ARIMA-Xgboost Based Pricing and Replenishment Strategy for Perishable Goods

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Abstract. Based on the enterprise sales data, the study analyzes the correlation between sales of commodities, taking vegetable products as an example, and takes into account the impact of replenishment, pricing, and sales of perishable products, and considers the joint decision-making problem of pricing and dynamic replenishment of perishable products, and designs the ARIMA-XGBoost joint decision-making model. The results show that there is a sales correlation between different commodities, and through sales, big data can be a more accurate prediction of the replenishment amount in the future period, so based on the pricing and the maximization of the revenue model set up by the study can achieve more accurate replenishment and pricing decisions.

Keywords: Perishable Goods, ARIMA Time Prediction, XGBoost Regression, PCA Principal Component Analysis, Replenishment Strategy.

1. Introduction

Enterprises usually make purchasing plans in advance to meet sales demand, and an effective purchasing strategy can improve the enterprise's capital turnover and rate of return and enhance competitiveness. However, perishable products such as vegetables, fruits, and milk are often subject to wear and tear due to transportation and storage. Unlike general merchandise such as cell phones and daily necessities, perishable products are difficult to meet demand by stocking large quantities in advance. According to studies, in China or other developing countries, the percentage of perishable fruit and vegetable products often reaches more than 15% [1], and effective replenishment decisions have become a key factor in the profitability and operation of a business.

Over the past decades, scholars have conducted in-depth research on the problem of replenishment and management decisions of perishable products from different perspectives. From the existing demand studies, Mandal et al [2] argued that the demand and inventory of perishable products have a linear relationship $D=c+dq$, where D and q are demand and inventory, respectively, and replenishment based on a rational analysis of the demand can be a better designation of replenishment strategy. In contrast, Giri et al [3] proposed a nonlinear demand-inventory relationship $D=dq$^b, where b and d are suitable constants. In particular, Mahato et al. pointed out that the demand is not only affected by the inventory but also by the selling price [4], moreover, the optimal solution of the model is given considering the conditions that a large amount of inventory will harm the consumers [5], and the limited inventory capacity.

Most of the existing literature studies on perishable product stocking decisions consider the influence of a single demand factor, and there is less relevant literature that considers the joint influence of demand and pricing and actual sales volume. There are even fewer studies on the construction of prediction models to specify replenishment and pricing strategies through big data collected over a long period. In the case of fruit and vegetable commodities, for example, the demand for different categories and varieties of fruit and vegetable products changes dynamically over time and depends on pricing decisions [6]. Product demand also tends to have some correlation with the products sold at the same time. Therefore, this paper considers the correlation between different types of products from the perspective of sales replenishment of perishable products and considers the joint decision-making problem of pricing and dynamic replenishment of perishable products based on historical big data.

In this paper, principal component analysis is used to delve into the characteristics of sales data. Fresh fruit and vegetable commodities, as common perishable products, are characterized by associated purchases and repetitive purchases in daily life [7]. Taking fruit and vegetable products as the research object, the statistical descriptive analysis of sales data is conducted to better understand the overall characteristics and internal connections of the data and provide a new perspective for the research of the replenishment model. Combined with historical sales replenishment, pricing, and sales data, using ARIMA time series analysis to predict the replenishment volume, using XGBoost regression resume sales volume and pricing decision-making model. The study shows that there is a correlation between product sales of the characteristics of the sale of the product is not the highest-selling goods is the main component of the sale of the product, there is a steady demand and replenishment of the product tends to be more enough in the dominant position in the market, while the results show that replenishment and sales volume has a certain time can be predicted, to achieve better replenishment and pricing strategy to maximize the benefits.

2. Perishable goods sales correlation analysis

2.1. Data preprocessing and modeling assumptions

This paper analyzes vegetable products as perishable products, assuming that the merchants do not know the single product category and purchase price of the day's purchase when they purchase goods daily, but the vegetable products can only be sold on the same day. The data studied in this paper includes three years of daily sales of vegetable products in the store for each product totaling 878,405 big data, including sales, selling price purchase price, and other information. Vegetable products are categorized into six categories, namely cauliflower, foliage, eggplant, pepper, edible mushrooms, and aquatic rhizomes, with a total of 251 varieties, and the sales data of vegetable products and the data of the shipping rate of each category in the past three years are provided. Data were obtained from the mathematical modeling website http://www.mcm.edu.cn.

