Study on Cargo Volume Forecasting and Binning Planning Based on Prophet Time Series and Taboo Search

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Abstract. With the rapid development of artificial intelligence, domain-specific prediction tasks such as optimizing the storage of goods in warehouses are becoming increasingly important. In this paper, we investigate categorized warehouse planning that integrates multiple attributes of goods. To solve the daily sales forecasting problem, a Prophet model is used to predict the data for the next three months with respect to the temporal correlation and seasonal characteristics of inventory and sales, which improves the computational efficiency. For the optimization problem of inventory distribution scheme, a multi-objective planning model is established, based on the fuzzy evaluation method to evaluate the optimization cost, capacity utilization, capacity utilization and category relevance, and finally the dynamic stochastic model is used to find out the results, and a program is written by LINGO to solve the optimal solution when the objective function is maximum, which results in the "one product, one warehouse distribution scheme ". For the further optimization of the "one product, one warehouse" model, the individual priority taboo search of the optimal solution is used, and the model algorithm can flexibly deal with constraints such as warehouse capacity. The model can be extended to the prediction of energy consumption and other aspects, and the prediction accuracy can be improved by dynamically updating the data.

Keywords: Prophet Time Series Model, Mixed Integer Programming Model, Forbidden Search.

1. Introduction

With the booming development of artificial intelligence, the warehouse management problem of e-commerce enterprises has become increasingly complex and important. Current models commonly used for warehouse planning rely on the center of gravity method[1] and mixed integer linear programming (MILP)[2], emphasizing static optimization based on quantitative metrics such as transportation cost and inventory turnover. However, these models have limitations in dealing with the dynamic complexity in modern warehousing systems, including insufficient adaptability to demand fluctuations. To alleviate the limitations of current warehouse planning models, dynamic demand forecasting and stochastic optimization methods have become important analytical tools, such as Prophet time series forecasting model and dynamic stochastic planning, which combine real-time data updating and probabilistic optimization to adapt to complex warehouse environments.

In this paper, we use Prophet Cargo Prediction Model to predict the average monthly inventory and daily sales of the storage network, and establish mixed integer programming model based on the prediction results to complete the prediction of one product, one warehouse and one bin scheme. In order to further optimize the binning scheme and solve the combinatorial optimization problem, the forbidden search algorithm is used to predict the binning scheme of one product and multiple warehouses and seek the optimal solution. The research aims to promote economic development through artificial intelligence technology, based on the warehouse capacity and capacity of the upper limit of the rational warehouse planning, the optimal category warehouse program.

Warehouse Planning Forecasting Model development is characterized by a shift from simple statistical methods to complex artificial intelligence techniques, and traditional methods are difficult to cope with modern supply chain dynamics and uncertainty. Prophet model is introduced into the field of warehousing demand forecasting, which is suitable for dealing with seasonal, holiday effects and trend mutation data, bringing more accurate warehousing planning optimization, with a better accuracy than the traditional SARIMA model[3]. Dynamic planning is used in warehousing modeling to improve decision adaptability. Combining the advantages of forbidden search with Prophet model improves response speed.

Research trends in recent years show that the hybrid framework of Prophet Plus mixed integer planning model is becoming a new paradigm for warehouse optimization, and the warehouse planning model is shifting from static optimization to dynamic intelligent decision making. This paper innovatively applies the Prophet model, proposes a hybrid optimization framework, introduces the forbidden search algorithm, and provides a systematic intelligent decision-making scheme for e-commerce warehouse management.

2. Model

2.1. The Prophet Model

The Prophet model is a time series forecasting framework open-sourced by Facebook that effectively identifies and processes information such as holidays and fits trends in time series data by week, month, and year. The principle is based on an additive model, which decomposes the time series into a combination of trend terms, period terms, holiday terms, and residual terms, so as to realize effective forecasting of the time series.

After analyzing the historical inventory and sales data of each category, it is found that the time series shows a trend, so this paper considers the use of the prophet model to forecast the average monthly inventory as well as sales of each category for the next three months.

A Prophet model[4] is created for each category of data and its prediction formula[5] is as follows:

$$y(t)=g(t)+s(t)+h(t)+\epsilon(t) \tag{1}$$

where $g(t)$ denotes the trend term, which indicates the trend of the time series on top of the non-period; $s(t)$ denotes the period term or seasonal term, which is considered in this paper in terms of months; $h(t)$ denotes the holiday term, which indicates the potential impact in the time series on the predicted values caused by non-fixed-period holidays; and $\epsilon(t)$ denotes the error term, which indicates the fluctuations that the model is predicting for the predicted fluctuations, which obey the Gaussian distribution.

