Risk Assessment and Comparative Analysis for Technical Standards Alliance based on Fuzzy-AHP Method and BP Neural Network Method

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Abstract--**Establishing unified industrial technical standards for a single enterprise in a highly global integrated market is becoming increasingly difficult. In recent years, enterprises in leading positions have often built technical standards alliances around a key core technology to develop industrial standards together so that they can learn from each other and optimise their resource allocation. The competition of maintaining and raising technical standards among the enterprises can be avoided in order to achieve a mutually profitable situation. Although such technical standards alliances bring huge gains to their members, their internal and external risks also threaten both the alliances and their members. Compared to other forms of strategic alliance, technical standards alliances have a much larger scale and the relationships between their internal members are more complex. Moreover, the structural hierarchy of a technical standards alliance is large and its risk has fuzzy characteristics. Furthermore, it is difficult to fully and accurately identify the real state of such an alliance. This paper uses a fuzzy pattern-recognition method to evaluate the risks of technical standards alliances and to clearly depict the essence of its risks. A fuzzy analytic hierarchy process (AHP) evaluation and the back propagation (BP)-logic fuzzy neural network methods are used to construct a risk-evaluation model of technical standards alliances, taking the alliance centred around new-energy automobiles in Zhejiang as an empirical example. Then, the two evaluation models are contrastively analysed and cross validation is carried out for the evaluation results. Finally, the advantages, disadvantages and applicable scope of the two kinds of evaluation methods are clearly identified in order to provide theoretical guidance and support for the application of two fuzzy evaluation models in practice.**

I. INTRODUCTION

Against the background of economic globalisation, competition among enterprises has moved from the domain of products to that of technological innovation, and thus, to the scramble for technical standards. In recent years, the relationships among enterprises have transformed from competition to competition and cooperation. Leading enterprises often set up technical standards alliances by centring on a key core technology in order to establish an industrial standard together. They can draw on each other's strengths and optimise their resource allocation. The competition among enterprises to maintain and raise technical standards can be avoided and a mutually profitable situation can be realised. Although such alliances bring huge earnings to their members, their risks may also threaten the alliance and its members. Technical standards alliances have larger scales than typical strategic alliances, the relationships among the insiders are more complicated and more layers of structure are involved. However, the risks are vague. Therefore, there is a need to further study the scientific and systematic identification and evaluation of risk management in technical standards alliances.

II. LITERATURE REVIEW

As an important means for the strategic adjustment of modern enterprises, technical standards alliances have already become a significant way for enterprises to maintain competitive advantages. When technical standards alliances are mentioned in the literature, terms like technical alliances, standards alliances, technical standardisation alliances and enterprise alliances are often applied and there are few clear definitions of the subject. DAI Yihua and ZHANG Ping considered a technical standards alliance to be a strategic alliance formed by enterprises centring on technical standards and stated that enterprises establish technical standards alliances to promote technical standardisation and to acquire standard values by utilising the diffusion effect of technical standards [1]. LI Daping and ZENG Deming thought, "Technical standards alliance is actually the aggregation of a series of license agreements. Various enterprises of the alliance reach agreements through negotiation and then form a contractual relationship. Technical standards alliance is a typical contractual alliance." [2] Based on the analysis of technical standards alliances in existing literature, this study considers technical standards alliances to be institutional arrangements based on technology and market power, formed by enterprises by centring on technical standards. The fundamental purpose of enterprises in establishing such alliances is to determine, spread and commercialise technical standards, so as to achieve competitive advantages.

On the one hand, the existing studies about technical standards alliances have discussed and analysed their formation mechanism; they have postulated that such alliances are formed to acquire technical standards with advantages in the market and to realise the objective of improving market competitiveness[3-5]. On the other hand, the basic modes and governance mechanisms of technical standards alliances have also been discussed, and different modes and governance thoughts have been proposed[6-7]. The existing studies have seldom investigated issues of risk related to these alliances. In the following, the main literature concerning enterprise alliance risk management is summarised:

In the classification of enterprise alliance risks, Grabowski and Roberts inferred the risk factors influencing enterprise alliances from the perspective of organisational science and risk factors affecting traditional and reliable organisation systems, including the tasks executed, technology adopted, organisation and human mistakes, organisational structure and organisational culture [8]. CHEN Jian, JIA Ping et al. classified risks into internal and external components according to the layer and origin of the risks[9-10]. YE Fei et al. divided risk types from life cycle stages of the alliance[11-12]. ZHANG Qingshan classified risks according to their influence scope[13].

