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Retraction

Retracted: Intelligent Application of Raw Material Supply Chain Planning System Based on Genetic Algorithm

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] F. Xu, Y. Zhang, Y. Su, J. Li, and J. Zhu, "Intelligent Application of Raw Material Supply Chain Planning System Based on Genetic Algorithm," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 5054529, 13 pages, 2022.

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Research Article

Intelligent Application of Raw Material Supply Chain Planning System Based on Genetic Algorithm

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For the ordering and transportation of raw materials of production enterprises, an intelligent supply chain planning system based on genetic algorithms has been researched and developed. Based on the consideration of multicycle and multiraw materials, by constructing a multiobjective function, taking into account the optimal supplier, the optimal economic ordering scheme, and the minimum loss transshipment scheme, an optimal supply planning model based on genetic algorithm is proposed, and the optimal supply chain combination of the next 24 cycles is predicted by using the model, and its applicability is verified. The study shows that the supply chain planning system has good operation convenience, fast, intuitive, practical application effect of the function and can adapt to modern intelligent logistics and transportation.

1. Introduction

Under the current world development trend, the competition of a single enterprise has transitioned to the competition between supply chains. For manufacturing enterprises, the ordering research of enterprise raw materials continues to heat up. Faced with the current environmental trends, traditional manufacturing industries should consider how to build a selection and evaluation system for raw materials and suppliers, formulate and optimize the ordering and transportation plans for raw materials before production, and fully realize the optimization of their supply chain system. However, reasonable supply chain pricing and ordering decisions are very difficult and require long-term unremitting efforts.

In view of the current situation of the ordering and transportation of raw materials of production enterprises, this paper studies the following problems: (i) using relevant data to evaluate the supply characteristics of enterprise suppliers; (ii) quantitative analysis of supply characteristics, establishing a mathematical model that reflects the importance of ensuring the production of enterprises, and using data; (iii) taking whether suppliers are selected as a decision-making variable, using the 0-1 planning model with the least number of suppliers as the target function, and solving the choice of suppliers; (iv) according to the most economical enterprise for the expected goal of the ordering program; (v) introduce new indicators to formulate the transfer scheme of the expected state; and (vi) finally construct a multiobjective system, use genetic algorithms to solve the objective function, and obtain a new optimal ordering scheme and transshipment scheme under the agreed conditions.

In this article, we build an intelligent supply chain planning system. And under the premise of ensuring the supply and demand of raw materials of enterprises, and taking into account the optimization of many factors such as upstream and downstream enterprises in the raw material supply chain, such as the most economical ordering scheme and the transhipper scheme with the least loss, a genetic algorithm model is established to optimize the allocation of the supplier team and predict the possible optimal supply chain combination of raw materials in the next 24 weeks. Through the information-based supply chain planning system, the logistics activities, quantity, and speed are effectively adjusted and planned. The research method in this paper has good practicality and innovation in the prediction of optimal supply chain combination of enterprises.

2. Literature Review

In recent years, the adjustment of the global supply chain pattern is accelerating, and the effective coordination of upstream and downstream supporting industries will increase the viscosity of the supply chain. Due to the changes in the overall situation of the world, how to optimize and upgrade the supply chain of traditional manufacturing enterprises has become a topic of research by many scholars. There are already many excellent scholars who have provided models and schemes for the raw material ordering scheme of enterprises according to different influence ordering angles.

Chen et al. [1] proposed an EPQ integration model for spoiled items that considers both the inventory cost of finished products and raw materials in the inventory study of inventory management. The optimal solution of the model is obtained by using the iterative optimization method to obtain the optimal number of raw material orders in the planning period, the optimal production times, and the optimal service level in the raw material ordering cycle. Huo and Xuan [2] mentioned in the article that the demand for products of production enterprises is affected by sales prices, and the size of product demand will inevitably affect the economic batch of raw materials. Peng et al. [3] proposes a rolling procurement strategy based on time series for the procurement of raw materials in the manufacturing process of complex products. The core idea of this strategy is to implement rolling procurement under normal processing conditions. According to the future price fluctuations of raw materials, a multistage procurement model with the goal of minimizing total cost is established to solve the optimal purchase volume of each stage. Sutrisno [4] proposed that raw material sourcing and product mixing planning are two important components of the manufacturer's industry, based on their significant contribution to production costs and profits. It describes a newly developed mathematical model in the form of multiobjective optimization as an alternative method that may be used to improve multi-period raw material procurement and product mixing planning under uncertain demand.

Research on the analysis of raw material supply chains based on genetic algorithms, for example, Wang and Li [5] used Sheffield University's genetic algorithm toolbox to combine genetic algorithms with linear programming algorithms to solve the model. It is also shown that the influence of demand change is greater than the effect of distance change, and the effect of demand stochastic on the optimal cost and the optimal individual is not large. Dai [6] used genetic algorithms to construct a collaborative supply chain network to improve the effectiveness and efficiency of the supply chain network. However, previous studies are relatively simple, most of them study the same cycle supply chain problem, or assume that only one raw material is used to produce products. But in real life, there may be more than one raw material used in the production of products, and the supply chain network is a multicycle process. Therefore, under the premise of considering multicycle and multiraw materials, this paper also considers the optimization of the schemes of forwarders and suppliers and builds an optimization model of the supply chain system and proves that the system has good applicability in reality.

3. Basic Assumptions

To address this issue, we make the following assumptions: (i) that the data we collect on data related to suppliers and forwarders is true and reliable; (ii) that the forwarder defaults to the maximum capacity in terms of the quantity of raw materials to be transported; (iii) that the prices of raw materials in categories A, B, and C remain unchanged during the study period and future forecast periods; and (iv) that the company will continue to use categories A, B, and C by default for the next 24 weeks.

