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Application of Prediction Models Based on Moving Average, Exponential Smoothing and Trend Analysis on Indonesian Palm Oil Exports

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ABSTRACT

Palm oil is a strategic commodity for Indonesia, significantly contributing to state revenue and foreign exchange. In 2022, its export value reached USD 33.7 billion. Accurate forecasting of palm oil exports is crucial due to fluctuating market conditions influenced by global demand, prices, and government policies. However, existing studies on forecasting Indonesian palm oil exports are limited, with most research focusing on other agricultural commodities. This study applies Moving Average, Exponential Smoothing, and Trend Analysis methods to forecast palm oil exports and determine the most accurate method. The results show that the Trend Analysis method yields the lowest Mean Absolute Deviation (MAD = 18505.67) and Mean Squared Error (MSE = 436747200), indicating superior accuracy compared to the other methods. The findings suggest that Trend Analysis can provide stakeholders government, companies, and farmers with valuable insights for strategic decision-making. This research contributes to the development of more precise forecasting models, supporting Indonesia's palm oil industry in maintaining its global competitiveness.

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INTRODUCTION

Palm oil is a strategic commodity for Indonesia with a significant contribution to state revenue and foreign exchange (Arsyad et al., 2020). In 2022, the export value of Indonesian palm oil will reach USD 33.7 billion, making it one of the largest contributors to the non-oil and gas trade balance (Badan Pusat Statistik, 2024). The growth of the middle class and population in developing nations is expected to fuel the ongoing increase in the demand for palm oil worldwide (Khatiwada et al., 2021). Therefore, it is important for Indonesia to maintain and increase the production and competitiveness of its palm oil exports (Rosyadi et al., 2021). Determining the level of demand is a crucial component in making palm oil exports more competitive (Ata, 2024). Proper forecasting can help stakeholders in the palm oil industry, such as governments, palm oil companies, and smallholders, make informed strategic decisions related to production, logistics, and marketing (Shukla & Tiwari, 2017). Export is the trade or sale of goods from within the country to abroad: therefore, exports are one of the drivers of economic growth, especially in developing countries. Palm oil commodities have great potential to compete in foreign markets, and this potential can bring foreign exchange to Indonesia (Tandra et al., 2022). Demand forecasting is conducted to meet export demand.

Forecasting predicts things that may happen in the future and is carried out to make decisions in each field of activity (Iheanacho, 2020). Research on palm oil export forecasting has not yet been conducted. **Some studies** have used forecasting methods for tea (Shiferaw, 2023), tobacco (Marpaung et al., 2023); wood production (Huda et al., 2023), and rice products (Airlangga et al., 2019).

Issues pertaining to Indonesian palm oil's export potential include those involving its export fluctuations, which occasionally see notable swings due to a variety of factors like global economic conditions, government regulations, and international prices. This creates uncertainty for those involved in the palm oil industry. Therefore, the accuracy of palm oil export predictions is very important for various parties, such as the government, companies, and farmers to make the right decisions (Khan et al., 2021). Fluctuations in palm oil export prices and demand can have a major impact on economic stability and community welfare (Aziz et al., 2024). Therefore, more accurate forecasting methods are needed to help stakeholders in the palm oil industry make informed decisions. The disadvantages of traditional methods such as simple averages and simple moving averages, include being less sensitive to changes in data trends and not taking into account seasonal factors. Superiority Moving Average (Sari, 2023), Exponential Smoothing with Trend (Ramadhani & Ardhiansyah, 2022), and Trend Analysis (Hudisasmoko, 2023), where these three methods have a better level of accuracy than traditional methods, especially those related to identifying data trends, taking into account seasonal factors, and producing more accurate predictions for the long term.

Based on this background, this study **aims** to apply the Moving Average, Exponential Smoothing, and Trend Analysis methods to forecast the number of Indonesian palm oil exports and compare the accuracy of the three forecasting methods. Therefore, in this study an accurate forecasting model is obtained for the number of Indonesian palm oil exports and provides useful information for stakeholders in the palm oil industry to make the right strategic decisions.

