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Research on Dynamic Adjustable Linear Replenishment Model of Vending Machine

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Abstract

Aiming at the problem that the traditional empirical replenishment method used by domestic vending machines affects the sales volume of vending machines, this paper puts forward a replenishment strategy that can be dynamically adjusted according to the predicted sales volume. This method first forecasts the sales demand, and then uses the reinforcement learning algorithm to train the proportional relationship between the commodity surplus and the replenishment quantity, so as to minimize the replenishment loss. Through the simulation of vending machine data provided by a platform in pycharm environment, it is concluded that the dynamically adjustable replenishment model can effectively reduce the replenishment loss on the basis of meeting the sales demand and maximize the interests of operators.

Keywords

Vending Machine; Sales Forecast; Replenishment Strategy.

1. Introduction

With the wide application of modern Internet technology, big data and cloud computing, the new retail mode of "Internet plus retail" has been developing and expanding, and has become the mainstream development direction of retail industry. [1], vending machine is also coming into being. Vending machine is a new type of retail commodity, which is based on the automatic payment of coins and users. At present, the main types of vending machines are beverage vending machines, food vending machines, integrated vending machines, etc. Vending machines are not affected by time, place and people. They can be traded anytime and anywhere. They are the product of commercial automation. They are also called 24-hour supermarkets. Because of its low rent, high floor efficiency and low investment, vending machines have quickly opened the domestic market and become an essential product in railway stations, subway stations, campus corners and other places.

With the rapid development of vending machines, although some vending machines have realized intelligence and can accurately and timely feed back the inventory, sales and logistics information in the machines to customers and managers [2], most vending machines are non intelligent. Non intelligent machines have many problems, such as uncertain sales volume, small inventory, single commodity type and so on. The disadvantages of small inventory and single commodity type are closely related to the replenisher's replenishment. Whether the replenisher replenishes in time and how to limit the quantity of each commodity replenished are the key factors affecting the vending machine. Therefore, it is necessary to study the replenishment quantity and type of replenishment.

When studying the replenishment of vending machines, we must first study the sales volume of vending machines, and then we can study the replenishment behavior on this basis. The factors affecting the sales volume of vending machines include: weather, holidays, epidemic situation, commodity surplus, etc., among which the solvable factors include holidays and commodity surplus. The sales volume forecast takes into account the above solvable factors to supplement the historical sales volume data or modify the predicted sales volume results.

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This paper attempts to use the hybrid prediction model to predict the sales volume of cargo machines, and then use the linear replenishment model to obtain the replenishment volume, so as to reduce the replenishment cost on the basis of meeting the sales demand.

2. Related Research

In terms of sales volume prediction of vending machines, the general prediction algorithms include trend extrapolation prediction method, regression prediction method, combination prediction method, neural network prediction and so on. Liu Qing et al. [3] the method of wavelet transform combined with dispersion coefficient is used for outlier processing, and prophet is convenient for sales volume prediction_ LSTM hybrid prediction model; Ge Haoyu et al. [4] used the sales volume prediction method of small sample data, which is composed of the characteristic model based on time distance and the sales volume model based on deep transfer learning; Wang Qingyang [5] et al. Changed the cycle length of the time series, took the demand in the cycle as the prediction sequence, and predicted the sales volume in each sales cycle by ARIMA and Holt winters models; Hong Peng et al. [6] used RBF neural network model to predict the sales volume of vending machines, and used ARIMA model to compensate and optimize the prediction results; Qian Yongwei et al. [7] used BP neural network to predict the sales volume of vending machines. In the above sales volume prediction model, or the neural network model does not take into account the factors affecting the sales volume of vending machines. If the complex neural network algorithm is used in vending machines, although the prediction accuracy can be improved, it will require a huge amount of data and high machine performance due to the need for a large number of packages.