4. Enterprise Upstream Supply Chain Efficient Management Implementation Path Analysis

4.1. Construction of Raw Material Supplier Evaluation System Based on TOPSIS Improved Factor Analysis

4.1.1. Research Thought. First, visualize the data to visually observe the changes in the weekly order quantity of the enterprise and the weekly supply of suppliers; then divide the indicators into 5 indicators: supply capacity (total average supply), supply stability, and effective supply rate, the actual weekly average value of supply and raw material cost, use factor analysis to determine the indicators and their weights [7], establish a supply feature evaluation model, and construct an evaluation system with 5 indicators extracted from the data, and use a factor analysis model based on the TOPSIS distance method to determine factor weights, calculate composite factor scores and scores [8], and rank businesses, as shown in Figure 1.

We can see that the order quantity of the enterprise and the supply quantity of the supplier change periodically, and there is a certain rule. The subsequent model construction problem can be analyzed according to this.

4.1.2. Model Preparation. First, visualize the data of enterprise order quantity and supplier supply quantity. Figure 2 shows the data change chart of the company's order volume, and Figure 3 shows the supply quantity of the supplier change periodically, and there is a certain rule, and the subsequent model construction problem can be analyzed according to this.

Next, taking into account the factors affecting the development of the upstream supply chain of an enterprise, a multilevel evaluation structure should be established to

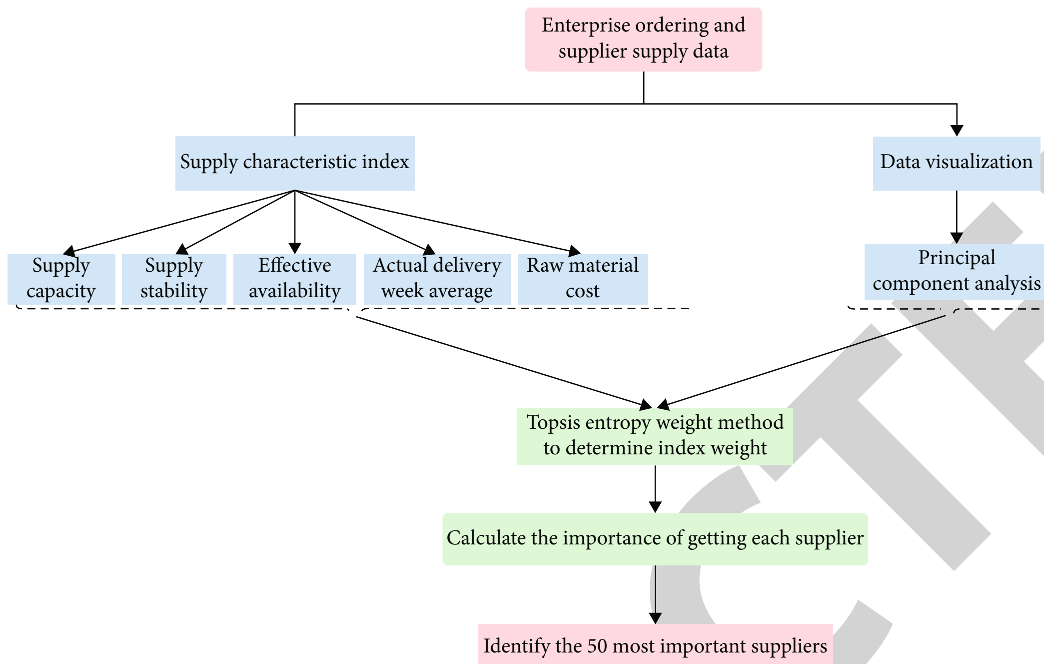

Figure 1: Overall thinking process.

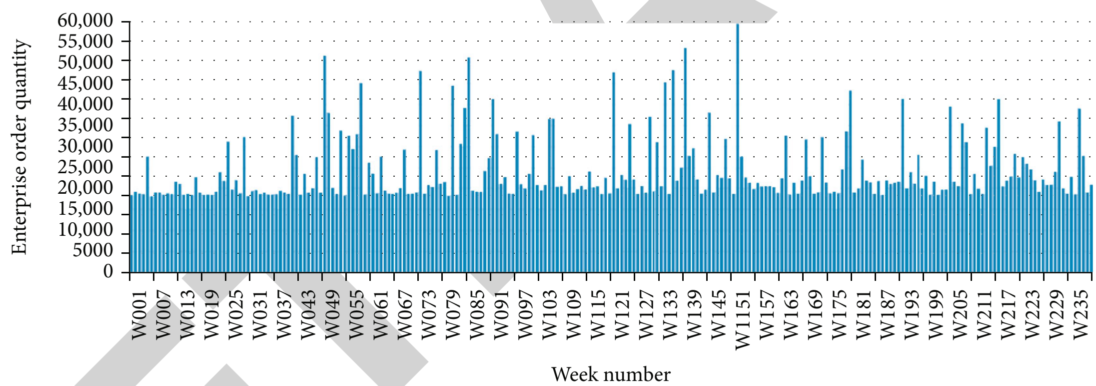

Figure 2: The change curve of the order quantity of the enterprise with time.

evaluate raw material suppliers. We mainly analyzed five indicators including supply capacity (total average supply), supply stability, effective supply rate, actual supply week average, and raw material cost. Each aspect corresponds to several specific indicators.

Among them, the supply capacity is the average of the total supply of each supplier in 240 weeks, the supply stability is the sum of the actual supply cycles in 240 weeks, and the actual weekly average is the supply and supply stability of each supplier [9]. The ratio of availability, the effective supply ratio, the ratio of the sum of the number of cycles to the actual order quantity to provide the supply quantity that matches the order quantity or the excess order quantity, and the raw material cost. The weight is [0.75, 0.25], and on this basis, the three materials of ABC are simply quantified.

