

The Fuzzy Neural Network Model of Smart Grid Risk Evaluation Based on Bayes

Li Yanmei

School of Business and Administration, North China Electric Power University
Baoding, China
Email: liyanmei28@yahoo.com.cn

Wang Jingmin

School of Business and Administration, North China Electric Power University
Baoding, China
Email: jingminwang126@126.com

Li Shuangtao

State Grid International Development Limited, Beijing, China
Email: lishuangtao@sgid.sgcc.com.cn

Abstract—Developing smart grid has been a new trend of all countries in the world. The smart grid will face risks in the future because of some uncertain factors, at present the risks are centered in technology, management, decision-making, operation and marketing etc. The paper firstly sets up classification index system about strong smart grid of our country, uses Bayes to reduce indexes and then combines fuzzy comprehensive evaluation and neural network model to compute the index system, which can help us to confirm the risk level and offer eference foundation for related departments.

Index Terms—smart grid; Bayes; Fuzzy; neural network

I. INTRODUCTION

Smart grid is a developing concept. The idea in our country is defined as strong smart grid. The key stage is Extra-High Voltage grid with long distance and high-capacity, which is determined by the feature of Chinese economy progress and concentrative distribution of energy. The smart grid in China includes six links, generation, transmission, tranfmatation, disribution, utilization and dispatch, which has smart characteristic of informatization, digitization, automation and interaction.

The smart grid will face risks in the future because of some uncertain factors, at present the risks are centered in technology, management, decision-making, operation and marketing etc. The evaluation of smart grid project aims at the uncertainties during the development and operation, which will improve the aware of necessity and urgency for risk management, defence in advance and respond to risk initiatively. We should construct uniform operational risk and safeguard mechanism of risk management, which can creat outstanding social benefits, economical benefits and sustainable development.

Fuzzy system and neural network all imitate human intelligence from a different angle. The former selects the point of view from top to botom, but the latter uses the way from botton to top. They all can creat systematic non-linear model and apply parallel processing structure in data processing forms from the input/output datas of given system. However, there are many differencies between fuzzy system and neural network. Neutral Network can learn from examples and has a strong ability of studying. However, it is a set of no models. To make Neutral Network" s results satisfied, it needs a lot of trained data. Moreover, the relationship of input/output obtained by Neutral Network is hardly to express in an easy accepted way. On the contrary, the fuzzy system based on expert knowledge has rapid convergence.

Mixing together fuzzy theory and neural network, B.Kosko etc gave full play to the two methods and improved the abilities of self-learning and expression of the whole system, at the same time, the expert knowledge and data information were employed. So the fuzzy neural network has been researched in broad scale .

The paper first use the above Bayes algorithm to reduce the factors that influencing the risk of smart grid and eliminate the indexes that have less relation with the decision-making, then evaluate the index system combining the fuzzy comprehensive evaluation and neural network, the result of which can help to confirm the risk level and offer the reference foundation for related departments.

II. BAYES DECISION THEORY

The good according to that Bayes viewpoint , essential points work out one decision-making , the information ought to make use of possessions to be able to gain, include sample book information and all information first in sampling and come from experience , consciousness ,

the subjective knowledge judging, these subjective knowledge same be valuable knowledge wealth, the middle responding to the formal introduction arrive at the deduction counting and making policy goes to, but this exactly is that classics statistics has not given think. In classical statistics deduction, only, admit and make use of sample information, but nonrecognition, or make use of the subjective judgment and consciousness. Bayes theory exactly is to hope that the judgment and intuition lead subjectivity into the basis arriving at the analysis process counting deduction and building information thereby in decision analysis, inferring and making policy synthetically formally.

Bayes decision theory concept and method are used for fields such as engineering, management science already by broad field, adaptively selects input features step with Bayes method as follows:

A. Ascertains a priori probability distribution

The priori probability $P(\bar{\omega}_j)$ represents the estimation to the probability distribution of the variable $\bar{\omega}_j$, it has reflected a priori knowledge to the variable, has included practical experience and subjective judgment etc. And that a priori probability scatters in load forecasting, is what be remained to be chosen influencing factor and their probability aggregation, restricting condition is whose necessary probability greater than zero, whose combination is 1. The load at the same time, forecasting (namely "big close small distant" distance according to load forecasting nearest segment of period affects maximal) and "identical date load type similarity" characteristic, the priori probability distribution is

$$\begin{cases} P_{per} = \alpha P_{dis} \\ P_{equ} = \beta P_{div} \\ P_{per} = \gamma P_{equ} \\ \sum P_{per} + \sum P_{dis} + \sum P_{equ} + \sum P_{div} = 1 \\ P_{per} > 0, P_{dis} > 0, P_{equ} > 0, P_{div} > 0 \end{cases} \quad (1)$$

In the formula, P_{per} and P_{dis} represent the distance from influencing factor of forecasted point far or close; and respectively, P_{equ} and P_{div} represent the priori probability of influencing factor that having identical or different date type; Take α, β, γ value range being $(1, \infty)$, may look at concrete conditions but fix. When $\alpha = 1, \beta = 1, \gamma = 1$, the priori probability distribution is an uniform one.

