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Evaluating Energy Enterprise Safety Performance Based on An Improved Fuzzy Comprehensive Evaluation Model

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Abstract. *Safety performance assessment, an effective method to prevent serious accidents, is of great significance for the safe running of energy enterprises. In order to guarantee the accuracy of safety and effectiveness of assessment results, BP (back propagation neural network along with entropy weight method were applied in this research to calculate the objective weight of training index and develop a modified fuzzy comprehensive evaluation method. Furthermore, the developed modified fuzzy comprehensive evaluation method was applied to the evaluation of safety performance of an energy enterprise, aiming to provide proper improvement solutions for the re-finery enterprise. The results show that the safety performance of the refinery is poor, and the refinery needs to be improved from safety objectives, staff safety awareness, working environment and equipment safety, emergency management, staff unsafe behavior, safety training and other aspects.*
Keywords: Safety performance assessment, BP (back propagation) neural network, Entropy weight method, Modified fuzzy comprehensive evaluation, Energy enterprises.

1. **Introduction.** Adopting effective safety evaluation methods can improve global safety production. In recent years, some scholars have put forward various safety evaluation methods. In recent years, safety production has been improved globally due to more effective safety assessment methods proposed by many researchers. However, it should

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be noted that safety production of each enterprise faces new challenges with the development of economy [1]. Accidents occur frequently in the field of energy production, and the situation of work safety is relatively severe. Safety performance is extensively applied as an important index for measuring the safety behavior of energy enterprise management. Safety performance evaluation method has become a hot topic since it is effective in finding safety management defect [2]. Therefore, the establishment of a complete and effective safety performance evaluation method is of utmost significance in enhancing safety production conditions and avoiding serious incidents. In fact, many researchers around the world have made important progress in safety performance evaluation methods. Bellamy et al. [3] developed a pyramid model considering guarantee system, work allocation, accident prevention and control, and dispute resolution and applied it to conduct subjective evaluations on safety performance. Ranveig et al. [4] used safety self-test tool to investigate safety performance from four perspectives of people's safety awareness, rules and regulations and safety measures. Bodil et al. [5] established relational judgment matrix model for the evaluation of safety performance and used analytic hierarchy process (AHP) to analyze the influence and importance of different indicators on safety performance. Zhao et al. [6] adopted some flight dispatchers of Chinese airlines as research object and applied structural equation model to construct a hypothetical model for dispatcher resource management and airline operation control safety performance. It can be seen that one limitation of the existing evaluation methods is based on subjective factors or methods. Although such methods are effective, they are significantly affected by artificial conditions. Especially in the evaluation process, they highly rely on the experiential understanding of the industry of the evaluator. The other limitation of these methods is mainly based on accurate mathematical or statistical methods. The methods are rational and objective, but have demanding requirements. Generally, accurate results require accurate measurement of indicators. Among the many safety performance evaluation methods, the artificial neural network evaluation method using fuzzy system theory can solve the complexity problem. Artificial neural network evaluation method is an intelligent algorithm that simulates the complex working principle of human brain neurons and finds the internal connection between input and output through sample learning and training, so as to solve the problem [7]. At present, artificial neural network has made great achievements, related theories have developed into an interdisciplinary discipline, applied to image processing, optimization design and other aspects. In recent years, researchers have proposed an evaluation method combining fuzzy system theory and neural network, which can well solve the problems of index fuzziness and relationship complexity [8-11]. The fuzzy evaluation model of safety performance using artificial neural network has certain advantages. Accordingly, an index system of safety performance evaluation model was established which combined the adaptability of BP (back propagation)neural network, objectivity of entropy weight method and fuzziness of fuzzy comprehensive evaluation. This method fully considered the high incidence of accidents in energy enterprises, reduced the subjective influence of individual experience weight, and made the evaluation more objective. At the same time, the model also had certain adaptability to qualitative indexes that could not be accurately measured in order to maintain high accuracy and reduce harsh requirements of index measurement.

2. **Safety Performance Evaluation System.** In fact, early studies to evaluate the performance indicators and industry mainly power and nuclear power industry, such as the IAEA [12] inspired by peers, from staff operating links and power plant configuration management puts forward more detailed safety management and operation of the performance evaluation indicators, and carried out called "operation safety indicators project"

research study. A few years later, Kam et al. [13] proposed a relatively objective SPE safety performance system in the field of engineering project management in view of the development of Hong Kong's construction industry. Later, Wang et al. [14] in China further expanded the safety performance evaluation system and proposed that policy vision, enterprise goal planning, education and training and other indicators should also be considered in the establishment of safety performance indicator system. In recent years, there have been a number of researchers on safety performance evaluation, but most of them summarized and refined supplements based on previous studies. For example, Chen [15] added indicators such as full-staff participation in safety communication and emergency management based on the characteristics of the copper mine industry. Therefore, no matter what kind of enterprise, management and human factors, such as enterprise security organization and employee participation, should be considered when conducting safety performance evaluation. The second is the evaluation or control of risk and so on.

According to the above analysis, the evaluation system adopted in this study for energy enterprises is composed of primary indicators and secondary indicators. First-level indicators are obtained from literature summary, and second-level indicators are obtained from detailed decomposition of first-level indicators, as shown in Table 1. "QN" stands for quantitative indicators, and "QL" stands for qualitative indicators.