We use the evaluation indicators established above to establish the evaluation model, taking into account the following:

(1) The stronger the supply capacity (total average supply capacity), the higher the importance of guaranteeing the production of the enterprise

(2) The better the supply stability, the higher the importance of ensuring the production of enterprises

(3) The greater the effective supply rate, the higher the importance of ensuring the production of enterprises

(4) The more the actual weekly average of supply, the higher the importance of guaranteeing the production of enterprises

(5) The lower the raw material cost, the higher the importance of ensuring the production of enterprises

(6) After establishing the index system, we obtained the data of 402 raw material suppliers of the company in the past five years from the official website. Because

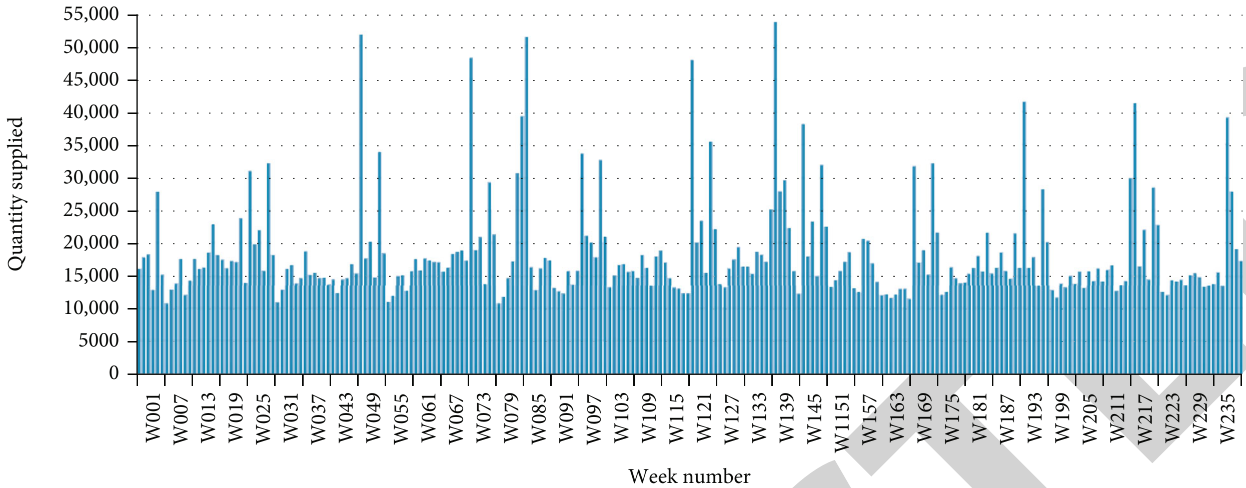

FIGURE 3: The change curve of the supply quantity of the enterprise with time.

the original data is large and incomplete, it is necessary to preprocess the data [10]

(i) Step 1: according to the existing literature materials, the initial criteria for supplier selection are established: when the supplier's supply volume is 0 for more than one year (48 weeks), it is determined that the transaction viscosity with the enterprise is low, and this type of supply quotient data will be excluded

(ii) Step 2: secondary screening of the data generated by condition (i): when the supplier has a supply volume greater than 80 m^3 for ≧1 week, it is determined that the supplier and the enterprise have a high-intensity transaction relationship under special circumstances, so the supplier will be retained, merchant data.

(iii) Step 3: data normalization and data standardization:

For positive indicators,

$$x_{ij} = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}}. \tag{1}$$

For contrarian indicators,

$$x_{ij} = \frac{\max x_{ij} - x_{ij}}{\max x_{ij} - \min x_{ij}}. \tag{2}$$

The indicator data values are uniformly transformed into the [0, 1] interval. The model uses linear transformation method to standardize the index data [11]. Among them, x_{ij} is the standardized index. In the raw material supplier evaluation system, x_{ij} represents the actual value of the sample data of the jth index of the ith supplier.

4.1.3. Model Establishment and Solution. There are several steps in the process of establishing TOPSIS and the entropy weight model. According to the established index system, SPSS software was used to calculate and solve the model.

(i) KMO and Bartlett's sphericity test: when performing factor analysis, it is necessary to carry out feasibility test on the data and pass the test. The result is credible. The results of the data feasibility test were obtained through SPSS analysis, as shown in Table 1. When the data that is usually suitable for factor analysis is tested, the KMO value is greater than 0.5, which is more suitable for factor analysis [12]. Bartlett's sphericity test corresponds to a P value of 0. 000 ($0.000 < 0.001$), indicating that we reject the null hypothesis at the 99% confidence level, there is a strong correlation between the variables, and the selected indicators are suitable for factor analysis [13]

(ii) Extract the common factor: the common factor variance table can reflect the extracted information of each original variable, and most of the indicators have been extracted about 90% of the information, indicating that most of the information of the original variables has been preserved [14], and the established model can reflect corporate credit risk

As shown in Table 2, the characteristic root and variance contribution rate table, in this paper, according to the two common factors extracted from the gravel diagram, the variance contribution rates are 40.073% and 32.913%, respectively, and the cumulative variance contribution rate reaches 72.986%. Therefore, keeping the first 2 common factors preserves most of the information of the original variable.

(iii) Naming of common factors. According to the common factor, we use the maximum variance rotation

Table 1: KMO and Bartlett's test.

KMO sampling suitability quantity		0.578
Bartlett's sphericity test	Approximate chi-square	279.351
	Degrees of freedom	10
	Salience	≤0.001

method to rotate the factor, simplify the factor structure, and make the actual meaning of the common factor clearer. The rotated composition matrix is shown in Table 3

The first common factor has a larger load on the average of total supply and the average of actual supply weeks, which reflects the quantity of raw materials supplied by suppliers, so it is named as supplier supply. The second common factor is the supply stability, the effective supply rate, and the raw material cost, which has a larger load, reflecting stability and quality of the supplier's supply [15], so it is named the supplier's supply quality factor. The rotation method adopts the Caesar normalization maximum method, expressed as the rotation has converged after 3 iterations.

