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Application of an innovative combined forecasting method in power system load forecasting

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Abstract

To fully integrate the advantages of several forecasting models and improve the accuracy of load forecast results, the application of the combined forecasting method to power system load forecasting is introduced in this paper. The evolutionary programming and fuzzy comprehensive evaluation methods are employed to deduce the weight coefficients of each model. Practical cases are studied using the two methods and tested to be feasible and effective. © 2001 Elsevier Science B.V. All rights reserved.

Keywords: Combined forecasting method; Load forecast; Evolutionary programming; Fuzzy comprehensive evaluation

1. Introduction

Power system load forecasting, the foundation of power network planning and power network construction, receives close attention from engineers. A consummate forecasting model can accurately predict future load demands. Though there are various forecasting models, no single one has performed well enough because each model can take just several or usually only one relevant factor into consideration. A good model may not be ideal when the power industry and the power network has developed into an advanced stage. In practical applications, engineers often try several kinds of models. The result of each forecasting model is compared and analysis has to be done by experienced forecasters to get the best forecasting result.

To fully utilize the useful information from the models, the combined forecasting method is introduced in this paper. It is one of the most popular subjects in the field of forecasting methods [1–3]. The theory of the combined forecasting method is based on a certain linear combination of various results from different forecast models. The fitting capacity of the combined forecasting model is greatly improved, and the combined forecasting result will show higher precision. Formulations have been developed in the past literatures for the optimal combined forecasting method, whose deviation reaches the minimum and is less than that of each single forecasting method. The application of the combined forecasting method can combine separate methods and integrate merits of each model to provide a more accurate result.

2. Principles of the combined forecasting method

For a certain forecasting problem, assume the historical recorded value in period t is y_t $(t=1, 2, \ldots, n)$ and there are m kinds of forecasting models. Let the fitting value in period t by model i is f_{it} $(i=1, 2, \ldots, m)$, then the corresponding deviation is $e_{it}=y_t-f_{it}$. Suppose the weight coefficient vector is $W=[w_1, w_2, \ldots, w_m]^T$, $\sum_{i=1}^{m} w_i=1$, w_i is the weight coefficient of model i. The combined forecasting model can be expressed as follows:

$$\hat{y}_t=\sum_{i=1}^{m} w_i\, f_{it} \quad (t=1, 2, \ldots, n) \tag{1}$$

or

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$$\hat{Y} = FW \qquad (2)$$

Where, $\hat{Y} = [\hat{y}_1, \hat{y}_2, \cdots \hat{y}_n]^T \quad F = [f_{it}]_{n \times m}$

The key of the combined forecasting method is to determine the weight coefficients of each model. There are various optimization criteria for the derivation of the weight coefficient vector. In this paper, two methods: Evolutionary Programming and Fuzzy Comprehensive Evaluation are introduced.

3. Optimizing the combined forecasting method

3.1. Determining weight coefficients by evolutionary programming

The absolute error and the proportional error of the combined forecasting model in period t are expressed, respectively, as follows:

$$e_t = y_t - \hat{y}_t \qquad (3)$$

$$\eta_t = \frac{e_t}{y_t} 100\% \qquad (4)$$

When constructing a combined forecasting method, an appropriate weight coefficient vector should be chosen to minimize e_t and η_t of the combined forecasting model. A normal performance index is employed:

$$\min J_1 = (\sum_{t=1}^{n} |e_t|^p)^{1/p} \qquad (5)$$

$$\min J_2 = (\sum_{t=1}^{n} |\eta_t|^p)^{1/p} \qquad (6)$$

Regarding the absolute error e_t is used as the optimized criteria, the optimization problem of the combined forecasting is transformed into the problem of constrained non-linear programming problem:

$$\begin{cases} \min J_1 = (\sum_{t=1}^{n} |e_t|^p)^{1/p} \\ y_t - \sum_{i=1}^{m} w_i f_{it} = e_t \quad (t = 1, 2, \ldots, n) \\ \sum_{i=1}^{m} w_i = 1 \\ w_i \geq 0 \end{cases} \qquad (7)$$