3. **Establishment of Safety Performance Evaluation Model.**

In this research, BP neural network analysis method was combined with entropy and fuzzy comprehensive evaluation methods to evaluate enterprise safety performance. Specifically, index weights were measured with artificial neural networks and entropy method, and then, fuzzy comprehensive evaluation was developed.

3.1. **Measurement of training weights.**

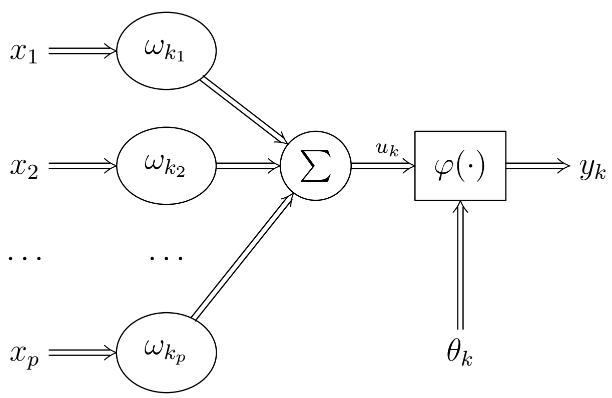

FIGURE 1. The structure of the developed artificial neural network

3.1.1. *Artificial neural network.* As shown in Figure 1, the structure of the developed artificial neural network could be divided into three parts; namely, signal input, summation and activation function. Signal input is expressed as the weighted value of each connection strength. The function of summation part is summing the value of all signal inputs. Activation function is used to limit neurons to a certain range, generally in the range of

TABLE 1. Safety performance index system

First-grade indicators	Second-grade Indicators	Analytical Method
Safety Awareness of Managers	Security Attitude of Managers Security Goals of Enterprise Enterprise Security Investment	QL QL QN
Safety Participation and Technical Capabilities of Employees	Safety Awareness of Employees Safety Technical Capabilities of Employees The Rate of Employees safe Behavior	QL QL QN
Corporate Security Organization and Security Training	The Status of The Security Organization Number of Safety Managers Proportion of Safety Training Effect of Safety Training	QL QN QN QN
Corporate Safety Culture	Safety System Culture Safety Material Culture Safety concept Culture	QL QL QL
Cecurity Goal Planning	Safety Goal Completion Rate Safety Plan Improvement	QN QL
Risk Assessment and Control	Risk assessment situation Rectification Rate of Hidden Danger	QL QN
Operating Environment and Equipment	The State of The Working Environment Safety of Operation Equipment Situation of Safety Protection Equipment Status of equipment Management	QL QN QN QL
Contingency Management	The Development of Accident Emergency Plan Emergency Plan Training Rate Status of Emergency Supplies Review and Improvement of Emergency Plan	QL QN QL QL
Accident Situation	Accident Rate Accident Loss Cost Casualties	QN QN QN

0 to 1 or -1 to 1. The three parts were expressed as **Equation 1**

$$\begin{cases} u_k = \sum_{k=1}^{p} w_{kj} x_j \\ v_k = u_k - \theta_k \\ y_k = \varphi(v_k) \end{cases} \tag{1}$$

where $x_j (j = 1, 2, \ldots, p)$ is input signal, $w_{kj} (j = 1, 2,)$is the weight of neuron k , u_k is combined result, θ_k is threshold, $\varphi(\cdot)$ is activation function and y_k is final output value.

Regarding the accuracy of evaluation results and the complexity of calculating process, activation function was expressed as a sigmoid function, as given in **Equation 2**.

$$\varphi(v_k) = \frac{1}{1 + e^{-\alpha v_k}} \tag{2}$$

3.1.2. *Determination of weight using BP neural network algorithm.* The procedure of determining weight using BP neural network algorithm was performed as following steps [16–18].

Step 1: Determination of the number of hidden layers Generally, networks with a few hidden layers could meet application requirements for normal circumstances. In this research, we chose the number of hidden layers as one. considering the number of indicators and the complexity of calculation process.

Step 2: Determination of the number of input layer units The number of input layer units represented node number of needing trained. In this study, the number of input layer units was adopted to be 28, which corresponded to second-grade safety performance index value after initialization.

Step 3: Determination of the number of hidden layer units The number of hidden layer units depended on problem complexity and was generally determined by empirical equations [13, 14]. In this work, due to calculation complexity, **Equation 3** was applied to determine the number of hidden layer units. Therefore, the number of hidden layer units was assumed to be 10.

$$M = \sqrt{n + m} + a \tag{3}$$

where M is the number of hidden layer units, n and m are the number of neuron units in input and output layers, respectively, and a is a constant value between 0 and 10.

Step 4: Determination of the number of output layer units. In this study, the number of first-grade indicators was 9 and that of output layer units was 9 (i.e. $k = 1, 2, \ldots, 10$).

Step 5: Selection of transfer function Activation function was considered as a sigmoid function. When output value was or, output layer could also be expressed as a sigmoid function. In this research, output value was not within the effective range of sigmoid function, and thus output layer was set to pure line-function with good scaling characteristics. Additionally, pure line-function could change the output value of sigmoid function to an arbitrary value.

