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Research on Supply Chain Inventory Demand Forecasting and Optimization Model Based on Spatio-Temporal Data Mining Methods

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Abstract Supply chain inventory management faces the problems of inaccurate demand prediction and large inventory fluctuation, and the accurate prediction and optimization method based on spatio-temporal data mining can effectively improve the operational efficiency and decision-making quality. This study constructs a supply chain inventory demand forecasting model and optimizes inventory management through spatio-temporal data mining methods. The study adopts ARIMA model for inventory demand forecasting and combines the system dynamics method to establish the supply chain inventory optimization model. Based on the historical inventory data of a Guangzhou food company (Company A) from January 2012 to December 2023, the data from January 2012 to June 2019 are used as the training set, and the data from July to December 2023 are used as the test set for empirical analysis. The optimal forecasting model is identified as ARIMA(0,1,1) through the series smoothing test, white noise test and model order fixing. The results show that the ARIMA(0,1,1) model performs better in forecasting the first quarter of 2026 with a MAD value of 167 and a MAPE value of 5% compared to the Winters multiplicative model, which has a MAD value of 461 and a MAPE value of 9%. Based on the demand forecasting results, a two-level supply chain (supplier and retailer) system dynamics model was constructed, containing 10 constant parameters and 27 dynamic variables. The simulation analysis was carried out by VENSIM software for a 50-day cycle, and the optimized model showed that the fluctuation of the inventory curve was reduced, the order quantity decision was more accurate, and the value of the unsatisfied demand was greatly reduced and smoother. The conclusion of the study shows that the demand forecasting and inventory optimization method based on spatio-temporal data mining can effectively reduce the inventory risk and improve the efficiency of supply chain operation, and it is suggested that enterprises should strengthen the construction of the information sharing mechanism, and shorten the supply chain lead time through the optimization of the business process and the delaying strategy.

Index Terms Spatio-temporal data mining, supply chain, inventory demand forecasting, ARIMA model, system dynamics, inventory optimization

I. Introduction

Inventory problem has been an important issue for many manufacturing companies [1]. Insufficient inventory will lead to production can not be carried out, resulting in labor, machine cost waste, because the order can not be delivered in a timely manner will also lead to default payment loss, customer orders to reduce or even loss of customer losses [2]-[4]. Excessive inventory will also lead to waste of expired materials, insufficient storage capacity, increased inventory management costs, occupy a large amount of capital, etc. Liquidity is the blood of the enterprise, when there is too much inventory and too much occupied liquidity, the enterprise may close down because of the difficulty of capital turnover [5]-[7]. In addition, the enterprise can use the working capital for other aspects of construction and investment, the inventory occupies the capital is undoubtedly the less the better. What's more, inventory hides a large number of management problems in the enterprise, at present, the inventory cost accounts for 20%-40% of the value of inventory items, so it has great room for improvement [8], [9]. To control inventory, you must start with good demand forecasting. Demand forecasting is the basis for activities such as production planning, and inaccurate forecasting of needs is usually the most important factor leading to excess inventory in a business [10].

There are three types of production methods used by firms, namely, make-ready production, make-to-order production, and hybrid make-to-order and make-ready production. Stock-ready production is a traditional production method, i.e., the enterprise's production is based on the market demand forecast, and likewise the procurement of materials is also based on the forecast data, once the market demand forecast changes, or the enterprise's forecasting method is not scientific enough, so that the predicted demand is greater than the actual demand, or the predicted demand time is later than the actual demand time, inventory will be generated [11], [12]. Production to order, that is, the enterprise according to the orders received to arrange production, according to the orders to arrange the procurement of raw materials, according to the definition of this production method is no need to do demand forecasting, will not be due to inaccurate demand forecasting leads to inventory. However, in actual production, in order to be able to cope with urgent orders, especially urgent orders from some important customers, the enterprise adds its own set of stocking mechanism under the production-by-order method, i.e., using a hybrid production-by-order and stocking-type production, which will lead to a large amount of inventory once the forecasting is inaccurate, as in the case of stocking-type production [13]-[16].

For good demand forecasting, it is essential that firms upstream and downstream of the supply chain work closely together and forecast collaboratively, rather than individual firms forecasting demand in isolation [17]. This is because, enterprises that forecast in isolation can easily lead to stock-outs or high inventories. In today's supply chain management environment, the inventory problem of an enterprise does not only affect the interests of a particular enterprise itself, but also affects the upstream and downstream enterprises associated with it [18]. When each enterprise in the supply chain can operate healthily and efficiently, the supply chain will have strong competitiveness, which makes the member enterprises in the supply chain realize the supply chain [19], [20]. Therefore, how to forecast demand and inventory management from the perspective of supply chain is an important part of supply chain management. Improving the accuracy of supply chain demand forecasting, realizing information sharing among enterprises in the supply chain and shortening the lead time will be beneficial for all enterprises in the supply chain to reduce unnecessary inventory costs and overproduction costs due to fluctuations in market demand, reduce unnecessary waste, and achieve a win-win situation, thus improving the competitiveness of the whole supply chain [21]-[24].

