TGPFM: An Optimized Framework for Ordering and Transporting Raw Materials for Production

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Abstract. Developing efficient raw material ordering and transshipment strategies for companies with uncertain supply has attracted extensive interests from both academic and industrial researchers. Some methods have been proposed, such as obtaining a strategy using a heuristic algorithm, or developing an ordering scheme and a transportation scheme separately. These methods can work in some cases, but they can also lead to local optimization. To address this problem, we proposed the TGPFM framework, which takes raw material ordering, transshipment, and inventory into account. The TGPFM is made up of a supply capacity grey cycle prediction model, a transporter time series prediction model, a supplier PCA evaluation model, a multi-objective ordering scheme planning model, and a transshipment planning model. As a result, the problem of local optimization, which is induced by considering each process separately, can be effectively avoided. We conducted experiments on data from national competitions to verify the framework's validity. The results show that putting a weight limit on inventory and material types in the ordering model, as well as using a PCA-based supplier ranking table, can help get a better overall plan. The time series of transit loss outperforms the grey prediction, and the grey prediction model combined with the excess fluctuation function can better predict supplier supply quantity.

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1 Introduction

Thanks to the global economy's integration and the development of the Internet, supply chains, and other technologies, people can now choose from a growing number of manufacturer brands when purchasing goods. As a result, the number of suppliers available to manufacturers is steadily growing. Manufacturers would prefer to spend the majority of their costs on the product and avoid the costs of ordering, forwarding, and stocking the goods in order to maximize profits. The cost composition varies by segment; for example, when ordering raw materials, consider the supply and demand balance, cost price, supplier selection, and so on. The importance of an effective materials ordering plan and supplier selection strategy has been revealed by [10]. The choice of supplier, according to [5], can affect the project schedule. Failure to choose the right supplier, according to [6], will increase the cost of ordering as well as the cost of implementing the project. The volume of goods being forwarded, the forwarder chosen, and other factors should all be considered when evaluating forwarding. Stock capacity, the amount of goods arriving, and other factors should all be taken into account when planning inventory. Although [17] takes into account both project scheduling and material procurement, it neglects to account for warehouse capacity, which does not correspond to reality. At the same time, the aforementioned connections are interconnected. According to [16], if the project schedule and material procurement are not taken into account as a whole, the total project cost will rise. Consequently, the better the coordination, the lower the total project cost.

The following sub-problems have been refined to reduce the total cost of goods in the ordering, forwarding, and warehousing processes while still meeting business needs.

- RQ1: How to measure the supplier's ability to supply?
- RQ2: How can historical data be used to forecast a supplier's ability to supply over time in order to arrive at a good ordering solution when supply and demand are uncertain?
- RQ3: How to set the cost-cutting objective function and constraints for ordering and forwarding solutions?
- RQ4: How to maximize total cost savings by combining ordering, forwarding solutions, and inventory restrictions?
- RQ5: How can attrition rates for forwarders be accurately predicted?

To address the aforementioned sub-problems, we proposed the TGPFM framework, which takes into account the ordering and transportation of raw materials in its entirety. To forecast future availability over a given time horizon, a grey forecasting model and a fluctuating model of excess output were first combined. Second, using time series weighted shifts, the forwarders' weekly attrition rates were predicted. The order plan for the next 24 weeks is created by using the multi-objective programming model to add the ratio of material A and B as a preference in the objective function with the goal of minimizing cost. By establishing 11 supplier indicators, the PCA-based supplier evaluation form was created. The predicted forwarder attrition rate was used to establish a forwarder ranking table. The forwarding scheme was implemented by substituting the ordering scheme and the two ranking tables into the 0–1 planning model.

In summary, this article makes the following contributions.