Step 6: Calculation of output value According to BP neural network model, was expressed as **Equation 4**

$$y_k = m_k \bullet \left[1 + e^{-\alpha \sum_{j=2}^{p} w_{kj} x_j - \theta_k} \right]^{-1} + b_k \tag{4}$$

where x_j is input signal, w_{kj} is connection weight from k to j , and initial weight is randomly set within the range of 0 to 1, θ_k is critical value.

Step 7: Determination of index weight BP neural network describes the relationship between first-grade and the second-grade indicators. Further calculations were necessary to obtain specific weight relationships. In this study, correlation coefficient and correlation index were used for weight calculation.

Equation 5 presents the calculation equation of correlation coefficient.

$$r_{kj} = \sum_{k=1}^{p} w_{kj} \left(1 - e^{-w_{ki}}\right) / \left(1 + e^{-w_{ki}}\right) \tag{5}$$

where w_{kj} is weight value between input and hidden layer neurons and w_{ki} is weight coefficient between output and hidden layer neurons.

The relevant index could be obtained via $R_{kj} = |(1 - e^{-w_{ki}}) / (1 + e^{-w_{ki}})|$ and weight was calculated by $A_{kj} = R_{kj} / \sum\limits_{k=1}^{n} R_{kj}$ where n is the number of input layer units.

3.2. **Calculation of second-grade index weight by entropy weight method.** As discussed above, trained BP neural network could only be applied to obtain weight relationship between first-grade and second-grade indicators. Further analysis was required to determine the weight relationship of evaluation index to overall performance evaluation system.

Entropy method, a mathematical method to judge index dispersion degree, is generally applied for describing the influence degree of indicators on system evaluation effectiveness [19]. Based on first-grade and second-grade index weight relationship calculating method, entropy weight method was employed to describe the influence degree of refined second-grade indicators on safety performance evaluation systems and then the following fuzzy weight vector was obtained, as stated in **Equation 6**

$$\begin{cases} p_{ij} = \dfrac{x_{ij}}{\sum\limits_{i=1}^{n} x_{ij}} \\ e_j = -k \sum\limits_{i=1}^{n} p_{ij} \ln(p_i j) \\ k = \dfrac{1}{\ln n} \\ T_i = \dfrac{1 - e_j}{\sum\limits_{j=1}^{m} (1 - e_j)} \end{cases} \quad i = 1, 2, \ldots, n; j = 1, 2, \ldots, m \tag{6}$$

where x_{ij} represents the weight value of the $j-$th second-grade indicator to the i-th first-grade indicator, p_{ij} is the weight of x_{ij} to the sum of $j-$th column weights, e_j is the proportion value of index j , T_i and is the weight of each index.

3.3. **Fuzzy comprehensive evaluation.** Fuzzy mathematics is widely applied to solve fuzzy problems via mathematical tools. Accordingly, fuzzy and uncertain factors could be quantified by fuzzy comprehensive evaluation systems [20], which applies fuzzy relation synthesis principle to comprehensively explore the subordinate status of objects from multiple factors. The specific procedures of fuzzy comprehensive evaluation are not discussed here.

4. **Example Application.**

4.1. **Survey and data collection.** In this research, An energy enterprise – an oil refinery was adopted as an example for the verification of the rationality and validity of the proposed evaluation system.

4.2. **Collection method of indicators.** In this study, 28 indicators were applied for the evaluation of the oil refinery, in which 13 indicators were quantitative indicators. These 13 indicators could be directly obtained from the historical data of the company and on-site survey. The remaining 15 indicators were qualitative analysis indicator. Therefore, questionnaire surveys were performed in this work to obtain the values of these qualitative indicators. During questionnaire process, a stratified sampling method was applied and 120 questionnaires were distributed. Finally, 107 questionnaires were returned and the effective response rate was 93%.

4.3. **Classification of evaluation indicators.** As discussed above, quantitative indicators were measured by consulting materials of an enterprise, on-site surveys and statistics. Meanwhile, according to previous literatures [17–19] and corresponding implementation standards, quantitative indicators were then revised by the professionals of this industry. Finally, the scores and ratings of the 13 second-grade quantitative indicators were determined, which was divided into 5 levels.

For qualitative indicators, the critical value of the average score of each option was calculated for each indicator. According to the calculated critical values, second-grade qualitative indicators were divided into five levels described by quantitative intervals; namely good, better, general, poor and bad. Combining the classification of second-grade indicators and the opinions of experts, the final evaluation scales of first-grade indicators were obtained, as summarized in Table 2.

4.4. **Sample selection.** Before using BP neural network for the determination of indicator weights, it was necessary to determine training samples. The reliability of the model depended on the accuracy of the samples. Generally, the input spaces of the samples relied on the specific measurement values of evaluation indicators while the output spaces of the samples were determined by previous specific evaluation results or those obtained by other evaluation methods such as expert scoring and Delphi method [21–27].

Chen et al. [28] and Cui et al. [29] developed new sample selection methods. Specifically, the evaluation classifies were completed by expert review and then, training samples were determined according to specific classification thresholds. Another new method was based on survey data for the calculation of subordinative degrees, which were subsequently classified for the determination of learning samples and studying the rule of fuzzy classification systems. Both above methods avoided subjectivity and contradiction in sample output by expert scoring or Delphi method. Additionally, they also avoided the hysteresis of taking previous specific evaluation results as training samples, which were verified by empirical re-search. In this paper, training samples were determined based on the indicator classification threshold of 4.3.

