The Transitional Data Presumption、 Expected Daily Maximizing Profit and Inventory Optimization of the First Associated Product of One Product with Surging Sales in the FMCG Enterprise

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Abstract: *The consumer market is fickle. The increase in surging sales of a certain product will be often sudden and has time-effectiveness due to some reason. Meanwhile, there are incomplete sales data or vague information in the early stage of product sales surge. Although the sales volume of products associated with product with surging sales is also sudden and time effective, it is predictable and diverse. Enterprises are faced with many challenges if they want to seize the market sales opportunities of such related products and get the maximum expected profit and inventory optimization management. Here, our research in this area becomes important. This paper presents a new method to simulate the transition and replacement process from presumptive data to real data, especially the balance between profit decision and inventory optimization. Emphasize the importance of associated product screening, maximizing expected profits and inventory optimization. Basic steps and modules include: firstly, grey relational analysis has the feature of finding the relational degree between variables in the complex system with incomplete data and fuzzy information, and using this feature to find the first associated product and relational degree of the product with surging sales before the sales did not surge. The second step: the limited sales data of the product with surging sales is multiplied by the relational degree to obtain the presumptive sales data of the first related product after sales surge; The third step: based on the presumptive sales data of the first associated product after the sales surge calculated in the second step, the newsboy model is used to calculate the optimal daily order quantity. Finally, because this kind of sales phenomenon is sudden and time effective, the grey forecasting model is used to optimize inventory management, so as to avoid the cost waste caused by inventory overstocking. The modules will be connected in series using MATLAB software series instructions. Theoretical analysis and software programming simulation are carried out to determine the effectiveness and feasibility of the scheme. The advantage of this system can help enterprises quickly find associated target products, seize sales opportunities, maximize expected profits and optimize inventory management when the early data is incomplete or fuzzy.*

Keywords: Grey relational analysis; Division function; Newsboy model; Grey model; The first associated product; Maximum expected profit; Inventory optimization;

Introduction

The consumer market is the final destination of all products in the manufacturing industry. However, following the rapid development of society, the demand of the consumer market changes rapidly and unpredictably. It will be affected by factors such as the public reputation of consumers, environmental changes or national policies and so on, resulting in a sudden surge in demand for a certain product in a short period of time. This process often does not leave sellers much time to react, so this opportunity is often quickly lost. But the sales of products related to the product with

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surging sales often rise later, such as upriver and downriver products or combination products. When consumers buy one accessory in the supporting products, the other accessory in the supporting products is likely to be necessary for consumers, which leaves relatively sufficient arrangement and response time for sellers. However, because the products related to the products with rapid increase in sales volume have not entered the period of rapid increase in sales volume at this time, there is not enough surge data as data support to predict the next order quantity and inventory arrangement. For this situation, if the enterprise can build a system. Before the sales surge period of these products associated to product with surging sales is coming, using before and after data of this product with surging sales and the relational degree between product with surging sales and associated products to generate the presumptive data after the surging sales of the first associated product as a transitional basic data support. In the case of incomplete data or vague information in the early period, in order to predict the optimal daily sales volume, order quantity and inventory availability in the short transition period, the real daily sales data are collected in this process to constantly replace the calculated presumptive data, so that the actual situation is closer and closer to the real environment. Of course, it should be noted that during the short transition period, only the optimal daily sales volume and order quantity are predicted, and inventory optimization is carried out without inventory reserve. When all the calculated presumptive data are replaced by real sales data, the inventory reserve prediction and deployment in the next week will be carried out using real data, which means that the inventory reserve prediction and deployment will be carried out after the transition period. Avoid the increase of inventory overstock cost due to sudden cut-off of surging sales volume condition of associated product for some reason, such as the emergence of new alternatives or market changes and so on. Existing similar literature studies mainly focus on the correlation analysis of normal daily sales products, such as the correlation study of the classic case of diapers and beer sales, or a single study on the optimal order quantity or inventory optimization. Our direction is to systematically analyze and forecast the selection of the first associated products and the construction of the first associated product transition data and the optimal order quantity and inventory optimization when the sales of a product suddenly increase for some reason.