This study adopts the idea of combining theoretical modeling and empirical analysis, firstly constructs the framework of supply chain inventory demand forecast based on ARIMA model, starts from the definition of the model, systematically explains the mathematical principles of autoregressive part (AR), difference part (I) and moving average part (MA), and proposes a forecasting method that includes four steps, namely data preparation, series smoothing test, white noise test, and model order fixing. analysis method. Subsequently, the actual inventory data of a food company in Guangzhou is used for empirical analysis, and the model prediction effect is verified through the division of training set and test set, and ARIMA (0,1,1) is identified as the optimal prediction model. On the basis of demand forecasting, research turns to the inventory optimization problem, adopts the system dynamics method to analyze the causal relationship between the factor variables in the supply chain inventory system, constructs the system flow diagram, and establishes a mathematical model containing 38 variables. Simulation experiments are carried out through VENSIM software to compare and analyze the system performance of the current model and the optimization model, and finally two optimization directions are proposed, namely, strengthening information sharing and shortening lead time, to provide theoretical support for enterprise inventory management practice.

II. Supply chain inventory demand forecasting model based on the ARIMA model

II. A. Trend Forecasting in ARIMA Models

II. A. 1) ARIMA model definition

The ARIMA model [25] is denoted as ARIMA (p,d,q), where p denotes the order of the autoregressive part, d denotes the order of the difference part and q denotes the order of the moving average part. The model consists of three parts: the autoregressive part (AR), the difference part (I) and the moving average part (MA).The relevant concepts of the ARIMA model are as follows:

(1) Autoregressive part (AR): represents the relationship between the current observation and the past observation, which is used to predict the past value of the next value. The AR model describes the relationship between the current value and the historical value, and uses the observation at the past time point to predict the value at the current time point. AR (p) indicates that the observations at the past p time points are considered in the model, and the general p-order autoregressive model AR (p) is defined as:

$$\begin{aligned} & x_t = \phi_0 + \phi_1 x_{t-1} + \phi_2 x_{t-2} + \cdots + \phi_p x_{t-p} + \mu_t \\ & \phi_p \neq 0 \end{aligned} \tag{1}$$

From the above equation, it can be seen that the predicted value at a point in time can be represented by a linear combination of all its historical values in some past time period. In Eq:

p denotes the number of time lags used, i.e., the historical values of the previous p period are used to predict the current value.

ϕ_i denotes the coefficient of the i th lag, representing the relative influence of the i th lag on the current point in time.

x_{t-i} denotes: the i th historical data value before the time point x_i.

μ_i denotes: the error term at time point t, the error term in a strict autoregressive model is a white noise $\mu_t = \varepsilon_t$.

(2) Differential part (I): Used to process non-smooth time series data, it specifies the number of differential operations to be performed on the series, and the purpose of performing differential operations on the data is to keep it smooth. The non-smooth time series is transformed into a smooth time series by performing difference operations on the original data. Difference order is essentially the next value, minus the previous value, mainly to eliminate some of the fluctuations to make the data smooth, non-smooth series can be transformed into a smooth series through the differential transformation, usually denoted as d.

(3) Moving average component (MA): represents the relationship between the current observation and the past prediction error, and defines the number of past prediction errors in predicting the future value. the MA(q) model uses a linear combination of past prediction errors to predict the value at the current point in time, which describes the current value of the time series that has no relationship with the historical data but relies only on the cumulative past prediction error, and this past prediction error can be expressed as a variety of unforeseen contingencies or unexpected events in the past period of time.MA(q) indicates that the prediction errors of the past q time points are taken into account in the model, and the general q-order moving average model MA(q) is defined as:

$$\begin{aligned} &x_t = \mu + \varepsilon_t - \theta_1\varepsilon_{t-1} - \cdots - \theta_q\varepsilon_{t-q} \\ &\theta_q \neq 0 \end{aligned} \tag{2}$$

From the above equation, it can be seen that a time series is a weighted average of the noise of several past periods, i.e., the current observation is obtained from the past white noise by a certain linear combination. The formula:

μ denotes the mean or expected value of the time series.

ε_{t-i} denotes the white noise term i moments ago.

θ_i denotes: the degree of influence of the corresponding white noise on the current time point.

q denotes: the first q white noise is included in the model.

