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# The Best Time Series Model For Elotex Demand Forecasting

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**A B S T R A C T**

Inventory management is carried out to ensure the accuracy of raw material stock in the warehouse. In a chemical raw material distribution company, stockpiling or shortages of raw materials often occur due to fluctuating customer demand. The company is at risk of indirect losses if the product is not sold immediately or if it becomes unavailable. When products are not sold promptly, there is a potential loss due to the limited shelf life of the goods. On the other hand, when products are not available, the company risks losing its customers. The objective of this study is to design a time series model to predict the quantity of chemical raw materials by comparing the accuracy of the Moving Average, ARIMA, and ARMA models. The comparison results will be based on historical demand data for one of the company's products. The product selected in this study is the chemical raw material Elotex, which has the highest demand. The sample data used spans from 2015 to 2023 in daily units. The selection of the best method in this study is determined by considering the model with the lowest RMSE (Root Mean Square Error) value. The research results show that the RMSE value for the Moving Average (MA) model is 3052.7560, the ARIMA model is 4247.9554, and the ARMA model is 4241.8059. Thus, the Moving Average (MA) model, having the lowest RMSE value, is the most accurate model for forecasting the purchase of Elotex chemical raw materials.

## 1. INTRODUCTION

Inventory management involves the counting, monitoring, and prevention of stock discrepancies in warehouses to ensure sufficient product availability for customers without experiencing overstock or stockouts [1]. Its primary goal is to maintain customer satisfaction and minimize the risk of losing customers to competitors. In the distribution industry, a common issue is errors in order classification, which can lead to unavailability or excess inventory. This also relates to managing goods that are at risk of expiration or becoming dead stock [2]. Therefore, accurate forecasting and effective inventory control policies are crucial to prevent losses and meet customer needs. This study focuses on a chemical raw material distribution company located in South Tangerang, which faces various challenges related to demand forecasting, stock control, and fluctuating delivery schedules.

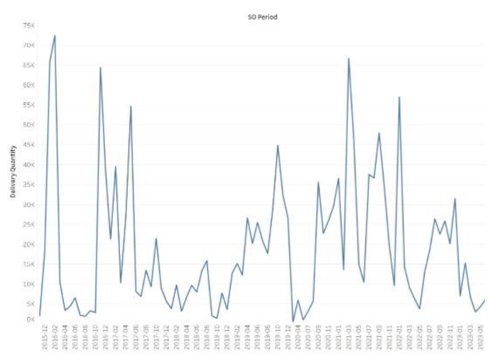

**Figure 1.** Delivery of Goods to Customers

Figure 1 illustrates the high fluctuations in the delivery of goods to customers, indicating issues in forecasting and the calculation of reorder points at the chemical raw material distribution company. These issues lead to warehouse overstock, the risk of slow-moving items, and product expiration. This study aims to optimize inventory management by implementing a system with minimal errors. The methods used include Moving Average, ARIMA, and ARMA to forecast raw material needs and improve forecasting accuracy. Several problems have been identified, including delays in delivery schedules, inaccuracies in determining reorder points due to opportunistic pricing from suppliers, and stockpiling of goods resulting in high storage costs. This research focuses on Elotex, a type of chemical raw material, as the sample product to address these challenges and enhance the efficiency of inventory management.

## 2. LITERATURE REVIEW

### *2.1. Inventory Management*

Inventory management is a strategy used by companies to efficiently manage stock in order to maintain a balance between availability and customer demand. The primary goal is to avoid stockouts and overstocking, which can lead to lost sales opportunities, customer dissatisfaction, and high storage costs [3]. Inventory management also plays a key role in cost optimization by reducing expenditures related to purchasing, storage, ordering, and stock shortages [4].

Inventory can be categorized based on type and function, including raw materials, assembly components, auxiliary materials, work-in-process goods, and finished goods [5]. Functionally, inventory includes fluctuation stock to handle demand variability, anticipation stock for seasonal spikes, lot size inventory to benefit from bulk purchasing discounts, and pipeline inventory for items in transit [6]. Inventory management also involves various costs, such as storage costs, ordering costs, production setup costs, and shortage costs, all of which can negatively impact company operations.

To optimize inventory management, companies can implement various systems such as computerization, Just-In-Time (JIT), outsourcing, ABC analysis, and Material Requirement Planning (MRP) to increase efficiency and reduce costs [6]. With the right system, companies can maintain stock balance, improve customer satisfaction, and minimize the risk of losses due to ineffective inventory control.