This paper presents a qualitative research method using model combination to screen the first associated product of product with surging sales, maximize the expected profit forecast and inventory optimization of the first associated product. Shadow data is constructed based on various existing data and relational degree. Shadow data is calculated presumptive data, and relational degree is used as correlation coefficient. Real data generated every day is used to continuously replace shadow data to achieve a stable state, and then prediction is made. The whole process through the establishment of a combined mathematical model or theoretical model to describe the specific problem, show its working principle and process, while using MATLAB software to demonstrate the solution.

The main goal is to help enterprises quickly find the associated target product of the product with surging sales in the case of incomplete data or vague information, seize sales opportunities, maximize expected profits and optimize inventory management. This process solves the problem of unreasonable prediction of sales volume and expected profit and inventory optimization due to incomplete data or fuzzy information in the early days before the sales surge of associated product, which improves the sales opportunities of enterprises and strengthens cost management, so as to obtain more profits for enterprises in the increasingly competitive market.

The concept of proposed approach in terms of the first associated product of a certain product with surging sales

This section describes the concept of the method for the selection of the first associated product、forecasting to obtain the maximum expected profit, and inventory optimization, which is based on four steps. Figure 1 shows the composition of the entire system process and work distribution.

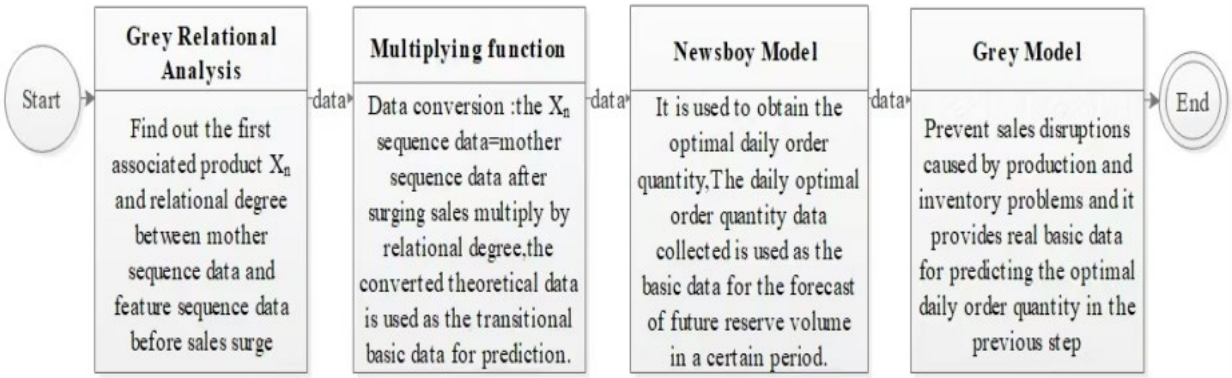

Figure 1. The composition of the entire system process and work distribution

Source: Authors' own research results/contribution.

In today's fierce market environment, seizing more sales opportunities means that enterprises will get more profits and be able to survive better in the competition. At present, every product with surging sales will drive the sales of its associated products to increase rapidly, this is a good sales opportunity. The work of this paper is to propose an organization decision system integrating associated products screening, data transformation, maximum expected profit forecast and inventory optimization. The steps are divided into four steps as follows:

Step 1: Grey relational analysis

Find out the first associated product Xn and relational degree β between mother sequence data and feature sequence data before sales surge。

Step 2: Multiplying function

Data conversion: the Xn sequence data=mother sequence data after surging sales multiply by relational degree, the converted presumptive data is used as the transitional basic data for prediction.

Step 3: Newsboy model

It is used to obtain the optimal daily order quantity, the daily optimal order quantity data collected is used as the basic data for the forecast of future reserve volume in a certain period.