Firstly, the preprocessed data is loaded into Python and the prophet model is fitted to each category of data using the fit function. Secondly, the prediction date range is set to be three months in the future. Finally the prediction is made on the given data by the predict function.

2.2. The Dynamic Stochastic Programming Model

First, two utilization rates and correlations were assessed using the fuzzy evaluation method:

The pandas library[6] in Python is utilized to read the data, and the describe method of Data Frame is utilized to describe the data statistically. Since linear programming[7] often has only one objective function, as for the case of multiple objective functions, the algebraic forms of all the objectives can be made to be linked together by weights. To simplify the problem, the objective function is defined as:

$$\min z = \alpha_1 g_1 + \alpha_2 g_2 + \alpha_3 g_3 \tag{2}$$

where $\alpha_1, \alpha_2, \alpha_3$ are the weights of the three objective g_1, g_2, g_3 functions.

Considering a number of factors, such as different prices spent on storage in different warehouses, consideration of warehouse capacity utilization and capacity utilization, and the upper limit of storage capacity in warehouses, the final model obtained is as follows:

$$\max\ z = -0.5g_1 + 0.25g_2 + 0.25g_3$$
$$= -0.5\sum_{i=1}^{350}\sum_{j=1}^{140} Y_{ij}D_j + 0.25\sum_{i=1}^{350}\sum_{j=1}^{350} R(i,j) + 0.25\sum_{i=1}^{140}\left(\frac{C}{C_{1j}}+\frac{S}{C_{2j}}\right) \tag{3}$$

Where,$D_j$is the storage cost corresponding to each warehouse numbered as j, where C_{1j} denotes the upper limit of storage capacity read about the warehouse j, and C_{2j} denotes the upper limit of capacity of the warehouse j.

Then, a dynamic stochastic planning model is constructed to solve the problem:

Month by month analysis, the establishment of a planning model about each month, in order to avoid compliance problems[8], so the monthly inventory of a single warehouse is required to be greater than the sum of the subsequent month's demand. However, the goods in the warehouse cannot be too much, otherwise it will cause a decrease in the utilization rate. Then the final planning is:

$$\max z = -0.5\sum_{i=1}^{350}\sum_{j=1}^{140} Y_{ij} D_j + 0.25\sum_{i=1}^{350}\sum_{j=1}^{350} R(i,j) + 0.25\sum_{i=1}^{140}\left(\frac{C}{C_{1j}}+\frac{S}{C_{2j}}\right)$$

$$s.t\begin{cases}\sum_{i=1}^{140} Y_{ij} \le 1 \\ \sum_{j=1}^{350} C_j Y_{ij} \le C_{imax}\ ,\forall j \in (1{,}140)\cap N^+ \\ \sum_{j=1}^{350} Y_{ij}\sum_{d=1}^{d_{max}} S_{d,i} \le B_{imax}\,,\forall j \in (1{,}140)\cap N^+ \\ C_j \ge \sum_{d=1}^{d_{max}} S_{d,i} \\ C_j \le 1.25\sum_{d=1}^{d_{max}} S_{d,i}\end{cases} \tag{4}$$

With respect to $S_{d,j}$, where $d = 1$ indicates the first day of the month and d_{max} indicates the last day of the month. If July, then $d_{max} = 31$. If September, then $d_{max} = 30$.

2.3. The Taboo Search Algorithm

Taboo search algorithm is a modern heuristic algorithm, whose basic principle is: on the basis of local search, it avoids repeated searches by entering the taboo criterion, and at the same time, it uses the contempt criterion to pardon some forbidden good states, so as to realize global optimization. It uses a neighborhood selection search method to continuously improve the quality of the solution through an iterative process.

It is not possible to let the search process execute endlessly when searching, so some intuitive termination rules need to be set up first.

(1) Determine the step termination, if the solution cannot be guaranteed, the current optimal solution should be recorded to record the current optimal solution; in this paper, the step termination is set as.

(2) Frequency control principle, when a solution, target value or sequence of elements of multiple occurrences, that is, the frequency of occurrence of more than a pre-given value, the termination of the calculation; this paper, the number of frequency is set to 10.