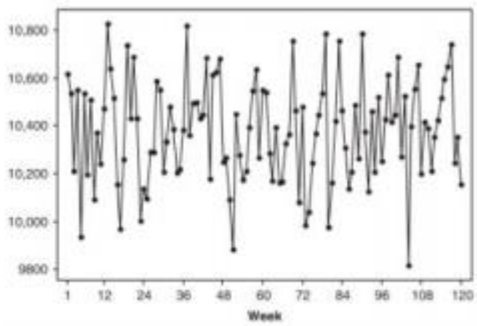
The novelty of this study is that it compares the performance of three different forecasting methods and identifies the best method to forecast Indonesian palm oil exports. This study also integrated other factors that can affect palm oil exports into the forecasting model. The **benefits** of this research for the government are needed to formulate policies and strategies for the development of the palm oil industry for companies, it can be used to make decisions related to production, logistics, and marketing and for farmers, it can be used to plan the production and sale of crops. This research, can also produce more accurate palm oil export predictions and help in making the right decisions to advance the palm oil industry.

RESEARCH METHOD

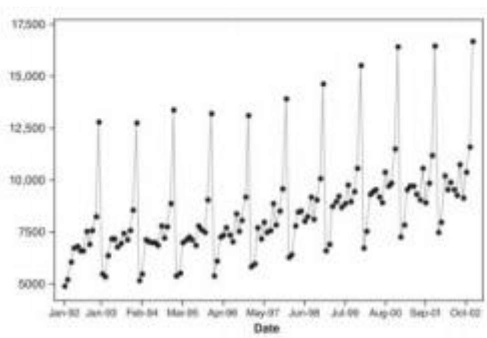
Forecasting is a method of estimating future values using past data (Cerqueira et al., 2020); (Siti Wardah, 2024). Forecasting is the art of predicting future events. Forecasting involves taking historical data (last year's sales) and projecting them into the future using mathematical models (Juliana et al., 2023). Mathematical and statistical models can be used to analyze historical data and identify patterns that can be used to predict future values (Kumar & Garg, 2018). According (Koutsandreas et al., 2022), forecasts are always sought to:

1. Minimizing the influence of uncertainty on a problem.
2. Forecasting aims to get a forecast that can minimize forecast errors
3. Forecasting is usually measured by MSE (Mean Squared Error), MAE (Mean Absolute Error), and so on.

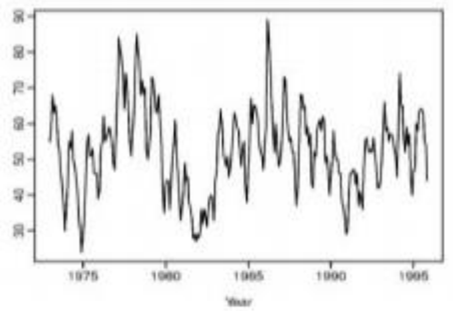
A set of variables observed at the same spatial time interval is called a periodic series (Nur et al., 2024). Assuming that pattern combinations will always be repeated in the future, the underlying pattern can be identified from the historical data of the row. The data pattern type was used to select the appropriate method for periodic series analysis (time series). According (Singh et al., 2024), the four common types of data patterns for time-series data are shown in Figure 1.



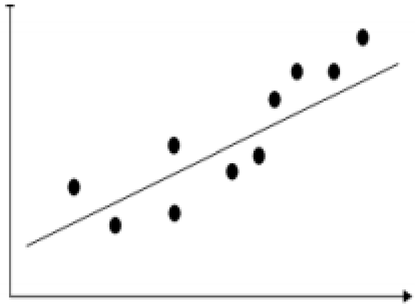
a. Horizontal Data Patterns



b. Seasonal Data Patterns



c. Cyclic Data Patterns



d. Trend Data Pattern

Figure 1 Types of forecasting patterns.

A horizontal pattern occurs when the value of data moves around a constant or stationary average relative to its average. Seasonal factors can be quarters of the year, months, or days of a week. Seasonal patterns occur when a dataset has a tendency to rise or fall consistently. Cyclical patterns occur when a time series dataset is affected by long-term fluctuations. Patterns that occur in the event of a long-term secular rise or fall in the data have a cyclical component that is beneficial for long-term forecasting. Trend data patterns occur when there is a long-term secular increase or decrease in data.

