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Research Article

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Supply chain performance evaluation model for integrated circuit industry based on fuzzy analytic hierarchy process and fuzzy neural network

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Abstract: To foster the advancement of telecommunications enterprise supply chains and facilitate their transition toward global market competitiveness, the author advocates for a novel performance evaluation framework tailored for the integrated circuit industry supply chain. This framework integrates the fuzzy analytic hierarchy process and fuzzy neural network methodologies to devise a comprehensive supplier performance assessment model. Leveraging extensive historical supplier data, the author employs MATLAB's neural network toolbox for model training and simulation. The results indicate that the error value output after running the validation sample is relatively small. This indicates that the model can be effectively applied to the performance evaluation of common integrated circuit product suppliers in CM company. According to the performance results of the model application, all participating suppliers have performance scores greater than 0.7, indicating that in the supply and service process of butterfly integrated circuit products, the performance evaluation scores of each supplier meet the requirements of qualified suppliers, among them, suppliers DS1, DS8, and DS9 with a comprehensive performance score greater than 0.8 are relatively excellent suppliers. The model's effectiveness and accuracy have been confirmed, demonstrating its practical applicability to CM Company. Moreover, its insights provide valuable guidance for establishing supplier performance evaluation systems across various product categories within telecommunications enterprises.

Keywords: supplier performance evaluation, fuzzy analytic hierarchy process, fuzzy neural network, evaluation model

1 Introduction

In today's closely connected global economy, the integrated circuit industry has become the core pillar of the information technology field. With this trend, the emerging management model of supply chain management has also emerged, and it has quickly been widely used in the industry [1,2]. However, since the supply chain of the integrated circuit industry involves multiple complex and changeable links, such as raw material procurement, manufacturing, packaging testing, and logistics and distribution, there is a high degree of uncertainty and ambiguity between the links, which makes supply chain management face many challenges [3]. Traditional supply chain performance evaluation methods often rely too much on the subjective judgment of

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experts or precise quantitative indicators, making it difficult to comprehensively and objectively reflect the true situation and potential risks of the supply chain. To this end, this study proposes to introduce the Fuzzy analytic hierarchy process (FAHP), which is an effective tool that performs well in dealing with complex decision-making problems and uncertainty factors. By integrating the theories and methods of fuzzy mathematics, FAHP can fully consider various vague and uncertain factors in the evaluation process, thereby improving the accuracy and practicality of the evaluation. In addition, this research also focuses on constructing a performance evaluation model of the supply chain of the integrated circuit industry that combines fuzzy hierarchical analysis methods and fuzzy neural networks (FNNs) [4,5]. The model will closely integrate the characteristics of the supply chain and the actual needs of performance evaluation, and establish a multi-level and all-round evaluation index system through in-depth analysis of the key factors affecting the performance of the supply chain. We hope that through this model, we can provide enterprises with more scientific and accurate supply chain performance evaluation methods, and help enterprises stand out in the fierce market competition.

The main innovation point of this work is to construct a new model for the performance evaluation of the supply chain of the integrated circuit industry. The model combines fuzzy hierarchical analysis (FAHP) with FNNs to deal with complexity, high uncertainty, and ambiguity in the supply chain. Traditional performance evaluation methods are limited by excessive dependence on accurate data or subjective judgment, and it is difficult to fully reflect the true situation and risks of the supply chain. The FAHP method used in this work has significant advantages in dealing with complex decision-making and uncertainty. It can fully consider the fuzzy factors in the evaluation process, thereby improving the accuracy and practicality of the evaluation. In addition, through the combination with FNNs, the model can use historical data for self-learning and optimization, and realize intelligent evaluation of supply chain performance. This innovative method not only breaks through the limitations of traditional evaluation methods but also provides enterprises with a more scientific and objective performance evaluation tool to help enterprises more accurately identify the advantages and disadvantages of the supply chain, and provide strong support for decision-making optimization.

2 Literature review

He and Zhu developed a model for selecting regional strategic emerging industries. They investigated the geographical distribution of these industries in Sichuan Province using ArcGIS. Furthermore, they established a strategic roadmap for prioritizing the development of emerging industries within the province. This was achieved by synergizing the fuzzy comprehensive evaluation method with the analytic hierarchy process (AHP), enabling a nuanced assessment and ranking of strategic sectors [6,7]. Vafadarnikjoo et al. identified the obstacles to the adoption of blockchain technology in the manufacturing supply chain using the neutrophil analysis hierarchical process, and proposed an action plan framework for verifying blockchain technology in developing economies, which can help industry managers and experts in emerging economies more clearly identify obstacles to the implementation of blockchain technology and show them how to successfully adopt blockchain technology in their supply chains [8]. Wang and Wai introduced a cutting-edge method called the Adaptive Fuzzy Neural Network Power Decoupling (AFNNPD) strategy. This approach is designed to regulate virtual synchronous generators (VSGs) within microgrids using online training techniques. They began by investigating the power coupling mechanisms in VSG control within microgrids and then crafted a system dynamics model for their innovative power decoupling method. Following this, they devised a fully sliding mode control (TSMC) strategy specifically for power decoupling. This choice was based on its recognized strengths in robustness and swift dynamic response [9]. Ben-Daya et al. explored the role of the internet and its impact on supply chain management through extensive literature review. Important aspects of the Internet of Things in supply chain management include the definition of the Internet of Things, the main promoters of the Internet of Things technology, and various supply chain management processes and applications [10]. Mathew et al. delved into the interplay between uncertainty and flexibility in assessing supply chains through modeling. Their findings underscored that overlooking these interrelations might result in inaccurate evaluations of supply chain effectiveness. The influence of uncertainty and flexibility on supply chain variability fosters numerous dynamic interactions, posing intricate challenges in appraising the effects of supply chain enhancements on overall system performance [11].