On top of the above parts, the AR(p) model is combined with the MA(q) model to become the ARMA(p,q) model [26]. It indicates that the current values of a time series can be explained by its own historical values as well as by a random perturbation term, where the data for the model must be a smooth series. The ARMA(p,q) model is defined as:

$$x_t = \phi_0 + \phi_1 x_{t-1} + \phi_2 x_{t-2} + \ldots + \phi_p x_{t-p} + \varepsilon_t - \theta_1\varepsilon_{t-1} - \cdots - \theta_q\varepsilon_{t-q} \tag{3}$$

The ARIMA(p,d,q) model is a combination of the ARMA(p,q) model and the difference method, where d is the order in which the data need to be differenced. Since the ARMA(p,q) model requires the data to be a smooth series, it is necessary to differentiate the non-semi-stable data into smooth data and then analyze them, so the ARIMA(p,d,q) model is developed.

II. A. 2) Steps in model prediction analysis

The predictive analysis of time series ARIMA models can usually be divided into the following steps:

(1) Data preparation. Import the data to the calculation software, read the data and perform visualization operations. The calculation software used in this paper is SPSSPRO.

(2) Sequential smoothing test to determine the d-value. Since the ARIMA model can only be modeled using smooth data, it is necessary to conduct a smoothness test on the original data. Smoothness is required by the sample time series obtained by the fitted curve, in the future period can still follow the existing pattern of “inertia” continues.

(3) White noise test. After obtaining the smoothed data, it is necessary to perform a white noise test on the smoothed data to verify whether the useful information in the series has been extracted.

(4) Model ordering: The ordering of ARIMA model is to determine the values of parameters p and q in the model, and the model ordering can be initially determined by the autocorrelation coefficient plot (ACF) and partial autocorrelation coefficient plot (PACF).

II. B.Data sources and description

The data sources used in the analysis part of the experiment are all from a food company in Guangzhou - Aviation A. The inventory data of the machine supply warehouse of A is uniformly stored in the company's import and export ERP management system. The historical inventory demand data of machine supply S from January 2012 to December 2023 are filtered and organized based on the original machine supply inventory data.

At the same time, in order to facilitate the verification of the prediction effect of the combination prediction model, the inventory demand data of machine supply goods S is divided into training set samples and test set samples for empirical analysis. In this paper, we mainly want to construct a short-term prediction model of the inventory demand of aircraft supplies for airline catering enterprises, so as to provide the procurement department of the catering company with more accurate data on the inventory demand of aircraft supplies, to help formulate the demand plan of aircraft supplies and effectively reduce the excess inventory backlog of aircraft supplies, while the factors affecting the inventory demand of aircraft supplies are changing every day, so when the time span of the prediction cycle is extended, the model prediction accuracy tends to decrease. Therefore, when the time horizon, i.e., the forecasting period, is extended, the accuracy of the model prediction tends to decrease. Therefore, this chapter only investigates the short-term inventory demand forecasting problem of machine-supplied product S. According to the sample division principle and combining with the actual data, the historical values of inventory demand from January 2012 to June 2019 are selected as the training set samples, which are used to train the model and to determine the model system; the forecasting period of the samples is set as 6 periods, i.e., the data from July 2023 to December 2023 are used as the test set samples In the experimental session, the test set samples will be used to calculate the prediction error and verify the performance of the prediction model.

II. C.ARIMA prediction results and analysis

II. C. 1) ARIMA model prediction results

Since the ARIMA model prediction requires the series to be smooth and the given series has a clear upward and seasonal trend, the original data series needs to be preprocessed first. The original series was subjected to first-order period-by-period differencing and first-order seasonal differencing, (first-order differencing $\nabla Z_t = Z_t - Z_{t-1}$), and the results are shown in Figure 1.