Forecasting Methods

Metode Moving Average.

Moving average is a forecasting method that calculates the average of data over a specific period to flatten fluctuations and see data trends more clearly (Ensafi et al., 2022). Reducing or eliminating unpredictability in a time series is the primary goal of utilizing moving averages. When using the moving average technique to a time series, a set of observed values is averaged, and the average values are then used as a forecast for the upcoming period (Montgomery et al., 2015).

The value of the most recent data was calculated using the moving average technique, whereas older or older data were deleted. The average number of data points is calculated with the moving average number from price 1 to the value of N data. This average number can be calculated using (1).

$$F_{t+1} = \frac{1}{N} \sum_{i=t-N+1}^{t} Xi \qquad (1)$$

where t is the last value and t+1 is the next period for which a prophecy is made.

F_{t+1} = Predictions for the following periods, t+1
$X_{t,t-1,t-2}$ = Observation/actual value of the variable in period t,t-1,t-2,...
N = The moving average's calculation count of observations.

All observed data have the same weights that constitute the average in the moving average model. However, the most recently observed data should have more weight than the previously observed data, which is considered a weakness of this moving average method.

Middle Score

Consider a set of data consisting of N periods, the last time, and T of the first data point. The initialization group was used as the data group, and the test group was used for the remaining sections. The simple averaging method takes the average of all data in the initialization group as follows:

$$\overline{X} = \sum_{i-1}^{T} X_i \, IT = F_{T+1} \qquad \textbf{(2)}$$

As a forecast for the period (T + 1), we can calculate the error value when the period data (T+1) are available.

$$e_{T+1} = X_{T+1} - F_{T+1} \qquad \textbf{(3)}$$

The new average value is obtained because there is one more data point in the previous historical data group:

$$\overline{X} = \sum_{i-1}^{T+1} X_i \, I(T+1) = F_{T+2} \quad \textbf{(4)}$$

And a new error element, if X_{T+2} be:

$$e_{T+2} = X_{T+2} - F_{T+2} \quad \textbf{(5)}$$

Simple Moving Average

One way to change the influence of the past on the median value as a prediction is to determine the number of previous observation values from the outset calculate the median value. This procedure is described by the term moving average because each time there is a new observation value, the oldest value is discarded and the most recent value is added.

Double Simple Moving Average

The linear moving average method was created to reduce systematic errors that occur when moving averages are used to trend the data. This method relies on the calculation of multiple moving averages, known as MA (M x N), where MA is the M period of MA N-Period. The moving average forecasting method comprises three components:

1. Using a single moving average on time t (s'_t).
2. Adjustment which is the difference between a single and double moving average at time t ($S'_t - S'_t$).
3. Adjustment of the tendency from period t to period t+1 or t+m. In situations where the trend is linear and the random error component is not strong, the two-adjustment method is the most effective.

This adjustment is effective because a single MA lags behind the series of data indicating a trend. If the data series show a trend, a single MA will produce something similar to a systematic error, and the difference between the values of the single and double moving averages can reduce the systematic error. Equations 6-10 can be used to explain the linear moving average procedure.

$$S'_t = \frac{X_t + X_{t-1} + X_{t-2} + \dots\ X_{t-N+1}}{N} \quad \textbf{(6)}$$

$$S''_t = \frac{S_1 + S'_{t-1} + S_{t-2} + \dots\ S_{t-N+1}}{N} \quad \textbf{(7)}$$

$$a_t = S'_t + (S'_t - S''_t) = 2S'_t - S''_t \quad \textbf{(8)}$$

$$b_t = \frac{2}{N-1}(S'_t - S''_t) \quad \textbf{(9)}$$

$$F_{t+m} = a_t + b_{t+m} \quad \textbf{(10)}$$

Metod Exponential Smoothing

The exponential smoothing technique reduces the average value of smoothing historical values from the time-lapse data, thereby improving forecasting over time. The single exponential smoothing (SES) method, also known as single exponential smoothing, assumes that the data does not have a consistent growth pattern or trend and moves around a fixed mean value (Restyana et al., 2021). Equation 11 can be used to determine the forecast value.

$$F_t = aX_t + (1-a)F_{t-1} \quad \textbf{(11)}$$

Where:
Ft = Forecasting for the time frame t.
Xt = Value in actuality over time t-1
Ft-1= Making predictions at time t-1
A = The exponential parameter has a value between 0 and 1.

