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# Forecasting Model of Indonesia's Oil & Gas and Non-Oil & Gas Export Value using Var and LSTM Methods

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**ABSTRACT**

As a country with abundant natural resources in the form of mineral and non-mineral products, Indonesia is characterized by its ability to fulfill domestic and foreign needs through export activities categorized into two commodities: oil and gas and non-oil and gas. Export activities are an indicator of the country's economic growth that often fluctuates in value, and these conditions are fundamentally caused by a decrease in production quantity and the instability of the global economic climate. The strategy to overcome these problems is to create a forecasting model. This research aims to develop a forecasting model using time series analysis methods, including vector autoregressive (VAR) and long short-term memory (LSTM) methods based on oil and non-oil and gas value parameters. The results of the Granger causality test stated that the values of oil and gas and non-oil and gas affect each other. The VAR model with the optimum lag produced by the Akaike Information Criterion (AIC) test obtained an accuracy value of MAPE oil & gas and non-oil and gas of 18.4% and 32.1%, respectively. LSTM generates the best model with a MAPE value of 6,23% for oil & gas and 8,18% for non-oil and gas.

## INTRODUCTION

As a country with abundant resources, both in the mineral and non-mineral sectors, Indonesia is characterized by its ability to fulfill domestic needs and contribute to fulfilling the supply of foreign needs through export activities. Exporting is an economic activity selling domestic products to foreign markets [1]. Based on the type produced, Indonesia's export activities are divided into two commodities: oil and gas and non-oil and gas [2]. Oil and gas commodities are vital for the national economy, consisting of oil and gas and their derivatives [3]. Non-oil and gas commodities are commodities other than oil and gas, consisting of agricultural products, fisheries, manufacturing, and mineral mining [4]. Export activities are one of the pillars of the economy, with indicators of increased export value determining the success of a country's economic growth with the support of increased domestic production [4][5].

In May 2023, the value of non-oil and gas exports was US$ 20.398,2 million, which increased by 2,02% compared to the same period in 2022 with a value of US$ 403,0 million, for oil and gas commodities obtained a value of US$ 1.308,6 million, said to have decreased in value from the same period in 2022 by US$ 189,5 million [2]. These figures show fluctuations in the value of both commodities over the same period each year. The value of exports obtained may have decreased from the previous period to increase economic growth through the export sector. The value of exports obtained may have decreased from the previous period to increase economic growth through the export sector. This is caused by several possibilities, including technical factors of production that cause a decrease in the quantity of production, a decrease in the needs of foreign markets, and global economic climate conditions caused by the escalation of geo-political tensions that affect currency exchange rates that cause fluctuations in all sectors, especially exports. Forecasting is a method of projecting future values based on finding patterns in historical values with a mathematical approach [6]. With the increasing complexity of economic problems, the basis for forecasting methods has continued to develop until now [6]. Thus, this study's forecasting approach related to export value is important.

The time series forecasting model focuses on the number of parameters and the trend variance in the data [7]. Time series forecasting is highly dependent on the number of data samples being analyzed, which creates problems when faced with limited historical data records [7]. The number of data samples used in this study was 372, which is relatively small when compared to the historical time series data records in the study [8],[9],[10].

Based on studies on previous research, research [8] created a forecasting system to predict BBRI shares using the LSTM method, obtaining an RMSE value of 227,470. Research [11] Forecasting was conducted to predict the divorce rate in the Pekanbaru district using the VAR method, obtaining a MAPE accuracy value of 47,678%. Research [12] Forecasting performed on aviation data obtained a VAR accuracy value with an RMSE of 0,160 and LSTM accuracy with an RMSE of 1,161. Based on the literature study, this research will develop a forecasting model with the VAR and LSTM methods to forecast the value of Indonesia's oil and gas and non-oil and gas exports. The two methods were chosen because they have quite different approaches, where the VAR method requires the data analyzed to be stationary, while the LSTM method can perform forecasting on data that has a trend (nonstationary). The advantages and disadvantages of each method are shown in Table 1.