- We propose a TGPFM framework that includes a time series forecasting model, a grey forecasting model, a PCA, an excess volatility function, and a multi-objective planning model for picking the optimal strategy for minimizing raw material costs throughout ordering, transportation, and storage.
- We used a functional approximation to forecast supply capacity and a grey forecasting model to forecast supply fluctuations. Ultimately, the weighted and summed results were used to determine the final supplier supply.
- To obtain the forwarding scheme, we created a supplier and forwarder ranking table and substituted the obtained ordering scheme into the planning model with the two ranking tables.
- Inventory weights and raw material weights were added to the ordering scheme's objective function to balance inventory and ordering costs, as well as to limit stock levels.
- We conducted extensive experiments on the Mathematical Modelling National Competition dataset to validate the effectiveness of our proposed framework. Experiments have shown that TGPFM can develop lower-cost ordering and transshipment schemes for raw materials in the face of supply and demand uncertainty.

2 Background

The globalization of the economy has resulted in the formation of dynamic supply chain alliances. Companies can use supply chain management to cut costs, such as procurement, distribution, and storage, and thus gain a competitive advantage in the marketplace. However, many businesses are concerned about how to achieve quality management; one of the challenges is supply chain uncertainty, which manifests itself in supply, demand, articulation, and business operations. The uncertainty of supply (variations in the number of available suppliers) and the uncertainty of convergence are discussed in this paper (losses in transit). See Fig. 1 for the specific process.

Heuristic algorithms and planning models are the two main types of solutions that have been developed for the ordering scheduling problem in enterprises.

For very large data sets, intelligent algorithms are required, but recent research has revealed that there is still a risk of falling into a local optimum. The Resource-Constrained Project Scheduling Problem (RCPSP) has a wide range of applications, and its research is both academically and practically important. Large-scale, strongly constrained, multi-objective, uncertain, and NP-hard are

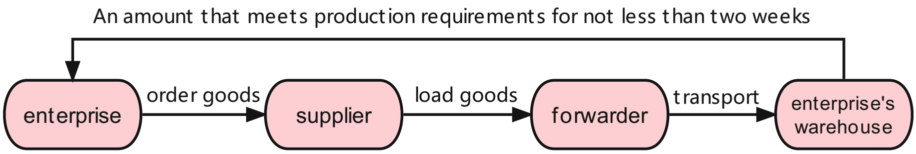


Fig. 1. Ordering and shipping process

some of the complexities. As a result, a variety of heuristic and meta-heuristic algorithms to solve it have been proposed. [14] proposed a multi-stage stochastic mixed-integer programming with endogenous uncertainty and a heuristic search for feasible solutions, lowering the total cost significantly. [2] proposed a method for project scheduling that took into account material ordering, procurement, and supplier selection all at the same time in order to maximize profit and improve the heuristic algorithm with a restart mechanism. However, there is no single heuristic or meta-heuristic algorithm that can solve the RCPS-DC problem in a reasonable amount of time.

Although methods that use planning models to solve the ordering transit problem can produce optimal results, none of them have produced more specific scheduling and ordering solutions. The use of a mixed-integer programming model to obtain optimal ordering solutions under multiple constraints was proposed by [7], and computational experiments showed that large computers are not required to solve problems with relatively large data sizes. To find the ordering solution, [23] used linear programming with value-at-risk as the objective function. The above schemes, as can be seen, do not take into account ordering, transshipment, and inventory as a whole.

3 Methodology

This section delves into the specifics of the components that make up the framework provided in this paper. Specifically, the TGPFM model is composed of time series prediction, grey prediction, multi-objective programming, PCA, and periodic wave function. Grey forecasting and periodic fluctuation constitute the supplier quantity forecasting model. The supplier multi-objective model is combined with the supplier quantity forecasting model to solve the ordering scheme. The ordering scheme combines supplier ranking table (PCA algorithm), transportation loss prediction (time series), and a multi-objective programming model of forwarder to get the transportation scheme. The specific steps are shown in Fig. 2.

