Electronics Spare Part Goods Demand Forecasting Using Markov Model

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(Received: 6 Nov 2023, revised: 4 Des 2023, 13 Jan 2024, accepted: 16 Jan 2024)

Abstrak

Customer demand forecasting plays an essential part in inventory management in retail companies. Accurate customer demand forecasting will increase a company's competitiveness and play a crucial role in making the right decisions for inventory management. Without demand estimation, products are often purchased more than needed, resulting in overstock or understock product storage in the warehouse. In this paper, we present the results of the Markov Chain method for predicting the quantity of demand for goods in the future to assist decision-making regarding the procurement of commodity goods within the company, especially in the procurement of electronics spare parts in retail companies. This study aims to develop a software-based forecasting system for retail companies using the Markov Model with predictive capabilities. The system will also provide purchasing quantity recommendations to fulfill the stock, calculated from the minimum stock and forecasted demand from customers and suppliers. Using the Markov Chain model, this study predicts electronics spare parts demand using data on item sales during 2022 in a retail company. The forecasting of electronics spare part demand resulted in 88.2% accuracy. The software-based forecasting system has been implemented and tested using black box testing. The testing result shows that the Markov forecasting system is feasible and can be used as a reference in providing electronics spare parts purchasing recommendations for retail companies.

Keywords: Forecasting, Inventory Management, Markov Chains, Purchase Recommendation

I. INTRODUCTION

At present, almost all companies have implemented digital technology in determining methods that can support company operations in integrating transactions, systems, manufacturing activities, inventory, and customers. Implementing this technology aims to collect and distribute company functionalities in real time and obtain market information between company stakeholders [1]–[3]. In recent years, along with the widespread use of applications, retail companies have also developed rapidly [4]. The health of a nation's economy is highly correlated with the retail sectors, which include hypermarkets, supermarkets, and convenience stores. According to Maslow's hierarchy of needs, these industries meet the most fundamental needs and require good inventory management because the variety and quantity of inventory are huge, as is the need for responses. Hence, retail companies continue to improve inventory management so that stock is always available as needed [5]–[7]. Forecasting is one of the methods required to enhance company planning activities [8]. It has an essential impact on the decision-making process and the company's final results [9]. An important amount of the resources used by retail businesses are allocated to inventory investment. An organization's competition will improve, and accurate demand forecasting is crucial for managing inventory [10]. Until now, retail companies still need forecasting methods that are efficient, accurate, and in accordance with company needs [11], [12]. Forecasting the demand for commodities required by customers is an important part of inventory management. Therefore, accurate customer demand forecasting is essential for retail companies, so inventory management forecasting has been the subject of much discussion and research [3], [13], [14]. One of the forecasts needed is forecasting the number of requests and the time of demand [13].

One method that can be used to forecast demand is the Markov model. Markov was a stochastic model discovered by Prof. Andrei A. Markov (1856-1922) in 1906. The Markov model is used to model a system that changes randomly by assuming that future events depend on current conditions, not previous ones. The Markov Model itself is divided into four, namely the Markov Chain, Markov Decision Process (MDP), Partially Observable Markov Decision Process (POMDP), and Hidden Markov Model (HMM) [15]. Each Markov Model is used in different situations depending on each sequential state, whether it can be observed or not [16].

Markov Chain is a type of Markov that discusses the order of a random variable in a particular system that is influenced from the last time [15]. The value of the variable that comes out can change depending on external conditions that affect it, so it can cause changes in results from before. An example of this type of Markov is when consumers may change brands from one product to another, which advertising factors, special product promotions, and others can cause. HMM is a type of Markov that can be used to determine the part that is not defined or known as the estimated result of a problem [15]. HMM is the result of the representation of the stochastic function of the Markov Chain, so it can be called a double stochastic process. This model can handle random heterogeneous states through the Markov Chain as the basis, while the distribution function will fill the undefined part. This type of Markov usually occurs in natural events such as speaking, speech recognition, writing characters, etc.