In vending machine replenishment, the commonly used models include periodic replenishment, batch replenishment, random replenishment and so on. Lu Yuting et al. [8] adopted the multi product Newsboy replenishment model. Facing the problem of uncertain demand, they used the combination of prediction distribution function and cargo channel constraint to obtain the optimal replenishment quantity of each commodity; The replenishment strategy mentioned by Wang Rongxin et al. [9] adopts a multi-level replenishment network, comprehensively considers the relationship between the predicted demand and the real demand of the vending machine, and dynamically formulates the replenishment strategy considering factors such as transportation cost and transportation time; Yun manjiao et al. [10] proposed an optimized replenishment strategy using dynamic matrix model. The strategy calculates the replenishment value according to the relationship between sales volume, predicted sales volume, inventory and the number of goods in the vending machine. The replenishment personnel can dynamically adjust the replenishment cycle according to the replenishment matrix; Zhou Siyu et al. [11] proposed a joint replenishment strategy combined with the robust optimization method. First, the robust optimization method is used to solve the minimum total cost in the supply chain, and then the internal and external two-layer iterative algorithm is used to obtain the replenishment cycle and replenishment number. In the above replenishment strategy, the replenishment volume is derived according to the relationship between the predicted sales volume and the inventory volume, but it does not have the function of real-time adjusting the replenishment parameters and optimizing the replenishment model. Because the sales volume of vending machines is affected by many factors, the sales law at each stage is uncertain, so the model cannot be dynamically adjusted in real time according to the sales characteristics of vending machines, It will lead to slow response and high error rate of the model.

In view of the problem that using complex neural network algorithm in the sales volume prediction model will reduce the machine performance, this paper proposes a hybrid sales volume prediction model, which includes three simple and effective prediction algorithms, which can complete the prediction without huge amount of data and high machine performance. In view of the above problem that the replenishment quantity of the vending machine cannot be dynamically adjusted, this paper proposes a linear replenishment model of the vending machine. The model mainly aims at the situation that when the replenisher replenishes all the goods of all the vending machines in his area, the type and quantity of the goods are uncertain, resulting in the impact on the sales volume of the goods and the waste of the replenishment cost, It also dynamically adjusts the parameters of the linear replenishment model of the vending machine according to the loss caused by shortage each time, so as to reduce the replenishment cost on the basis of meeting the sales demand. It can dynamically adjust the replenishment model in real time and successfully solve the problem of large error caused by the unstable sales volume of the vending machine.

The key technologies of this paper include: (1) design a compound sales volume prediction algorithm in line with the characteristics of vending machine sales data; (2) An algorithm is designed to dynamically adjust the linear replenishment model of the vending machine according to the predicted sales volume.

3. Dynamically Adjustable Replenishment Strategy

3.1 Logic Flow Chart of Replenishment Strategy

This paper includes three modules: sales volume prediction algorithm, linear replenishment model and optimization replenishment model parameter algorithm. In this paper, the predicted sales volume is generated through the sales volume prediction algorithm, and then the replenishment matrix is generated through the linear replenishment model. Replenishment is generated according to the replenishment matrix, and the replenishment loss is generated after t days of the replenishment cycle. Finally, the parameter algorithm of the replenishment model is optimized, that is, a new linear replenishment model is generated through the algorithm of adjusting the linear replenishment model through the previous round of replenishment loss, To reduce the total loss of replenishment. See Figure 1 for details.

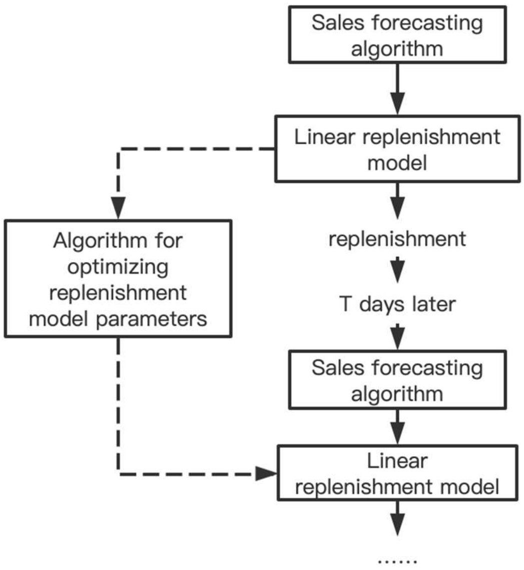

Figure 1. replenishment flow chart

3.2 Prediction Strategy Algorithm

The sales volume prediction algorithm is mainly used to predict the sales volume of all goods in all vending machines in the replenisher's management area in the future replenishment cycle t. It consists of two parts. One part is to predict the sales value of a single commodity in a single vending machine in the future cycle T, and the other part is to integrate the sales prediction value of all commodities in all vending machines in the jurisdiction in the future replenishment cycle T into a matrix form.

In the sales volume prediction algorithm of a single commodity in a single vending machine, input the historical sales volume sequence s into the algorithm and output the sales volume of the first day. In the next prediction, use the historical sales volume sequence s plus the predicted sales volume to obtain the predicted sales volume of the second day. Cycle T rounds to obtain the sales volume of the

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commodity in the vending machine in the future replenishment cycle t. The specific implementation steps are shown in Figure 2 below.