3.1 Problem Definition

Assume that different raw materials are ordered at varying prices, but that transportation and storage costs are the same per unit. A manufacturing company requires N raw materials in a certain quantity. How to establish a strategy for

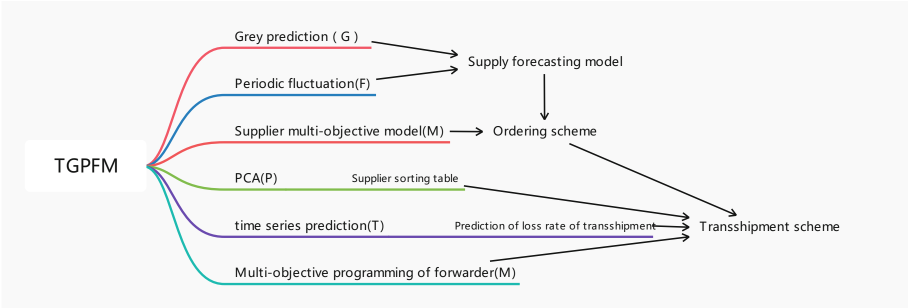


Fig. 2. The framework of TGPFM model

ordering and moving raw materials over the following T weeks. In this study, we suppose that there are three types of raw materials and that T equals 24 weeks.

3.2 Supplier Supply Forecast Based on Historical Data

The 240 weeks are divided into ten stages, with an average supply quantity determined for each stage. Furthermore, to reflect the supply rule of providers over time, it was integrated into the grey prediction model.

Grey System Prediction. This paper uses the GM(1, 1) model [22] to expand. The model's prediction premise is as follows: by accumulating a given data series, a collection of new data series with a clear trend is formed. Next, for prediction, a model is created based on the new data series' developing tendency. The original data series is then recreated using the accumulation and subtraction approach, resulting in the predicted result. The modeling process is rough as follows:

Step 1: Let a set of original data be $x^{(0)} = \left(x^{(0)}(1), x^{(0)}(2), \ldots x^{(0)}(n)\right)$, n is the number of data. Accumulate $x^{(0)}$ to weaken the volatility and randomness of the random sequence, and get a new sequence as follows:

$$x^{(1)} = \left(x^{(1)}(1), x^{(1)}(2), \ldots x^{(1)}(n)\right) \tag{1}$$

$$x^{(1)}(k) = \sum_{i}^{k} x^{(0)}(i), k = 1, 2, \ldots, n \tag{2}$$

Step 2: Generate adjacent mean equal weight column of $x^{(1)}$:

$$z^{(1)} = \left(z^{(1)}(2), z^{(1)}(3), \ldots z^{(1)}(k)\right), k = 2, 3, \ldots, n \tag{3}$$

$$z^{(1)}(k) = 0.5x^{(1)}(k-1) + 0.5x^{(1)}(k), k = 2, 3, \ldots, n \tag{4}$$

Step 3: Establish a first-order unitary differential equation of the whitening form of t for $x^{(1)}$ according to grey theory:

$$GM\left(1,1\right):\frac{dx^{(1)}}{dt}+ax^{(1)}=u \tag{5}$$

Among them, a, u are the coefficients to be solved, which are called development coefficient and grey action quantity, respectively. The effective interval of a is $(-2, 2)$, and the matrix formed by a,u is grey parameter $\hat{a}=\begin{pmatrix} a \\ u \end{pmatrix}$ As long as the parameters a, u are obtained, $x^{(1)}(t)$ can be obtained, and then the predicted value of $x^{(0)}$ can be obtained.

Step 4: Average the accumulated generated data to generate B and a constant term vector Y_n:

$$B=\begin{bmatrix} -z^{(1)}\left(2\right) & 1 \\ -z^{(1)}\left(3\right) & 1 \\ \vdots & \vdots \\ -z^{(1)}\left(n\right) & 1 \end{bmatrix}=\begin{bmatrix} -\frac{1}{2}\left(x^{(1)}\left(1\right)+x^{(1)}\left(2\right)\right) & 1 \\ -\frac{1}{2}\left(x^{(1)}\left(2\right)+x^{(1)}\left(3\right)\right) & 1 \\ \vdots & \vdots \\ -\frac{1}{2}\left(x^{(1)}\left(n-1\right)+x^{(1)}\left(n\right)\right) & 1 \end{bmatrix} \tag{6}$$

Step 5: Use the least square method to solve the grey parameter $\hat{a}$, then

$$\hat{a}=\left(B^{T}B\right)^{-1}B^{T}Y_n \tag{7}$$

Step 6: Substitute grey parameter $\hat{a}$ into $\frac{dx^{(1)}}{dt}+ax^{(1)}=u$, and solve $\frac{dx^{(1)}}{dt}+ax^{(1)}=u$ to get

$$\hat{x}^{(1)}\left(t+1\right)=\left(x^{(1)}\left(1\right)-\frac{u}{a}\right)e^{-at}+\frac{u}{a} \tag{8}$$

Step 7: Subtract and restore the above results to get the predicted value.