3 Research methods

3.1 Collection and organization of model data

Suppliers can be classified into strategic suppliers, preferred suppliers, proprietary product suppliers, and general suppliers based on the importance of the purchased products and the size and size of the purchased products [12]. The company can use the Karajak model to classify suppliers, as shown in Figure 1.

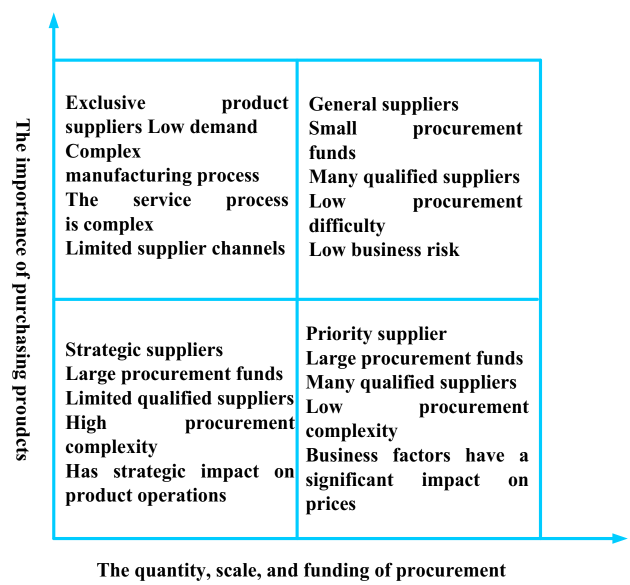

Figure 1: Karajak matrix. Source: Created by the authors.

The author has established a supplier evaluation index system for common integrated circuit products of CM Company, as shown in Figure 2.

After determining the evaluation index system of CM Company, the authors collected data from 18 common integrated circuit product suppliers of CM Company. The collected data are mainly derived from the network, which are collected and collated through the public data of the CM company on the network, thus obtaining the data of the basic index sample of the 18 CM company suppliers. The commonly used normalization methods include the extremum method and the sum method [13–16].

The calculation formula for the maximum value method is as follows:

$$\hat{x} = \frac{x_i - x_j}{x_{\min\max} - x_{\min}}. \tag{1}$$

The calculation formula for the sum method is as follows:

$$\hat{x} = \frac{x_i}{\sum_{i=1}^{n} x_i}. \tag{2}$$

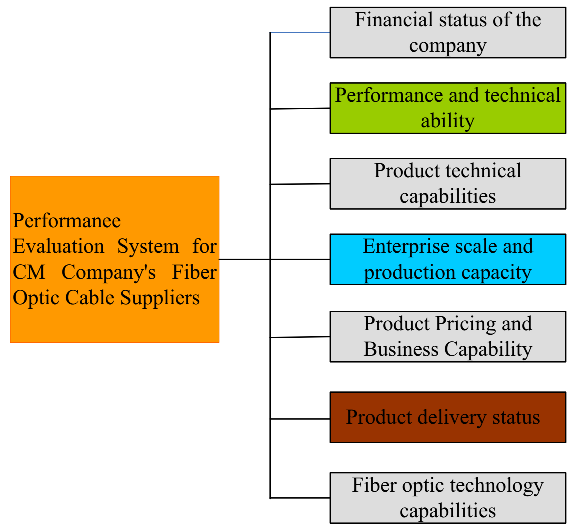

Figure 2: Distribution of evaluation system indicators. Source: Created by the authors.

The authors used the maximum value method to normalize the data values of 18 CM company supplier basic indicator samples collected in the early stage, selecting 15 as training samples and the remaining 3 as testing samples. The data of the standardized training samples are shown in Table 1.

Table 1: Normalized sample data

	S1	S2	S3	...	...	S14	S15
X1	1	1	1	...	...	1	1
X2	1	1	1	...	...	1	1
X3	0.804	0.807	0.773	......	...	0.781	0.828
X4	0.822	0.814	0.822	...	...	0.822	1
X5	1	0.802	0.780	...	...	0.175	0.15
X6	1	1	0.883	...	...	0.387	0.617
X7	0.8	0.8	0.7	...	...	0.7	0.5
X8	1	1	0.75	...	...	0.144	0.206
X9	1	1	1	...	...	1	0.208
X10	1	1	1	...	...	1	0.483
X11	1	1	1	...	...	1	0.172
X12	1	1	1	...	...	1	0.718
X13	1	1	1	...	...	1	1
X14	1	1	0.803	...	...	1	0.107
X15	1	1	1 .000	...	...	1	1
X16	1	1	1	...	...	1	1
X17	1	0.8	0.8	...	...	0.64	0.676
X18	1	1.000	1	...	...	1	1
X19	1	1	1.000	...	...	1	0.7
X20	0.866	0.852	0.834	...	...	0.782	0.78
X21	0.835	0.826	0.801	...	...	0.754	0.765
X22	0.881	0.877	0.864	...	...	0.845	0.857
X23	0.683	0.686	0.682	...	...	0.723	0.731

Based on the past supply history and performance evaluation indicators of common integrated circuit suppliers in CM company, and based on the evaluation indicators mentioned by the authors, combined with the evaluation opinions of previous supplier review experts, the performance scores of suppliers S1 to S15 are obtained as the expected output values of the model sample. Combined with the company's internal evaluation records and the subjective evaluation opinions of previous supplier evaluation experts, each index is scored or rated. Finally, the performance scores of each supplier were synthesized by weighted average or other statistical methods and were used as the expected output value of the model sample for subsequent model training and validation, as shown in Table 2.

