Forecasting Non-Oil and Gas Exports in Indonesia Using Double and Triple Exponential Smoothing Methods

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ABSTRACT

Non-oil and gas exports could be forecasted using exponential smoothing for future periods. This study examines non-oil and gas export data in Indonesia from January 2015 to May 2021, indicating trends and seasonality. Based on the data characteristics, the obtained data were analyzed using Holt's double exponential smoothing method and triple exponential smoothing with multiplicative and additives Holt-Winters. The MAPE for all three models is less than 10%, indicating that the method is very good and could be used to forecast the next period. Using MAPE as a comparison, the best model for non-oil and gas exports is the additive Holt-Winters method triple exponential smoothing, which has the lowest MAPE of any model. The best method was employed to forecast data, making it possible for us to anticipate the pattern of non-oil and gas exports. This forecast data could be used as the basis for policymakers' decision-making. The forecast results using this method indicate that the value of non-oil exports will increase for the next period.

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1. INTRODUCTION

The Manufacturing Industry is still one of the largest contributing sectors to Indonesia's Gross Domestic Product (GDP). In the third quarter of 2021, the role of the processing industry was recorded at 19.86%, whereas the role of the non-oil and gas processing industry was 17.90% of the national GDP. The non-oil and gas processing industry's trading performance in 2021 indicates significant growth. This is evident in the processing industry's surplus value from January to October 2021, which increased by 69.07% compared to the same period in 2020. Between January and October 2021, BPS data showed a processing industry surplus of US $ 19.77 billion. This was driven by a strong increase in exports from January to October 2021, when non-oil and gas processing industry exports grew 35.53% over the same period in 2020. Given this, it is critical to conduct an analyzes of total non-oil and gas export so that the government can get an understanding of the present circumstances of total non-oil and gas export. (Kementerian Perindustrian Republik Indonesia, 2021).

Non-oil and gas exports contribute to Indonesia's economic growth in international trade. Non-oil and gas exports fell by 10.67 percent in May 2021 compared to April 2021 (Badan Pusat Statistik, 2021). In the January-December 2021 period, it increased by 41.52 percent to US$219.27 billion over the same period in 2020, while total Indonesian exports increased by 41.88 percent to US$231,54 billion. Non-oil and gas exports from the processing industry increased by 35.11 percent from January to December 2021 compared to the same period in 2020, whilst also agricultural exports raised 2.86 percent, and mining and other exports enhanced 92.15

percent (Badan Pusat Statistik, 2022).

This fluctuation in total trade can be predicted using time series analyzes, making it possible decision makers to devise the best policies to increase export growth. A time series data analyzes can be chosen by considering the types of data patterns to be processed, such as horizontal, cyclical, trend, or seasonal patterns. One of the most widely used methods is the Holt–Winters exponential smoothing, which has two algorithmic methods, multiplicative and additive Holt–Winters. The purpose of this research is to forecast the outcomes of non-oil exports using Holt-Winters Exponential Smoothing. The forecast results can be used to advise the government's decision on non-oil and gas exports.

Previous research using several exponential smoothing methods was applied to forecast real palm oil production from 2010 to 2014. This data has both trend and seasonal elements. The results demonstrate that a triple exponential smoothing additive can better forecast palm oil real production than other models (Siregar et al., 2017).

Time series analyzes using additive and multiplicative methods was used in another study to forecast Brazilian natural gas production. It was determined that the multiplicative method performed well (Ribeiro, 2019). In research for the export value of East Borneo Province, Forecasted export values using the Holt Double Exponential Smoothing, additive Holt-Winter Triple Exponential Smoothing, and multiplicative Holt-Winter Triple Exponential Smoothing with golden part optimization method had a MAPE about less than 10%, indicating that the prediction was excellent (Andriani et al., 2022).

2. LITERATURE REVIEW

Forecasting is a significant issue that affects many fields. The time series method is one of the quantitative forecasting methods. Time series analyzes is the process of retrieving relevant summary and statistical information from points that are ordered chronologically. It is used to both diagnose past behavior and forecast future behavior (Nielsen, 2020).

A time series is a sequential or time-oriented series of observations on a variable of interest (Montgomery et al., 2008). A time series on some variable x is generally symbolized by x_t, in which the subscript t represents time. The observation period refers to the entire set of times t = 1, 2, …, T, where T is the last period.

The goal of time series analyzes is commonly important for two reasons: to acknowledge or model the stochastic mechanism that produces an observed series and to predict or forecast the future values of that series based on its history and possibly other related series or factors (Cryer & Chan, 2008). Because time series observations are inherently dependent or correlated, the order of the observations is essential (Wei, 2006). Variables that are collected during a time series over a specific period of time, such as seconds, minutes, hours, days, weeks, months, or years, are examples of time series data (Rosadi, 2014). Because the observations are typically measured at equal intervals, the order in which they arrive is crucial (Mills, 2019).

