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Load Forecasting Research of Power System Based on Fuzzy Sets Algorithm

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Abstract

In this paper, adjust the system parameters back-propagation algorithm based on fuzzy similarity interval type proposed by the fuzzy rule base to streamline redundant fuzzy sets, we can also merge with the means to reduce the number of redundant fuzzy rules, then singular value decomposition method is preferred fuzzy rules. The algorithm can effectively eliminate the adverse effects caused by redundant fuzzy rule, which improve the interpretability of fuzzy rules to reduce the computational complexity of the fuzzy reasoning process, and to improve the approximation accuracy of the system. Based on the long-term and short-term load power load characteristics analysis, to identify the influence of the load itself changes and related factors, gray system theory, neural network model and chaotic time series methods, models and methods for forecasting power load range were research. Examples verified, interval prediction has better precision, demonstrate the effectiveness of the interval prediction algorithm, the research results can be used in power market analysis and forecasting systems, power system operation and provide scientific basis for management decisions.

Keywords*: Fuzzy sets; prediction; time series forecasting; total quantity of knowledge*

1. Introduction

Type-2 fuzzy logic fuzzy logic to make up for a lack of dealing with uncertainty, and uncertainty can be modeled directly, you can better use the language of human experience in the form of experts for high-end, varying parameters, large Delays and random interference serious complex nonlinear systems, which will be from the date of birth has been duly noted [1]. Fuzzy Measure very versatile, fuzzy similarity, fuzzy inclusion degree and fuzzy entropy is one of the more important three, has been in image processing, neural network, fuzzy reasoning and fuzzy control and other fields have been successful applications. This paper studies the set of fuzzy similarity sense, two fuzzy inclusion degree and two fuzzy entropy, a measure of the other do not do in-depth research [2].

Identification of fuzzy system structure identification identify problems include structural identification and parameter identification fuzzy system includes input, output space mapping between partition and fuzzy, especially fuzzy numbers rule [3-6]. Fuzzy optimal system architecture will allow subsequent identification of parameters to be in the vicinity of the optimum value and improve the learning speed parameter, learning can avoid falling into local extreme point, help to improve modeling accuracy. Parameter Identification of fuzzy system mainly refers to identify problems and rules before entering the fuzzy system. In many cases, structure identification and parameter identification is not independent of the work can be carried out simultaneously. Identification Method fuzzy system is generally composed of fuzzy system identification methods [7].

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The forecast is based on science and ensure the right decisions, improve accuracy of load forecasting is the inevitable requirement of power system planning and operation. Currently many scholars to spare no effort to study load forecasting, a more advanced theories and methods to improve the forecast accuracy, provide a powerful guarantee for the economy and security of power system operation. But because too many random factors load, highly nonlinear, and theoretical methods, there are still some traditional limitations and other issues, the new theory and new technology has been promoting the continuous development of load forecasting [8-9].

From the perspective of the range forecast is proposed range of short-term load forecasting method of chaotic time series. According to the results of phase space reconstruction, using clustering algorithm to determine the point in time relative to the current state of similarity, according to local chaos forecasting method to predict future load fluctuation range. Calculation examples are given prediction interval and the corresponding probability confidence level, the results show that interval prediction method has good prediction results and a high level of confidence; analyzes the influencing factors range predictions and the problems that exist, for clustering threshold, interval length control and other issues will need further study.

2. The Related Theory

2.1 Research Status of Fuzzy Systems

Currently, studies on two fuzzy entropy of small, mainly in the field of interval type-2 fuzzy entropy, Bustincc [10] and Burill [11] by a fuzzy concept of entropy extend an interval type-2 fuzzy entropy is attached. Zeng [12] and Li proposed a new interval type-2 fuzzy entropy, and discusses its relationship with the interval type-2 fuzzy similarity. Li [13] made the interval type-2 fuzzy entropy integral expression. Zhang discussed the distance based interval type-2 fuzzy entropy and interval type-2 fuzzy similarity relationship.