Table 2: Normalized sample expected values

Number	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15
Output value	0.878	0.866	0.852	0.848	0.846	0.844	0.833	0.830	0.823	0.823	0.823	0.806	0.803	0.801	0.804

3.2 FAHP

3.2.1 Process method

tThe FAHP combines the advantages of the traditional AHP and fuzzy logic to deal with the uncertainty of decision-makers by using a fuzzy numerical value. Constructing a fuzzy consistency judgment matrix and fuzzy priority calculation can make the decision-making process more flexible and adapt to the complex real scene. The FAHP effectively deals with the fuzziness in human judgment and converts the results into a clear decision basis through de-fuzzification technology, to help decision-makers make more reasonable and reliable choices.

The key to the FAHP is to construct a fuzzy consistency judgment matrix, which considers the possible fuzziness that decision-makers may have when judging the relationships between levels. Hierarchical analysis (AHP) is a systematic decision analysis method. It forms a multi-level analytical structure model by dividing the complex decision problem into different constituent factors and combining factors at different levels according to the correlation between factors. In addition, the implementation process of the FAHP is relatively simple and fast, allowing decision-makers to complete the entire analysis process more quickly and make effective decisions. The detailed steps are depicted in Figure 3:

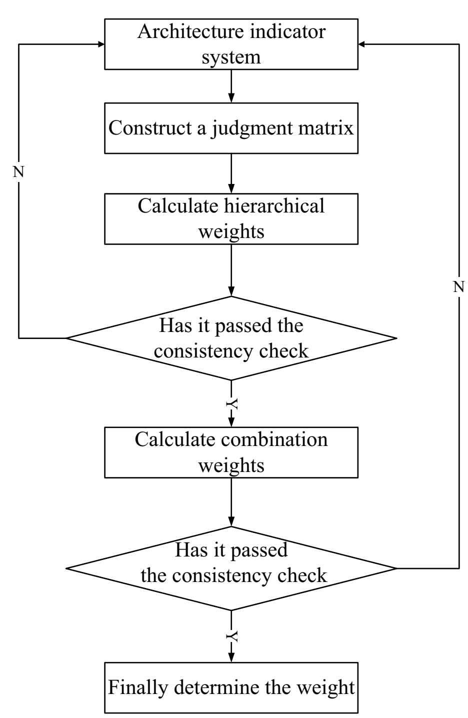

Figure 3: Flow chart of FAHP. Source: Created by the authors.

3.2.2 Definition of fuzzy judgment matrix

3.2.2.1 Definition of fuzzy matrix

For matrix $B = (b_{ij})_{m\times n}$, if it conforms to $0 \le b_{ij} \le 1(i = 1, 2, \ldots, m; j = 1, 2, \ldots, n)$, it is called a fuzzy matrix.

The definition variables of the fuzzy matrix are explained in Table 3.

Table 3: Definition variables of fuzzy matrix

Sequence	Variable	Meaning
1	B	Fuzzy matrix
2	b_{ij}	Elements of matrix B
3	m	The number of rows of the fuzzy matrix
4	n	The number of columns of a fuzzy matrix
5	$0 \le b_{ij} \le 1$	Conditions

3.2.2.2 Definition of fuzzy complementary judgment matrix

Recognizing that all factors are qualitative, mathematical tools cannot be directly applied for calculation without preprocessing methods. Consequently, completing the model solution becomes unattainable, and understanding the relationships among various factors proves challenging. This facilitates a more structured approach to factor assessment and aids in elucidating their relative significance within the model, a fuzzy judgment matrix $A = (a_{ij})_{m\times n}$ will be obtained. If the obtained matrix meets the requirements of equation (3), it is called a fuzzy complementary judgment matrix [17,18].

$$\begin{aligned} a_{ii} &= 0.5(i = 1, 2, \ldots, n) \\ a_{ii} + a_{ij} &= 1(i = 1, 2, \ldots, n)^{\cdot} \end{aligned} \tag{3}$$

3.2.2.3 Establishing weight judgment matrix

In the FAHP, it is necessary to manually assign weights to each element for the first time. Although this allocation is subjective and may have some errors, it can be reduced by listening to expert advice and searching for sufficient information. By using a comparison scale table, the fuzzy judgment matrix of equation (4) can be obtained, which is used to express the fuzzy relationships between different elements.

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix}. \tag{4}$$

By establishing the above judgment matrix and using the 1–9 scaling method, the relationship between various indicators can be obtained. Additionally, it is apparent that the matrix possesses the following mathematical properties:

$$\begin{aligned} a_{ij} &> 0, \\ a_{ij} &= \frac{1}{a_{ji}}, \\ a_{ij} &= 1. \end{aligned} \tag{5}$$

From the above properties, it can be inferred that only the upper or lower triangular elements need to be judged. $a_{\mathrm{Ad}j}$ represents the importance of comparing elements i and j.