B. Ascertains a likelihood function

The likelihood function has been a condition probability essentially it has reflected sample information, whose function value has been called likelihood rates, has been. $P(\bar{x}_1, \bar{x}_2, \dots, \bar{x}_N | \bar{\omega}_j)$. During the period of load forecasting, if the input variable is selected as $\bar{\omega}_j$, we may make use of N samples $\bar{x}_n (n = 1, \dots, N)$ to calculate the Error E according to the follow formula.

$$E_i = \frac{1}{n} \sum_{j=1}^n R_{valid_j} [f_{train}] \quad (2)$$

$$R_{valid_j} [f_{train}] = \frac{1}{N_{valid}} \sum_{\bar{x}_j \in Z_{valid}} \frac{|y_j - f_{train}(\bar{x}_j)|}{y_j} \times 100\% \quad (3)$$

$R_{valid_j} [f_{train}]$ be relative mean error in style, from training collection to get regression function f_{train} relativity on effective set; N_{valid} be an effective set Z_{valid} all together sample book number; y_j be that actual load value; $f_{train}(\bar{x}_j)$ be forecasting load value.

C. Calculates posterior probability

The formula of posterior probability $P(\bar{\omega}_j | \bar{x}_1, \bar{x}_2, \dots, \bar{x}_N)$ is

$$P(\bar{\omega}_j | \bar{x}_1, \bar{x}_2, \dots, \bar{x}_N) = \frac{P(\bar{x}_1, \bar{x}_2, \dots, \bar{x}_N | \bar{\omega}_j) P(\bar{\omega}_j)}{\sum_{j=1}^J P(\bar{x}_1, \bar{x}_2, \dots, \bar{x}_N | \bar{\omega}_j) P(\bar{\omega}_j)} \quad (4)$$

Among them, a priori probability and likelihood function action input vectors, a posteriori probability is output vector. Because a posteriori probability has synthesized a priori knowledge and sample book information, ultimateness being to decide which group of influencing factors to choose being input vector is standard. A posteriori probability is increasingly big, the probability that input vector is pitched on is increasingly big.

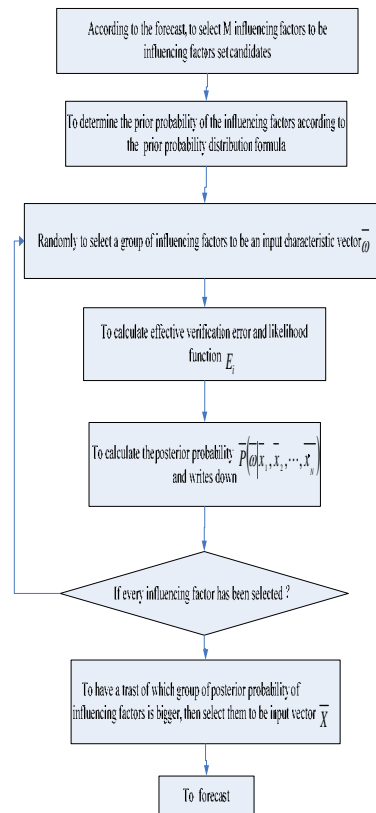


Figure 1. The logic block diagram of input variables adaptively selected based on Bayes.

D. Chooses input vector $\bar{\omega}_j$

According to the actual characteristic being unlike area load, choose M may affect bigger factor composition to load waiting for choosing influencing factor, again out of, the random chooses different influencing factor combination, forms input vector $\bar{\omega}_j$.

Owing to Bayes theory, the logic block diagram of input variable adaptively selected will be shown

III. BP NEURAL NETWORK MODEL

Artificial neural network is a complicated network composed by a lot of simple information units named nerve cell, which are used to imitate the structure and behaviour of human mind neural network. Artificial neural network not only has many excellent qualities, such as self-adaptation, self-organization etc, but it has the ability of making-decision from similar, uncertain and even conflictive knowledge environment. The BP neural network model in this paper is a most widespread used one at present. It has been proved theoretically that BP neural network with 3 layers can approach any mapping relation with arbitrary precision. The BP neural network with 3 layers is shown as Fig. 1. Supposing x_1, x_2, \dots, x_n are input values of the network; u_1, u_2, \dots, u_j are the output values of the hidden layer; y_1, y_2, \dots, y_m are the output values; the weight from the hidden layer neurons j to the output neurons k is v_{jk} ; θ_j and h_j express the offset of the hidden layer and the output layer.

