Hindawi
Journal of Function Spaces
Volume 2022, Article ID 2593487, 9 pages
https://doi.org/10.1155/2022/2593487

Research Article

The Optimal Supply Decision Based on Dynamic Multiobjective Optimization and Prediction

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Received 5 April 2022; Accepted 26 May 2022; Published 8 June 2022

Academic Editor: Muhammad Gulzar

Different material supply-related decisions intensively affect the efficiency of manufacturers. To obtain a suitable supply-related protocol, this study proposes a supply selection model which considers both manufacturers' development orientation and material ordering. In contrast to traditional approaches that rely on expert opinions, the proposed approach in this study allows the time series analysis (ARIMA) to forecast the trend in manufacturers' development during the execution of the plan. Based on the predicted trend, taking the minimum of total material management cost as the objective function, the control function and optimization conditions are constructed to select the appropriate protocol. The dynamic prediction protocol is obtained by considering the variation in production and material costs by an evolutionary algorithm. The model enables users to determine material supply protocol in continuous time and autonomously adapt to changes in the manufacturers' production goals within a lower convergence time.

1. Introduction

The material ordering management solution needs to determine the quantities and ordering paths for product raw materials in a time-varying environment. In some papers, different relative operators were investigated in the last years. Inventory issues and the selection of material-control solutions have been important parts of the overall supply chain coordination process and have been the focus of attention in the field of supply chain management research. The final object of the economical activities is to increase the people's happiness [1], and the optimal program can save resources then thus contributing to promoting the people's satisfaction. The optimal program can save resources and thus is to contribute to people's happiness. And the model can also be used to optimize other domain issues, such as some transportation schedules. In this study, ordering planning is based on a manufacturer's perspective consideration of several questions from a theoretical point of view, but also from a practical one: What factors influence ordering planning? How will changes within the company orient the ordering planning of raw materials? How should the planning model respond to this orientation? These questions not only suggest how the corresponding model should be built but also determine the situation in which the model needs to be adapted. The study improves the adaptability and generalization of the prediction model and optimizes the information interaction and response speed of the ordering and distribution network.

This paper is outlined as follows. In Sections 2 and 3, (1) we investigate the research background of this problem, (2) we propose dynamic multiobjective optimization based on development prediction, and (3) we propose an evolutionary algorithm combined with dynamic strategy (RS/AS) to solve dynamic multiobjective optimization problem. In Section 4, we investigate two cases to clearly demonstrate the experimental process and to prove the effectiveness of the method. In Section 5, a brief conclusion is provided to prove insights from above researches.

2. Literature Reviews

Recent years have witnessed remarkable progress in material ordering and transportation, with a variety of approaches proposed in some papers and applied in the real application. The method of finding the optimal ordering strategy that minimizes the total inventory by an EPQ model has been extensively studied in the past literature. Wagner and Whitin [2] proposed a forward dynamic algorithm for minimum dynamic inventory for the assessment of the manufacturer's raw material demand situation and gave the ordering strategy in this case. Mirmohammadi et al. [3] proposed a material demand planning based on a limited period and constructed an optimal sequential tree to solve this problem, but its computational time may increase in exponential form with the sharp growing number of data. The rapid development of the computer and information sciences has witnessed that the big financial data used broadly in the investment field [4]. And actually, the text data by crawling can also be applied to the optimal decision of the supply chain. Qiao and Zhang [5] applied the dynamic multiobjective algorithm to wastewater treatment and showed that the parameters of the Pareto front undergo some changes during the multiobjective optimal control process, but there is no need to restart the optimization process due to the similarity of two consecutive changes. However, the above methods still suffer from limited accuracy and premature convergences. By combining the above literatures, this study establishes an adaptive dynamic multiobjective optimization model for the dynamically changing process of material ordering control to analyze the ordering and storage strategies under different goal orientations and obtain the optimal results using multiple search algorithms which save computational resources and increase rate of convergence by exploiting the similarity of dynamic scenarios and proposes precise suggestions for different goal orientations according to the differences like policy orientations and material properties.