Fuzzy clustering structure identification of fuzzy systems is a common means of streamlining of fuzzy rules. When using the site to identify the magnitude of the input-output fuzzy system, often large amount of data, resulting in a system with a lot of fuzzy rules and difficult to achieve. In this case, you can use fuzzy clustering technology input-output data sorted, so the amount of change in the data of the same class smallest variation between different types of data the most, with a fuzzy rule corresponds to a type of data, it is determined the input-output fuzzy domain space is divided mapping and the number of rules.

2.2 Load Forecasting Issues to Consider

Time series prediction refers to the prediction target value for some time within the next forecast. It needs to be based on analysis of historical data to predict an object, get variation, predict the future. Time series prediction results, there are three forms:

(1) Point forecast, or "uncertain value" and that it is the most practical application of a type of prediction, the prediction of the results for a future period is to determine the value.

(2) Interval Forecasting: For a future period, the range of predicted results is not a simple deterministic value, but a range, and this range also corresponds to a probability of a certain level of expectation.

(3) The probability density forecast: gives the full probability distribution of future values.

For the vast majority of the prediction target, the variation was affected by other factors. Therefore, try to consider these factors in forecasting are an effective way to improve prediction accuracy. Taking into account relevant factors predicted basic idea shown in Figure 1.

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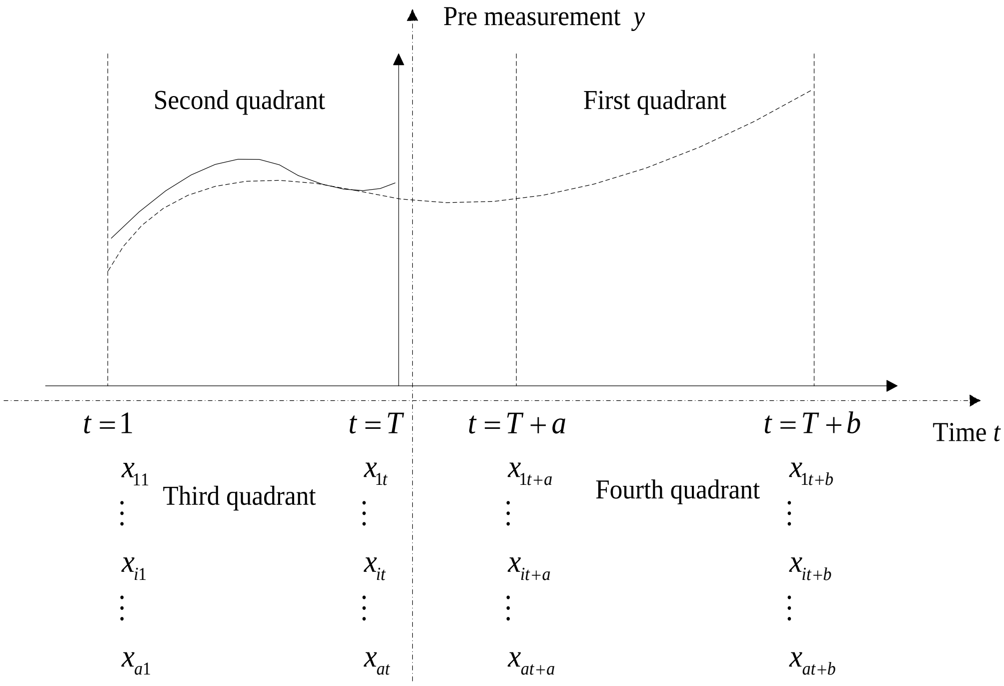

Figure 1. Sketch Map of Forecast Considering the Relevant Factors

In the drawing, the horizontal axis considered to "now" where the vertical point of time as the longitudinal axis, it can be seen as a two-dimensional coordinate system, "now" where the point of this period is the origin of coordinates. To coordinate centered at the origin, it can be divided into four quadrants. Under the given conditions is known, in fact, is the first or fourth quadrant data, predict the first quadrant. If further distinction is actually the second and third quadrant of data by curve fitting forecasting model; while the fourth quadrant data as a predictive model of input, resulting in the first quadrant of the forecast results.