In optimisation and evaluation of enterprise alliance risks, many scholars have adopted many qualitative methods, quantitative methods and combinations of the two to study the issue of enterprise alliance risk evaluation from different angles. FENG Weidong studied virtual enterprise risks, raised a risk-transfer algorithm to discuss the issue of enterprise alliance risk evaluation and provided methods and models for realising risk evaluation and risk bottleneck unit identification issuing this algorithm [14]. CAO Hongyi et al. studied risk projects organised in the form of an activity network in an enterprise alliance, established a project risk-optimisation model and solved the model with a genetic algorithm [15]. In addition, scholars have also explored different methods, such as common double-factor evaluation, three-factor evaluation and game evaluation, analytic hierarchy processes, Monte-Carlo simulations and Markov analyses have been generated on such bases. The above studies have two main problems. First, it is not reasonable to directly give a mathematical model for evaluation results and evaluation values for a quantitative solution when the alliance risk evaluation mechanism has not been clearly established. Second, it is not reasonable to solve problems with obvious non-linear relationships via linear methods.

Since the 2000s, enterprise alliance risk evaluation methods based on fuzzy mathematics have substantially increased in prediction accuracy. As a representative, the fuzzy comprehensive evaluation method is widely used in risk evaluation and early warning [16-17]. This method is suitable for cases involving obscure boundaries and situations, where quantitative analysis cannot be performed. It is superior in multi-layer complex problem evaluation and its performance is better than that of traditional statistical methods, but this method has defects such as lack of weights that can be updated automatically and inability to dispose of noisy data. Moreover, risk factors influencing technical standards alliances are changing constantly, so neither traditional statistical methods nor fuzzy comprehensive evaluation methods can solve the problem of dynamic evaluation on standards alliance risks. Therefore, in order to break these limitations, this paper introduces the BP neural network model to evaluate risks of technical standards alliances.

III. BACK PROPAGATION NEURAL NETWORKS AND OPTIMISATION

BP neural networks are multi-layered feed-forward neural networks in error back-propagation. A large number of neurons with non-linear relationships between them are united extensively to form a multi-layer network. [18] With the ability to judge complex problems through sample learning in a complex environment by utilising a large amount of uncertain information, these networks have been applied to estimation and pre-judgment of complex processes in recent years. Therefore, they are very suitable for evaluating the risks of technical standards alliances.

BP neural networks are composed of input, hidden and output layers; there can be one single hidden layer or multiple ones. Suppose that the structure of a BP neural network is $n \times q \times m$; the network includes weight from neuron i at the input layer to unit j at the hidden layer w^I_{ij}($i = 1,2,\ldots,n$; $j = 1,2,\ldots,q$); weight from neuron j at the hidden layer to neuron k at the output layer, w^H_{jk}($j = 1,2,\ldots,q$; $k = 1,2,\ldots,m$); the threshold value, θ^H_j, of neuron j in the hidden layer and the threshold value, θ^O_k, of neuron k at the output layer, as shown in Fig. 1.

The BP algorithm adopts a negative-gradient method to correct weights in order to realise network convergence and a situation where output error is smaller than the allowable value. Its learning process is composed of forward

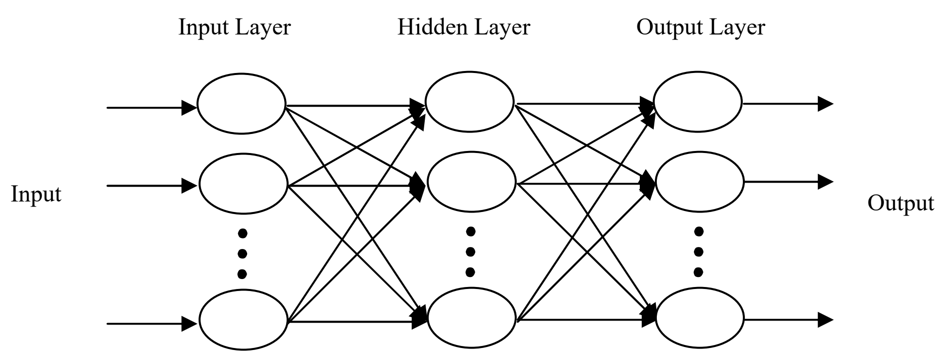

Fig.1. B-P networks model structure

propagation of signals and back propagation of errors, and the specific algorithm is as follows:

1) Forward propagation of the network

Suppose that the input of data samples of group p is $x_p = (x_{1p}, x_{2p}, \ldots, x_{np})$, the expected output is $t_p = (t_{1p}, t_{2p}, \ldots, t_{mp}), p = 1,2,\ldots,L$, and L represents the total number of samples; then, the output information of neuron j at the hidden layer is:

$$H_{jp}=f\left(\sum_{i=1}^{n} w_{ij}^{I} x_{ip} - \theta_j^{H}\right),\ j=1,2,\ldots,q;\ p=1,2,\ldots,L \tag{1}$$

The hidden layer transfers output information to the output layer, and the final output result is as follows:

$$Y_{jp}=f\left(\sum_{i=1}^{\eta} w_{jk}^{H} x_{jp} - \theta_j^{o}\right),\ k=1,2,\ldots,m;\ p=1,2,\ldots,L \tag{2}$$

Suppose that the actual output of samples of group p is y_p; then the error sum of squares, E, of the network can be represented as:

$$E = \frac{1}{2}\sum_{P=1}^{L}\sum_{K=1}^{M}(y_{kp} - t_{kp})^2 \tag{3}$$

Whether E converges to the given learning accuracy ε is judged. If E ≤ ε, the algorithm will be terminated and the network will stop training; otherwise, the following steps will be continued.

2) Error back-propagation

Starting from the output layer, the steepest-descent method in non-linear programming is adopted, back propagation is conducted for output errors at various layers along the original road and the connection weights of the network are corrected continuously. The modification formula for the weights is as follows:

$$w_{ij}(n+1) = w_{ij}(n) - \eta\frac{\partial E(n)}{\partial w_{ij}(n)} \tag{4}$$

Here, $w_{ij}(n+1)$ means the weight of learning at the n[th] timestep and η represents the step value or network learning rate.

The first two steps are repeated and the training is terminated when the output error of the sample satisfies the predetermined conditions.

The BP neural network algorithm has problems such as low convergence rate, existence of local minima in the objective function and contradiction between learning rate and stability. In order to overcome these problems, this study tries to conduct the following improvements when establishing a technical standards alliance risk-evaluation model using BP neural networks:

a) An anti-symmetric function is used to replace the common sigmoid function, and the convergence rate is often higher than that of the sigmoid function.
b) A momentum term is added in the error back-propagation process to solve the contradiction between the learning rate and stability. Therefore, (4) is changed to:

$$w_{ij}(n+1) = w_{ij}(n) - \eta\frac{\partial E(n)}{\partial w_{ij}(n)} + \alpha\Delta w(n) \tag{5}$$

c) Optimum selection through multiple tests is adopted to improve the veracity of the setting neuron quantity in the hidden layer in order to to overcome the defect by which the BP algorithm might fall easily into a local minimum.
d) A conjugate gradient learning algorithm, quasi-neuron algorithm or Levenberg–Marquardt (L–M) optimisation algorithm is adopted, and these algorithms markedly improve the speed of the BP algorithm.

IV. RISK-ASSESSMENT MODEL FOR TECHNICAL STANDARDS ALLIANCES

A. Risk-assessment Index System for Technical Standards Alliances

By summarising the research results of enterprise alliance risks and the results of risk research combined with the features of technical standards alliances, we found that the main sources of risk for technical standards alliances include: 1. **collaboration risk** related to collaboration among members, 2. **opportunism risk** generated from information asymmetry, 3. **external environmental risk** generated from the uncertainty of external factors, 4. **strategic risk** related to the strategic decision-making by the core members of the alliance, 5. **resource-loss risk** generated from the knowledge-spillover effect and 6. **Competence risk** related to the competence of alliance members. The above risk sources are regarded as first-class indices and are used as a basis to set the second-class indices, thereby constructing the risk-index system for technical standards alliances, as shown in Table 1.

B. Sample Collection

Developing strategic emerging industries has become a significant national strategy for seizing the commanding heights of new economic and technological development. It is significant for transforming economic development patterns, promoting industry transformation and upgrading and promoting international competitiveness. Constructing technical standards alliance around a core technology can contribute to scaling and continuous development of strategic emerging industries. In December 2013, the *Development Planning for Standardizing Strategic Emerging Industries* was published in China. In this paper, the technical standards alliances for a strategic emerging industry in China were chosen as the object of the study.