4.5. **Weight training and weight calculation.**

4.5.1. *Weight training of BP network in combined model.* In the current research, the number of BP network input layer elements in combined model was 28 and those of output layer units and hidden layers were 9 and 1, respectively. The number of hidden layer units was 10. Activation function was a sigmoid function, while pure line-function was selected for the output layer. The input space of training samples comes from the first-grade indicators evaluation classification threshold, and the output space is the first-grade indicators evaluation classification results. The evaluation results of first-grade indicators from great to bad were represented as $1, 2, 3, 4, 5$, respectively. For example, the output result of nine first-grade indicators with good evaluation scale was $[1, 1, 1, 1, 1, 1, 1, 1, 1]$.

In addition, this investigation relied on classification threshold to select 35 data sets as training, verification and test samples. Meanwhile, Levenberg-Marquardt method was applied to train the network in order to improve convergence speed. , The training results obtained from Matlab2018b neural network toolbox are shown in Figures 2 and 3.

Figure 2 presents error surface gradient diagram. It was observed that the training, verification, and test sample errors were gradually decreased. After 54 iterations of training, training was completed with the error reaching a predetermined lower limit. Surface gradient error value was 0.046709. In the error histogram of Figure 3, it was clearly seen that

Table 2. Evaluation rating scale of first-grade indicators

First-grade Indicators	Second-grade Indicators	Analytical Method Good	Better	General	Poor	Bad
Safety awareness of managers X_1	Security Attitude of Managers X_{11}	$[4.2, 5.0]$	$[3.4, 4.0]$	$[2.6, 3.4]$	$[1.8, 2.6]$	$[1.0, 1.8]$
	Enterprise's Security Goals X_{12}	$[4.2, 5.0]$	$[3.4, 4.0]$	$[2.6, 3.4]$	$[1.8, 2.6]$	$[1.0, 1.8]$
	Enterprise Security Investment X_{13}	$[0.3, 0.4]$	$[0.2, 0.3]$	$[0.1, 0.2]$	$[0.05, 0.1]$	$[0, 0.05]$
Safety participation and technical capabilities of Employees X_2	Safety Awareness of Employees X_{21}	$[4.2, 5.0]$	$[3.4, 4.0]$	$[2.6, 3.4]$	$[1.8, 2.6]$	$[1.0, 1.8]$
	Safety Technical Capabilities of Employees X_{22}	$[4.2, 5.0]$	$[3.4, 4.0]$	$[2.6, 3.4]$	$[1.8, 2.6]$	$[1.0, 1.8]$
	Employee Unsafe Behavior Rate X_{23}	$[0, 0.60]$	$[0.60, 0.70]$	$[0.70, 0.80]$	$[0.80, 0.90]$	$[0.90, 1]$
Corporate Security Organization and Security Training X_3	The status of The Security Organization X_{31}	$[4.2, 5.0]$	$[3.4, 4.0]$	$[2.6, 3.4]$	$[1.8, 2.6]$	$[1.0, 1.8]$
	Number of Safety Managers X_{32}	> 15	$[10, 15]$	$[5, 10]$	$[2, 5]$	$[0, 2]$
	Proportion of Safety Training X_{33}	$[0.95, 1]$	$[0.85, 0.95]$	$[0.75, 0.85]$	$[0.65, 0.75]$	$[0, 0.65]$
	Effect of Safety Training X_{34}	$[0.95, 1]$	$[0.85, 0.95]$	$[0.75, 0.85]$	$[0.65, 0.75]$	$[0, 0.65]$
Corporate Safety Culture X_4	Safety System Culture X_{41}	$[4.2, 5.0]$	$[3.4, 4.0]$	$[2.6, 3.4]$	$[1.8, 2.6]$	$[1.0, 1.8]$
	Safety Material Culture X_{42}	$[4.2, 5.0]$	$[3.4, 4.0]$	$[2.6, 3.4]$	$[1.8, 2.6]$	$[1.0, 1.8]$
	Safety Concept Culture X_{43}	$[4.2, 5.0]$	$[3.4, 4.0]$	$[2.6, 3.4]$	$[1.8, 2.6]$	$[1.0, 1.8]$
Security Goal Planning X_5	Safety Goal Completion Rate X_{51}	$[4.2, 5.0]$	$[3.4, 4.0]$	$[2.6, 3.4]$	$[1.8, 2.6]$	$[1.0, 1.8]$
	Safety Plan Improvement	$[0.9, 1]$	$[0.8, 0.9]$	$[0.7, 0.8]$	$[0.5, 0.7]$	$[0, 0.5]$
Risk Assessment and control X_6	Risk Assessment Situation X_{61}	$[4.2, 5.0]$	$[3.4, 4.0]$	$[2.6, 3.4]$	$[1.8, 2.6]$	$[1.0, 1.8]$
	Rectification Rate of Hidden Danger X_{62}	$[0.96, 1]$	$[0.94, 0.96]$	$[0.92, 0.94]$	$[0.88, 0.92]$	$[0, 0.88]$
Operating Environment and Equipment X_7	The State of The Working Environment X_{71}	$[4.2, 5.0]$	$[3.4, 4.0]$	$[2.6, 3.4]$	$[1.8, 2.6]$	$[1.0, 1.8]$
	Safety of Operation Equipment X_{72}	$[0, 0.05]$	$[0.05, 0.1]$	$[0.10, 0.15]$	$[0.15, 0.20]$	$[0.20, 0.25]$
	Situation of Safety Protection Equipment X_{73}	$[0.90, 1]$	$[0.80, 0.9]$	$[0.70, 0.80]$	$[0.6, 0.7]$	$[0, 0.6]$
	Status of Equipment Management X_{74}	$[4.2, 5.0]$	$[3.4, 4.0]$	$[2.6, 3.4]$	$[1.8, 2.6]$	$[1.0, 1.8]$
Contingency Management X_8	The Development of Accident Emergency Plan X_{81}	$[4.2, 5.0]$	$[3.4, 4.0]$	$[2.6, 3.4]$	$[1.8, 2.6]$	$[1.0, 1.8]$
	Emergency Plan Training Rate X_{82}	$[0.95, 1]$	$[0.85, 0.95]$	$[0.75, 0.85]$	$[0.65, 0.75]$	$[0, 0.65]$
	Status of Emergency Supplies X_{83}	$[4.2, 5.0]$	$[3.4, 4.0]$	$[2.6, 3.4]$	$[1.8, 2.6]$	$[1.0, 1.8]$
	Review and Improvement of Emergency Plan	$[4.2, 5.0]$	$[3.4, 4.0]$	$[2.6, 3.4]$	$[1.8, 2.6]$	$[1.0, 1.8]$
Accident Situation X_9	Accident Rate X_{91}	$[0, 0.1]$	$[0.1, 0.2]$	$[0.2, 0.3]$	$[0.3, 0.4]$	$[0.4, 0.5]$
	Accident Loss Cost	$[0, 0.1]$	$[0.1, 0.2]$	$[0.2, 0.6]$	$[0.6, 0.8]$	> 0.8
	Casualties	$[0, 3]$	$[3, 5]$	$[5, 10]$	$[10, 15]$	> 15

