Optimization of Metal Commodity Purchasing Plan for E-commerce Platform

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Abstract. It is crucial for e-commerce platform operators to improve operational efficiency. The e-commerce platform selected in this paper is a functional platform implements centralized procurement, however, the platform's procurement plan for metal commodities does not match the demand for the commodities. In this paper, we optimize the metal commodity procurement plan in the platform. Activity based classification is used to classify metal commodities into three categories, and Bayesian linear regression prediction model considering promotion factors and sales season factors is set up. On this basis, the optimized procurement plan for metal commodities was carried out, and a multi-objective procurement quantity allocation model with cost, quality and delivery time as the optimization objectives, and minimum order quantity and maximum supply quantity as the constraints was established. Meanwhile, the NSGA-II algorithm was applied to solve the problem. With the typical commodity, the A class commodity 4.0 model electrodes, a comparative analysis of the optimization scheme with the original scheme was carried out, which proves the validity of the optimization model.

Keywords. Procurement plan; Bayesian linear regression; Multi-objective optimization

1 Introduction

The ability to meet customer needs while remaining economically efficient is critical to business success. Globalization and the growth of e-commerce have led to product diversification[1]. The increase in the number of products sold can complicate management issues. Through the establishment of the model, the number of purchases of enterprises can be predicted more accurately, so that enterprises can better understand the market demand. Wang[2] build an information-based sales forecasting model representing the sales characteristics of each brand to maximize the total sales. Chen et al.[3] established a newsvendor model based on Bayesian prediction under the condition that the ordering cost exists, and explained the influence of purchasing cost and market demand information on inventory strategy through sensitivity analysis. In addition, the supplier selection plays a vital role in procurement management. Appropriate suppliers and reasonable procurement quantity allocation can effectively reduce procurement costs. Cao et al.[4] considered the economic and environmental factors, and constructed a hybrid fuzzy multi-criteria decision-making model. The weighted fuzzy multi-objective linear programming method is used to assign orders to suppliers. Fan and Hu[5] constructed a multi-objective order allocation optimization model to minimize transaction costs, minimize procurement costs, and maximize the matching degree between logistics tasks and suppliers. The effectiveness of the model was verified by genetic algorithm. Safaeian et al.[6]

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established a multi-objective model of supplier selection and order allocation considering material cost, transportation cost, holding cost and its control and interest incremental discount, and used NSGA-II to solve the established model.

Through the analysis of demand forecasting and procurement plan optimization, this paper selects a domestic e-commerce platform for research. Through investigation and analysis, it was found that the e-commerce platform did not take into account the influencing factors of the current month when forecasting the procurement volume of customers. Meanwhile, the platform's metal commodities had multiple orders for the same commodity dispersed for shipment, which increased commodity procurement costs. The main research contents of this paper are as follows:

(1) A Bayesian linear regression model taking into account the promotion factor and the sales season factor was established to predict the demand for type 4.0 electrodes in A products. The prediction results were compared with the prediction value of exponential smoothing method to verify the reasonableness of the optimization model in this paper.

(2) A multi-objective procurement optimization model based on NSGA-II algorithm was established according to the predicted value and finally the optimization scheme was compared with the original scheme of the platform to illustrate the effectiveness of the model.

2 Problem description

Procurement plan is the enterprise procurement personnel according to the market supply and demand situation and enterprise resources, in the production and operation activities gradually grasp the law of commodity procurement, according to the production department or other use of the department's plan to develop a plan form[7]. It includes enterprise procurement materials, procurement quantity, supplier information and other contents. After investigation and research, the main problems of platform procurement plan are as follows:

(1) There are more than 7,000 types of metal commodities on the platform, but the demand for commodities varies greatly and there is a lack of differentiated management.

(2) Purchasing demand forecasts for metal commodities do not take into account the influencing factors of the current month, resulting in inaccurate purchasing.

(3) Purchase orders are often generated based on orders submitted by customers when placing orders, without considering the quantity of commodities and supplier information. Splitting the procurement of material into multiple batches results in high transaction costs, and makes it difficult to increase the bargaining power of the procurement platform[8].

3 Commodity Classification and Demand Forecast

3.1 Metal commodity classification

The ABC classification is applied to categorize the metal commodities in the platform. By analyzing the purchases of 90 metal commodities in the platform in February 2023 and sorting the commodities according to the purchase amount, 17 commodities with a cumulative amount of 70% are classified as A commodities, 32 commodities with a cumulative amount of 20% are classified as B commodities, and 41 commodities with a cumulative amount of only 10% are classified as C commodities.