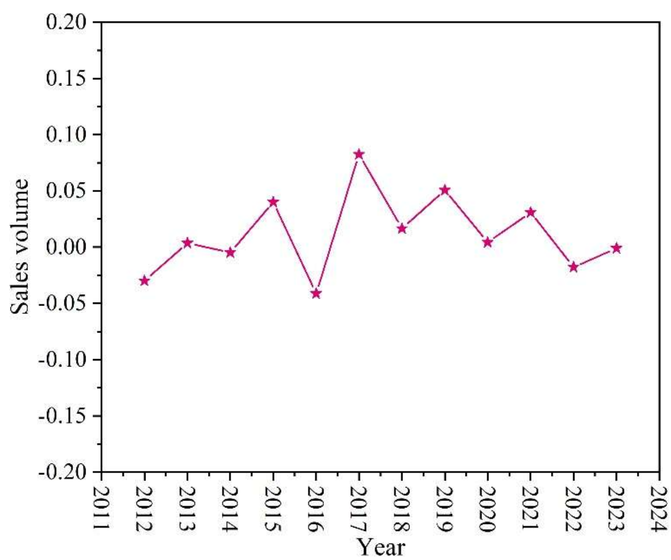
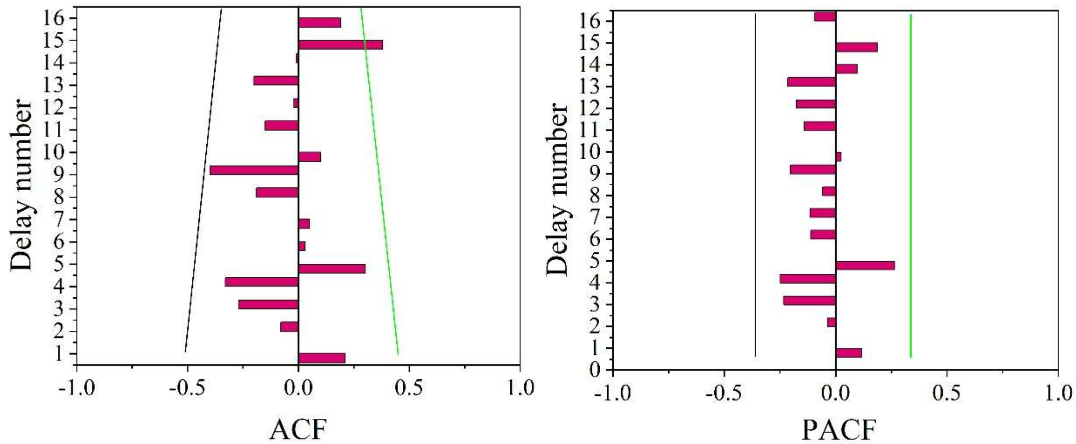


Figure 1: The total quantity of product sales in the quarterly and 2023 quarterly

The autocorrelation (ACF) and partial autocorrelation (PACF) plots of the differenced series are analyzed as shown in Fig. 2, where the coefficients are shown in red, the upper confidence limit is shown in green, and the lower confidence limit is shown in black. The residual ACF and residual PACF are both within the confidence interval, which shows that the data have been stabilized.



(a) Autocorrelation (b) Partial autocorrelation

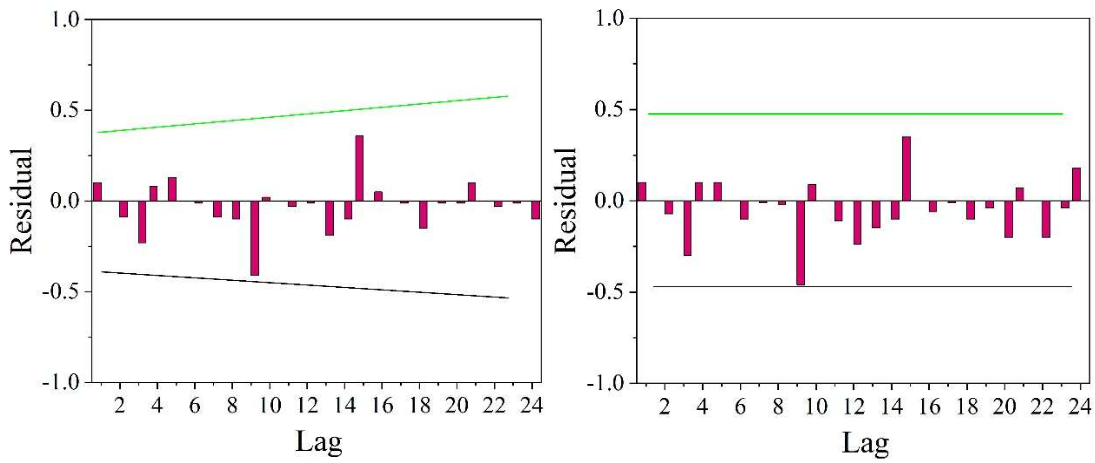
Figure 2: Autocorrelation and partial autocorrelation of first-order difference

The optimal prediction model is ARIMA(0,1,1) obtained through SPSS modeling after several tests, and the statistics of the model are shown in Table 1.

Table 1: Model statistics

Model	Predicted variable number	Model fitting statistics				Ljung-BoxQ (18)			Dispersion number
		Smooth R2	R2	MAPE	MAE	Statistic	DF	Sig.	
Sales total - model _1	0	0.125	0.996	3.815	141.087	14.802	18	0.685	0

ARIMA(0,1,1), the autoregressive function image of the model residuals and the partial autoregressive function image are shown in Fig. 3. Observation shows that the residual ACF and residual PACF of ARIMA(0,1,1), the model are both within the confidence interval, which indicates that the prediction model meets the prediction requirements.



