Movement of Oil and Gas and Non-Oil and Gas Import Export Values in Indonesia: A Time Series Analysis

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Abstract **– Export and import activities are fundamental components of a nation's economy. Exports refer to goods and services produced domestically and sold to foreign countries, generating revenue and contributing to a positive trade balance. In Indonesia, oil and gas have traditionally been significant export commodities, providing substantial foreign exchange earnings and supporting economic growth. Alongside oil and gas, non-oil and gas sectors, including agriculture, manufacturing, and services, also play a vital role in diversifying the export base and enhancing economic stability. This study aims to analyze the movement of oil and gas and non-oil and gas export-import values in Indonesia from 1975 to 2023 using time series analysis. Various models, including double moving average, double exponential smoothing, ARIMA, time series regression, and neural network, were evaluated for forecasting accuracy. The results indicate significant differences between training and testing data, with high MSE and RMSE values in testing data suggesting overfitting. The neural network model performed best on training data but showed poor performance on testing data. External factors such as global commodity price fluctuations, international trade policies, and currency exchange rates significantly impact forecasting outcomes.**

Keywords – Double Moving Average, Double Exponential Smoothing, ARIMA, Time Series Regression, Neural Network, Export, Import, Oil and Gas

I. INTRODUCTION

International trade is a crucial component of global economic integration, involving the buying and selling of goods and services across national borders [1]. It is a crucial component of modern economies, allows countries to specialize in the production of goods and services that they can produce most efficiently [1]. This specialization and exchange enhance overall economic welfare by increasing the availability of goods, reducing costs, and fostering innovation and competition.

Indonesia, as one of the largest economies in Southeast Asia, plays a significant role in international trade. The country's main exports include oil and gas and non-oil and gas products [2]. The value of Indonesia's exports has fluctuated over time, with both migas and non-migas exports contributing to the overall value.

Migas exports have been a significant contributor to Indonesia's economic growth [2]. The country's oil and gas reserves are a major source of revenue, and the export of these commodities has been a key driver of economic development. However, the value of migas exports can be volatile due to fluctuations in global oil prices and demand. Non-migas exports, on the other hand, have been more stable and have contributed significantly to Indonesia's economic growth [2]. These exports include a wide range of products such as textiles, electronics, and food products. The value of non-migas exports has also fluctuated over time, but it has generally been more stable than migas exports. The value of both migas and non-migas exports has a significant impact on Indonesia's economic growth [3]. The country's economic growth is influenced by various factors, including the value of its exports, domestic consumption, and investment [3]. The value of exports can affect the country's balance of payments, inflation, and employment rates [3].

Previous studies have investigated the impact of migas and non-migas exports on Indonesia's economic growth. For instance, Afrinaldi (2006) found that migas exports have a positive impact on economic growth, while Djatmiko and Nugroho (2019) discovered that non-migas exports are more stable and contribute significantly to economic growth [1][2]. Jalunggono et al. (2020) analyzed the influence of foreign investment, net migas and non-migas exports, and foreign loans on Indonesia's foreign exchange reserves and found that foreign investment and net migas exports have a significant impact [3].

In this research, we will use several methods, such as double moving average, double exponential smoothing, ARIMA, time series regression, and neural network to analyze the movement of the value of oil and gas and non-oil and gas exports and imports in Indonesia.

Double moving average method involves calculating two moving averages, the first moving average smooths the original data, and the second moving average smooths the first moving average. This method helps to reduce noise and highlight the underlying trend in the data. It is particularly useful for time series data with relatively stable trends and no significant seasonal patterns. The double moving average provides a more refined trend estimate, which can be crucial for making accurate short-term forecasts [4].

Double Exponential Smoothing, also known as Holt's Linear Trend Model, extends the concept of single exponential smoothing by adding a component for trend. This method applies two smoothing constants to account for the level and the trend of the time series. It is particularly effective for data with a trend but without seasonality. The double exponential smoothing method adjusts for both the level of the series and its trend, making it suitable for forecasting in environments where the data exhibit consistent upward or downward movements [5].