Periodic Wave Function. We apply the function fitting and averaging to acquire the basic supply capacity of 402 providers in the next 24 weeks because the supplier's supply amount given in the table is related to the orderer's ordering quantity as well as its own supply capacity. We consider every 24 weeks to be an ordering cycle because this company orders and transships raw goods every 24 weeks [8].

Firstly, the average supply quantity r_1 is calculated, and the data of supply quantity greater than two times of average r_1 is regarded as oversupply. After deleting the over-supply data, the average r_2 of the remaining data is calculated, that is, calculating the number of times m of excess supply, and the average r_2 is taken as the basic supply capacity of each supplier.

$$\begin{cases} r_1=\frac{\sum x}{240} \\ r_2=\frac{\sum x}{m}, x\leq 2r_1 \end{cases} \tag{9}$$

For the oversupply data, we get the mean r_3 and the times t. Divide the number t by 10 to get the frequency T of oversupply in each order cycle.

$$\begin{cases} r_3 = \frac{1}{t}\sum x, x > 2r_1 \\ T = \frac{t}{10} \end{cases} \tag{10}$$

The sine function is used to construct a 24-week fluctuation function, and the probability of overproduction fluctuation is introduced.

$$\sin\left(\frac{\pi}{12} * T * i\right) > 0.95, i \in (1, 24) \tag{11}$$

After adding the excess supply fluctuation, the supply capacity of the current week is:

$$G = r_2 + r_3 + \varepsilon, \varepsilon \sim N\left(r_1, \sigma^2\right) \tag{12}$$

Finally, add the general error ε of normal distribution based on historical data, and we can get the forecast supply in the next 24 weeks. Where ε^2 is the variance of the supplied sample.

Supplier Supply Quantity Prediction

The average value of function fitting was given 4/5 weight, the grey prediction model was given 1/5 weight, and the final prediction result was solved after adding.

3.3 Ordering Scheme Model Based on Multi-objective Programming

Preliminary Analysis of ABC Raw Material Supplier

In normal circumstances, businesses purchase raw materials at a lower unit price and utilize fewer raw resources. The Table 1 shows that Class A materials use less energy and are less expensive. Because Class B raw materials have the greatest cost per unit price for finished products, firms will choose to use Class A raw materials, followed by Class C. In addition, fitting historical data reveals that just 24% of weekly orders of Class B materials can meet capacity requirements. Therefore, we limited the weight of C and B products in the objective function [4].

Table 1. Cost performance of raw materials

Type of raw materials	The unit price	Unit consumption of finished products	Unit cost of finished products
A	1.2	0.6	0.72
B	1.1	0.66	0.726
C	1.0	0.72	0.72

Establishment of Ordering Scheme Model

As far as practicable, each supplier selects just one forwarder per week, and each forwarder's transshipment capacity is limited to 6,000 cubic meters. When each provider's volume is greater than 6,000 per week, the organization receives just 6,000 per week from each supplier. If it is less than 6,000, the supplier is responsible for providing the real supply to the company. The accumulated items of suppliers are carried to the enterprise warehouse as soon as feasible to simplify the examination of difficulties and practical problems. As a result, the untransported items of suppliers are estimated and will arrive at the enterprise warehouse the following week.

We used a single week as an example to build a multi-objective programming model with the most cost-effective ordering strategy. The overall weekly supply of raw materials must fulfill the production needs. To keep the steel industry's costs down, that is, to keep the purchase and warehouse inventory costs as low as possible [21].