(a) Self regression function (b) Partial self-regression function

Figure 3: The image of the function of the model of the ARIMA (0,1,1) model

Through the analysis of the above steps, the optimal forecasting model is derived as the ARIMA(0,1,1) model, and the forecasting effect of this model on the original series is shown in Figure 4, which shows that the predicted trend is basically consistent with the actual trend. The model is used to predict the total sales volume of Company A's products in each quarter in 2026 for forecasting, and the forecast results are shown in Table 2.

Table 2: The ARIMA (0,1,1) model predicts the results

Model		Q12015	Q22015	Q32015	Q42015
Sales total - model _1	Forecast	2103.04	4988.85	7364.7	9343.4
	UCL	2411.34	5835.95	9042.5	11841.7
	LCL	1953.74	4332.75	6278.1	7770.1

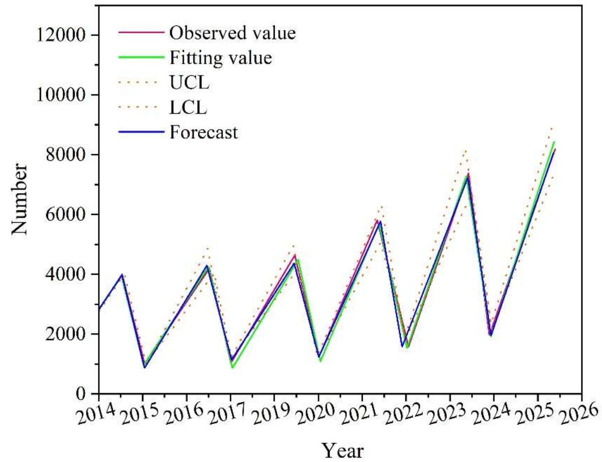


Figure 4: The ARIMA (0,1,1) model predicts the rendering

II. C. 2) Comparison of predicted results

Next, the Winters multiplication method is compared with the ARIMA model prediction results, and the comparison results are shown in Table 3. From the table, it can be seen that the MAD and MAPE of ARIMA model are smaller than Winters model, which shows that the prediction effect of ARIMA model is better and more in line with the demand prediction of enterprise A. Therefore, enterprise A should use ARIMA (0,1,1) model to predict the demand of products.

Table 3: The analysis of the prediction results of the winters method and the ARIMA model

Prediction period	Actual value	Winters multiplication			ARIMA(0,1,1)		
		Predictive value	MAD	MAPE	Predictive value	MAD	MAPE
The first quarter of 2026	2183	2293	461	9%	2357	167	5%
The second quarter of 2026	4983	5183			5072		
The third quarter of 2026	7271	7842			7459		
The fourth quarter of 2026	9158	9865			9547		

III. Supply chain inventory optimization based on demand forecasting

III. A. System dynamics inventory control modeling

III. A. 1) Analysis of causal relationships between system factor variables

Based on the operation process of Company A's product supply chain, this paper analyzes Company A's product supply chain inventory management system by taking the two-level supply chain (supplier and retailer) as the research object. According to the specific characteristics of the operation process of Company A's product supply chain, the interaction relationship between the factors in the system is clarified, and the causality diagram of Company A's product supply chain inventory model is constructed as shown in Figure 5. In this causality diagram, there are several feedback loop chains, and this paper selects and shows four of the main loop chains to highlight the key causal relationships and their role in the system dynamics.

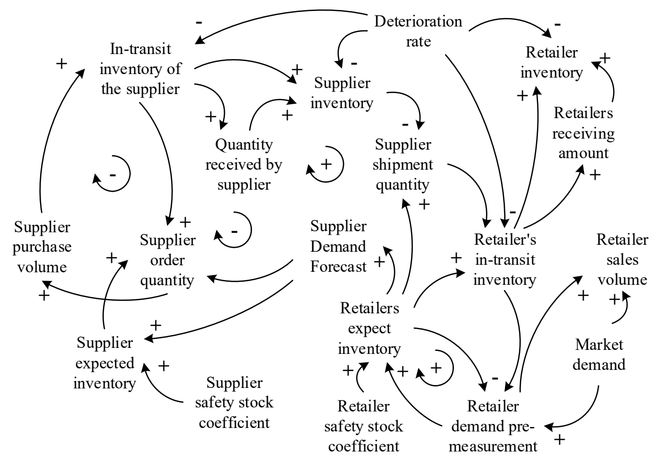


Figure 5: The causality of the inventory system of a company's product supply chain

III. A. 2) System SD flow diagrams

The system dynamics flow diagram [27] is used to describe the cumulative effects affecting the dynamic performance in the feedback system and further distinguish different types of variables. On this basis, the system causality diagram in Fig. 5 can be refined, and the flow diagram structure of the system can be constructed, respectively, to establish the system dynamics flow diagram of the collaborative supply chain management inventory model as shown in Fig. 6.