3. Methods

3.1. Future Demand Forecast. According to the need of constructing the model, it is necessary to have a general understanding of the development cycle of the manufacturer's business. It is more interpretable to humans to quantify the impact of both environment and the manufacture itself. The special events such as COVID-19 pandemic have brought great to the price volatility [6], and further, the price volatility will influence the supply chain. Time series forecasting reveals future trends through the historical data of the time series, i.e., the seasonal cycle can be obtained through time series forecasting thus facilitating the development of the length of time for which the ordering strategy applies similarly to the method which Benvenuto et al. used [7]. The outliers in this prediction are clustered and denoised to obtain a data series that is easy to deal with [8]. After data processing and cleaning, a general observation of the data shows that the series contains both a long-term trend and a seasonal effect with a 24-week cycle, and the sum of seasonal factor is approximately zero, so the seasonal model could apply to the forecast.

From the above method, we get the maximum amount of products that can be produced by the manufacturer in the current week in the case of sufficient raw materials compared with the production capacity. For different material suppliers, except for some extreme cases where the supply is always large and close to 0, the quantity of supplied materials mostly obeys the production law of the manufacturer, i.e., there is a cyclical supply law with a 24-week cycle. We demonstrate these advantages through using supplier S007 as an example:

To determine and separate the seasonal components, seasonal indices need to be calculated to determine the seasonal effects in the time series and assume weekly supply of suppliers be the forecast object indicator X. We linearly combine the forecast object indicator X as follows:

$$x_i = S_t + Y_i + \varepsilon_i (t = i \bmod 24), \tag{1}$$

where S_t is the seasonal term, Y_i is the linear fit term, and ε_i is the error term. Using approximately six months (24 weeks) as a period, the 240 weeks of data were divided into 10 groups. We define the average value of each group as set of features from class i:

$$\overline{x_i} = \frac{\sum_{j=1}^{24} x_{ij}}{24} (i = 1, 2, \cdots, 10). \tag{2}$$

Hence, we know that x_{ij} is t, the value of week j, group I, and $\overline{x_i}$ is the average value of group i.

We define the season term of that series is as follows from class j.

$$S_j = \frac{\sum_{i=1}^{10} \left(X_{ij} - \overline{x_i}\right)}{10} (j = 1, 2, \cdots, 24). \tag{3}$$

After obtaining the seasonal term index, the series with the seasonal term removed can be obtained which is $Y_{ij} = X_{ij} - S_j$, and after sorting this decomposed series Y_{ij}, a regression fit is performed on this array $y_1, y_2, \cdots y_{240}$.

3.2. Model Definition. We define these variables which are required in the following models:

(i) S_{ij}. The supply of the supplier i in the week j

(ii) W_{ij}. The zero-one variable of whether the supplier i in week j supplies

(iii) M_j. The original material storage at the beginning of week j

Next, a nested weighted recurrent network [9] can be used to investigate supply chain network coherence. Based on the results of the time series analysis, the weekly raw material ordering forecast for each seasonal cycle can be obtained, and based on this forecast and the manufacturer's production capacity, the weekly material stock quantity state transfer equation can be established in (4).

$$M_j = M_{j-1} - \min\left\{2.82 \times 10^4, M_{j-1}\right\} + S_j (j = 1, 2, 3 \ldots 24). \quad (4)$$

(i) $M_0 = 0$

(ii) $\min\{2.82 \times 10^4, M_{j-1}\}$ is the material consumption of week $(j-1)$

(iii) $S_j = \sum S_{ij} \times W_{ij}$

The optimization strategy uses a combination of continuous-time model and multiobjective optimization model to measure the uncertainty constraint and to ensure the reliability of the optimal design through the hybrid optimization strategy [10] which is an important step of our pipeline.

3.3. Establishment of Flexible Constraints for Multiobjective Planning. In this section, for a complex optimal supply problem, the complexity of the working conditions and uncertainty quantification as well as the relationship between objectives and constraints are fully considered. In addition, since multiple objectives need to be balanced, multiobjective optimization is required to make decisions by balancing the objectives when the constraints are satisfied.