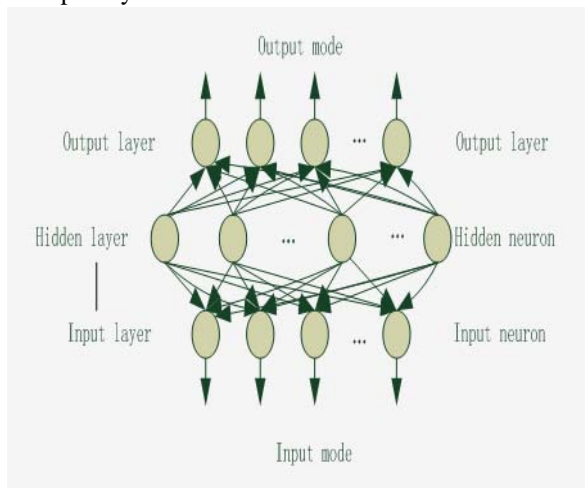


Figure 2. Typical schematic diagram of BP neural network with 3 layers.

The input of hidden layer in 3-layer BP neural network:

$$u_j = f\left(\sum_{i=1}^n w_{ij}x_i + \theta_j\right), j = 1, 2, \dots, s \tag{5}$$

The output of output layer unit is:

$$y_l = f\left(\sum_{k=1}^s v_{lk}u_k + h_l\right), l = 1, 2, \dots, m \tag{6}$$

During them, $f(\cdot)$ adopts the function of sigmoid:

$$f(z) = \frac{1}{1 + \exp(-z)} \tag{7}$$

BP arithmetic is a learning algorithm under supervision. If the input learning sample number is p , the corresponding teacher to is T^1, T^2, \dots, T^p . Learning algorithm modifies the threshold limit value of linking point according to the error of the actual output between Y^1, Y^2, \dots, Y^p and T^1, T^2, \dots, T^p , which can make the output Y getting as close as possible to the required T . To the P samples, the learning error of the error function of square model is:

$$E = \frac{1}{2} \sum_{l=1}^p \sum_{r=1}^m (t_r^l - y_r^l)^2 \tag{8}$$

Among them, y_l^i expresses the actual output value of No. i of the first sample, and t_l^i is the corresponding teacher. To the given precision ε , if $E < \varepsilon$, then network computing stop.

The total learning process is divided into two periods: the first period computes from bottom to top of the network. With the structure and weight setted, the output neuron can be computed according to the input learning samples. In the second period, the weight and offset will be modified, and the order is from the topmost layer to the bottom. Computing and modifying the weight linked with the topmost layer from the known weight, and then trimming the weight and offset of each layer, the two periods alternate repeatedly until the network converges. The concrete step is as follows:

Step 1: network status initialization: Using the smaller random function to set initial value of weight and offset of the network.

Step 2: Inputting the first learning model.

Step 3: Computing the output of hidden layer and output layer according to the given formula.

Step 4: Solving the error of each layer, to the each of known sample the offset and the error linked with the output layer unit k is:

$$\delta_k = (y_k - t_k)y_k(1 - y_k) \tag{9}$$

The offset and the error linked with it of hidden layer unit j are:

$$\sigma_j = \sum_k \delta_k v_{kj} u_j (1 - u_j) \tag{10}$$

Step 5: Modifying the weight and the offset. The weight and offset that inputted into hidden layer is:

$$w_{ji} = w_{js} + \alpha \sigma_j x_i \tag{11}$$

$$\theta_j = \theta_j + \beta \sigma_j \tag{12}$$

The weight and offset from hidden layer to output layer is:

$$v_{kj} = v_{kj} + \alpha \delta_k u_j \tag{13}$$

$$h_k = h_k + \beta \delta_k \tag{14}$$

Step 6: Inputting the next learning model.

Step 7: If there is learning model, then go to step 3.

Step 8: Renewing the learning times, if it is under the setted number, then go to step 2.

IV. FUZZY COMPREHENSIVE EVALUATION

A. Fuzzy comprehensive evaluation model.

Fuzzy comprehensive evaluation method has been widely used. During evaluating some object, we often encounter such question as comprehensive one. Because every object is decided by many aspects, so it is necessary to evaluate every factor. On the basis of having evaluated every factor, we appraise all the factors.

The basic idea of fuzzy comprehensive evaluation is as follows: the border of many objects are not very clear, so it is difficult for us to classify them into some sort. We firstly evaluate single factor, then go to fuzzy comprehensive evaluation for all factors, which can avoid of leaving out any statistics or information loss of halfway.

The concrete step of fuzzy comprehensive evaluation

Step 1. Deviding the assumed comprehensive evaluation factor set U into S subsets, which are recorded as U_1, U_2, \dots, U_s , and they should meet the conditions as follows:

$$U = \{U_1, U_2, \dots, U_n\}, U_i \cap U_j = \phi, i \neq j$$

The faactor of set i is U_i , and it meet the conditions:

$$U_i = \{U_{i1}, U_{i2}, \dots, U_{in}\}, i=1, 2, \dots, s$$

During them, $n = n_1 + n_2 + \dots + n_s$, n expresses the number of factor U and n_i expresses the number of factor U_i .