MDP is also referred to as stochastic dynamic programming. MDP is used in solving multi-period dynamic decision problems under stochastic conditions [16]. The use of MDP is considered complex in terms of research and application because each MDP model has a different method. Examples of MDP are communication, signal processing, artificial intelligence, stochastic schedules, manufacturing systems, management, and economics [16]. POMDP is a MDP generalization. POMDP is used to model various real-world sequential decision-making processes. Case examples of this type of Markov use are robot navigation problems, engine repairs, and other problems under uncertainty.

Several intermittent demand forecasting methods have been developed using Markov models [14], such as the machine learning method [17], the Bootstrap method applied to forecasting aircraft parts [18], the aggregation approach method [13]. Markov Combined Method (MCM) [11], CTMC model [19], Markov Decision Process with Policy Iteration Method [20], and many more. Based on these data, research using the Markov Model to predict intermittent demand for retail companies is rarely done. Based on the explanation of the types of Markov Model above, it can be seen that the Markov Chain is a type of Markov model suitable to be applied in this study because the demand for goods is constantly changing. Consumers can switch from one product to another of the same kind due to certain factors. Furthermore, Markov Chains have a particular property: the probability of the process developing in the future depends only on the current state and not on past events.

Motivated by the abovementioned issues, we developed a software-based forecasting system with predictive capabilities for retail companies. For this study, we selected a retail business selling electronic spare parts as a case study. Currently, the company procures goods from suppliers, relying only on human estimations without considering client demand. Consequently, there is frequently an excess of inventory in the warehouse, while occasionally, there is insufficient stock, leading to delays in fulfilling customer orders. However, it is necessary to predict the customer demand to avoid overstocking (or understocking) goods and know the amount that should be purchased. Using the Markov Model, we present the results of the method for predicting the quantity of demand for goods in the future to assist decision-making regarding the procurement of commodity goods within the company, especially in the procurement of goods. A goods procurement system that is equipped with predictions of the number of requests will enable procurement staff to know the estimated number of requests so that the amount of stock availability that must be provided in the warehouse can be known, as well as recommendations for the number of purchases that must be made. The system will also advise purchasing quantities to fulfill the stock of goods. The purchase recommendation is calculated from the minimum stock and ordered goods from customers and suppliers. This research uses retail companies selling spare parts for electronic goods in Indonesia as a case study.

II. RESEARCH METHOD

In this research, we perform four stages, as seen in Figure 1. First, we conducted data collection and preparation. We collect item sales data from an electronics spare part company in Indonesia from 1st January until 31st December 2022; then, we select the Top 10 highest item sales data in the period for the next stage. There are several steps in carrying out statistical test analysis, namely determining the test hypothesis, determining the value of the significance level (α), collecting data, determining test statistics, calculating statistical test results, determining critical values, comparing the results obtained during the process, and making conclusions based on the analysis. Therefore, the next stage is to determine the hypothesis and significance level before performing item data analysis (statistical testing). Then we calculate ($\chi 2$) and critical value ($\chi 2\alpha$; df), compare the results, and make conclusions in statistical testing.