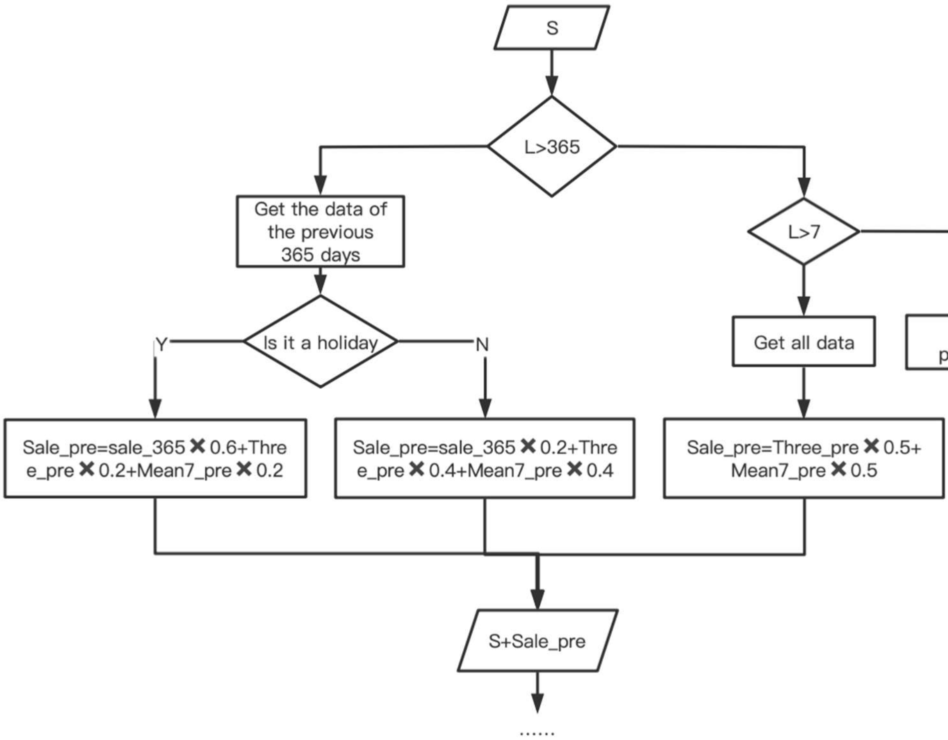

Figure 2. specific implementation flow chart of sales volume prediction algorithm

Figure 2 is the flow chart of the specific implementation of the sales volume prediction algorithm, where s is the sales volume data, l is the length of each sales volume data, and sales_ Pre is the predicted sales volume, sales_ 365 is the sales volume on the corresponding date of last year, three_ Pre is the predicted value of cubic exponential smoothing, mean7_ Pre is the average sales volume in the previous 7 days.

In the figure, first judge which kind of sales prediction algorithm to use according to the time length of sales data of a commodity in a vending machine, and provide different prediction algorithms according to different lengths. When the data length is greater than 365 and it is a national legal holiday, use the formula:$\text{Sale\_pre} = \text{sale\_365} \times 0.6 + \text{Three\_pre} \times 0.2 + \text{Mean7\_pre} \times 0.2$, Make the sales volume of last year's corresponding date dominant, and the other two methods play a regulatory role; When the data length is greater than 365, but it is not a national legal holiday, the formula is used:$\text{Sale\_pre} = \text{sale\_365} \times 0.2 + \text{Three\_pre} \times 0.4 + \text{Mean7\_pre} \times 0.4$, The smooth prediction results of the three indexes and the average sales volume of the first seven days are relatively dominant, and the sales volume on the same date last year plays a regulatory role; When the data time length is less than 365, use all data for prediction, and use the formula:$\text{Sale\_pre} = \text{Three\_pre} \times 0.5 + \text{Mean7\_pre} \times 0.5$, The two prediction results have the same status; When the data time length is less than 7, the prediction is not carried out directly. In the second round of prediction, the data used is the historical sales volume data plus the prediction data to predict until the predicted sales volume of the commodity in the vending machine in the future replenishment cycle T is obtained.

In 1.1, the predicted daily sales volume of each commodity in each vending machine in the replenishment cycle T has been obtained. In order to make the data format meet the data requirements in the linear replenishment model, the above data needs to be processed.

