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Load Interval Prediction of the Power System based on Type-2 Fuzzy Theory

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Abstract

According to the power load has strong randomness and difficult to forecast, the introduction of the two types of fuzzy logic in order to improve the prediction accuracy. The interval type two non-single valued two type Mamdani fuzzy model for power load time series forecasting, and reverse the spread of a similarity of a singular value decomposition iterative blending algorithm to simplify the redundant rules in the model of fuzzy sets and redundant fuzzy rules, in order to eliminate the adverse effects. For ordinary type-2 fuzzy sets, uncertainty of the trace and once the membership function is the most important factor, therefore in the calculation formula for construction of two kinds of measure when considering these two factors; analysis of the ordinary type-2 fuzzy inclusion degree properties; discussed two kinds of conversion between the new measure of the relationship, revealing its internal relations; finally through an example to verify the performance of the new measure ordinary type-2, and the fuzzy similarity and Yang Shih clustering method combining cluster analysis used in Gauss plain type-2 fuzzy sets, obtained the reasonable clustering results, verify the rationality of the new measure and effectiveness.

***Keywords**: Type-2 fuzzy sets; prediction; time series forecasting; total quantity of knowledge*

1. Introduction

Power load fluctuation is an unsteady stochastic process, affected by many natural and social factors, various factors are also changing, uncertain, so the accurate prediction of the difficulty is very big [1]. Prediction of some traditional methods because of the existence of many problems and is difficult to obtain ideal prediction effect, in this context, to find a efficient method to deal with uncertainty to improve the accuracy of load forecasting is very important. People give their attention to some modern methods based on artificial intelligence theory, including two type fuzzy logic has excellent ability of dealing with uncertainty, stand out in a variety of artificial intelligence technology. Castilfo and Melin is used to verify the two type of fuzzy logic in the time series prediction has an advantage over the artificial neural network method, it is introduced into the field of electric power load forecasting is very important [2-5].[1]

Interval type two fuzzy logic to overcome the common type two fuzzy logic calculation complexity, is currently a hot topic of theoretical research and practical application. According to the characteristics of interval type two fuzzy logic, based on three kinds of

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interval type two fuzzy measure axiomatic definition, proposed a new interval type two fuzzy similarity, fuzzy inclusion degree and fuzzy entropy [6]. Considering the interval type two fuzzy sets depends on the characteristics of the membership function, operation, put forward the corresponding calculation formula of three kinds of measurement; analysis of interval type two fuzzy inclusion degree; discussed three kinds of conversion between new measure [7]. Finally, the performance of the new measure is verified by an example, laid the theoretical foundation for the application of the next step.

With the progress of society, businesses demand for electricity is growing, the power protection industry has become a pillar industry of the national economy and stable development, power load forecasting is the power industry is an important work load forecasting is on the basis of full consideration of the power system characteristics and their natural and social conditions on the use of effective methods, based on historical data to determine the technical future time load value [8]. Accurate power load forecasting of power system planning decisions are based, have capacity and reasonable arrangements conducive to rebuilding the grid as an important basis for power system dispatch sinks. Accurate load forecasting is to achieve a balance of power system supply and immediate premise favor the formation of ordered electricity order to maximize the limited power resources to meet the needs of the community.

Accurate load forecasting is still reasonable arrangements grid internal generators running on an important basis and maintenance plan, you can reduce the production and consumption of electrical energy into the wood. At present, the development of China's power industry in order to supply the main guide mainly oriented to the needs of the transition period, the accurate prediction of power load of great significance to the achievement of sustainable development of power industry [9, 10]. This paper focuses on two types of fuzzy system identification, pointing out the deficiencies of stage presence, the type two fuzzy measure is applied to the two type of fuzzy system identification Electric power load forecast is the power system planning, construction, operation, maintenance of production, as well as an important basis for the safe operation of the electric power load fluctuation, and has strong uncertainty, it is difficult to predict. Two types of fuzzy logic has the ability of dealing with uncertainty, is introduced to the field of electric power load forecasting is very important.