The sales data were processed to exclude outliers from missing values as follows Table 1, the first column shows the vegetable merchandise sales from July 1, 2020, to June 30, 2023, the name of the individual items, and the classification.

Table.1. Sales of perishable vegetable commodities (partial)

Sales Date	Sales volume (kg)	Sales unit price (yuan/kg)	Item Name	Classification name	Wholesale prices
2020-07-01	0.396	7.60	Bubble Pepper	Pepper	4.32
2020-07-01	0.849	3.20	Brassica Pekinensis	Foiliage	2.1
2020-07-01	0.251	10.00	Kogua	Aquatic Rhizomes	5.65
2020-07-01	0.251	6.00	Yunnan oilseed rape	Foiliage	3.44
2020-07-01	0.217	18.00	Shiitake Mushroom	Edible Mushroom	10.8

2.2. Exploratory sales data analysis

In this paper, for six categories of vegetable commodity sales volume in annual units, the total annual sales volume of the average value of the vegetable commodity sales volume is generally stable. The overall presentation from 2020 to 2021 sales fell and then rose and then 2022 to 2023 annual selling price exceeded the 2020 to 2021 sales, which, foliage vegetable commodities sales are much larger than other categories as shown in Table 2. Corresponding to the foliage category of vegetable types of cabbage, choy sum, spinach, baby bok choy, yellow bok choy, and other vegetable varieties that are most consumed in daily life.

Table.2. Average Sales Volume of Vegetable Goods by Category

timing	Aquatic rhizomes	philoden dron	cauliflower (Brassica oleracea var. botrytis)	eggpl ant	capsic um	edible mushroom
2020/07-2021/06	33.482	197.232	47.042	24.657	73.563	75.241
2021/07-2022/06	32.501	132.169	26.862	21.905	59.072	44.685
2022/07-2023/06	46.434	220.544	41.720	15.414	121.339	90.933

Stability analysis of sales volume of each category of vegetable commodities, select the variance as a measure of indicators, to obtain the daily sales of each category for the unit of days, the data of each category is normalized and then multiplied by the maximum coefficient of λ, to compare the variance of the different varieties of different varieties, after the calculation of the variance of the obtained Table 3. it can be found that the sales stability of leafy vegetable commodities is the best in the year's sales activities always have a stable supply and sales market. and sales market. The stability of aquatic root vegetables is poorer, and it is known through the literature that aquatic root vegetables tend to have a certain seasonality [8] and tend to show a seasonal pattern of high yield and large sales in fall and winter.

Table.3. Variance of sales volume of vegetable commodities by category (after standardization)

timing	Aquatic rhizomes	philoden dron	cauliflower (Brassica oleracea var. botrytis)	eggpl ant	capsic um	edible mushroom
2020/07-2021/06	5.79	0.63	1.60	2.35	2.35	3.25
2021/07-2022/06	4.94	1.45	2.94	2.72	2.71	2.55
2022/07-2023/06	4.68	1.87	2.61	4.61	1.89	2.72

2.3. Principal component analysis sales volume correlation analysis between categories

From the EDA exploratory data analysis, we can see that we want to find out the different categories of sales data correlation can be transformed into which category of vegetables is the sales of the most important and influential vegetable mainstay, it is not difficult to find out that this is a multi-causal analysis of the process of the correlation of the number of vegetable categories that have an impact on the correlation of the number of vegetables, and the relationship between the various categories of complexity.

The principal component analysis is commonly used for multivariate data dimensionality reduction, and its basic idea is to reduce the dimensionality of the data by transforming the original variables into a set of mutually unrelated principal components through a linear transformation. In the study of vegetable merchandising data, the aim is to discover the potential correlations and explore the relationships among vegetable categories by comprehensively evaluating the sales data.

