Scalable Computing: Practice and Experience, ISSN 1895-1767, http://www.scpe.org
© 2024 SCPE. Volume 25, Issues 4, pp. 2783–2794, DOI 10.12694/scpe.v25i4.2817

EVALUATION AND SELECTION OF MANUFACTURING SUPPLIERS UNDER THE PERSPECTIVE OF SMART MANUFACTURING COMBINED WITH BILEVEL PROGRAMMING

FENG DU*

Abstract. To address the issue of supplier evaluation and selection in the current intelligent manufacturing industry, a supplier intelligent evaluation and selection model combining bilevel programming is proposed. Firstly, based on existing research results and the current situation of the manufacturing market, a manufacturing supplier evaluation index system is constructed, and the principal component analysis method is used to simplify it; Then, the simplified indicator system is input into the back propagation neural network to build a supplier intelligent evaluation model and achieve supplier intelligent evaluation; A mathematical model for supplier selection problem is constructed based on bilevel programming, and an optimized sparrow search algorithm is put forward to solve it. A supplier intelligent selection model is constructed to achieve intelligent supplier selection. The lab findings denote that the F1 value of the supplier intelligent evaluation model is 0.953, the accuracy is 0.985, the area under the curve is 0.962, and the error of the output comprehensive evaluation value is 0.003; The output accuracy of the supplier intelligent selection model is 0.8. The above results indicate that the model raised in the article has good application effects in supplier evaluation and selection, and has a certain promoting effect on the development of the intelligent manufacturing industry.

Key words: Smart manufacturing; Bilevel programming; Suppliers; Smart evaluation; Sparrow search algorithm

1. Introduction. China's manufacturing industry still has great room for development and needs to transform from traditional manufacturing to intelligent manufacturing. Supply chain management as an important content in manufacturing industry, intelligent, scientific and reasonable evaluation and choose of suppliers is an important and hard content. Research data show that the cost of raw materials in the manufacturing industry accounts for 65%-80% of the total cost of products, while the remaining 30% of the cost is other human costs [1, 2, 3]. Therefore, the most direct way to reduce costs and increase efficiency in the manufacturing industry is to reduce costs. And from the manufacturer's perspective, it is the supplier who is linked to the cost of raw materials, and the supplier is also the source of supply chain management [4]. In the trend of manufacturing intelligence, supply chain management also faces intelligent transformation, and how to do a good job of supplier evaluation and selection (SES) has become a problem, which also needs to be changed to meet the times [5]. To this end, the study combines the current situation of manufacturing industry and existing research literature, constructs a supplier evaluation index system, and uses BP neural networks (BPNN) for supplier evaluation; then, based on the bilevel programming model, constructs a mathematical model of supplier selection problem, and proposes an improved Sparrow Search Algorithm (SSA) is applied to solve it, so as to realize the intelligent selection of supplier solutions. The first point is to construct a manufacturing supplier evaluation index system, and principal component analysis (PCA) is utilized to lessen its dimensionality, and then BPNN is adopted to achieve intelligent and comprehensive supplier evaluation; the second point is to propose an improved backward learning and logarithmic spiral strategies to improve the SSA. SSA is improved to enhance its performance, and then the improved SSA is applied to address the mathematical model of supplier selection problem to achieve intelligent supplier selection. The main structure of the study includes four parts. The first is to analyze the current research status; the second is to construct the ISSA-PCA-BPNN SES model by combining the bilevel programming model; the third part is to verify the effect of the improved SSA-PCA-BPNN SES model; the last part is to conclude the whole study. The last part is a summary of the whole study.

*School of Medicine & Health Sciences, Chongqing Youth Vocational & Technical College, Chongqing 400712, China (dufeng815@126.com)

2. Related works. The solution of the lower-level function and the computational parameter of the upper-level function is bilevel programming which can be broadly classified into two methods, analytic and heuristic algorithms, proposed in the study of competition in non-equilibrium economic markets.

Lotfi R et al. argued that selecting an appropriate location is a key factor in establishing a power plant, which needs to satisfy various criteria, and innovatively applied robust bilevel programming techniques and game theory to this problem to locate renewable Wei J et al. proposed a bilevel programming demand management approach based on the marginal price of the distribution location to improve the economic results of industrial parks and to efficiently distribute their electricity bills among industrial users through CHP units and PV panels [6]. The outcomes denoted the function of the raised method in reducing the electricity bills in industrial parks and achieving efficient distribution among users [7].

Yi et al. concluded that virtual power plants have become a useful method for managing an increasing number of flexible resources, posing a technical challenge to distribution system operators, and proposed a bilevel programming for the collaborative management of active distribution networks with multiple VPs [8].

Zhang B et al. considered that previous studies only considered the impact of waiting time on the design of EV charging station networks, and a multi-objective bilevel programming model was designed to fill this research gap. The results showed the applicability of the method in practical site-selection planning problems [9].

Aghababaei B et al. proposed a possible bi-objective bilevel programming for optimizing the management of scarce drug supply and rationing in emergency situations like a new crown pneumonia epidemic. The outcomes showed the applicability and practicality of the proposed model compared with the traditional likelihood approach [10].