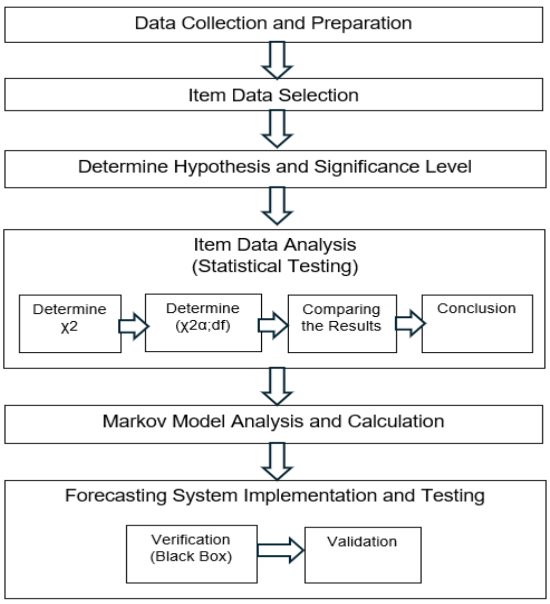

Figure 1. Research Methodology

 DOI: 10.34148/teknika.v13i1.709

In the fifth stage, we perform multiple steps to forecast the demand for electronic goods and recommend purchasing them. Figure 2 shows the detailed steps of Markov Model analysis and calculation. At first, it is necessary to input the goods to predict the length of time for forecasting and the value used in forecasting. After that, a first check will be made on the final stock of the goods to forecast. If the final stock of the item to be predicted is less than two units, then the item cannot be forecasted because it cannot form a matrix for forecasting. However, if the final stock of goods is more than two units, a matrix will be formed with the size according to the stock of goods to be forecasted.

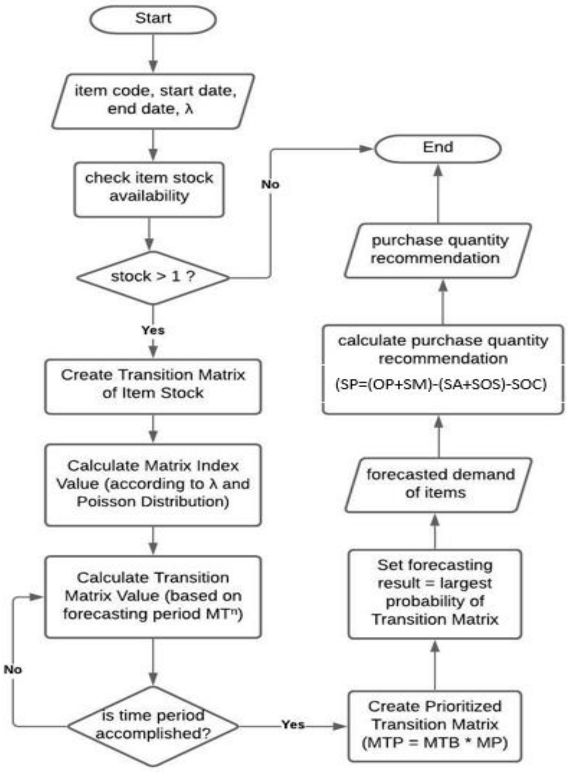

Figure 2. Markov Model Analysis and Calculation

After the matrix is formed, the value of each matrix index based on the value of the item and the value of the Poisson distribution will be calculated, then the rank of the Transition Matrix (MTn) is calculated according to the specified period. The calculation process will continue until the matrix has reached the specified period and generates a New Transition Matrix (MTB). Then the New Transition Matrix will be multiplied by the Priority Matrix (MP) to produce a Priority Transition Matrix (MTP).

After the value of the Priority Transition Matrix has been obtained, the system will choose the most significant probability value resulting from the prediction of the number of requests for goods in the period specified by the user. Then, the system will process the prediction results to obtain purchase suggestions that can assist users in determining the number of purchases of goods to suppliers. The formula for calculating purchase advice can be seen in (1), which will produce purchase suggestions that the store can use to make purchases of goods to suppliers.

$$SP = (OP + SM) - (SA + SOS) - SOC \quad (1)$$

Where SP is the suggested number of product purchases produced, OP is the predicted output, SA is current stock (available stock) of the product, SOC is stock on order customer (customer orders that have not been sent), SM is the minimum stock of the product, and SOS is stock on order supplier (orders to suppliers that have not been received).

The final stage of this research is developing a computer-based forecasting system. This system is required to ensure the selected model is feasible and correctly implemented. We perform verification and validation testing to ensure the forecasting system to ensure that the software is error-free and meets the company's requirements. Verification is performed using black box testing, and the validation is conducted by comparing the forecasting results with the company's actual sales data.

III. RESULT AND DISCUSSION

In this section, we provide the results of our research and discuss them. We divide the results into six subsections based on our research methodology in Figure 1.

A. Data Collection and Preparation

In this research, we chose an electronic spare-part retail company as a case study. We collect all products sold from 1st January until 31st December 2022 in this company, resulting in 125 item products.