The objective control principle, if the current optimal value does not change within a pre-given determined number of steps, the search procedure can be terminated by setting the step size at which the optimal value remains unchanged to 10.

The optimized binning scheme is then derived by the forbidden search algorithm.

Finally, the solution can be tested to see if it is optimal by utilizing the simplex test table in LINGO.

3. Results and Analysis.

3.1. Solution to The Prophet Model

3.1.1. Construction of a model for predicting monthly sales volume of a category based on the prophet model

After analyzing the historical inventory and sales data of each category, it is found that the historical inventory and sales data by time series show a trend, so this paper considers the use of the prophet model to predict the average monthly inventory as well as sales of each category in the next three months.

3.1.2. Data Preprocessing

First, before building the model, this paper preprocesses the data before building the model. First, the conditional format function of Excel is used to check and find that there are no missing values in the inventory and sales of each category. Through Excel's screening and other functions, it was found that there were only nine historical data of inventory quantity for each category, with a small sample size, and there was not much correlation between the inventory quantity data of different categories, so this paper concluded that there were no outliers in the inventory quantity of each category; for the sales volume of different categories, the same Excel's filtering function was used, and it was found that the number of 249, 329, 332, 336, 339, 345, 348 categories of sales data is very little, and the sales volume is basically 0, considered as an outlier, so this paper considers the elimination of the relevant data of these seven categories. First exclude the relevant data regarded as outliers, the given data for the statistical line description, the initial understanding of the basic situation of the historical inventory and sales of each category.

In this paper, we found that after the data preprocessing to exclude the data of the 7 categories, most of the remaining data of each category have 183 historical sales data, and the sales volume of the same category on different dates does not vary much; from the overall sales data, the sales volume of each category is mostly under 10,000, and there are about 2% of the historical sales volume of the category is more than 10,000; the following figure shows the historical sales volume of the representative categories.

The following Figure 1. shown in the figure above category282 represents the majority of categories, which is characterized by sales in the average level near the level, and the data for 183; category254 represents a large number of categories; category23 represents the amount of data in the 50 to 150 categories, which is characterized by some of the date of the sales of 0, the average daily sales are low; category288 represents a category with very little data and mostly 0 sales.

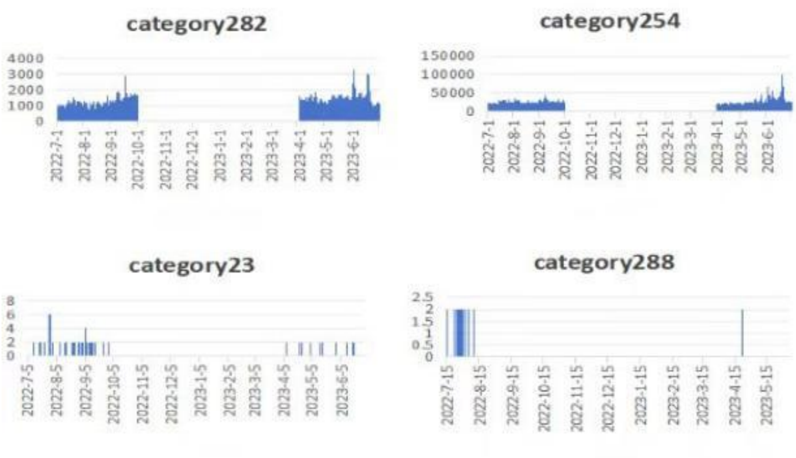

Figure 1. Sales by category (partial)

3.1.3. Application and solution of the model

Before building the model, the data is first described in statistical rows to get a preliminary understanding of the basic situation of the historical inventory and sales of each category. Due to the large number of categories, only the average monthly inventory of some categories are shown here, as shown in Table I below:

Table 1. Average monthly inventory by category (partial)

Category	Average Monthly Inventory	Category	Average Monthly Inventory
category1	6231.11	category113	2449.22
category10	701.56	category114	30780.89
category101	3499.22	category116	16278.89
category103	74849.00	category118	32946.78
category104	233461.89	category119	3247.44

Then, the preprocessed data is loaded into Python and the prophet model is fitted to the data of each category using the fit function; next, the range of prediction dates is set to be three months in the future; and finally the prediction is made by the predict function on the given data. Similarly, we apply the above prophet model to solve the expected sales for each category. The following Figure 2. shows some of the predicted results of the expected sales: category1, 14, 173, 245, 2, 84 respectively represent the sales volume from low to high growth category sales forecast data. The following figure shows part of the daily sales forecast data:

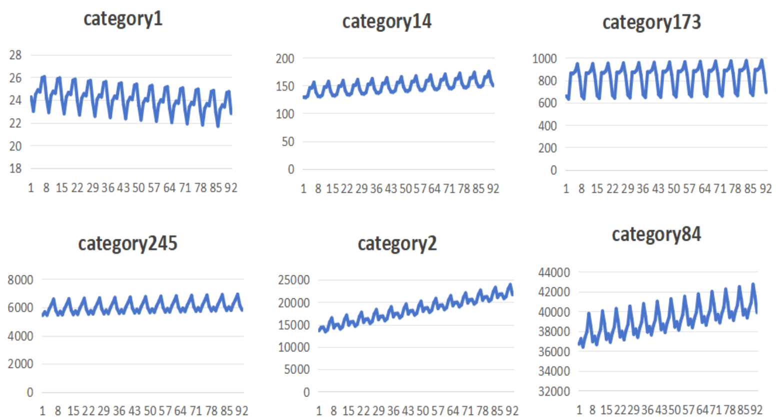

Figure 2. Forecasted sales by category (partial)

3.2. Solution to The Dynamic Stochastic Programming Model

First of all, the mining and construction of variables: category (Category): on behalf of the i^{th} category ($i = 1,2,\cdots,350$); Warehouse (Warehouse): on behalf of the j^{th} warehouse ($i = 1,2,\cdots,140$), in particular, is a set that indicates which categories are stored in the warehouse numbered j.

$$\mathrm{W_j} = \{\mathrm{C_{i1}}, \mathrm{C_{i2}}, \mathrm{C_{i3}}, \mathrm{C_{i4}}, \cdots, \mathrm{C_{in}}\} \tag{5}$$

Indicates that the category $C_{i1}, C_{i2}, C_{i3}, C_{i4}$, with the number $i_1, i_2, i_3, i_4, \cdots, i_n$ is stored in the warehouse W_j.

Then it is based on the fuzzy evaluation method to assess the two utilization rates and correlation, to use the fuzzy evaluation method for correlation, first of all, we need to make a division of the data distribution for the “correlation” and to generate the value of each statistical bit of the data. Use the pandas library in Python to read the data, and use the describe method of Data Frame to statistically describe the relevant data. The following Figure 3. shown is the correlation diagram of each group of categories made to visualize the correlation between the categories. From the graph we can know that the correlation of data volume, mean and variance are 3164, 593, 2980 and other data respectively:

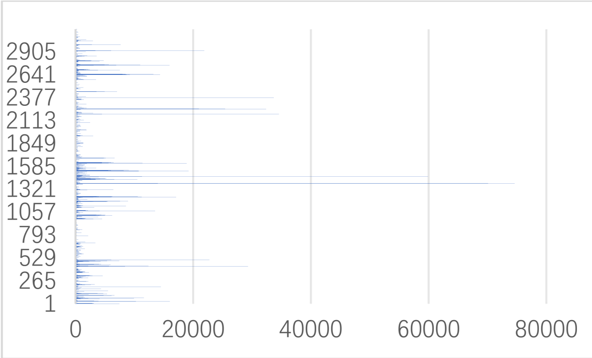

Figure 3. Correlation between groups of categories

Establish fuzzy evaluation criteria based on the above statistics: for any two categories C_{i1} and C_{i2}, let their Relevancy be $R_{i1,i2}$. If the relevancy of the two categories does not appear in Annex 4, it is filled with 0.

Finally, it is based on the dynamic stochastic programming model for solving the rational inventory binning scheme. As in formula (5): define the 0-1 type variable $Y_{i,j}$,which indicates whether the first i category is stored in the first j warehouse or not, if it is stored, the value of $Y_{i,j}$ is 1, if it is not stored, the value of $Y_{i,j}$ is 0. For example, if $Y_{134,234} = 1$, it means that the category numbered 234 will be stored in the 134th warehouse, as the following shows.

$$Y_{i,j} = \begin{cases} 0 & C_i \notin W_j \\ 1 & C_i \in W_j \end{cases} \tag{6}$$