Much work has been done in the application of evolutionary programming to power system in recent years [4–6]. The optimization using evolutionary programming avoids the difficulties encountered by conventional optimization methods, such as the phenomenon of local optimum, the construction of constrained conditions and objective functions, and the dimension disaster. Variables need not be binary encoded and decoded when using evolutionary programming. Compared with Genetic Algorithms, it is a better choice for successive optimization problems [7]. By the operators: selection, crossover and mutation, the optimal result can be reached. Here, the weight coefficients are regarded as variables to be encoded and J_1 in Eq. (7) is chosen as the fitness function. The optimal weight coefficients satisfying Eq. (7) will come out by solving the optimal problem.

3.2. Determining weight coefficients by fuzzy comprehensive evaluation

As a basic application of fuzzy set theory, fuzzy comprehensive evaluation is quite suitable for the evaluation of multi-factor and multi-level problems. It takes all correlated factors into consideration, and applies principles of fuzzy variation and membership function analyzing, to make the comprehensive evaluation.

3.2.1. Fuzzy semantic operators and semantic values

As the expression form of thoughts inside our brains, the natural fuzzy language differs distinctly from the abstract mathematically defined formal language for its fuzziness. It objectively reflects the semantic transition among different evaluation levels, rather than the exact but rigid formal language. From this viewpoint, the fuzzy language contains much more evaluation information.

For various evaluating semantic, the concepts of fuzzy set and membership function are introduced. According to the theory of Fuzzy Semantic Quantitative and the definition of Fuzzy Language Variable, the fuzziness of natural language's semantic can be quantitatively depicted.

Usually, for central words 'bad', 'ordinary' and 'good', in the discussed universe $X[0,1]$, the semantic fuzzy sets S_{bad}, S_{ordinary}, S_{good} are defined, and the memberships for elements $x \in X$ are formulated respectively, as follows:

$$\mu_{S_{\text{bad}}}(x) = \begin{cases} e^{-(x-0.15)^2/2 \times 0.1060^2} & 0.15 \leq x \leq 1 \\ 1 & 0 \leq x < 0.15 \end{cases} \qquad (8)$$

$$\mu_{S_{\text{ordinary}}}(x) = e^{-(x-0.5)^2/2 \times 0.1060^2} \qquad (9)$$

$$\mu_{S_{\text{good}}}(x) = \begin{cases} e^{-(x-0.85)^2/2 \times 0.1060^2} & 0 \leq x \leq 0.85 \\ 1 & 0.85 < x \leq 1 \end{cases} \qquad (10)$$

The word 'operator' is a concept borrowed from mathematics, which can adjust the semantic meaning of its central word. Here, two kinds of semantic operators are used:

3.2.1.1. Centralizing semantic operators. Words like 'very', 'much', 'greatly', 'tremendously' etc, accentuate the semantic meaning of the central word. The membership distribution of the semantic fuzzy sets in the universe X will be centralized.

3.2.1.2. Scattering semantic operators. Words like 'some', 'fairly', 'a little' etc, weaken the semantic meaning of the central word. Just opposite to the centralizing operators, they scatter the distribution of the membership in the universe X to both fringes.

The effects of the semantic operators 'fairly', 'very' and 'tremendously' can be defined respectively as follows:

$$H_{\text{fairly}}\mu_S(x) = (\mu_S(x \pm 0.07))^{0.5} \quad (11)$$

$$H_{\text{very}}\mu_S(x) = (\mu_S(x \pm 0.09))^{2.0} \quad (12)$$

$$H_{\text{tremendously}}\mu_S(x) = (\mu_S(x \pm 0.11))^{3.0} \quad (13)$$

In the equations, the upper operator and the lower operator are corresponding to the central words 'bad' and 'good' respectively. And the membership functions of each semantic fuzzy set in the universe X can be illustrated as Fig. 1.