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The first step is to sum the predicted sales volume of each commodity in each vending machine in the replenishment cycle T. the second step is to integrate all data into a one-dimensional matrix according to all vending machines and all commodity types in the jurisdiction, where M represents the quantity of all vending machines in the jurisdiction, n represents the quantity of all commodity types in the jurisdiction, and sales_ T represents the total sales volume in replenishment period T, and the format is shown in Figure 3.

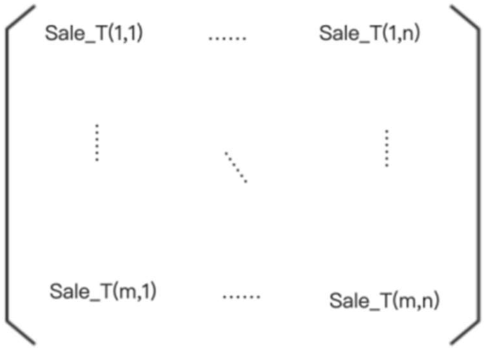

Figure 3. forecast sales volume matrix

3.3 Linear Replenishment Model

In the linear replenishment model, the input is the dimensional predicted sales matrix and the dimensional commodity surplus matrix, and the output is the dimensional replenishment matrix. As shown in Figure 4.

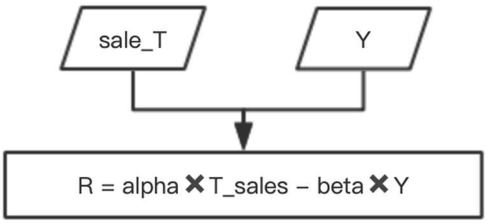

Figure 4. linear model of replenishment quantity

Figure 4 is a linear model for calculating replenishment quantity, where sale_ T is the predicted sales volume matrix of dimension, R is the replenishment quantity matrix of dimension, M is the maximum inventory of goods in dimension, y is the remaining quantity matrix of goods in dimension, where alpha and beta are the proportion coefficients. The process of optimization is to train these two coefficients to minimize the total loss mentioned later.

In this model, the maximum storage quantity m and remaining quantity y of all goods of all vending machines in the jurisdiction are obtained from the cargo Lane configuration and event information, and then the replenishment quantity calculated by multiplying the sales volume of goods in the future t time obtained in the above content by the proportion coefficient is as follows: $Replenishment\ quantity = \mathrm{alpha} \times \mathrm{sale}_{\mathrm{T}} - \mathrm{beta} \times \mathrm{Y}$ .After calculating the replenishment quantity, compare each replenishment quantity with its corresponding maximum storage quantity. If the replenishment quantity plus the margin is greater than the maximum storage quantity, the replenishment quantity will be the maximum storage quantity minus the margin. On the contrary, the replenishment quantity will remain unchanged.

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3.4 Algorithm for Optimizing Replenishment Model Parameters

Optimize the parameter algorithm of the replenishment model, that is, after replenishment according to the linear replenishment model, there will be replenishment loss, labor loss and distance / time loss. The process of optimizing the linear replenishment model by using the generated loss is the model optimization process. This part includes two parts: the schematic diagram of replenishment loss and the schematic diagram of linear replenishment model optimization.