3.2.3 Weight calculation

Once the feature vector W is computed, it is crucial not to directly employ it, as doing so could result in considerable errors and contravene the scientific principles underlying the model construction. In the hierarchical analysis (AHP), although the eigenvector W represents the relative importance weight between the factors, there may be errors in directly using the original calculated eigenvectors. This is because the judgment matrix is constructed based on the subjective judgment of the decision maker and may be inconsistent. The direct use of unverified and corrected feature vectors as weights may introduce bias and affect the scientificity and accuracy of the final decision.

Therefore, preprocessing is also necessary to ensure that it meets $\sum_{i=1}^{n} W_i = 1$ requirements, using this approach ensures the accurate acquisition of weight data for each indicator. Numerous methods exist for determining eigenvectors, including geometric averaging, arithmetic averaging, and eigenvalue methods, among others.

3.2.4 Consistency check

The process of selecting evaluation indicators initially relies on methods like expert consultation and online research, thus inherently containing a notable degree of human subjectivity. At present, the process of selecting the evaluation index of the fuzzy level analysis method relies more on the systematic construction strategy and rigorous logical analysis. It combines the professional knowledge and experience judgment of experts and also uses quantitative models to deal with uncertainty and ambiguity, weakening the influence of a single subjective judgment. This process emphasizes the scientific classification and hierarchical division of the evaluation indicators and handles the complex evaluation relationship through fuzzy mathematical theory to ensure that the evaluation process is more objective, scientific, and comprehensive. Therefore, after obtaining $\lambda_{\max}$, consistency testing is required to reduce errors and improve the accuracy of the results [19]. The specific inspection method is as follows.

Calculate the consistency index CI as follows:

$$\mathrm{CI} = (\lambda_{\max} - n)/(n - 1) \quad a_{ij} = 1. \tag{6}$$

Calculate the consistency ratio CR as follows:

$$\mathrm{CR} = \mathrm{CI}/\mathrm{RI}. \tag{7}$$

When the CR falls below 0.1, falling within the acceptable range defined by academic standards, it indicates that the construction of the matrix adheres to the principles and is suitable for practical research applications. Naturally, a smaller CR signifies a higher level of consistency between the judgment matrix and the decision objective.

3.3 FNN

3.3.1 Introduction to FNNs

Fuzzy theory and artificial neural networks are two active parts in the fields of artificial intelligence and intelligent computing in recent years. The effective combination of fuzzy theory and artificial neural networks can complement each other and leverage their respective advantages [20,21]. Fuzzy theory is good at handling uncertainty and fuzzy information, while artificial neural networks are good at learning complex nonlinear mapping relationships. After combination, it can not only process fuzzy data efficiently but also optimize the decision-making process through self-learning to improve the adaptability and intelligence level of the system, to show stronger ability and flexibility in the decision-making of complex problems. In essence, the FNN stands out as a superior theoretical framework that seamlessly integrates fuzzy theory with artificial neural networks, leveraging the strengths of both methodologies.

3.3.2 Takagi–Sugeno (T–S) model for fuzzy systems

Many literatures show that there are two kinds of fuzzy models widely used in fuzzy systems at present: (1) Mamdani model representation is the standard model representation of fuzzy systems, and the consequent of Mamdani model fuzzy rules is a fuzzy set of outputs; (2) The T–S model of fuzzy systems represents that, compared to the Mamdani model, the fuzzy rule consequence of the T–S model is a function of input language variables and a linear combination or constant of output variables. Among them, when it is a linear combination, it is the first-order T–S model representation; when it is a constant, it represents the zero-order T–S model [22]. For the purpose of better comparative research with FNN models, the authors select the T–S model of fuzzy systems to establish a FNN model for evaluating the risk of industrialization of patent technology in universities. Here the network structure and learning algorithm of T–S model in fuzzy systems are briefly introduced.

The fuzzy rule consequence of the T–S model is a linear combination of input variables, i.e., Rj; If x_1 is A_1^j, x_2 is A_2^j, and x_n is A_n^j, then

$$y_j = p_{j0} + p_{j1}x_1 + p_{j2}x_2 + \ldots + p_{jn}x_n\left(j = 1, 2, 3, \ldots, m; m \leq \prod_{i=1}^{N} m_i\right). \tag{8}$$

Equation (9) illustrates that the output of a fuzzy system is derived from the weighted average of the outputs generated by each rule.

$$y = \frac{\sum_{j=1}^{m} \alpha_j y_j}{\sum_{j=1}^{m} \alpha_j} = \sum_{j=1}^{m} \vec{\alpha}_j y_j, \tag{9}$$

where $\vec{\alpha}_j = \frac{\alpha_j}{\sum_{i=1}^{m} \alpha_i}$ (α_j represents the applicability of each rule).

3.3.3 Learning algorithms for FNNs

We can first determine the fuzzy number of input components based on actual situations and expert knowledge. Under these conditions, the FNN parameters that need to be learned include not only the connection weight $p'_{ji}(j = 1, 2, \ldots, m; i = 1, 2, \ldots, n; l = 1, 2, \ldots, r)$ of the posterior networkbut the parameter values of the membership functions for each node in the second layer of the antecedent network also need to be determined [23].