Since the storage volume needs to meet the enterprise's capacity demand, xx_i is obtained by converting the material volume into the enterprise's capacity. Write E_t as the storage volume of week t, which is determined by the storage volume of last week E_{t-1}, the usage of raw materials in production this week L and the new transportation volume.

$$E_t = E_{t-1} - L + \sum xx_i \tag{13}$$

$$min\ Cost = q \cdot (1.2a + 1.1b + 1.0c) + 2000 \cdot b + 100 \cdot c + p \cdot E_t \tag{14}$$

$$s.t. \begin{cases} a = \sum 0.6x_i, x \in A \\ xx_i = x_i/0.6, x \in A \\ b = \sum 0.66x_i, x \in B \\ xx_i = x_i/0.66, x \in B \\ c = \sum 0.72x_i, x \in C \\ xx_i = x_i/0.72, x \in C \\ L = 28200 \\ E_t > 28200, E_t = E_{t-1} - L + \sum xx_i \end{cases} \tag{15}$$

In the formula, a,b and c represents the purchased quantity of three types of raw materials (unit: cubic meter), p is the weight of purchase cost, q is the weight of storage quantity, p is 2/5 and q is 3/5. Assume that $E_1 = 56400$.

In the formula, Cost is the cost of purchasing all raw materials, a,b,c is the volume of purchasing three kinds of raw materials, where x_i is the supply quantity of the supplier i and L is the consumption of raw materials in stock in the current week.

Following the acquisition of the supply situation, it is vital to minimize transportation loss in order to save money on purchases, ensure that goods are not lost, and reduce the number of selected transporters. The results of the ordering scheme model were used to fill in the gaps in the above-mentioned transportation scheme model.

3.4 Measuring Supplier's Importance

To measure the importance of suppliers, we define the following indicators (Fig. 3).

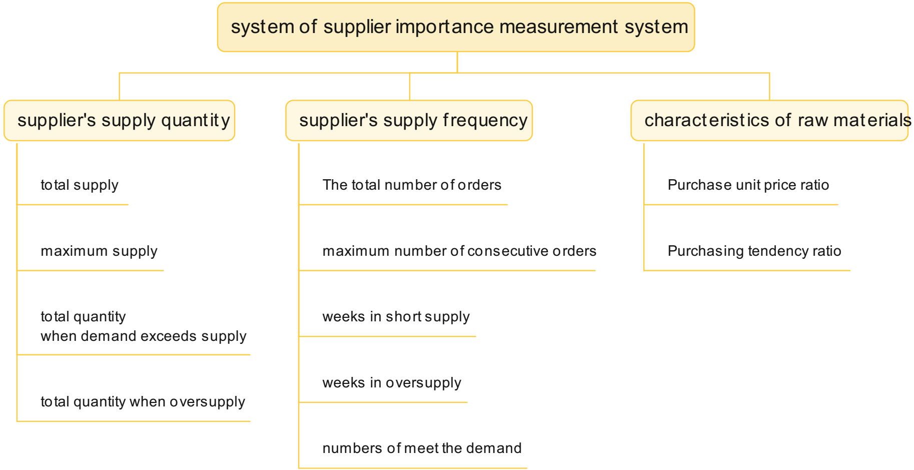


Fig. 3. Index system diagram of supplier's importance

(1) Unit purchase ratio [20]

Definition: With the purchase price of Class C raw materials as the unit purchase price, the purchase price of Class A raw materials: the purchase price of Class B raw materials: the purchase price of Class C raw materials = 1.2:1.1:1.

(2) Procurement propensity ratio

Definition: Consumption of all kinds of raw materials per cubic meter of products, class A: class B: class C = 0.6:0.66:0.72.

Supplier Importance Evaluation Model Based on PCA

The method of determining the relevance of a supplier is multi-cause and one-effect. PCA is a statistical analysis method that divides a large number of variables into a few comprehensive indices. Its aim is to reduce the dimension of the original data characteristics and limit information loss following dimensionality reduction while guaranteeing that as little "information is lost" as possible. As a result, we opted to employ 11 index data to construct a principal component analysis-based evaluation of supplier importance. The specific process shows in Fig. 4.