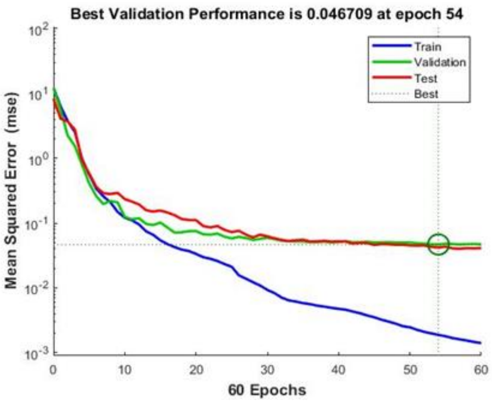

FIGURE 2. Error surface gradient map

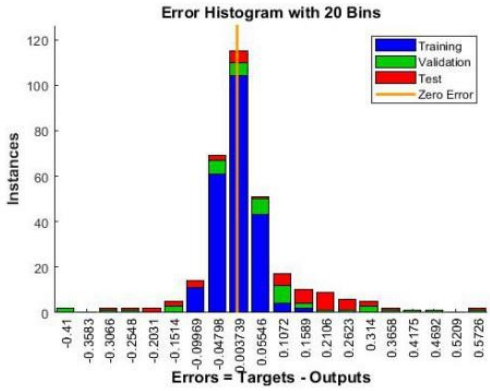

FIGURE 3. Error histogram

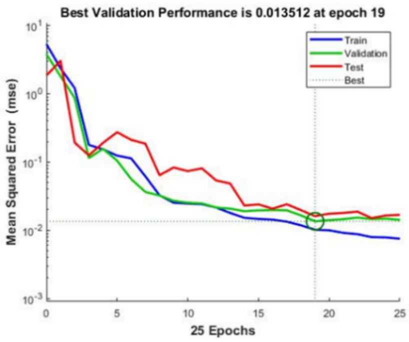

FIGURE 4. Error surface gradient map

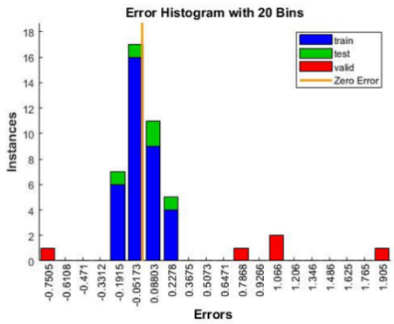

FIGURE 5. Error histogram

training, verification, and test sample errors were mainly concentrated in 0.003739, indicating that the developed training network had a certain degree of classification accuracy and provided better simulation results.

4.5.2. *Weight training for a single BP network.* In order to reveal the combined effect of BP neural network and entropy weight method, a single BP neural network was applied in this research to compare training results. Using the same 35 sets of data as the training, validation, and test samples, The Levenberg-Marquardt method is applied to train the network, and the results are shown in Figures 4 and 5:

Figure 4 shows that, after 19 iterations of training, error reached the predetermined lower limit and training was completed. Error surface gradient value was 0.013512. As was seen from Figure 5, training and test sample errors were mainly concentrated at about -0.05173 and the error distribution of verification sample was relatively discrete. It was seen that the combination of BP neural network and entropy weight method provided higher training accuracy and stability compared with using only BP neural network.

