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Research Article

Forecasting the Export Unit Value Index in Indonesia Using the Single Input Transfer Function

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Abstract.
Export is one of the factors that increase the economic growth of a country. One measure of export activity that can describe economic growth in Indonesia is The Export Unit Value Index, which is an index that measures changes in the price of export commodities sold by residents of one country to residents of other countries. The purpose of this study is to predict the unit value index of exports in Indonesia using a single input transfer function model and to see the influence of the value of oil and gas and non-oil and gas exports on the unit value index of exports in Indonesia. The single input transfer function model is a model that describes the future forecast of a series (output series) obtained based on the past values of the output series and other time series (input series) that affect the output series. The results of this study obtained a transfer function model with the order (0,0,1) with a noise series following ARIMA (1,0,1). Based on this model, the export unit value index at time t is influenced by the unit value export index in the previous month and is influenced by the oil and gas and non-oil and gas export value in the same month. As indicated by its MAPE value of 4.89%, the forecast value does not diverge much from the actual value, which suggests that the transfer function model can be used to predict the export unit value index in Indonesia.

Keywords: forecasting, export unit value index, single input, transfer function

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1. INTRODUCTION

Export is one of the factors that can cause an increase in the economic growth of a country. Export is defined as an attempt to sell commodities to other countries by expecting payment in foreign currency [1]. One measure of export activity that can describe economic growth in Indonesia is the Export Unit Value Index, which is an index that measures changes in the price of export commodities sold by residents of one country to residents of other countries.

The export unit value index can describe the price development of export commodity groups. This index can also be referred to as the export price index. The benefit of the export unit value index is to calculate the Gross Domestic Product (GDP) on a fixed price basis. In addition, the export unit value index is also used to calculate the terms of trade by comparing the development of the export unit value index with the import unit value index [2].

The transfer function is a forecasting method that can be used for multivariate time series data. The single input transfer function is a transfer function model that describes that future forecasts of a time series (output series) are obtained based on past values of the time series itself and on another time series (input series) that affect the output series. Several studies that have used the single input transfer function method [3–7] concluded that this method is good to use because it produces a small MAPE value. Based on those results, this research uses the single input transfer function method to forecast the unit value index of exports. In addition, we want to know the effect of the value of oil and gas and non-oil and gas exports as an input series on the export unit value index as an output series.

2. RESEARCH METHOD

This study uses the index data of Indonesia's unit value of exports as the output series and the export value of oil and gas and non-oil and gas as the input series from January 2014 to October 2021. The data was obtained from the Central Statistics Agency and the Ministry's websites. The data used are 94 and are divided into 88 training data (from January 2014 to April 2021) and 6 testing data (from May 2021 to October 2021). Training data is used to create a transfer function model, while testing data is used to ensure that the model is accurate.

The steps of an analysis data in this research are as follows.

1. Check the data plot of the input series and output series

2. Check the stationarity of the data both on the mean and the variance. The Augmented Dickey-Fuller (ADF) test is used to determine the data's stationarity of mean, whereas lambda value from box-cox plot is used to determine the data's stationarity of variance. Differencing is used if the data is not stationary in the mean, and transformation is used if the data is not stationary in the variance.

3. Build a transfer function model with the following steps:

4. Build an ARIMA model for a stationary input data series [8].

$$\phi_p(B)(1-B)^d Z_t = \theta_q(B)\alpha_t (1)$$

where ϕ_p is the p-order autoregressive (AR) parameter, θ_q is the q-order moving average (MA) parameter, Z_t is observation value of t^{th} period, p is autoregressive order, q is the moving average order, d is the order of differencing, α_t is residue at t^{th} time, and B is the backshift operator.

1. Prewhitening the input series and the output series following the ARIMA model equation of the input series by replacing x_t to be y_t and α_t to be β_t.
2. Cross-correlation between the input series and the output series that have gone through the prewhitening process [9].

$$r_{\alpha\beta}(k) = \frac{c_{\alpha\beta(k)}}{S_\alpha S_\beta} (2)$$

where $r_{\alpha\beta}(k)$ is cross correlation sample between α_t and β_t on the k^{th} lag, $c_{\alpha\beta(k)}$ is cross covariance sample between α_t and β_t on the k^{th}lag, S_α and S_β are a standard deviation of the α_t and β_t series respectively.

1. Identify the values of b, s, and r from the cross-correlation plot [10].

The following criterias are to be used for determining the value of b, s, and r.