Step 4: Grey model

Prevent sales disruptions caused by production and inventory problems and it provides real basic data for predicting the optimal daily order quantity in the previous step and make inventory optimization management in the future period of time.

Theoretical analysis and software programming simulation are carried out to determine the effectiveness and feasibility of the scheme. In this process, it is necessary to achieve the optimal state through continuous testing and optimization to determine its practical application effect, and make corresponding improvements or adjustments.

Figure 2 shows the process and cycle of the whole system. We will use the series command of MATLAB software to connect the 4 modules in series for associated products screening, data conversion, daily maximum expected profit prediction and inventory optimization. The following are the model series instructions and process:

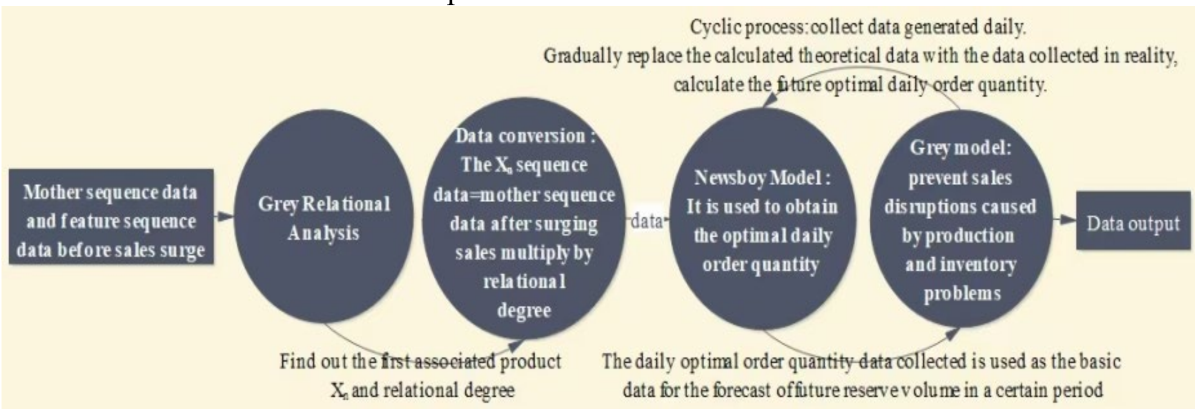

Figure 2. The whole work flow chart

Source: Authors' own research results/contribution.

Grammar:

1	series
2	sys = series(sys1,sys2)
3	sys = series(sys1,sys2,outputs1,inputs2)

Description:

Series connects two model objects in a serial manner. This function accepts any type of model. The two systems are either continuous or discrete and have the same sampling time. The static gain is neutral and can be specified as a regular matrix.

Series 1: Connect grey relational analysis model sys1 and the division function sys2 in series according to the following instructions: sys=series(sys1,sys2,outputs1,inputs2) to form a common series connection, sys1 outputs the first associated product Xn and relational degree β to sys 2, and sys 2 converts the data to output new Xn sequence data :

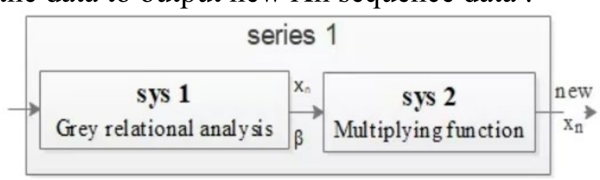

Figure 3. Grey relational analysis model and the multiplying function in series

Source: Authors' own research results/contribution.

The index vectors outputs1 and inputs2 should connect the output Xn and β of sys1 and the input Xn and β of sys2.

Series 2: Connect the multiplying function sys 2 and the newsboy model sys 3 in series according to the following instructions: sys = series (sys2, sys3) to form a basic series connection as shown below and Xn and β is the input data of sys 2 and new Xn is the output data of sys 2 and the input data of sys 3:

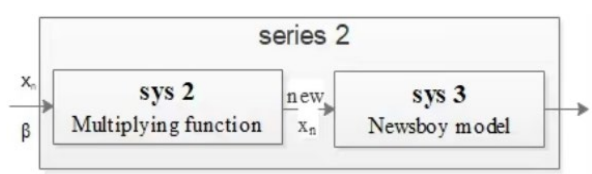

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Figure 4. The multiplying function and the newsboy model in series

Source: Authors' own research results/contribution.