Objective 1. Excessive suppliers may lead to cumbersome handover, so it is necessary to ensure that as few suppliers as possible are selected to meet production requirements. The price ratio of A, B, and C raw materials in the data set is 0.72 : 0.726 : 0.72. Take the example of group A suppliers who supply A raw materials in the data set, group A contains 146 suppliers, and the plan will cover the next 24 weeks. The zero-one variable $\sum_{i=1}^{146} S_A(i,j)$ measures whether the supply is provided in (5).

$$\min \left[\sum_{i=1}^{146} S_A(i,j) + \sum_{i=1}^{134} S_B(i,j) + \sum_{i=1}^{122} S_C(i,j)\right] (j = 1, 2, \cdots, 24). \quad (5)$$

Objective 2. To minimize the ordering cost, the quantities of raw materials A, B, and C ordered are set to x, y, and z. Since in practice, the unit prices of raw materials A and B are 20% and 10% higher than those of raw materials C, respectively, and the price of C is set to be the unit price, this optimization objective can be expressed as (6).

$$\min\,(1.2x + 1.1y + z). \quad (6)$$

Objective 3. To minimize the relative difference between the products that can be produced with the order quantity and the production capacity, the difference is defined as $d+ > 0$ when the products that can be produced with the weekly intake are greater than the weekly production capacity, and as $d- > 0$ when the products that can be produced with the weekly intake are less than the weekly production capacity. The objective of keeping this relative difference as small as possible is established:

$$\min\left(d^+ - d^-\right). \quad (7)$$

3.4. Linear Weighted Transformation for Multiobjective Planning. The three objective functions are dimensionless and normalized using the linear weighting method:

$$\min\left(P_1 \frac{A}{A_{\max}} + P_2 \frac{B}{B_{\max}} + P_3 \frac{C}{C_{\max}}\right). \quad (8)$$

3.5. Solution for Dynamic Multiobjective Planning. The difficulty of multiobjective optimization is affected by the change of Pareto-optimal solutions (PSs) and different ways of its moving. We commonly use population evolutionary algorithm to find the PS. By the end of evolutionary, the diversity of population will loss and then make a decline in the adaption competency. In this study, we use the evolutionary algorithm combining with dynamic strategy (including the RS and AS) to significantly improve the convergence rate.

3.5.1. Reset Strategy (RS). When the environment changes, we use a small amount of new environment information earlier to predict the possible movement direction of PS in the new environment [11]. Then, we also reinitialize the population by using the estimated direction and local search, making it close to the Pareto-optimal solution set in the new environment.

Half of the crowd is generated by the direction of PS movement estimated by the new environmental information, and the other half is generated by a local search of the current crowd. PS_t is the noninferior solution obtained by the algorithm in the t-th environment, and the moving step between two environmental changes is the Euclidean distance between the centroids of two noninferior solution sets.

$$S^t = \left\|C^t - C^{t-1}\right\|_2. \quad (9)$$

This distance S^t reflects the movement direction of PS in the new environment. Through the domain search of individuals in PS_t, we obtain the predicted distribution set and the noninferior order depending on individual adaptation. Then, we notice that we can obtain the predicted movement direction by calculating the centroid C^S of the set.

$$D = \frac{C^s - C^t}{\left\|C^s - C^t\right\|_2}. \quad (10)$$

We design the corresponding moving step L_t by integrating historical environmental moving distance and current environmental information. A new evolutionary population P_{t+1} can be obtained by screening half of P_t from the crowding distance.

3.5.2. Adjust Strategy (AS). We investigate the PS with higher speed of convergence by adjust strategy (AS). After

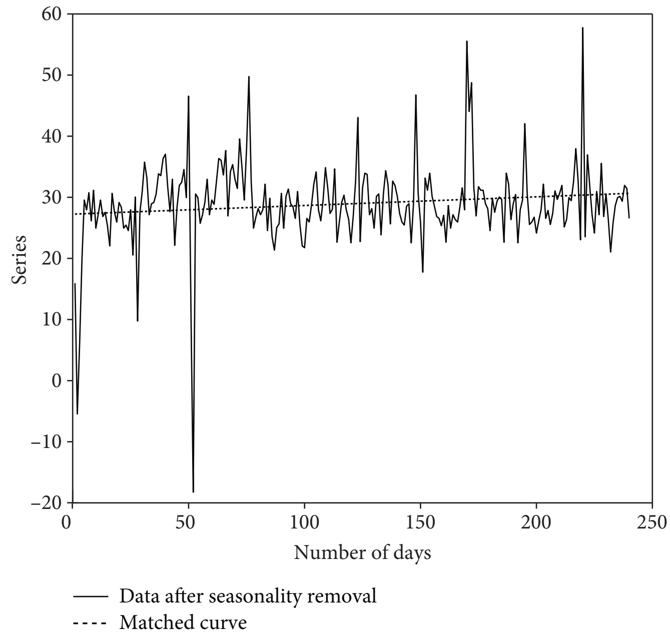

Figure 1: Time fitted series (take the example of data centralization provider 007).