3.2.2. Comprehensive evaluation by fuzzy language

Let $U = [u_1, u_2, \ldots, u_m]$ be the factor set to evaluate different schemes. For a certain scheme, according to the factor set U, suppose it receives a comment set $V = [v_1, v_2, \ldots, v_m]$ (v_i stands for the comment of fuzzy language evaluation for factor u_i and it reflects the uncertainty of evaluating the semantic extension). Express the discussed universe X as a finite set F with n elements: $F = [x_1, x_2, \ldots, x_n]$. Each element has a membership to the semantic fuzzy set of each comment according to the corresponding membership function in the universe X. For n elements in the finite set F and m comments corresponding to m factors, a $m \times n$ evaluation matrix $R_{m\times n}$ is deduced:

$$R = [r]_{m\times n} \quad (14)$$

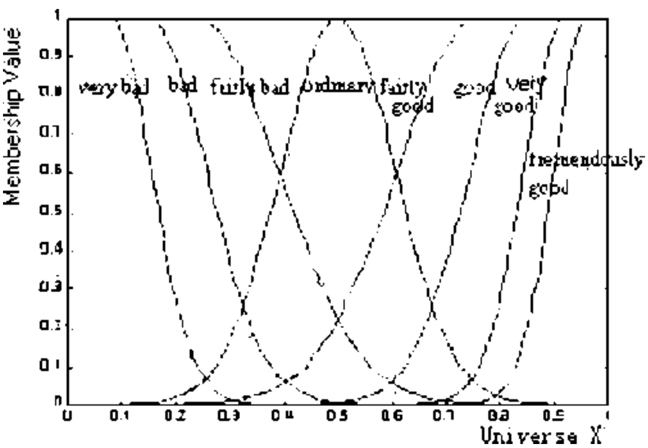

Fig. 1. Membership function of each comment.

where, r_{ij} stands for the membership value of x_n to the fuzzy set of comment v_m.

The scheme receives different comments for different evaluation factors, and each factor has various influences on the comprehensive evaluation. So, a fuzzy vector $\underset{\sim}{A} = [a_1, a_2, \ldots, a_i, a_m]$ should be taken into account to denote the various importance of each factor. a_i stands for the membership value of u_i to $\underset{\sim}{A}$, which is the weight coefficient of u_i. After the fuzzy vector $\underset{\sim}{A}$ and the fuzzy comprehensive evaluation matrix $R = [r]_{m\times n}$ are deduced, the fuzzy vector $\underset{\sim}{B}$ of first level comprehensive evaluation can be got by fuzzy transformation:

$$\underset{\sim}{B} = \underset{\sim}{A} \circ \underset{\sim}{R} = [b_1, b_2, \ldots, b_n]$$

$$b_j = (a_1 \dot{*} r_{1j}) \overset{+}{*} (a_2 \dot{*} r_{2j}) \overset{+}{*} \cdots \overset{+}{*} (a_m \dot{*} r_{m1j}) \quad (15)$$

Where, b_j stands for the membership value of element x_j to $\underset{\sim}{B}$, which is expressed as model $M(\dot{*}, \overset{+}{*})$. As for symbols "$\dot{*}$, $\overset{+}{*}$", there are different choices. In this paper, model $M(\wedge, \vee)$, $M(\text{power}, \wedge)$ and $M(*, +)$ are used, which are defined as follows:

- $M(\wedge, \vee)$

$$b_j = \bigvee_{i=1}^{m} (a_i \wedge r_{ij})$$

$$\underset{\sim}{B} = [b_1, b_2, \cdots b_n] = \left[\bigvee_{i=1}^{m}(a_i \wedge r_{i1}), \bigvee_{i=1}^{m}(a_i \wedge r_{i2}), \cdots, \bigvee_{i=1}^{m}(a_i \wedge r_{in})\right] \quad (16)$$

Here, '$\wedge$' is the 'Minimize' operator and '$\vee$' is the 'Maximize' operator. For example, $a_i \wedge r_{ij} = \min(a_i, r_{ij})$; $a_i \vee r_{ij} = \max(a_i, r_{ij})$.