ARIMA is a popular and versatile time series forecasting method that combines autoregression (AR), differencing (I) to make the series stationary, and moving average (MA). The ARIMA model is specified by three parameters: p (the number of lag observations), d (the number of times the raw observations are differenced), and q (the size of the moving average window). This model is powerful for capturing various structures in time series data, including trends and patterns [6]. ARIMA models are widely used in economic and financial forecasting due to their flexibility and robustness in handling different types of time series data.

Time series regression is a statistical method that models the relationship between a dependent variable and one or more independent variables over time [7]. It is particularly useful in analyzing and forecasting time-dependent data by accounting for trends, seasonality, and autocorrelation [7]. Time series regression is widely used in fields such as economics, finance, environmental science, and healthcare for tasks like forecasting GDP, stock prices, climate data, and patient volumes. Its flexibility allows for the incorporation of multiple predictors, including lagged variables and external factors, while its interpretability provides insights into the relationships between variables.

Neural networks, specifically designed for time series forecasting, such as Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks, are capable of learning complex patterns in data. These models are advantageous for their ability to handle non-linear relationships and interactions between variables. Neural networks can model intricate dependencies in time series data, making them suitable for forecasting tasks where traditional methods might fail to capture underlying complexities [8]. The flexibility and adaptability of neural networks make them highly effective for large and complex datasets, including those with seasonality and trend components.

Several studies have analyzed the movements of oil and gas and non-oil and gas export-import values in Indonesia using various forecasting methods. Research by Sari and Wahyudi (2019) explored the use of the double moving average method to predict the export values of palm oil in Indonesia. Their study highlighted the method's effectiveness in smoothing short-term fluctuations and capturing underlying trends [9]. They found that double moving average provided a more stable trend line, which was crucial for making short-term export forecasts in the highly volatile agricultural sector [9]. Although their focus was on palm oil, the methodology and findings can be extended to other commodities, including migas and non-migas exports. Previous research on double exponential smoothing (DES), also known as Holt's linear trend model, has demonstrated its effectiveness across various applications. Studies have shown DES to be highly effective in forecasting electricity consumption, sales data, financial time series, and climate data by capturing linear trends and providing accurate short-term forecasts. For instance, research by Suyanto and Rahmawati effectively utilized DES to model electricity consumption trends [10].

On the other side, Sinaga, Sari, and Nurviana (2023) applied the Box-Jenkins method, a form of ARIMA, to predict the export-import movements of both oil and gas and non-oil and gas sectors [11]. Their findings demonstrated that ARIMA models could capture the intricate patterns and trends within the data, providing accurate forecasts over medium to long-term horizons [11].

Previous research on time series regression has demonstrated its utility in various fields. For example, a study analyzing the impact of oil and gas exports and imports on the Indonesian Rupiah exchange rate from 1980 to 2020 found that imports had a significant effect on the exchange rate, while exports and inflation did not [12]. Similarly, research has applied time series regression to explore the relationship between climatic variables and dengue fever incidence, the impact of air pollution on respiratory health, macroeconomic forecasting, and the effect of climate variability on agriculture [12]. Junita and Kartikasari (2024) applied the Neural Network Autoregressive (NNAR) method to forecast the value of oil and gas exports in Indonesia. Their study found that the NNAR method, which does not assume normality of residuals, effectively captured the trends and provided accurate forecasts, with the NNAR (2,3) model achieving a MAPE value of 11.75640% [13].

The export-import activities of oil and gas and non-oil and gas sectors are subject to various internal and external factors. Internal factors include domestic production capacity, technological advancements, and government policies, while external factors encompass global commodity prices, international trade agreements, and currency exchange rates. Therefore, this research aims to analyze the trends and patterns in the export-import values of oil and gas and non-oil and gas commodities in Indonesia from 1975 to 2023.

II. METHODOLOGY

A. *Dataset*

The data used in this research are export-import values of both oil and gas and non-oil and gas commodities in

Indonesia. The data spans a considerable period, ranging from 1975 to 2023, providing a comprehensive overview of the country's trade activities over several decades. This extensive dataset has been sourced from the Badan Pusat Statistik, which is the central agency responsible for collecting and disseminating statistical data in Indonesia.