(iv) Comprehensive factor scores and Rankin

Divide the respective variance contribution rates of the common factors by the cumulative variance contribution rates to calculate the relative variance contribution rates after factor rotation [16]. The relative variance contribution rates of the supplier supply capability factor and the supplier supply quality factor are 66.20% and 66.20%, respectively. 33.80%, which is then assigned as a weight.

According to the component score coefficient matrix, calculate the score function of supplier supply ability factor and supplier supply quality factor:

$$Y_1 = 0.889X_1 + 0.439X_2 + 0.258X_3 + 0.917X_4 - 0.310X_5 \tag{3}$$

$$Y_2 = 0.249X_1 + 0.761X_2 + 0.793X_3 - 0.009X_4 + 0.613X_5. \tag{4}$$

The comprehensive score function is obtained by the calculated relative variance contribution rate:

$$Y = 0.662Y_1 + 0.338Y_2. \tag{5}$$

Solve to get the comprehensive score of each company and rank it, and select the top 15 suppliers are shown as Figure 4.

As shown in Figure 4, we can see that in the 5 indicators of the established raw material supplier evaluation model, in terms of supply capacity and actual supply cycle, there are still deficiencies in the upstream industrial chain of enterprises, and corresponding improvement plans need to be made.

5. Optimal Ordering and Transport Model Based on Multiobjective Optimization and Genetic Algorithm

5.1. Research Thought. We seek the best raw material ordering and transshipment solutions and select the least transfer options on this basis. First of all, we take whether the supplier chooses as the decision variable, takes the minimum number of suppliers as the objective function, establishes a planning model [17, 18], and obtains the minimum number of suppliers supplied; then in the ordering process, the weekly supply of the requested supplier is taken as the decision variable, and the most economical raw material price is taken as the target function; in the transfer process, the supply data is used to obtain the optimal transfer scheme with the lowest transfer loss rate as the target function [19], and finally, we construct a multiobjective function to find the optimal solution. Through the genetic algorithm, the constraints are included in the moderate evaluation, which effectively improves the solution quality, overcomes the disadvantages of local optimization [20], and searches for the optimal solution in the global situation in a faster way, which is suitable for this large-scale optimization problem.

5.2. Model Preparation. Before the model can be established, it is first necessary to design a minimum supplier scheme and find the minimum number of suppliers, that is, each supplier selected should supply as much as possible to the production enterprise [21].

(i) Step 1: the model assumes: first, the loss rate in the transshipment process is taken as 2%, and the receiving volume of the production enterprise is uniformly regarded as 98% of the supply [22]. Second, the maximum supply that each supplier can provide in the past and each cycle point is set as a fixed value, which is expressed as $\mathrm{MAX_A}$, $\mathrm{MAX_B}$, and $\mathrm{MAX_C}$.

$$\mathrm{MAX_A} = \begin{pmatrix} 2 & 0 & \cdots & 1 \\ 65 & 64 & \cdots & 84 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 \end{pmatrix} \tag{6}$$

(ii) Step 2: decision variables. For each supplier, it is only necessary to judge whether to choose or not. Therefore, taking the 146 suppliers of supply A as an example, the selection of 146 suppliers in 24 weeks is made into a matrix of 24 rows and 146 columns S_A as a decision variable, and the value of each position can only be 0 or 1, 1 is expressed as the selection of the supplier, and the purchase is based on the maximum supply [23], or 0 means no purchase. S_B, S_C too

(iii) Step 3: objective function. With the help of a matrix S_A, S_B, S_C, add up the 24-selection data for each column of each house, and if this data is not equal to 0, then the store is selected during the supply process.

Table 2: Characteristic root and variance contribution rate.

Element	Total variance explained								
	Initial eigenvalues			Extract the load sum of squares			Rotational load sum of squares		
Serial	Total	Variance percent	Accumulation (%)	Total	Variance percent	Accumulation (%)	Total	Variance percent	Accumulation (%)
1	2.416	48.316	48.316	48.316	48.316	48.316	2.004	40.073	40.073
2	1.233	24.669	72.986	1.233	24.669	72.986	1.646	32.913	72.986
3	0.853	17.057	90.042	—	—	—	—	—	—
4	0.339	6.778	96.820	—	—	—	—	—	—
5	0.159	3.180	100.00	—	—	—	—	—	—

Table 3: The rotated score coefficient matrix.

Element	1	2
Total supply average	0.899	0.249
Supply stability	0.439	0.761
Effective availability	0.258	0.793
Average weekly index of actual supply	0.917	-0.009
Raw material cost	-0.310	0.613

The target function z_1 expression is as follows:

$$\begin{aligned} \min\ z_1 = &\ \mathrm{num}\left(\sum_{i=1}^{24} (S_A)_{ij} \neq 0\right) \\ &+ \mathrm{num}\left(\sum_{i=1}^{24} (S_B)_{ij} \neq 0\right) \\ &+ \mathrm{num}\left(\sum_{i=1}^{24} (S_C)_{ij} \neq 0\right) \end{aligned} \quad (7)$$

(iv) Step 4: according to the above planning model, the enterprise should select at least 118 suppliers to supply raw materials to meet the demand for production, and the selected suppliers are shown in Figure 5

5.3. Model Establishment. Different from the optimization algorithm based on gradient descent commonly used in mathematical theory research [24–28], genetic algorithm is an optimization algorithm that draws on the principles of genetics and is widely used to solve transportation problems, supply chain network problems, and site selection and allocation problems [29]. Its essence is an efficient, parallel, global search method that automatically acquires and accumulates knowledge about the search space during the search process and adaptively controls the search process to find the best solution [30, 31]. The basic steps of the genetic algorithm are shown in Figure 6.