Zhou et al. considered the importance of rational arrangement of relief material transfer facilities and effective arrangement of rescue supplies transportation in the beginning after an earthquake, and formulated the fusion problem of transfer facility place and relief material transportation as a gray mixed integer based on the characteristics of a bilevel programming emergency logistics system [11].

Homaee et al. considered coordinating the scheduling actions of two interconnected ADNs and formulated the coordination problem as robust bilevel programming underprice uncertainty [12].

With the rapid development of the economy, competition among firms evolved into competition in the supply chain, thus SES is important for the development of the manufacturing industry. Kaviani M A et al. raised a new uncertainty decision framework to address the current challenges regarding supplier selection in the oil and gas industry which has significant methodological shortcomings. The results show that the proposed method offers strong results in SES and can be applied for future applications [13].

Amiri M et al. argue that sustainability has become one important problem in the supply chain management, and a model for sustainable supplier selection with a triangular fuzzy approach is proposed to help people choose sustainable suppliers [14].

Durmić et al. argued that sustainability in supply chain management has become an increasingly important issue and suppliers are selected to achieve sustainability [15].

Yazdani et al. proposed an comprehensive decision model including a decision test and evaluation laboratory and an improved evaluation with the average solution distance method for the supplier selection [16].

Badi et al. argued that in modern supply chain management, the effectiveness evaluation of potential suppliers is based on multiple criteria, which makes the selecting the best supplier complex and difficult, and proposed the implementation of a hybrid gray theory MARCOS approach in supplier selection decisions to help them compete [17].

Pamucar et al. argued that uncertainty conditions in the chain should urge decision makers and experts to use a fuzzy-based assessment platform, and a fuzzy neutrophil decision method for SES was proposed to reduce the risks and disruptions, provide the satisfying models for solving the problems, and keep the support system stable [18].

Rouyendegh et al. argued that green supplier selection has become an important problem aimed at achieving lean, agile, environmentally sensitive as well as addressing sustainability and durability [19].

In summary, although many previous scholars and scientists have realized the significance of SES for the growth of the manufacturing, and the criteria for evaluation and selection are constantly changing, it has also proved that bilevel programming has played a significant role in solving positioning problems, coordination

Table 3.1: Manufacturing Supplier Evaluation Index System

Primary indicators	Code	Secondary indicators	Code
Product Competitiveness	A	Price	U1
		Quality	U2
		Product Innovation	U3
Enterprise management capability	B	Basic Information of the Enterprise	U4
		Service Level	U5
		Cooperation ability	U6
		Sustainable management capability	U7
		Research and development capability	U8
Production supply capacity	C	Supply coordination ability	U9
		Storage capacity	U10
		Transportation and distribution capacity	U11
		Flexibility	U12
Information degree	D	Information processing capability	U13
		Integrated interconnection capability	U14

problems, and supply chain management problems. However, the current research results of SES combined with bilevel programming are not satisfactory. In order to remedy this deficiency, the research combines BPNN, ISSA and bilevel programming models, and constructs ISSA-PCA-BPNN SES model to realize intelligent SES, which has important practical application value and prospect for smart manufacturing industry.

3. Manufacturing SES combined with bilevel programming. In the era of rapid economic development, the level of prosperity of a country is often positively correlated with its manufacturing industry, which is an extremely important lifeline in the process of national development. Currently, various developed countries have proposed strategies for intelligent manufacturing, combining traditional manufacturing with many new technologies. However, there is still great room for development in China's manufacturing industry, and there is an urgent need to transform from traditional manufacturing to intelligent manufacturing. As an important link in the supply chain, in this context, the SES of manufacturing are very important. The research combines models such as bilevel programming and BPNN to achieve intelligent evaluation and selection of manufacturing suppliers.

3.1. Intelligent evaluation of manufacturing suppliers based on PCA-BPNN. To achieve manufacturing SES, selecting suitable indicators and constructing a scientific, reasonable and effective manufacturing supplier evaluation index system is the basis. Based on the selection principles of comprehensiveness, objectivity, reconfigurability, scientific and operability, the study selects suitable indicators to build a manufacturing supplier evaluation index system by combining existing research results and the current situation of the manufacturing market. In this index system, five dimensions, such as product competitiveness, enterprise management capability, production chain supply capability, and Informaonization degree, are used to evaluate manufacturing suppliers, as presented in Table 3.1.

In Table 3.1, all the indicators were able to obtain the corresponding data through the supplier enterprise management system. The KMO test and Bartlett's method are used to test the reliability and validity of the evaluation index system shown in Table 1 to verify its reasonableness, and the test findings are displayed in Table 3.2. It shows that the evaluation index system of manufacturing suppliers constructed by the study has good reasonableness and scientific, so the scientific evaluation of manufacturing suppliers under the view of smart manufacturing can be carried out according to Table 3.1.