4.5.3. *Weight calculation by entropy weight method.* The weight of each second-grade indicator to the safety performance evaluation system was calculated by the entropy weight method, as summarized in Table 3.

Table 3. Second-grade indicator weight information

X_{11}	X_{12}	X_{13}	X_{21}	X_{22}	X_{23}	X_{31}	X_{32}	X_{33}	X_{34}	X_{41}	X_{42}	X_{43}	X_{51}
0.0255	0.0140	0.0486	0.0422	0.0362	0.0636	0.0362	0.0351	0.0452	0.0339	0.0191	0.0394	0.0202	0.0391
X_{52}	X_{61}	X_{62}	X_{71}	X_{72}	X_{73}	X_{74}	X_{81}	X_{82}	X_{83}	X_{84}	X_{91}	X_{92}	X_{93}
0.0255	0.0140	0.0486	0.0422	0.0362	0.0636	0.0362	0.0351	0.0452	0.0339	0.0191	0.0394	0.0202	0.0391

4.6. **Sensitivity analysis.**

4.6.1. *Single factor evaluation.* For single factor evaluations, scoring method is commonly applied to determine the subordinative degree of each factor. In order to alleviate the effects of subjective factors, percentages were applied for the determination of the subordinative degree of single factors.

According to the evaluation standard that has been formed, for quantitative indicators, the subordinative degree of any given evaluation indicator was considered to be 1, while those of other indicators were 0. Qualitative indicators were determined according to fuzzy statistical method. For example, questionnaires involved two questions for a survey on manager attitude. The subordinative degree of indicator for each evaluation element was determined by the average proportion of corresponding evaluation elements in the two questions. Subsequently, V_1 was one evaluation element of corresponding evaluation set V for question one. Also, the proportion of the people that presented V_1 evaluation result was V_1^0 . For question two, V_2 was one evaluation element of corresponding evaluation set V and the proportion of V_2 evaluation result was V_2^0 . Therefore, the subordinative degree of management attitude was obtained as $(V_1^0 + V_2^0)/2$.

4.6.2. *Fuzzy relation matrix.* According to the calculation method of fuzzy comprehensive evaluation [26,27], fuzzy relationship matrix between second-grade indicators and evaluation set was obtained as given in **Equation 7**

$$R = \begin{pmatrix} 0.0650 & 0.0695 & 0.1400 & 0.3220 & 0.4015 \\ 0 & 0 & 1 & 0 & 0 \\ 0.0650 & 0.0103 & 0.2150 & 0.4860 & 0.1310 \\ 0.0900 & 0.0776 & 0.2397 & 0.3087 & 0.2837 \\ 0.0840 & 0.0885 & 0.3410 & 0.3180 & 0.1680 \\ 0 & 0 & 1 & 0 & 0 \\ 0.0560 & 0.0930 & 0.1310 & 0.2520 & 0.4670 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0.0930 & 0.5510 & 0.2150 & 0.1400 & 0.1780 \\ 0.0560 & 0.0560 & 0.2240 & 0.5420 & 0.1210 \\ 0.0750 & 0.0470 & 0.5610 & 0.1400 & 0.1780 \\ 0 & 0 & 1 & 0 & 0 \\ 0.0470 & 0.1030 & 0.1400 & 0.5140 & 0.1960 \\ 0.0740 & 0.0840 & 0.3270 & 0.2100 & 0.2945 \\ 0 & 0 & 0 & 0 & 1 \\ 0.0930 & 0.0840 & 0.2430 & 0.4300 & 0.1500 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0.1310 & 0.0750 & 0.1210 & 0.1680 & 0.5050 \\ 0.0930 & 0.0370 & 0.1120 & 0.5230 & 0.2340 \\ 0 & 0 & 0 & 1 & 0 \\ 0.0650 & 0.0650 & 0.1870 & 0.2520 & 04300. \\ 0.1210 & 0.0470 & 0.1030 & 0.4860 & 0.2430 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{pmatrix} \tag{7}$$

4.6.3. *Multi-factor fuzzy comprehensive evaluation.* After normalization, comprehensive evaluation result vector of each level indicator was obtained. Based on the weights of second-grade indicators in safety performance evaluation system, the subordinative degree vector of safety performance was determined. Specific results are shown in Table 4:

TABLE 4. Subordinative degree vector of safety performance

	Good	Better	General	Poor	Bad
Subordinative degree vector	0.04088630	0.13527655	0.37245684	0.24954584	0.19718259

In order to quantify fuzzy comments, the scores of the fuzzy subsets of the comment set were measured based on hundred-mark system. The "good" score corresponded to 100 and "better" score indicated "80", while the "general" score was "60" and "poor" and "bad" scores corresponded to 40 and 20, respectively. According to $N_k, N_k = B_k S^T, S^T = [100, 80, 60, 40, 20]$, the grading system was obtained as shown in Table 5. Finally, specific scores of safety performance were calculated and the obtained results are shown in table 6.

TABLE 5. Subordinative degree vector of safety performance

	$90-100$	$80-90$	$60-80$	$40-60$	$20-40$
Score Grading	Good	Better	General	Poor	Bad

Table 6. Subordinative degree vector of safety performance

Score Grading	Score Value (approximate)
	51.2

4.7. **Results Analysis.** As shown in Table 6, safety performance score was 51.2. Consequently, the safety performance of the oil refinery was at "poor" level and needed to be improved.