Six vegetable categories (edibles, peppers, eggplants, aquatic roots, and tubers, foliage, and cauliflower) were selected as indicator data. Sales data were obtained for each category in terms of total daily sales, and some of the 2022 data are shown in Table 4.

Table.4. Total Daily Sales of Vegetable Goods by Category (Partial)

Date	edible mushroom	capsicum	eggplant	Aquatic rhizomes	philodendron	cauliflower (Brassica oleracea var. botrytis)
1	90.656	57.833	18.428	82.658	138.402	38.272
2	59.918	45.828	13.349	27.438	110.543	26.605
3	59.045	81.754	12.782	59.009	90.081	38.027
......	63.48	58.207	8.174	46.598	70.388	45.257
365	178.021	198.248	5.574	103.271	329.509	39.573

Before principal component analysis, KMO and Bartlett's test were performed to ensure the suitability of the data. For the interpretation of the KMO value, it is usually considered that above 0.8 is very suitable for principal component analysis, between 0.7-0.8 is generally suitable, between 0.6-0.7 is not very suitable, between 0.5-0.6 indicates poorly, and below 0.5 indicates extremely unsuitable. Bartlett's test, on the other hand, is used to determine whether the covariance matrix of the original data is a multiple of the unit matrix. Table 5 demonstrates the results of KMO and Bartlett's test, in which the KMO value is 0.866 and the P-value of Bartlett's test is much less than 0.05, indicating that there is a correlation between the variables of the data on daily sales volume of vegetable categories that we selected, which is very suitable for principal component analysis.

Table.5. Results of KMO and Bartlett's test

KMO test and Bartlett's test		
KMO value		0.866
Bartlett's test of sphericity	approximate chi-square (math.)	1438.784
	df	15
	P	0.000***
Note: ***, **, * represent 1%, 5%, and 10% significance levels, respectively.		

In order to study the sales relationship between vegetable categories in depth, PCA was carried out with these categories as the object of study. Through the linear transformation of the original data, multiple variables with high correlation are transformed into principal components that are not related to each other. With the six categories as the research object, the vegetable category as the analysis of the analysis index p, then have a total of three years to unfold the principal component analysis, after standardization of the raw data, the correlation coefficient matrix R is calculated as

$$R = \frac{\sum_{k=1}^{n}(x_{ki}-\bar{x}_i)(x_{ki}-\bar{x}_j)}{\sqrt{\sum_{k=1}^{n}(x_{ki}-\bar{x}_i)^2\sum_{k=1}^{n}(x_{kj}-\bar{x}_j)^2}} \tag{1}$$

The eigenvalues and corresponding eigenvectors of the covariance matrix are obtained by eigenvalue decomposition of the correlation coefficient matrix. The eigenvalues represent the importance of the principal components, while the eigenvectors indicate the direction of the principal components The eigenvalues are semi-positive definite matrices.

$$tr\,(R) = \sum_{k=1}^{p}\lambda_k = (p), \lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_p \geq 0, \tag{2}$$

After obtaining the eigenvalues and eigenvectors, the sharing rate (contribution rate) of each principal component is calculated, as well as the cumulative sharing rate. The sharing ratio reflects the extent to which each principal component contributes to the overall information, while the cumulative sharing ratio indicates the cumulative contribution of the previous principal components to the overall information. Calculate the principal component sharing ratio as well as the cumulative sharing ratio:

$$\text{Contribution rate} = \frac{\lambda_p}{\sum_{k=1}^{p}\lambda_k} \tag{3}$$

$$\text{Cumulative contribution rate } = \frac{\sum_{k=1}^{i}\lambda_p}{\sum_{k=1}^{p}\lambda_k},\ (i = 1,2,\cdots,p), \tag{4}$$

Based on the analysis results of the cumulative sharing rate, this paper chooses to keep the principal components with cumulative sharing rate more than 80% to ensure that the comprehensive contribution of the principal components is higher. On this basis, the principal component expression was obtained as F1 = 0.219 × edible mushrooms + 0.239 × chili peppers + 0.0155 × eggplant + 0.227 × aquatic roots and tubers + 0.227 × flowers and leaves + 0.2212 × cauliflower. Variance interpretation was performed by SPSS to generate a component matrix table containing the component (factor) score coefficients corresponding to each category. The component score coefficients indicate the weight of each category in the principal components, which in turn allows the contribution of each category to the principal components to be calculated. The component matrix was normalized to obtain the component matrix table 6 to ensure that the weights of the factors in the principal components are on the same scale.