Step 2. Evaluating comprehensively in regard to single factor U_i .

Assuming the appraisal set as $V = \{v_1, v_2, \dots, v_m\}$, the weight distribution of factors in U_i is:

$$A_i = \{a_{i1}, a_{i2}, \dots, a_{in_i}\}, \text{ which should meet the conditon of } a_{i1} + a_{i2} + \dots + a_{in_i} = 1$$

Assuming R_i as the fuzzy evaluation matrix from U_i to V, then $R_i = (r_{ij,k})_{n_i \times m}$, $i=1, 2, \dots, s$; $j=1, 2, \dots, n_i$; $k=1, 2, \dots, m$, $r_{ij,k}$ expresses the degree of membership U_{ij} . The paper determines the degree of membership using expert evaluation. The process the pratice is: Inviting expert group (at least 10 people) to evaluate the index system, and defining the comment set as very good, better, good, worse. The expert have to tick at one point according to their judge, and then deal with all datas using he way of statistics and uniformization in order to obtain corresponding degree of membership.

So the first grade comprehensive evaluation vector is:

$$B_i = A_i \cdot R_i = (b_{i1}, b_{i2}, \dots, b_{im}), i=1, 2, \dots, s$$

Step 3. The second grade comprehensive evaluation for U.

Looking every factor U_i as one part of U and B_i as its single factor comment vector, which can form the fuzzy evaluation matrix from U to V.

$$R = \begin{pmatrix} B_1 \\ B_2 \\ \vdots \\ B_s \end{pmatrix} = \begin{pmatrix} b_{11} & b_{12} & \dots & b_{1m} \\ b_{21} & b_{22} & \dots & b_{2m} \\ \dots & \dots & \dots & \dots \\ b_{s1} & b_{s2} & \dots & b_{sm} \end{pmatrix}$$

As one part of U, every U_i reflects some attribute of U and may give weight distribution according to their importance.

$$A = (a_1, a_2, \dots, a_s)$$

So the second grade comprehensive evaluation vector is:

$$B = A \cdot R = (b_1, b_2, \dots, b_m)$$

The b_k expresses the degree of membership when some evaluation system is rated as v_k . According to the maximum membership principle, the corresponding comment vector factor to the maximum membership in B is the final evaluation result, which can decide the risk rate of smart grid project.

Step 4. Evaluating multiple smart grid project

If there are p smart grid projects with similar economic benefit, environmental benefit and social benefit, we give them comprehensive evaluation for the risk and rate them. Firstly we use the above mentioned way to evaluate every project risk and obtain p evaluation result B_1, B_2, \dots, B_p (every factor B_i has been uniformed). If in the evaluation vector V, $v_1=10, v_2=8, v_3=6, v_4=4$, then the comprehensive score of number 1 project is:

$$S_l = \sum_{k=1}^m b_{lk} \cdot v_k, l = 1, 2, \dots, p$$

A. The selection of fuzzy operator

There are many fuzzy operators to be selected. The paper choose add by operator to compute for more accurately.

The first grade comprehensive evaluation model is:

$$b_{ik} = \sum_{j=1}^{n_i} a_{ij} \cdot r_{ij}, k = 1, 2, \dots, m$$

The second grade comprehensive evaluation model is:

$$b_k = \sum_{i=1}^s a_i \cdot r_{ik}, k = 1, 2, \dots, m$$

V. CASE STUDY

The experiment data originates from some province electric power company history load data. For the target is in progress discuss that China-Israel depending on the analysis that short-term load forecasts and building a model, day peak load forecast, and take a round number counting load the data, collects a data every 15 minutes, from 96 data choose everyday peak load in load.

A. Determining the index system of the risk of smart grid

During the development of smart grid, there are many risks, such as technology risk, management risk, decision-making risk, operation risk, market risk etc, and in every risk, there are sub-factors, the system is shown as block Fig 2:

B. Building the fuzzy evaluation matrix

In all the effect factors of the risk of smart grid, there are not only quantitative factors but also qualitative factors, and we should apply different ways for different factors. We use the normal fuzzy distribution to determine the membership degree for the quantitative factors. To the qualitative factors, we should first use expert consultation method or expert evaluation method to quantify, and then use the relevant membership function to determine the membership degree.

In the established index system, some indexes are dimensional, and other indexes are dimensionless.