5.3.1. Coding Design. This model will use three layers of coding: (i) the selection of the least supplier in layer 1 (the 118 suppliers solved in the 5.2 model) will be coded from 0 to 1, with 0 when the supplier is not selected and 1 when the supplier is selected; (ii) the most economical ordering scheme for layer 2, which is integer coded for the supplier's supply, and each floating point number represents the supplier's supply during the week [32]; and (iii) the layer 3 loss is minimal, that is, the forwarder's choice is 0-1 coded, when a supplier chooses, 0 if the forwarder is not selected, 1 when the forwarder is selected [33].

5.3.2. Decision Variables. Let us assume that A raw material supplier, taking the first week as an example, the supply volume of each store in the first week consists of a matrix of 146 rows and 1 column as G_A, and defines G_B, G_C in the same way; at the same time, suppose that the matrix of 402 rows and 8 columns is the cooperation matrix S_Z between supplier and forwarder, which is a 0-1 matrix. Taking the first week as an example, the loss rate of each forwarder is recorded as ρ_1.

$$\rho_1 = \begin{pmatrix} 1.91 \\ 0.74 \\ \cdots \\ 0.64 \end{pmatrix}. \quad (8)$$

5.3.3. Fitness Function

(i) In order to reduce the need to reduce costs, it is planned to purchase as much class A as possible and class C raw materials as little as possible. Objective functions can be expressed by empowerment, it is advisable to give a class A raw material weight of 50, a class C raw material weight of 1, then there is a mathematical expression:

$$\max z_2 = 50 \times \sum_{i=1}^{146} (G_A) + 1 \times \sum_{i=1}^{122} (G_C) \quad (9)$$

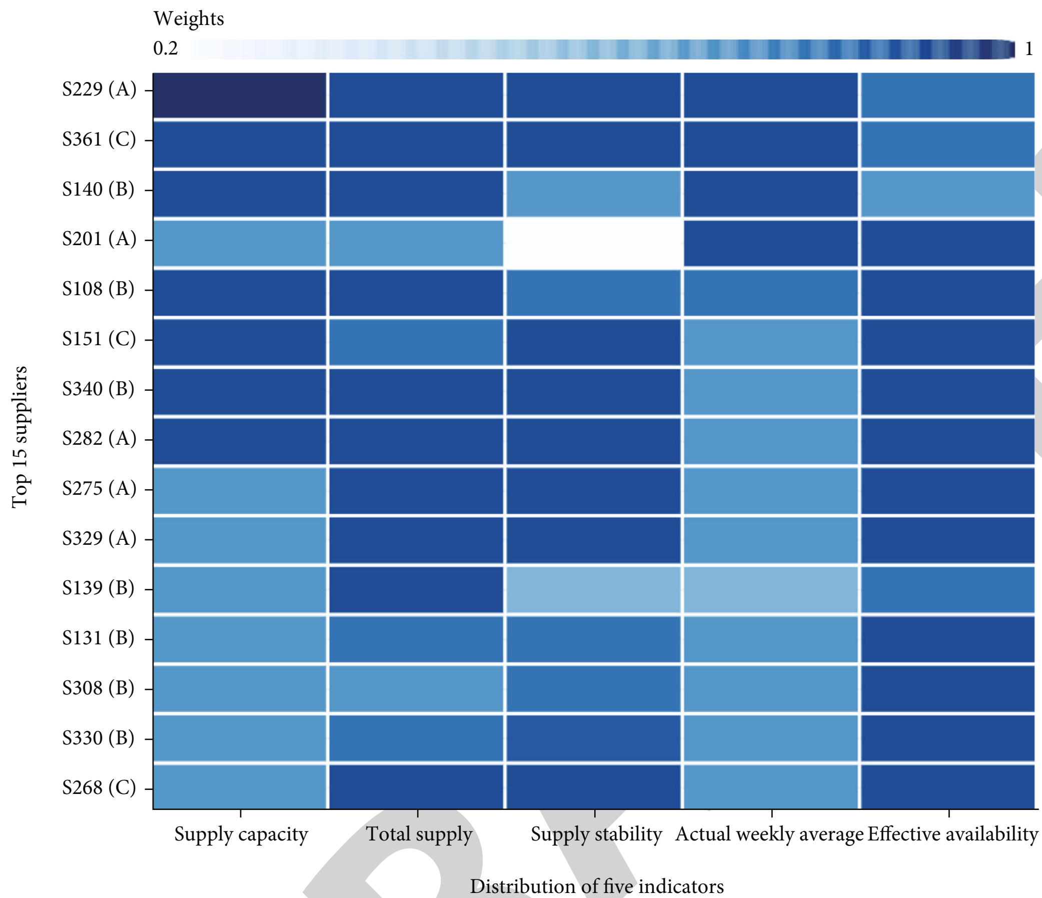

FIGURE 4: The top 15 most important suppliers and the proportion of each evaluation index.

(ii) To make the transshipment loss rate of the forwarder as small as possible, the expression is

$$\min z_2 = \begin{pmatrix} G_A \\ G_B \\ G_C \end{pmatrix} \cdot S_Z \cdot \rho_1 \tag{10}$$

5.3.4. Constraint Condition

(i) The most economical order plan. This article assumes that the total supply of raw materials A, B, and C is greater than the demand by 18,000 cm^3. And each week, the raw materials needed for the next week should be prepared in advance. For example, the math expression for the first week

$$95\% \times \left(\frac{\sum_{i=1}^{X} (G_A)_{ij}}{0.4} + \frac{\sum_{i=1}^{X} (G_B)_{ij}}{0.48} + \frac{\sum_{i=1}^{X} (G_C)_{ij}}{0.62} \right) \geq 3.85 \times 10^4 \tag{11}$$

The weekly supply from suppliers cannot exceed the maximum supply that their suppliers can provide.

Take the first week as an example:

$$G_A \leq \mathrm{MAX}_{A,1} \tag{12}$$

(ii) Assuming that a supplier is transported by only one forwarding company per week, and there must be a forwarding company to help it transfer:

$$\sum_{j=1}^{8} (S_Z)_{ij} = 1 \tag{13}$$

5.3.5. Generate the Initial Population. Depending on the constraints, a viable solution with a definite size is randomly generated as the initial population, with a population of 500 [34].