3.2 Demand forecast modeling

In this paper, we select the welding rod commodity in category A commodity to carry out the demand forecast research. Moreover, the Bayesian linear regression model is used for the prediction of customer demand.

Bayesian linear regression considers the model parameters as random variables and calculates the corresponding posterior values according to their prior values[9]. Assuming that the demand for metal commodities is y, the variables affecting the demand are x, the weight of the ith variable affecting the demand is ω_i, and the random disturbance term is ε. Then,

$$y = \omega^T x + \varepsilon, \varepsilon \sim N(0, \beta^{-1}) \tag{1}$$

where $\omega^T = (\omega_1, \omega_2, \cdots, \omega_n)$, $x^T = (x_1, x_2, \cdots, x_n)$

$$p(y \mid x, \omega, \beta) \sim N(y \mid y(x, \omega), \beta^{-1}) \tag{2}$$

For a training dataset, maximum likelihood function is shown in equation (3),

$$p(y \mid x, \omega, \beta) = \prod_{i=1}^{N} N(y_n \mid y(x_n, \omega), \beta^{-1}) = (\frac{\beta}{2\pi})^{\frac{N}{2}} e^{-\frac{\beta}{2}\sum_{i=1}^{N}(y(x_n,\omega)-y_n)^2} \tag{3}$$

The conjugate prior distribution corresponding to ω is the zero-mean Gaussian distribution: $p(\omega) = N(\omega \mid m_0, S_0)$, where m_0 is the mean and S_0 is the covariance, and this distribution is controlled by an accuracy parameter α, see equation (4),

$$p(\omega \mid \alpha) = N(\omega \mid 0, \alpha^{-1} I) \tag{4}$$

Since the posterior distribution is proportional to the likelihood function multiplied by the prior distribution, there is equation (5),

$$p(\omega \mid x, y, \beta) = p(y \mid x, \omega, \beta) p(\omega \mid \alpha) \tag{5}$$

where $p(\omega \mid \alpha) = N(\omega \mid m_N, s_N)$, $m_N = \beta s_N X^T y$, $s_N^{-1} = \alpha I + \beta X^T X$. The estimate of ω can be obtained from the expected value, which is: $\omega = \beta S_N X^T y$.

The distribution of predicted values according to the posterior distribution and the likelihood function can be obtained by integrating over the marginal function in equation (6).

$$p(y \mid y, x, \alpha, \beta) = \int p(y \mid \omega, \beta) p(\omega \mid y, \alpha, \beta) d\omega = N(y \mid m_N^T x, \sigma_N^2) \tag{6}$$

where the final predicted value is obtained from the expectation of the predictive distribution as $y = m_N^T x$.

4 Optimization of procurement planning

Purchasing is an important business activity of the enterprise, if the enterprise purchases according to the demand of the e-commerce platform, considering the scrap rate, delivery time and other factors to develop a procurement plan, it can reduce a large number of costs, and achieve a balance between purchasing and sales [10].

4.1 Model assumption

This section establishes a deterministic multi-objective optimization model for the supplier selection and order allocation problems of product procurement, combining the purchasing characteristics of the platform and making the following assumptions:

(1) A single product is procured from multiple suppliers at the same time; (2) The minimum order quantity and supply capacity of suppliers are determined; (3) The total demand of ordering is fixed; (4) The superiority rating of the supplier's service level is ignored.

4.2 Notation

A description with regard to the parameters is given in the Table 1.

Table 1. Parameters description

Parameter name		Parameter name	
Total ordering requirements	D	Prices offered by vendor *i*	p_i
Number of vendors	I	Scrap rate for vendor *i*	q_i
Minimum order quantity for vendor *i*	M_i	Proportion of late deliveries by vendor *i*	t_i
Maximum supply for vendor *i*	S_i	Objective	Z_k

4.3 Modeling

According to the interviews with platform procurement personnel and customer evaluation, it is concluded that the three indexes of purchasing cost, quality and delivery time have an important impact on the allocation of the order, so this paper is mainly aimed at establishing a multi-supplier ordering model with the objectives of cost, quality and delivery time.The target model is shown in equation (7), (8), (9).