Table.6. Matrix of components

name (of a thing)	ingredient
Edible mushroom	0.219
Capsicum	**0.239**
Eggplant	0.015
Aquatic rhizomes	0.227
Philodendron	0.227
Cauliflower	0.222

From the results of the component matrix table, it is shown that chili pepper goods show a significant correlation with other vegetable goods in the sales process. During consumers' shopping in the superstore, their tendency to purchase chili pepper commodities is more significant, and they are more likely to choose to purchase chili peppers in combination with other vegetables.

Further comparing the results of EDA exploratory data analysis and PCA principal component analysis, the study found that the flower and leafy vegetables stood out with their highest sales volume. In the principal component analysis, the component values of the floral and leafy vegetables were similar to those of the aquatic root vegetables, and despite the higher sales of the floral and leafy vegetables, they could be replaced by vegetables such as cauliflower and root vegetables that are used as main dishes.

The indispensability of chili vegetables as a key condiment in daily cooking, on the other hand, is in line with the needs of consumers' lives and possesses an important position in the sales of vegetables. It is also confirmed that there are associations and influences in the sales of vegetable items, which is valuable for the study of replenishment strategies, and the related influences can be incorporated into replenishment and pricing decisions.

3. Replenishment and pricing decisions for perishable goods

3.1. Commodity return maximization analysis

Companies researching merchandise replenishment and pricing need to forecast sales in advance to specify replenishment and pricing strategies. Vegetable commodity pricing is often taken to adopt the cost-plus pricing method of marketing, based on the actual cost of goods and interest rates to determine the sales price. According to the research data can be derived from the cost-plus pricing formula [9]. category pricing = category unit cost (1 + markup rate).

In particular, we denote the relationship between total sales and the cost-plus pricing method as f_j that can be derived:

$$n_j = f_j(p_j) \tag{5}$$

In this case, category pricing and category unit costs are easy to find, and we need to know the relationship between markup rates:

$$\text{Markup rate} = \text{profitability} = \frac{\text{Total Profit}}{\text{Total Sales}} \tag{6}$$

And superstore profit = category sales volume $n_j \times x$ Category Sales Rate a_j , maximum total profit = total profit on sales $-$ Costs, Total Sales = Incoming Volume *x* Wastage Rate, so you can list the formula for Maximum Profit:

$$Max\ F = \sum_{j=1}^{6} n_j a_j \tag{7}$$

Replenishment costs C Consider shipping losses b_i of the case, based on the sales volume p_i The expression is obtained as:

$$C = \frac{p_i c_i}{(1-b_i)}, \tag{8}$$

The profitability of a category requires the profitability of all individual items in the category (sales profit) $-$ total cost), to get the profit margin:

$$a_j = \frac{\sum_i p_i s_i - \frac{p_i c_i}{(1-b_i)}}{n_i} \tag{9}$$

Average sales pricing for the category P_j Sums the ratio of the total sales profit of each individual item to the total sales volume of the item:

$$P_j = \frac{\sum_i p_i s_i}{\sum_i s_i}, \tag{10}$$

Substituting (5)(8)(9)(10) in (7), we can finally get the mathematical model of maximum profit in this paper:

$$Max\ F = \sum_{j=1}^{6} f_j\left(\frac{\sum_i p_i s_i}{\sum_i s_i}\right) \frac{\sum_i p_i s_i - \frac{p_i c_i}{(1-b_i)}}{n_i}, \tag{11}$$

Under the ideal condition that replenishment is only on same-day sales, maximizing revenue also requires predicting the replenishment volume and finding the relationship between total sales and cost-plus pricing method. In this paper, we use XGBoost regression model to fit the relationship function and use ARIMA time series to predict the replenishment volume and specify the replenishment and pricing decisions based on historical sales big data.