1. The value of b is determined based on the first significant lag in the cross-correlation plot.
2. The value of s is determined based on the lag of the cross-correlation plot before there is a decreasing pattern in the next lags.
3. The value of r is determined based on the significant lag after the first significant on the cross-correlation plot.
4. Identify the ARIMA model of the noise series (n_t).

$$\hat{n}_t = y_t - \hat{\upsilon}(B)\, x_t (3)$$

5. Estimate the new parameters of the transfer function model that has been merged by the noise series (n_t) [8].

$$y_t = \frac{\omega(B)}{\delta(B)} x_{t-b} + \frac{\theta_q(B)}{\phi_p(B)} \alpha_t (4)$$

6. Test the feasibility of the transfer function model. The transfer function test consists of a correlation test between the transfer function model residual and the input series after the prewhitening process and the transfer function model residual autocorrelation test. The model can be said to be feasible if there is no significant correlation on the residual of the model.

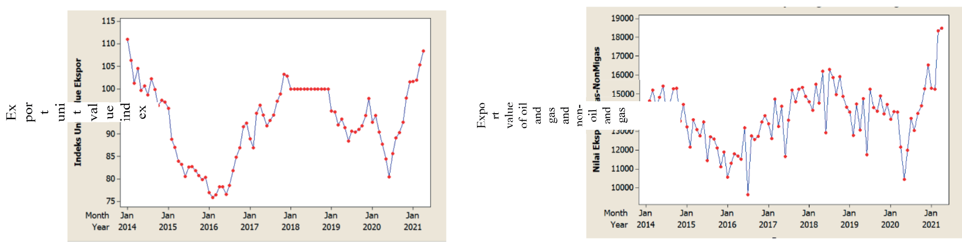
7. Forecasting the export unit value index on testing data using the best transfer function model. One measure of error that can be used is the Mean Absolute Percentage Error (MAPE). The formula of MAPE is as follows [10]

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{y_t - \hat{y}_t}{y_t} x\ 100\% (5)$$

where n, y_t, and $\hat{y}_t$ are amount of data, actual value of t^{th} period and the predicted value of t^{th} period respectively.

3. RESULTS AND DISCUSSION

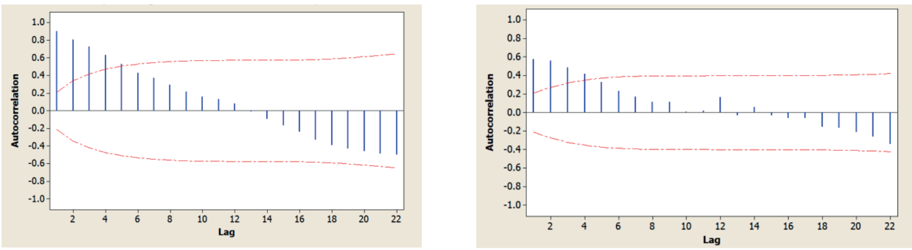
Checking the stationary of data is required before building a model. The export unit value index data plot in Fig. 1(a) shows that the data is non-stationary both in the mean and the variance. The export value of oil and gas and non-oil and gas data plotted in Fig. 1(b) also shows that the data is non-stationary both in the mean and the variance. Stationary time series can also be shown on both of the data's ACF plot that are shown in Fig. 1.



(a) (b)

Figure 1: (a) The export unit value index data plot as the output series, (b) The export value of oil and gas and non-oil and gas data plot as the input series.

Fig. 2 shows that the ACF plot of both of the data have lags that come out of the confidence line in the first lag then dies-down slowly, which means that the export unit value index data and the export value of oil and gas and non-oil and gas data in Indonesia are not stationary because they have a trend pattern. Then checking the lambda value from the box-cox plot is used to determine the data's stationarity of variance. From the box-cox plot of the export unit value index in Indonesia, the lambda



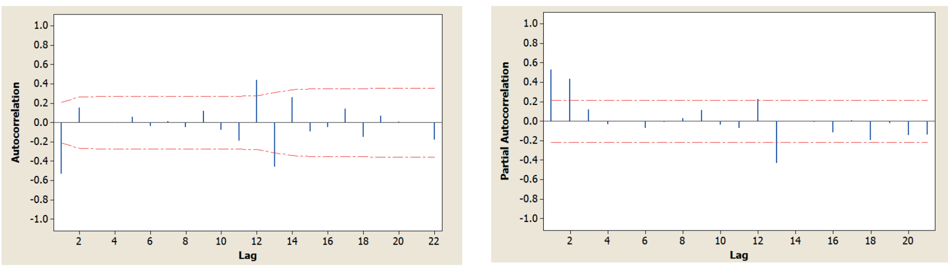
(a) (b)