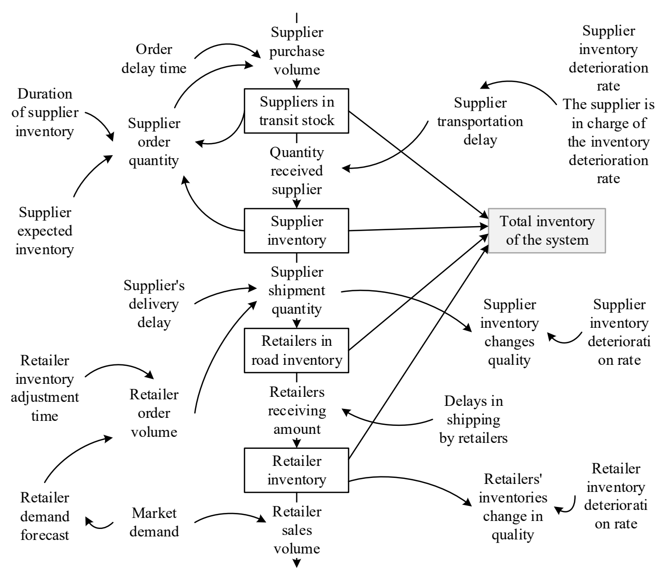


Figure 6: A company product inventory system SD flow chart

III. A. 3) Model equations

In the actual situation, the operation links of Company A's product supply chain are very complicated. In order to facilitate the research and focus on the analysis of fresh agricultural products supply chain inventory management model, this paper sets 10 constant parameters and 27 dynamic variables to simulate the operation mechanism of Company A's product inventory system according to the actual characteristics of Company A's product inventory operation. The model contains a total of 38 variables (market demand variables are not set for the time being), and it is assumed that the simulation period of the model is 120 days, with a step size of 1 day, in order to fully reflect the dynamic change characteristics of the system.

The variable-related equations are as follows:

(1) Supplier shipments = MIN (supplier inventory, retailer order quantity).

(2) Supplier Inventory in Transit = INTEG (Supplier Purchases - (Supplier Receipts + Supplier Inventory in Transit Variable Quality), 2000).

(3) Supplier Inventory in Transit Variation Rate = RANDOMUNIFORM(-0.01,0.01,0.01)+0.02.

(4) Vendor Inventory in Transit Deterioration Rate = Vendor Purchases * Vendor Inventory in Transit Deterioration Rate.

(5) Vendor Inventory = INTEG(Vendor Receipts - Vendor Shipments - Vendor Inventory Deterioration Rate, 5000).

(6) Vendor Inventory Deterioration Rate = RANDOMUNIFORM(-0.01,0.01,0.01)+0.02.

(7) Vendor Inventory Deterioration Rate = MAX(Vendor Inventory, 0)*Vendor Inventory Deterioration Rate.

(8) Supplier Received Inventory = DELAYFIXED(Supplier Purchased Inventory - Supplier Inventory Variables in Transit, Supplier Transportation Delay, 0).

(9) Supplier Desired Inventory = IFTHENELSE (Supplier Demand Forecast = 0,3000, Supplier Demand Forecast * Supplier Safety Stock Factor * Supplier Inventory Adjustment Period).

(10) Supplier Order Quantity = IFTHENELSE(Supplier Inventory + Supplier In-Transit Inventory <= Supplier Desired Inventory, 1,0) Supplier Demand Forecast * Supplier Inventory Duration * (PULSETRAIN1,3,5,120*1).

(11) Supplier Purchase = DELAYFIXED(Supplier Order Quantity, Order Delay Duration, 0).

(12) Supplier Demand Forecast = SMOOTH(Retailer Order Quantity, Supplier Move Smoothing Time).

(13) Total System Variable Mass = INTEG(Supplier Inventory in Transit Variable Mass + Supplier Inventory Variable Mass + Retailer Inventory in Transit Variable Mass + Retailer Inventory Variable Mass, 0).