Trend Analysis Method

The method of extracting three components from the basic pattern usually distinguishes economic and business data series. Trend, cyclical, and seasonal factors exist. A straight line can be matched to stationary (horizontal) data by minimizing the MSE, as in Equation 12-15.

$$\overline{X} = \sum_{i=1}^{n} X_i \quad \textbf{(12)}$$

Linear trend lines applicable to periodic series data:

$$X_t = a + bt \quad \textbf{(13)}$$

The following equation can be used to obtain the values of a and b that minimize the MSE:

$$b = \frac{n \sum tX - \sum t \sum X}{n \sum t^2 - (\sum t)^2} \quad \textbf{(14)}$$

$$a = \frac{\sum X}{n} - b \frac{\sum t}{n} \quad \textbf{(15)}$$

Where:
a = Intersep
b = Slope

Forecast Yield Measures

Four general metrics, which are errors pertaining to the extent of discrepancy between forecast results and actual demand, are used to assess the accuracy of forecast results:

1. Mean Absolute Deviation (MAD)
   MAD is the average absolute error over a period of time, regardless of whether the forecast outcome is greater or smaller than it actually is. In general, the MAD is formulated as follows:

$$MAD = \Sigma \left| \frac{A_{t-F_t}}{n} \right| \quad \textbf{(16)}$$

   Where :
   A_t = Actual demand in period–t
   F_t = Demand forecasting in the periode-t
   n = Number of forecasting periods involved

2. Mean Square Error (MSE)
   The MSE can be calculated by adding the sum of the sum squares of the forecast errors in each period and dividing it by the number of forecasting periods. MSE was systematically formulated as follows:

$$MSE = \Sigma \frac{(A_t - F_t)^2}{n} \quad \textbf{(17)}$$

   Where:
   A_t = Real Demand during Period-t
   F_t = Forecasted demand for the period t
   n = The number of forecasting periods included

3. Mean Forecast Error (MFE)
   MFE is an effective tool for determining whether a particular forecasting outcome is too high or too low over a period of time. The MFE value can be calculated by summing all forecasting errors during the forecasting period and dividing it by the number of forecasting periods. Systematically, MFE is expressed as follows:

$$MFE = \Sigma \frac{(A_t - F_t)}{n} \quad \textbf{(18)}$$

   Where:
   A_t = Real Demand during Period-t
   F_t = Forecasted demand for the period t
   n = The number of forecasting periods included

4. Mean Absolute Persentage Error (MAPE)
   The MAPE is a relative error measure. MAPE states the percentage of errors that the forecast results make against the actual demand over a given period, which provides information that the percentage of errors is too high or too low. Therefore, MAPE is usually more significant than MAD. MAPE is expressed as follows:

$$MAPE = \left(\frac{100}{n}\right) \Sigma \left| A_t - \frac{F_t}{A_t} \right| \quad \textbf{(19)}$$

   Where:
   A_t = Real Demand during Period-t

F_t = Forecasted demand for the period t
n = The number of forecasting periods included

Verification and Control of Forecasting

Once the forecast is created, the next important step is to verify it so that the results truly reflect past data and the cause-and-effect system. As long as the actuality of the forecast is reliable, the forecast results will continue to be used. If, during the verification process, there is any doubt about the validity of the method used, then it should look for another method that is more suitable. Its validity must be tested using appropriate statistical methods.

There are doubts regarding when the forecasting methods should be added. Forecasting should always be regularly compared with actual demand. If there is convincing evidence of a change in demand patterns or if a change in demand patterns is already known, then forecasting methods should be changed as soon as they are known.

Changes in demand patterns are influenced by several tools that can be used to verify forecasting and identify changes in the causal system. Forecasting control maps that are similar to quality control maps can be created using relatively simple data conditions.