Because of the differency of their dimension, some are focus on benefit, others are focus on cost, it is difficult to carry on the comprehensive comparison, so we should do dimensionless treatment in order to eliminate the influence of dimension of indexes, that is standardization and normalization for evaluation indexes. Because the indexes focus on cost are the smaller the better, so they are belong to inverse indexes, which can be described by some model of Cubic Parabola little deviation distribution.

$$f(x_i) = \begin{cases} 0 & x_i \leq x_{\min} \\ \left(\frac{x_i - x_{\max}}{x_{\max} - x_{\min}}\right)^2 & x_{\min} \leq x_i \leq x_{\max} \\ 1 & x_{\max} = x_{\min} \end{cases}$$

It is the bigger the better for the indexes focus on the benefit, which can be described by some model of Cubic Parabola large deviation distribution.

$$f(x_i) = \begin{cases} 0 & x_i \leq x_{\min} \\ \left(\frac{x_i - x_{\max}}{x_{\max} - x_{\min}}\right)^2 & x_{\min} \leq x_i \leq x_{\max} \\ 1 & x_{\max} = x_{\min} \end{cases}$$

In the above function, x_{\max} expresses the maximum value, x_{\min} expresses the minimum value and x_i expresses the actual value of some index of the evaluation system. In fact the model is the degree of membership of the fuzzy set of good function, which has the followed characteristic: The first is strict monotonicity, that is the model is strictly monotonic when it's rangeability is in the area of evaluation system. The second is there is standard value capable of comparing, that is the maximum value and the minimum value of some index. The third is when the direct index has lower value, the degree of membership increases along with the increasing of the index value. When the direct index value increases with great degree, the degree of membership increases

accelerately. The fourth is the function $f(x)$ describes the fuzzy set if good function.

In the index system, the dimensionless indexes are described by function increased linearly to calculate conveniently.

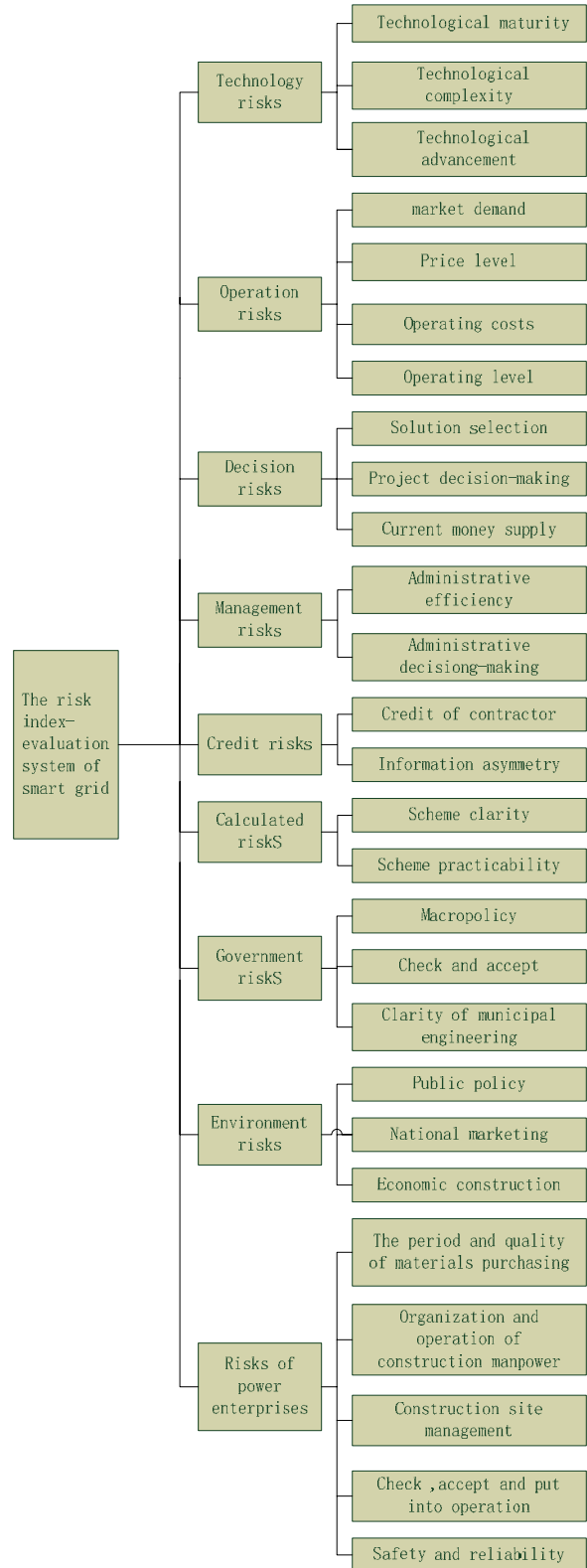


Figure 3. The risk index-evaluation system.

$$g(x_i) = \begin{cases} 0 & x_i \leq x_{\min} \\ \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} & x_{\min} \leq x_i \leq x_{\max} \\ 1 & x_{\max} = x_{\min} \end{cases}$$

The model has characteristic of the function $f(x)$.