Let the error function be as follows:

$$E = \frac{1}{2}\sum_{i=1}^{r} (t_i - y_i)^2, \tag{10}$$

where t_i and y_i represent the expected output and actual output, respectively. Below is the learning algorithm for parameter p_{ji}^1. Similar to the derivation of the BP algorithm, according to the chain rule and Delta learning rule, there are the following equations:

$$\frac{\partial E}{\partial p_{ji}^l} = \frac{\partial E}{\partial y_l}\frac{\partial y_l}{\partial y_{lj}}\frac{\partial y_{lj}}{\partial p'_{ji}} = -(t_l - y_l)\bar{\alpha}_j x_i, \tag{11}$$

$$p_{ji}^1(k+1) = p_{ji}^1(k) - \beta\frac{\partial E}{\partial p_{ji}^1} = p_{ji}^1(k) + \beta(t_l - y_l)\bar{\alpha}_j x_i, \tag{12}$$

where $j = 1, 2, \ldots, m; i = 1, 2, \ldots, n; l = 1, 2, \ldots, r.$

Taking the Gaussian membership function as an example, this study explores the learning problem of its center σ_{ij}.

It is evident that the simplified structure closely resembles the architecture of the FNN based on the standard model. When the connection weight $y_{ij} = W_{ij}$ of the last layer is set, the results obtained by the standard model (Mamdani model) of the fuzzy system can be borrowed, as shown in equations (15)–(18).

$$\delta_i^{(5)} = t_i - y_i (i = 1, 2, \ldots, n), \tag{13}$$

$$\delta_j^{(4)} = \sum_{i=1}^{r} \delta_i^{(5)} y_{ij} (j = 1, 2, \ldots, m), \tag{14}$$

$$\delta_j^{(3)} = \delta_j^{(4)} \sum_{\substack{i=1\\i=1}}^{m} \alpha_i / \left(\sum_{i=1}^{m} \alpha_i \right)^2 (j = 1, 2, \ldots, m), \tag{15}$$

$$\delta_{ij}^{(2)} = \sum_{k=1}^{m} \delta_k^{(3)} s_{ij} e^{\frac{(x_1 - c_{ij})}{\sigma_{ij}^2}} (i = 1, 2, \ldots, n;\ j = 1, 2, \ldots, m), \tag{16}$$

where if the cancellation operation is used, then it is an input to the rule node; otherwise, it is not. Finally, the following equations are obtained:

$$\frac{\partial E}{\partial c_{ij}} = -\delta_{ij}^{(2)} \frac{2(x_i - c_{ij})}{\sigma_{ij}^2}, \tag{17}$$

$$\frac{\partial E}{\partial \sigma_{ij}} = -\delta_{ij}^{(2)} \frac{2(x_i - c_{ij})^2}{\sigma_{ij}^2}, \tag{18}$$

$$c_{ij}(k + 1) = c_{ij} - \beta \frac{\partial E}{\partial c_{ij}}, \tag{19}$$

$$\sigma_{ij}(k + 1) = \sigma_{ij} - \beta \frac{\partial E}{\partial \sigma_{ij}}, \tag{20}$$

where $\beta > 0$ is the learning rate, $i = 1, 2, \ldots, n;\ j = 1,2, \ldots, m$

For the neural network model introduced above, when given an input, only a small number of elements in the $\alpha = [\alpha_1, \alpha_2, \ldots, \alpha_m]^T$ of the third layer of the antecedent network are greater than 0, and most of the other elements are either 0 or close to 0. Therefore, in the above network, the mapping from input x to membership vector a is very similar to the nonlinear mapping of the radial basis function neural network [24].

3.4 Revision of FNN model

3.4.1 Learning rate

The learning rate dictates the extent of adjustment in weights induced by each training session. By sequentially setting the learning rate parameters net.trainParam.lr = 0.01, 0.02, 0.03, 0.04, 0.05, 0.06, 0.07, 0.08, 0.09, and 0.1 in the programming language, the FNN model is repeatedly debugged and trained after setting the corresponding learning rate value each time. In this experiment, the value of the learning rate is determined by step-by-step testing and evaluation of different learning rates. The selection of these parameters is based on common machine learning practices and is designed to cover a range of low to high learning rates to observe the impact of each learning rate on the model's training performance. The training data are shown in Table 4 and Figure 4.

Table 4: Training results corresponding to the number of hidden layer nodes

Learning rate	Mean squared error	Training steps
0.01	0.00101	166
0.02	0.00250	160
0.03	0.00207	107
0.04	0.00321	100
0.05	0.00248	60
0.06	0.00334	101
0.07	0.00282	104
0.08	0.00501	44
0.09	0.00278	116
0.1	0.00845	110

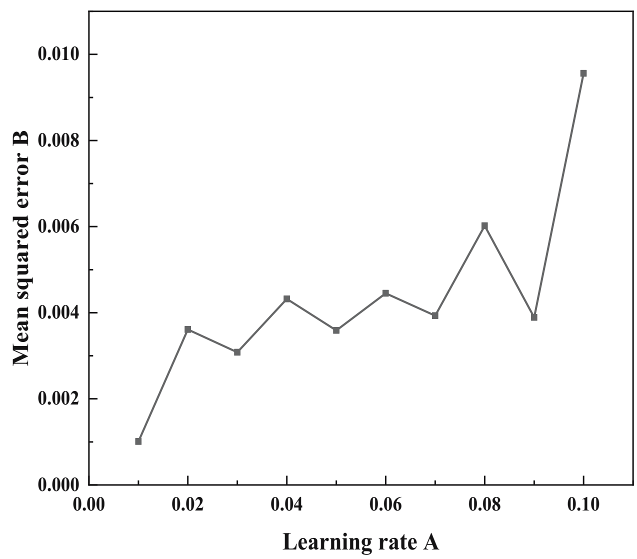

Figure 4: Error corresponding to the number of hidden layer nodes. Source: Created by the authors.