It uses the questionnaire survey and expert scoring manners to obtain the corresponding weights of each index, and then the data corresponding to each index are used as input vectors and input to the BPNN model for learning and training, which can effectively realize the intelligent evaluation of manufacturing suppliers according to the fitting results of BPNN. However, in Table 3.1, there are more indicator data involved, and the number of secondary indicators reaches 14. If the BPNN model is constructed directly according to Table 3.1,

Table 3.2: Reliability and validity testing

Project		Value
KMO inspection		0.882
Bartlett sphericity test	Approximate chi-square	7725.036
	DF	0.735
	Significance	0.000

Table 3.3: Correlation analysis between 14 indicators and common factors

Indicator code	Common factor serial number			
	1	2	3	4
U1	-.123	.935	.106	.394
U2	.953	.143	-.205	.188
U3	.436	.352	.173	.035
U4	.114	.394	.043	.254
U5	-.152	.163	.396	.098
U6	.105	.282	.035	.172
U7	.173	.285	-.205	-.233
U8	-.128	.173	.147	.417
U9	.133	.155	.921	.134
U10	.254	-.133	.333	-.208
U11	.362	.302	-102	.916
U12	.084	.185	.174	.133
U13	.325	-.142	.250	-102
U14	.133	.108	.105	.372

14 input layer nodes need to be constructed in the BPNN network, which will lead to an overly complex BPNN model. And the complexity of the model will directly affect the training efficiency and evaluation accuracy. Therefore, study uses PCA to extract the common factors, so as to realize the dimensionality reduction of the input vectors in the BPNN network model and improve the model performance. After processing with the PCA method, four public factors with a combined value greater than 1 were obtained among 14 indicators, and their cumulative total variance contribution rate exceeded 82%, which had a high variable explanatory power and could reflect the situation of manufacturing suppliers more comprehensively. Descriptive statistics were used to extract the factor component matrix to obtain the correlations between the 14 indicators and the public factors shown in Table 3.1, as shown in Table 3.3.

Based on the above, the input nodes of the BPNN network model are constructed based on four indicators, including U2: product quality, U1: product price, U9: supply coordination capability and U11: transportation and distribution capability, to effectively reduce the complexity and improve the efficiency and accuracy. Based on the above, the intelligent evaluation model of PCA-BPNN manufacturing suppliers can be constructed to realize the intelligent evaluation of manufacturing suppliers.

3.2. Intelligent supplier selection for manufacturing combined with bilevel programming. In the foregoing, the study constructs an evaluation system for manufacturing suppliers, and on this basis, an intelligent evaluation model of PCA-BPNN manufacturing suppliers is constructed to realize the intelligent evaluation of manufacturing suppliers. On the basis of intelligent evaluation of manufacturing suppliers, manufacturing supplier selection can be carried out. Based on manufacturing SES, then manufacturing supplier management can be realized, and its general process is shown in Figure 3.1.

Supplier management is an important part of the development of manufacturing companies, so manufacturing SES is very significant. In the actual situation of supplier selection in the manufacturing industry, priority will be given to procurement cost, followed by supplier quality. However, high quality suppliers often also repre-

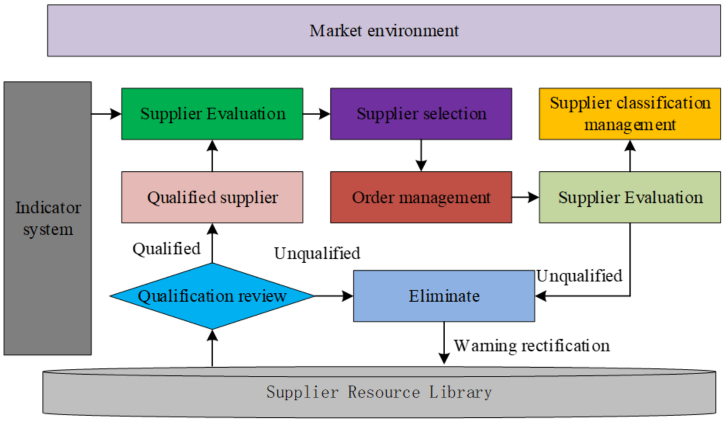


Fig. 3.1: Supplier management

sent higher procurement costs, thus creating a paradoxical situation of benefits. Therefore, a balance between procurement cost and supplier quality needs to be considered when making supplier selection in manufacturing. The bilevel programming model is a system optimization with a bilevel programming structure containing multiple objective functions and corresponding constraints, and the bilevel programming model can be used to avoid the benefit paradox problem more effectively, so that the balance between procurement cost and suppliers can be considered comprehensively. Therefore, the study is based on a bilevel programming model for manufacturing supplier selection. From the perspective of manufacturing enterprises, the upper-level planning model should make the procurement cost as small as possible. According to this principle, the mathematical model of the upper-level planning model is established in Equation 3.1.

$$\begin{cases} \text{U:min F} = \min(\sum_{i=1}^{n} \lambda_i d_i x_i r_i + \sum_{i=1}^{n} \lambda_i c_i x_i) \\ s.t \sum_{i=1}^{n} \lambda_i \geq 2 \qquad\qquad\qquad , i = 1, 2, \ldots, n \\ (\lambda_i - 1)\lambda_i = 0 \end{cases} \tag{3.1}$$

