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## Implementation of Autoregressive Integrated Moving Average Model to Forecast Raw Material Stock in The Digital Printing Industry

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**Abstract.** The technology used in the printing industry is currently growing rapidly. Generally, the digital printing industry uses raw materials in the form of paper production. The use of paper material with large volumes is clear badly in need of purchasing large quantities of paper stock as well. The purchase of paper stocks with a constant amount at the beginning of each month for various types of paper causes a buildup or lack of material stock standard on certain types of paper. During this time the purchase and ordering of raw materials only based on the estimates or predictions of the owner. In this paper proposed forecasting will be carried out in the digital printing industry by applying the ARIMA model for each type of raw material paper with the Palembang F18 digital printing case study. The ARIMA modeling applied will produce different parameters for each materials paper type so as to produce forecasting with the Akaike Information Criterion (AIC) value averages 13.0294%.

**Keywords:** Forecasting, ARIMA, Raw Material Stock, Digital Printing, Modelling.

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### 1 Introduction

Digital Printing is one of the subcategories of commercial printing that has the advantage of the speed of printing document sheets directly through a computer without going through intermediaries such as film or plate printing as in conventional printing [1]. The products produced to use the main raw materials in the form of paper and ink.

One of the products produced by the digital printing industry is POD (Paper on Digital). The digital printing industry is one of the industries that have the most frequent reorder point of raw materials, this is due to the pattern of consumers who order POD products more than one type of paper. This causes the company to prepare all types of paper, storage of raw materials for all types of paper can be an obstacle due to the limited temporary storage of raw materials.

Production process based on consumer needs for ordered products and availability of raw materials for production. The unavailability of raw materials can cause the order response to a long time. To avoid the availability of raw material inventories that are too large or too small, an analysis is needed based on the order relationship

between the types of paper by consumers, because it requires a prediction method for raw material used so that order responses can be accelerated.

Paper raw material is the material to be examined in this study because the paper is the main raw material that is most widely used in production. F18 digital printing which is located in Palembang city in 1 day produces an average of 6000 pieces of paper with a frequency of job orders of 140 consumers for various types of paper. Ordering paper raw materials must be based on the most economical needs so as not to cause loss and accumulation of raw materials on paper types that are rarely used. Purchasing the amount of paper is always constant at the beginning of each month for various types of paper so that there is often a buildup and lack of stock in certain types of paper because so far the amount of paper purchases and orders is based solely on the owner's estimates.

In some previous studies have been carried out to support activities to analyze sales data and the amount of raw material production. These studies produced various techniques to identify predictions of the number of raw materials for production, among others: making the optimal inventory control model for order quantities of raw materials predicted using the Fuzzy Logic (FL) approach and Economic Order Quantity (EOQ) [2] and predict the trend stock market with the Artificial Neural Network (ANN) technique [3] and predict sales stocks using the ARIMA method [4].

One model that can be used in production forecasting is Autoregressive Integrated Moving Average (ARIMA). ARIMA is a model that applies a combination of Autoregression (AR) and Moving Average (MA) methods. Several previous studies have used the ARIMA method [4] [5] [6], in which the model design was designed to predict various types of categories including ARIMA modeling with interventions to predict and analyzing Chinese stock prices [6], forecasting coconut production in the Philippines [5] and making decision support applications for forecasting raw material supplies for blowing and inject plastic production using ARIMA method [7]. The application of the ARIMA model in the study resulted in a level of accuracy in forecasting with fairly good value, but in some of these studies, there is no modeling applied to the digital printing industry to predict raw materials in paper production.

In this study, ARIMA modeling will be applied to estimate the stock of paper production raw materials in the printing industry with a case study on the Palembang F18 digital printing. The research was conducted by measuring the level of prediction of raw material production of paper from 2016 January to March 2019, then the efficiency comparison of the results of paper raw material predictions using the ARIMA model was carried out with datasheet of paper raw material used for the last 3 years.

## 2 Forecasting Stock

Stock is a part of wealth or assets contained in a company that is used in a series of production processes in the form of raw material supplies (raw material), semi-finished goods (work in process), and finished goods. Whereas according to Porter [8] stock is material that is placed along with the network of production processes and distribution lines. Stock is goods that are stored, used and sold in the future period. Stock can be in the form of raw materials stored for processing, goods in process in manufactured products, and finished goods stored for sale.