3.2. Research on XGBoost regression pricing strategy

In order to get to the relationship function f_j , it is known that there is a certain functional relationship between total sales and pricing, based on the good performance of XGBoost model in regression problems, this paper uses the XGBoost model for the regression of the relationship function. According to the historical data to find the relationship between the total sales and pricing, excluding the average selling price of 246 individual products that are not involved in the sales in the data, as shown in Table 7 below:

Table.7. Handling of total sales and average unit price of individual items (partial)

product code	item total sales volume	Average sales per item	Average unit price per item	Item Name	categorization
102900005115168	899.837	8.821931373	3.896359674	beefsteak lettuce	foliage
102900005115199	333.223	2.206774834	31.6537733	Sichuan Red Toon	foliage
102900005115250	2810.716	2.574893617	4.581887291	Xixia Mushroom	edible mushrooms
102900005115625	121.02	7.811695652	4.003375095	baby bok choy	foliage
102900005115748	718.676	8.031592126	5.002251855	cabbage moss	foliage

XGBoost is capable of multithreaded parallel computation, and iteratively generates a new tree, which can combine multiple weak learners with low classification performance into one strong learner with high accuracy. XGBoost uses random forests for field sampling and introduces the regular term into lossy two-counts, thus prevent model overfitting and reduce model computation. Assuming that the model has k decision trees, the XGBoost fitting formula can be expressed as

$$\hat{y}_i = \phi(x_i) = \sum_{k=1}^{K} f_k(x_i), \tag{12}$$

The effect of the model on the sample x_i The predicted value of $\hat{y}_i$ that $\phi(x_i)$ denotes the model's prediction of the input sample x_i The predicted output of the model for the input sample, k is the number of trees as a hyperparameter, and $f_k(x_i)$ denotes the kth tree's predictive contribution to the input sample x_i the predictive contribution of the kth tree to the input sample. Each tree $f_k(x_i)$ can be represented as

$$\hat{y}_i = \phi(x_i) = \sum_{k=1}^{K} f_k(x_i), \tag{13}$$

where $w_{q(x_i)}$ is the leaf node $q(x_i)$ the weights of the leaf nodes, and $R_{q(x_i)}$ is the sample x_i region to which the leaf node points are assigned. The goal of XGBoost is to minimize the following loss function.

$$\mathcal{L}(\phi) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{14}$$

where:$l(y_i, \hat{y}_i)$ is the loss function, which measures the model's sample x_i prediction error of the model. In regression problems, the mean square error (MSE) is usually used as the loss function.$\Omega(f_k)$ is the regularization term, which is used to control the complexity of each tree and prevent overfitting.

The fitting formula of XGBoost is done by combining multiple trees, each fitting a region of the input data, and the final prediction of the input samples is a weighted sum of the multiple trees, where the weights are determined by the loss function and regularization terms, and the parameter and hyper-parameter settings affect the model's performance and fitting ability. The complex relationship between sales volume and pricing is revealed and predicted by XGBoost, and the development of optimal replenishment and pricing strategies provides strong support.

Set 70% of the data as the training set and 30% of the data as the test set and train the preprocessed average sales volume of a single item and average unit price of a single item. The combined accuracy of XGBoost on the training set R^2 is 0.812, which performs well in the regression problem, but performs well in the test set, Table 8 records the results of the regression various types of metrics.

Table.8. XGBoost model evaluation results

	MSE	RMSE	MAE	MAPE	R^2
training set	16.437	4.054	3.036	43.654	0.812
test set	142.549	11.939	6.355	75.090	0.366

The study evaluates the performance of XGBoost model on the problem of replenishment and pricing strategy for vegetable items. RMSE is the square root of MSE which is used to indicate the average difference between predicted and true values. The RMSE is 4.054 on the training set and 11.939 on the test set. The smaller RMSE indicates that the model fits better on the training set, but the increase on the test set may indicate that the model generalization performance needs to be improved. Taken together, the model performs well on the training set, but there is a certain degree of performance degradation on the test set, which requires further adjustment of the hyperparameters of the model or other methods to improve the generalization performance.