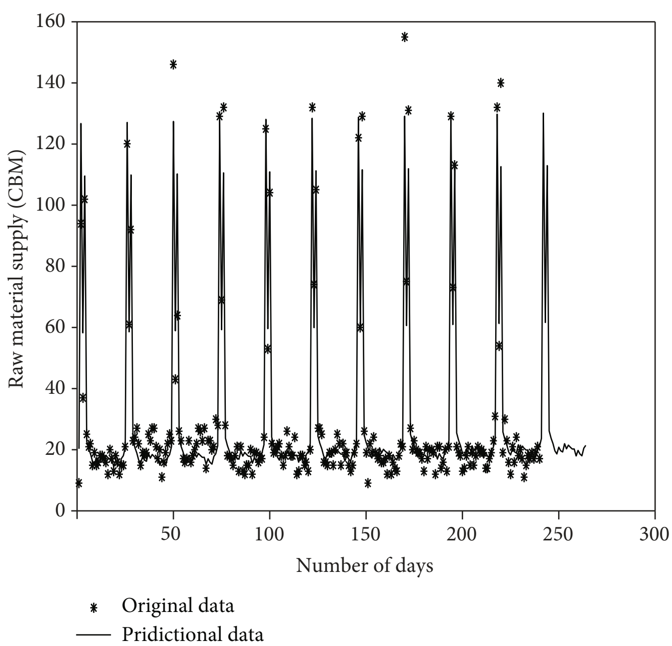

Figure 2: Comparison of original data and predictional data.

obtaining more information of the new environment, we adjust and update the current population to make more individuals close to the Pareto-optimal solution set of the new environment in the current population and to accelerate the speed of convergence.

When the new environment information increases, we obtain the PS movement direction by the current group's center of mass C^*.

$$D^* = C^* - C. \tag{11}$$

Similar to the RS strategy, we train to generate estimations of new members of the population and replace $\alpha \times N$ underperforming individuals by crowding distance. Y is a complement to the diversity of population in the new environment during AS strategy.

$$y = x + D^* + \delta^t \bullet N(0,1) \bullet I. \tag{12}$$

$x\epsilon PS^t$, $N(0,1)$ is random normal function, $I = (1, 1 \cdots)$ is $n * 1$vector, and $\delta^t = S^t/2\sqrt{n}$.

Table 1: The manufacturer's material utilization rate for next 24 weeks.

Week	1	2	3	4	5	6	7	8
Utilization efficiency	0.7188	0.9832	0.8800	1	0.9747	0.9767	0.9353	1
Week	9	10	11	12	13	14	15	16
Utilization efficiency	1	1	1	1	1	1	1	1
Week	17	18	19	20	21	22	23	24
Utilization efficiency	1	1	1	1	1	1	1	1

Table 2: The CRICTIC score of all suppliers.

Supplier ID	Grade	Score	Week of supply
S282	1	0.676545207	24
S275	2	0.626091153	23
S329	3	0.581412859	23
S229	4	0.575577464	23
…	…	…	…

By combining traditional evolutionary algorithms with adjustment strategies, we obtain solutions approaching to PS in the new environment. Since we predict the position of Pareto-optimal front (PF) more accurately, we can also obtain the PS of the set more accurately, which content the requirements of algorithm design.

4. Result

4.1. Practical Ordering Example

4.1.1. Time Series Forecasting. In this section, we investigate the feasibility of each module in the proposal method. Considering the class A supplier S007 in the dataset to confirm our thoughts, the time series analysis is performed according to this pipeline, and the final fitted function is shown in Figure 1. After removing the effect of the seasonal term, the data is fitted as a gently rising straight line, from which the trend of supply and demand can be known.

The data series can be further verified to be a seasonal series based on the comparison between the series with the seasonal term removed and the original series.

As shown in Figure 2, the original data are more consistent with the predicted values, so the prediction of the data combines the strength both accurate and reliable. Therefore, it is feasible to transform the original series into a smooth series through the low-order difference and then use the ARMA model to fit the smooth series, which can provide information on the seasonal development pattern required for the model building. After removing the seasonal factor, since the lag coefficient P of ARMA tends to 0 at this point, it is known that the data series is smooth.