### *2.2. Forecasting*

Demand forecasting is essential to reduce the gap between market demand and the level of production and inventory at the factory. Forecasting refers to the assumption of product demand over a specific future period and serves as the foundation for short-, medium-, and long-term planning for the company [7]. Inventory is a crucial asset in a company's operations, playing a central role in both purchasing and sales activities [8]. Forecasting patterns include trend (a gradual increase or decrease in data), cyclic (patterns influenced by long-term economic fluctuations), seasonality (recurring patterns over specific periods), and horizontal (data fluctuating around a stable average value) [9].

### *2.3. Moving Average Model*

In statistical and time series analysis, the moving average is a technique used to smooth out fluctuations in data over a specific period in order to identify trends or patterns [10]. This method calculates the average of a specified number of the most recent data points in the time series, based on a predetermined period length.

#### *2.3.1. Types of Moving Average*

1. Simple Moving Average (SMA): Calculates the average of data values over a specific period without weighting.

   Formula:

   $SMA = X_t + X_{t-1} + X_{t-2} + .... + X_{t-n+1} / n$ ...................(1)

   where:
   $X_t$ = Actual data at a specific period t.
   W = Weight (applies to weighted averages, not to simple moving averages).

2. Weighted Moving Average (WMA): Assigns higher weights to the most recent data.

   Formula:

   $WMA = \sum(X_t \times W) / \sum W$.........................................(2)

   where:
   $X_t$ = Actual data at a specific period t.
   W = Weight

3. Exponential Moving Average (EMA): Weights decrease exponentially over time.

   Formula :

   $EMA = ((2/ t + 1) \times (X_t - F_{t-1})) + F_{t-1}$......................(3)

   where:
   t = Period
   $X_t$ = Actual data at a specific period t.
   $F_{t-1}$ = Previous EMA value

### *2.4. ARIMA Model*

ARIMA (Autoregressive Integrated Moving Average) is a time series analysis model that combines autoregression (AR), moving average (MA), and differencing (I) components. This model is expressed as ARIMA(p,d,q).

Steps for Using ARIMA

a. Plot Data: To check for stationarity, if the data is not stationary, differencing is performed.

   *First Differencing (d = 1):*

   $\nabla Xt = Xt - Xt - 1$..............................................................(4)

   *Second Differencing (d = 2):*

   $Xt = 12 \nabla Xt - Xt - 1$........................................................(5)

b. Model Identification: Perform stationarity tests, determine pp, dd, and qq using ACF, PACF, and unit root tests.

c. Parameter Estimation: Performed using the Least Squares method for the AR model and non-linear optimization methods for the MA model.

d. Diagnostic Checking: Test the model's adequacy based on the distribution of residuals.

Forecasting: The ARIMA model is more accurate for short-term forecasting compared to structural models [11]. The ARIMA model, based on the Box & Jenkins concept, is defined as follows:

$Yt = \varphi 1Yt\text{-}1 + \varphi 2Yt\text{-}2 + ... + \varphi pYt\text{-}p + \varepsilon t^*$..........................(6)

where:

Yt: is the data value at time t.

Yt-1, Yt-2, ..., Yt-p: adalah nilai data pada waktu t-1, t-2, ..., t-p (nilai-nilai masa lalu yang digunakan untuk memprediksi nilai saat ini).

Yt-1, Yt-2, ..., Yt-p: are the data values at times t−1, t−2, ..., t−p (past values used to predict the current value).

φ1, φ2, ..., φp: are the autoregressive coefficients (parameters that indicate how much past values influence the current value).

p: is the order or degree of the AR (how many past values are used in the model).

εt: is the residual (error) at time t.

### *2.5. ARMA Model*

Autoregressive Moving Average (ARMA) is a statistical model used in time series analysis and forecasting. This model combines two main components: autoregressive (AR) and moving average (MA) [12]. The ARMA model predicts the current period's value based on the regression of previous period values, so future values depend on past values [13].

The ARMA(p,q) model is a combination of AR(p) and MA(q) that is assumed to have constant volatility (homoskedastic). This model was introduced by Box & Jenkins (1976) to predict financial variables.

Formula ARMA Model:

$$Xt=\phi 1Xt-1+\phi 2Xt-2+...+\phi pXt-p+et+\theta 1et-1+\theta 2et-2+...+\theta q\ et-q$$

If the data is non-stationary, differencing (d) is applied to make it stationary, leading to the use of ARIMA [14];[15]