C. Assuring single factor evaluating matrix R.

w_1, w_2, \dots, w_n is the output value of hidden layer of network and the network only has an output O_p . The weight from the input unit i to the hidden unit j is $w_{ij} (j = 1, 2, \dots, n)$, and the weight from the hidden unit to the output unit is w_j . θ expresses the threshold value of the output unit and ϕ_j expresses the threshold value of the hidden unit. The input unit number and the hidden unit number is n_1 and n_2 . $R_{\rho 1}, R_{\rho 2}, \dots, R_{\rho n}$ expresses the attribute value of the sample P in the total n_1 evaluation indexes, so S sample sets create the following attribute value matrix.

$$R = \begin{bmatrix} R_{11} & R_{12} & \dots & R_{1n} \\ R_{21} & R_{22} & \dots & R_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ R_{S1} & R_{S2} & \dots & R_{Sn} \end{bmatrix} = [R_{\rho j}]_{S \times N}$$

E. Building the fuzzy evaluation matrix

The paper first use the above Bayes algorithm to reduce the factors that influencing the power plant selection and eliminate the indexes that have less relation with the decision-making, then obtain typical samples to train the network. After the reduction of Bayes algorithm, the left variables are 18, there are the maturation of technology(x_1), the complexity of technology (x_2), the advancement technology (x_3), mark demand(x_4), level of

operation and management(x_5), Solution Selection (x_6), current money supply (x_7), efficiency of management organization(x_8), decision-making of management organization(x_9), trustworthiness of contractor(x_{10}), macropolicy(x_{11}), uncertainty of municipal engineering (x_{12}), economic construction (x_{13}), period and quality of materials purchasing (x_{14}), organization and coordination of construction manpower (x_{15}), field management of construction(x_{16}), check, accept and put into operation (x_{17}), safe reliability (x_{18}).

F. Designing the evaluating model

Using 3 layers BP Neural Network model to calculate, according to Kolmogorov theorem, the middle layer has 19 nodes since the input layer has 9 nodes. Network layer neuron transfer function using S-type tangent function, the output layer neuron transfer function using S-type logarithmic function, because the output function in the interval [0,1] between the output precisely meet the requirements. The learning algorithm uses a faster convergence Levenberg-Marquardt dynamic numerical optimization algorithm. Training error indicators set to 0.01, taking into account the network structure more complicated, the number of training set for 1000. Tab.1 and Tab.2 are shown the experiment training data with membership degree after quantifying and fuzzy processing.

The paper evaluates the risks of 15 smart grid project, shown as Tab.1 and Tab.2. Select 10 groups of representative data as training Set and the left 5 groups of data as testing set to imitate the object to be evaluated. For more to reflect the evaluated result, we should classify it, if the evaluation score is between 0.8 and 1.0, then it is defined as excellent, which shows the risk of construct project is very low; if the evaluation score is between 0.7 and 0.8, then it is defined as good, which shows the risk of construct project is low; if the evaluation score is between 0.5 and 0.7, then it is defined as better, which shows the risk of construct project is higher; if the evaluation score is under 0.5, then which shows the risk of construct project is very high.

TABLE I. INPUTTING SAMPLES

project number	X ₁₀	X ₁₁	X ₁₂	X ₁₃	X ₁₄	X ₁₅	X ₁₆	X ₁₇	X ₁₈	score
1	0.86	0.85	0.83	0.90	0.93	0.82	0.85	0.9	0.93	0.93
2	0.85	1.00	0.75	0.80	0.89	0.82	0.89	0.72	0.80	0.79
3	0.73	0.66	0.50	0.80	1.00	0.76	0.35	0.93	0.76	0.74
4	0.63	0.67	0.48	0.60	0.67	0.66	0.67	0.72	0.67	0.81
5	0.93	0.93	1.00	0.95	1.00	0.96	1.00	0.98	0.94	0.96
6	0.80	0.72	0.89	0.82	0.89	0.8	0.75	1.00	0.85	0.83
7	0.75	0.75	0.67	0.66	0.67	0.62	0.49	0.68	0.63	0.69
8	0.79	0.80	0.88	0.85	0.77	0.8	0.75	0.67	0.75	0.75
9	0.67	0.55	0.56	0.58	0.65	0.6	0.59	0.66	0.66	0.58
10	0.49	0.53	0.44	0.43	0.45	0.44	0.49	0.45	0.49	0.51