Table 3 summarizes the second-grade indicators of the oil refinery, which indicated that several factors were of great importance, including security goals, safety awareness of employees, safety of equipment and their operating environment, emergency management, unsafe behavior of employees, and safety training. There-fore, the oil refinery l operators and managers should focus on above factors.

5. **Sensitivity analysis.** After combining BP network and entropy weight method, the quality of BP network training directly affected model weight calculation results. The effects of different factors on the performance of model were discussed in terms of the number of hidden layers, the number of training epochs and the proportion of training sets.

5.1. **Number of hidden layers.** The mean square error of the target was as assumed to be 0.001 and the maxi-mum number of misjudgment errors in the verification set was 6. By keeping other network parameters constant, the number of hidden layers was changed and the obtained experimental results are summarized in Table 7. With increasing the number of hidden layers by more than 3 layers, the number of misjudgment of trained BP network was gradually increased and iteration was terminated before mean square error reached the target.

Table 7. Experimental results of different hidden layers

Number of Hidden Layers	MSE	The Number of Epochs to Terminate The Iteration	Network Misjudgment
1	0.000973	54	0
2	0.000986	76	2
3	0.016122	22	6
4	0.002133	47	6

5.2. **Number of training epochs.** The maximum number of errors and iteration epochs in the verification set were changed while other network parameters remained constant. It was seen from Table 8 that with the increase of the number of iterative steps, the mean square error of training network was gradually decreased and the number of misjudgments in the verification set was first decreased and then increased.

Table 8. Experimental results under different iteration steps

Iteration Epochs	MSE	Network Misjudgment
50	0.00201	10
100	0.000339	5
200	0.000102	3
300	$2.4e-05$	3
500	$4.71e-05$	10

5.3. **Proportion of training set.** Table 9 summarizes network performance variations under different training sets. It was found that by increasing the proportion of training set in the sample, the number of iterative epochs required by training network to achieve the target mean square error was also increased and the number of misjudgments in verification set was decreased.

TABLE 9. The changes of network performance under different training sets.

Proportion of Training Set	Iteration Epochs	Network Misjudgment
50%	55	40
60%	60	10
70%	69	2
80%	75	0

6. **Conclusions.** (1) This study summarized the evaluation methods of previous research works on safety performance evaluation systems. Current safety performance evaluation methods have certain limitations. For example, evaluation results are subjective. In addition, few studies have considered complex relationships among different indicators during evaluation process. This investigation proposed a new evaluation method combining the self-adaptability of BP neural network, objectivity of entropy method and fuzziness of fuzzy comprehensive evaluation, which could effectively solve above problems.

(2) Based on the existing principles for establishing a safety performance indicator system and results reported in previous literatures, a second-grade safety performance evaluation system of energy enterprises was developed in this study. BP neural network and entropy weight method were combined for the calculation of relationship weights among layer indicators and the weight of safety performance evaluation, which was applied for the modification of fuzzy comprehensive evaluation method.

(3) Using the improved evaluation method to evaluate the safety performance of an energy enterprise, it is concluded that the safety performance of the refinery is poor. Using the safety performance evaluation model proposed in this paper, it can be concluded that the oil refinery had to improve the following aspects: safety objectives, safety awareness of employees, working environment and equipment safety, emergency management, unsafe behaviors of employees and safety training.

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REFERENCES

[1] R.-C. Li, and Y. Tang, "Three Orientations of Integrated Development and Safety Governance:An Analysis Based on the Field of Production Safety," *Journal of Guangzhou University(Social Science Edition)*, vol. 21, no. 04, pp. 33-42, 2022 .

[2] T.-Y. Wu, Y.-Q. Lee, Ch.-M. Chen, Y. Tian, N. A. Al-Nabhan, "An enhanced pairing-based authentication scheme for smart grid communications," *Journal of Ambient Intelligence and Humanized Computing*, 2021, https://doi.org/10.1007/s12652-020-02470-2.

[3] L.J. Bellamy, "A literature review on safety performance indicators supporting the control of major hazards," RIVM Report 620089001/2012, National Institute for Public Health and the Environment, Ministry of Health, Welfare and Sport, The Neth-erlands.

[4] K.T. Ranveig, H. Jan, "Safety diagnosis criteria development and testing", *Safety Science*, vol. 41, no. 7, pp. 575 -590, 2013 .

[5] A. Bodil, "Implementation and evaluation of the safety element, method at four mining sites," *Safety Science*, vol. 31, no. 3, pp. 231- 264 , 1999.

[6] N.-N. Zhao, Y.-T. Zhao, "Research on the relationship between dispatch resource management and safety performance based on factor analysis," *Mathematics in Practice and Theory*, vol. 47, no. 20, pp. 29-36, 2017.

[7] J. Xia, Z. Ma , X.-F. Dai , Z.-K. Hu, "Efficiency Model of Intelligent Cloud Based on BP Neural Network," *Computer Science*, vol. 49, no. 02, pp. 353-367, 2022 .