The trend predicted by ARMA gives a rough limitation of the availability of suppliers, which is further used as a constraint in the multiobjective optimization process, and the model can be solved as described in Methods.

The trend in time series shows a significant increase in supply availability in weeks 1 and 5 but also shows that in most weeks, the supply is less than the supply limitation, and there is a hidden danger of oversupply for the producer. Therefore, in order to ensure that inventory levels are always no less than the number of raw materials stocked to meet the two-week production demand and to even out the transportation pressure across weeks, more stock can be predetermined to be stocked in weeks 1 and 5.

4.1.2. Rigid Requirements for Multiobjective Planning.

$$\begin{cases} \dfrac{x}{0.6} + \dfrac{y}{0.66} + \dfrac{Z}{0.72} + d^{+} - d^{-} = \begin{cases} 2.82 \times 10^{4} (j \neq 1, 5), \\ 4.23 \times 10^{4} (j = 1, 5), \end{cases} \\ x = \sum_{i=1}^{146} \sum_{j=1}^{24} \mathrm{S_A}(i, j) * w_A(i, j), \\ y = \sum_{i=1}^{134} \sum_{j=1}^{24} \mathrm{S_B}(i, j) * w_B(i, j), \\ z = \sum_{i=1}^{122} \sum_{j=1}^{24} \mathrm{S_C}(i, j) * w_C(i, j), \\ S_A, S_B, S_C \in \{0, 1\}, \\ d^{+} d^{-} = 0. \end{cases} \tag{13}$$

The supply is replenished at the peak 1 and 5 weeks of the forecasted incoming stock; the weekly availability of the three raw materials is defined; one of the offset variables $d+$ and $d-$ must be 0 is affirmed. Inspired by these constrains, we develop a new algorithm to solve such multiobjective planning problem.

4.1.3. Result of Multiobjective Planning. In this section, we address the problem arising from the trade-off between objectives and constraints. The result of multiobjective planning was solved by linear weighted transformation. Through the multiple search algorithm, it is found that the best results are obtained at 7 : 2 : 1 by using plane separation [12]. Based on the allocation of the supply selection status for that week, the supply efficiency is calculated using the total supply forecast table as follows in (10).

$$\eta_j = \frac{g_j}{w_j} = \frac{\sum_{i=1}^{402} g(i, j)}{\sum_{i=1}^{402} w(i, j)} (j = 1, 2, \cdots, 24), \tag{14}$$

where $g(i, j)$ is the total amount of materials ordered for the i-th supplier in week j and $w(i, j)$ is the total amount of

```
1.  INPUT: Population P, Maximum Iteration, Time Step(t=0), Evolution Generation(i=1)
2.  OUTPUT: Approximated POF
3.  BEGIN
4.          Randomly initialize a population P
5.          Iterate (until Maximum Iteration)
6.          If change has appeared
7.                  t=t+1
8.                  Collect old and new environment information
9.                  If evolution generation meet the adjustment conditions
10.                         Calculate the new allocation ratio score
11.                         Aggregate the scores and calculate the rank
12.                         Exact search results for different empowerment goals
13.                         Comparing weight combinations and optimal solutions
14.          Perform the domination process among population, i=i+1
15.          Select the highest domination and crowding distance as output POF
16.END
```

Algorithm 1: Algorithm for dynamic multiobjective optimization.

materials provided by the i-th supplier in week j. The resulting utilization rates for each state are shown in Table 1 which presents the manufacturer's utilization rate for raw materials for the next 24 weeks, which shows that the utilization rate for materials purchased according to the ordering plan is basically greater than 93%.

4.1.4. Feasibility Verification of Result. The industry has a monopoly or dominant position in the larger supply of suppliers. The top-ranked suppliers are selected by CRICTIC importance assessment and compared with the planning results obtained from the multiobjective optimization strategy and provided that the two can be verified with each other, and it means that the selected strategy has feasibility. To verify that, the following results are proposed to confirm our proposal.

A matrix of size $n * p$ is constructed, with n representing the number of suppliers and p representing the number of evaluation indicators. By dimensionless processing, all indicators are normalized to positive indicators. We investigate this method to consider the standard deviation between indicators to measure their difference fluctuation and the correlation between indicators to solve the endogeneity problem. We complement our method with considering the size of the information entropy of indicators for weight assignment, and get the weight score ranking by program. Then, by comparison, it can be seen that the manufacturer material sources are mainly the top 50 suppliers in this ranking such as in Table 2.