The Research Methodology Framework used for this study is as seen in Figure 2.

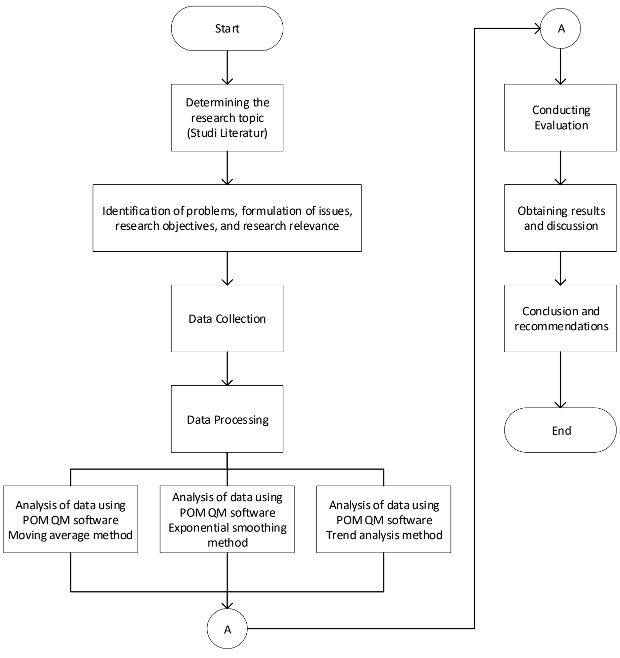


Figure 2. Research framework

Data used in the data collection stage of this study. The following is the type of secondary data needed for this study obtained from https://bps.go.id data from to2012-2023, the next step is to process the data using a computer application program, namely POM-QM (Quantitative Methods) for Windows 5.2. Dta processing aims to make it possible to draw conclusions or answer the problem being researched using methods such as moving averages, exponential smoothing, and trend analysis. Then an analysis was carried out to identify the current problem and draw conclusions from the research. The author uses a quantitative method to meet this need, namely by using formulas related to the method used.

RESULTS AND DISCUSSION

Data plots must first be created before processing the data. Forecasting becomes easier because we can determine the pattern of the data flow that we predict using the data plot. From the plot of actual sales data, it can be concluded that the distribution of the data is seasonal. This was based on a data plot that tended to increase.

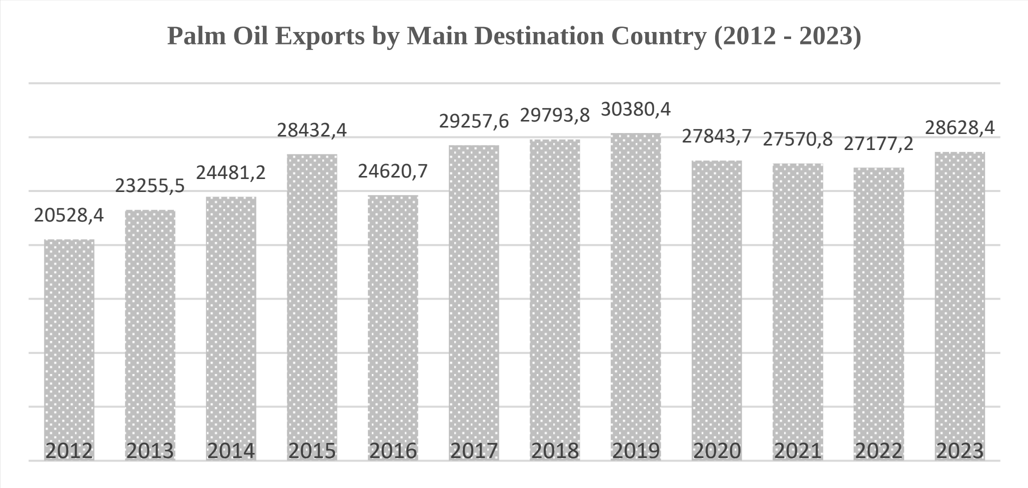


Figure 3. Graph of Palm Oil exports for 2012-2023 (Source: BPS, 2024)

Forecasting Analysis of Each Method
Metode Moving Average

The authors used the three-period moving average method (periods 1, 2 and 3) to obtain more effective forecasting results.