Generally, suppose prediction models abstract expression:

$$y = f(S, X, t) \tag{1}$$

Or write to the corresponding period in the form of points as follows:

$$\hat{y}_t = f(\hat{S}, \overline{X}_i, t), \quad 1 \le t \le T \tag{2}$$

Objects from the prediction, the power load forecast include future electricity demand (power) and to predict future consumption (energy) prediction and forecasting load curve. According to the prediction target time, the power load forecasting can be divided into ultra short-term forecast, short-term forecasting, medium-term and long-term forecasts predict four. Ultra-short-term load forecasting means to predict the future load within 1 hour in security surveillance state requires less than forecast 5-10s in preventive controls and the need to predict the state of emergency within 10min to 1h load forecasting is about to happen, week load forecasting, according to their schedule daily, weekly scheduling program, including the unit start-stop, hydro-thermal coordination, economic load distribution, reservoir operation and maintenance, and other equipment; short-term forecast, the need for full study load variation of the grid, and analysis Some effects (weather, day type) and short-term factors that affect load changes.

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3. Type Two Fuzzy Logic Theory

3.1 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:

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

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

$$(N3)\quad N(\tilde{E},\tilde{E}) = \max_{\tilde{A},\tilde{B}\in IVFSs} N(\tilde{A},\tilde{B}); \tag{3}$$

(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:

$$N(\tilde{A},\tilde{C}) \le N(\tilde{A},\tilde{B})$$
$$N(\tilde{A},\tilde{C}) \le N(\tilde{B},\tilde{C}) \tag{4}$$

(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.

$$N(\tilde{A},\tilde{B}) = \frac{1}{2}\frac{\int_{x\in X}\min\{\overline{\mu}_{\tilde{A}}(x),\overline{\mu}_{\tilde{B}}(x)\}dx}{\int_{x\in X}\max\{\overline{\mu}_{\tilde{A}}(x),\overline{\mu}_{\tilde{B}}(x)\}dx} \tag{5}$$

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:

$$E(\tilde{A}) = \frac{\int_{x\in X}\min\{\overline{\mu}_{\tilde{A}}(x),1-\underline{\mu}_{\tilde{A}}(x)\}dx}{\int_{x\in X}\max\{\overline{\mu}_{\tilde{A}}(x),1-\underline{\mu}_{\tilde{A}}(x)\}dx} \tag{6}$$

Interval type-2 fuzzy set is a simplified version of the ordinary type-2 fuzzy sets, the application omitted the second membership function selection process. The upper and lower membership function in the fuzzy set interval type plays a major role in the operation.

3.2 Error Analysis Based on Grey Theory

Gray system used the posterior variance ratio, a small error probability, correlation and other indicators to measure the effect of modeling.

1) Historical data mean square deviation $S_1 = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-\overline{y})^2} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}u_i^2}$

2) Residual value mean square deviation $S_2 = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(v_i-\overline{v})^2}$

3) Posterior difference ratio $c = S_2 / S_1$

4) Small error probability $p = P\{|v_i-\overline{v}| < 0.6745 \cdot S_1\}$

5) Pointwise correlation coefficient $\xi_i = \frac{v_{\min} + \rho \cdot v_{\max}}{|v_i| + \rho \cdot v_{\max}}$

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In which, ρ is correlation calculation coefficient (resolution coefficient). Generally $0 < \rho < 1$, such as $\rho = 0.5$

6) Correlation $\xi = \frac{1}{n}\sum_{i=1}^{n} \xi_i$

Gray systematic error analysis results was shown in Table 1.

Table 1. Predictive Accuracy Rating Scale

Grade	Small error probability *p*	Posterior difference ratio *c*	Grade	Small error probability *p*	Posterior difference ratio *c*
One-level (good)	[0.95, 1.00]	[0.00, 0.35]	Three-level (reluctantly)	[0.70, 0.80]	[0.50, 0.65]
Two-level (qualified)	[0.80, 0.95]	[0.35, 0.50]	Four-level (unqualified)	[0.00, 0.70]	[0.65, 1.00]

3.3 Long Term Load Forecasting Model Range

Power system is not an isolated system, which affected economic development, gross domestic product and other factors. Therefore, the introduction of load forecasting some major factors to improve prediction accuracy has become the consensus. If you can find the relevant factors to predict the influence of the object, and then used to predict the process, it is possible to obtain a better prediction. Regression analysis is a basic and long-term load forecasting methods take into account relevant factors, so this paper mathematical statistics regression analysis to determine the relationship between the load and the impact of variables to achieve load range forecast.