In Equation 3.1, n is the total amount of alternative suppliers; λ_i is the upper-level decision variable, when the value of λ_i is 1, it denotes that the ith supplier is selected, and when the value of λ_i is 1, it means that the ith supplier is not selected; is the sourcing volume offered by the $x_i$$i$th alternative supplier; d_i is the unit price offer of the ith alternative supplier; r_i is the volume discount rate offered by the ith alternative supplier; and c_i is the unit shipping cost of the ith alternative supplier. In the lower-level planning model, the procurement volume is divided among the selected suppliers in the case of multiple suppliers so that the output supplier composite evaluation value of the intelligent evaluation model of PCA-BPNN manufacturing suppliers is as high as possible, and the objective function is constructed as shown in Equation 3.2.

$$L : maxB = max \sum_{i=1}^{n} H_i \lambda_i x_i \tag{3.2}$$

In Equation 3.2, x_i is the lower-level decision variable; H_i is the comprehensive evaluation value of the i supplier output by the intelligent evaluation model of PCA-BPNN manufacturing suppliers. In Equation 3.2, it is necessary to satisfy that the total procurement task volume Q is fully allocated, so there are constraints in Equation 3.3.

$$s.t \sum_{i=1}^{n} \lambda_i x_i = Q \tag{3.3}$$

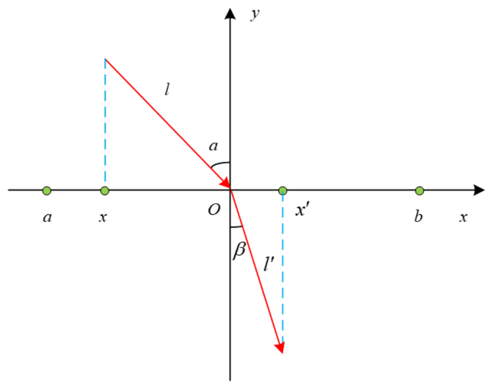


Fig. 3.2: Improving the Principle of Refractive Reverse learning

According to the half-ratio principle, a particular selected supplier needs to be allocated less than 1/2 of its maximum capacity, and therefore has constraints, as in equation 3.4.

$$0 \leq x_i \leq \frac{1}{2}M_i \tag{3.4}$$

In Equation 3.4, M_i denotes the maximum capacity of the i supplier. The above model can be solved by intelligent optimization algorithm (IOA) to get the best supplier selection solution. In the solution of the bilevel programming model, the commonly used IOAs generally use genetic algorithm (GA) or particle swarm optimization (PSO), but the solution performance of these two algorithms is not satisfactory. The SSA has a low structural complexity and high performance in finding the best performance, and it has a very remarkable performance in various optimization problems. However, it still has certain drawbacks, such as the use of backward learning to expand the search range, but in the late iteration, it often falls into local optimum. For this reason, it puts forward a refractive backward learning method to raise the generalization ability of SSA. The principle of improved refractive backward learning is shown in Figure 3.2.

By means of refractive backward learning, the corresponding candidate solutions can be obtained, thus enabling the algorithm not to belong to local optima in the late iteration. The refractive backward learning candidate solutions are shown in Equation 3.5.

$$x'_{i.j} = \frac{a_j + b_j}{2} + \frac{a_j + b_j}{2k} + \frac{x_{i,j}}{k} \tag{3.5}$$

In Equation 3.5, $x'_{i.j}$ and $x_{i,j}$ are the refractive inverse solution and the original solution of the i sparrow individual in the j dimension, respectively. In SSA, there are two types of sparrow individuals, discoverers and joiners. Among them, the joiner will fly in the direction indicated by the discoverer to get the best solution. In this search method, the joiner's search has a significant blindness, which affects the joiner's position update and the algorithm's ability to gain the best solution. In the early iteration of SSA, the joiners are required to expand the scope of the search space to obtain more candidate solutions, i.e., to expand the global search capability; while in the later iteration, the joiners are required to search in a small range of space, thus reducing the search time and improving the convergence. According to the above, the study uses variable logarithmic spiro to optimize and improve the update of joiners. The traditional logarithmic spiral is shown in Figure 3.3.

The study sets the constant in the traditional logarithmic spiro as a variable that changes dynamically according to the number of iterations, thus making the SSA have a larger search range in the early iterations and a better convergence performance in the later ones. At this point, the joiners are renovated in the manner

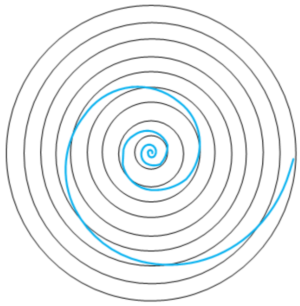


Fig. 3.3: Logarithmic spiral

shown in Equation 3.6.