As shown in Figure 4, it can be observed that the training performance of the FNN model at different learning rates shows obvious differences. First of all, although a lower learning rate (such as 0.01) can achieve a lower mean square error, more training steps are required, which indicates that the learning process is slower. With the increase in the learning rate, the training steps are significantly reduced, indicating that the convergence speed is accelerated, but at the same time, the mean square error begins to fluctuate, especially when the learning rate is too high (such as 0.1), the mean square error increases significantly. This may be due to the unstable training process caused by the excessive learning rate, and it is difficult for the model to converge to the optimal solution. On further analysis, we found that there is an optimal learning rate interval. In this interval, the model can not only maintain a fast convergence speed but also obtain a relatively low mean square error. When the learning rate is 0.01, the corresponding mean square error value is the smallest; therefore, the learning rate is determined to be 0.01.

3.4.2 Training function

The authors used the commonly used training functions to train the constructed network model. To improve the accuracy of the model, the comparison of the mean-variance, correlation coefficients, and training steps before and after model calibration are shown in Table 5.

Table 5: Comparison of training results before and after model correction

	Mean squared error	Correlation coefficient	Training steps
Before model correction	0.00101	0.92145	166
After model correction	0.00068	0.95188	178

4 Result analysis

When verifying the integrated circuit industry supply chain performance evaluation model based on the fuzzy hierarchical analysis method and FNN, we have taken several measures to improve the rigor and science of the experiment. First of all, in terms of data processing, more refined operations have been implemented, including data cleaning and normalization processing, to eliminate noise in the data and ensure the consistency and accuracy of the input data. These measures have effectively improved the accuracy of the model's identification of performance differences between different suppliers. Second, to set a reasonable reference value for data standards, a comprehensive reference is made to the industry average level, historical optimal performance, and expert opinions, and a comprehensive benchmark value that can reflect the general compliance level of supply chain performance is established. By comparing this benchmark value with the forecast results of the model, we can visually evaluate the performance level of each supplier and discover potential areas for improvement. In addition, to test the stability and generalization ability of the model, a cross-verification strategy has been introduced. By randomly dividing the training set and test set multiple times and calculating the average performance index, we effectively avoid the problem of overfitting the model and ensure the stability and consistency of the model in different data environments. In summary, by improving data processing methods, setting clear data standard reference values, and adopting cross-verification strategies, we have made the experimental verification process more rigorous and scientific, so that we can more accurately evaluate the feasibility and effectiveness of the constructed model.

4.1 Application of fuzzy network models

4.1.1 Model validation

To verify the feasibility and effectiveness of the performance evaluation model for CM company's ordinary integrated circuit product suppliers after completing design and revision training, the following steps and MATLAB programming statements are used to validate the model. Use the normalized data from three suppliers, S16, S17, and S18, as the test matrix for the inspection samples and import it into MATLAB. Historical performance data for these suppliers are collected through CM's supplier management system. To create a comprehensive performance benchmark, data from industry reports, historical best performance indicators, and expert opinion are also combined. This ensures that the evaluation criteria are not only relevant to CM companies but also reflect industry standards. The hypothesis is that the FNN model can accurately evaluate supplier performance and reflect the real performance differences among suppliers based on standardized operational data. Recall the already trained FNN model for simulation. The cross-validation strategy was adopted to verify the results, and the training set and the test set were randomly divided several times. The comparison between the specific output results and the expected results is shown in Table 6 and Figure 5.

From the model validation results in the table above and Figure 5, it can be seen that the error value output after running the validation sample is relatively small.

Table 6: Model verification results

Supplier	S16	S17	S18
Target value	0.8552	0.8354	0.8004
Output value	0.8650	0.8351	0.8016
Error value	0.00877	−0.00014	−0.00854
Error ratio	1 .13%	−0.01%	−1.06%

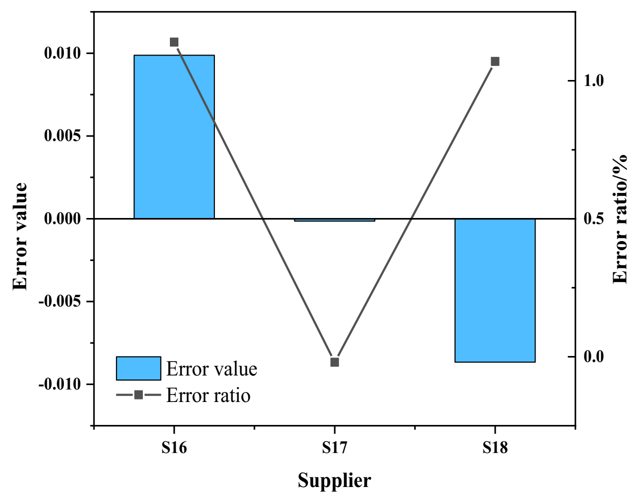

Figure 5: Model validation error. Source: Created by the authors.

4.1.2 Application of the model

The supply chain management department of CM Company have used various types of integrated circuit products in the engineering construction process. In this section, we will use the established and debugged FNN model to select one type of integrated circuit product, namely, a butterfly integrated circuit, for the application of supplier performance evaluation. We will use the relevant data of various suppliers of butterfly integrated circuit products from CM Company from 2022 to 2023 and normalize them as the input matrix. Subsequently, we input these data into the model and run an FNN simulation to evaluate supplier performance. After the operation, we will obtain the performance evaluation results of ten suppliers of butterfly integrated circuit products and compare them with the actual supplier management requirements. The results are shown in Table 7.