Given the complexity of sample collection, the technical standards alliance of the new-energy automobile industry in Zhejiang is analysed in this paper. This is Zhejiang's most competitive industry and takes the leading position in the entire country. Its technical standards alliance was constructed nearly ten years ago and is in the growth stage of its life cycle. By 2015, a synthesis of three standards had been developed. Nine badly-needed critical national standards were established, covering nearly 100 standards of all the levels needed by new-energy automobiles. This helped the new-energy automobile industry in China to construct a

TABLE 1 RISK ASSESSMENT INDEX SYSTEM OF TECHNICAL STANDARDS ALLIANCES

Risk factors	Risk variable indexes
B1 Cooperation	B11 Cultural and Management Conflict
	B12 Poor Transition of Complementary Technologies and Products
	B13 Poor Communication
	B14 Difficulty of Technology Convergence
B2 Opportunism	B21 Ethical Risk
	B22 Possibility of Defaulted Launch
B3 External Environment	B31 Inadequate Financial Support from Government
	B32 Inadequate Support of Standard Organization Information
	B33 Technical Standard Upgrading Outside
	B34 Change in Consumers' Demands
B4 Strategy	B41 Cognitive Limitations
	B42 Inaccurate Establishment of Key Technology
	B43 Inaccurate Identification of market opportunities
B5 Resource Loss	B51 Loss of Intellectual Property
	B52 Talent Loss
	B53 Irrational Profit Distribution
B6 Capacity	B61 Poor Technical Standardization Capacity
	B62 Poor R&D Capacity
	B63 Poor Productivity of Technology Standard Products
	B64 Poor Market Promotion Capacity

standard system for electric vehicles. The targets for the next stage are to fulfil more than 150 standards for new-energy automobiles, to lead or to participate in establishing five to eight international standards in the field of new-energy automobiles and to help complete the Chinese standards system for this industry.

In this paper, a questionnaire inquiry is adopted to collect sample data from the members of the technical standards alliance for new-energy automobiles and the questionnaires are given to those middle-senior managers who work in the alliance member organisations and are familiar with standardisation. Out of the 152 questionnaires that were given out, 140 were recycled. Out of those 140, 136 were valid. By testing the internal-consistency reliability of the questionnaires, the Cronhach's coincidence indicator was found to be 0.923, indicating a favourable reliability of the data from the questionnaires.

C. Construction of the BP Neural Network Model

According to the process in Fig.2, the BP neural network-based risk-assessment model for technical standards alliances is constructed in this paper.

1) Normalisation of Data

To reduce the difficulty of network training and avoid problems like overfitting, pre-treatment is conducted on the sample data. Pre-treatment can reduce the divisibility of data to a reasonable level, such that those data of different dimensions and different orders of magnitude can be compared with each other. In this paper, the linear range transformation is adopted to normalise the data:

$$x_i' = \frac{x_i - min_i}{max_i - min_i} \tag{6}$$

Here, x_i is an original sample data point, and x_i' is a new data point from the transformation.

2) Confirmation of BP Neural Network Structure

A BP neural network with a single hidden layer is able to map all continuous functions. It has been proved by Robert Hecht-Nielson [19] that a three-layer BP neural network, which only contains one hidden layer, is able to fulfil mappings from n dimensions to m dimensions. This is why the risk-assessment model based on the technical standards alliance of a BP neural network is only equipped with one hidden layer. The input and output layers of the neural

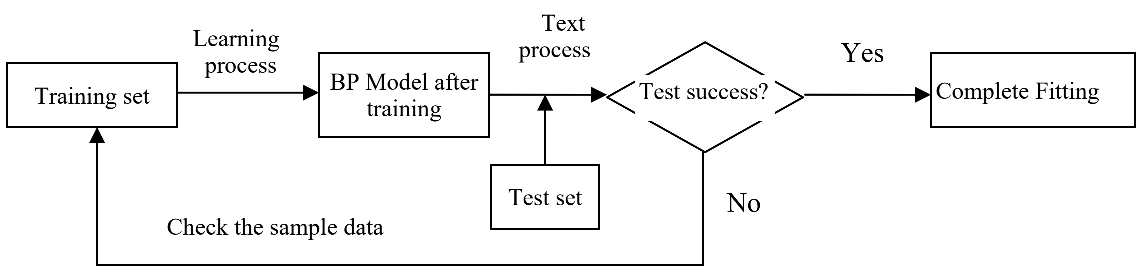

Fig. 2.Operation process of BP neural network

network, which are usually connected with specific problems, have practical meanings, while the hidden layer is set according to the requirements of the model and the complexity level of the problems. As a result, the input and output layers should be confirmed before the hidden layer.

① The Confirmation of the Input Layer

According to the risk-assessment index system for technical standards alliances built in the above paragraph, the input layer contains the 20 indices in the Table 1, meaning that the number of nerve cells in the input layer is 20.