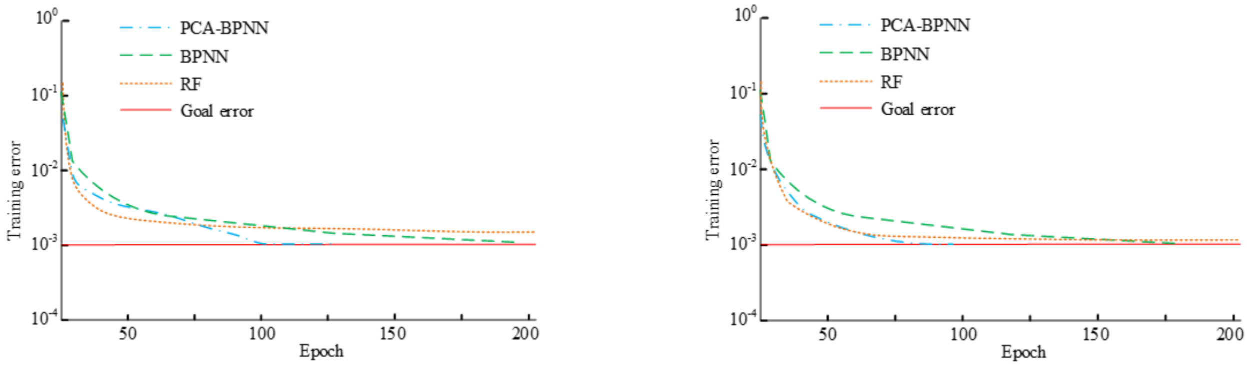
$$X_i^{(t+1)} = \begin{cases} Q \cdot \exp\left(\frac{X_{\text{worst}}^t - X_i^t}{i^2}\right) \cdot e^{\theta t_1} \cdot \cos(2\pi t_1), & \text{if } i > \frac{T}{2} \\ X_i^{(t+1)} + |X_i^t - X_P^{(t+1)}| \cdot A^+ \cdot L \cdot e^{\theta t_1} \cdot \cos(2\pi t_1), & \text{if } i \leq \frac{T}{2} \end{cases} \tag{3.6}$$

In Equation 3.6, is the position of the $X_i^{(t+1)}$ individual joiner in the iteration; tQ is a random number obeying normal distribution; L is a matrix with all elements 1; $X_P^{(t+1)}$ is the position of the best finder in the iteration$t$; $X_{worst}^{(t+1)}$ is the global worst position in the t iteration; A is a matrix with all elements randomly assigned to -1 or 1; $t_1 \in [-1, 1]$; $\theta = 5 - \frac{t}{T}$, where T is the upper limit of the iteration of the algorithm. Based on the above, the optimization of SSA is completed to construct ISSA. The ISSA-PCA-BPNN SES model is constructed by synthesizing the above elements to obtain the optimal supplier selection scheme.

4. Analysis of th effect of ISSA-PCA-BPNN SES model. The effect of ISSA-PCA-BPNN SES model is analyzed in two main aspects. The first part is the analysis of the effect of PCA-BPNN on the evaluation of manufacturing suppliers, and the second part is the analysis of the effect of ISSA algorithm on solving the mathematical model of manufacturing supplier selection based on bilevel programming. To verify the performance of the ISSA-PCA-BPNN SES model proposed in the study, it is analyzed through the data of its management system in 2020 2021, taking an automobile manufacturing company as an example. In 2020 2021, the company has seven alternative suppliers that have passed the preliminary qualification audit to supply support roller bearing parts A, which are recorded as S1 S7. The corresponding data are input into PCA-BPNN model, BPNN and Random Forest (RF) models to compare the evaluation accuracy of several models on suppliers. First, the error variation of several models during the training process is compared, as displayed in Figure 4. The PCA-BPNN converges faster during the training process in both 2020 and 2021, and the convergence node is about 100 iterations later. In contrast, the BPNN and the RF converge more slowly, and both only approach the target value after 200 iterations without fully reaching it, but the training effect of the BPNN is slightly better than that of the RF.

After the models were fully trained, the F1 values, accuracy rates, and AUC values of the above models were tested five times, and the average value was regarded as the final outcome to avoid errors in the experimental results due to chance. The F1 values, accuracy rates, and AUC values of the PCA-BPNN, BPNN, and RF in the sample data of 2020 are expressed in Table 4. In the sample data of 2020, the F1 value of the PCA-BPNN model, expressed as a mean value, is 0.953, which is 0.037 and 0.058 higher than the BPNN and RF models, respectively; the accuracy rate is 0.985, which is 0.033 and 0.049 higher than the BPNN and RF models, respectively; the AUC value is 0.962, which is 0.962 higher than the BPNN and RF models, respectively. The AUC value was 0.962, which was 0.025 and 0.045 higher than the BPNN and RF models, respectively.