5.3.6. Genetic Strategies

(i) Crossover: set the crossover probability P_C of the population to 0.6. Two chromosomes are randomly selected, and when the crossover condition is met, 2 intersection points are randomly generated, and the $t1$ cycle data of chromosome 1 is exchanged with the $t2$ cycle data of chromosome 2 [35]

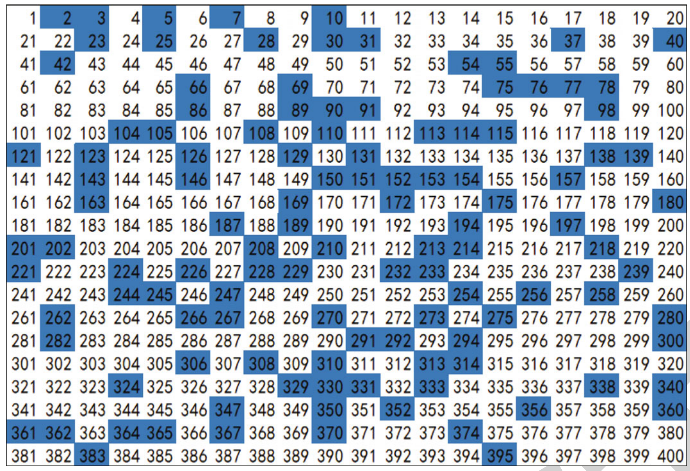

Figure 5: 118 suppliers.

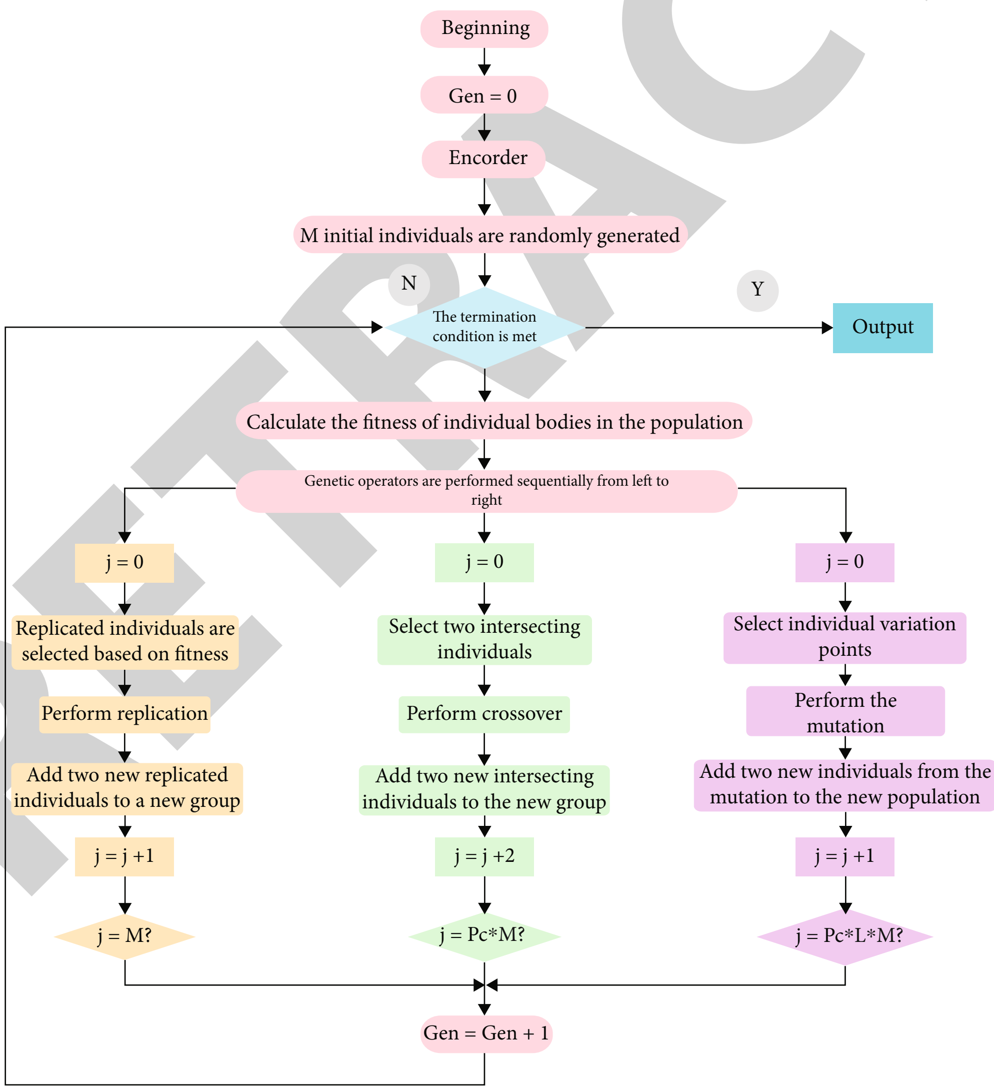

Figure 6: Genetic algorithm flowchart.