② The Confirmation of the Output Layer

As the purpose of constructing the BP neural network model is to confirm the risk level of technical standards alliances, the number of nerve cells in the output layer is one, and the economic implication is the final assessment score of the technical standards alliance. The actual output of all training samples in this paper is assessed by experts: according to the actual situation of the technical standards alliance's operation, experts will show specific quantified data as the actual output of the network training samples. The output data of the network is an arbitrary real number from 1 to 5, which achieves a quantitative reflection of the risk situation of technical standards alliances.

③ The Confirmation of the Hidden Layer

A unified and integrated guiding theory for confirming the number of nerve cells in the hidden layer is still lacking. A recognised principle is: in the circumstance without other experiential knowledge, it is best to provide the simplest (i.e. smallest-scale) network that conforms to a given sample (i.e. is consistent). This means that, under the condition of sample points deviating within an allowed range, the smoothest function can be applied to approach unknown non-linear mappings [20].

Therefore, the procedure for confirming the number of nerve cells in the hidden layer is to first calculate the range of m by an empirical formula, which in this paper is given by

$$m = log_2 n \tag{7}$$

$$m = \sqrt{n+l} + a \tag{8}$$

Here, m is the number of nerve cells in the hidden layer; n and 1 signify the numbers of input and output nodes, respectively; a is a constant, falling in the range of 1 to 10. Then, Matlab is used to change m and conduct training within the same sample set until the network error reaches its minimum, so as to confirm the number of nodes in the hidden layer.

Taking the collaboration risk factor as an example, its m is found in the range from 2 to 12 by (7) and (8). Through repeated experiments for this range in Matlab, it is found that, when m is 4, the error in the model is minimized and the model fulfils requirements. Thus, collaboration risk has four nodes in the hidden layer. The numbers of nerve cells in the hidden layer for other risk factors are shown in Table 2.

TABLE 2 THE NUMBER OF NEURONS IN THE HIDDEN LAYER

Risk factors	B1	B2	B3	B4	B5	B6
The number of neurons in the hidden layer	4	2	4	2	2	4

3) Confirmation of the Transmission Function

① A logarithmic sigmoid function is adopted as the transmission function from the input layer to the hidden layer, as this function maps the input range of nerve cells from [-∞,+∞] to [0,1]:

$$\Phi(x)=log\ sig(n) = \frac{1}{1+e^{-n}} \tag{9}$$

② The pure line function is adopted as the excitation function from the hidden layer to the output layer, as this function maps the input range of nerve cells from [0,1] to [-∞,+∞].

$$\Psi(x)=purelin(n)=a*n+b \tag{10}$$

4) Confirm the Training Sample and Carry-out Sample Learning

In this paper, the input layer data of the BP neural network is acquired through questionnaires. The questionnaire contains 20 questions, corresponding to 20 risk-assessment indices in Table 1. A five-level scale is adopted to grade all questions, where 1 means poor (dangerous); 2 means fairly poor (fairly dangerous); 3 means medium (with general risk); 4 means fairly good (fairly safe); 5 means good (safe).

We obtained 136 valid questionnaires in total; 70% of them, that is 95, were taken as training samples and the remaining 41 as simulation samples. The network was trained with Matlab software in this paper, and the detailed training parameters are set as shown in Table 3.

The Matlab neural network toolbox offers various training functions, and the four most representative algorithms are selected in this paper: traingdx, trainrp, traincgp and trainscg. They were first compared by training and then were selected according to the experimental results. The result of the training-collaboration risk factor is shown in Table 4.

TABLE 3 TRAINING PARAMETERS SETTING OF BP NEURAL NETWORK

Training Parameters	Meaning	Parameter Choice
net.trainParam.epochs	Training Steps	10000
net.trainParam.goal	Target Error of Training	1e-2
net.trainParam.show	The Interval of Displaying Training Results	1
net.trainParam.tim	The Maximum Time for Training	inf
net.trainParam.mingrad	The Minimum Gradient in Training	1e-2

TABLE 4 THE TRAINING RESULTS OF TRAINING FUNCTIONS IN BP NEURAL NETWORK (FOR COOPERATION RISK FACTOR)

Functions	Algorithms	Iteration number	MSE	Gradient
traingdx	Momentum Gradient Descent Algorithm of Variable Learning Rate	4250	0.000101	0.00503
trainrp	BPRO Algorithm	578	0.000100	0.00172
traincgp	Conjugate Gradient Algorithms	319	0.000099	0.00115
trainscg	Scaled Conjugate Gradient Algorithm	251	0.000099	0.00138

It can be seen from the comparison in Table 3 that it takes 251 iterations for the trainscg function to reach the required training accuracy. Its rate of convergence is the fastest amongst the listed algorithms; hence it is selected as the training function for the risk-assessment model of technical standards alliances. In Matlab, the training function net.1ainFen= ‘trainscg’ is called to train based on the test samples.

