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Research on the Optimal Scheme of Raw Material Ordering and Transportation in Production Enterprises

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Abstract: *According to the characteristics of data, five indicators are proposed: supply satisfaction, supply quantity, supplier contribution rate, and production frequency and production variance. Then TOPSIS evaluation model is constructed, and entropy weight method is adopted to enhance the discrimination significance of indicators. The 50 most important suppliers are obtained by solving the model. Finally, the supplier selection model is established, and the Lagrange function is constructed under the objective function and constraint conditions, and the supplier and quantity selection results are obtained by greedy algorithm. After analyzing the relationship between transport loss rate and time, the ARIMA model was established for 8 transporters. Based on the obtained data, the greedy algorithm is used to get the transfer scheme. The model results showed that 36 suppliers were needed, and the production satisfaction rate was 100%, the average inventory satisfaction rate was 95%, and the total attrition rate was 0.16%.*

Keywords: *TOPSIS, entropy weight method, Lagrange function, ARIMA model.*

1. Introduction

With the development and improvement of economy, the market is constantly expanding, market competition is also constantly intensifying, and it is more and more difficult for businesses to obtain profits, and the profit space is also constantly shrinking. For construction and decorative plate enterprises, how to make future raw material ordering plan and transportation plan according to the supply situation of suppliers, the loss rate of transporters and their own capacity is very important to improve enterprise profits and subsequent capacity. By analyzing the existing problems, this paper puts forward the feasible ordering and transshipment arrangement strategy.

2. Data preparation and analysis

TOPSIS evaluation method[1] can accurately reflect the gap between each evaluation program by using the original data information given. Ranking is carried out by calculating the distance between the evaluation object and the optimal solution and the worst solution. If the evaluation object is closest to the optimal solution and furthest away from the worst solution, it is the best. The optimal solution means that all index values reach the optimal value of each evaluation index. Each index of the worst solution reaches the worst value of each evaluation index. According to the characteristics of data, five indicators are proposed: supply satisfaction, supply quantity, supplier contribution rate, and production frequency and production variance.

Supply satisfaction is a supply matrix. Represents that in the last five years, when the supplier's supply quantity S_{ij} of manufacturer I on week j is greater than or equal to the ordered quantity Q_{ij} of the enterprise, it means that the demand of the week is met, and the position in the matrix is 1; otherwise, it is 0.

$$\begin{bmatrix} s_{11} & \cdots & s_{1n} \\ \vdots & \ddots & \vdots \\ s_{m1} & \cdots & s_{mn} \end{bmatrix} \tag{1}$$

Supply quantity represents the total number of goods produced by each supplier in the last five years.

$$W_i = \sum_{j=1}^{n} S_{ij} \tag{2}$$

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Supplier contribution rate represents the total quantity of goods produced by each supplier in the last five years W_i/ (the weight of such goods P_x* the total quantity of goods produced in the last five years W_n)

$$C_i = \frac{W_i}{P_x * W_n} \tag{3}$$

Production frequency represents the number of weeks N_0 in which the supply quantity of the supplier is not 0 in the total 240 weeks in the recent five years/240 weeks.

$$F_v = \frac{N_0}{n} \tag{4}$$

Production variance represents the variance of P_i, the difference between the order quantity of enterprises and the supply quantity of suppliers in the recent five years, which can reflect the stability of the goods provided by suppliers.

$$P_s = \sum_{i=1}^{n}\left(P_i - \overline{X}\right)^2 \tag{5}$$

Entropy weight method is a method to determine index weight by evaluating indexes under objective conditions, which can enhance the discrimination significance and difference of indexes and avoid the analysis difficulties caused by too small difference of indexes. The data were processed and analyzed based on TOPSIS method and indicators, and the 50 most important suppliers were sorted.

