma}_k}\right)^2\right] \tag{12}$$

$$u_{x_k}(x_k) = \exp\left[-\frac{1}{2}\left(\frac{x_k - x_k^*}{\sigma_k}\right)^2\right] \tag{13}$$

where, k =1, 2... , p , p is the input dimension, x_k^* is the input crisps. The precision value is in the Gauss membership function center, $m_k = x_k^*$ and the variation range of [σ_k , $\bar{\sigma}_k$] is the mean variance.

(2) Rule Database

The rule form of the IT2FLS is represented in Eq. (6). Interval type-2 fuzzy set is the selected forehead of fuzzy rules. The Gaussian function with uncertainty is the main membership function, whose upper and lower MFs are shown in Eq.(14) and Eq. (15). Due to adopting the Center-of-sets type reducer, the interval set uses the Center of mass mode, which is shown in Eq. (16).

$$\bar{u}_{\bar{F}_k^l}(x_k) = \begin{cases} \exp\left[-\frac{1}{2}\left(\frac{x_k - m_k^l}{\sigma_k^l}\right)^2\right] & x \le m_k^l \\ 1 & m_k^l < x \le \bar{m}_k^l \\ \exp\left[-\frac{1}{2}\left(\frac{x_k - \bar{m}_k^l}{\sigma_k^l}\right)^2\right] & x > \bar{m}_k^l \end{cases} \tag{14}$$

$$u_{\tilde{F}_k^l}(x_k)=\begin{cases}\exp\left[-\frac{1}{2}\left(\frac{x_k-\bar{m}_k^l}{\sigma_k^l}\right)^2\right] & x\le\frac{m_k^l+\bar{m}_k^l}{2}\\ \exp\left[-\frac{1}{2}\left(\frac{x_k-m_k^l}{\sigma_k^l}\right)^2\right] & x>\frac{m_k^l+\bar{m}_k^l}{2}\end{cases}\quad(15)$$

where, $l=1$, 2, ..., M. l represents the number of the membership functions. Mean range [m_k^l , $\bar{m}_k^l$] is composed of the main MFs of the former part in fuzzy rules.

$$y^l=[y^l,\bar{y}^l]\quad(16)$$

(3) Inference Machine

In inference process, upper and lower MFs are involved in calculation for IT2FS, whose output is shown in Eq. (9).

(4) Type Reducer

The center-of-sets type reducer method was adopted, which was used to calculate weighted average on the centrefold of each fuzzy rule, and the interval set is the result of type reducer shown in Eq. In practical use, the Karnik-Mendel iterative process is generally used to realize calculation.

(5) Defuzzifier

The system with an interval set output is name as IT2FS. The defuzzifier is to calculate center of interval endpoints.

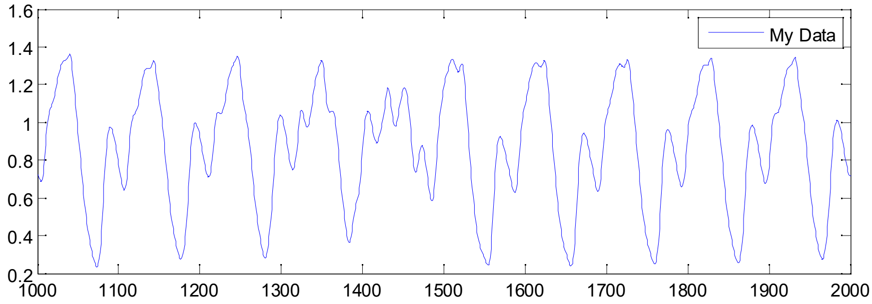
IV. Simulation Experiments and Result Analysis

A. *Simulation on Forecasting Chaotic Time Series*

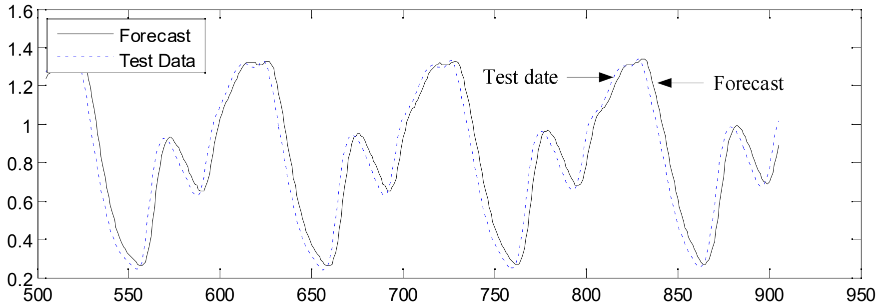
The adopted chaotic time series were produced by using Mackey-Glass differential delay equation, which is described in Eq. (17).