2. The Related Theory

a. Research status of type two fuzzy systems

Fuzzy grid method using some fixed division method to divide the input space into several regions, and then for each region to select a fuzzy membership function, the general regional center as fuzzy membership function of the center, as the adjacent intersection region boundary fuzzy membership function. Fuzzy system so established fixed, is a former member is simple, but do not consider the distribution characteristics and language information of the training data, the system has a large amount of redundancy in some performance index.

In recent years, the application of fuzzy measure is more and more widely, SeineS *et al* [11] proposed a use of a type of fuzzy similarity to streamline the new method of a fuzzy system rule base, can also eliminate the adverse effects of redundant fuzzy sets and redundant fuzzy rules is brought, the interpretability of fuzzy rules to improve the system, to reduce the computational complexity degree, make the system easy to use and understand the design. Uncu [12] and Turksen [13] proposed a fuzzy clustering method based on fuzzy similarity, can be used for the identification of fuzzy system. In short, the fuzzy similarity is simple and easy to understand, in accordance with people's thought, has a good application prospect in the field of fuzzy system identification.

b. Research status of electric power load forecasting

The traditional power load forecasting techniques such as unit consumption method, trend extrapolation method, elastic coefficient method, linear regression method, the state space method and time series prediction method has been more mature. The time series forecasting method to predict the next few moments or load values by several recent moment load value, only need to load value of time series model can be established, so pay attention. It is the randomness in the big occasions not applicable. In recent years, the emergence of some artificial intelligence method provides an opportunity for the development of the technology of power load forecasting, the model and method from the traditional mathematical model previously to the intelligent prediction of machine learning and transformation, which is representative of the artificial neural network, genetic algorithm and fuzzy logic.

Excellent ability of fuzzy logic to deal with uncertainty and has gained wide attention, people will also be introduced to the field of electric power load forecasting. Chow and Tram proposed a model of spatial load forecasting based on fuzzy logic method, the prediction results can be used as the basis of formulating the distribution plan. A type of traditional fuzzy logic cannot deal effectively with fuzzy rule uncertainty, type two fuzzy logic to make up for this deficiency, so it is more applicable to electric power load forecasting, and now this work has not been done.

c. Type-2 fuzzy theory

Type two fuzzy sets and membership degrees of the element of all union known as the uncertainty of the trace:

$$FOU(\tilde{A}) = \bigcup_{x \in X} J_x \tag{1}$$

FOU is a very important concept, its range is the direct embodiment of the uncertainty of wood, provides a direct description of the set time membership support membership function for type two. Fou, the lower limit of the corresponding membership function:

$$\mu_{\tilde{A}}(x = x', u) = \mu_{\tilde{A}}(x = x') = \int_{u \in J_{x'}} f_{x'}(u) / u \tag{2}$$

In it: $u \in J_{x'} \subseteq [0,1], \;\; 0 \le f_{x'}(u) \le 1$

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.

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

3. Type Two Fuzzy Logic Theory

a. Interval type two fuzzy similarity

A real function $N : IVFSs \times IVFSs \to [0,1]$ was called the fuzzy similarity of interval type two, when N satisfies the following axioms:

$(N1)\;\; N(\tilde{A}, \tilde{B}) = N(\tilde{B}, \tilde{A});$

$(N2)\;\; N(D, D^c) = 0, \;\; \forall D \in P(X);$

$(N3)\;\; N(\tilde{E}, \tilde{E}) = \max_{\tilde{A}, \tilde{B} \in IVFSs} N(\tilde{A}, \tilde{B});$ (4)

(N4) for any interval type two fuzzy sets $\tilde{A},\ \tilde{B}\ and\ \tilde{C}, if\ \tilde{A}\subseteq\tilde{B}\subseteq\tilde{C}$, then:

$$N(\tilde{A},\tilde{C})\le N(\tilde{A},\tilde{B})$$
$$N(\tilde{A},\tilde{C})\le N(\tilde{B},\tilde{C}) \tag{5}$$