Series 3: Connect the newsboy model sys 3 and the grey model sys 4 in series according to the following instructions: sys = series (sys3, sys4) to form a basic series connection as shown below:

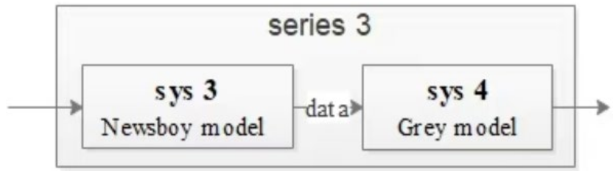

Figure 5. The newsboy model and the grey model in series

Source: Authors' own research results/contribution.

Through the above three-step MATLAB instructions, the four models can be arranged in series, the data can be input and processed in sequence, and finally target data can be output.

Step 1 - Grey relational analysis

Step 1 of the system is based on the gray correlation analysis model (Sifeng L. et al., 2023), which selects the first associated product of the product with surging sales volume as the sales opportunity target and calculates the relational degree as the conversion medium of using the sales data of the product with surging sales volume to calculate the presumptive sales data of the first associated product in the second step.

Grey relational analysis is based on grey relational degree (Aqin H. & Naiming X., 2024). By comparing the geometric relation and the similarity degree of geometric shape of data series to analyze the correlation degree of each factor in the system. Here, we will assume the theoretical derivation method to analyze the relational degree between a certain product with surging sales and all its upriver and downriver associated products, find the kind of product with the greatest relational degree and calculate the relational degree value between them, the steps are as follows:

Process 1: Determine the mother sequence and feature sequence (subsequence) (Prashant K.P. et al., 2024):

The mother sequence (evaluation criteria is the product with surging sales) is:

$$X_0^* = (x_0^*(1), x_0^*(2), \ldots, x_0^*(m))^T \tag{1}$$

The comparison sequence (the feature sequence is all upriver and downriver associated products of the product with surging sales) is:

$$[X_1^* \quad X_2^* \quad \ldots \quad X_n^*] = \begin{bmatrix} x_1^*(1) & x_2^*(1) & \ldots & x_n^*(1) \\ x_1^*(2) & x_2^*(2) & \ldots & x_n^*(2) \\ \vdots & \vdots & \vdots & \vdots \\ x_1^*(m) & x_2^*(m) & \ldots & x_n^*(m) \end{bmatrix} \tag{2}$$

Process 2: Carry out dimensional unification of indicator data:

In order to truly reflect the actual situation, the influence of different subsequence and the wide difference between their numerical values or quantities is excluded. To avoid the occurrence of unreasonable phenomena, it is necessary to carry out dimensional unification of each sales data element in each subsequence. Here, the mean normalization is used to carry out dimensional unification. That is, calculate the mean of each subsequence, and then divide each element in the each subsequence by the mean of that each subsequence. The dimensionally unified value formula of each data element in each subsequence is:

$$\tilde{x}_i(k)=\frac{x_i^*(k)}{\frac{\sum_{k=1}^{m}x_i^*(k)}{m}},k=1,2,3,\cdots,m;\quad i=1,2,3,\cdots,n \tag{3}$$

Process 3: Calculate the correlation coefficient. The correlation coefficients of the corresponding elements of each comparison sequence (subsequence) and reference sequence (mother sequence) are calculated respectively by the following formula:

$$\begin{gathered}\lambda_{(\tilde{x}_0(k),\tilde{x}_i(k))}=\frac{\triangle\, min+\rho\triangle\, max}{\triangle\, ik+\rho\triangle\, max}\\ \triangle\, min=\min_i\ \min_k|\tilde{x}_0(k)-\tilde{x}_i(k)|\\ \triangle\, man=\operatorname*{man}_i\ \operatorname*{man}_k|\tilde{x}_0(k)-\tilde{x}_i(k)|\\ \triangle\, ik=|\tilde{x}_0(k)-\tilde{x}_i(k)|\end{gathered} \tag{4}$$

ρ is the resolution coefficient, which is in (0,1) value, the smaller the resolution coefficient, the greater the difference between the correlation coefficients, the stronger the differentiation ability, usually the selected value is 0.5.