$$\dot{x}=\frac{0.2x(t-\tau)}{1+x^{10}(t-\tau)}-0.1x(t)\quad(17)$$

The main function of Eq. (17) is adopted to forecast the behind numbers with former numbers. Firstly, realize a point D , which is the time sequence with the interval $\triangle$, that is the mapping from [$x(t-(D-1)\Delta),\cdots,\ x(t-\Delta),\ x(t)$] to the forecasting future numbers. The numerical solution D of the above equation is obtained by adopting fourth-order Runge-Kutta algorithm. The adopted time interval is 0.1, $x(0)=1.2$ and $\tau=17$. By adopting integral number, the format of $x(t)$ is $[x(t-18),x(t-12),x(t-6),x(t),x(t+6)]$. The 1000 sets of data from $t=1001$ to 2000 are extracted as the simulation data, where the first 500 as the training data, and the remaining data as the test data. In this paper, the future value of chaotic time series is predicted by the interval type-2 fuzzy system and the interval type-1 fuzzy system. The simulation results are shown in Fig. 2 and Fig. 3.

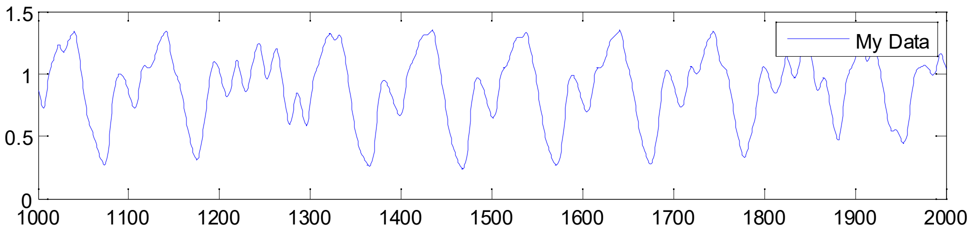


(a) Simulation data

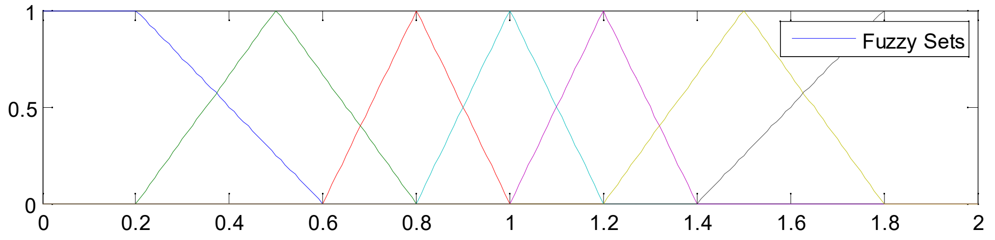


(b) Predicted Results

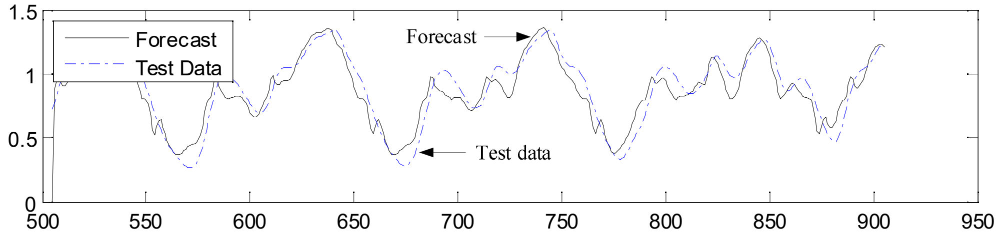
Fig. 2. Forecasting results based on IT1FS on Mackey-Glass time series.



(a) Simulation data



(b) Membership function graphs of fuzzy set



(c) Predicted Results

Fig. 3. Forecasting results based on IT2FS on Mackey-Glass time series.