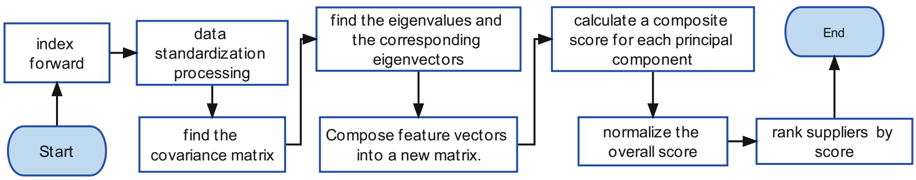


Fig. 4. The process of PCA

The quantitative definition in this model is based on the data in Annex 1, and it is clear that the higher the final comprehensive score, the larger the importance.

3.5 Prediction of Loss Rate of Transporters

Firstly, the 240-week data was divided into ten cycles, with the data of the corresponding week in each cycle being processed using the weighted moving average approach. Since the most recent facts carried more weight in predicting the future [15,18].

Let the time series be $f_1, f_2...$, the formula of weighted moving average method is

$$Mean = \frac{w_1 f_t + w_2 f_{t-1} + w_3 f_{t-2} + \cdots + w_N f_{t-N+1}}{w_1 + w_2 + w_3 + \cdots + w_N} \tag{16}$$

$Mean$ was the weighted moving average, $w_i$was the weight of f_{t-i+1}, $w_1 > w_2 > \cdots > w_N$ shows that recent data is more important to mean, and Mean was used as the prediction of the loss rate.

3.6 Establishment of Transport Scheme Model

The weekly is also used as an example for multi-objective programming with the lowest attrition rate transshipment system. The raw materials must be transferred once a week, but the transporter's weekly transport capacity must not exceed 6000. Furthermore, since each transporter has the same turnover volume and transportation cost, transportation losses should be avoided, and the number of transporters should be reduced to save costs [11,13].

$$min\ loss = \sum x_{ij} \cdot t_j \tag{17}$$

$$s.t. = \begin{cases} \sum_{i=1} x_{i1} \leq 6000 \\ \vdots \\ \sum_{i=1} x_{i8} \leq 6000 \\ \sum_{j=1} x_{1j} \geq X_1 \\ \vdots \\ \sum_{j=1} x_{kj} \geq X_k \end{cases} \tag{18}$$

where loss was the total loss rate of all transport schemes.x_{ij} represents the number of goods from supplier i to be moved by the shipper j.t_j is the loss rate of the j forwarder and X_i is the order quantity of the i supplier. Please refer to the Fig. 5 for details.

The forwarder ranking table is rated according to the expected weekly loss of forwarders, while the supplier ranking table is ranked according to the supplier ranking table derived by PCA.