(N1) the interval type two fuzzy similarity with symmetric (N2) indicating the exact value set and its complement is completely similar. (N3) showed equal interval type two fuzzy sets (N4) that is most similar. Type two fuzzy interval similar degree with the transfer law. Therefore, these four axioms intuitive understanding of interval type two fuzzy similarity.

$$N(\tilde{A},\tilde{B})=\frac{1}{2}\frac{\int_{x\in X}\min\{\bar{\mu}_{\tilde{A}}(x),\bar{\mu}_{\tilde{B}}(x)\}dx}{\int_{x\in X}\max\{\bar{\mu}_{\tilde{A}}(x),\bar{\mu}_{\tilde{B}}(x)\}dx} \tag{6}$$

For any interval type two fuzzy sets A and B, a definition in the domain of the two type of interval X fuzzy entropy can be expressed as:

$$E(\tilde{A})=\frac{\int_{x\in X}\min\{\bar{\mu}_{\tilde{A}}(x),1-\underline{\mu}_{\tilde{A}}(x)\}dx}{\int_{x\in X}\max\{\bar{\mu}_{\tilde{A}}(x),1-\underline{\mu}_{\tilde{A}}(x)\}dx} \tag{7}$$

Among them, ∫ is the integral sign, for the discrete case, and type Σ, instead of ∫.

Measure of fuzziness of different types can be transformed into each other under certain conditions, a lot of scholars have done in-depth research, made a lot of achievements.

The main disadvantage of fuzzy logic is the redundancy problem of fuzzy rule base, caused by the two aspects of redundant fuzzy rules and fuzzy sets in fuzzy system identification factors. In the process, determine the number of fuzzy rules and reasonable is very important, too many rules will cause the system to complex and difficult to achieve, the fewer rules and make the system weakened and cannot reach the ideal approximation accuracy, the curse of dimensionality is the main problem is the existence of a large number of fuzzy, the fuzzy inference process with little effect or repeated fuzzy rules. The redundant fuzzy sets is a fuzzy rule contains a large number of highly overlapping or minor role of fuzzy set, fuzzy high degree of overlap with the set membership of the same or similar values in the same domain, on behalf of the same or similar meaning, resulting in the fuzzy rules can not be explained and complexity.

b. Type-2 fuzzy logic system

Type-2 fuzzy logic system based on type-2 fuzzy sets, generally includes the fuzzifier, rule base, the inference engine, drop type device and the defuzzification part five, as shown in Figure 1, a type of fuzzy logic system of more than one drop type links.

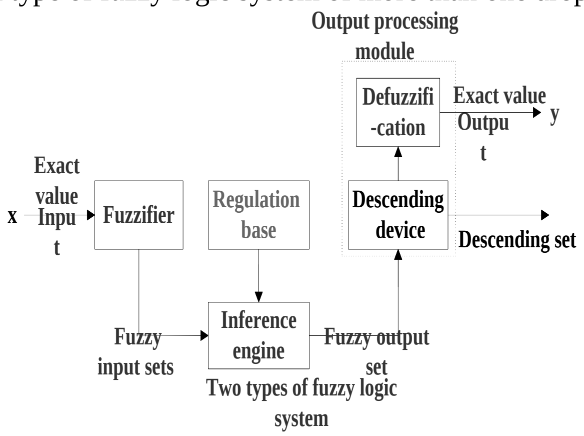


Figure 1. The Inference Engine, Drop Type Device and the Defuzzification

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 type-2 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.

c. Interval type-2 fuzzy similarity

A real function $N : IVFSs \times IVFSs \to [0,1]$ satisfies the following conditions, called the fuzzy similarity interval type-2, when N satisfies the following axioms:

$$\begin{aligned} &(N1)\ N(\tilde{A},\tilde{B}) = N(\tilde{B},\tilde{A}); \\ &(N2)\ N(D,D^c) = 0,\ \forall D \in P(X); \\ &(N3)\ N(\tilde{E},\tilde{E}) = \max_{\tilde{A},\tilde{B}\in IVFSs} N(\tilde{A},\tilde{B}); \end{aligned} \tag{8}$$