Moving Average with Period I

The output of Table 1 shows the estimated value of 286284 for the next period; there is a MAD value of 20118 MSE of 636210200, and a bias value of 7363.636, with a standard error of 27885.31. Thus, the error rate of using this method was 27885.31 MAD and 636210200 MSE.

Table 1. Forecasting Result Moving Average Period I

Measurement	Value
Error Measures	
Bias (Mean Error)	7363.636
MAD (Mean Absolute Deviation)	20118
MSE (Mean Squared Error)	636210200
Standard Error (denom=n-2=8)	27885.31
MAPE (Mean Absolute Percent Error)	7.483%
Forecast Next Period	286284

Moving Average with Period 2

Table 2 shows the estimated sales value for the next period of 279028, MAD value of 20998.9, MSE value of 565069700, bias value of 8697.3, and standard error value of 26577.0. Thus, we can conclude that the error rate when using this method is 20998.9 MAD and 565069700 MSE. However, to determine whether to use this method, we compared it with other methods.

Table 2. Forecasting Result Moving Average Period 2

Measurement	Value
Error Measures	-
Bias (Mean Error)	8697.3
MAD (Mean Absolute Deviation)	20998.9
MSE (Mean Squared Error)	565069700
Standard Error (denom=n-2=7)	26577.0
MAPE (Mean Absolute Percent Error)	7.579%
Forecast Next Period	279028

Moving Average with Period 3

The output of Table 1 shows the estimated value of 277921.3 for the next period; there is an MAD value of 23289.04 MSE of 738288100, and a bias value of 10121.26, with a standard error of 30809.54. Thus, the error rate of using this method was 23289.04 MAD and 738288100 MSE.

Table 3. Forecasting Result Moving Average Period 3

Measurement	Value
Error Measures	
Bias (Mean Error)	10121.26
MAD (Mean Absolute Deviation)	23289.04
MSE (Mean Squared Error)	738288100
Standard Error (denom=n-2=8)	30809.54
MAPE (Mean Absolute Percent Error)	8.156%
Forecast Next Period	277921.3

As a preliminary comparison, we can compare the 1st, 2nd and 3rd period moving average models. The results of data processing showed that the value of MAD 1 (20118) was less than MAD 2 (20998.9) and MAD 3 (23289.04) and the value of MSE 2 (565069700) was less than MSE 1 (636210200) and MSE 3 (738288100). Overall, the trend showed an increase in bias, MAD, and Standard Error from Period 1 to Period 3, reflecting a tendency to decrease accuracy in the prediction models. However, the MAPE remained in a fairly good range (<10%), despite a gradual increase. The decline in MSE in Period 2 shows a more stable performance compared to Periods 1 and 3, therefore, the prediction of Period 2 can be considered more optimal than the other two periods.

Exponential Smoothing Method Using Trend α = 0.5 and β = 0.5

The output from Table 3 shows the estimated value for the next period, which was 282179.4, the MAD value was 21036.8, the MSE value was 573023800, the general bias value (Mean Error) was 7065.4, and the standard error was 26464.4. Based on this output, we can conclude that the forecasting error rate is 21036.8 for MAD and 573023800 for MSE.

Table 3. Exponential Smooting Forecasting Outcome With Trends α = 0.50 and β = 0.50

Measurement	Value
Error Measures	-
Bias (Mean Error)	7065.4
MAD (Mean Absolute Deviation)	21036.8
MSE (Mean Squared Error)	573023800
Standard Error	26464.4
MAPE (Mean Absolute Percent Error)	7.8%
Forecast Next Period	282179.4

Metod Trend Analysis

The output of Table 4 shows the forecast value for the next period of 299007.6, MAD value of 19810.54, MSE value of 495042300, mean error value of 0.006 and standard error value of 24597.8. Based on theses data, we can conclude that the error rates of forecasting this method are 19810.54 for MAD and 495042300 for MSE. This approach has a lower error rate than the exponential smoothing with trend and moving average approaches, according to the patterns dispersed in the forecasting charts.