The F1 values, accuracy rates, and AUC values of the PCA-BPNN, BPNN, and RF in the sample data for 2021 are displayed in Figure 5. In the sample data of 2020, the F1 value of the PCA-BPNN model, expressed as a mean value, is 0.956, which is 0.028 and 0.053 more than the BPNN and RF models, respectively; the



(a) 2020

(b) 2021

Fig. 4.1: Error changes of several models during training

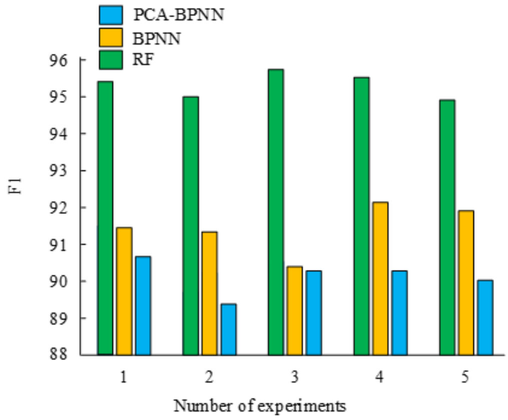
Table 4.1: F1 value, accuracy and AUC value of the model in the 2020 sample data

Index	Number of experiments	Model		
		PCA-BPNN	BPNN	RF
F1	1	0.937	0.908	0.883
	2	0.962	0.925	0.905
	3	0.953	0.914	0.911
	4	0.947	0.933	0.884
	5	0.966	0.901	0.892
	Average value	0.953	0.916	0.895
Accuracy	1	0.983	0.962	0.944
	2	0.992	0.941	0.936
	3	0.986	0.955	0.928
	4	0.994	0.932	0.931
	5	0.972	0.968	0.940
	Average value	0.985	0.952	0.936
AUC	1	0.962	0.953	0.902
	2	0.953	0.941	0.914
	3	0.971	0.935	0.938
	4	0.965	0.940	0.920
	5	0.958	0.916	0.911
	Average value	0.962	0.937	0.917

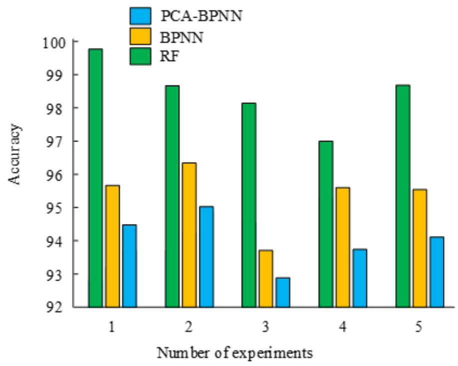
accuracy rate is 0.986, which is 0.032 and 0.046 more than the BPNN and RF models, respectively; the AUC value is 0.965, which is 0.025 and 0.046 more than the BPNN and RF models, respectively.

The output composite evaluation values of several models were compared with the actual composite evaluation values of seven suppliers, so as to analyze the evaluation accuracy of several models, as presented in Figure 4.3. In Figure 4.3, the PCA-BPNN model has the minimum error between the output and the actual composite evaluation value, with an average error of 0.003 for the seven suppliers, which is 0.008 and 0.011 lower than the BPNN model and the RF model, respectively.

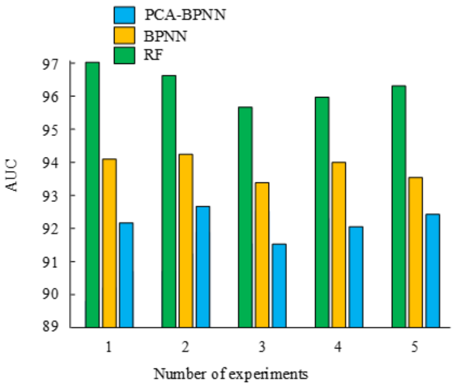
Next, the supplier selection model performance based on the bilevel programming model with ISSA algorithm is verified. In 2020 and 2021, there are 2 suppliers of the support roller bearing component A required by the automobile manufacturer, so the final output of the algorithm is also 2. If both companies are the



(a) F1



(b) Recall



(c) AUC

Fig. 4.2: F1 value, accuracy and AUC value of the model in the 2021 sample data

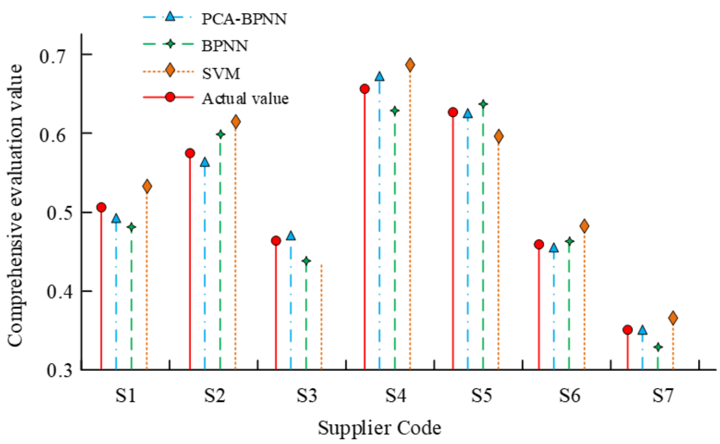


Fig. 4.3: Differences between model evaluation values and actual values

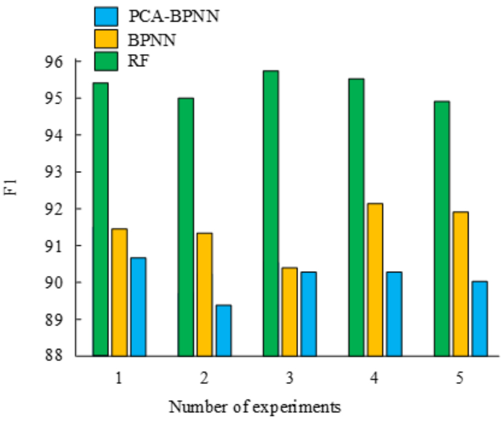
Table 4.2: Output results of several algorithms