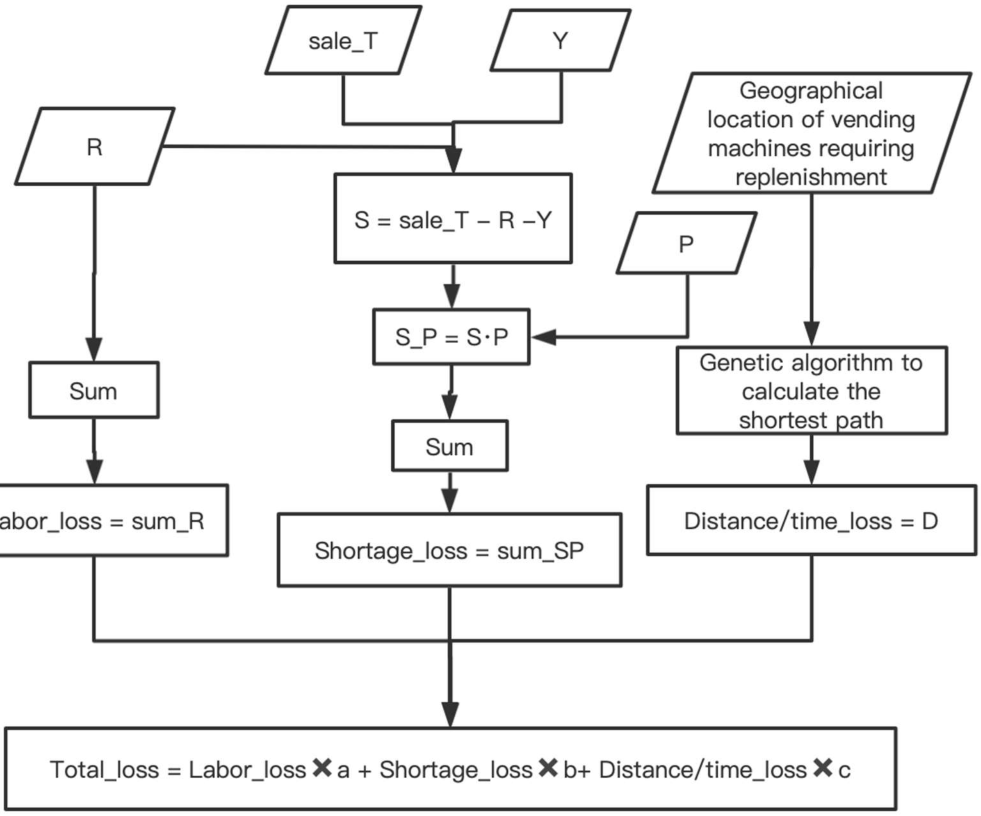

Figure 5. schematic diagram of replenishment loss

Figure 5 is the schematic diagram of replenishment loss, showing the solution methods of labor loss, shortage loss and distance / time loss. Among them, sale_ T is $n \times \mathrm{m}$ Dimensional forecast sales matrix, R is $n \times \mathrm{m}$ Dimensional forecast sales matrix, Y is $n \times \mathrm{m}$ Dimensional forecast sales matrix,S is $n \times \mathrm{m}$Dimensional forecast sales matrix, P is $n \times \mathrm{m}$Dimensional forecast sales matrix, S_P is $n \times \mathrm{m}$ Dimensional replenishment loss matrix for each product and each vending machine, sum_ R is the sum of all elements in the replenishment matrix R, sum_ SP is the shortage loss matrix s_ Sum of all elements in P, total_ Loss is the total loss, labor_ Loss refers to manual loss and shortage_ Loss is out of stock loss, distance / time_ Loss is the distance / time loss, D is the replenishment distance, and a, B and C are the proportional coefficients of labor loss, shortage loss and distance / time loss respectively.

In the total loss, the labor loss is the product of the replenishment amount and the proportional coefficient of labor loss, the out-of-stock loss is the product of the out-of-stock amount, the commodity price, and the proportional coefficient, and the distance/time loss is the product of the distance and the proportional coefficient, which needs to be explained. Yes, the proportionality coefficient is to adjust the large difference between the three losses due to different units, so as to ensure that the proportion of the three losses in the total loss is relatively close.

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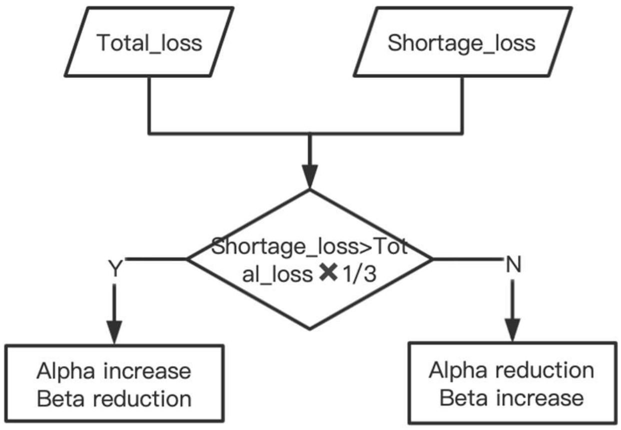

Figure 6. schematic diagram of replenishment model optimization

Figure 6 is the schematic diagram of replenishment model optimization, in which shortage_ Loss is the shortage loss, total_ Loss is the total loss, alpha and beta are the proportion coefficients of the predicted sales volume matrix and the commodity surplus matrix when calculating the replenishment matrix.

In this model, the replenishment quantity depends on the relationship between the sales volume and the commodity surplus in the future t time. The relationship is determined by two parameters: alpha and beta. In each round of replenishment operation, the change direction of alpha and beta is determined according to the proportion of out of stock loss in the total loss. When the shortage loss is greater than one-third of the total loss, it means that the proportion of shortage loss is large, so it is necessary to reduce the total loss by increasing the replenishment volume, that is, alpha increases and beta decreases; On the contrary, when the replenishment loss is less than one third of the total loss, it means that the proportion of out of stock loss is small, so the total loss can be reduced by appropriately reducing the replenishment volume to reduce the manual loss and distance / time loss, that is, alpha decreases and beta increases.