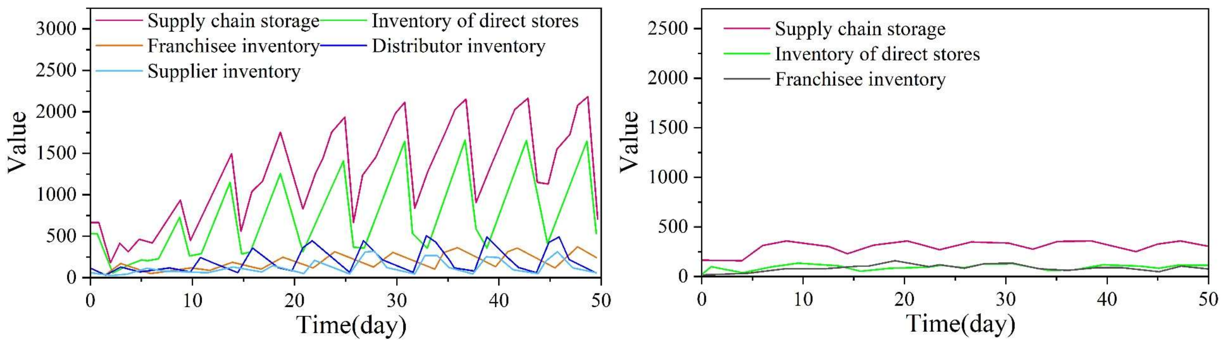
(14) Total System Inventory = Supplier Inventory in Transit + Supplier Inventory + Retailer Inventory in Transit + Retailer Inventory.

(15) Retailer Inventory in Transit = INTEG(Supplier Shipments - (Retailer Inventory Variable Mass + Retailer Receipts), 1000).

III. B. Supply Chain Inventory Management Model Simulation and Result Analysis

On the basis of the inventory management model of the product supply chain of Company A, VENSIM software is used to simulate the simulation. According to previous modeling experience, the main factors and factor relationships in the model cannot be obtained directly from internal data, so they need to be converted into quantitative data according to the actual situation. The total simulation time was set to 50 days, the statistics and collection of data was set to 1 time/day, and the simulation interval of the model was set to 1 day. The simulation results are shown in Fig. 7, Fig. 8 and Fig. 9, respectively.

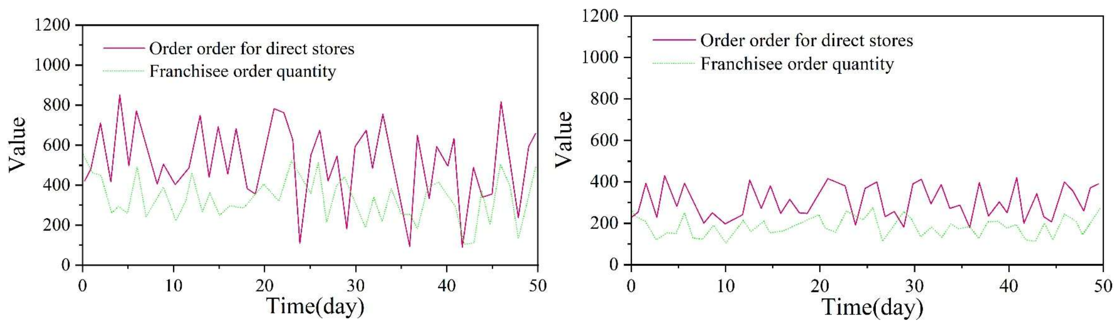
As can be seen from Figure 7, under the supply chain inventory management model, the inventory curve fluctuates greatly and the trend is uneven, which is mainly due to the seller's inventory pressure leads to its inventory fluctuation, and the distributors and suppliers are affected by the seller's inventory fluctuation, which results in the increase of the whole supply chain overall inventory pressure, and increases the amplitude of the fluctuation of the inventory curve. The optimized inventory curve is smoother, mainly because the joint inventory center bears most of the inventory risk under this model, and the setting of safety stock can effectively control the inventory risk of the joint inventory center, in addition, the inventory pressure of manufacturers and sellers is reduced, which directly reduces the inventory of the whole supply chain.



(a) Simulation results of the current model (b) Optimized model simulation results

Figure 7: Inventory curve contrast diagram

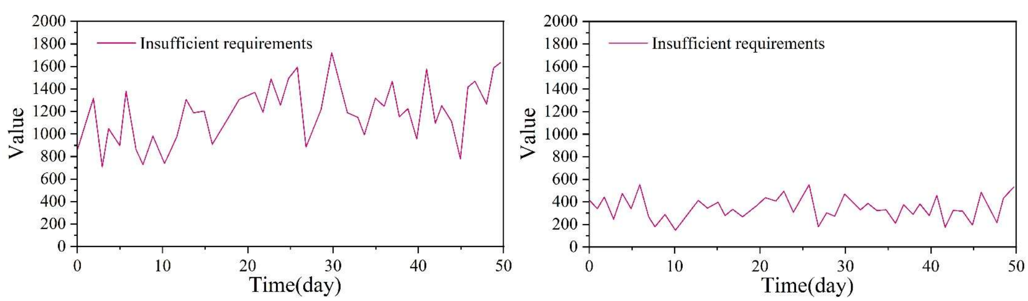
As can be seen in Figure 8, under the current supply chain inventory management model, the order quantity of franchisees and directly-managed stores varies a lot, which is mainly due to the low information communication between the node enterprises, the low efficiency of cooperation, and the large deviation of the prediction of the market, which leads to the sellers' inability to make accurate ordering decisions. In contrast, the optimized model, with a high degree of integration of node enterprises, information sharing and enhanced cooperation, makes the ordering strategy of the seller more accurate and reliable.