4.2. Dynamic Multiobjective Change in Practical Ordering Example. Considering the well solved on prior constraints, we further use the more challenging changing situation to evaluate the proposal method. Assume that the ordering scenario has a new dynamic due to the larger volume of material C, which requires more transshipment resources. The emergence of new objectives and changes in the original objectives lead to a consequent change in the optimization, which is the result of the combined conflicting objectives of the optimization algorithm [13]. To save transshipment resource plan to purchase as much as possible of material A and as little as possible of material C, set the quantity of material A ordered to x, the quantity of material B ordered to y, and the quantity of material C ordered to z. Optimization objective one is replaced by the following:

$$\min \left(x_j - z_j\right)(j = 1, 2, \cdots, 24). \tag{15}$$

The approximated POF is searched based on similar scenarios by a multiple search algorithm which referring some similar multiobjective optimization methods [5, 14, 15].

The optimal allocation ratio can be solved by this program as the algorithm in Algorithm 1, in this case, changes to $0.80:0.15:0.05$.

We investigate our method with contrastive learning to further combat the results of the two optimizations in Table 3 which compares the different order quantity between the second ordering scenario and the first ordering scenario after changing the optimization objective, reflecting the consideration of dynamic factors for this scenario. Solution for multiobjective optimization is the fundamental problems in this study. Our algorithm has proven to be highly effective and efficient in dynamic multiobjective ordering strategy because of the saved storage costs. The empirical results show that the method satisfies the manufacturer's need for planning for ordering materials, satisfies reasonable strategy changes under target differences and can recommend for the planning of material ordering problems.

4.3. Practical Transport Example

4.3.1. Model Definition. The process of transshipment is similar despite the different optimization objectives and can be modeled analogously:

(i) $g(i, j)$. The amount of material available from supplier i in j-th week

(ii) $c(i, j)$. Whether supplier i provides material in week j (0-1 variable)

Table 3: The different order quantity after changing the optimization objective (unit: m^3).

Week	1	2	3	4	5	6	7
Plan A	30665.8	20400.6	20405	16994.6	34012.5	20340.2	13866.2
Plan B	30645.3	20401	20407.5	16994.6	34020.3	20345.8	13866.2
Order difference	20.5	-0.4	-2.5	0	-7.8	-5.6	0

Table 4: Table of suppliers to transporters (1-12 weeks).

Transporter ID Week	1	2	3	4	5	6	7	8
1	924	2018	3006	6000	6000	2252	6000	1536
2	0	1609	5179	209	2317	3271	0	6000
3	0	1860	5837	0	6000	3110	0	1887
4	0	1810	5772	209	2371	2942	0	2327
5	5433	2227	5988	6000	1202	2602	6000	1499
6	0	2077	6067	1521	6624	3390	0	739
7	0	1955	5075	227	657	3247	0	657
8	0	1887	5460	236	712	4135	0	941
9	0	2464	5959	259	862	5013	0	1244
10	0	3394	5891	266	737	5114	0	1131
11	0	4546	5111	272	802	4986	0	1245
12	0	5169	5412	268	656	5080	0	1004

(iii) $t(i, j)$. Whether supplier i uses forwarder j to deliver material (0-1 variable)

(iv) $c(i, j)$ and $t(i, j)$ are decision variables

Optimization objective

$$\max \left(\sum_{j=1}^{24} \sum_{i=1}^{402} g(i, j) * c(i, j) \right). \tag{16}$$

Requirements for multiobjective planning

$$\begin{cases} \sum_{j=1}^{8} t(i, j) = 1, (i = 1, 2, \cdots, 402), \\ \sum_{i=1}^{402} t(i, j) \cdot g(i, k) \cdot c(i, k) \leq 6000, (j = 1, 2, \cdots, 8)(k = 1, 2, \cdots, 24), \\ t(i, j) \in \{0, 1\}, (i = 1, 2, \cdots, 402)(j = 1, 2, \cdots 8), \\ c(i, j) \in \{0, 1\}, (i = 1, 2, \cdots, 402)(j = 1, 2, \cdots 24). \end{cases} \tag{17}$$

Due to the constraints mentioned in this section, the solution of this model requires a trade-off between the objectives and the limitations, and the same algorithm as above can be used to solve for the optimal transportation method. Considering its variable correlation, the yield can be expressed by a topological network of recursive form [16]. On this basis, the maximum capacity of yield can be accommodated is inverted by setting the weekly capacity to M and the weekly production to P as follows:

Table 5: Table of suppliers to transporters (13-24 weeks).