3.3. ARIMA time series forecast replenishment strategy

For accurate forecasting of merchandise replenishment in the coming period, this study uses the ARIMA time series model to forecast replenishment from July 1-5, 2023.The ARIMA model is widely used for modeling and forecasting time series data due to its ability to take into account the autocorrelation, differencing, and moving average properties of the time series [10]. The model consists of three components, autoregressive (AR), differential (I), and moving average (MA), and its expression is as follows.

$$ARIMA(p, d, q) = AR(p) + I(d) + MA(q), \tag{15}$$

Where, p is the autoregressive order, which indicates that the model takes into account the observations of the past p time steps, and d is the difference order, which indicates that the model performs a d-order difference on the time series in order to make it smooth. q is the moving average order, which indicates that the model takes into account the prediction error (white noise) of the past q time steps.

This study begins with the ARIMA data smoothness test and model order establishment. By observing the graphs of the autocorrelation functions ACF and PACF, appropriate values of p, d and q are selected. Based on the model fitting and diagnostics, the selected parameters are used to build the ARIMA model. The model residuals are checked to see if they satisfy the nature of white noise, and if not, the model needs to be further adjusted. Finally, the fitted model is used to predict future values and provide targeted recommendations for replenishment of goods. A smoothness test was performed on each vegetable sales data column, and the results showed that first-order differencing was able to smooth the data. Therefore, we chose $d=1$.

In the process of forecasting the restocking volume for the coming week, two differencing operations were performed to remove the trend given the unstable trend in the time series data. After the preprocessing of the data was completed, the autocorrelation and partial correlation coefficients of the data were calculated to test whether the preprocessed data met the requirements of AR modeling. Based on the truncation of the partial correlation coefficients, the fitted AR model order was judged to be 5.

Subsequently, the parameters are estimated using the least squares method, the residual variance and AIC values of the model up to order 10 are calculated, and the AIC criterion is applied to set the model order. We choose the model with the smallest AIC value and finalize the order as 5. Based on the calculation, the value here is 0.442 and the model representation of AR (5) is:

$$\begin{gathered} X(t) = W(1) * X(t-1) - W(2) * X(t-2) - W(3) * X(t-3) \\ -W(4) * X(t-4) - W(5) * X(t-5) + at\,, \end{gathered} \tag{16}$$

Get the sample approximation prediction curve Figure 2, the dotted line is the original sample data, * line is the sample data model approximation curve. The prediction results were compared with the actual data, and a better-fitting effect can be seen in the figure 1.