Generally, $a_1 = a_2 = \ldots = a_m = 1$ is used.

- $M(\text{Power}, \wedge)$

$$b_j = \bigwedge_{i=1}^{m} (r_{ij}^{a_i})$$

$$\underset{\sim}{B} = [b_1, b_2, \cdots b_n] = \left[\bigwedge_{i=1}^{m} r_{i1}^{a_i}, \bigwedge_{i=1}^{m} r_{i2}^{a_i}, \cdots, \bigwedge_{i=1}^{m} r_{in}^{a_i}\right] \quad (17)$$

Generally, $a_1 = a_2 = \ldots = a_m = 1$ is used.

- $M(*, +)$

$$b_j = \bigwedge_{i=1}^{m} (a_i r_{ij})$$

$$\underset{\sim}{B} = [b_1, b_2, \cdots b_n] = \left[\sum_{i=1}^{m} a_i r_{i1}, \sum_{i=1}^{m} a_i r_{i2}, \cdots, \sum_{i=1}^{m} a_i r_{in}\right] \quad (18)$$

Generally, $a_1 = a_2 = \ldots = a_m = 1/m$ is used.

The application of different models will lead to different evaluate results: $\underset{\sim}{B}_1$, $\underset{\sim}{B}_2$ and $\underset{\sim}{B}_3$. The index $\underset{\sim}{B}_1$ evaluates the scheme from the most advantageous side. The index $\underset{\sim}{B}_2$ evaluates the scheme from the most adverse side. And the index $\underset{\sim}{B}_3$ evaluates the scheme from the average viewpoint. Using only one of these

Table 1
Fitting values of power supply in Yancheng by each single model (10^9 kW h)

Year	1988	1989	1990	1991	1992	1993	1994	1995
History records	17.33	19.87	21.51	23.34	25.36	27.40	30.57	33.84
Model 1	16.97	19.25	21.52	23.80	26.07	28.35	30.63	32.90
Model 2	21.12	20.28	21.12	21.67	23.62	26.10	30.34	34.73
Model 3	18.26	19.95	21.78	23.79	25.98	28.37	30.99	33.84
Model 4	17.29	18.91	20.69	22.63	24.76	27.08	29.62	32.41
Model 5	14.57	17.31	20.05	22.78	25.52	28.26	31.00	33.74

indexes will lose the information about the evaluation from other viewpoints, and will lead to a unilateral evaluation. All indexes of $\underset{\sim}{B}_1, \underset{\sim}{B}_2, \underset{\sim}{B}_3$ should be integrated comprehensively into the secondary level evaluation. For the index set $\underset{\sim}{B} = [\underset{\sim}{B}_1, \underset{\sim}{B}_2, \underset{\sim}{B}_3]$, a weight vector $\underset{\sim}{W} = [w_1, w_2, w_3]$ ($w_i \geq 0$ and $\Sigma_{i=1}^{3} w_i = 1$ is given. The fuzzy vector P from the second comprehensive evaluation is formulated as:

$$\underset{\sim}{P} = \underset{\sim}{W} \cdot \underset{\sim}{B} = [p_1, p_2, \ldots, p_n] \quad (19)$$

p_i stands for the membership value of the x_i ($x_i \in X$) to the semantic fuzzy set of the comprehensive evaluation. According to the comprehensive evaluation fuzzy vector $\underset{\sim}{P}$, the semantic fuzzy set S_i of the comprehensive evaluation in the discussed universe X and its membership function $\mu_{Si}(x)$ can be established.