Process 4: Calculate the relational degree:

The weighted average of the correlation coefficients of the corresponding elements of each subsequence (Shun W. et al., 2023) and mother sequence were calculated respectively to reflect the correlation relation between each feature sequence and the reference sequence, which was called the relational degree, denoted as:

$$\lambda_{0i}=\frac{1}{m}\sum_{k=1}^{m}W_k\,\zeta_i(k) \tag{5}$$

Process 5: Calculate the results separately:

According to the grey weighted relational degree, the correlation order of each evaluation object is established. The greater the relational degree, the greater the importance of the subsequence to the mother sequence.

MATLAB run instructions are as follows

```
clear;clc
load gdp.mat
Mean = mean(gdp);
gdp = gdp ./ repmat(Mean,size(gdp,1),1);
disp(gdp);
Y = gdp(:,1);
X = gdp(:,2:end);
absx̃0_x̃i= abs(X - repmat(Y,1,size(X,2)))
a = min(min(absx̃0_x̃i))
b = max(max(absx̃0_x̃i))
rho = 0.5;
lambda = (a+rho*b) ./ (absx̃0_x̃i  + rho*b)
disp('relational degree of each sequence in the subsequence')
disp(mean(lambda))
```

The result of the run will display the relational degree value β of each subsequence and mother sequence. The greater the value, the greater the degree of correlation between the sub-sequence and the mother sequence, and then find out the first associated product (subsequence). Finally, the first associated product sequence data and relational degree values are transferred to step 2 to calculate the presumptive sales data of the early period after the surging sales volume of the first associated product, which is used for data analysis and prediction in the transition period, because the data is rare or incomplete or the information is fuzzy when the sales volume of the first associated product surges at the beginning.

Step 2- Multiplying function

The function of the step 1 is to select the first associated product and calculate the correlation degree between the sales data of the first associated product and the reference sequence (mother sequence) product before the sales surge. The function of this step 2 is mainly to carry out data conversion. By multiplying the sales data of the reference sequence (mother sequence) products in a period of time after the sales surge by the correlation degree to get the sales data of the first associated products in a period of time after the sales surge in theory ,which can be used as the basic data analysis of the transition period. This process provides the supporting data used in the early analysis for the step 3 to predict the optimal daily order quantity of the first associated product due to incomplete data and fuzzy information at the beginning of the period of sales surge.

MATLAB run instructions are as follows:

```
clc,clear
β= [ ... ]
X0*↑= [ ...,...,...,...,...]
Xn*↑= β*X0*↑
end
```

Here, the β is the value of the relational degree between the product with surging sales and its first associated product; X_0*↑ is the daily sales volume of the reference sequence (mother sequence) product within one week after the sales surge; X_n*↑ is the presumptive calculated sales volume of the first related product in the next week during the transition period when the sales volume begins to surge.