Transporter ID Week	1	2	3	4	5	6	7	8
13	0	2868	5682	266	3787	6000	0	1312
14	0	3046	5835	271	845	5465	0	1147
15	0	3030	5870	305	837	5504	0	1550
16	0	2981	5573	336	825	5302	0	1213
17	0	4194	5791	328	880	5063	0	1406
18	0	3876	5338	322	707	5619	0	1082
19	0	5990	5375	309	813	5728	0	1250
20	0	3683	4963	296	896	5313	0	1233
21	0	5766	5112	291	938	5573	0	1197
22	0	3936	6000	290	764	5326	0	1040
23	0	2822	5545	291	2396	5020	0	1152
24	0	3332	5648	276	935	5384	0	947

$$\begin{cases} M \geq \dfrac{P_1}{2}, \\ k \cdot M \geq \sum_{i=1}^{k} P_i (i = 2, 3, \cdots, 24). \end{cases} \tag{18}$$

4.3.2. Result of Multiobjective Planning. The specific transporters corresponding to each supplier in regular situation are allocated according to Tables 4 and 5, which allows for the most rational allocation plan and a stable partnership between the suppliers and the transporters. Tables 4 and 5 show the weekly volume of each transporter where 0 means no shipment and the corresponding value represents the shipment of the corresponding value. We notate the utilization efficiency and quantify it by the data in Tables 4 and 5.

$$\eta_j = \frac{\sum_{i=1}^{24} tw(i, j)}{\sum_{i=1}^{24} \operatorname{sgn}(tw(i, j))} (j = 1, 2, \cdots, 8). \tag{19}$$

This equation characterizes the ratio between the average and maximum transshipment volume of the j-th transporter, where $tw(i, j)$ refers to the week i of the j-th transporter in the equation, and $\sum_{i=1}^{24} \operatorname{sgn}(tw(i, j))$ represents the total number of weeks carried by the transporter. We obtain that the efficiency of each transporter is greater than 60%. In particular, the efficiency of transporter 2 is as high as 91.31%, which shows the high efficiency of the model and the improvement over the current state-of-the-art.

5. Conclusion

The study assisted in the establishment of the ordering and transportation strategy, and a time series prediction model was established to forecast the corresponding material supply based on the historical data of manufacturer and supplier capacity and supply, analyzing its trend and seasonality. At the same time, considering the number of suppliers and material procurement costs, dynamic multiobjective programming model is established. Then, multiple search algorithm using a minority new environment information and the old environment information to adjust the population with candidate solutions is used to solve this problem thus improving the convergence speed of the algorithm to meet market demand and business needs when a change in the environment is detected. The experience in the paper considers the minimum inventory strategy and empirically proves the good adaptability of the model through the establishment of a hybrid strategy model. Through the comparison of ordering strategies under dynamic target changes, it is found that the method provides decision reference and theoretical support to the customization of raw material ordering strategies for actual projects.

The empirical results of the ordering strategy show that, first, the positive effects of material storage space and seasonal factors on the supply chain system should be increased to facilitate centralized decision-making for greater benefits; second, the dynamic ordering strategy model responds to the digital representation of demand and has a positive effect on the overall efficiency improvement of the supply chain. The prediction process in our study can be similar to the prediction of coke price [17] combining with the deep learning model to improve the consideration of internal and external variables. Moreover, this paper does not consider the impact of nonimmediately decaying materials on ordering, storage, and preservation, which will be further considered in future studies.

Data Availability

The original data of this paper comes from the data of competition question C for CUMCM-2021(China University mathematical modeling competition), which can be downloaded publicly from the official website.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

Kejia He contributed to conceptualization, data curation, writing—original draft, and writing—review and editing. HongYu Cheng contributed to software and visualization. Yuchen Zhou contributed to methodology and project administration. CuihuaXie contributed to funding acquisition, supervision, and validation.

Acknowledgments

This study was supported by a project grant from Zhejiang Philosophy and Social Sciences Foundation (Grand No. 19NDJC145YB).

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