3.2.3. Advantage relationship determination and the combination of schemes

For normal convex fuzzy sets defined in the same discussed universe X, the advantage degree of fuzzy set S_i to fuzzy set S_j is expressed as:

$$q_\delta(s_i, s_j) = \vee(\mu_{\leq s_i}(x) \wedge \mu_{\leq s_j}(x))*\frac{x_i^*}{x_j^*} \quad x \in X \quad (20)$$

Where,

$$\mu_{\leq \mathrm{si}}(x) = \begin{cases} \max \mu_{\mathrm{Si}}(x) & x < x_i^* \\ \mu_{\mathrm{Si}}(x) & x \geq x_i^* \end{cases}$$

x_i^* stands for the minimum value which makes $\mu_{S_i}(x_i^*) = \max \mu_{S_i}(x)$; x_j^* stands for the minimum value which makes $\mu_{S_j}(x_j^*) = \max \mu_{S_j}(x)$.

From the definition of 'advantage' $q_\delta(S_i, S_j)$, we can get the advantage relationship matrix Q of the fuzzy set S containing n fuzzy sets S_i ($i = 1, 2, \ldots, n$):

$$Q_\delta = \begin{bmatrix} q_\delta(1,1) & q_\delta(1,2) & \cdots & q_\delta(1,n) \\ q_\delta(2,1) & q_\delta(2,2) & \cdots & q_\delta(2,n) \\ \cdots & \cdots & \cdots & \cdots \\ q_\delta(n,1) & q_\delta(n,2) & \cdots & q_\delta(n,n) \end{bmatrix} \quad (21)$$

$q_\delta(i, j)$ stands for the advantage degree of fuzzy set S_i to S_j.

Define the fuzzy vector $\underset{\sim}{W} = [w_1, w_2, \cdots, w_n]$, $w_i = \wedge q_\delta(i, j)$ (w_i stands for the comprehensive advantage degree of scheme i to other schemes). Then, the vector $\underset{\sim}{W}$ is normalized to vector W, which is regarded as the weight coefficient vector.

$$W = \left[\frac{w_1}{\sum_{i=1}^{n} w_i}, \frac{w_2}{\sum_{i=1}^{n} w_i}, \cdots, \frac{w_n}{\sum_{i=1}^{n} w_i} \right] \quad (22)$$

By combining every scheme according to their weight coefficients expressed in vector W, an optimized combined scheme comes out.

4. Load forecasting for Yancheng city using the combined forecasting method

The history recorded data of power load and the correlated statistics are initialized at first. The following proper forecasting models are chosen: Trend Analysis, Correlation Analysis, Elasticity Coefficient Analysis, Increasing Rate Analysis and Brown Adaptive Exponential Smoothing, Per Production Consumption, Triple Exponential smoothing, Gompertz Growth Curve Fitting, GM (1,1) Gray System and Fuzzy Polynomial Curve Fitting model.

4.1. Combined forecasting method by evolutionary programming

Five models: Trend Analysis model (Model 1), Correlation Analysis model (Model 2), Elastic Coefficient Analysis model (Model 3), Increase Rate model (Model 4), Brown Adaptive Exponential Smoothing model (Model 5) are used to dispose the history record of the power supply and the peak load in Yancheng. The fixed values of each record are derived as shown in Tables 1 and 2. Table 3 shows the forecasting results in 2000.

In this paper, the combined optimized forecasting model is based on the single forecasting models, and sets the minimized absolute errors as the optimization criterion, as Eq. (7) expresses. Let the normal perfor-

Table 2
Fitting values of peak load in Yancheng by each single model (10^4 kW)

Year	1988	1989	1990	1991	1992	1993	1994	1995
History records	32.80	33.70	34.80	38.00	40.50	43.60	50.10	54.10
Model 1	29.18	32.68	36.17	39.67	43.17	46.66	50.16	53.66
Model 2	35.39	34.18	35.39	36.17	38.97	42.53	48.60	54.88
Model 3	34.03	36.36	38.85	41.51	44.35	47.39	50.63	54.10
Model 4	32.63	35.28	38.14	41.23	44.58	48.19	52.10	56.33
Model 5	25.20	29.52	33.84	38.16	42.48	46.80	51.12	55.44

mance index $p = 2$. By evolutionary programming, the following results as shown in Tables 4–6 are deduced.

As Table 6 shows, the square deviation of the combined forecasting model is less than that of any single forecasting model. Table 7 shows the forecast results of the power supply and the peak load of Yancheng in 2000 by the combined optimized forecasting model.