Step 3 - Newsboy model

The order quantity is determined according to the demand, but the demand is also random, so if the unit time order quantity is not enough to sell, company will earn less money; if the unit time order quantity is too large, it will cause inventory overhang, even the goods are always unsold or expired, it will cause price reduction and cost waste, so the unit time demand is random, and the unit time income is also random. Therefore, the measure of income cannot be the income per unit of time, but the long-term average income, which from the perspective of probability theory is equivalent to the expected income per unit of time, hereinafter referred to as the average income. At the same time, the process needs to clarify the following points:

- Purchase the first associated product of the product with surging sales;
- Purchase only once in a purchasing cycle;
- Do not know the exact actual demand at the time of purchase;
- There will be a backlog of goods, causing cost waste and price reduction;

Assume here: the unit time is day; The wholesale price is b and the retail price is a for each product per day; If the product is overstocked for a long time, the discount price of a single product in the later period is c; The revenue of daily purchase volume n is G(n); If the demand r<=n on that day, then the sales volume is r, and the product backlog is N-R; If the demand r=>n on this day, then the sales volume is n and the product backlog is 0; The probability of the quantity demanded (Guanqun N., 2023) is f (r), so:

$$G_{(n)} = \sum_{r=0}^{n} [\,(a-b)r - (b-c)(n-r)]f_{(r)} + \sum_{r=n+1}^{\infty} (\,a-b)nf_{(r)} \tag{6}$$

The problem comes down to finding n to maximize G (n) when a,b,c,f (r) is known.

Generally, the values of demand quantity r and purchase quantity n are both large (Suraj V. et al., 2023), and r is regarded as a continuous variable for easy analysis and calculation. At this time, probability f(r) is converted into probability density p(r), so the formula G (n) becomes:

$$G_{(n)} = \int_{0}^{n} [(a-b)r - (b-c)(n-r)]\, p_{(r)} dr + \int_{r=n+1}^{\infty} (a-b) n p_{(r)} dr \tag{7}$$

MATLAB run instructions are as follows:

```
clear
clc
r = 0:1:N;
p = normpdf(r,N*,µ);
g1 = @(r,n)((b-a).*r-(a-c).*(n-r)).*normpdf(r,N*,µ);
g2 = @(r,n)(b-a)*n*normpdf(r,N*,µ);
for n = 1:1:(N-1)
    G(n) = integral(@(r)g1(r,n),0,n)+integral(@(r)g2(r,n),n+1,N);
end
%a=integral(@(r)g1(r,n),0,n)+integral(@(r)g2(r,n),n+1,N)
%G = integral(g1,0,N*)+integral(g2,N*+1,N);
[p,q]=max(G)
n=1:1:N-1;
plot(n,G)
xlabel('Purchase quantity n')
ylabel('income')
title
```

Suppose: The daily demand obeyed mean N* and standard deviation µ; N is the maximum daily purchase quantity.

This process is mainly to calculate the optimal order quantity per unit time to obtain the maximum profit per unit time, as in this case, the unit of time is day. At the same time, as mentioned above, the demand quantity and purchase quantity are random, so the optimal order quantity calculated every day is based on the sales data in reality, which means that the basic data used for forecasting analysis is time-sensitive (Chaiyasoonthorn W. et al., 2024), such as: To predict the optimal order quantity for tomorrow, data center need to take the daily sales data of the previous 7 days from now as the analysis data. This dynamic process is that the new data constantly replaces the old data, especially the presumptive data calculated during the transition period is quickly replaced with actual sales data, so that the forecast is more realistic. In addition, since the step 3 is from the perspective of long-term average daily income, that is, the daily order quantity is averaged, but in the actual process, there will be excess or insufficient product sales every day, which requires the step 4 to optimize inventory. At the same time, this process needs to collect and record the purchased quantity and actual sales volume per unit time to calculate the remaining inventory in the unit time, so as to prepare for the inventory optimization and the expected reserve quantity in the future set time in Step 4, so as to prevent the shortage of goods in the sales process to result in loss of sales opportunities or the formation of backlog.

Step 4 - Grey model

Since step 3 is from the perspective of long-term daily income, that is, the daily order volume is average, but in the actual process, there may be excess or insufficient product sales every day. The main function of this step is to optimize the inventory, forecast the pre-sales data in the short term and prepare the inventory reserve, so as to prevent problems such as sales supply shortage or inventory overstocking due to some reasons.