**Table 1.** Advantages and Disadvantages of Each Method

| Method | Advantages | Disadvantages |
|---|---|---|
| VAR | Find relationships between time series variables [13]. | Requires the data to be stationary [11]. |
| | Perform large-scale economic analysis efficiently [14]. | Overestimation of parameters for large variables and lags [13]. |
| LSTM | Accurate in forecasting nonstationary time series data [15]. | Complexity of tuning parameters [16]. |
| | Solving non-linear problems [17]. | The smaller dataset causes overfitting [18]. |

This research aims to create a forecasting model to project the value of Indonesia's oil & gas and non-oil and gas exports by comparing the VAR and LSTM methods. The VAR method is used in this study because it can overcome statistical problems for multivariate time series analysis by using a linear model on many interdependent features in the time series [12]. The LSTM method is used in this study because it is a variant of the RNN model that is quite effective in accommodating excess gradients and mismatches in RNNs by using gate mechanisms and cell memory to accumulate information [19].

## METHOD

The development of forecasting models using the VAR and LSTM methods consists of a series of processes represented using a flow design. Flow design provides a global overview of the forecasting model of Indonesia's oil and gas and non-oil and gas export values using both methods. The images displayed provide information on the continuous flow of the process. The stages in this study refer to the flow design in Figure 1, which explains the stages from data preprocessing to model evaluation using MAPE.

The dataset used in this study is data on the value of Indonesia's oil & gas and non-oil & gas exports from 1993 to 2023, compiled by Badan Pusat Statistik (BPS). The discussion of methods is grouped based on the methods used in developing forecasting models, namely VAR and LSTM. The VAR model is developed based on the optimum lag value generated by the AIC test. The preprocessing stage of each model uses a different approach, as described in Figure 1. The similarity of the preprocessing stages used by both models is in the dataset splitting stage to divide the training data and test data with a ratio of 80:20.

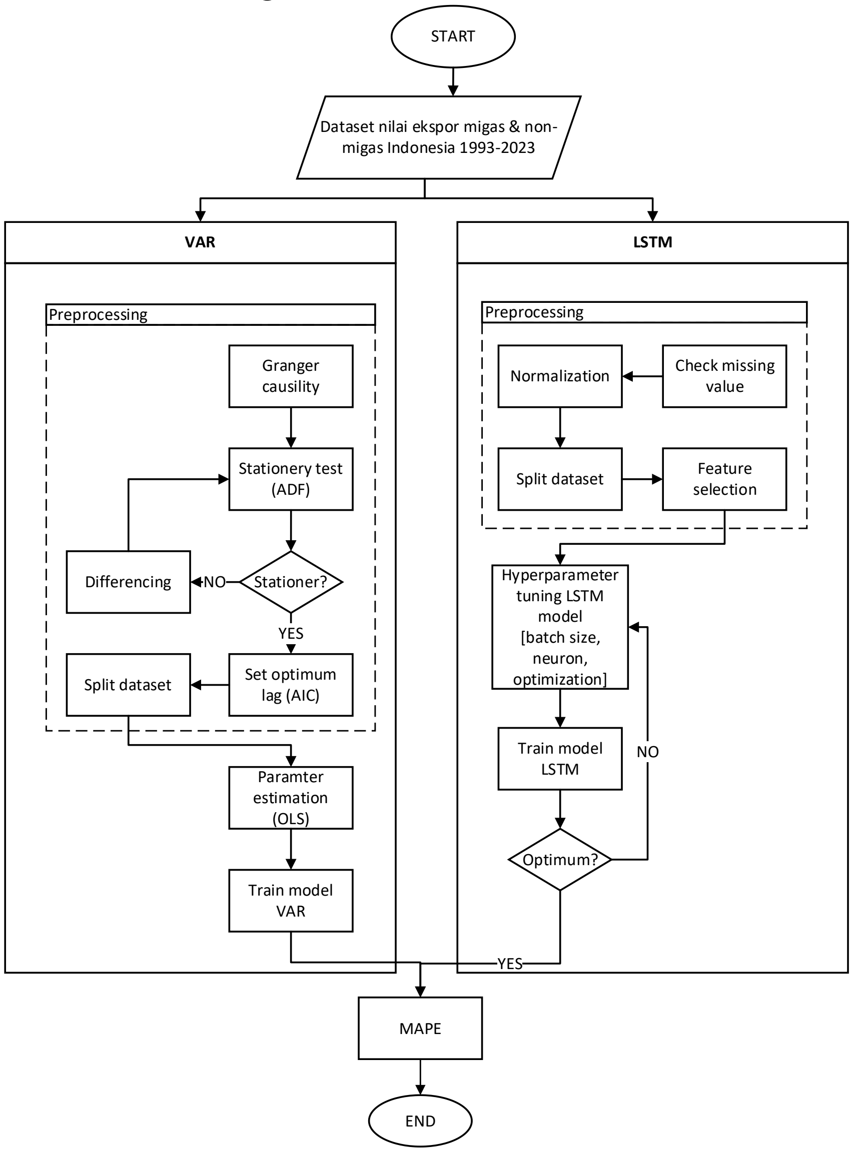


**Figure 1.** Research Flow Design

## Forecasting Model

a. VAR Method

The stages of developing a forecasting model using the LSTM method in this study are described in stages 1-6