Figure 2: (a) ACF plot of the export unit value index, (b) ACF plot of the export value of oil and gas and non-oil and gas.

is equal to 1, which means the export unit value index in Indonesia has been stationary in variance and there is no need to do a transformation. Meanwhile the lambda is equal to 2 for export value of oil and gas and non-oil and gas in Indonesia. It means that the export value of oil and gas and non-oil and gas data in Indonesia is not stationary in variance and needs to transform the data.

After once of the transformation process on the export value of oil and gas and non-oil and gas data, the lambda is equal 1, which means that the data is stationary in variance. The next step is checking the stationary in mean using ADF test. In the ADF test of the output series, the ADF test value equals 0.5468, which means that the data is not stationary yet in the mean. Also, in the ADF test of the input series, the ADF test value equals 0.8713, which means that the data is not stationary yet in the mean. Because the output and input series are not stationary yet in mean, it is necessary to do differencing on both of the data. The p-value of ADF test on the output and input series after once differencing is smaller than 0.05, it means that the data were stationary in mean.

The transfer function model starts from an ARIMA model of a stationary input series. The ARIMA model can be identified based on the ACF and PACF plots from the stationary input series data.



(a) (b)

Figure 3: (a) ACF plot of the export value of oil and gas and non-oil and gas after differencing, PACF plot of the export value of oil and gas and non-oil and gas after differencing.

Figure 3. shows that the ACF plot of input series data is significant at lag 1, meanwhile the PACF plot is significant at lag 1 and lag 2. Based on that plots, ARIMA model that can be selected for trial and error process is ARIMA (2,1,1), ARIMA (1,1,1), ARIMA (2,1,0), and ARIMA (0,1,2).

Table 1: Parameter estimates of ARIMA model for input series.

Model	Parameters	Coefficient	p-value	AIC
ARIMA (1,1,0)	Constant	1500181.2	0.5085	3256.42
	AR(1)	-0.52888	<0.0001	
ARIMA (1,1,1)	Constant	1320479.2	0.4698	3255.7
	AR(1)*	0.29895	0.1455	
	MA(1)*	-0.32666	0.0926	
ARIMA (2,1,0)	Constant	1350941.8	0.4691	3255.21
	AR(1)	-0.6372	<0.0001	
	AR(2)*	0.0291	0.0792	
ARIMA (0,1,2)	Constant	1429474.2	0.4746	3254.457
	MA(1)	0.66668	<0.0001	
	MA(2)	-0.25131	0.0291	

*Parameter is not significant at 0.05 level of significance

Table 1 shows that ARIMA models that have parameter estimates that are all significant are ARIMA (1,1,0) and ARIMA (0,1,2). Furthermore, the residuals of both models will be tested for diagnostic models using the Ljung-Box test. The Ljung-Box test for residuals of ARIMA (0,1,2) model has a p-value greater than 0.05 for the first 18 lag, so that the residual does not have an autocorrelation. Meanwhile, the residual of the ARIMA (1,1,0) model has a p-value less than 0.05, which means that the residual has an autocorrelation. The ARIMA (0,1,2) model can be written with the following equation,

$$(1-B)\,X_t = \left(1-\theta_1 B-\theta_2 B^2\right)\alpha_t$$

$$(1-B)\,X_t = (1-0.666B-0.2513B^2)\alpha_t + 1429474.2$$

$$X_t = X_{t-1} - \alpha_t - 0.666\alpha_{t-1} - 0.2513\alpha_{t-2} + 1429474.2(6)$$

The prewhitening procedure will begin after acquiring the proper ARIMA model, specifically ARIMA (0,1,2). The input series prewhitening model based on the ARIMA (0,1,2) model equation is

$$\alpha_t = X_{t-1} - X_t - 0.666\alpha_{t-1} - 0.2513\alpha_{t-2} + 1429474.2.(7)$$

Prewhitening of the input series is done in the same way as prewhitening of the input series. The export unit value index output series prewhitening model is as follows

$$\beta_t = Y_{t-1} - Y_t - 0.666\alpha_{t-1} - 0.2513\alpha_{t-2} + 1429474.2.(8)$$

Next, cross-correlation will be calculated. Cross correlation is calculated to determine how the input series can influence the output series. The result of the cross-correlation between α_t and β_t obtains a p-value smaller than 0.05, it indicates that there is a significant cross-correlation between α_t and β_t. Therefore, the transfer function model for the output series and the input series is feasible to build.