Analyze month by month to build a planning model about each month, assuming that the warehouse stocking pattern is the first day of the month for external supply throughout the month. Until the beginning of the next month again into the goods. In order to avoid performance problems, it is required that the monthly inventory of a single warehouse is greater than the sum of the subsequent month's demand. However, the goods in the warehouse can not be too much, otherwise it will cause a decline in utilization. Then the final planning is:

$$\max z = -0.5\sum_{i=1}^{350}\sum_{j=1}^{140} Y_{ij} D_j + 0.25\sum_{i=1}^{350}\sum_{j=1}^{350} R(i,j) + 0.25\sum_{i=1}^{140}\left(\frac{C}{C_{1j}} + \frac{S}{C_{2j}}\right)$$

$$s.t\begin{cases} \sum_{i=1}^{140} Y_{ij} \le 1 \\ \sum_{j=1}^{350} C_j Y_{ij} \le C_{imax} \ , \forall j \in (1,140) \cap N^+ \\ \sum_{j=1}^{350} Y_{ij} \sum_{d=1}^{d_{max}} S_{d,i} \le B_{imax} \, , \forall j \in (1,140) \cap N^+ \\ C_j \ge \sum_{d=1}^{d_{max}} S_{d,i} \\ C_j \le 1.25 \sum_{d=1}^{d_{max}} S_{d,i} \end{cases} \tag{7}$$

As shown in Table II , using LINGO to write the program, show part of the reasonable inventory binning solution, which shows that according to the “one product, one warehouse” program, category 1 is placed in warehouse 115, category 31 is placed in warehouse 99, category 61 is placed in warehouse 106, and so on. All of them test the number, so it is indeed the optimal solution.

Table 2. Demonstration of the "one product, one warehouse" warehousing program (partial)

category	warehouse
category1	115
category31	99
category61	106
category91	11
category121	15
category181	77
category211	30
category241	12
category271	15
category301	9
category331	41

3.3. Continued optimization based on the taboo search algorithm

If each category is labeled according to piece type as well as advanced categories, allowing a category can be stored in multiple warehouses, the more similar the quality of the items should be placed in a warehouse, then the weight of the relevance objective function is changed from the original 0.25 to 0.5, and at the same time the cost objective function is adjusted from the original 0.5 to 0.25.

Then there is the formula：

$$\begin{aligned}\max z &= 0.5g_2 - 0.25g_1 + 0.25g_3 \\ &= 0.5\sum_{i=1}^{350}\sum_{j=1}^{140} R(i,j) - 0.25\sum_{i=1}^{350}\sum_{j=1}^{350} Y_{ij}D_j \\ &+0.25\sum_{i=1}^{140}\left(\frac{C}{C_{1j}}+\frac{S}{C_{2j}}\right)\end{aligned} \tag{8}$$

At the same time a category can be put in more than one warehouse, but not more than 3, then

$$\sum_{i=1}^{140} Y_{ij} \leq 3 \tag{9}$$

In order to find the global optimal solution as well as to solve the combinatorial optimization problem effectively, this paper considers the use of forbidden search algorithm for the solution.

3.3.1. Forbidden Search Algorithm Model Construction

- Evaluation function

$$H_i = \begin{cases} 3 & \text{Commodity i is A} \\ 2 & \text{Commodity i is B} \\ 1 & \text{Commodity i is C} \end{cases} \tag{10}$$

Where $\Delta H_{i,j} = |H_i - H_j|$ denotes the degree of similarity between the two categories. Put the correlation function $R(i,j) = R_0(i,j) + \Delta H_{ij}$,where $R_0(i,j)$is the original correlation function. Setting the initial state,

$$Y(0) = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 & \cdots & 1 \\ 1 & 1 & 1 & 0 & 0 & 0 & \cdots & 0 \\ 0 & 1 & 1 & 1 & 0 & 0 & \cdots & 0 \\ 0 & 0 & 1 & 1 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 & \cdots & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & \cdots & 1 \end{bmatrix} \tag{11}$$

Let t time implement the invertible transformation of $(t-1)$ to $X(t-1)$, then the evaluation function has

$$\mathrm{Z(t)} = 0.5\mathrm{R_i} \cdot \mathrm{R_j^T} - 0.25\left(\mathrm{Y(t)} \cdot \mathrm{D_j}\right)^{\mathrm{T}} + 0.25\frac{\sqrt{\mathrm{C} \cdot \mathrm{C^T}}}{\mathrm{C_1}} + 0.25\frac{\sqrt{\mathrm{S} \cdot \mathrm{S^T}}}{\mathrm{C_2}} \tag{12}$$

The warehouse capacities of the 140 warehouses in Annex 4 form the vector C_1 and the capacity data form the vector C_2.