B. Naïve Method

Naïve forecasting methods is a simple forecasting method where the forecast for the next period is set to be equal to the last observed value. This method works well for time series that follow a random walk pattern. Two commonly used naïve methods are the naïve additive and naïve multiplicative models.

- Naïve additive model : This method assumes that the future value of a time series is equal to the current value plus a constant. The formula for naïve additive model is :

$$\hat{Y}_{t+1} = Y_t + (Y_t - Y_{t-1})$$

- Naïve multiplicative model : Unlike the additive model, the multiplicative model assumes that the future value of a time series is equal to the current value multiplied by a constant factor. The formula for naïve multiplicative model is :

$$\hat{Y}_{t+1} = Y_t \frac{Y_t}{Y_{t-1}}$$

C. Double Moving Average

The double moving average method is an advanced smoothing technique used in time series forecasting to reduce the noise and highlight the underlying trends in data. Double moving average method involves calculating both short-term and long-term moving averages. Unlike the simple moving average, which uses a single set of averages, the double moving average method applies the moving average technique twice, thus providing a smoother and more refined trend line.

The formula for double moving average is :

$$M_t = \hat{Y}_{t+1} = \frac{(Y_t + Y_{t-1} + \cdots + Y_{t-n+1})}{n}$$

$$M_t{}' = \frac{(M_t + M_{t-1} + \cdots + M_{t-n+1})}{n}$$

$$a_t = 2M_t - M_t{}'$$

$$b_t = \frac{2}{n-1}(M_t - M_t{}')$$

$$\hat{Y}_{t+p} = a_t + b_t p$$

D. Double Exponential Smoothing

Double exponential smoothing, also known as Holt's linear trend model, is a sophisticated time series forecasting technique that extends the simple exponential smoothing method by considering both the level and the trend of the data. This method is particularly useful for data with a trend component, allowing for more accurate and responsive forecasts. . The equations used are :

$$A_t = \alpha Y_t + (1-\alpha)(A_{t-1} + T_{t-1})$$

$$T_t = \beta (A_t - A_{t-1}) + (1-\beta)T_{t-1}$$

$$\hat{Y}_{t+p} = A_t + pT_t$$

E. ARIMA (Autoregressive Integrated Moving Average)

The Autoregressive Integrated Moving Average (ARIMA) method is a widely used statistical technique for time series forecasting. ARIMA models are particularly powerful because they can capture various components of a time series, such as trend, seasonality, and cycles, making them suitable for a wide range of forecasting applications.

ARIMA models capture various structures in the data through three components, autoregression (AR), differencing (I), and moving average (MA). The ARIMA model is specified as ARIMA(p,d,q) where :

- p is the number of lag observations
- d is the degree of differencing
- q is the size of the moving average window

The general form of the ARIMA model is :

$$\phi_p(B)(1-B)^d Z_t = \theta_0 + \theta_q(B)a_t$$

where :

$$\phi_p(B) = 1 - \phi_1(B) - \cdots - \phi_p B^p$$

$$\theta_q(B) = 1 - \theta_1(B) - \cdots - \theta_q B^q$$

F. Time Series Regression

Time series regression is a method used to model and predict the behavior of variables over time. Unlike traditional regression models that assume the data points are independent, time series regression models take into account the temporal ordering of the data, making them suitable for analyzing data that evolves over time. This method explicitly considers the sequential order of observations, allowing the value of a variable at a certain time to depend on its previous values.

A basic time series regression model can be expressed as :

$$Y_t = \beta_0 + \beta_1 X_{t-1} + \beta_2 Y_{t-1} + \epsilon_t$$

where :

- Y_t is the dependent variable at time t
- X_{t-1} is the independent variable at time t-1
- Y_{t-1} is the lagged value of the of the dependent variable
- $\beta_0, \beta_1, \beta_2$ are the coefficients to be estimated
- ϵ_t is the error term

G. *Neural Networks*

Neural networks, particularly Long Short-Term Memory (LSTM) networks, are used for capturing non-linear relationships and complex dependencies. Neural networks are a class of machine learning models inspired by the human brain's structure and function. The architecture of LSTM is designed to remember information for long periods, making it suitable for time series forecasting. The neural network model is trained using historical data to learn patterns and make future predictions. These models are particularly effective in handling complex and nonlinear relationships in data, making them a powerful tool for time series forecasting.