Number of experiments	2020			2021		
	ISSA	NSGA-II	IACO	ISSA	NSGA-II	IACO
1	1	0	1	1	1	1
2	1	1	1	1	1	0
3	0	1	0	1	1	1
4	1	0	-1	1	1	1
5	1	1	0	1	0	0
6	1	1	0	1	-1	1
7	1	1	1	0	1	1
8	0	1	1	1	1	-1
9	1	0	1	1	1	1
10	1	1	0	1	0	1
Average value	0.8	0.7	0.4	0.9	0.6	0.6

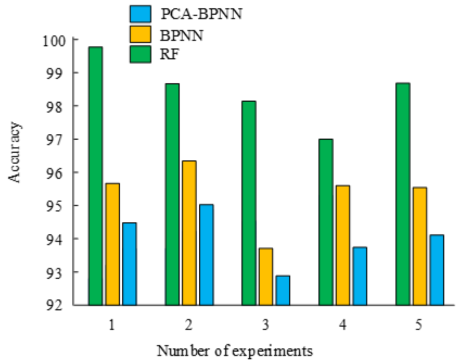
same as the actual selection result, the output of the algorithm is counted as 1; if only one is the same, it is recorded as 0; if both are different, it is recorded as -1. 10 experiments are conducted on the data samples of both 2020 and 2021 to avoid chance errors affecting the experimental results. The two main state-of-the-art intelligent algorithms currently used for supplier selection are the second-generation Non-dominated Sorting Genetic AlgorithmII (NSGAII) and the Improved Ant Colony Optimization Algorithm (IACO). Therefore, the differences between the output results of ISSA, NSGAII and IACO after solving the mathematical model based on bilevel programming and the actual outcomes are compared in Table 4.2. In 2020, the output accuracy of ISSA is 0.8, which is 0.1 and 0.4 more than that of NSGAII and IACO, respectively; in 2021, the output accuracy of ISSA is 0.9, which is 0.3 and 0.3 more than that of NSGAII and IACO, respectively.

In the automotive manufacturing enterprise, 10 management personnel responsible for procurement, 20 ordinary employees, and 15 experts in the industry were invited to evaluate the solution effectiveness of several algorithms, with a score of 0-100. The higher the score indicate more reasonable effect of the model's solution. The scores of several algorithms are shown in Figure 7. ISSA scores were significantly higher than NSGA-II and IACO. In summary, the ISSA-PCA-BPNN model proposed in the study has good application effects SES. It can quickly, scientifically, and reasonably evaluate suppliers comprehensively and provide corresponding selection plans, achieving intelligent evaluation and selection of manufacturing suppliers, and has positive significance for the development of the manufacturing industry.

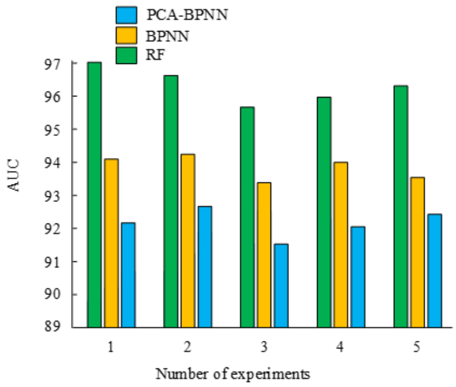
5. Conclusion. With the advent of the information age, intelligence, information technology and digitalization have become the mainstream development trend of the manufacturing industry. Manufacturing suppliers are an important part of the manufacturing industry chain, which affects the effectiveness of the whole supply chain and the construction and development of the market environment. Therefore, it is very important to realize the intelligent evaluation and selection of manufacturing suppliers under the view of intelligent manufacturing. To this end, an ISSAPCABPNN SES model is proposed in the study. The lab outcomes denote that the convergence node of PCABPNN model is better than BPNN model and RF model after roughly 100 iterations; in the sample data of 2020, the F1 value of PCABPNN model is 0.953, which is 0.037 and 0.058 more than BPNN model and RF model, respectively; the accuracy rate is 0.985, which is 0.985 more than BPNN model and RF model 0.033 and 0.049 more than the BPNN and RF models, respectively; the AUC value is 0.962, 0.025 and 0.045 more than the BPNN and RF models, respectively; in the sample data of 2021, its F1 value is 0.956, 0.028 and 0.053 more than the BPNN and RF models, respectively; the accuracy rate is 0.986, more than the BPNN and RF models, respectively The output accuracy of ISSA is 0.8, which is 0.1 and 0.4 higher than that of NSGAII and IACO respectively. 0.4; in 2021, the output accuracy of ISSA is 0.9, which is 0.3 and 0.3 higher than NSGAII and IACO, respectively; the score is significantly higher than NSGAII and IACO. In summary, the ISSAPCABPNN model proposed in the study has a good application in SES, and has positive significance for the development of manufacturing industry. However, the index system constructed



(a) Management Layer



(b) Staff



(c) Expert

Fig. 4.4: Score of several algorithms

by the study has the limitation of timeliness and needs to be updated continuously in the follow-up to ensure its accuracy.