## 3. METHODOLOGY

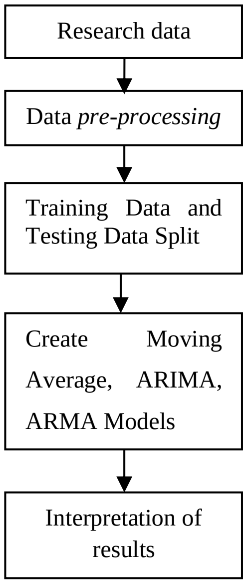


**Figure 2.** Research Flowchart

The data used in this study consists of historical data from a chemical raw material company, covering the years 2015 to 2023. Data pre-processing was then performed. In this study, pre-processing ensures that the data used is relevant and facilitates model fitting. The date format will be changed to datetime, and only important columns such as the quantity of goods delivered (delivered) will be selected. The data is then cleaned of anomalies and errors to ensure accuracy. Subsequently, analysis is conducted to determine the stationarity of the data using decomposition plots, ADF, and ACF. Data is considered stationary if the mean, variance, and autocorrelation remain constant, with significant values below 5%. If the data is non-stationary, transformations or differencing are applied. For forecasting reorder points, the methods used include Moving Average, ARMA, and ARIMA, with delivery data as the basis for predicting future order quantities.

The data for prediction is compared using the Moving Average, ARIMA, and ARMA models. Training data is used to train the models, while test data is used to assess accuracy. The ratio of training and test data impacts model performance. If accuracy is high, the model can be used for predictions; if low, retraining with different data or parameters is needed. This study compares different data splitting ratios, with the results showing the ratio that yields the best accuracy. The evaluation of this study is conducted by comparing the smallest mean error (MSE). The analysis includes the calculation of MSE, RMSE, and MAE for three data samples to assess the discrepancy between predicted production in each model.

## 4. RESULTS AND DISCUSSION

This study aims to compare three time series models: Moving Average (MA1), ARIMA, and ARMA, in predicting the inventory needs of ELOTEX 2050 chemical raw material in a distribution company. The evaluation is conducted using Root Mean Squared Error (RMSE) as the primary indicator of model accuracy.

**Table 1.** Comparison of RMSE values for each model

| *Model* | *RSME* |
|---|---|
| *Moving Average* | *3052,76* |
| *Arma* | *4241,81* |
| *Arima* | *4247,96* |

The Moving Average model produced the smallest RMSE value of 3052.76, indicating that this model has the lowest prediction error among the three models tested. This model successfully smooths out daily fluctuations in the ELOTEX demand data, making the resulting predictions closely follow the actual pattern. Additionally, the residual error from this model is relatively small and stable, reinforcing the accuracy of the forecast results. The simple characteristics of the Moving Average make it suitable for applying to inventory data patterns in the company that are fluctuating but do not show a strong long-term trend.

The ARMA model produced an RMSE value of 4241.81, which is higher compared to the Moving Average. The ARMA prediction graph shows a more dispersed pattern compared to the actual data, with larger residual errors. This suggests that the ARMA model is less capable of accommodating fluctuating patterns without a clear trend, as seen in the ELOTEX data.

The ARIMA model produced an RMSE value of 4247.96, the highest error value among the three models. This model applies differencing to address non-stationarity, but in this case, it caused the model to overfit the noise in the data. As a result, the predictions generated were less stable and did not closely follow the actual pattern, with larger residual errors.

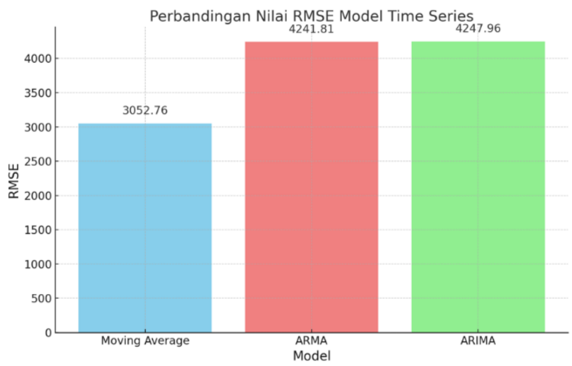


**Figure 3.** Time series model comparison chart

From the time series model comparison graph above, the comparison between actual data and predictions from the three time series models shows that the Moving Average model yields the lowest RMSE value compared to ARMA and ARIMA. This difference confirms that for fluctuating data without a strong trend, the Moving Average method is more accurate than the more complex models.

## 5. CONCLUSION

Based on the testing and analysis results, it can be concluded that Moving Average (MA1) is the best model in forecasting the demand for ELOTEX-type chemical raw materials, with the lowest RMSE value of 3052.76 and the prediction pattern closest to the actual data. Meanwhile, the ARMA and ARIMA models produce higher RMSE values and less stable predictions, thus are less recommended for data conditions with fluctuating patterns without trends as in this company.

The implementation of the Moving Average model in the inventory management process can help the company, reduce the risk of overstock and stock-out, optimize the use of warehouse space, improve the accuracy of raw material purchase planning, and increase customer satisfaction through more stable product availability.

This study recommends the use of the Moving Average (MA1) method in the company's raw material planning system. In addition, for future development, a combination of Moving Average with Machine Learning methods such as LSTM can be considered to address more complex data pattern changes.

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