Forecasting is commonly classified as short-term, medium-term, and long-term forecasting. Short-term forecasting entails predicting events that occur only in the future (days, weeks, months). Medium-term forecasting covers one to two years ahead, while long-term forecasting can be more than the next several years (Ahmar et al., 2022; Montgomery et al., 2015). Time series data is classified into four types (Hoarau, 2022):

1. univariate time series data,
2. continuous multivariate data,
3. event-based multivariate data, and
4. multiple time series data.

The time series analyzes is chosen based on the data patterns, which can be horizontal, seasonal, cyclical, or trend (Makridakis et al., 1999). Besides, the main assumption in time series is stationarity. The basic concept of stationarity is that the probability laws that govern the process's behavior do not change over time (Cryer & Chan, 2008).

Stationary data could be visualized visually using time series plots or tested using the Augmented Dickey-Fuller (ADF) test. Using the τ test statistic, this ADF test attempts to determine whether the coefficient of the Autogerresive (AR) model has a value of one or not (Wei, 2006). After testing whether a data set is stationary or not, and if it is not, what form of nonstationarity it exhibits (Mills, 2019).

One form of time series analyzes is exponential smoothing, which is a moving average forecasting technique that is weighted by exponentially averaging past data values from time series data (Makridakis et al., 1999). In other words, exponential smoothing refers to a broad class of forecasting procedures that use simple updating equations to generate forecasts (Chatfield & Xing, 2019). There are three types of forecasting in this analyzes: single, double, and triple exponential smoothing. The single exponential smoothing method is a short-term forecasting technique that can be used to forecast time series data that lacks trend or seasonality.

The double exponential smooth is forecasting data with a trend component. Holt created this method by combining two smoothing constants, α and β. Using different weights, the trend's value can be smoothed. However, because these two parameters must be optimized, selecting the best parameter combination is more difficult than using only one parameter (Siregar et al., 2017).

Holt and Winters proposed the triple exponential smoothing method, which can be applied to data with the trend and seasonal elements (Makridakis et al., 1999). The Holt-Winters method employs three equations, namely initial smoothing, trend smoothing, and seasonal smoothing, with three smoothing constants, namely, α, β, and γ (Hyndman & Athanasopoulos, 2014).

As previously stated, this method is much better than simple exponential smoothing at tracking time series with trend and/or seasonality. Holt-Winters forecasting has additive and multiplicative versions, similar to decomposition and seasonal adjustment (Woodward et al., 2015). Fitting both additive and multiplicative models and selecting the best model based on model adequacy checks is recommended. The model gives more weight to recent values while giving less weight to values from the distant past (Emmanuel et al., 2014).

Following the calculation of several exponential smoothing methods, the forecasting error is measured in order to select the best model. The model with the lowest forecast error may be the best for time series forecasting (Ramadania, 2018). One of them can use the Mean Absolute Percentage Error (MAPE) to measure the accuracy of the forecast value, which is expressed as the average absolute percentage of forecasting error (Illukkumbura, 2021). MAPE can be used to assess the accuracy of different forecasting models. A good forecasting model has a lower MAPE (Chang et al., 2007). The following are the MAPE criteria:

1. MAPE < 10 %: Excellent
2. 10% < MAPE < 20 %: Good
3. 20% < MAPE < 50 %: Reasonable
4. MAPE > 50 %: Bad

3. METHODOLOGY

3.1. Data

The variable used in this study is secondary from the Central Bureau of Statistics, namely the Value of Export non-oil and gas (Million US$) (BPS-Statistics) in January 2015 – May 2021.

3.2. Research steps

The following are the steps taken in this study:

1. Initialization: The collecting and cleaning of data.
2. Create time series plots to identify data patterns using R software.
3. The Augmented Dickey-Fuller (ADF) testing to identify trend and seasonal patterns. The rejection criteria used if $\tau < \tau_{\alpha,n}$ with a value of $\tau_{\alpha,n}$ can be seen in the Dickey-Fuller table or p-value > α. τ is computed using Equation 1.
$$\tau = \frac{\hat{\phi} - 1}{SE(\hat{\phi})} \quad (1)$$
4. Determine the starting point of various exponential smoothing methods: α and β for double exponential smoothing and α, β, and γ for Triple Exponential smoothing.
5. Estimate the optimal smoothing constant for each method.
6. Determine the predicted value of double and triple exponential smoothing.
7. Select the best model by comparing the MAPEs of each model.
$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\frac{|x_t - F_t|}{x_t} \times 100\% \quad (2)$$
8. Forecasting value of non-oil and gas exports in Indonesia for the coming period.
9. Forecasting value of non-oil and gas exports in Indonesia for the coming period.
10. Interpret the Model to see the non-oil and gas exports in Indonesia.