TABLE II. INPUTTING SAMPLES

project number	X ₁	X ₂	X ₃	X ₄	X ₅	X ₆	X ₇	X ₈	X ₉
1	0.88	0.79	0.85	0.72	0.77	0.69	0.73	0.76	0.82
2	0.8	0.87	0.89	0.82	0.78	0.80	0.75	0.33	0.67
3	0.67	0.93	0.22	0.75	1.00	0.80	0.49	0.66	0.73
4	0.92	0.8	0.89	0.92	0.89	0.80	1.00	1.00	0.79
5	0.87	0.93	1.00	1.00	1.00	1.00	1.00	1.00	0.94
6	0.80	0.72	0.89	0.82	0.89	0.80	0.75	1.00	0.85
7	0.67	0.72	0.67	0.66	0.67	0.60	0.49	0.66	0.63
8	0.72	0.80	0.78	0.75	0.78	0.80	0.75	0.66	0.75
9	0.60	0.60	0.56	0.58	0.56	0.60	0.49	0.66	0.57
10	0.47	0.47	0.44	0.41	0.44	0.40	0.49	0.35	0.49

TABLE III. TRAINING RESULT

Project number	1	2	3	4	5	6	7	8	9
Training result	0.781	0.752	0.673	0.727	0.915	0.795	0.611	0.733	0.567
Desired output	0.783	0.749	0.671	0.725	0.917	0.792	0.615	0.729	0.565

TABLE IV. TEST RESULT AND RISK RANKING

Project	1	2	3	4	5
Training result	0.394	0.597	0.75	0.494	0.663
Desired output	0.39	0.595	0.754	0.499	0.66
Simulation classify	Very high	higher	low	Very high	higher
Specialist classify	Very high	higher	low	Very high	higher
Risk rating	5	3	1	4	2

E. Training BP Neural Network

Putting the index membership into network, taking judgement value as desired output, determining the initial value and learning parameter 0.1~0.8 of network, it is beginning to train the network. We get the evaluation and order of the scheme after putting the test samples into trained network, which are shown as TABLE III.

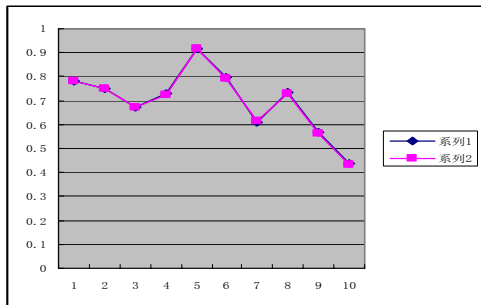


Figure 4. The output curve from training result and desired output.

VI. CONCLUSION

The neural network has high non-linear mapping relationship. The mapping can learn a lot of mapping relationship from other models and have no use for any known mathematical model to describe the relationship

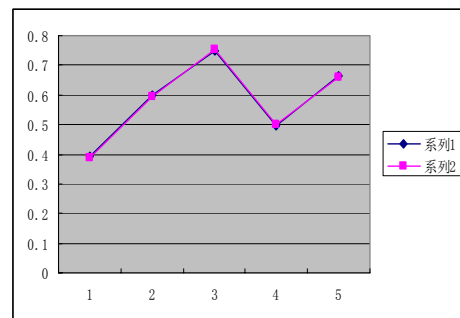


Figure 5. Testing outcome curve.

between input and output, which can avoid of influence of anthropogenic factor in the way of fuzzy comprehensive evaluation and get objective and reliable evaluation result.

The paper reducing the influence factors of risk of smart grid adopting Bayes algorithm, eliminating the less correlated attribute with decision-making, obtaining typical samples to be the input variables of BP Neural Network, using the calculating results in evaluation and decision-making, which resolves the risk problem when evaluating the risk of smart grid. The method is not only suitable for single comprehensive evaluation of smart grid, but also for several projects to be compared and preferred, which is an effective and practical method and

can provide reference for the evaluation and decision-making for the risk of smart grid.