B. Item Data Selection

Data analysis was conducted to determine the distribution of demand for goods. Sales data represent the demand for goods. We selected the top 10 products with the highest sales from 1 January until 31 December 2022, resulting in 10 items listed in Table 1.

Table 1. Highest Product Sales Data in 2022

No	Product Name	Total Sales	Current Stock
1	IRFP 260N (IRFP)	280	6
2	Steel Mechanic Screwdrivers (SMS)	51	5
3	Terminal 5 Copper Cable 5m (TKT)	31	2
4	Hot Glue Gun 40 Watt (HGG)	35	4
5	Elco Condensator (EC)	201	50
6	Diode 1A 4007 (D1A)	164	50
7	Avometer Tester Multitester Digital (ATMD)	32	3
8	Insulating Varnish Beck (IVB)	26	4
9	DC Fan 5cm Thin 12V (DCF)	40	3
10	Connection Terminal 6mm Copper Arde (CTCA)	43	10
	TOTAL	**903**	**137**

C. Hypothesis and Significance Level

The hypothesis testing is made as a limitation during the testing process. The limitation in question is that the user can understand the test's purpose so that he does not do anything outside the specified test criteria. After that, the significance level (α) value was calculated to determine the level of confidence or generalization of the object under study. In general, the value used is 1% (0.01) or 5% (0.05). The hypothesis of this research is shown below:

H0 : Data is Poisson Distributed
H1 : Data is not Poisson Distributed
Step 2: Set Significance Level (α)
α = 1% (0,01)

D. Item Data Analysis (Statistics Testing)

After determining the system testing criteria and determining the value of the significance level (α) of the test, it can be continued by determining and calculating the results of the test statistics per item.

1. IRFP 260N (IRFP)

Step 1: Determine and Calculate Statistics Testing Result (χ2)

Details of sales statistics for IRFP goods during 2022 can be seen in Table 2. Based on the existing table data, the next step can be continued by calculating the results of statistical tests, while the results of calculating test statistics can be seen in Table 2.

Table 2. Item Sales Statistics Of IRFP In 2022

IRFP (2022)		
	Total Sales	**Current Stock**
	280	6
	51	5
	31	2
	35	4
	201	50
	164	50
	32	3
	26	4
	40	3
	43	10
TOTAL	**903**	**137**

Table 3. Calculation Result Of χ2 (IRFP)

No	Total Item Sales (X)	Frequency (Oi)	$P_i(X=x)$ $\frac{e^{-\lambda}.\lambda^{-x}}{x!}$	Ei = n * Pi	χ^2 $\sum_{i=1}^{k}\frac{(O_i-E_i)^2}{E_i}$
1	5	3	0,0224	0,5828	10,025
2	6	2	0,0411	1,0685	0,8121
3	7	3	0,0646	1,6790	1,0393
4	8	1	0,0888	2,3087	0,7418
5	9	1	0,1085	2,8217	1,1761
6	10	3	0,1194	3,1039	0,0035
7	11	2	0,1194	3,1039	0,3926
8	12	1	0,1094	2,8452	1,1967
9	13	4	0,0926	2,4075	1,0534
10	14	1	0,0728	1,8916	0,4202
11	16	2	0,0367	0,9537	1,1480
12	17	2	0,0237	0,6171	3,0992
13	19	1	0,0084	0,2183	2,7987
	Total	26	0,9078	23,6017	23,9070

Based on Table 3, the test statistic value (χ2) is 23.9070 for IRFP items. After knowing the value of the test statistic, the next step is to determine the degree of freedom. Degree of Freedom is the difference between the degree of freedom obtained from the total number of observations in the sample and the number of accessible (linear) controls or restrictions on IRFP goods, obtaining a Degree of Freedom of 11.

Step 2: Determine the Critical Value (χ2α;df)

After obtaining the value of the Degree of Freedom, the next step is to determine the critical value. The critical value is the error value limit for rejecting the null hypothesis (H0). The critical value can be obtained based on the Degree of Freedom value, and the significance level value (α), where the critical value obtained can be seen in the chi-square table. For example, the critical value (χ2α;df) for IRFP items based on the chi-square table is 24.7250.