$$\min Z_1 = \sum_{i=1}^{I} p_i x_i y_i \tag{7}$$

$$\min Z_2 = \sum_{i=1}^{I} q_i x_i y_i \tag{8}$$

$$\min Z_3 = \sum_{i=1}^{I} t_i x_i y_i \tag{9}$$

the constraints are as follows,

$$\sum_{i=1}^{I} x_i y_i = D, 0 \le x_i \le S_i$$

where $\min Z_1$ denotes the lowest total purchase cost, $\min Z_2$ denotes the least amount of scrap in the material purchased, and $\min Z_3$ denotes the least number of delayed deliveries. For the procurement optimization model in this paper, NSGA-II has certain applicability: (1) The objective function can be directly used as the fitness evaluation function; (2) The initial population can be randomly generated according to the constraints; (3) The target model belongs to the global optimization problem[11]. Based on these, NSGA-II is selected as the algorithm for solving nonlinear multi-objective optimization problems in this paper.

5 Case study

In this section, we test the validity of the models by applying the firm's purchasing data to the forecasting model and the multi-objective procurement quantity allocation model. All of experiments were run on MATLAB R2019a and accomplished on a personal computer with an Intel(R) Core(TM) i7-9750H CPU @ 2.60 GHz, 8.0 GB of memory, and 64-bit.

5.1 Application and comparative analysis of optimization methods

(1) Bayesian linear regression prediction model. 1328 valid data were obtained from ERP system of the platform. Pearson's correlation coefficient method was applied to filter out the two main factors: sales season factor and promotion factor. Through calculation, the predicted demand for welding rods and the root mean square error of Model 4.0 are shown in Table 2.

Table 2. Predicted demand for electrodes for Model 4.0

Date	Sales volume	Forecast volume	RMSE	Date	Sales volume	Forecast volume	RMSE
2022/1	17.562	17.320	0.7201	2022/9	18.371	18.586	0.5435
2022/2	17.653	17.577	0.7442	2022/10	18.643	18.842	0.5875
2022/3	16.533	17.833	0.7743	2022/11	21.778	21.135	0.6493
2022/4	18.626	17.303	0.7074	2022/12	20.655	21.391	0.6514
2022/5	18.513	17.559	0.6127	2023/1	17.998	17.320	0.6046
2022/6	20.821	19.851	0.5621	2023/2	18.097	17.576	0.5210
2022/7	18.427	18.072	0.4877	2023/3	-	17.833	-
2022/8	18.399	18.329	0.5038				

According to the predicted values derived from the Bayesian linear regression model, the prediction values are plotted against each other and the predictions are shown in Figure 1.

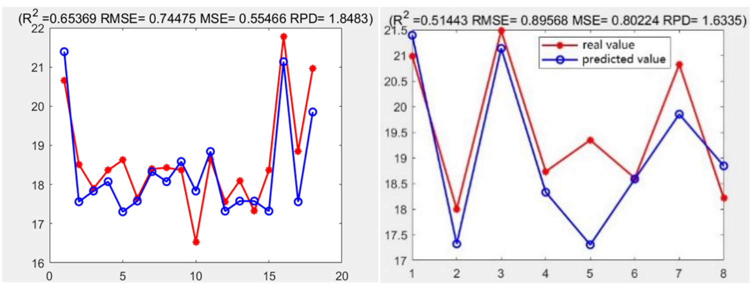

Figure 1. Comparison of prediction results between training and test sets

(2) Demand forecasting results of exponential smoothing method. The best parameters are found to be the initial value of 18.364, α value of 0.050, and RMSE value of 1.365. The absolute error value is the difference between the original value and the predicted value.

(3) Comparative analysis. The root-mean-square error values of the Bayesian model predictions(R1) and the primary exponential smoothing method predictions(R2) are placed in the same table, as shown in Table 3.

Table 3. Comparison of root mean square error values

Date	R1	R2	Date	R1	R2	Date	R1	R2
2022/1	0.7201	1.3234	2022/6	0.5621	1.4864	2022/11	0.6493	1.9112
2022/2	0.7442	1.3325	2022/7	0.4877	1.3619	2022/12	0.6514	1.2651
2022/3	0.7743	1.3535	2022/8	0.5038	1.4526	2023/1	0.6046	0.8281
2022/4	0.7074	1.3447	2022/9	0.5435	1.5650	2023/2	0.5210	0.7530
2022/5	0.6127	1.4102	2022/10	0.5875	1.7094	Average	0.6641	1.4005

As shown in Table 3, the model established in this paper predicts better than the prediction method used by the platform, and has good consistency with the actual purchasing volume, and if it is necessary to further improve the prediction accuracy, it is better to have the relevant data of the general macroeconomic environment as well as more historical data.