Process 1: Select the original sales data of the first associated product in the recent set period after the sales began to surge as follows:

$$x^0 = (x^0(1), x^0(2), \dots, x^0(n)) \tag{8}$$

n is the number of data, and x(0) is added together to weaken the volatility and randomness of the random sequence (Naiming X.,2022), and a new number column is obtained:

$$x^1 = (x^1(1), x^1(2), \dots, x^1(n)) \tag{9}$$

Therein:

$$x^1(k) = \sum_{i=1}^{k} x^0\,(i), i = 1,2, \dots, n \tag{10}$$

Process 2: Generate the adjacent-mean equal weight column for x (1)(Sandang G. et al.,2021) :

$$z^1 = (z^1(2), z^1(3), \dots, z^1(k)), k = 2,3, \dots, n \tag{11}$$

Therein:

$$z^1(k) = 0.5x^1(k-1) + 0.5x^1(k), k = 2,3, \dots, n \tag{12}$$

Process 3: According to grey theory (Lina J. & Mingyong P., 2024), the first order unitary differential equation GM (1, 1) is established for x(1) with respect to the whitening form of t:

$$\frac{dx^1}{dt} + ax^1 = u \tag{13}$$

Where, a and u are the coefficients to be solved, which are called the development coefficient and the grey action, respectively. The effective interval of a is (-2, 2), and the matrix composed of a and u is the grey parameter â=($\frac{a}{u}$)(Mohammed A. & Sifeng L. ,2024). As long as the values of the parameters a and u are solved here, the value of $x^{(1)}(t)$ can be solved, and the predicted value of $x^{(0)}$ can be solved.

Process 4: The cumulative addition generated data is averaged to generate B and constant quantity vector Y_n (Bingjun L. et al., 2022):

$$B = \begin{bmatrix} -z^1(2) & 1 \\ -z^1(3) & 1 \\ \vdots & \vdots \\ -z^1(n) & 1 \end{bmatrix} = \begin{bmatrix} -\frac{1}{2}(x^1(1) + x^1(2)) & 1 \\ -\frac{1}{2}(x^1(2) + x^1(3)) & 1 \\ \vdots & \vdots \\ -\frac{1}{2}(x^1(n-1) + x^1(n)) & 1 \end{bmatrix}, Y_n = \begin{bmatrix} x^0(2) \\ x^0(3) \\ \vdots \\ x^0(n) \end{bmatrix} \tag{14}$$

Process 5: Using the least square method to solve the grey parameter â, then $\hat{a}=(B^TB)^{-1}B^TY_n$.

Process 6: The gray parameter â is substituted into $\frac{dx^1}{dt}$ $+ax^1=u$, the $\frac{dx^1}{dt}$ $+ax^1=u$ is solved to obtain:

$$\hat{x}^{(1)}(t+1) = (x^{(1)}(1) - \frac{u}{a})e^{-at} + \frac{u}{a} \tag{15}$$

Process 7: The above results are reduced by cumulative subtraction to get the predicted value:

$$\hat{x}^{(0)}(t+1) = \hat{x}^{(1)}(t+1) - \hat{x}^{(1)}(t) \tag{16}$$

Process 8: Use model to make predictions:

$$\hat{x}^{(0)} = (\hat{x}^{(0)}(1), \hat{x}^{(0)}(2), \dots, \hat{x}^{(0)}(n), \hat{x}^{(0)}(n+1), \dots, \hat{x}^{(0)}(n+m)) \tag{17}$$

Process 9: The accuracy of the grey model will be tested (Joyce H.Y.C. et al., 2022):