V. EXPERIMENTAL RESULTS AND ANALYSIS

A BP neural network after training is used to simulate the questionnaire data from the technical standards alliance for new-energy automobiles, and the overall risk value of this alliance is found to be Y=2.6950, which is between 3 (moderate risk) and 2 (relatively high risk). Specifically speaking, the risk levels of various factors are:

Cooperation risk Y1=2.1286, Opportunism risk Y2=2.4557, External Environment risk Y3=2.7680, Strategy risk Y4=2.2446, Resource Loss risk Y5=2.5915, Capacity risk Y6=2.5813

A. Comparative Analysis on the Experimental Results of the BP Neural Network Model and the Fuzzy Analytic Hierarchy Process

The fuzzy analytic hierarchy process (fuzzy-AHP) is a comprehensive evaluation method based on fuzzy mathematics to process multi-factor and multi-layer complex systems by applying calculation methods like statistical mathematics and matrix algebra. Many previous studies in academic circles have applied fuzzy analytic hierarchy processes to enterprise alliance risk evaluation and considered the fuzzy analytic hierarchy process to be superior to traditional evaluation methods. Therefore, this paper makes a comparison between the fuzzy hierarchy model and the BP neural network model, so as to determine which is more suitable for risk evaluation of technical standards alliances.

In this study, a secondary fuzzy analytic hierarchy process is adopted for modelling, as shown in Fig. 3.

Firstly, the analytic hierarchy process is used to calculate the weights of sub-factors in Table 1, and the following weight matrix is obtained:

A1= {0.1732, 0.1732, 0.2865, 0.3671}
A2= {0.3326, 0.6674}
A3= {0.1818, 0.4546, 0.2727, 0.0909}
A4= {0.5715, 0.2857, 0.1428}
A5= {0.1428, 0.4286, 0.4286}
A6= {0.2308, 0.3846, 0.3077, 0.0769}

Secondly, the membership matrix of the sub-factors is established.

This paper uses the Delphi method; 10 experts were invited to conduct fuzzy evaluations of risk grades in the sub-factor. For comparison, the evaluation set established here is the same as that of the BP neural network model. In other words, the evaluation set is V = {1: poor (very risky), 2: relatively poor (relatively risky), 3: moderate (generally risky), 4: relatively good (relatively safe), 5: good (safe)}. After comprehensively analysing the membership of various evaluation indices according to the scores given by experts, the membership matrix is obtained as follows:

$$R1=\begin{bmatrix} 0 & 0.5 & 0.3 & 0.2 & 0 \\ 0 & 0.4 & 0.4 & 0.2 & 0 \\ 0 & 0.6 & 0.2 & 0 & 0.2 \\ 0 & 0.5 & 0.5 & 0 & 0 \end{bmatrix} \quad R2=\begin{bmatrix} 0 & 0 & 0.4 & 0.6 & 0 \\ 0 & 0 & 0.5 & 0.5 & 0 \end{bmatrix}$$