Step 3: Comparing the Results

After knowing the value of the test statistic (χ2) and the critical value (χ2α;df), the following comparison will be made between the test statistic value (χ2) and the critical value (χ2α;df). The comparison is conducted by seeing whether the data used is Poisson distributed (H0) or not Poisson distributed (H1) by the test hypothesis that has been made in step 1. Based on the results of the test statistic values (χ2count) and critical values (χ2α;df) that have been obtained, the result is lower.

Step 4: Conclusion

Based on the tests and analyses carried out for IRFP items, the data held has a Poisson distribution (H0). It is because the value of the test statistic (χ2count) is smaller than the critical value (χ2α;df) with a comparison of 23.9070 < 24.7250. Based on this, it can be referred that the value of the test statistic based on the analysis data held during 2022 did not exceed the value, which rejects the null hypothesis or rejects the Poisson distribution so that the data for IRFP goods during 2022 has a Poisson distribution.

2. Steel Mechanic Screwdrivers (SMS)

Step 1: Determine and Calculate Statistics Testing Result (χ2)

Details of sales statistics for SMS goods during 2022 is described in Table 4.

Table 4. Calculation Result Of χ2 (SMS)

No	Total Item Sales (X)	Frequency (Oi)	$P_i(X=x)$ $\frac{e^{-\lambda}.\lambda^{-x}}{x!}$	Ei = n * Pi	χ^2 $\sum_{i=1}^{k}\frac{(O_i-E_i)^2}{E_i}$
1	0	7	0.1353	3.5187	3.4442
2	1	5	0.2707	7.0374	0.5899
3	2	5	0.2707	7.0374	0.5899
4	3	5	0.1804	4.6916	0.0203

5	5	3	0.0361	0.9383	4.5299
6	6	1	0.0120	0.3128	1.5100
	Total	26	0.9052	23.6017	10.6841

Step 2: Determine the Critical Value (χ2α;df)

Based on the chi-square table, the critical value (χ2α;df) for SMS is 13.2770.

Step 3: Comparing the Results

Based on the results of the statistical test values (χ2count) and critical values (χ2α;df) that have been obtained, the comparison results for SMS are data with a Poisson distribution (H0).

Step 4: Conclusion

Based on the tests and analyses carried out for SMS, it can be inferred that the data held has a Poisson distribution (H0). It is because the value of the test statistic (χ2) is smaller than the critical value (χ2α;df) with a ratio of 10.6841 < 13.2770.

Based on this, it can be understood that the test statistic value based on the analytical data held during 2022 does not exceed the critical value, which rejects the null hypothesis or rejects the Poisson distribution. Thus, data on SMS during 2022 has a Poisson distribution.

Nine of the ten best-selling items sold by this company are Poisson distributed (H0). Based on the tests carried out, it can be concluded that store sales data can be used to predict demand for goods because it has a Poisson distribution with a default according to store sales data during 2022. The statistical results of the Poisson distributed goods test can be seen in Table 5.

Table 5. Poisson Distributed Items

No	Item Name	Test Result	
1	IRFP	23.9070	24.7250
2	SMS	10.6841	13.2770
3	TKT	6.7333	11.3450
4	HGG	9.3471	11.3450
5	EC	14.3693	16.8120
6	D1A	9.8520	20.0900
7	IVB	2.1528	9.2100
8	DCF	12.1773	15.0860
9	CTCA	5.7682	13.2770

E. Markov Model Analysis and Calculation

There are several steps in analyzing Markov calculations: making a transition matrix, determining the value of the transition matrix, calculating the transition matrix according to the specified period, and determining the prediction value based on the most significant probability value of the transition matrix. The Markov analysis will predict goods for the next two months using the final stock data of IRFP according to Table 1.