- Residual test

Residual error:

$$E(k) = x^{(0)}(k) - \hat{x}^{(0)}(k) \tag{18}$$

Relative error:

$$Q(k) = \frac{E^{(0)}(k)}{x^{(0)}(k)}, k = 2,3, \dots, n \tag{19}$$

- Posterior error reification

Mean value:

$$\bar{X} = \frac{1}{n}\sum_{k=1}^{n} x^{(0)}(k) \tag{20}$$

Variance:

$$S_1 = \sqrt{\frac{1}{n}\sum_{k=1}^{n} [x^{(0)}(k) - \bar{X}]^2} \tag{21}$$

The mean of residual error:

$$\bar{E} = \frac{1}{n-1}\sum_{k=2}^{n} E(k) \tag{22}$$

The variance of residual error:

$$S_2 = \sqrt{\frac{1}{n-1}\sum_{k=2}^{n} [E(k) - \bar{E}]^2} \tag{23}$$

Posterior error ratio:

$$C = \frac{S_2}{S_1} \tag{24}$$

The probability of small error:

$$P = P\{|E(k) - \bar{E}| < 0.6745 S_1\} \tag{25}$$

The comparison table of the levels of prediction accuracy is as follows (Dajiang L. et al., 2023):

Table 1. the levels of prediction accuracy

Excellent	*P>0.95 , C<0.35*
Good	P>0.80 , C<0.45
Pass	P>0.70 , C<0.50
Fail	P≤0.70,C≥0.65

Source: Authors' own research.

GM (1,1) model program based on MATLAB:

```
clear
syms a u;
c=[a,u]';
A=[...,...,...,...,...,..,...];
Ago=cumsum(A);
n=length(A);
for k=1:(n-1)
   Z(k)=(Ago(k)+Ago(k+1))/2;
end
```

```
Yn =A;
Yn(1)=[];
Yn=Yn';
E=[-Z;ones(1,n-1)]';
c=(E'*E)\(E'*Yn);
c= c';
a=c(1);
u=c(2);
F=[];
F(1)=A(1);
for k=2:(n)
   F(k)=(A(1)-u/a)/exp(a*(k-1))+u/a;
end
G=[];
G(1)=A(1);
for k=2:(n)
   G(k)=F(k)-F(k-1);
end
t1=1:n;
t2=1:n;
plot(t1,A,'bo--');
hold on;
plot(t2,G,'r*-');
title('forecast result');
legend('True value, predicted value');
e=A-G;
q=e/A;
s1=var(A);
s2=var(e);
c=s2/s1;
len=length(e);
p=0;
for i=1:len
   if(abs(e(i))<0.6745*s1)
      p=p+1;
   end
end
p=p/len;
```

In this process, the forecast period should be as short as possible, because the market changes quickly, and the effectiveness of the forecast should be ensured in real time. Therefore, the inventory reserve should not be too large and the reserve time should not be too long. In addition to the remaining quantity of goods that were not sold out in the last few days, the supplementary reserve quantity should meet the requirements of the recent sales volume as far as possible. At the same time, minimize the possibility of overstocking.

Conclusion

The combination of grey relational analysis, newsboy model and grey model can help sales enterprises seize the sales opportunity to screen associated products, obtain the maximum expected profit of associated products and optimize inventory, and systematically solve a series of problems.

The combination model has good revenue generating ability to seize sales opportunities in time, expected profit forecasting ability and inventory real-time management ability. There are great improvements and innovations in flexibility and reliability, which can help sales enterprises find accurate sales opportunities and obtain the maximum expected profit, improve the relationship between sales and inventory supply in real time, and improve sales mobility and inventory supply guarantee ability. It enables enterprises to seize sales opportunities in time during the profit period to continuously obtain the maximum expected profit and strengthen cost management.

However, combinatorial models also have certain limitations, due to the connection between the models, which is inevitable, so there is no best model, only a better model. At present, the sales industry is mainly affected by consumer demand, consumption power, poor access to information, and the constraints of various technology applications and popularization, but in the future, with the mature combination and popularization of artificial intelligence technology, Internet of Things, big data and cloud computing as well as developed logistics, the sales industry will have stronger decision-making, management, scheduling and profitability. Consumers will also have more choices and ways to shop.

In the future, our work will focus on the application of artificial intelligence and big data technology, and even the Internet of Things technology. However, since the current development and maturity of these technologies have not yet reached universality, this will be an important challenge for future work.

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