*Step 1: Stationarity test*. It is a process of testing data to be declared stationary if variables have time constancy in one moment with another [20]. One of the stationarity tests can be done with the unit root test approach using the Augmented Dickey-Fuller (ADF) test [20] using Equation (1). Where the variable $\Delta$ is the first-difference operator, the variable $Y_t$ is the value of the $Y$ variable at time $t$, $\beta$ is the time trend coefficient, $\alpha$ is the VAR model parameter, $\delta$ is $p$-$1$, $p$ is the lag, and $\varepsilon$ is the error value.

$$\Delta(Y_t) = \beta_1 + \beta_2 + \delta Y_{t-1} + \sum_{t=1}^{p} \alpha_p \Delta Y_{t-p} + \varepsilon_t \quad (1)$$

*Step 2: Differencing*. Stages of differencing transformation on time series data with nonstationary variables to turn them into stationary ones [20] based on Equation (2). The value of variable *Zt* is the value of differencing time t, variable yt is the value of variable *y* at time *t*, and variable $y_{t-1}$ is the value before variable $y_{t-1}$.

$$z_t = y_t - y_{t-1} \quad (2)$$

*Step-3: Causality Test*. A causality test is conducted using the Granger Causality approach [11] to determine the relationship between variables in the VAR model. Granger testing is obtained through Equation (3). Where the variable *Yt* is the *Y* variable at time *t*, the *Yt-i*, variable *Xt-i* is the value of the variable *Y, X* at time *t-i*, and *α* the coefficient of the *i*-th lag variable *Y, X*, is the time trend coefficient.

$$Y_t = \sum_{t=1}^{p_1} \alpha_{11}^{p} Y_{t-i} + \sum_{t=1}^{p_0} \alpha_{12}^{p} X_{t-i} + u_{1,t} \quad (3)$$

*Step-4: Set Optimum Lag*. The traditional approach to over-parameterization is to determine the lowest lag order using least squares estimation in the hypothesis test [21]. One approach to determining the lag in the VAR model is using the Akaike Information Criteria (AIC) method [11]. Determination of lag using AIC is obtained through Equation (4). Where *k* is the estimated number of lags, and *l* is the loglikehood.

$$AIC = 2k - 2l \quad (4)$$

*Step-5: Parameter Estimation*. This study's parameter estimation of the VAR model uses the Ordinary Least Square (OLS) method to minimize the error value [20]. The OLS equation is expressed by Equation (5). Where the variable $\hat{\beta}$ is a vector of estimated parameters *(p + 1) x 1*, the variable *Y* is a vector of observations *(m x 1)*, and the variable *X* is a matrix of predictor variables *(p + 1) x m*.

$$\hat{\beta} = YX'(XX')^{-1} \quad (5)$$

*Step-6: VAR*. The VAR method is generally used in multivariate forecasting of time series data with the assumption that the current value of a variable is caused by the past value of the variable involved [22]. The VAR method is described in Equation (6). The variable Yt is a matrix of Y variables at time t, the $Y_{t-1}$, $Y_{t-p}$ is a matrix of *Y* variables at time *t* up to the lag value (*p*), and *β* is a constant matrix of *Y* variables.

$$Y_t = \delta + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \cdots + \beta_p Y_{t-p} + \varepsilon_t \quad (6)$$

b. LSTM Method

The stages of developing a forecasting model using the LSTM method in this study are described in stages 1-3.

*Step-1: Data Normalization*. Data normalization is commonly used in the preprocessing stage of data mining by transforming data to speed up model training [23]. This research uses the Min-Max Normalization method in normalizing data through linear transformation to produce consistent interval values (0-1) [24][25]. The calculation of Min-Max Normalization is explained in Equation (7). Where the variable $X_n$ represents the normalized value, the variable $X_0$ is the actual value, and the variables $X_{min}$, and $X_{max}$ are the minimum and maximum values of the actual data.

$$X_n = \frac{X_0 - X_{min}}{X_{max} - X_{min}} \quad (7)$$

*Step 2: LSTM*. Long short-term memory (LSTM) is a derivative of Recurrent Neural Network (RNN), which consists of one state and three gates, including cell state ($C_t$), input gate ($I_t$), output gate ($O_t$), and forget gate ($F_t$) [19][24]. LSTM cells can connect before and after information effectively, which is why LSTM is used in the case of time series forecasting [8].