If the boundary function, i.e., paths beyond the boundary need to be deleted, each node is $cdot_i$ and each node needs to be inside the feasible domain specified in Formula (6). Then it can be expressed as

$$\mathrm{F}(\mathrm{cdot_1}, \mathrm{cdot_2}, \cdots, \mathrm{cdot_n}) = \begin{bmatrix} \mathrm{sgnf}(\mathrm{cdot_1}) & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \mathrm{sgnf}(\mathrm{cdot_n}) \end{bmatrix} \tag{13}$$

That is, F is semipositive or positive definite[9] and all eigenvalues of F are greater than or equal to 1.

◆ Prohibited lengths[10]

The shorter the taboo length is, the less memory is occupied by the machine and the larger the unblocking range is, but it is easy to cause the search loop to fall into the local optimum too early. The longer the taboo length, the longer the computation time, which is set to 1×10^7.

◆ Termination rules test

a. Step termination: save the current optimal solution when the preset number of steps is reached; in this paper, the step termination is set to 5×10^6 .

b. Frequency control: terminate when the solution/target value is repeated more than 10 times; the number of frequencies in this paper is set to 10.

c. Objective control: stop the search if the optimal value is not updated in 10 consecutive steps; set the step size of the optimal value unchanged to 10.

Table III shows the final results of some of the binning schemes optimized by the taboo algorithm:

Table 3. Demonstration of the "one product, many warehouses" warehousing program (partial)

category	warehouse	warehouse	warehouse
category1	43	79	71
category31	36	128	16
category61	75	89	21
category121	38	111	25
category151	82	16	45
category181	98	14	27
category211	116	22	4
category241	75	107	13
category271	104	3	81
category301	21	89	118
category331	104	88	100

3.3.2. Testing whether a solution is optimal or not

In operations research the optimal solution result of a planning problem must be at the vertex of the feasible region. Convert the three-planning problem to standard form:

$$\begin{cases} \min -z = C^T x \\ s.t \quad Ax = B \\ x \geq 0 \end{cases} \tag{14}$$

As shown in Table IV , which demonstrates the results obtained by utilizing the simplex test table in LINGO, the number of tests in the second row are all less than zero, indicating that the above binning scheme is indeed the optimal solution.

Table 4. Simplex test table

x_1	x_2	...	x_{350}	RHS
-0.1291	-0.2039	...	-4.3280	967793.2123
-6.1560	14.1931	...	29.0800	-3.5384
7.4807	2.9158	...	8.2521	-8.235
-1.9241	1.9781	...	13.7897	-15.7705
8.8861	15.8769	...	-10.5818	5.0797
-7.6484	-8.0446	...	-4.6861	2.8198
-14.0226	6.9662	...	-2.7246	0.3347
-14.2237	8.3508	...	10.9842	-13.3367
4.8819	-2.4371	...	-2.7787	11.2749
-1.7737	2.1567	...	7.0154	3.5017
-1.9605	-11.6584	...	-20.5181	-2.9906

4. Conclusion and outlooks

This study adopts a multi-model fusion strategy to optimize e-commerce inventory: firstly, the Prophet model which needs to be manually adjusted but the result is reliable is used to predict the sales volume of 350 categories in the next 3 months; then, based on the constraint of "one item, one warehouse", the dynamic programming model is used to minimize the cost of warehouse allocation; finally, the taboo search algorithm is used to optimize the scheme. Each model has complementary advantages - Prophet accurate prediction, dynamic planning global optimization, and taboo search to break through the local optimization. The combination strategy significantly improves the scientific and practical aspects of inventory management, and the application effect is remarkable.

In terms of model optimization: Prophet can introduce external features such as holidays, promotions, etc., combined with grid search to optimize parameters and improve prediction accuracy; fuzzy evaluation model can integrate objective data to optimize weights, reduce subjectivity and improve fuzzy division through data mining; dynamic planning can perform parameter sensitivity analysis and add actual business constraints (e.g., cargo category, manpower, etc.) to enhance practicality; taboo search Taboo length can be dynamically adjusted and shortened at a later stage to fine search for the optimal solution.

The model in this paper has good prospects for development and can be used in various aspects such as mountain fire prediction, daily life water consumption prediction, weather forecasting, supply chain management, financial risk assessment, energy consumption prediction, healthcare, transportation planning, environmental science, manufacturing, retailing, etc., with corresponding optimization of the model according to the actual situation in different fields.

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