Stock-based on the type can be divided into several types or classifications, namely [9]:

1. Raw material, which is the raw material that has not been processed and will

- become finished goods.
2. Semi-finished products, which are processed raw materials before they become finished goods, some of which will be further processed into finished goods, and some sometimes sold to other companies.
  3. Finished products, namely goods that have been finished produced or processed, and are ready for sale.
  4. General goods and spare parts (general materials and spare parts), namely all types of goods or spare parts used for operations.
  5. Maintenance, repair, and operation of the factory/company to run the company/factory and maintain the equipment used.
  6. Project goods (work in process), namely items that are stacked to await the installation of a new project.
  7. Merchandise (commodities), namely goods purchased, are already finished goods and stored in the warehouse waiting for resale with certain profits.

The company requires raw materials in production activities. Therefore production activities can run smoothly and produce a product if there are raw materials in the production process, without good raw materials, then the production of a company becomes less good and can reduce the quality value of the products produced.

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## 2.1 Forecasting Time Series Model

Time series is data arranged in a sequence of times or data collected from time to time. With the time series, then the data movement pattern or variable values can be followed or known. For several years various types of research on the prediction of goods with time series (time series) have been developed [10], several methods using autoregressive (AR), moving average (MA), and merging the two models. The Autoregressive Integrated Moving Average (ARIMA) is a development method of autoregression (AR) and moving average (MA) [11]. ARIMA is a globally recognized statistical forecasting model. ARIMA can predict future observations from time series based on several linear functions of past values and white noise based on predetermined basic rules. Thus, these models use inherent linearity constraints on functions to generate data.

### 2.1.1 Differentiation Process

In the forecasting process, there is the term stationarity which means there is no increase or decrease in data, which is a very important assumption in a time series analysis. If there is no change in the time series trend data, the data can be called stationary. That is, the average series of observations at all times is always constant. If the data is not stationary then a process of differentiation is needed on the data. The definition of Differentiation process here is calculating the change or difference in the value of the observed data. If the data used in the forecasting process is still not stationary then it is necessary to do a one-time differentiation process until the data to be used in forecasting is stationary.

AR and MA modeling has a basic theory of correlation and stationarity. That is, AR and MA can be used when the time series has formed a stationary graph or does not form up or downtrends. But if the time series data is not stationary, it is necessary to do a differentiation process to change the data until it becomes stationary before it can be processed through AR and MA.

Univariate components of stationary residual time series (X) can be modeled by the AR and MA models with the parameter (p) and (q), denoted as AR and MA (p, q). This technique allows one to capture temporal dependence in (X) [12] [13]. A zero-stationary stochastic process (X) is said to be ARMA (p, q). Data that has been differentiated and then processed with AR and MA is called ARIMA by adding a new parameter (d) to ARIMA (p, d, q) where the parameter (d) shows the number of differentiation processes carried out.

### 2.2.2 ARIMA Forecasting Model

The prediction model on ARIMA uses the Box-Jenkins approach [14] [15] [16] for estimation and forecasting. The Autoregressive (AR) model was first introduced by Yule in 1926. Then research was continued by Slutsky in 1937 by presenting the Moving Average (MA) scheme and subsequently developed in 1938. The ARMA model combines both the AR and MA schemes and shows that the ARMA process can be used to model a large class of stationary time series in the appropriate sequence of p, the number of AR, and q, the number of MA, determined precisely. The Autoregressive integrated moving average (ARIMA) model is a generalization of a simple regressive auto model (AR) that uses three tools for modeling serial correlation [13]:

1. The AR model (1) only uses first-order terms, but generally can use high-level AR requirements for additions. Each AR term corresponds to the use of the residual value of the residual in the forecasting equation for unconditional residues. The autoregressive model of order p, AR (p) as shown in equation 1.

$$X_{t1} = \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + \dots + \alpha_p X_{t-p} + \varepsilon_t \quad (1)$$

2. Each integrated sequence is related to differencing series into a form of forecasting. Components that are integrated with first order means designed for the first difference (first difference) of the original series. Components in the second order are related using the second difference (second difference), and so on.

$$X_{t2} = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_1 \varepsilon_{t-1} + \dots + \theta_q \varepsilon_{t-q} \quad (2)$$

3. The moving average model uses lagged values of errors increasing estimates in the current forecast. The term first-order moving average uses the latest approximate errors; second-order terms use forecast errors from the latest 7 to periods, and so on. MA (q) has the form of equation 3 and 4. The Autoregressive and Moving Average specifications can be formed into an ARMA (p, q).

$$X_t = X_{t1} + X_{t2} \quad (3)$$

From equation 3 is described as equation 4.