Seen from Fig. 2 and Fig. 3, the prediction root mean square error (RMSE) by adopting IT1FS for Mackey-Glass time series is 0.1006, and IT2FS is 0.1087. Both methods have the high accuracy. Because IT2FS is more complicated than IT1FS in the structure and algorithm, the membership functions and rules need to be studied for a long time in the prediction process. The predict accuracy of IT2FS is less than IT1FS in a limited study time in that the discussed time series forecasting problem is relatively simple.

B. *Prediction of Short-term Load of Power System*

For the power load forecasting, the power load dosage data in a year for a given area are collected. The data is for 365 days a year and every half an hour for every day has a data record. The 3000 data are captured as the predict data. Then the IT1FLS and IT2FLS were used to realized the power short-term load prediction. In the historical load sequence, because of the influence of the randomness factors, the difference point will be generated. Some time of the day will produce the load point that is abnormal at the previous operation mode. This is named as the difference point. Due to the infiltration of different points, the normal load sequence has the overall increased noises and the load curve similarity has also been affected. So its unpredictability is greatly enhanced. Therefore, it is very important to eliminate the difference data and smooth the load curve. Therefore, in order to avoid the above situation, the statistical methods are adopted to tackle the historical data so as to further highlight the operation trend of the power loads. Suppose the load sequence is represented as $x(i,n)$, where $i=1,2,\ldots,48$ represents a day is divided into 48 time internals. $E(i)$ represents the data of various loads taking form N days. Then the mean $E(i)$ and variance $V(i)$ of N day load for each period of 48 periods are calculated by:

$$E(i)=\frac{1}{N}\sum_{k=1}^{N}x(i,k) \tag{18}$$

$$V(i)=\sigma_i^2=\frac{1}{N}\sum_{k=1}^{N}[x(i,k)-E(i)]^2 \tag{19}$$

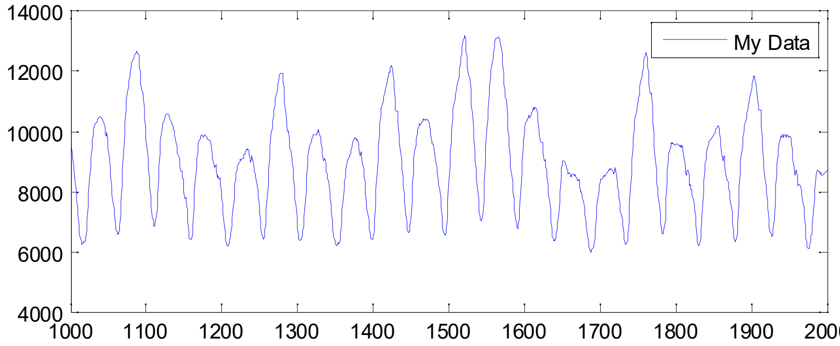
Define $\rho(i,n)$ as the deviation of load, whose value is calculated by Eq. (2).

$$\rho(i,n)=\frac{|x(i,n)-E(i)|}{\sigma_i} \tag{20}$$

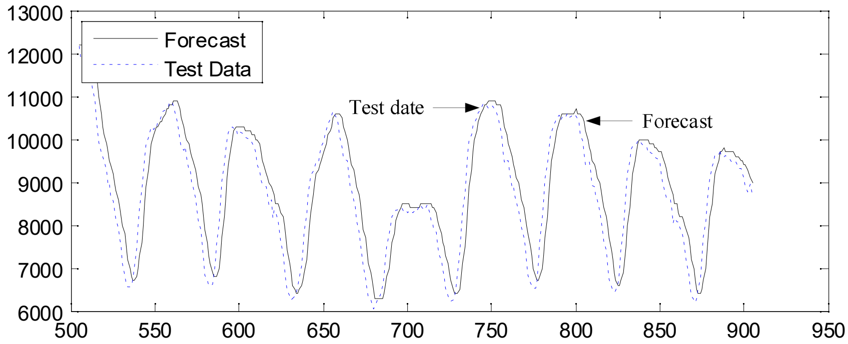
So deviation rate $\rho(i,n)$ can be calculated, where $i=1,2,\ldots,48$ and $n=1,2,\ldots,N$. When the composite data is actually processed, the following criterion can be applied to the application. When $\rho(i,n)\geq 1.1$, the load point at this time will be determined as the abnormal point. When $\rho(i,n)<1.1$, the load point was normal. When the load point is identified as an exception point, it should be removed. Then $\bar{x}(i,n)$ in Eq. (21) is adopted to replace the exception point.