4. RESULTS AND DISCUSSION

Figure 1 shows a time series plot of the value of non-oil and gas export (Million US$) data from January 2015 to May 2021.

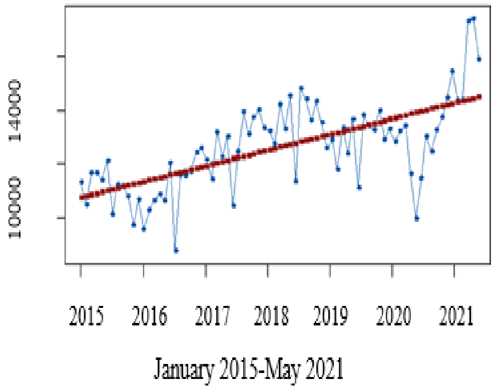

Figure 1. Time series plot of non-oil and gas export

Figure 1 shows that there is a seasonal pattern due to monthly fluctuations. The increasing fluctuation from the bottom left to the top right indicates the presence of a trend pattern. The graph indicates that the data is not stationary since it contains trend and seasonal patterns. This is coherent with the Augmented Dickey-Fuller (ADF) test results, which demonstrate that the data is not stationary at a 5% significance level.

Data with trend or seasonal elements can be analyzed using the double and triple exponential smoothing methods. In Holt, double exponential smoothing, α = 0.430444 and β = 0.21233, are obtained. Forecasting results are presented in Table 1. Forecasting values are pretty good and are not significantly different from actual values.

Table 1. Forecasting using Holt double exponential smoothing

Time	Forecast (Million US$)
January 2015	-
February 2015	-
March 2015	9552.9
April 2015	9778.3
May 2015	10077.9
⋮	⋮
January 2021	15120.5
February 2021	15168.0
March 2021	15118.3
April 2021	16616.1
May 2021	17587.7

There are two methods used in Triple Exponential smoothing: the multiplicative Holt-Winters method and the additive Holt-Winters method. The optimum smoothing for the multiplicative Holt-Winters method is. α = 0.4781801. β = 0.01871419 and γ = 1. with the Holt-Winters Additive method yielding values of α = 0.45243710. β = 0.02704478. and γ = 1. Table 2 reveals the multiplicative and additive Holt-Winters forecasting.

The forecasting results of the three methods differ. The model with the best forecast is chosen by comparing forecasting errors using MAPE. Table 3 shows the forecasting error calculation.

Table 2. Forecasting using the multiplicative and the additive Holt-Winters method

Time	Forecast (Million US$)
Multiplicative Holt-Winters method	
January 2016	9761.60
February 2016	10392.47
March 2016	10626.15
⋮	⋮
March 2021	14830.91
April 2021	14696.16
May 2021	15777.48
Additive Holt-Winters method	
January 2016	9788.97
February 2016	10402.49
March 2016	10631.93
⋮	⋮
March 2021	14799.81
April 2021	14860.28
May 2021	16127.17

Table 3. Forecasting errors calculation using MAPE

Methods	MAPE
Holt	8.31%
Multiplicative Holt-Winters	6.64%
Additive Holt-Winters	6.52%

Table 3 shows that MAPE in the additive Holt-Winters method has a lower forecasting error than other methods. This demonstrates that the model effectively forecasts future period data (MAPE < 10%). Table 4 shows the forecast for the value of non-oil and gas exports (Million US$) in Indonesia using the Holt-Winters additive method from June 2021-December 2021. Forecasting was obtained at 16762.83 (Million US$) in June, increased to 18484.24 (Million US$) in July, decreased slightly in August, and grew again in September. In general, forecasting is carried out following the initial pattern of actual data. Our data is the value of non-oil and gas export (Million US$) data from January 2015 to May 2021, which is why the forecast is also in Million US$ instead of the physical unit of oil and gas export.

Table 4. Forecasting using the best model for the period June 2021-December 2021

Months	Non-oil and gas exports (Million US$)
June	16762.83
July	18484.24
August	18172.38
September	18706.60
October	19129.55
November	19152.63
December	19369.61

Figure 2 shows actual and forecast data plots. The time series plot shows that the prediction results of the additive Holt-Winters method have increased over the next period. Forecasting data is only shown for the next seven months so that the model can accurately identify trends and seasonal features based on present conditions. The government can use the forecast results to make a non-oil and gas export policy.