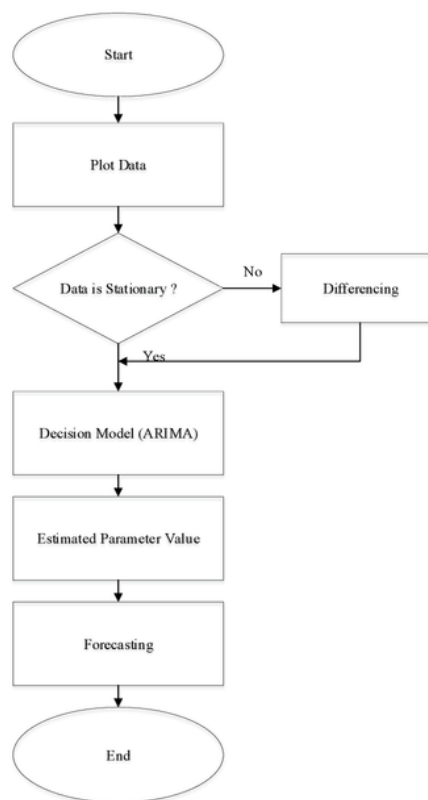
$$X_t = \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + \dots + \alpha_p X_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_1 \varepsilon_{t-1} + \dots + \theta_q \varepsilon_{t-q} \quad (4)$$



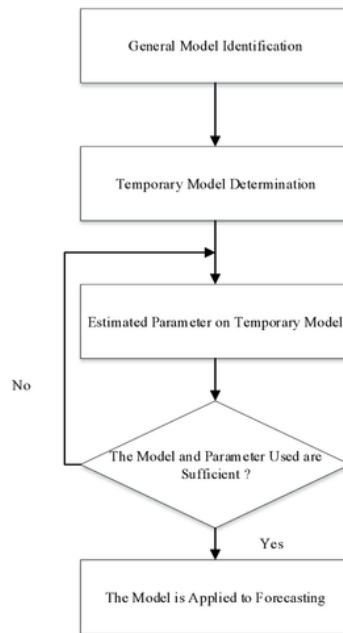
### 3 Design of ARIMA Model

In this section will be explained about the analysis of the condition of paper stock data obtained and analysis of the model used. In addition, this section also explains the dataset processing and algorithm implementation starting from data preparation, making feature datasets, and implementing the model so that later it can be used for training, testing and data analysis.

Based on the analysis of the problem, the conditions of the data and methods used, the method design in this study can be seen in Figure 1. The first process is the plot of data that will be used in stock forecasting, in this process aims to prepare data as needed and analyze the stationary data. After the data is ready then enter the process of checking the data, whether the data used is stationary, if the data used is not stationary then the data needs to be differenced, but if the data used is stationary then AR and MA can be determined to formulate and determine parameters (p, d, q) used. Furthermore, after determining the parameter value with the best model that has been obtained, it can be directly forecasted on the stock to be used.



**Figure 1.** Design Method ARIMA



**Figure 2.** Application Model

In designing the method in Fig. 1, there is an application of the model used, where the process of applying the model will be used through the stages shown in Fig. 2. The first step that needs to be done in the process of applying the model is to identify the formulation in the model in general. After the model is identified, a temporary model will be applied to obtain the best model through a trial and error process after obtaining the best value through the process, estimating the parameter values that will be used for the model can be done.

The parameter values specified in the ARIMA model apply the equation used in general, then check whether the model and parameters that have been applied are sufficient, if the model and parameters that have been implemented are not sufficient then the process will return by determining the different parameter values.