The transition matrix for the IRFP item is a matrix of size 7x7 because the final stock for the IRFP item is six pieces, and the transition matrix will make the size from zero to six. The matrix created will be in the form of a two-dimensional matrix, where the index on the left of the matrix shows the amount of inventory stock held at the end of the period (Xt). In contrast, the top of the matrix index shows the inventory stock owned by the store at the end of the following period (Xt+1). The matrix contents are values that fill in each coordinate point of the matrix whose value is obtained through the Poisson distribution table according to the parameter obtained in the previous test statistical analysis, which is 11. The transition matrix for the IRFP item can be seen in Figure 3.

$$\begin{array}{cc} \mathit{State} & \begin{array}{ccccccc} 0 & 1 & 2 & 3 & 4 & 5 & 6 \end{array} \\ \begin{array}{c} 0\\1\\2\\3\\4\\5\\6 \end{array} & \begin{bmatrix} 1{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 \\ 0{,}9589 & 0{,}0411 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 \\ 0{,}9365 & 0{,}0224 & 0{,}0411 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 \\ 0{,}9263 & 0{,}0102 & 0{,}0224 & 0{,}0411 & 0{,}0000 & 0{,}0000 & 0{,}0000 \\ 0{,}9226 & 0{,}0037 & 0{,}0102 & 0{,}0224 & 0{,}0411 & 0{,}0000 & 0{,}0000 \\ 0{,}9216 & 0{,}0010 & 0{,}0037 & 0{,}0102 & 0{,}0224 & 0{,}0411 & 0{,}0000 \\ 0{,}9214 & 0{,}0002 & 0{,}0010 & 0{,}0037 & 0{,}0102 & 0{,}0224 & 0{,}0411 \end{bmatrix} \end{array}$$

Figure 3. IRFP Transition Matrix (1)

Based on the transition matrix in Figure 3, it can be seen that the matrix created will form a lower triangular matrix because there is no purchase of goods from suppliers to fulfill stock, so the item will continue to decrease until the stock runs out. After obtaining the results for the transition matrix, it can be continued by multiplying the matrix according to the specified period. For example, the total rank of the transition matrix for predictions for the next two months is four because, in one month, there are four weeks, and sales of the best-selling items can run out in approximately two weeks until the store reorders to the supplier. Then the forecasting value is calculated by dividing every two weeks for two months. The results of the transition matrix for the next two months can be seen in Figure 4.

$$\begin{array}{cc} \mathit{State} & \begin{array}{ccccccc} 0 & 1 & 2 & 3 & 4 & 5 & 6 \end{array} \\ \begin{array}{c} 0\\1\\2\\3\\4\\5\\6 \end{array} & \begin{bmatrix} 1{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 \\ 1{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 \\ 1{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 \\ 1{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 \\ 1{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 \\ 1{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 \\ 1{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 \end{bmatrix} \end{array}$$

Figure 4. IRFP Transition Matrix (2)

After obtaining the transition matrix for the next two months in Figure 4, the calculation will continue by multiplying the transition matrix by the priority matrix to get the largest probability. The results of the multiplication between the transition matrices and the priority matrices can be seen in Figure 5.

$$\begin{array}{cc} \mathit{State} & \begin{array}{ccccccc} 0 & 1 & 2 & 3 & 4 & 5 & 6 \end{array} \\ \begin{array}{c} 0\\1\\2\\3\\4\\5\\6 \end{array} & \begin{bmatrix} 1{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 \\ 1{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 \\ 1{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 \\ 1{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 \\ 1{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 \\ 1{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 \\ 1{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 & 0{,}0000 \end{bmatrix} \end{array}$$

Figure 5. Multiplication Result of Transition Matrix and Priority Matrix

F. System Implementation and Testing

In this research, we created a computer-based forecasting system to perform demand forecasting and purchase recommendations. This software is implemented using Laravel Framework and MySql DBMS [21]. We perform verification using black box testing and then compare the forecasting results with the company's actual sales data. For example, we conduct testing by forecasting each product in Table 1. Each experiment is performed five times within 52 days (2 January 2022 until 22 February 2022). As shown in Figure 4, the user chooses forecasting periods (2 January 2022 until 22 February 2022) for the Steel Mechanic Screwdrivers (SMS) product. Then, the system will calculate the customer demand for the SMS product, resulting in seven boxes on 22 February 2022 (Figure 6).