Neural networks consist of interconnected layers of nodes, or neurons. Each neuron processes input data and passes it through an activation function to produce an output. The basic structure includes an input layer, one or more hidden layers, and an output layer.

III. Evaluation Metrics

In time series forecasting, evaluating the accuracy and reliability of predictive models is crucial. Two widely used metrics for assessing the performance of forecasting models are Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). These metrics provide insights into the model's predictive accuracy and its ability to generalize to unseen data.

A. *Root Mean Squared Error (RMSE)*

RMSE is a standard measure of the average magnitude of forecasting errors. RMSE places a higher weight on larger errors due to the squaring of differences, making it particularly useful for identifying models that may have significant errors in certain predictions. It is calculated by taking the square root of the average of the squared differences between predicted and actual values. The formula for RMSE is :

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (F_i - A_i)^2}$$

where :

- F_i represents the forecasted value at time i
- A_i represents the actual value at time i
- n is the number of observations

B. *Mean Absolute Percentage Error (MAPE)*

MAPE is another widely used metric that expresses forecasting errors as a percentage. It measures the average absolute percentage difference between predicted and actual values. The formula for MAPE is :

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{A_i - F_i}{A_i} \right| x\ 100$$

where :

- F_i represents the forecasted value at time i
- A_i represents the actual value at time i
- n is the number of observations

IV. Results and Discussions

Evaluation metrics, such as Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE), play a crucial role in assessing the performance of forecasting models developed using the dataset. These metrics provide quantitative measures that reflect the accuracy and reliability of the models' predictions.

A. *Naïve Model*

The naïve model makes forecasts based solely on historical data without the use of any sophisticated statistical or machine learning techniques. There are two primary variants of the naïve model for trend data, namely additive and multiplicative. The performance of this model is evaluated and compared with other forecasting techniques using key metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE).

Table 1. Comparison of Naïve Additive and Multiplicative Model

	Naïve (Additive)		**Naïve (Multiplicative)**	
	Training	Testing	**Training**	**Testing**
RMSE	5575.693	77460.191	**6178.095**	**75314.786**
MAPE	11.093	31.283	**11.778**	**30.181**

From the table, it is evident that both models exhibit a significant increase in error when transitioning from training to testing data, which indicates a potential issue with model generalization. Specifically, the naïve additive model has a training RMSE of 5575.693 and a training MAPE of 11.093%, but these values increase drastically on the testing data to an RMSE of 77460.191 and a MAPE of 31.283%. This significant rise in error metrics highlights the model's poor performance.

On the other hand, the naïve multiplicative model shows relatively better performance in terms of RMSE and MAPE on the testing data. The training RMSE for the naïve multiplicative model is 6178.095 and the training MAPE is 11.778%. On the testing data, the RMSE increases to 75314.786 and the MAPE to 30.181%. This suggests that while both models struggle with generalization, the naïve multiplicative model might be a slightly better choice for prediction accuracy in this context.

B. Double Moving Average Model

The double moving average model is an extension of the simple moving average technique, used in time series forecasting to smooth out short-term fluctuations and highlight longer-term trends or cycles. The double moving average is calculated by first computing the moving average of the original time series data and then applying another moving average to the resulting smoothed series. The performance of this model is evaluated and compared with other forecasting techniques using key metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE).