In the multiple factors affecting the long-term load, it is possible by sensitivity analysis and elasticity analysis, selection of a single factor significantly affected the establishment linear regression prediction model.

In a linear regression, the independent variable is a factor, with x represents the dependent variable is the electrical load represented by y. Suppose the relationship between x and y is:

This relationship x and y is called a linear regression model. This model can be written as:

$$y = a + bx + \varepsilon \tag{7}$$

According to the least squares method to estimate a, b, to give:

$$y = a + bx + \varepsilon, \quad \varepsilon \sim N(0, \sigma^2) \tag{8}$$

After the regression models have been tested and identified practical value, an important regression equation is given prediction point, you can find the corresponding point of the predicted value prediction and prediction confidence interval.

$$\begin{cases} \hat{b} = \dfrac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sum_{i=1}^{n}(x_i - \overline{x})^2} \\ \hat{a} = \overline{y} - \hat{b}\overline{x} \end{cases} \tag{9}$$

In which,

$$\overline{x} = \frac{1}{n}\sum_{i=1}^{n} x_i , \quad \overline{y} = \frac{1}{n}\sum_{i=1}^{n} y_i \tag{10}$$

In simple neural network for short-term load forecasting method generally it requires a lot of training samples to map the complex nonlinear relationship between load change factors and load values, so the training process error is too large. To select the proper number of valid sample chapter fuzzy clustering method. First, from a historical sample sampling, factors that influence the value of the load change, fuzzy clustering analysis, a number of samples to be predicted date information similar historical day sample information; then, these historical date information and relevant samples historical daily load value input neural network, the network is trained to be the last day of the forecast sample information input, thus achieving load forecast.

4. The Experiment and Analysis

4.1 Prediction Analysis

Included in this four kinds of electricity sequence of three approximately exponentially increase (electricity 1-3), but the growth rate varies, it simulates in early development, small and medium sized cities in the intermediate stage of electricity volume growth; having a saturation characteristic curve approximate Gompertz growth law (electricity 4), which simulates the growth in electricity demand in a number of large cities in developed countries; a press approximate logistic growth curve. Four kinds of representative electricity sequence verified, as shown in the specific consumption of typical data sequence as shown in Table 2.

Table 2. Power Consumption Test Data

Year number	Power consumption 1	Power consumption 2	Power consumption 3	Power consumption 4
1	0.99900	0.99900	0.99900	0.99900
2	1.06290	1.10628	1.28531	6.57555
3	1.12637	1.22018	1.64707	7.16021
4	1.9840	1.35120	2.11910	7.80440
5	1.26988	1.49033	2.71556	8.44764
6	1.35121	1.65037	3.49383	9.15464
7	1.43190	1.82030	4.47721	9.85424
8	1.52348	2.01577	5.76036	10.62180
9	1.61446	2.22332	7.38167	11.37430
10	1.71772	2.46206	9.49722	12.19910
20	3.12989	6.69258	115.700	21.40560
Average rate	6.1837%	10.5171%	28.4025%	8.2125%

To analyze the parameters p and r model prediction accuracy for a significant degree, the basic comparison NGBM model GM (1, 1) prediction results, adaptability and validation NGBM models were considered a parameter optimization and two parameters At the same time optimization.

Interval predicted and actual values shown in Figure 2. The upper limit curve and the strip-shaped area range limit curve is composed of load change intervals. As can be seen from the figure, in most point, the actual values fall within the strip area, which indicates IABP network range forecasting is feasible. But in point 6 and point 14, the actual value falls outside the range of the load; secondly 17, 18, 20-22 five points, the prediction

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interval length is too large, resulting in a lack of practical significance prediction interval. So, how to further improve the accuracy of prediction interval is worthy of study.