Table 1: Top 50 suppliers

1	S140	11	S330	21	S55	31	S275	41	S367
2	S348	12	S37	22	S210	32	S208	42	S292
3	S201	13	S308	23	S284	33	S291	43	S365
4	S139	14	S229	24	S340	34	S364	44	S194
5	S151	15	S338	25	S74	35	S3	45	S80
6	S374	16	S361	26	S131	36	S273	46	S5
7	S307	17	S282	27	S352	37	S40	47	S218
8	S108	18	S356	28	S114	38	S154	48	S244
9	S126	19	S143	29	S329	39	S78	49	S150
10	S395	20	S86	30	S306	40	S268	50	S189

3. Model establishment and solution

3.1. Supplier selection model

Based on the above analysis results, the matrix $A_{20\times24}$, $B_{12\times24}$, $C_{18\times24}$ are established to represent the matrix of class A raw materials, the matrix of class B raw materials, and the matrix of class C raw materials. Initialize σ_A, σ_B, σ_C as 0-1 matrices corresponding to matrices A, B, and C. k_A =1/0. 6, k_B=1/0. 66, and k_C=1/0. 72 are the corresponding conversion rates of different materials required per cubic meter of product. $\eta = 99\%$ is the transport loss rate. $\Delta_1 = (c_i)_{1\times24}, \{i|1 \le i \le 24, i \in N^+\}$ is the cost vector, $\Delta_2 = (p_i)_{1\times24}, \{i|1 \le i \le 24, i \in N^+\}$ is the output vector.

Construct Lagrange function[3]:

$$L(\sigma_A,\sigma_B,\sigma_C,\lambda,\mu) = \sigma_A^T\sigma_A + \sigma_B^T\sigma_B + \sigma_C^T\sigma_C + (1.2\sigma_A^T A + 1.1\sigma_B^T B + \sigma_C^T C - \Delta_1)\lambda + [\eta(k_A\sigma_A^T A + k_B\sigma_B^T B + k_C\sigma_C^T C) - \Delta_2]\mu \tag{6}$$

According to KKT conditions:

$$\nabla L(\sigma_A,\sigma_B,\sigma_C,\lambda,\mu) = 0 \tag{7}$$

Then the objective function is:

$$f(x) = \min\ (x_A + x_B + x_C)_i$$
$$s.t.\begin{cases}(k_A x_A + k_B x_B + k_C x_C)_i \ge 56400 \\ x_A \ge 0 \\ x_B \ge 0 \\ x_C \ge 0\end{cases} \tag{8}$$

ARIMA is the summation autoregressive moving average model, refers to the model established by

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transforming non-stationary time series into stationary time series, and then regression the dependent variable only to its lag value and the present value and lag value of the random error term[2]. ARIMA model can be divided into moving average process, autoregression process, autoregression moving average process and ARIMA process according to the smoothness of the original sequence and the different contents of regression. MA uses the moving average method to eliminate random fluctuations in the prediction and define a single variable time series data:

$$y_t = c + \omega_t + \beta_1\omega_{t-1} + \cdots + \beta_p\omega_{t-p} = \omega_t + \sum_{t=1}^{p}\beta_i\omega_{t-i} \tag{9}$$

q order automatic regression process is defined as follows:

$$y_t = \mu + \varepsilon_t + \sum_{i=1}^{q}\theta_i\varepsilon_{t-i} \tag{10}$$

ARIMA(p, d, q) model formula is expressed as:

$$\hat{y}_t = \alpha_0 + \sum_{i=1}^{p}\alpha_i y'_{t-i} + \varepsilon_t + \sum_{i=1}^{q}\beta_i\varepsilon_{t-i} \tag{11}$$

$$y'_t = \Delta^d y_t = (1-L)^d y_t \tag{12}$$

$$\left(1 - \sum_{i=1}^{p}\alpha_i L^i\right)(1-L)^d y_t = \alpha_0 + \left(1 + \sum_{i=1}^{q}\beta_i L^i\right)\varepsilon_t \tag{13}$$

Where p represents the lag number of time series data adopted in the prediction model, d represents the difference order of time series data, and q represents the lag number of prediction errors adopted in the prediction model.

3.2. Model solution

The supplier selection obtained by solving model and the prediction results of transport operator attrition rate based on ARIMA model are shown in the figure below.