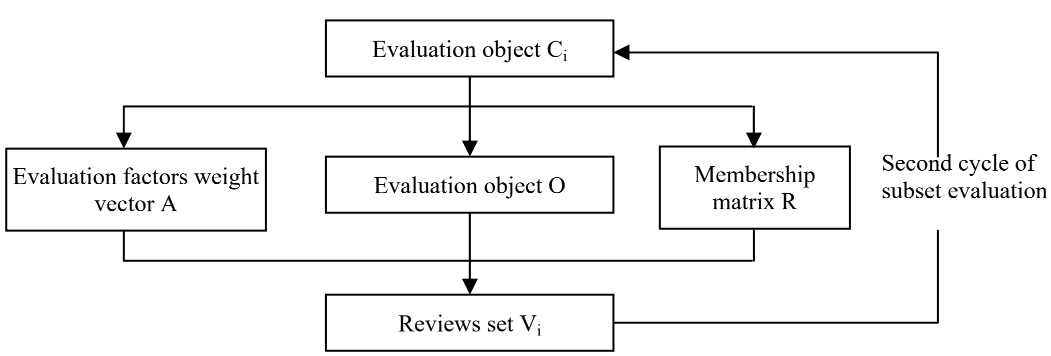

Fig.3. Modeling program of Fuzzy-AHP

$$R3=\begin{bmatrix}0.2 & 0 & 0 & 0.4 & 0.4\\ 0 & 0 & 0.2 & 0.4 & 0.4\\ 0.3 & 0 & 0 & 0.5 & 0.2\\ 0.3 & 0 & 0 & 0.4 & 0.3\end{bmatrix} R4=\begin{bmatrix}0.4 & 0 & 0.2 & 0.4 & 0\\ 0.8 & 0 & 0 & 0.2 & 0\\ 0.6 & 0 & 0.2 & 0.2 & 0\end{bmatrix}$$

$$R5=\begin{bmatrix}0 & 0.3 & 0.5 & 0.2 & 0\\ 0.2 & 0.4 & 0.4 & 0 & 0\\ 0 & 0.5 & 0.5 & 0 & 0\end{bmatrix} \quad R6=\begin{bmatrix}0 & 0.4 & 0.2 & 0.4 & 0\\ 0 & 0.2 & 0.4 & 0.4 & 0\\ 0 & 0.4 & 0.2 & 0.4 & 0\\ 0 & 0.4 & 0.3 & 0.3 & 0\end{bmatrix}$$

Thirdly, first-class fuzzy comprehensive evaluation is conducted; in other words, the influence of the underlying factors on factors at the upper layer is calculated. The M ($\wedge$, $\vee$) (where $\wedge$ and $\vee$ represent min and max operations, respectively) composition operator is applied to work out fuzzy evaluation of the primary indices, and the calculation formula is:

$$b_j = \vee_{i-1}^{n}(a_i \wedge r_i) \qquad (j=1,2,3,\ldots\ldots m) \qquad (6)$$

Therefore, a second-class evaluation matrix, B, is obtained:

$$B=\begin{bmatrix}0 & 0.3563 & 0.1563 & 0.4874 & 0\\ 0.0827 & 0.4027 & 0.2293 & 0.2853 & 0\\ 0 & 0.1448 & 0.4269 & 0.2750 & 0\\ 0 & 0.2268 & 0.5330 & 0.1268 & 0.1134\\ 0.0715 & 0.2667 & 0.3951 & 0.2667 & 0\\ 0 & 0.3563 & 0.1563 & 0.4874 & 0\end{bmatrix}$$

Fourthly, according to the calculation formula for second-class fuzzy evaluation:

$$C=A*B$$

The second-class fuzzy comprehensive evaluation matrix is determined as:

$$C=\{0.0367, 0.1881,0.3292, ,0.3292,0.1168\}$$

Finally, the overall risk level of the technical standards alliance for new-energy automobiles and the risk values of various risk factors are calculated, as shown in Table 5.

Table 5 also gives the evaluation results of the BP neural network and fuzzy comprehensive evaluation models. The overall risk values calculated by the two models are similar, and the same conclusion is reached: the risk of the technical standards alliance for new-energy automobiles is between moderate and relatively high.

However, the two models do not make the same judgments for the evaluations of various risk factors. The fuzzy analytic hierarchy process considers the major risks faced by the alliance to be cooperation risk and strategic risk. However, the BP neural network model concludes that the abilities of alliance members and the support of the external environment are weaknesses in the development of technical standards alliances.

By considering practical situations, the technical standards alliance for new-energy automobiles is at the growth stage of its life cycle, and the cooperation among various members of the alliance is gradually becoming orderly. At this time, the major objective of the alliance is to perfect the technical standards system and to expand these standards. Therefore, the strength of the members has a relatively great influence upon the operations of the alliance, which include the production capacity of technical standard products, market promotion capacity, supporting capacity of the service platforms and connections between complementary technologies and products. Meanwhile, external environmental factors (such as government funds, policy support and technical support of standardisation institutions) are also necessary at this stage. It appears that the judgment of the BP neural network model is more suitable for the practical situations of the technical standards alliance for new-energy automobiles at present compared to the fuzzy analytic hierarchy process.

B. Characteristics of the BP Neural Network Model and the Fuzzy Analytic Hierarchy Process

The BP neural network model and the fuzzy analytic hierarchy process have their own characteristics with different scopes of application to the risk-evaluation of technological standards alliances.