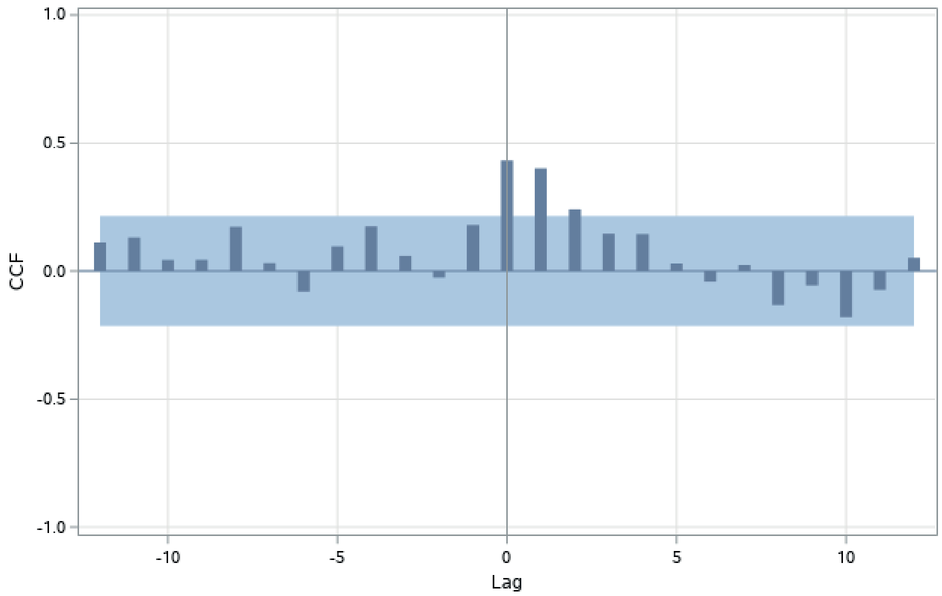


Figure 4: The cross-correlation plot between the output series and the input series.

The identification of the transfer function model is determined based on the cross-correlation plot between the input series and the output series that has been pre-whitened. The cross-correlation plot in Fig. 4 shows that the first significant lag is the 0^{th} lag so that the value of b is 0. The lag before the decreasing pattern occurs is the 0^{th} lag so that the value of s is 0. The value of r can be seen from the correlation plot of the stationary output series which shows a significant lag after the first significant lag, namely the lag that significant after the 0^{th} lag that is 1^{st} lag.

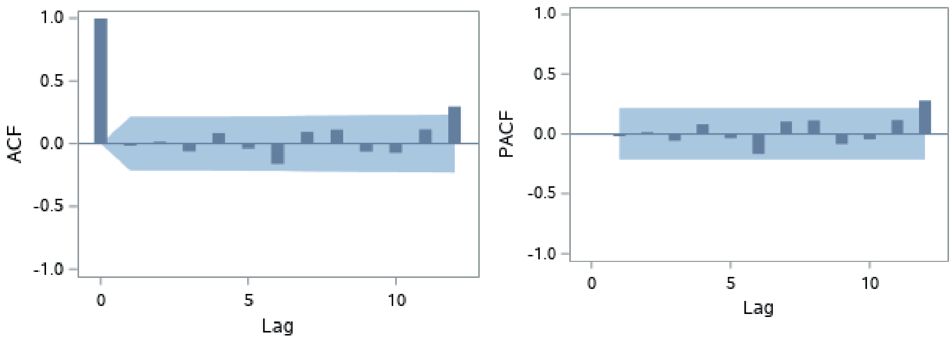
So it can be identified that the first function model is a model with values of b=0, s=0, and r=1 because the assumed parameter is significant. Based on calculations using SAS software, the parameter obtained that significant is $\omega_0 = 0.0000000845$, so the first transfer function model can be written as follows

$$Y_t = 0.0000000845X_t + \eta_t (9)$$

The first transfer function model is used to calculate the value of η_t. The calculation of the value is obtained by transforming the transfer function model so that the value of η_t is obtained with the following equation

$$\eta_t = Y_t - 0.0000000845X_t (10)$$

After obtaining the results of noise series, the ARIMA model identification for the noise series is done. Figure ?? shows the ACF plot of the noise series, while Fig. 5 shows the PACF plot of the noise series. Based on Fig. 5, ARIMA model that can be selected for trial and error process is ARIMA (1,0,0), ARIMA (0,0,1), and ARIMA(1,0,1). The results of the ARIMA model of noise series can be seen in Table 2.