(a) Simulation results of the current model (b) Optimized model simulation results

Figure 8: Order quantity comparison chart

As shown in Figure 9, under the current supply chain inventory management model, the value of unsatisfied demand in the supply chain system of Company A's products is large, and the value of unsatisfied demand of the optimized model has a large reduction, and the curve also shows a smoother curve, in terms of the whole supply chain system, the reduction and smoothness of the unsatisfied demand will have a direct effect on the supply chain system, making the whole system more stable.



(a) Simulation results of the current model (b) Optimized model simulation results

Figure 9: Contrast of the unbounded demand curve

III. C. Supply chain optimization methods

III. C. 1) Strengthening of information-sharing mechanisms

Information sharing can bring the following benefits to Company A: inhibit the bullwhip effect, reduce the inventory level and inventory cost of each enterprise in the supply chain; increase the inventory turnover rate and shorten the lead time; reduce the total cost of the supply chain, effectively improve the workflow; improve the overall service level of the supply chain; improve the overall competitiveness of the supply chain; and facilitate the allocation of resources, enhance the competitiveness of the enterprise and the flexibility of the enterprise to respond to the changes in the market. Therefore, Company A must take active measures to participate in information sharing so that decision-making can be based on more valuable information.

III. C. 2) Reduction in supply chain lead time

In today's competitive market environment, time has been one of the important factors of competition, and a shorter lead time is one of the key factors for successfully obtaining orders.To improve the competitiveness of its supply chain, Company A must achieve a fast and effective customer response, and minimize the customer service response cycle by means of optimizing its internal service processes and supply chain management. Therefore, it is essential for Company A to shorten the supply chain lead time.

(1) Optimize business processes. Business processes have a greater impact on logistics lead time and information lead time, and improving business processes can shorten the supply chain lead time to a greater extent. Business process improvement principles include: batch processing, parallel processing, cross-processing, reducing waiting, deleting non-value-added processes, increasing resources at bottlenecks, etc. With regard to non-bottleneck segments, Company A can adopt a small-lot, multi-lot production method, so that their inventory levels only need to ensure that the demand for materials on the bottleneck process can be, thus reducing the lead time for inventory.

(2) Use delaying strategy. The main means include production delay and logistics delay. Production delay is the basic idea of punctuality, that is, in the absence of accurate customer demand and the exact purchase intention before, not premature production and processing, but strictly in accordance with the order to produce products. The most common means of production delay is to try to keep the product in semi-finished products, or the use of modular production means, so that after receiving the order, you can quickly carry out the subsequent processing, so as to batch production of semi-finished products or modules, to obtain economies of scale, and the last according to the requirements of the order to use different processes, not only to meet the diversity of demand, but also conducive to shorten the lead time for delivery.

IV. Conclusion

In this paper, we have conducted a systematic study on the supply chain inventory demand forecasting and optimization problem using spatio-temporal data mining methods.

In terms of inventory demand forecasting, the ARIMA(0,1,1) model performs well, with a smoothed R^2 of 0.125, an overall R^2 as high as 0.996, a MAPE of 3.815%, and a MAE of 141.087. Compared with the Winters multiplicative model, the ARIMA model has a MAD of 167 for the first quarter of 2026 forecast, a MAPE of 5%, while the Winters model has a MAD of 461 and a MAPE of 9%.

In the four quarterly forecasts, the ARIMA model predicts values of 2357, 5072, 7459 and 9547, which are closer to the actual values of 2183, 4983, 7271 and 9158.

In terms of supply chain inventory optimization, the two-level supply chain model constructed based on system dynamics contains 10 constant parameters and 27 dynamic variables, and the simulation analysis of 50-day cycle through VENSIM software shows that the optimized system inventory curve fluctuation decreases and tends to flatten, the order quantity decision is more accurate and reliable, and the value of the unfulfilled demand decreases significantly and becomes smoother.

The study proposes two optimization strategies: one is to strengthen the construction of information sharing mechanism to suppress the bullwhip effect; the other is to shorten the supply chain lead time through business process optimization and delaying strategy. This study provides theoretical guidance and methodological support for enterprise supply chain management.

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