The parameters and model values are adequate, then the best models and parameters can be applied in the form of stock forecasting so that it can produce a minimum error of the amount of stock forecasting carried out.

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#### 4 Result and Discussion

In this section, we will discuss the analysis and results of the tests carried out, as well as matters related to the testing process in the form of data descriptions, testing, and analysis of the test results in predicting paper inventories.

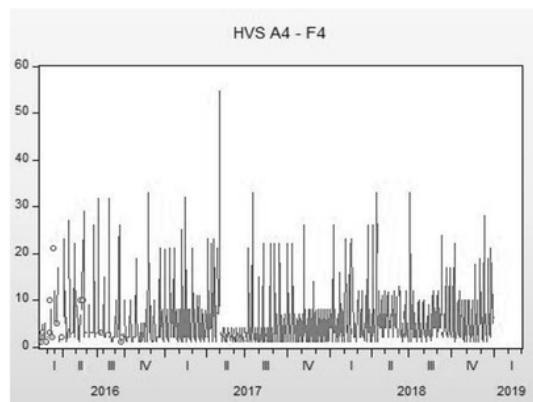
Before testing the data to be predicted, it is necessary to analyze the condition of the raw paper inventory data to see the state of the data obtained and adjust to the needs in predicting paper inventories. Table 1 shows the data condition on F18 Digital Printing.

**Tabel 1.** Data Condition of F18 Digital Printing

No	Raw Material	Size (cm)	Product	Capacity	Unit	Volume
1	Kromo Paper	32.5 x 48	Kromo Paper	5	RIM	500
2	Linen Paper	32.5 x 48	Linen Paper	9	RIM	500
3	Art Paper 120 Gr	32.5 x 48	Art Paper 120 Gr	20	RIM	500
4	Art Paper 150 Gr	32.5 x 48	Art Paper 150 Gr	120	RIM	500
5	Art Paper 190 Gr	32.5 x 48	Art Paper 190 Gr	48	PACK	250
6	Art Paper 210 Gr	32.5 x 48	Art Paper 210 Gr	48	PACK	250
7	Art Paper 230 Gr	32.5 x 48	Art Paper 230 Gr	48	PACK	250
8	Art Paper 260 Gr	32.5 x 48	Art Paper 260 Gr	144	PACK	250
9	HVS A3 80 32.5x48	32.5 x 48	Book	3	RIM	500
	HVS A3 80gr	29.7 x 42		12	RIM	500
10	HVS A4 80 gr	21 x 29.7	Letterhead	5	RIM	500
	HVS F4 70GR	21 x 33		5	RIM	500
11	PVC ID Card F4	21 x 29.7	ID CARD	3	PACK	250
	PVC ID Card A3	32.5 x 48		5	PACK	250
12	Pvc Sticker	32.5 x 48	Pvc Sticker	100	PACK	100
13	Transparent Sticker	32.5 x 48	Transparent Sticker	5	PACK	100
14	Kromo Sticker	32.5 x 48	Kromo Sticker	95	PACK	250

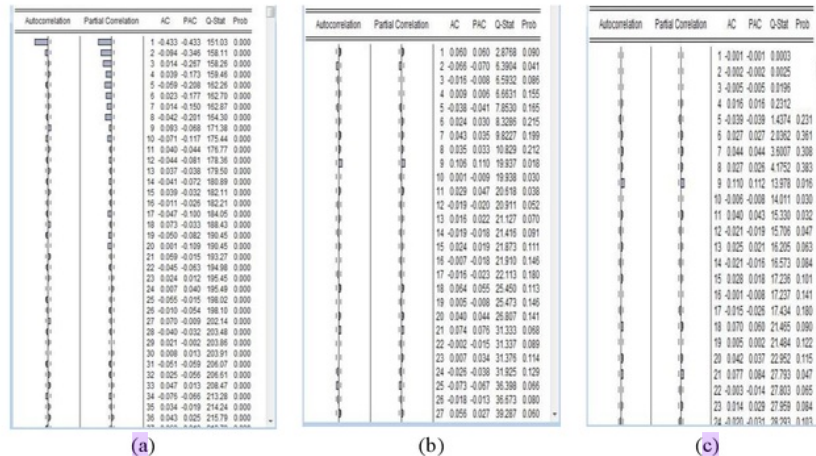
Based on table 1, the amount of paper storage stock in each material has a different value. Like HVS paper types that are often used as books only have a storage capacity of 3 and 12 RIM with different types, with a value of 1 RIM is as much as 500 papers. From this table, in this study, approximate analysis of each raw material will be carried out with the amount of data used for 3 years.