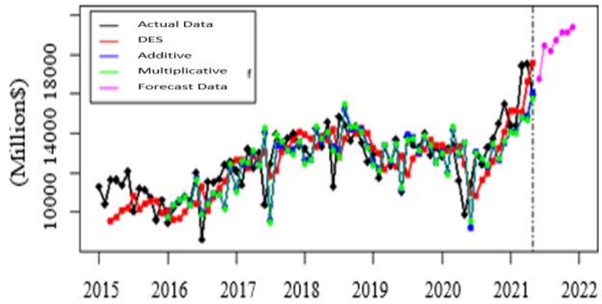

Figure 2. Actual and forecast data plots January 2015 – December 2021

Predictions indicate that the value of non-oil and gas exports will continue to grow until the end of the year. This also demonstrates that worldwide demand is high in accordance with the government's policy management. This also demonstrates that economic activity in this industry is very strong.

5. CONCLUSION

Based on the results and discussions, the additive Holt-Winters method has a lower MAPE (6.52%) than the other methods. The forecast results from this method indicate that the non-oil and gas exports would then rise in the coming period, from 16762.83 in June 2021 to 19369.61 in December 2021. Because this exponential smoothing analyzes employs weighted exponentially averaging, it would be preferable if the data used always included the most recent data in order to obtain more significant forecasting results in each period ahead.

REFERENCES

Ahmar, A. S., Fitmayanti, F., & Ruliana, R. (2022). Modeling inflation cases in South Sulawesi Province using single exponential smoothing and double exponential smoothing methods. *Quality and Quantity*, *56*(1), 227–237.

Andriani, N., Wahyuningsih, S., & Siringoringo, M. (2022). Application of Double Exponential Smoothing Holt and Triple Exponential Smoothing Holt-Winter with Golden Section Optimization to Forecast Export Value of East Borneo Province. *Jurnal Matematika, Statistika, & Komputasi*, *18*(3), 475–483.

Badan Pusat Statistik. (2021). *Perkembangan Ekspor dan Impor Indonesia Mei 2021* (Issue 44).

Badan Pusat Statistik. (December, 2022). *Perkembangan Ekspor dan Impor Indonesia* (Issue 05).

Chang, P. C., Wang, Y. W., & Liu, C. H. (2007). The development of a weighted evolving fuzzy neural network for PCB sales forecasting. *Expert Systems with Applications*, *32*(1), 1–11.

Chatfield, C., & Xing, H. (2019). *The analysis of time series: An introduction with R (7th ed)*. CRC Press.

Cryer, J. D., & Chan, K.-S. (2008). *Time Series Analysis* *with Application in R (2nd ed)*. Springer.

Emmanuel, O. O., Adebanji, A., & Labeodan, O. (2014). Using Holt Winter's Multiplicative Model to Forecast Assisted Childbirths at the Teaching Hospital in Ashanti Region, Ghana. *Journal of Biology, Agriculture and Healthcare, 4*(9), 83-88.

Hoarau, M. (2022). *Time Series Analysis on AWS*. Packt Publishing.

Hyndman, R. J., & Athanasopoulos, G. (2014). *Forecasting: Principles and practice*. OTexts.

Illukkumbura, A. (2021). *Introduction to Time Series Analysis*. Anusha Books

Kementerian Perindustrian Republik Indonesia. (2021). *Laporan Informasi 2021*. Kementerian Perindustrian Republik Indonesia. https://kemenperin.go.id/download/27418/Laporan-Informasi-Industri-2021

Makridakis, S., Wheelwright, S. C., & McGee, V. E. (1999). *Metode dan aplikasi peramalan*. Erlangga.

Mills, T. C. (2019). *Applied time series analysis*. Elsevier.

Montgomery, D. C., Jennings, C. L., & Kulahci, M. (2008). *Introduction to Time Series Analysis and Forecasting*. Wiley.

Montgomery, D. C., Jennings, C. L., & Kulahci, M. (2015). *Introduction to Time Series Analysis and Forecasting (2nd ed).* Wiley.

Nielsen, A. (2020). *Practical Time Series: Prediction with Statistics & Machine Learning*. O'Reilly.

Ramadania, R. (2018). Peramalan harga beras bulanan di tingkat penggilingan dengan metode weighted moving average. *Buletin Ilmiah Matematika, Statistika Dan Terapannya (Bimaster), 7*(4), 329-334.

Ribeiro, R. C. M. (2019). Holt-Winters Forecasting for Brazilian Natural Gas Production. *International Journal of Innovation Education and Research*, *7*(6), 119-129.

Rosadi, D. (2014). *Analisis runtun waktu dan aplikasinya dengan R*. UGM Pres.

Siregar, B., Butar-Butar, I. A., Rahmat, R. F., Andayani, U., & Fahmi, F. (2017). Comparison of Exponential Smoothing Methods in Forecasting Palm Oil Real Production. *Journal of Physics: Conference Series, 801,* Article 012004.

Wei, W. W. S. (2006). *Time Series Analysis: Univariate and Multivariate Methods (2nd ed)*. Pearson.

Woodward, W. A., Sadler, B. P., & Robertson, S. D. (2015). *Time Series for Data Science*. CRC Press.

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