5.2 Application and Comparative Analysis of Purchasing Planning Models

5.2.1 Parameter setting

The platform adopts the regular order method to purchase welding rod products, according to the prediction in the previous chapter, the demand for 4.0 model welding rod is 17.833 tons, considering the error of the prediction, temporarily set D = 18 tons (including ± 2 tons of tolerance). At present, there are five suppliers of electrodes of model 4.0, and the supply capacity of the five suppliers is shown in Table 4.

Table 4. Parameter setting on actual data

i	p_i	q_i	M_i	S_i	t_i
1	5600	0.7	0.01	5	9
2	6400	0.6	0.02	7	7
3	6600	0.4	0.02	5	4
4	7600	0.2	0.02	6	2
5	6900	0.3	0.01	5	3

The NSGA-II algorithm is applied for simulation based on the objective function and constraints, and the optimal solution set can be found finally.

5.2.2 Analysis of results

(1) **Optimization results**. Figure 2 shows the set of optimal solutions after NSGA-II calculation, X-axis is the procurement cost, Y-axis is the number of rejects, Z-axis is the number of delayed deliveries, and the dots represent the optimal solutions that satisfy the total demand and the constraints, which is the result of the above steps after 50 iterations.

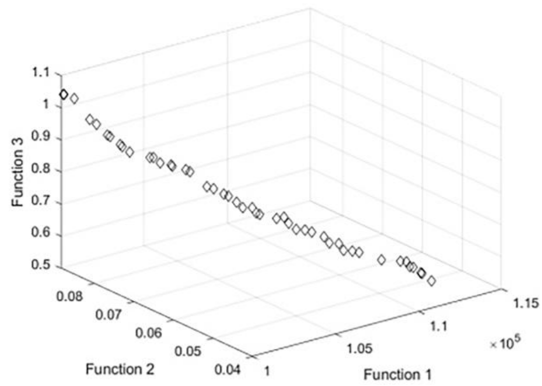

Figure 2. Optimal solution set obtained by NSGA-II

(2) **Comparative analysis**. The current procurement planning method of the platform is linear weighting method. The weighted values of the three indicators of procurement cost, scrap rate and delayed delivery rate are (0.3, 0.5, 0.2) respectively. By establishing a linear programming model, the optimal solution of the linear weighting method is :

$$x_1 = 5, x_2 = 7, x_3 = 4, x_4 = 0, x_5 = 0$$

Six optimal solutions obtained from the procurement model are randomly selected and compared with the optimal solution obtained by the linear weighting method, as shown in Table 5.

Table 5. Some of the optimal solutions obtained by the model

solution set	vendor1	Vendor2	vendor3	vendor4	vendor5	cost	Number of rejects	Number of late deliveries
1	4.85	5.90	3.18	0	2.06	100201	0.88	10.39
2	4.95	2.93	4.65	0	3.48	101113	0.81	9.41
3	3.92	2.88	4.35	0	4.84	102576	0.77	8.74
4	1.91	4.64	4.79	0	4.66	104179	0.74	8.28
5	4.68	0	4.19	2.70	4.43	104994	0.68	7.76
6	3.89	0	4.55	2.66	4.94	106068	0.66	7.33
7	5.00	7.00	4.00	0	0	100800	0.93	11.00

It can be clearly observed that the higher the cost, the fewer the number of scraps and the fewer the number of delayed deliveries. Furthermore, the linear weighting scheme has some drawbacks, as the solution obtained by the linear weighting scheme is biased towards the low-cost metrics due to the large coefficients of the objective function of the cost metrics. By using the NSGA-II to optimize the multi-objective decision-making problem for a single product, there are more options available to the purchaser, and the platform can flexibly choose the required option according to the actual situation.

6 Conclusion

This paper takes the optimization problem of metal commodity procurement plan in platform as the research background, and analyses the problems of procurement in platforms, which are mainly irrational procurement demand forecasting and "homogenisation" of procurement mode. A Bayesian linear regression prediction model considering promotional and seasonal factors is established, and the prediction volume is calculated based on the actual procurement data of the platform. Finally, based on the predicted quantity, a purchase order allocation model based on NSGA-II genetic algorithm is established to solve the problems of supplier selection and order allocation for product purchasing, which achieves better optimization results compared with the original procurement plan formulation method.

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