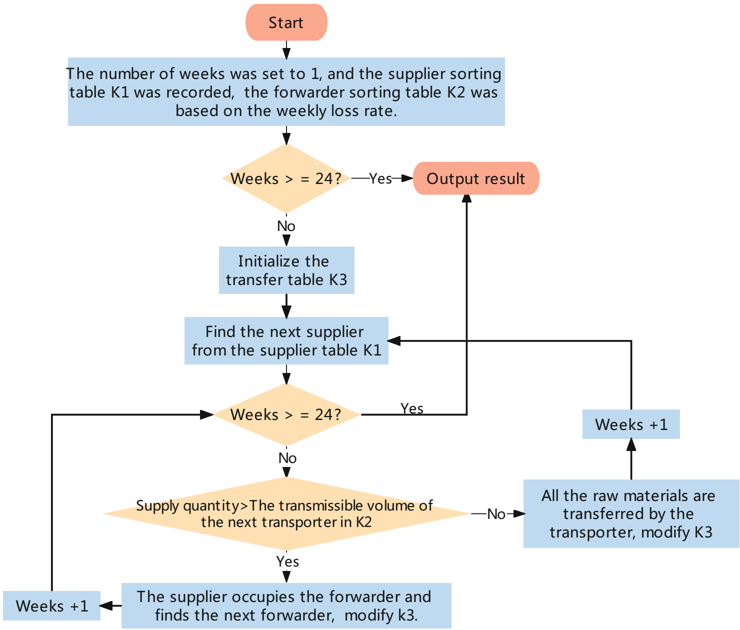


Fig. 5. Transfer scheme algorithm

4 Experimental Results

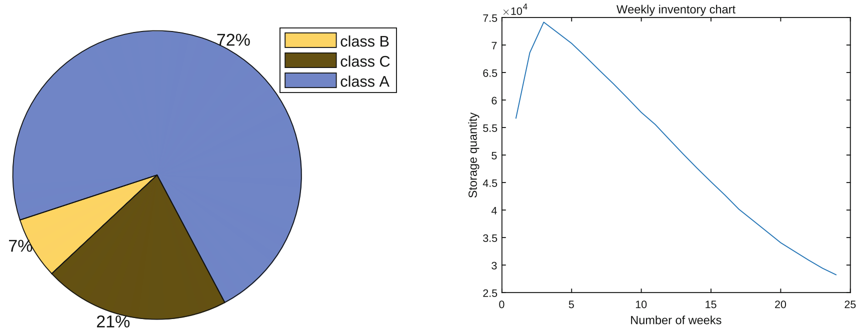
The difference between a multi-objective programming model and an intelligent algorithm is that it is the optimal solution obtained by traversing all combinations, while the optimal solution obtained by an intelligent algorithm is a random combination, which may fall into the local optimum. Therefore, the optimal solution in this paper does not need to be proved, and the calculation in this paper is basic addition and subtraction, and the multiplication is simple, so the speed of lingo operation is sufficient.

From the supplier proportion result in Fig. 6, it can be seen that Class A suppliers account for the most, followed by Class B suppliers. A total of 202 suppliers were selected, and the inventory was more than 28200.

4.1 Inspection Experiment of the Ordered Scheme

If the objective function didn't add the setting of the weight of material types, the result was that 402 companies were selected, which was obviously unreasonable. Moreover, the purchased quantity was small in the first week and the goods were purchased from all suppliers in the next 23 weeks, which obviously couldn't meet the demand in reality.

If the objective function didn't add weight to the warehouse cost and purchase cost, the purchase cost was higher than the result of this paper and the total



(a) Supplier Category Proportion (b) Weekly Inventory

Fig. 6. Forecast order result.

inventory was lower by 9074. Although more inventory will increase the storage cost. However, from the historical data, it is known that the supplier's supply capacity is limited, which actually can't reach the expected inventory. Moreover, the inventory cost is generally much lower than the purchase cost, and more inventory can make the enterprise run normally.

4.2 Prediction Accuracy Test of Transporter

The loss of the last cycle was predicted by using the historical data of forwarders in the first 9 cycles (24 weeks per cycle). And the error was compared with the tenth cycle.

Table 2. The comparison of different prediction results

Algorithm	Time series prediction	Grey prediction
MAE	0.4304	0.6034
RMSE	0.7626	0.8943

The results in Table 2 show that the prediction accuracy of time series prediction is better than that of grey prediction, and the overall deviation of data is small.

4.3 Test Experiment of Transport Scheme

The characteristics of forwarders' loss rate change obviously and the prediction accuracy is high, so the predicted loss was used for ranking. Because the forwarding scheme was made in advance, the risk of later prediction was taken into account, for example, the supplier that buys the most in the current week may be unable to supply goods due to its insufficient supply capacity, and the forwarder with the lowest loss will waste resources, resulting in more actual losses. Therefore, we did not adopt the optimal transshipment scheme, but adopted the supplier allocation table, and assigned the forwarder with the lowest loss to the supplier with the most likely large supply. Therefore, the question becomes whether to use the supplier ranking of materials or the supplier capability ranking table of PCA [12].

The predicted supply scale in the next 24 weeks, the order decision, and the predicted loss rate table were substituted into the transshipment scheme model. The difference was only the supplier ranking table.