Table 7: Model application results

Butterfly integrated circuit supplier	Performance evaluation results
DS1	0.8010
DS2	0.7166
DS3	0.7058
DS4	0.7201
DS5	0.7175
DS6	0.7474
DS7	0.7206
DS8	0.8084
DS9	0.8065
DS10	0.7281

According to the supplier grading management method of CM Company, suppliers with higher comprehensive scores can participate in the evaluation of excellent suppliers every year. The proportion of participation depends on different product settings. Among them, suppliers DS1, DS8, and DS9 with a comprehensive performance score greater than 0.8 are considered relatively excellent suppliers. This indicates that the model effectively identifies suppliers with better performance.

4.2 Model implementation suggestions

4.2.1 Improving the level of informatization and intelligence in supply chain management

The advantage of using FNN models for supplier performance evaluation is that they have good adaptability and generalization ability, and can be trained through historically accumulated sample data to scientifically and reasonably evaluate supplier performance [22,24]. However, considering that when general telecommunication companies choose to use FNNs, evaluators engaged in supplier management may not be able to quickly grasp the theoretical and practical knowledge of relevant models. Improper model parameter settings often lead to inaccurate evaluation results.

4.2.2 Correct and reasonable use of evaluation models and indicator data

In modern supply chain management theory, regardless of which performance evaluation indicators or methods are selected to evaluate suppliers, the primary prerequisite must be based on the supplier's true original indicator data. Therefore, when using FNNs to construct evaluation models for various product suppliers in telecommunication operators, it is necessary to rationally judge whether the supplier in that category is suitable to use evaluation methods based on FNNs; Second, it is necessary to consider whether objective and accurate basic indicator data can be obtained in a timely and effective manner. For the performance evaluation of CM Company's suppliers, it is important to start from the perspective of management system and supervision and to require and improve the objectivity, fairness, and consistency of evaluation indicators among many provincial companies. Obtaining the original basic data of true supplier evaluation indicators is an important prerequisite for conducting subsequent model simulation fairness. Otherwise, evaluation models constructed based on incorrect indicator data are worthless. Otherwise, relying too much on evaluation methods and models can often lead to losses outweighing gains. Not only does the efficiency of supplier management work not improve, but the value of data analysis applications cannot be highlighted.

4.2.3 Looking at supplier performance evaluation methods from a development perspective

There are multiple methods to evaluate supplier performance. The author chooses to use an FNN model to evaluate the performance of CM company's integrated circuit product suppliers, which is a relatively ideal, feasible, and highly operational evaluation method. On the one hand, due to the significant fluctuations in the upstream fiber preform and other raw material market for integrated circuit products, the tight supply of raw materials leads to a shortage of supply and an oversupply of raw materials, CM Company's classification and positioning of integrated circuit product suppliers should be different. At the same time, the selection of indicators in the evaluation model and the weight of various indicators in factor analysis will undergo significant changes. On the other hand, due to the different positions of the same type of product in different telecommunication operator enterprises, mobile communication operators and tower companies also have different classifications and positioning of the integrated circuit products and suppliers. The construction of a supplier performance evaluation index system should be combined with the actual situation of enterprise supply chain management work, realistic, constantly adjusted, improved, and optimized, facilitating the construction of a reasonable evaluation model that adapts to the characteristics of the enterprise and product types. In summary, supplier performance evaluation is not static but should be adjusted promptly based on the internal and external market environment and the development goals of the enterprise.

5 Conclusion

The author mainly introduces how to use MATLAB software to program and implement the performance evaluation model for CM company's ordinary integrated circuit product suppliers that were previously established. First, a brief introduction was given to the design and architecture of the supplier performance evaluation model. Second, the basic data of common integrated circuit product suppliers from CM company was selected for repeated training and validation of the model. Subsequently, the performance evaluation index data of suppliers of butterfly integrated circuit products of the same type from CM company was organized, and a trained evaluation model was used for evaluation simulation. The feasibility and effectiveness of the performance evaluation model for CM integrated circuit product suppliers based on FNNs were verified through simulation results. Finally, relevant reference suggestions were proposed to address the potential issues and situations that may arise during the implementation of the evaluation model in the CM company's supply chain management system. However, experimental results are highly dependent on the quality of the input data used. If the input data are biased, incomplete, or inaccurate, the results of the model output may not be trusted. Therefore, it is necessary to strengthen data collection and cleaning in the future to ensure the accuracy and integrity of data.