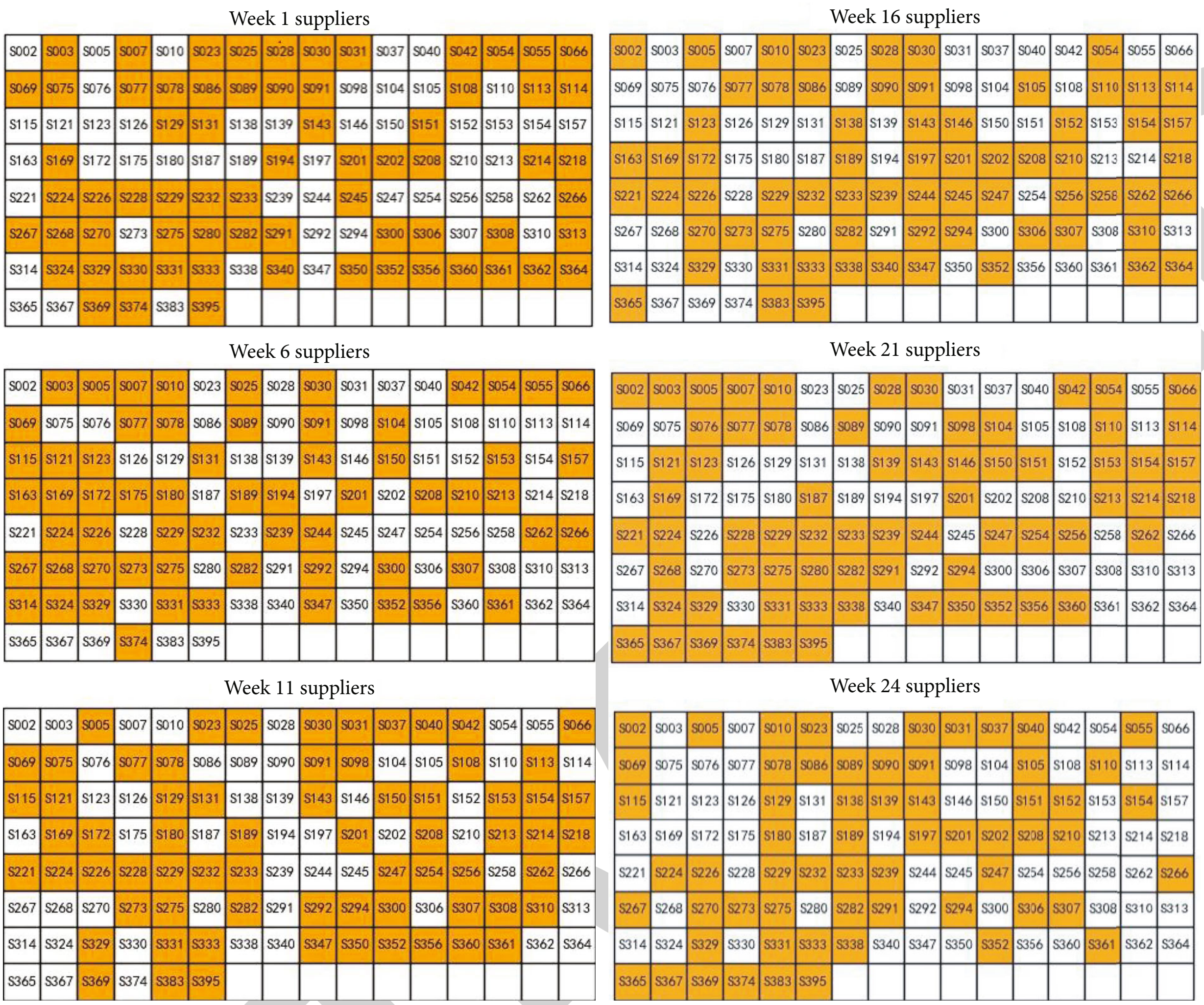

FIGURE 7: Supplier selection results.

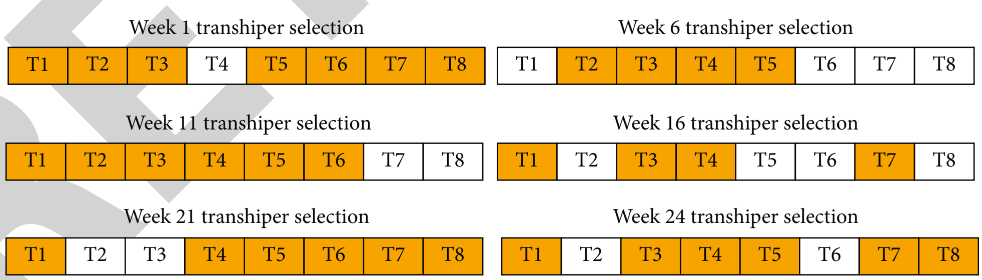

FIGURE 8: Transhipper selection results.

(ii) Variation: set the probability P_m of variation for the population p_m to 0. 01. A chromosome is randomly selected, and when the mutation condition is met, 2 mutation points $t1, t2 \in [1, T]$ are randomly generated, and the data of the $t1$, $t2$ cycles of the chromosome are exchanged [36, 37]

5.4. Model Solution. According to the above planning model, the company's raw material ordering and transshipment plan for the next 24 weeks and the weekly population evolution trend have been identified, due to the excessive length, here we give an example of the situation in weeks 1, 6, 11, 16, 21, and 24.

As shown in Figures 7 and 8, we can see the distribution of chromosomes, orange represents 1, and white represents 0. Under the optimization model of the genetic algorithm we designed, we provide suitable raw material suppliers and forwarders for each cycle according to the needs of enterprises, reducing the impact of subjective factors, which