(a) (b)

Figure 5: (a) ACF plot of noise series, (b) PACF plot of noise series.

Table 2: Identify the ARIMA model of noise series.

The ARIMA model of noise series	AIC
ARIMA(1,0,0)*	405.5004
ARIMA(0,0,1)*	438.2688
ARIMA(1,0,1)	403.9632

*There are parameters that are not significant at the 0.05

Based on Table 2, ARIMA(1,0,1) model is the best noise series ARIMA model because all the estimated parameter values are significant. The Ljung-Box test for residual of ARIMA (1,0,1) model has a p-value greater than 0.05 for the first 18 lag, so that the residual does not have an autocorrelation. Combining the first transfer function model with the noise series ARIMA model gets the final transfer function model with the following equation.

$$y_t = 0.000000045X_t + \frac{(1-0.25528B)}{(1-0.98664B)}\alpha_t$$

$$y_t = 0.9866y_{t-1} + 0.000000045X_t + \alpha_t - 0.9866\alpha_{t-1} + 66.9332 \quad (11)$$

The results of the feasibility test of the transfer function model show that there is no correlation between the residual of the transfer function model and the input series after prewhitening and there is no correlation between the residual of the transfer function model. Therefore, the model can be said to be feasible to use.

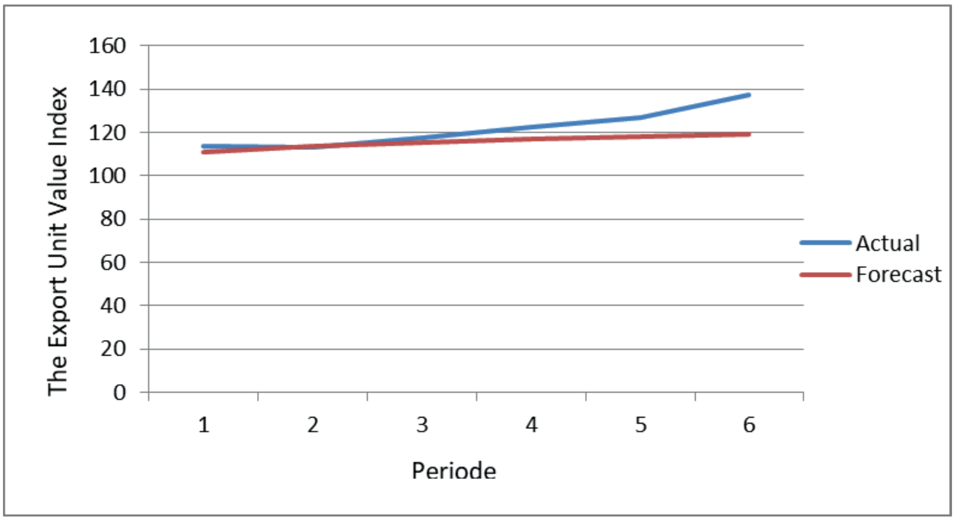


Figure 6: The actual value and the forecast value plot of the export unit value index in Indonesia.

Figure 6 shows that the forecast value with the single input transfer function model is not too much different from the actual value. Then, the forecasting accuracy value is calculated between the forecast value and the actual value using MAPE, and it was obtained of 4.89%, which means that the transfer function model is very good in predicting the unit value index of exports in Indonesia.

4. CONCLUSION

The transfer function model that is suitable to be used to predict the export unit value index is the transfer function model (0,0,1) with a noise series following the ARIMA (1,0,1) model. Based on this model, the export unit value index at t^{th} time is influenced by the export unit value index in the previous month and is influenced by the value of oil and gas and non-oil and gas exports in the same month. The resulting forecast value is not too much different from the actual value and the MAPE value is 4.89%, which means that the transfer function model is good at predicting the export unit value index in Indonesia.

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