[8] S.-M. Zhang, X. Su, X.-H. Jiang, M.-L. Chen, T.-Y. Wu, "A traffic prediction method of bicycle-sharing based on long and short term memory network," *Journal of Network Intelligence*, vol. 4, no. 2, pp. 17-29, 2019

[9] L. Chai, L. Ren, K. Gu, J.-X. Chen, B. Huang, Q. Ye, W. Cao, "Vision sensing based intelligent detection of surface defect and its industrial applications," *Computer Integrated Manufacturing Systems*, vol. 28, no. 07, pp. 1996-2004, 2022.

[10] L.-C. Jiao, Q.-G. Sun, Y.T. Yang, Y.-T. Yang, Y.-X. Feng, X.-F. Li, "Development,Implementation and Prospect of FPGA-Based Deep Neural Networks," *Chinese Journal of Computers*, vol. 45, no. 3, pp. 441-471, 2022.

[11] C.-M. Chen, L.-L. Chen, Y.-Y. Huang, S. Kumar, J. M.-T Wu, "Lightweight Authentication Protocol in Edge-based Smart Grid Environment", *EURASIP Journal on Wireless Communications and Networking*, 2021

[12] IAEA-TECDOC-600. "Numerical indicators of nuclear power plant safety performance," Vienna: IAEA, 1991.

[13] S.T. Ng, K.P. Cheng, R.M. Skitmore, "A framework for evaluating the safetyperformance of construction con-tractors," *Building and Environment*, pp. 1347-1355, 2005 .

[14] C.-J. Wang, G. Fu, "Discussion on safety performance index," *Mining Research and Development*, vol. 27, no. 6, 2007.

[15] C. Chen, "Research on safety management performance evaluation of copper mine enterprises," *Management World*, no.11, pp. 184-185, 2010.

[16] H.-X. Fu, H. Zhao, MATLAB Neural Network Application Design, 1st ed. *Machinery Industry Press*, Beijing, China, pp. 83-97, 2010.

[17] H.-J. Sun, X.-H. Wang, "Application of artificial neural network to determine the weight of evaluation index," *Journal of Shandong University of Science and Technology (Natural Science Edition)* , no. 03, pp. 84-86, 2001.

[18] F.-G. Zhang, T.-Y. Wu, Y.-O. Wang, R. X., G.-Y. Ding, P. Mei, L.Y. Liu, "Application of quantum genetic optimization of LVQ neural network in smart city traffic network prediction", *IEEE Access*, vol. 8, 104555-104564, 2020

[19] H.-Y. Zhao, B.-Q. Hu, "Evaluation of Guangxi Land Ecological Security Based on Entropy Method, " *Journal of Guangxi Normal University (Natural Science Edition)*, vol. 36, no. 1, pp. 127-131, 2019.

[20] W.-R. Cai "Enterprise employee performance evaluation based on fuzzy comprehensive evaluation method," *Value Engi-neering*, vol. 38, no. 12, pp. 46-48, 2019.

[21] L.-Q. Tao, "Research on Enterprise Safety Performance Evaluation Index System," Ph.Mdissertation, Capital University of Economics and Business, 2009.

[22] Q.-W. Tan, Z.-X. Duan, Y. Dong, S. Du, Q.-N. Liu, Y. Gao, "Research on a new method of systematic production safety accident classifi-cation," *Industrial Safety and Environmental Protection*, vol. 44, no. 4, pp. 10-13+17, 2018.

[23] G.-H. Qiao, "Research on Comprehensive Evaluation and Early Warning Management Model of Coal Mine Safety, " Ph.D. dissertation, China University of Geosciences, 2013.

[24] Y.-J. Liu, Y.-H. Ren, J.-J.Ren , D.-M. Huang, Z.-C. Tian, "Performance evaluation of coal mine safety management based on BP neural net-work," *Coal Engineering*, no. 2, pp. 135-137+140, 2013.

[25] S.-L. Zhang, W.-Q. Wang, "Coal mine safety performance evaluation model based on BP neural network," *Coal Technology*, vol. 36, no. 10, pp. 321-323, 2017 .

[26] W.-J. Zhao , M.-D. Xu, J.-J. Zhang, S.-F. Qi, "Application of BP neural network in mine ecological safety assessment," *Coal Technology*, vol. 38, no. 1, pp. 172-175, 2019 .

[27] B. Deng, R. Song, "Research on safety evaluation method based on BP neural network," *Safety and Environmental Engineering*, no. 02, pp. 61-64, 2005.

[28] W. Chen, "Research on Safety Performance Evaluation Model and Its Application in Enterprise S," Ph.M dissertation, University of Nanhua, Hengyang City, 2015.

[29] J.-L. Cui, "Performance evaluation of coal mine safety management based on fuzzy neural network," *Electronic Design Engineering*, vol. 24, no. 14, pp. 63-66, 2016.

[30] X.-D. Liu, Z.-W. Wang, S.-T. Zhang, H. Garg, "An approach to probabilistic hesitant fuzzy risky multi-attribute decision making with unknown probability information," *International Journal of Intelligent Systems*, vol. 36, no. 10, pp. 5714-5740, 2021.

[31] X.-D. Liu, Z.-W. Wang, S.-T. Zhang, H. Garg, "Novel correlation coefficient between hesitant fuzzy sets with application to medical diagnosis, " *Expert Systems with Applications*, No. 183: pp. 115393, 2021.