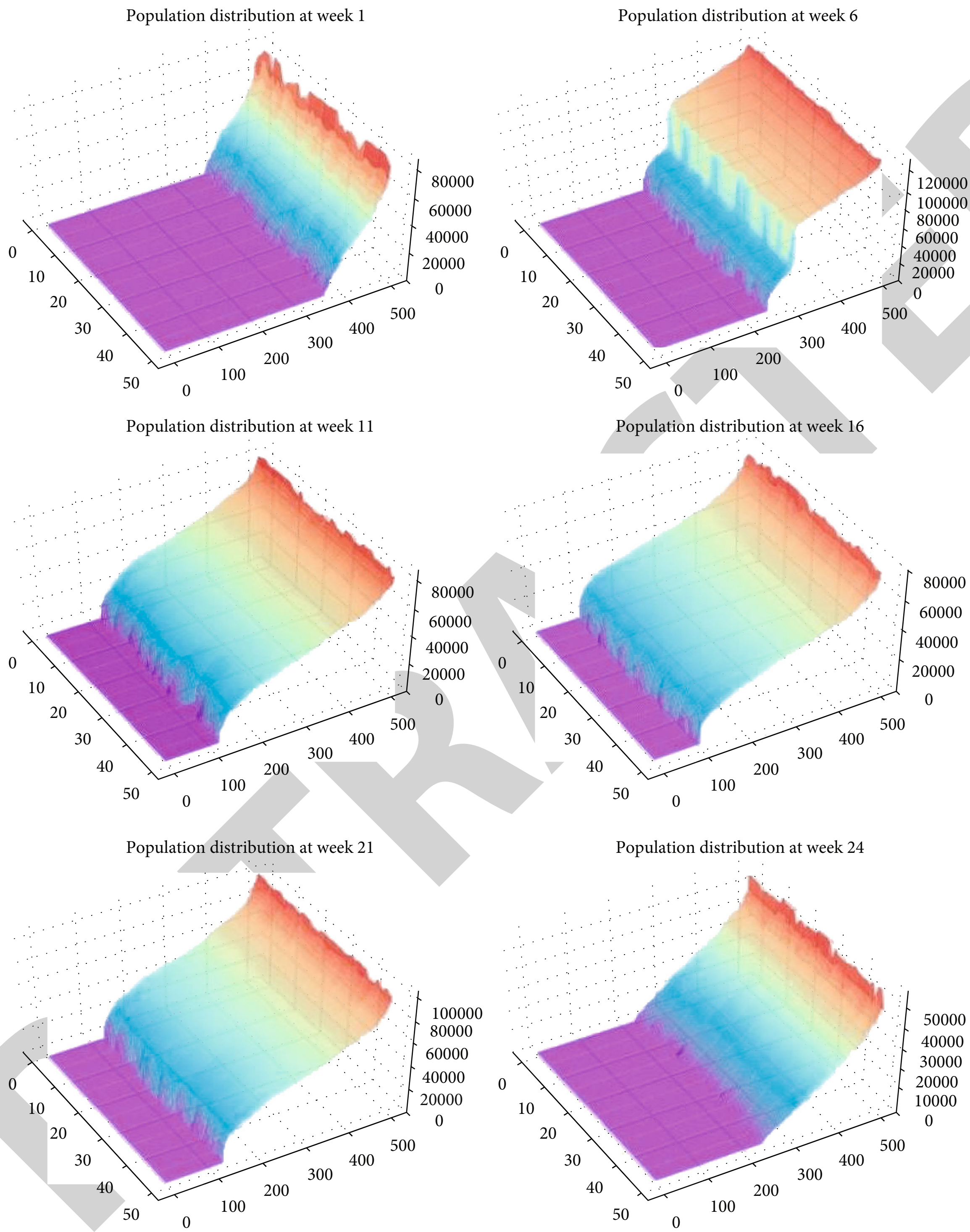

Figure 9: Population iteration results.

is conducive to enterprises to quickly lock in upstream supply chain partners, reduce costs and costs, and meet the raw material needs of enterprises in various periods [38, 39].

As shown in Figure 9, the genetic algebra used in the multiobjective genetic algorithm model we constructed is very small, with a maximum of no more than 50 generations. It can be seen that the convergence speed is very fast, which is suitable for the optimization of complex problems, and the optimal value of the supply chain system presents a cycle. It is in line with the multicycle characteristics of enterprises and has good applicability.

5.5. Calculation Verification. When verifying the model, we set the parameters of the genetic calculation as follows: the hybridization probability is 0.6, the mutation probability is 0.1, the initial population is 500, and the maximum

Table 4: Verified operation result.

Text	The algebra of iterating to the result	Initial population	Hybrid probability	Mutation probability	Best quality value
1	27	500	0.6	0.01	80921.81
2	25	500	0.6	0.01	80921.81
3	22	500	0.6	0.01	80921.81
4	26	500	0.6	0.01	80921.81
5	28	500	0.6	0.01	80921.81
6	21	500	0.6	0.01	80921.81
7	24	500	0.6	0.01	80921.81
8	25	500	0.6	0.01	80921.81

evolutionary generation is 50. For 8 consecutive calculations, the termination algebras of the 8 operations are shown in Table 4.

As shown in Table 4, the first terminates in the 22nd generation, the second terminates in the 23rd generation, the third terminates in the 24th generation, and the fourth terminates in the 25th generation. The sixth time ends at the 25th generation, the seventh time ends at the 23rd time, and the eighth time ends at the 24th time. The optimal value of the 8 calculations is 80921.81 yuan, which can prove that the genetic algorithm is effective.

6. Conclusion

In this paper, TOPSIS is used to improve the factor analysis model, and the evaluation index system to ensure the importance of enterprise production is constructed by mining 5 indicators from multiple angles, which is conducive to improving the use of raw materials by enterprises. Secondly, the genetic algorithm is used, and the constraint conditions are added, so that the objective function obtains a feasible solution under the agreed conditions, avoids local optimization, and thus achieves global optimization. By studying the optimization of the ordering and transportation of raw materials for production enterprises, it is conducive to improving the production efficiency of traditional manufacturing industries and promoting the improvement of production competitiveness of production and manufacturing industries. In view of the great advantages of deep learning technology in prediction and recommendation [40–43], in the next step, we will combine artificial intelligence technology to develop new algorithms to further optimize the ordering and transportation of raw materials.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Authors' Contributions

Feng Xu was responsible for the methodology; conceptualization; supervision and leadership. Yu-Meng Zhang was responsible for the conceptualization, visualization, software, validation, and data analysis. Yi Su was responsible for writing the manuscript, verification, and investigation. Jia Li was involved in data collation verification and method design. Jia-Ming Zhu contributed to the study conception and design, supervision, and review and editing. All authors read and approved the final manuscript.

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