4.2. Combined forecasting method by fuzzy language comprehensive evaluation

4.2.1. Comprehensive evaluations of each forecasting model using fuzzy language

For each single forecast model, take three evaluation factors into account $U = \{u_1, u_2, u_3\}$.

u_1, the fix degree of the model for long range forecast;

u_2, the deviation degree of fixed values compared with history records;

u_3, the trust degree of the decision maker to the model.

When applied to forecast the power supply, the comments of each model for three evaluation factors are shown in Table 8.

Express the discussed universe as a finite set with 51 members from 0.0 to 1.00 with interval 0.02. $X = [0.00, 0.02, 0.04, \ldots, 1.00]$. The fuzzy language comment matrixes of each model are deduced as $R_{3\times 51}$. Using model $M(\wedge, \vee)$, $M(\text{power}, \wedge)$ and $M(*, +)$, respectively, the first level comprehensive evaluation $\underset{\sim}{B}_1$, $\underset{\sim}{B}_2$ and $\underset{\sim}{B}_3$ are deduced. For each model, the same weight 1/3 is given. That is, $W = [1/3, 1/3, 1/3]$. Then the fuzzy vector P from the second comprehensive evaluation is got using Eq. (19). The membership functions charts of the fuzzy vector P for eight forecasting models in discussed universe are shown in Fig. 2.

4.2.2. Advantage relationships and the combination of the models

For each forecasting model, by analyzing the membership function chart of the comprehensive evaluation, the advantage relationship matrix Q_δ is given as Eq. (23).

Table 3
Forecasting results of the power supply and the peak load of Yancheng in 2000 by each single forecasting model

Forecasting models	Power supply (10^9 kW h)	Peak load (10^4 kW)
Model 1	44.28	71.14
Model 2	53.88	92.72
Model 3	58.35	91.69
Model 4	50.76	83.20
Model 5	47.43	77.03

Table 4
Weight coefficients of each single model in the combined forecasting model

Forecasting models	Weight coefficients	
	Power supply	Peak load
Model 1	0.168	0.113
Model 2	0.116	0.782
Model 3	0.435	0.053
Model 4	0.156	0.039
Model 5	0.125	0.013

Table 5
Fitting values by the combined forecasting model (10^9 kWh)

Year	Power supply (10^9 kW h)	Peak load (10^4 kW)
1988	17.76	34.38
1989	19.38	34.11
1990	21.27	35.75
1991	23.24	37.07
1992	25.47	39.99
1993	27.89	43.53
1994	30.64	49.05
1995	33.55	54.76

$$Q_\delta = \begin{bmatrix} 0.5557 & 0.0858 & 0.0473 & 0.0324 & 0.0275 & 0.0506 & 0.0517 & 0.0032 \\ 2.8898 & 0.5575 & 0.2461 & 0.1730 & 0.1619 & 0.2640 & 0.2848 & 0.0169 \\ 5.2239 & 1.0046 & 0.5557 & 0.5936 & 0.5557 & 0.5936 & 0.6074 & 0.5330 \\ 4.8904 & 0.9434 & 0.5203 & 1.0000 & 0.9362 & 0.5569 & 0.5706 & 0.8980 \\ 5.2239 & 1.0077 & 0.5557 & 1.0682 & 1.0000 & 0.5949 & 0.6095 & 0.9592 \\ 4.8904 & 0.9425 & 0.5203 & 0.5569 & 0.5214 & 0.5569 & 0.5699 & 0.4995 \\ 4.7793 & 0.9220 & 0.5084 & 0.5450 & 0.5102 & 0.5443 & 0.5577 & 0.4882 \\ 5.4461 & 1.0506 & 0.5794 & 1.1136 & 1.0426 & 0.6202 & 0.6355 & 1.0000 \end{bmatrix} \tag{23}$$