1) BP neural network

A BP neural network is an artificial neural network that simulates the behaviours of a human's neural network. It is composed of many neurons with information-processing capability. Furthermore, BP neural networks are characterised by excellent fault-tolerance, parallel processing and self-learning capabilities, as well as rather strong classification capability, which can better evaluate systems with incomplete information. When the studied data of the technological standards alliance showed fuzziness and incomplete information, the BP neural network method could use the sample data with enough testing to obtain the evaluation result via effective training. Therefore, BP neural networks are very well-suited to solving problems with the unknown mechanism.

TABLE 5 EVALUATION RESULTS OF FUZZY-AHP MODEL AND BP NEURAL NETWORK MODEL

Models	Text set sample						
	Overall risk	Risk factors					
		Cooperation risk	Opportunism risk	External Environment risk	Strategy risk	Resource Loss risk	Capacity risk
Fuzzy-ahp	2.5841	2.6725	3.1678	2.3828	2.8490	2.5118	2.2960
BP neural network model	2.4950	2.1286	2.4557	2.7680	2.2446	2.5915	2.5813

Meanwhile, as a non-linear mathematical model, a BP neural network can handle non-linear problems without setting the functional relationship between dependent and independent variables in advance. In theory, a BP neural network can get closer to functions with arbitrary precision.

The disadvantages of the BP neural network lie in very slow convergence, too much training time as well as complexity of the network structure and algorithm. The BP neural network is not applicable to analytical objects with too many influence factors or levels. Otherwise, with increasing training times, overfitting may occur with the additional calculation and memory space. This ultimately prevents accurate evaluation results and predicated values from being acquired.

2) Fuzzy analytic hierarchy process

The fuzzy analytic hierarchy process represents a combination of the analytic hierarchy process and a fuzzy comprehensive evaluation method, with both of their advantages. As a multi-criteria decision method, the fuzzy analytic hierarchy process is capable of rendering complex problems organised and hierarchical, which is quite effective for solving large-scale optimisation problems with multi-levels and multi-objectives.

Furthermore, due to the introduction of fuzzy mathematics, the fuzzy analytic hierarchy process can transform fuzzy and qualitative problems into mathematical linguistics for further quantitative description, so as to improve the comparability and objectivity of the evaluation objects. In particular, due to the large fuzziness of subjective factors, the fuzzy analytical hierarchy process offers advantages in comprehensive evaluation.

However, the weight of evaluation factors may vary due to the higher flexibility of man-made fixed weight and the different focuses of evaluators. The weight determination may be different from the objective reality due to human subjectivity, which may affect the accuracy of the evaluation results. In this case, some other methods, such as the BP neural network evaluation method, should be used to form a composite evaluation system, amend the deficiency of single-method evaluation and improve the accuracy of evaluation results.

VI. CONCLUSION

(1) This paper examined a strategic emerging industry as the object upon which to build a set of risk-evaluation indices for technological standards alliances and considered its characteristics and member relationships comprehensively. The index system included six first-level indices, including collaboration risk, opportunism risk, external environmental risk, strategic risk, resource-loss risk and competence risk, as well as 17 second-level indices.

(2) This paper selected the BP neural network for building the evaluation model due to the unclear evaluation mechanism and non-linearity of risk evaluation for technological standards alliances. With a strong non-linear mapping ability, BP neural networks can complete highly complex input, output and non-linear mapping with excellent non-linear fitting ability. BP neural networks are more advantageous than others when handling incomplete information of evaluation objects and unclear mapping relations.

To address deficiencies of trapping into local minima that probably contribute to thee BP neural network's slow convergence, this research put forward some improvements including adoption of a conjugate learning algorithm, optimisation of the number of hidden neurons and addition of momentum. Therefore, the evaluation result is consistent with the practical situation at the time of applying this model to conduct stimulation on the technological standard alliance of new energy automobiles. The comprehensive evaluation model based on the BP neural network can evaluate the risk of a technological standard alliance accurately and discover the deficiency of the technological standard alliance so as to provide a basis for decisions regarding its steady and healthy development.

(3) This paper compared the application conditions of fuzzy analytic hierarchy processes and BP neural networks for the risk evaluation of a technological standards alliance. The fuzzy analytical hierarchy process was mainly applied to the system evaluation with complex multi-factors that were multi-variate and multi-level. The comprehensive fuzzy evaluation method had advantages in cases with a large number of fuzzy phenomena arranged in a complex hierarchy with too many evaluation factors in the evaluated technological standards alliance. Therefore, the risk evaluation method should be selected reasonably according to the practical situation of the technological standards alliance, so as to check and evaluate the risk of the technological standards alliance accurately.

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