Table 2. Comparison of Double Moving Average Model

	n = 2		n = 3		n = 4		n = 5		n = 6		n = 7	
	Training	**Testing**	Training	Testing	Training	Testing	Training	Testing	Training	Testing	Training	Testing
RMSE	**5786.016**	**45316.719**	6331.611	41248.095	7090.072	66191.054	7975.629	78273.667	8571.394	79624.768	9226.089	86622.717
MAPE	**13.935**	**19.479**	14.484	23.707	18.126	48.225	20.733	64.569	20.826	66.326	21.500	77.873

From the table, it is clear that as the period n increases, both the RMSE and MAPE generally increase for both training and testing datasets. This suggests that increasing the period leads to poorer model performance and higher prediction errors.

For example, with n = 2, the Double Moving Average model achieves an RMSE of 5786.016 and a MAPE of 13.935% on the training data, and an RMSE of 45316.719 and a MAPE of 19.479% on the testing data. This indicates relatively low percentage errors. When the period increases to n = 3, the training RMSE rises to 6331.611 and the MAPE to 14.484%, while the testing RMSE increases to 41248.095 and the MAPE to 23.707%. This indicates that the errors have increased slightly. With n = 4, the training RMSE further increases to 7090.072 and the MAPE to 18.126%, while the testing RMSE and MAPE rise significantly to 66191.054 and 48.225%. This shows that with much higher error metrics indicating poorer forecasting accuracy. At n = 5, the training RMSE and MAPE continue to increase to 7975.629 and 20.733%, while the testing RMSE and MAPE rise to 75273.667 and 64.569%. This trend indicates that larger periods result in even higher errors.

With n = 6, the training RMSE is 8571.394 and the MAPE is 20.826%, while the testing RMSE and MAPE are 79624.768 and 66.326%. This shows that the errors continue to escalate. Finally, at n = 7, the training RMSE reaches 9226.089 and the MAPE 21.500%, with the testing RMSE and MAPE at 86622.717 and 77.873%. These values show the highest errors among the periods evaluated.

The best performance in terms of RMSE and MAPE for both training and testing datasets is observed at n = 2, making it the most optimal period among the ones evaluated. This indicates that smaller periods in the double moving average model provide better smoothing and forecasting accuracy.

C. Double Exponential Smoothing Model

The double exponential smoothing model is used to forecast future values based on historical data. The model's performance is evaluated and compared with other forecasting techniques using key metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE).

Table 3. Comparison of Double Exponential Smoothing Model

	α = 0.2 & β = 0.6		α = 0.3 & β = 0.7	
	Training	Testing	Training	Testing
RMSE	9873.381	50453.558	8034.095	41283.311
MAPE	31.911	30.545	22.075	18.777

	α = 0.4 & β = 0.8		α = 0.8 & β = 0.4	
	Training	Testing	Training	Testing
RMSE	6244.985	64760.855	5212.463	44264.174
MAPE	16.129	21.518	12.229	17.232

	α = 0.7 & β = 0.3		α = 0.6 & β = 0.2	
	Training	**Testing**	Training	Testing
RMSE	**5564.646**	**33954.117**	6031.795	39494.701
MAPE	**12.951**	**16.196**	14.694	20.187

The table shows that the performance of the double exponential smoothing model varies significantly with different combinations of smoothing parameters (α and β). The combination of α = 0.2 and β = 0.6 achieves an RMSE of 9873.381 and a MAPE of 31.911% on the training data, but these values increase substantially to 50453.558 and 30.545%, respectively, on the testing data. This indicates that the model has a significant error magnitude and percentage error when applied to unseen data. When the parameters are adjusted to α = 0.3 and β = 0.7, the RMSE on the training data improves to 8034.095, and the MAPE decreases to 22.075%. The testing data shows an RMSE of 41283.311 and a MAPE of 18.777%, indicating some improvement in performance.

With α = 0.4 and β = 0.8, the training RMSE further decreases to 6244.985 and the MAPE to 16.129%. However, the testing RMSE and MAPE rise to 64760.855 and 21.518%. In other side, the combination of α = 0.8 and β = 0.4 results in a training RMSE of 5212.463 and a MAPE of 12.229%. The testing performance also improves, with an RMSE of 44264.174 and a MAPE of 17.232%.