Using equation $w_i = \wedge\ q_\delta\ (i, j)$, the weight coefficient vector $\underset{\sim}{W}_{\text{supply}}$ can be obtained for the forecast of power supply:

$$\underset{\sim}{W}_{\text{supply}} = [0.0032, 0.0169, 0.5330, 0.5203, 0.5557, 0.4995, 0.4882, 0.5794]$$

Using Eq. (22), $\underset{\sim}{W}_{\text{supply}}$ can be normalized to vector W_{supply}:

$$W_{\text{supply}} = [0.0010, 0.0053, 0.1667, 0.1628, 0.1739, 0.1563, 0.1527, 0.1813]$$

Table 9 shows the forecast results of the power supply of Yancheng in 2000 using the combined optimized forecasting model. For the forecast of the peak load, similar methods can be used.

Table 6
Square deviations of each single model and the combined forecasting model

Forecasting models	Square deviation	
	Power supply	Peak load
Model 1	3.02	35.50
Model 2	23.04	16.98
Model 3	2.65	66.78
Model 4	5.60	70.80
Model 5	17.58	93.18
Combined model	0.84	6.21

Table 7
The forecast results of the optimized combined forecasting model

Forecasting year	Power supply (10^9 kW h)	Peak load (10^4 kW)
2000	52.92	89.21

5. Conclusions

In this paper, the application of the combined forecasting method in power system load forecasting is proposed and proved to be feasible. Results show that the optimization by evolutionary programming method is necessary and effective.

It is necessary for load forecasting to take various relevant factors into consideration when evaluating

Table 8
Comments of each model

Forecast models	Evaluation factors		
	u_1	u_2	u_3
Fuzzy Polynomial Curve fitting model	Ordinary	Very bad	Bad
Per production Consumption model	Ordinary	Bad	Ordinary
Elastic Coefficient analysis model	Very good	Ordinary	Good
Gomperta Growth Curve fitting model	Good	Fairly good	Good
GM(1,1)Gray System model	Very good	Fairly good	Good
Brown Adaptive Exponential Smoothing model	Good	Ordinary	Good
Correlation Analysis model	Ordinary	Good	Fairly good
Triple Exponential Smoothing model	Very good	Tremendously good	Very good

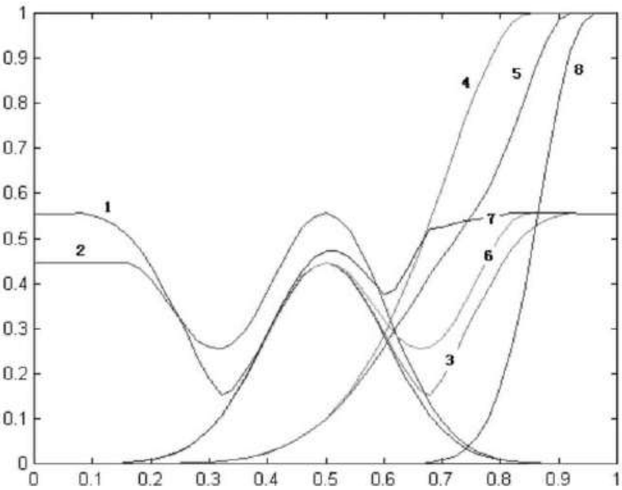

Fig. 2. Comprehensive evaluation results of each model.

Table 9
The forecast result of the power supply of Yancheng city in 2000 using the comprehensive evaluation methods

Load forecast models	Power supply (10^9 kW h)
Fuzzy Polynomial Curve fitting model	48.08
Per production Consumption model	50.12
Elastic Coefficient analysis model	58.35
Gomperta Growth Curve fitting model	55.32
GM(1,1)Gray System model	54.84
Brown Adaptive Exponential Smoothing model	47.43
Correlation Analysis model	53.88
Triple Exponential Smoothing model	53.98
Optimized combined forecast	54.01

each model. It is the precondition of comprehensively evaluating each model. The application of fuzzy language to the comprehensive evaluation can fully exert fuzzy language's descriptive ability of the objectivity. In some aspects they are more accurate than the formal language.

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