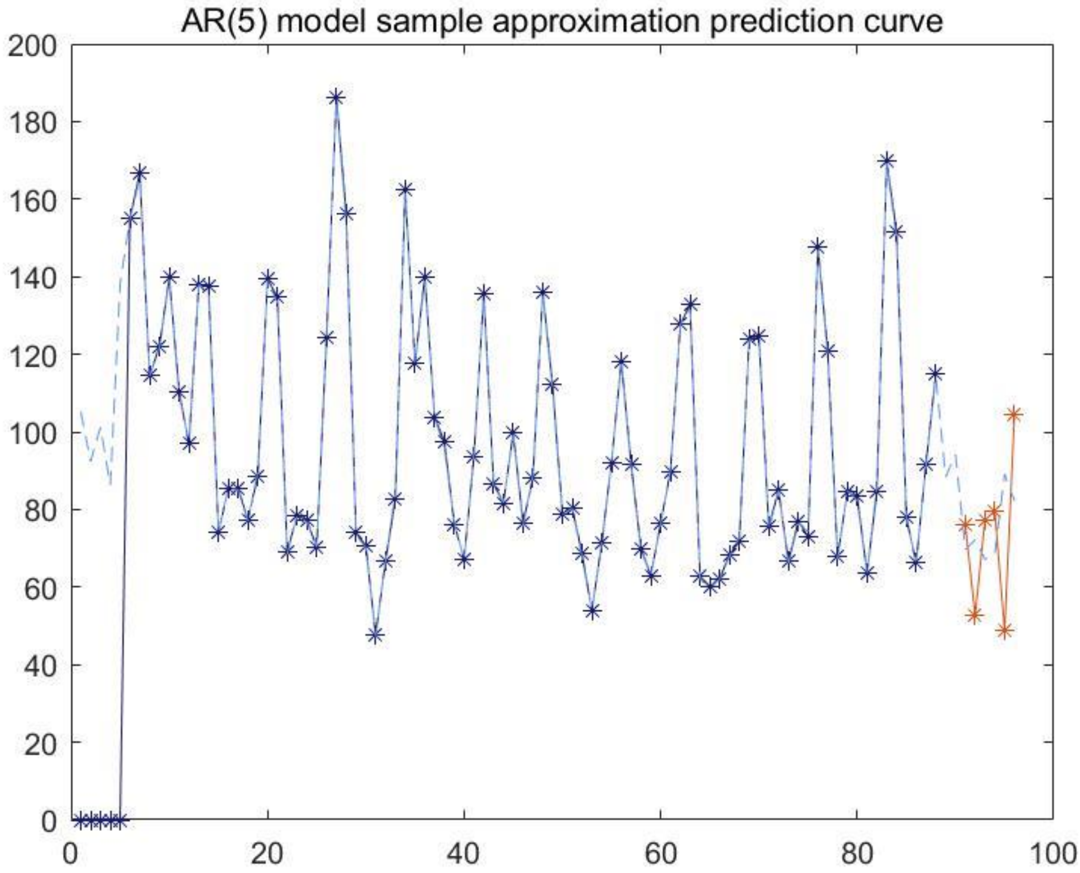

Fig.1. Sample Approximation Prediction Curve for AR (5) Model

The ARIMA-XGBoost model is ultimately enough to calculate the final profitable sales of the merchant, this decision is important for the development of marketing strategies and inventory management to optimize the management of the supply chain and pricing strategy of vegetable commodities and gain an advantage in the market competition, Table 9 shows the results of the replenishment of two predictions.

Table.9. Restocking Forecast for July 1-July 5

	7.1	7.2	7.3	7.4	7.5
foliage	19.4190	21.1820	19.1033	18.4410	16.8296
cauliflower	130.4640	132.7770	131.9120	130.7535	120.7076
aquatic rhizomes	28.0870	26.2270	22.8410	20.6988	18.1756
eggplant	24.5300	18.0205	17.2307	15.0267	16.2662
pepper	82.2860	85.6995	79.9777	76.7632	75.8476
edible mushrooms	39.5720	43.9430	47.2093	45.0840	43.9836

4. Conclusions

This study focuses on the replenishment and pricing decisions of perishable commodities (vegetables as an example) and aims to provide effective supply chain management and market competition strategies for enterprises through in-depth analyses of commodity revenue maximization, XGBoost regression pricing strategy, and ARIMA time series forecast replenishment strategy.

In order to establish a replenishment and pricing strategy for perishable commodities in enterprises, the study establishes a mathematical model of commodity revenue maximization through the cost-plus pricing method, which takes into account the total sales volume, the sales rate, and the replenishment cost, and introduces the XGBoost-ARIMA model to predict the future sales and replenishment volume. The complex relationship between total sales and pricing was regressed and analyzed using the XGBoost model. Through the training and testing of vegetable sales data, the model performs well on the training set, but there is a certain performance degradation on the test set, and the generalization performance on new data needs to be further improved in the future. Therefore, it is suggested that the model should be adjusted and validated more deeply in practical applications, and the model is too idealized in terms of design, which can be further fully considered in terms of the types of commodities to be imported, the quality of commodities, and the actual situation of the supply and demand of different individual products.

Finally, the study used the ARIMA time series model to accurately predict the amount of merchandise replenishment in the coming week. After performing difference operations and model fitting, we obtained the ARIMA (5,1,5) model suitable for business decision-making. By comparing the prediction results with the actual data, the accuracy of the prediction is good.

Targeted suggestions for merchandise replenishment are provided to merchants in practical applications. Through multi-level and multi-angle analysis, it provides scientific decision support for enterprises. It is recommended that enterprises combine specific business situations, adjust model parameters, and maintain sensitivity to market changes to achieve better decision-making results. Future research can further optimize the model and consider more factors to improve the accuracy and applicability of forecasts.

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