REFERENCES

- [1] Dong-Mei Zhao; Jin-Xing Liu; Ze-Hong Zhang: Method of Risk Evaluation of Information Security Based on Neural Networks , Machine Learning and Cybernetics, 2008 International Conference on , Vol: 2, pp. 1127 - 1132(2009).
- [2] ZHU Wen-xi, SHAN Mi-yuan: A Neural Network Model of Risk Analysis for Public Construction project, Journal of Harbin Engineering University vol. 27,pp. 142—147 (2006).
- [3] YING Jian-lie, HUA Guo-dong, LIU Yao-nian: Power System Load Forecasting Based on v-Support Vector Regression , Journal of Northeast Danli University(Natural Science), vol 27,no. 2,pp. 43—47 (2007).
- [4] CHEN Shu-zhen: Several Attributes Reduction Algorithm Analysis Based on Rough Set, Wuhan Institute of Industrial Journal, vol 24 , no. 3,pp. 118—121 (2005).
- [5] WANG Li-dong , LI Zhi-yu , WEN Jin-yu: Short-term load forecasting Based on Support Vector Regression. Relay, vol. 33,no. 9, pp. 17—21 (2005).
- [6] Yanmei Li; Wei Sun: The Model of Power Plant Selection Based on Improved Fuzzy Neural Network . ICRMEM '08. International Conference on , vol 28, no. 21, pp.39—42 (2008).
- [7] JIANG Yang-yi, Multi-factor Forecast Models Based on Rough Sets and BP Neural Network, Computer Engineering,pp. 281 –286 (2008).
- [8] ZHANG Qing-Bao and the others: Short-term Load Forecasting Based on Rough Sets Attribute Reduction Algorithm and Support Vector Machine, Grid Technology, vol. 30, no 8, pp. 56—60 (2006).
- [9] LIU Gang, GU Yu-gui: Short-term Load Forecasting Based on Improved BP Neural Network , DSM, vol. 7,no. 3,pp. 24—27 (2005).
- [10] ZHANG Yun-long, PAN Quan, ZHANG Hong-cai, New Synthetic Prediction Method Based on SVR and Its Application , Journal of Air Force Engineering University(Natural Science Edition),vol. 6,no. 3,pp. 19 – 22 (2005).
- [11] Changjun Zhu; Zhenchun Hao , Fuzzy Neural Network Model and Its Application in Water Quality Evaluation , Environmental Science and Information Application Technology, 2009 , Vol. 1 pp: 251 - 254(2009).
- [12] Liu Fang, Design for Self-Organizing Fuzzy Neural Networks Based on Evolutionary Programming , Computer Modeling and Simulation, 2009,Vol.2,pp:344-348(2010).
- [13] Changjun Zhu; Li Lihong, Fuzzy Neural Network Model and its Application in Teaching Quality Evaluation, Intelligent Ubiquitous Computing and Education, 2009 ,pp:239-242(2009).
- [14] Kun Han; Lunxin Tang; Bin Bin; Zhongbo Yang: Research on the Application of Priority Degree Evaluation Method in the Fuzzy Neural Network, Computational Intelligence and Software Engineering, 2009. CiSE 2009. pp:1-4(2009).
- [15] Rongjun Li; Zhibin Xiong: A Modified Genetic Fuzzy Neural Network with Application to Financial Distress Analysis, Computational Intelligence for Modelling, Control and Automation, 2006 and International

Conference on Intelligent Agents, Web Technologies and Internet Commerce, pp:120-125(2006).

- [16] Yuan Yao; Kai-Long Zhang; Xin-She Zhou: Implement TSK Model Using a Self-constructing Fuzzy Neural Network , Intelligent Systems, 2009. GCIS '09. WRI Global Congress on ,Vol.1,pp:479-483(2009).
- [17] Chen Xiaohui,Yang Kun: The Evaluation Method of Enterprise Facility Layout Base on Fuzzy-Neural Network Model, Value Engineering,Vol.6,pp:95-97(2008).
- [18] Liu Xiaojie, Cao Liming ,Wang Xiaoping, The Distribution Center Selection Based on the Fuzzy Neural Network Model,Vol.24,no.3,pp:15-17(2008).
- [19] Zhang Xinhong,The Comprehensive Evaluation Model of High-technology Project Investing Risk Based on BP Neural Network,Information System,Vol.24,no.5,pp:377-379.
- [20] Lou Wengao,Comprehensive Evaluation Model for the Investing Risk of Using Artificial Neural Network in the Hi-tech Projects, Technology and Innovation Management,Vol.26,no.3,pp:8-11.

Li Yanmei was born in Rinqiu city, Hebei Province, China, 1975-4-9. She earned the Bachelor's Degree from Department of Mechanical Engineering from Dalian University of Science and Technology in 1998. In 2005, she earned the master degree of management from North China Electric Power University , Baoding, China.

She has worked in Department of Economic Management, North China Electric Power University Since 2005. From 1998 to 2001, she worked in a designing institute. She has published many academic papers in the field of technical economy and management.

- [1] Yanmei Li; Wei Sun: The Model of Power Plant Selection Based on Improved Fuzzy Neural Network . ICRMEM '08. International Conference on , vol 28, no. 21, pp.39—42 (2008).
- [2] Yanmei Li, Wei Sun: Short-term Load Forecasting Based on Bayes and SVR. 2008ICIRA. International Conference on , pp.643—650 (2008).

She emerged herself in the research of information management and decision-making analysis for a long time, and at present she is studying the related areas of smart grid.

Wang Jingmin, born in Baoding city, Hebei Province, China, 1955-4, professor, tutor of a Ph.D. student. She worked in Department of Economic Management, North China Electric Power University, and the research field is information management and decision-making analysis.

Li Shuangtao, born in Rinqiu city, Hebei Province, China, 1981. He earned the master degree of engineering from North China Electric Power University , Baoding, China. At present, he works in State Grid International Development Limited. He studies in the field of the foreign electricity market, human resource (intensive) management in electric power enterprises and intensive supplies management in electric power enterprises.