Table 3. Comparison of results of PCA and material category

	Consumption of goods	Destination volume	Attrition rate
Ranking table result of PCA	2252.60	650714.0543	0.00346
Result of material category	2237.35	648604.9477	0.00344

It can be seen from the Table 3 that the supplier ranking in the transshipment scheme is the best according to PCA ranking, which not only had a large final destination transportation volume but also had a low loss rate.

4.4 Comparative Experiment of Supplier Ranking Algorithm

It can be concluded from the Table 4 that Suppliers selected by PCA based on ranking results and historical data are superior to TOPSIS comprehensive evaluation in terms of supply and supply frequency [9].

Table 4. Top 10 suppliers

Ranking	1	2	3	4	5	6	7	8	9	10
Pca ID	229	108	140	282	329	275	361	151	348	308
Topsis ID	151	229	361	108	374	348	140	330	308	282

4.5 Inspection of Supply Capacity Forecast and Ordering Scheme

Substitute the data of the first nine cycles into the order quantity forecasting model to obtain the supply of the tenth cycle, and put it into the objective function to get the order result, which was compared with the original order result of the tenth cycle. The results are in Fig. 7.

By observing the actual supply data of suppliers, it can be found that the inventory does not reach 56400 at the end of nine cycles. So it was assumed that

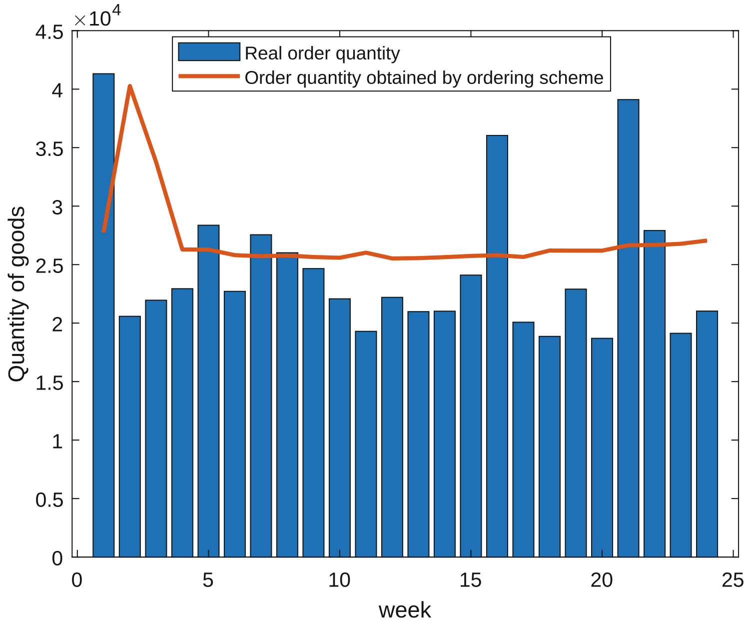


Fig. 7. Order quantity forecast inspection

there was an initial inventory of 35,000. The ordering plan table was obtained after the supplier prediction model and multi-objective model, with an average difference of 5932.244, which was acceptable relative to the supply quantity of 10,000 units. Moreover, the actual supply quantity obtained from the actual order quantity from the actual supply data cannot meet the inventory requirements. If the order quantity is larger, the supplier can provide more goods [1].

5 Conclusion

The TGPFM framework proposed in this paper is composed of a grey cycle prediction model of supply capacity, a time series prediction model of transporters, a PCA evaluation model of suppliers, a multi-objective ordering scheme planning model, and a transshipment planning model. The experimental results show that: 1. The objective function of the ordering scheme should limit the weight of inventory and material type value. 2. PCA-based supplier evaluation table in the transshipment strategy is superior to the supplier material ranking table and TOPSIS comprehensive evaluation Table 4. The prediction of supply capacity should be combined with the grey prediction model and the excess fluctuation function. 5. The prediction and planning effect of the model in this paper is good. However, the drawback of this paper is that the experimental data used is only the national competition data set. In the future, the amount of data should be increased for experiments. Our future research direction is to consider multi-supplier ordering and transshipment schemes [3] and stock sharing [19].

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