The optimal performance is observed with α = 0.7 and β = 0.3, where the model achieves the lowest RMSE and MAPE values on the testing data, specifically 33954.117 and 16.196%. The training RMSE is 5564.646, and the MAPE is 12.951%, indicating good predictive accuracy.

D. ARIMA Model

The ARIMA model is employed to forecast future values based on historical data. The performance of the ARIMA model is evaluated and compared with other forecasting techniques using key metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE).

Table 4. Comparison of ARIMA Model

	ARIMA (0, 1, 1)		ARIMA (0, 2, 1)	
	Training	Testing	Training	Testing
RMSE	4651.86	68598.99	4816.49	70966.802
MAPE	3183.38	56247.57	10.15	142.44
White Noise	Yes		Yes	
Normally Distributed	Yes		Yes	

The ARIMA (0, 2, 1) model has a higher RMSE but a significantly lower MAPE compared to the ARIMA (0, 1, 1) model. This suggests that while the absolute errors are slightly larger, the relative percentage errors are much smaller in the training data for the ARIMA (0, 2, 1) model. Specifically, the RMSE for the ARIMA (0, 2, 1) model is 4816.49 on the training data and 70966.802 on the testing data, whereas the RMSE for the ARIMA (0, 1, 1) model is 4651.86 on the training data and 68598.99 on the testing data. This indicates that the ARIMA (0, 2, 1) model has slightly higher errors in both training and testing phases in terms of RMSE. Both models show a considerable increase in RMSE and MAPE for the testing data, indicating poor generalization and high prediction errors on unseen data. However, the ARIMA (0, 2, 1) model exhibits a lower MAPE compared to the ARIMA (0, 1, 1) model, suggesting relatively better performance in terms of percentage error, despite the high RMSE.

Both models pass the diagnostic checks for normality of residuals. The residuals from both ARIMA models are independently distributed and follow a normal distribution. But, the residuals from both models do not pass the diagnostic check for white noise because both models are white noise.

In conclusion, although the ARIMA (0, 2, 1) model shows better performance in terms of percentage error (MAPE), both models demonstrate high prediction errors on testing data. And even though both models pass the diagnostic check for normality of residuals, both ARIMA (0, 1, 1) and ARIMA (0, 2, 1) do not meet the white noise assumption test so they cannot be used as final predictive models.

E. Time Series Regression Model

Time series regression models are powerful tools used to analyze and predict future values based on historical time series data. The performance of these models is evaluated using key metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE).

Table 5. Evaluation Metrics of Time Series Regression Model

	Time Series Regression	
	Training	Testing
RMSE	8877.481	94691.536
MAPE	27.866	99.545

The results reveal a significant discrepancy between the training and testing performances of the Time Series Regression model. While the model demonstrates moderate accuracy on the training data, as indicated by the RMSE of 8877.481 and MAPE of 27.866%, its performance on the testing data is substantially worse. The testing RMSE of 94691.536 and MAPE of 99.545% indicate that the model's predictions are highly inaccurate on the testing data. This stark contrast suggests that although the model can reasonably fit the training dataset.

The RMSE of 8877.481 on the training set implies that the model's average prediction error is relatively low when applied to the data it was trained on. Similarly, the training MAPE of 27.866% indicates that the model's predictions on the training data deviate from the actual values by an average of 27.866%, which is a moderate error rate. However, the drastic increase in RMSE to 94691.536 for the testing data highlights that the model's average error increases significantly when it attempts to predict new data, suggesting that the model may have overfitted to the training data.

F. Neural Network Model

The neural network model is employed to forecast future values based on historical data. The performance of the neural network model is evaluated and compared with other forecasting techniques using key metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE).

Table 6. Evaluation Metrics of Neural Network Model

	Neural Network	
	Training	Testing
RMSE	1460.139	88412.155
MAPE	4.034	111.955

The results indicate a stark contrast between the training and testing performances of the neural network model. While the model exhibits excellent accuracy on the training data, as evidenced by the low RMSE and MAPE values of 1460.139 and 4.034%, respectively, its performance on the testing data is poor. The significant increase in both RMSE and MAPE for the testing data, with values soaring to 88412.155 and 111.955%, respectively, suggests that the model is overfitting. This overfitting means that the model is capturing noise and patterns specific to the training dataset that do not generalize to new, unseen data.