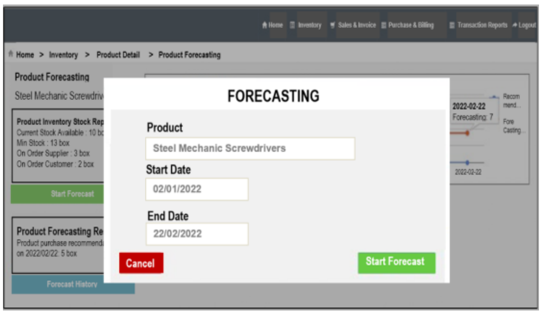

Figure 6. Forecasting Systems Example (Product and Forecasting Period)

Based on the forecasting result, the purchase recommendation quantity can be calculated using formula (1). SMS product has forecasting result (OP)=7, minimum stock (SM)=13, available stock (SA)=10, stock on order supplier (SOS)=3, stock on order customer (SOC)=2, then the purchase recommendation (SP) = (OP+SM) - (SA+SOS) - SOC = (7+13) - (10+3) - 2 = 5. This purchase recommendation result example is shown in Figure 7 and is also offered as a quantity recommendation when the user creates a new purchase order for the supplier (Figure 8).

Based on Table 6, we can conclude that two of the five items obtained forecasting results exactly or equal to the company's actual sales data. In comparison, the other three items produced results that were not too far from the original sales data with the most significant error of 28% only for IVB item. Based on this, the accuracy of the forecasting generated by the system is 88.2%, with sales data in 2022.

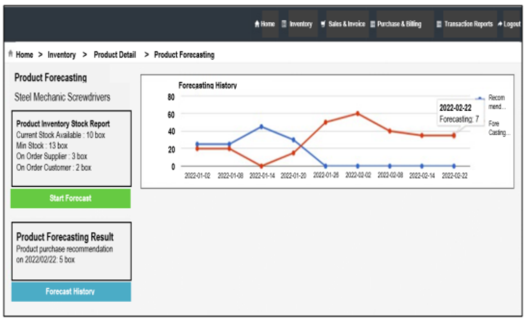

Figure 7. Forecasting Systems Example (Forecasting Result)

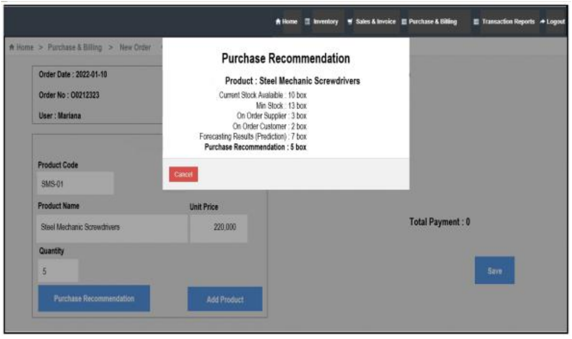

Figure 8. Forecasting System Example (Purchase Recommendation)

Table 6. Forecasting Results (Top 5 Sales Products)

No	Item Name	Stock	Forecasting Result	Actual Sales Data	% Error	% Accuracy
1	IRFP	5	3	3	0%	100%
2	SMS	13	7	7	0%	100%
3	D1A	64	15	19	21%	79%
4	IVB	7	5	7	28%	72%
5	DCF	15	9	10	10%	90%

IV. CONCLUSION

The Markov model is suitable for forecasting demand for electronics spare parts in retail companies and can be used in computer-based forecasting systems to provide sales demand prediction as a basis for company purchase decisions. It can be used as a reference for purchasing quantity recommendations at this electronics spare part retail company. However, the results of forecasting accuracy are still around 88.2%, which should be improved again by including seasonal elements and other external parameters such as people's purchasing power and store competitiveness with competitors.

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