Table 2: Supplier selection

1	S140	7	S151	13	S131	19	S143	25	S292	31	S154
2	S139	8	S108	14	S268	20	S194	26	S080	32	S273
3	S229	9	S308	15	S306	21	S282	27	S218	33	S348
4	S338	10	S275	16	S208	22	S040	28	S284	34	S150
5	S340	11	S356	17	S352	23	S291	29	S189	35	S307
6	S329	12	S114	18	S330	24	S074	30	S244	36	S078

Table 3: Prediction results

ID	W1	W2	W3	W4	W5	W6	W7	W8	W9	W10	W11	W12
T1	1.9331	1.9304	1.9235	1.9163	1.9102	1.9054	1.9018	1.8991	1.8972	1.8958	1.8949	1.8942
T2	0.5391	0.608	0.568	0.5775	0.5644	0.5616	0.554	0.5485	0.542	0.5359	0.5296	0.5233
T3	0.019	0.0142	0.0105	0.0068	0.0032	0	0	0	0	0	0	0
T4	0.1846	0.3783	0.4775	0.55	0.6633	0.7114	0.7709	0.8313	0.8608	0.9032	0.9348	0.9563
T5	0.4584	0.6609	0.8381	0.9848	1.0988	1.18	1.2303	1.253	1.2521	1.2325	1.1988	1.1559
T6	0	0.056	0.0454	4.6183	2.0064	5	0.4195	0.2367	0.1881	0.0866	0.0475	0.018
T7	1.5026	1.4991	1.5485	1.4645	1.6504	1.6263	1.5497	1.5997	1.5961	1.5924	1.5888	1.5851
T8	0	0.0391	0.0571	4.7937	2.8358	5	0.4121	0.1712	0.0655	0.0571	0.0328	0.0232

ID	W13	W14	W15	W16	W17	W18	W19	W20	W21	W22	W23	W24
T1	1.8937	1.8934	1.8932	1.893	1.8929	1.8928	1.8928	1.8927	1.8927	1.8927	1.8927	1.8927
T2	0.517	0.5106	0.5042	0.4977	0.4912	0.4847	0.4781	0.4715	0.4648	0.4581	0.4514	0.4446
T3	0	0	0	0	0	0	0	0	0	0	0	0
T4	0.9837	1.0014	1.0176	1.0346	1.046	1.0579	1.0687	1.0769	1.0857	1.093	1.0996	1.1061
T5	1.1079	1.0585	1.0108	0.9671	0.929	0.8977	0.8734	0.8561	0.8454	0.8406	0.8406	0.8446
T6	0.0085	0.0032	0.0074	0.0063	0.0042	0.0042	0.0042	0.0032	0.0011	0.0063	0.0032	0.0021
T7	1.5814	1.5778	1.5741	1.5705	1.5668	1.5632	1.5595	1.5559	1.5522	1.5486	1.5449	1.5413
T8	0.0148	0.0074	0.0074	0.0053	0.0053	0.0011	0.0053	0.0032	0.0032	0	0	0

The analysis of T1 transporter's model ARIMA(1, 0, 0) is as follows:

Table 4: Model statistics

Model statistics							
Model	Number of predictive variables	Model fitting degree statistics		Q(18)			The number of outliers
		Steady R^2	R^2	statistics	DF	significance	
var003-model_1	0	0. 507	0. 550	13. 271	17	0. 718	1

Table 5: Model fit

	Model fit									
	Fitting statistics	standard error	Min	Max	percentiles					
					5	10	25	50	75	90
Steady R^2	0. 507	0. 507	0. 507	0. 507	0. 507	0. 507	0. 507	0. 507	0. 507	0. 507
R^2	0. 550	0. 550	0. 550	0. 550	0. 550	0. 550	0. 550	0. 550	0. 550	0. 550
RMSE	0. 443	0. 443	0. 443	0. 443	0. 443	0. 443	0. 443	0. 443	0. 443	0. 443
MAPE	17. 919	17. 919	17. 919	17. 919	17. 919	17. 919	17. 919	17. 919	17. 919	17. 919
MaxAPE	112. 938	112. 938	112. 938	112. 938	112. 938	112. 938	112. 938	112. 938	112. 938	112. 938
MAE	0. 320	0. 320	0. 320	0. 320	0. 320	0. 320	0. 320	0. 320	0. 320	0. 320
MaxAE	1. 811	1. 811	1. 811	1. 811	1. 811	1. 811	1. 811	1. 811	1. 811	1. 811
BIC	-1. 561	-1. 561	-1. 561	-1. 561	-1. 561	-1. 561	-1. 561	-1. 561	-1. 561	-1. 561