The training RMSE of 1460.139 indicates that the model's predictions are very close to the actual values in the training dataset. Similarly, the training MAPE of 4.034% shows that, on average, the model's predictions deviate from the actual values by only 4.034%, which reflects high predictive accuracy during the training phase. However, when applied to the testing data, the RMSE drastically increases to 88412.155, indicating a much higher average prediction error. Moreover, the MAPE on the testing data rises to 111.955%, indicating that the model's predictions deviate from the actual values by more than 100% on average.

G. Comparison of All Models

The best model is identified as the one with the lowest values in both Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). Therefore, a comparison will be made between all methods to evaluate the best model.

This comparison aims to systematically assess each model's predictive accuracy and reliability by analyzing their respective RMSE and MAPE values

Table 7. Comparison of All Models

	Testing	
	RMSE	MAPE
Naïve (Multiplicative)	75314.786	30.181
Double Moving Average (n = 2)	45316.719	19.479
Double Exponential Smoothing (α = 0.7 & β = 0.3)	**33954.117**	**16.196**
Time Series Regression	94691.536	99.545
Neural Network	88412.155	111.955

The Double Exponential Smoothing model with parameters α = 0.7 & β = 0.3 significantly outperforms all other models examined in this study in terms of both Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). This model demonstrates the highest level of accuracy and exhibits the smallest prediction errors on the testing data, as evidenced by the lowest values recorded in both evaluation metrics.

Furthermore, the Double Moving Average model with n = 2 also performs well, showing significantly lower RMSE and MAPE values compared to the Naïve (Multiplicative) model. This reduction in error metrics suggests that the Double Moving Average model is more effective in capturing the underlying trends present in the time series data.

The Time Series Regression model, however, demonstrates a considerably higher RMSE of 94691.536 and a MAPE of 99.545% on the testing data, indicating that the model's predictions are highly inaccurate when applied to new, unseen data. This poor performance suggests that the model has significant overfitting issues.

The Neural Network model exhibits the highest RMSE and MAPE values among all the models analyzed. This indicates that the Neural Network model performs poorly, both in terms of error magnitude and percentage accuracy. This suggests that the model may be overfitting the training data or is not well-tuned for specific task of forecasting export-import values.

Meanwhile, the Naïve (Multiplicative) model, although straightforward and simple to implement, demonstrates higher error metrics when compared to the Double Moving Average and Double Exponential Smoothing models. This indicates its limited effectiveness in capturing the complexities inherent in the time series data.

V. Conclusion

This study aimed to evaluate and compare the performance of various time series forecasting models for predicting the export-import values of oil and gas and non-oil and gas commodities in Indonesia. The models assessed in this research include Naïve (Multiplicative), Double Moving Average, Double Exponential Smoothing, ARIMA, Time Series Regression and Neural Networks. To measure the performance and accuracy of these models, evaluation metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) were utilized.

The findings from the comparative analysis indicate that the Double Exponential Smoothing model with parameters α = 0.7 and β = 0.3 demonstrated the best performance across all metrics, achieving the lowest RMSE and MAPE values. This suggests that it provides the most accurate and reliable forecasts among the models evaluated. The Double Moving Average model with n = 2 also showed significant improvement over the Naïve model, with lower RMSE and MAPE values, indicating better accuracy and a stronger ability to capture underlying trends in the data.

Based on the results obtained, several recommendations can be made for future research to enhance the performance of forecasting models. Firstly, further optimization and tuning of the Neural Network model could enhance its performance. Techniques such as cross-validation, regularization, and hyperparameter tuning should be explored. Secondly, investigating hybrid models that combine the strengths of different forecasting methods could provide more robust and accurate predictions. For example, integrating ARIMA with Neural Networks or Exponential Smoothing techniques could yield better results. Thirdly, incorporating additional relevant features into the forecasting models, such as economic indicators, seasonal variables, or external factors, could improve their accuracy and reliability.

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