$$\bar{x}(i,n)=\frac{x(i,n-1)+x(i,n+1)}{2} \tag{21}$$

The IT1FLS and IT2FLS are adopted to realize carry out the electric power system short-term load forecasting on the data removed different points respectively. The 1000 set of data from $t=1001$ to 2000 in the collected 3000 points are adopted as simulation data, where the first 500 is the training data and the remaining data as test data. The simulation results are shown in Fig. 4 and Fig. 5. Seen from Fig. 4 and Fig. 5, RMSE by using IT1FS for electric power system short-term load is 601.7723, and IT2FS is 986.5963. Both methods have the high accuracy. Because IT2FS is more complicated than IT1FS in the structure and algorithm, the membership functions and rules need to be studied for a long time in the prediction process. The prediction accuracy of IT2FS is less than IT1FS in a limited study time. So in the later study, the optimization of membership function and its parameters of IT2FS should be carried out the related research so as to enhance its prediction accuracy.

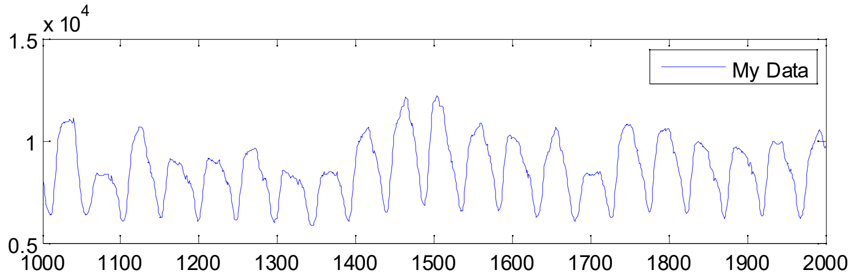


(a) Simulation data



(b) Predicted Results

Fig. 4. Prediction results based on IT1FS on power short-term load.



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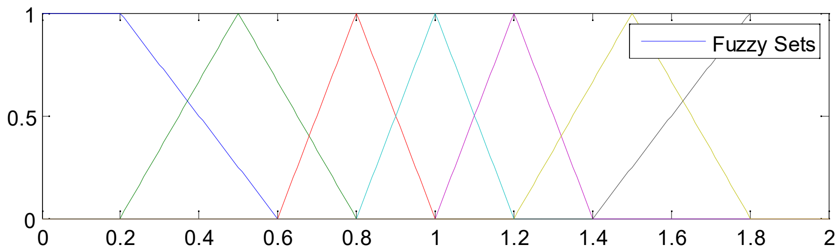
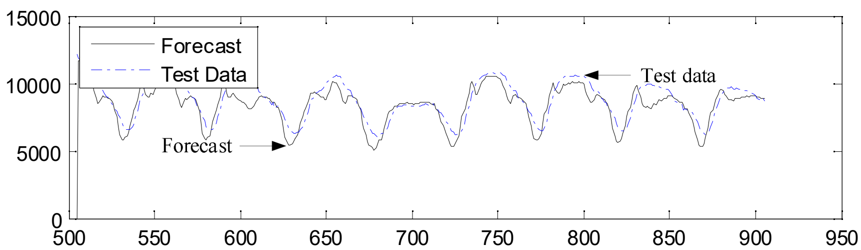


(b) Membership function graphs of fuzzy set



(c) Predicted Results

Fig. 5. Prediction results based on IT2FS on power short-term load.

V. CONCLUSION

In that many random variables having influence on the power short-term load, such as the random influence of power rationing behavior in load dispatching process and the power of the user behavior, the improvement of prediction accuracy on short-term load was limited. An ideal prediction model to decrease the influence of these disturbance variables was proposed based IT1FLS and IT2FLS. The prediction results in simulation experiments show that the proposed method has better prediction precision and satisfy the demand of electric power dispatching.

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