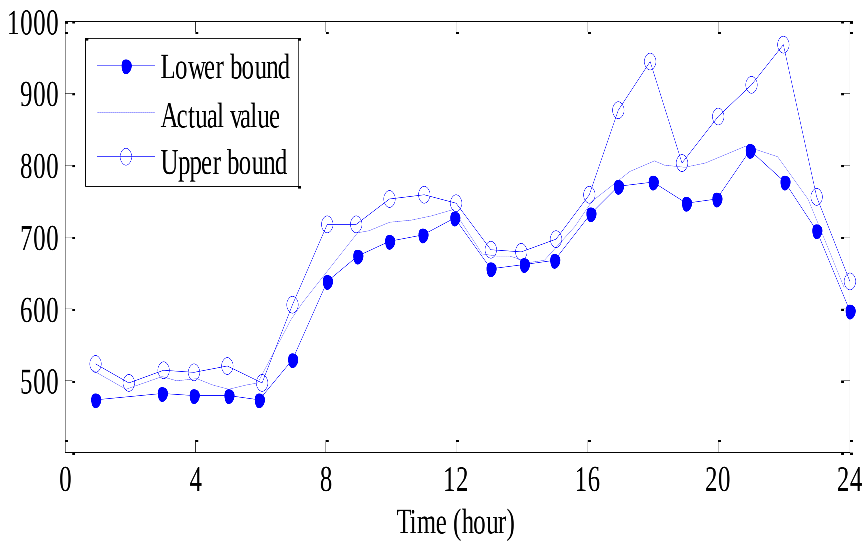

Figure 2. Interval Predicted and Actual Values

If you do need certainty predicted in the forecast (point forecast), you can consider the range predicted in value as the point predictions. The average absolute error in all sections of the actual value was 2.28%, so the range in value as deterministic prediction is acceptable.

4.2 Calculation Examples

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:

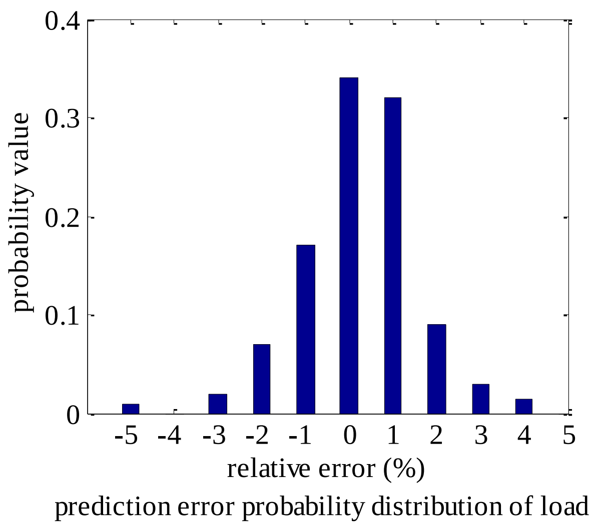

Figure 3. The Probability Distribution of the Fourth Layer

Short-term load forecasting for power system security, the economy has important significance. The large uncertainty of predictions forecasting methods for the development of Japanese power plan, schedule grid scheduling and other work is acceptable, but it is difficult to meet the demand for electricity in the comprehensive analysis of market risk under power market evolving market members. If we can get when analyzing the probability distribution of load forecast errors and probabilistic forecasts, will enable power companies to understand the statistical laws of prediction errors in its history, making production plans under market conditions, system safety analysis and other planning work to more well aware of the load may exist uncertainty of future power generation companies can under the circumstances prediction error distribution in the market for its better to take initiative.

5. Conclusion

Load forecasting is the basis for the work of power system planning and operation of the electricity market reform of the load forecast put forward new demands. Deterministic load forecasting results are difficult to meet the electricity market environment network planning, risk analysis needs, reliability assessment and other aspects, therefore, the power load studies and uncertainty analysis and prediction of the theory and methods have important academic significance. Based on the analysis of the existing deterministic load forecasting method based on the theory of power load forecasting range and methods of exploration and research, we have achieved some results have theoretical significance and practical value.

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