4. Experimental Results and Analysis

In order to develop this replenishment strategy program, this paper designs and implements it in pycharm environment. The database adopts mongodb. The data set is provided by a vending machine retail company, and the data is true and effective.

4.1 Basic Information Table

According to the real data of a vending machine retail company, obtain the sales volume data, cargo Lane configuration, event information, etc. of all goods in all vending machines in the jurisdiction, so as to determine the input and output of the program. The fields used in the input of sales volume data in the replenishment program are shown in table 1.

Table 1. sales volume of vending machines

Field name	Type	Field description
Machine_id	string	Vending machine ID
Goods_id	string	Commodity ID
sale	int	Number of sales
Sale_time	time	Sale time

The main fields used in the channel configuration information table entered in the replenishment program are shown in table 2.

Table 2. cargo Lane configuration information

Field name	Type	Field description
Machine_id	string	Vending machine ID
Goods_id	string	Commodity ID
C_id	string	Freight track number

The fields used in the event information table entered in the replenishment procedure are shown in table 3.

Table 3. event information table

Field name	Type	Field description
Machine_id	string	Vending machine ID
event	string	Vending machine door event

The basic information table of replenishment that needs to be output according to the actual demand is shown in table 4.

Table 4. basic information of replenishment

Field name	Type	Field description
Machine_id	string	vending machine id
Goods_id	string	product id
date	date	replenishment date

4.2 Validity of Replenishment Matrix

In order to verify the effectiveness of the experiment, this paper uses the above-mentioned hybrid prediction method for prediction, selects the real data of recent one year as comparison, based on the prediction data, assuming that the replenishment quantity of the next day is output each time, and determines the specific replenishment quantity according to the number of lanes occupied by each commodity. Take the replenishment matrix output by replenisher a on February 11 as an example, as shown in table 5.

Table 5. replenishment strategy output table

Vending machine ID	Item ID	Replenishment quantity
009	Esaxs81dba1sdschfdd3	5
010	Asaxs8iad82ddschfdd9	3
021	Ssaxsdjisjxaiianz88dd5	6
026	Esaxs81dba1sdschfdd3	8

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It can be seen from the above that the goal of daily predicted replenishment volume can be achieved, and the replenishment time and cost can be solved.

4.3 Replenishment Strategy Evaluation

In this paper, the mixed sales volume prediction method is used to predict the sales volume of vending machines. If the replenishment model that can be dynamically adjusted is not used for replenishment, the replenishment volume is directly equal to the predicted sales volume. Compared with the replenishment model in this paper, 15 days in the middle and late February are selected as the comparison, that is, the data from February 18 to February 28 are compared, as shown in Figure 7.

Figure 7. comparison chart of actual sales volume, predicted sales volume and replenishment volume in this paper

As shown in Figure 7, the replenishment volume in this paper is closer to the actual sales volume than the predicted sales volume in this paper.

4.4 Time Complexity of Replenishment Strategy

Suppose there are n vending machines, and the goods of each vending machine have m types. The replenishment strategy model takes out the predicted sales volume, inventory, number of lanes and event information of each commodity of each vending machine according to traversing the vending machine and goods. The time complexity of the replenishment strategy in this paper is O (n) × m) , because each replenisher is responsible for a certain number of vending machines in his area, and the goods of each vending machine are limited, the time complexity of this strategy is approximately equal to o (1).

5. Conclusion

For the dynamically adjustable vending machine linear replenishment model, this paper investigates the contents of a large number of research scholars, analyzes the characteristics and influencing factors of vending machine sales data, and puts forward a compound sales volume prediction algorithm. Then, according to the relationship between the predicted sales volume and the surplus of vending machine goods, a vending machine linear replenishment model with dynamically adjustable parameters is proposed, Finally, the effectiveness of the model is tested by using the sales data of a

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brand vending machine in a company in recent two years. The results show that the replenishment scheme can effectively reduce the replenishment cost on the basis of meeting the sales demand.

This model is suitable for the problem of replenishment of vending machines in fixed jurisdiction with serious loss of sales data, unclear regularity. The deficiency of the model is that in the solution of replenishment loss, the replenishment loss only uses the distance between vending machines and does not make route planning.

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