REFERENCES

[1] Hickey, P., Kamal, M. & Kozlovski, E. Viewpoint Enabling circular supply chains in a high-tech manufacturing industry. *Journal Of Enterprise Information Management*. **35**, 321-332 (2022)

[2] Shan, S., Wen, X., Wei, Y., Wang, Z. & Chen, Y. Intelligent manufacturing in industry 4.0: a case study of Sany heavy industry. *Systems Research And Behavioral Science*. **37**, 679-690 (2020)

[3] Alami, D. & Elmaraghy, W. cost benefit analysis for industry 4.0 in a job shop environment using a mixed integer linear programming model. *Journal Of Manufacturing Systems*. **59**, 81-97 (2021)

[4] Welborn, C., Bullington, K. & Abston, K. Recruiting students to an undergraduate supply chain management program. *Industry & Higher Education*. **36**, 190-199 (2022)

[5] Jain, K. & Saxena, A. Simulation on supplier side bidding strategy at day-ahead electricity market using ant lion optimizer. *Journal Of Computational And Cognitive Engineering*. **2**, 17-27 (2023)

[6] Lotfi, R., Mardani, N. & Weber, G. Robust bi-level programming for renewable energy location. international journal of energy research. 2021. (0)

[7] Wei, J., Zhang, Y., Wang, J. & Wu, L. Distribution LMP-based demand management in industrial parks via a bi-level programming approach. *IEEE Transactions On Sustainable Energy*. **12**, 1695-1706 (2021)

[8] Yi, Z., Xu, Y., Zhou, J., Wu, W. & Sun, H. Bi-level programming for optimal operation of an active distribution network

with multiple virtual power plants. *IEEE Transactions On Sustainable Energy.* **11**, 2855-2869 (2020)
[9] Zhang, B., Zhao, M. & Hu, X. Location planning of electric vehicle charging station with users' preferences and waiting time: multi- objective bi-level programming model and HNSGA-II algorithm. *International Journal Of Production Research.* **61**, 1394-1423 (2023)
[10] Aghababaei, B., Pishvaee, M. & Barzinpour, F. fuzzy bi-level programming approach to scarce drugs supply and ration planning problem under risk. fuzzy Sets and Systems. (2022)
[11] Zhou, Y., Zheng, B., Su, J. & Li, Y. The joint location-transportation model based on grey bi-level programming for early post-earthquake relief. journal of Industrial and Management Optimization. (2021)
[12] Homaee, O., Najafi, A., Jasinski, M., Tsaousoglou, G. & Leonowicz, Z. Coordination of Neighboring Active Distribution Networks under Electricity Price Uncertainty Using Distributed Robust Bi-Level Programming. *IEEE Transactions On Sustainable Energy.* **14**, 325-338 (2022)
[13] Kaviani, M., Karbassi Yazdi, A., Ocampo, L. & Kusi-Sarpong, S. An integrated grey-based multi-criteria decision-making approach for supplier evaluation and selection in the oil and gas industry. kybernetes. (2020)
[14] Amiri, M., Hashemi-Tabatabaei, M., Ghahremanloo, M., Keshavarz-Ghorabaee, M. & Zavadskas, E. new fuzzy BWM approach for evaluating and selecting an International Journal of Sustainable Development & World Ecology. (2021)
[15] Durmić, E. Stević Ž, Chatterjee P, Vasiljević M, Tomašević M. *Sustainable Supplier Selection Using Combined FUCOM-Rough SAW Model.* **1**, 34-43 (2020)
[16] Yazdani, M., Torkayesh, A. & Chatterjee, P. An integrated decision-making model for supplier evaluation in public healthcare system: the case study of a Journal of Enterprise Information Management. (2020)
[17] Badi, I. & Pamucar, D. Supplier selection for steelmaking company by using combined Grey-MARCOS methods. decision making: applications in management and Engineering. (2020)
[18] Pamucar, D., Yazdani, M., Obradovic, R. & Kumar, A. novel fuzzy hybrid neutrosophic decision making approach for the resilient supplier selection problem. *International Journal Of Intelligent Systems.* **35**, 1934-1986 (2020)
[19] Rouyendegh, B. & Yildizbasi, A. "Ust"unyer P. *Intuitionistic Fuzzy TOPSIS Method For Green Supplier Selection Problem.* **24** pp. 2215-2228 (2020)

Edited by: Zhengyi Chai
Special issue on: Data-Driven Optimization Algorithms for Sustainable and Smart City
Received: Nov 8, 2023
Accepted: Dec 27, 2024