In the preparation process, the data used is data storage of paper raw materials with a total of 1,185 data for each type of raw material. The stock retention time range starts from the beginning of January 2016 to the end of March in 2019, with an estimate of 4 year having 365 days. One data sample on the HVS paper type used for forecasting is shown in Fig. 3.

**Figure 3.** Data Plot HVS Paper



In the modeling process with ARIMA, the first process is to plot the data and check whether the data used has a high trend, if the data used still has a high trend, then the data is not stationary, so a differencing process is needed to create more stationary data before the parameters are given. The data plot used in the forecasting process using the ARIMA model is shown in the data sample in Fig. 3. Besides going through the graphs [3](#) the data plot, stationarity can also be seen through the data plot on the correlogram shown in Fig. 4.

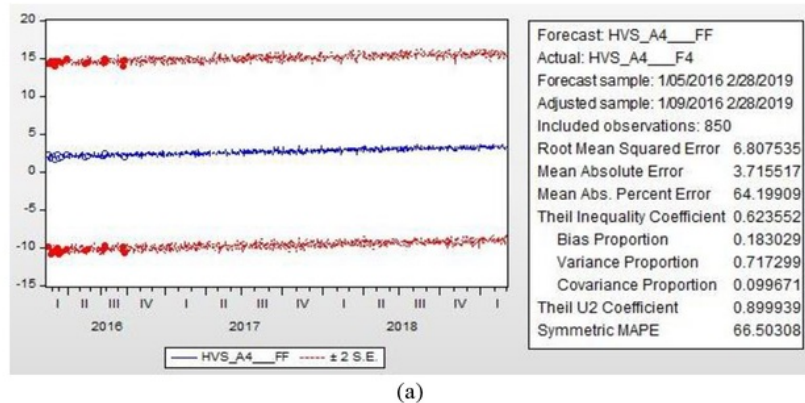


**Figure 4.** Correlogram Data; (a) Before Differencing, (b) 1st Differencing, (c) 2nd Differencing.

In Fig. 4 (a) it can be seen that the AC autocorrelation and PAC graphs on the correlogram state that the data to be processed is not stationary, because it still has several lags so that a differentiation process is needed so that the processed data can be processed.

Furthermore, the data that has been carried out the difference is shown in the correlogram of Fig. 4 (b). In Fig. 4 (b) the process of data differentiation is done once, the differencing process is done to obtain stationary data, this is seen from the number of lags in the AC and PAC which have been good from the previous data plot, but if the data to be processed is still not stationary, then the second differencing process is carried out, if one time the data differentiation is stationary then the parameter values (p), (d), (q) are used to determine the model and parameter values suitable for forecasting.

The process of formulating parameter values on the model to be used is shown in Fig. 4 (c). In Fig. 4 (c) the correlogram produced from the ARIMA (1), (1), (3) the best model determination in this process is determined based on data training. Based on the formulation of parameter values in the modeling process, the resulting correlogram will show stationary data. By checking the residual parameter values, based on the modeling, then the raw material stock forecasting will be applied as shown in Fig. 5.



(a)

Dependent Variable: D(HVS\_A4\_F4)  
Method: ARMA Maximum Likelihood (OPG - BHHH)  
Date: 03/02/19 Time: 11:57  
Sample: 1/08/2016 12/29/2018  
Included observations: 802  
Convergence not achieved after 500 iterations  
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.001520	0.001507	1.008187	0.3137
AR(1)	0.246661	0.640459	0.385132	0.7002
MA(1)	-1.185853	0.373183	-3.177672	0.0015
MA(2)	0.104565	0.475365	0.219968	0.8260
MA(3)	0.081290	0.182384	0.445706	0.6559
SIGMASQ	37.61500	11.82291	3.181536	0.0015
R-squared	0.474338	Mean dependent var		0.006234
Adjusted R-squared	0.471036	S.D. dependent var		8.464435
S.E. of regression	6.156178	Akaike info criterion		6.488665
Sum squared resid	30167.23	Schwarz criterion		6.523731
Log likelihood	-2595.955	Hannan-Quinn criter.		6.502135
F-statistic	143.6559	Durbin-Watson stat		2.001048
Prob(F-statistic)	0.000000			
Inverted AR Roots	.25			
Inverted MA Roots	1.00	.39	-.21	