Table 4. Forecasting Result Trend Analysis

Measurement	Value	Future Period	Forecast
Error Measures		13	304875.3
Bias (Mean Error)	0.007	14	310501
MAD (Mean Absolute Deviation)	18505.67	15	316126.7
MSE (Mean Squared Error)	436747200	16	321752.4
Standard Error (denom=n-2=9)	22893.16	17	327378.1
MAPE (Mean Absolute Percent Error)	6.95%	18	333003.8
Regression line		19	338629.4
Demand(y) = 231741,5		20	344255.1
+ 5625,681 * Time		21	349880.8
Statistics		22	355506.5
Correlation coefficient	.681	23	361132.1
Coefficient of determination (r^2)	.463	24	366757.8

25	372383.5
26	378009.2

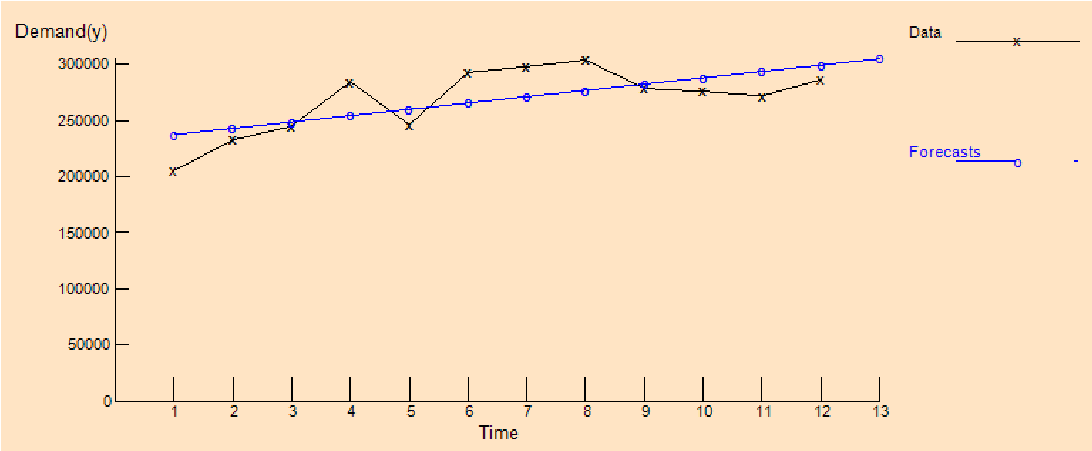


Figure 4. Chart Forecasting Result Trend Analysis

Analysis of Selected Forecasting Methods

Once all three forecasting methods are used, the next step is to determine which method is more effective and has a large forecasting value with a low error rate. The MAD, MSE, standard error, and near-zero bias values weare examined to select the best method for sales forecasting using seasonal data. Based on these parameters, we can determine the best method among several existing methods in this case. The MAD, MSE, standard error, and bias values for each method in this study were different. Therefore, to determine the most effective method, weighting values for the MAD factors, MSE, error standards, and bias are given. After weighting each factor, the next step is to compare the overall weighting value of each method for forecasting the amount of exports.

The smalllest value was obtained to assess each assessment factor for each method. This is done by assigning a value of 1 and so on to 4 for each method by looking at one factor, namely the MAD value. Once the MAD value is assessed, the MSE value is viewed along with the Standard Error and Bias values. Thus, this weighting process results in a final result for each method and makes it possible to choose which method is best suited for use. Based on the above analysis and data processing, we can see that the **trend analysis** method has a lower error rate compared to other methods with a bias value of zero, which indicates that it is the chosen method and has a value of almost zero. After the forecasting calculation is completed, **the trend analysis** forecasting method is chosen because it has a smaller error rate than other methods. The next forecast for palm oil exports was 304875.3.

CONCLUSION

With the smallest values, we can make predictions using the Moving Average, Exponential Smoothing with Trend, and Trend Analysis techniques. Based on the collected and processed data, it can be seen that trend analysis has a lower error rate than the other methods. With a MAD value of 18505.67, an MSE value of 436747200, a mean error value of 0.007 and a standard error value of 22893.16, the trend analysis method is considered the best. Based of the analysis, it is estimated that the number of exports is 304875.3.

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