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 inputs, 1 output, that is, with the first 3 moments of the load values to predict values after a moment.

$$\bar{\mu}_{F\xi}(x_k) = \begin{cases} \exp\left[-\frac{1}{2}\left(\frac{x_k - \underline{m}_k^l}{\sigma_k^l}\right)^2\right], & x \le \underline{m}_k^l, \\ 1, & \underline{m}_k^l \le x \le \underline{m}_k^l, \\ \exp\left[-\frac{1}{2}\left(\frac{x_k - \bar{m}_k^l}{\sigma_k^l}\right)^2\right], & x > \bar{m}_k^l, \end{cases} \tag{9}$$

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

How to fuzzy rule base system is a hot research topic. In a fuzzy system, people have proposed many kinds of rule base simplification methods, but most of these methods can only remove the redundant fuzzy rules, can not effectively eliminate the redundancy of the adverse effects of fuzzy sets fuzzy similarity. On the one hand shows the unique advantage. The use of fuzzy similarity can identify the redundant fuzzy sets, on the basis of the merge, delete and other means can effectively eliminate the number of fuzzy rules, but also has the potential to reduce the redundancy. A similar calculation, get the fuzzy similarity to other was listed in Table 1:

Table 1. The Fuzzy Similarity Listed

	$\tilde{A}_1$	$\tilde{A}_2$	$\tilde{A}_3$	$\tilde{A}_4$	$\tilde{A}_5$
$\tilde{A}_1$	1.2000	0.0029	0.0138	0.3282	0.0001
$\tilde{A}_2$	0.0029	1.2000	0.3973	0.0197	0.2069
$\tilde{A}_3$	0.0138	0.3973	1.2000	0.0702	0.0697
$\tilde{A}_4$	0.3282	0.0197	0.0702	1.2000	0.0015
$\tilde{A}_5$	0.0001	0.2069	0.0697	0.0015	1.2000

4. The Experiment and Analysis

a. Fuzzy system parameters

In the construction of a fuzzy system, if the selection of the singleton fuzzifier, Max product product synthesis, meaning and defuzzifier, system (10) can be used to describe the:

$$y(X) = f_x(X) = \frac{\sum_{l=1}^{M} \bar{y}^l \prod_{k=1}^{p} \mu_{F_k^l}(x_k)}{\sum_{l=1}^{M} \prod_{k=1}^{p} \mu_{F_k^l}(x_k)} = \sum_{l=1}^{M} \bar{y}^l \phi_l(X) \tag{10}$$

If the rules set by the former Gauss membership function, type (5-1) can be expressed as (11):

$$f_x(X) = \sum_{l=1}^{M} \bar{y}^l \phi_l(X) = \frac{\sum_{l=1}^{M} \bar{y}^l \prod_{k=1}^{p} \exp\left[-\frac{(x_k - m_{F_k^l})^2}{2\sigma_{F_k^l}^2} \right]}{\sum_{l=1}^{M} \prod_{k=1}^{p} \exp\left[-\frac{(x_k - m_{F_k^l})^2}{2\sigma_{F_k^l}^2} \right]} \tag{11}$$

The mapping process system: input X through a product of Gauss operator into $z^l = \prod_{i=1}^{p} \exp\left[-(x_k - m_{F_k^l})^2 \big/ 2\sigma_{F_k^l}^2 \right]$. The system can be viewed as a three layer feed forward network, as shown in Figure 2:

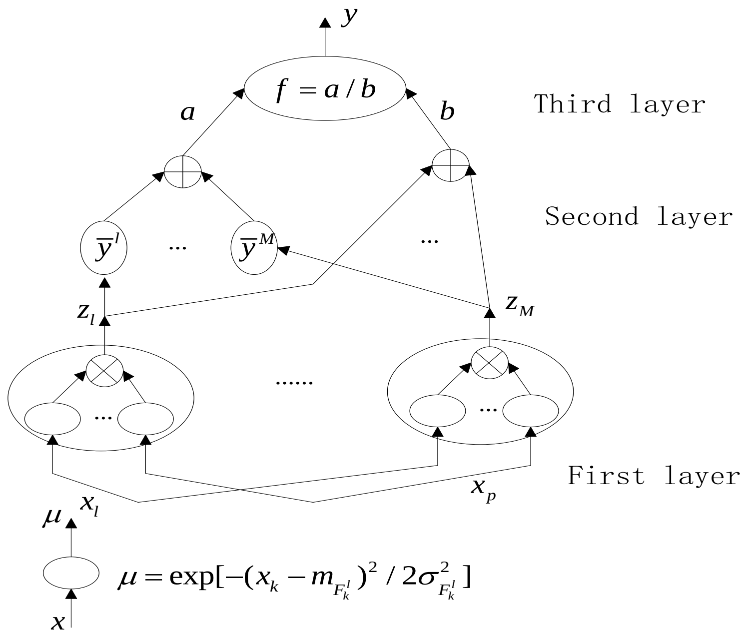


Figure 2. The System can be Viewed as a Three Layer Feed forward Network

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.

Selects the city in August 1, 2014 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:

$$E = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|f(x^{(k)}) - s(k+1)\right|}{s(k+1)} \tag{12}$$

Type: s (K + 1) is the actual data, f (x (k)) is a model to predict the data, is the model input data.

b. The design of the prediction modelvia type-2 fuzzy logic

The correlation degree of P =0.98, 3:00 interval prediction results median interval [469.77682.74] 576.255 as the deterministic forecasting results, belong to the same type and the fourth layer, according to the above calculation can get the probability distribution of different load level partition, the probability distribution of the fourth layer as shown in Figure 3:

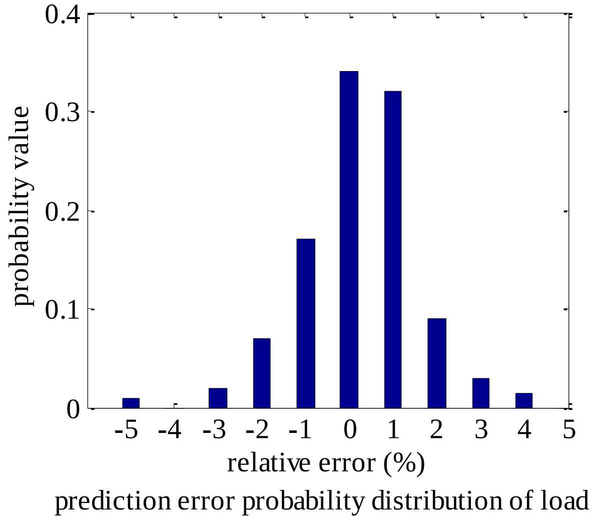


Figure 3. The Probability Distribution of the Fourth Layer

The median interval as 0 error value, then according to the probability of error, get the load probability distribution curve was shown in Figure 4:

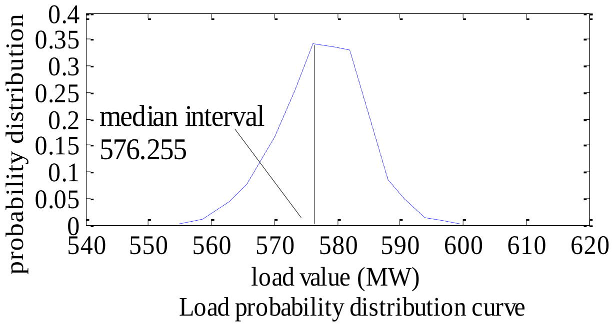
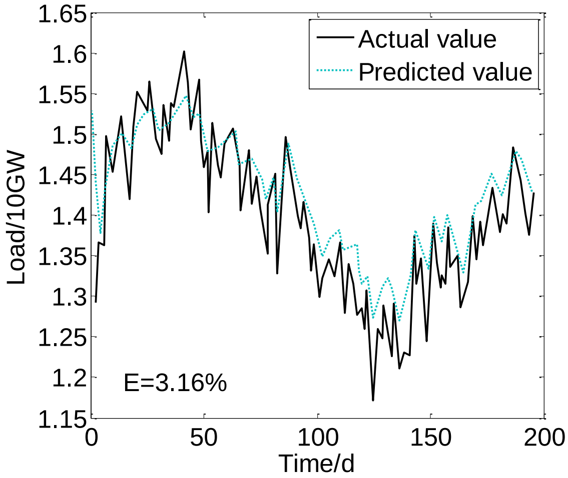


Figure 4. The Load Probability Distribution Curve

According to the method of interval estimation, 95% confidence interval [562.693, 589.817], the prediction interval [469.77, 682.74], contains the 95% confidence interval, so it can be considered that the confidence level of the prediction interval of at least 95%.



Prediction results of model second

Figure 5. The Actual Value of the Average Relative Error Value of 3.16%

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.

Ways of carrying out the interval type-2 fuzzy system parameter identification has two kinds: one is in part dependent on the method, first using the given input one output data on the parameters of a fuzzy system identification algorithm through the parameter learning, and then the parameters of a fuzzy system as the initial value to regulate the interval parameter of type-2 fuzzy systems; the two is all independent method, direct identification of parameters of type-2 fuzzy systems with interval parameters selection, arbitrary initial values. The relative ways and second, the prior approach gives a ideal initial interval type-2 fuzzy system parameter identification value, and the results and a fuzzy system can be used to test the baseline type-2 fuzzy system performance therefore, this paper selects, partially dependent method.

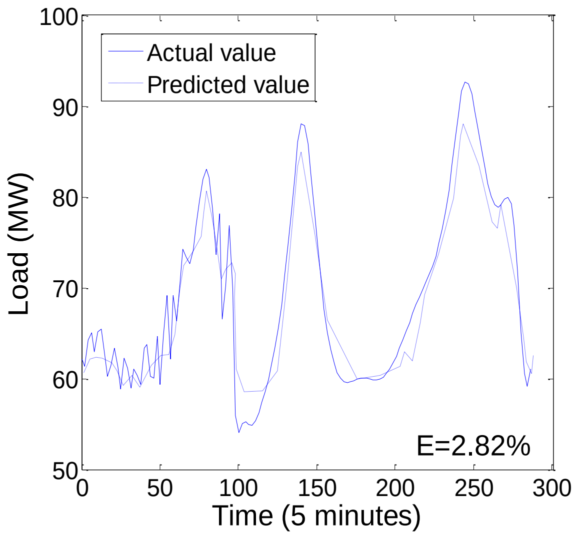


Figure 6. The Actual Value of the Average Relative Error Value of 2.82%

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 2.82% .

Conclusion

The design of the excellent performance of two type fuzzy system identification method is very necessary, the redundant fuzzy rule base is one of the most common problems, reducing the interpretability of fuzzy rules, an increase of unnecessary computation, affecting the accuracy of the system. Currently proposed for type two fuzzy system rule base number of streamline method only to the redundant fuzzy rules streamlined, but can not effectively simplify the redundant fuzzy sets. This paper focuses on the research of type two fuzzy measure and its application in type two fuzzy system rule base reduction in at the same time, in order to eliminate the adverse effects brought redundant fuzzy sets and redundant fuzzy rules, make up the shortage of the existing streamline method.

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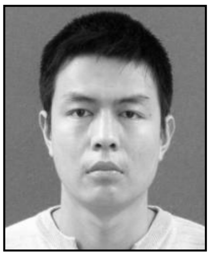

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