(b)

**Figure 5.** Forecasting Graph Result; (a) Forecasting Graph, (b) Variable Value

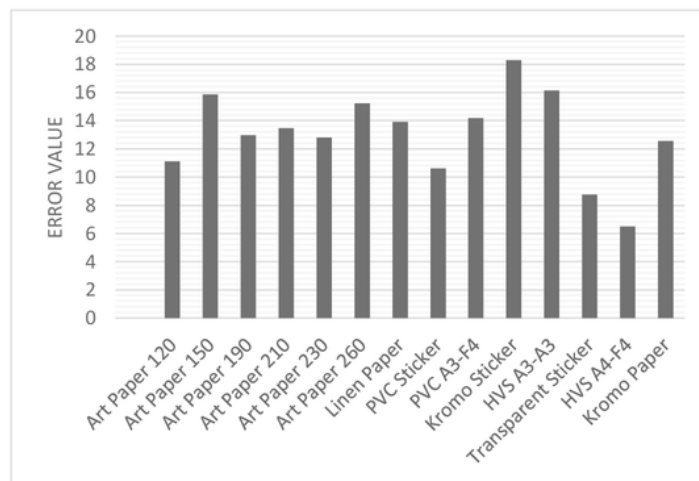
The forecasting chart in Fig. 5 (a) shows the comparison of HVS paper stock values with the estimated results, in the stock value indicated by the color of the blue line, while the estimated results are shown in the red graph. Through the estimated graph, the RMS (Root Mean Square) error value is 6.81, while the error value at the mean absolute is 3.71. Based on these data the value of the proportions of bias, variance, and covariance are 0.18, 0.72, and 0.1 respectively. The estimated results are based on coefficient values and probability values in the ARIMA modeling used. The coefficient values obtained from ARIMA modeling are shown in Fig. 5 (b).

In Fig. 5 (b), the coefficient value in the ARIMA model used is 0.0015 with a probability of 0.31, while the comparison for the coefficients of the value of AR (1) MA (1) and MA (3) is 0.2, 1.2, 0.08. The probability values obtained by AR (1) MA (1) and MA (3) are 0.7, 0.0015 and 0.66 respectively. With the coefficient value obtained the criteria assessment value for the Akaike model is 6.488 and the value of S.E. regression is 6.15.

The acquisition of values on the application of the ARIMA model with each paper obtained different parameters, it is based on the comparison of models made on each

paper by comparing the results of the residual data correlation, so that the probability value obtained in the best model  $<0.5$  with the acquisition of AIC ranging from a minimum value of 6.5 to 18.3.

Based on the modeling that has been applied, a graph of error values is obtained on forecasting paper raw materials using the AIC equation shown in Fig. 6.



**Figure 6.** The Graph of AIC Error Value

In Fig. 6 it can be seen that the smallest AIC error value is found on HVS-A4-F4 type paper with total error obtained at 6.4886%, while the biggest AIC error value is forecasting paper types with chrome sticker types with a total value of 18.2968%. From the acquisition of AIC error values on each type of paper, the average AIC error value was obtained at 13.0294%.

## 5 Conclusion

The application of the ARIMA method for stock forecasting in this study produces a model that can be applied to the forecasting process of raw materials paper in the digital printing industry. ARIMA modeling applied to forecast has different models on each paper with the best parameter values (p, d, q), so that the average error values obtained in this study for each type of paper is 13.0294%. With the highest error value, the prediction of chromo sticker raw material is 18.2968% and the smallest error value is found on HVS-A4-F4 paper with a value of 6.4886%. The application of the ARIMA method in this study is quite good if it is used for forecasting raw materials of constant value (not seasonal) stocks.

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