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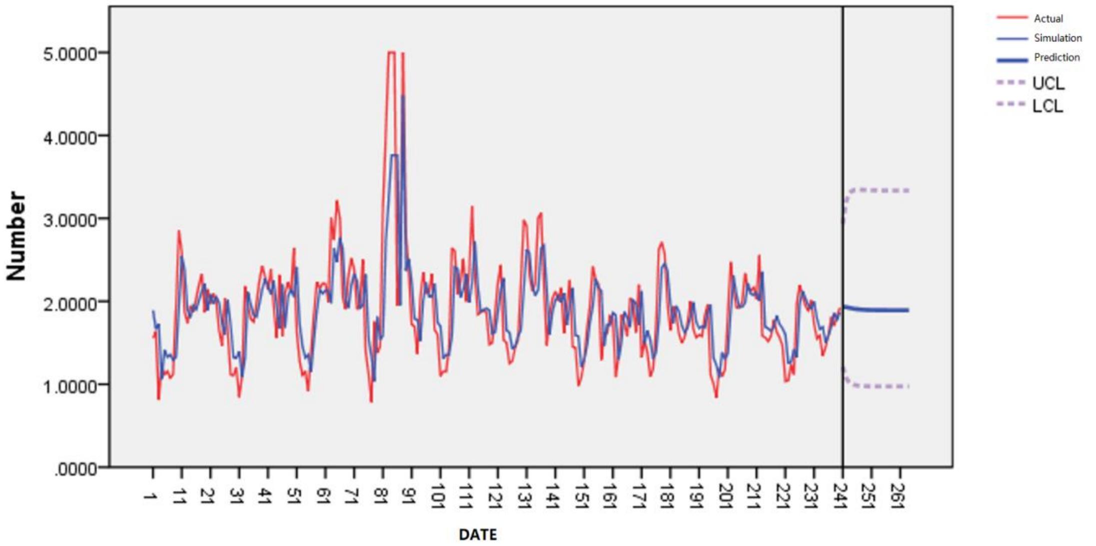

Figure 1: Model prediction chart

Table 6: Model analysis results

Total cost of 24 months	517741. 40
Yield satisfaction rate of 24 months	100%
Inventory satisfaction rate of 24 months	95%
Total production in 24 months(m^3)	716667. 58
Wastage of 24 months(m^3)	1152. 46
The total loss rate(%)	0. 16

The greedy algorithm[4] is used to solve the transportation scheme based on the obtained supplier and supply situation and the loss rate of the transporter. In order to ensure the optimality of each step of the allocation scheme, the suppliers' supply quantity is sorted in each step of the cycle. The model analysis results are shown in the table.

According to the analysis results, the yield satisfaction rate is 100%, the average inventory satisfaction rate is 95%, and the total attrition rate is 0. 16%, which meet the expected requirements.

4. Conclusion

(1) The model has strong generalization ability, which can test all feasible solutions to obtain the optimal solution, and has good long-term fitting and short-term prediction results. Quantitative analysis results are objective and scientific, and it is easy to analyze the importance of each feature. Through the allocation of weight, the evaluation of the target can be more reasonable and objective.

(2) Because the model searches all feasible solutions, the computation time complexity is high. For different types of indicators, a large amount of calculation is needed to transform and unify the properties of indicators when the amount of data is huge.

(3) According to the prediction results of ARIMA model, deep network can also be used for prediction, which can achieve a more stable and accurate effect. Or seasonal decomposition of the model, combined with winter addition or multiplication model, to better analyze the characteristics of time series.

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