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References

[1] Chien CF, Wu HJ. Integrated circuit probe card troubleshooting based on rough set theory for advanced quality control and an empirical study. J Intell Manuf. 2022;35(4):1–13. doi: 10.1007/s10845-022-02042-8.
[2] Santos KVD, Arantes FP, Leite MSA, Bornia AC. Supplier's performance evaluation in supply chains using item response theory. Int J Serv Oper Manag. 2023;45(4):530–51. doi: 10.1504/ijsom.2023.132858.
[3] Min S, Zacharia ZG, Smith CD. Defining supply chain management: In the past, present, and future. J Bus Logist. 2019;40(1):44–55. doi: 10.1111/jbl.12201.
[4] Wang P. Product modeling design method based on graph neural network and fuzzy inference theory. Alex Eng J. 2023;77:513–24. doi: 10.1016/j.aej.2023.07.005.
[5] Lamba D, Yadav DK, Barve A, Panda G. Prioritizing barriers in reverse logistics of E-commerce supply chain using fuzzy-analytic hierarchy process. Electron Commer Res. 2020;20(2):381–403. doi: 10.1007/s10660-019-09333-y.
[6] Piprani AZ, Jaafar NI, Mohezar Ali S. Prioritizing resilient capability factors of dealing with supply chain disruptions: an analytical hierarchy process (AHP) application in the textile industry. Benchmarking: An Int J. 2020;27(9):2537–63. doi: 10.1108/bij-03-2019-0111.
[7] He K, Zhu N. Strategic emerging industry layout based on analytic hierarchy process and fuzzy comprehensive evaluation: a case study of Sichuan province. PLoS One. 2022;17(3):e0264578. doi: 10.1371/journal.pone.0264578.
[8] Vafadarnikjoo A, Badri Ahmadi H, Liou JJ, Botelho T, Chalvatzis K. Analyzing blockchain adoption barriers in manufacturing supply chains by the neutrosophic analytic hierarchy process. Ann Oper Res. 2023;327(1):129–56. doi: 10.1007/s10479-021-04048-6.
[9] Wang Y, Wai RJ. Adaptive fuzzy-neural-network power decoupling strategy for virtual synchronous generator in micro-grid. IEEE Trans Power Electron. 2022;37(4):3878–91. doi: 10.1109/tpel.2021.3120519.
[10] Ben-Daya M, Hassini E, Bahroun Z. Internet of things and supply chain management: a literature review. Int J Prod Res. 2019;57(15-16):4719–42. doi: 10.1016/j.iot.2023.100982.
[11] Mathew AO, Yashas KN, Kamath GB. The relationship between the strategies of operations, supply chain, and information system, and its impact on supply chain performance. Int J Product Qual Manag. 2022;36(3):441–9. doi: 10.1504/IJPQM.2022.10049306.
[12] Srai JS, Lorentz H. Developing design principles for the digitalisation of purchasing and supply management. J Purch Supply Manag. 2019;25(1):78–98. doi: 10.1016/j.pursup.2018.07.001.
[13] Patrucco A, Frattini F, Di Benedetto A. Characteristics of supplier performance measurement systems in collaborative innovation projects: the role of the purchasing department. Supply Chain Manag: An Int J. 2022;27(2):207–31. doi: 10.1108/scm-11-2020-0551.
[14] Sarıçam C, Yilmaz SM. An integrated framework for supplier selection and performance evaluation for the apparel retail industry. Text Res J. 2022;92(17-18):2947–65. doi: 10.1177/0040517521992353.
[15] Pratap S, Daultani Y, Dwivedi A, Zhou F. Supplier selection and evaluation in e-commerce enterprises: A data envelopment analysis approach. Benchmarking: An Int J. 2022;29(1):325–41. doi: 10.1108/bij-10-2020-0556.
[16] Dutta P, Jaikumar B, Arora MS. Applications of data envelopment analysis in supplier selection between 2000 and 2020: A literature review. Ann Oper Res. 2022;315(2):1399–454. doi: 10.1007/s10479-021-03931-6.
[17] Aydas O, Ross A, Parker H, Alavi S. Using efficiency frontiers to visualize suppliers' performance capabilities: Moving beyond supplier rationalization. J Bus Anal. 2023;6(1):19–38. doi: 10.1080/2573234X.2021.1999179.
[18] Mahmoudi A, Abbasi M, Deng X. Evaluating the performance of the suppliers using hybrid DEA-OPA model: A sustainable development perspective. Group Decis Negotiation. 2022;31(2):335–62. doi: 10.1007/s10726-021-09770-x.
[19] Sabri Y, Micheli GJ, Cagno E. Supplier selection and supply chain configuration in the project environment. Prod Plan Control. 2022;33(12):1155–72. doi: 10.1080/09537287.2020.1853269.
[20] Więckowski J, Kizielewicz B, Shekhovtsov A, Sałabun W. How do the criteria affect sustainable supplier evaluation? -A case study using multi-criteria decision analysis methods in a fuzzy environment. J Eng Manag Syst Eng. 2023;2(1):37–52. doi: 10.56578/jemse020102.
[21] Helo P, Hao Y. Artificial intelligence in operations management and supply chain management: An exploratory case study. Prod Plan Control. 2022;33(16):1573–90. doi: 10.1080/09537287.2021.1882690.
[22] Saragih J, Tarigan A, Silalahi EF, Wardati J, Pratama I. Supply chain operational capability and supply chain operational performance: Does the supply chain management and supply chain integration matters. Int J Sup Chain Mgt. 2020;9(4):1222–9. doi: 10.59160/ijscm.v9i4.5268.
[23] Mostaghel R, Oghazi P, Parida V, Sohrabpour V. Digitalization driven retail business model innovation: Evaluation of past and avenues for future research trends. J Bus Res. 2022;146:134–45. doi: 10.1016/j.jbusres.2022.03.072.
[24] Kuo RJ, Hong SY, Huang Y. Integration of particle swarm optimization-based fuzzy neural network and artificial neural network for supplier selection. Appl Math Model. 2010;34(12):3976–90. doi: 10.1016/j.apm.2010.03.033.