LSTM utilizes a forgate gate to sort out the data stored in the memory cell, as Equation (8) explains.

$$F_t = \sigma(W_{xf} . x_i + W_{hf} . H_{t-1} + b_f) \tag{8}$$

The input gate controls the new value entering the cell by processing and sorting the information to be stored in the candidate state ($\widetilde{C_t}$) by using sigmoid activation to update the information and tanh activation to store the value described in Equation (9) and (10) [24].

$$l_t = \sigma(W_{xi} . x_i + W_{hi} . H_{t-1} + b_i) \tag{9}$$

$$\widetilde{C_t} = tanh(W_{xc} . x_t + W_{hc} . H_{t-1} + b_c) \tag{10}$$

Replace the old memory cell value with the new one in the cell state value in Equation (11). Forget gate maintains the value in the cell by replacing the cell memory value with the cell state [24]. The output gate sets the activation value of the LSTM unit with a sigmoid activation function to ignore the value and tanh activation to store the value described in Equation (12) and (13) [19][24]. Where the variables *Wxf*, $W_{xi}$, $W_{xc}$, *and* $W_{xo}$ are the weights of the forget gate, input gate, cell memory, and output gate matrices. The variables $b_f$, $b_i$, $b_c$, *and* $b_o$ are the bias matrix of the forget gate, input gate, cell state, and output gate. Variable $X_t$ is the sample data, and variable $H_{t-1}$ is the time *t-1* information.

$$C_t = F_t \odot C_{t-1} . H_{t-1} + l_t \odot \tilde{C}_t + b_c \tag{11}$$

$$O_t = \sigma(W_{xo} . x_i + W_{ho} . H_{t-1} + b_o) \tag{12}$$

$$H_t = O_t \odot tanh\, C_t \tag{13}$$

*Step 3: Hyperparameter tuning*. Hyperparameter tuning sorts parameter values to produce the best model performance [26]. The parameters tested in this study include batch size, neurons, activation with fixed parameters of epochs 100, hidden state three layers, and using Nasterov Adam (NADAM) optimization. The hyperparameter scheme in this study is shown in Table 2.

**Table 2.** Candidate Hyperparameters

| Parameter | Value |
|---|---|
| *Hidden state* | 3 |
| *Neuron* | [10,10,20],[50,50,100] |
| *Batch size* | 8, 16, 32 |
| *Activation* | *tanh, sigmoid, relu* |
| *Epoch* | 100 |
| *Optimizer* | *madam* |

c. Model Performance

The accuracy test of the forecasting model used in this study is the Mean Absolute Percentage Error (MAPE) to determine the difference between the actual and predicted values. The smaller the MAPE value, the more accurate the forecasting model developed [20]. The MAPE equation is shown in equation 14. Where *N* is the number of observed samples, variable $Y_t$ is the *t*-the actual value, and variable ($\widehat{Y_t}$) is the *t*-th predicted value. The MAPE criterion base on Tabel 3 [27].

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{Y_t - \widehat{Y_t}}{Y_t}\right| x\ 100\% \tag{14}$$

**Table 3.** MAPE Criteria

| MAPE Value | Criterion |
|---|---|
| MAPE < 10% | Very Good |
| 10% ≤ MAPE ≤ 20% | Good |
| 20% ≤ MAPE ≤ 50% | Enough |
| 50% ≤ MAPE | Worst |

## RESULT AND DISCUSSION

The test conducted in this study is to find the best forecasting model produced by the VAR and LSTM methods. The VAR method develops a model based on the optimum lag. The LSTM method develops a model with the architectural scheme shown in Table 1. Testing each forecasting model using MAPE on the value of Indonesia's oil & gas and non-oil and gas exports for 2023.

a. VAR Method

The Granger causality test is used to determine the effect of non-oil and gas value on oil and gas using hypothesis 1 and the effect of oil & gas value on non-oil and gas using hypothesis 2.

Hypothesis 1:

$H_0$: Oil and gas value value is not affected by non-oil and gas value, $p > \alpha$

$H_1$: Oil and gas value affected by non-oil and gas value, $\mathrm{p} < \alpha$

Hypothesis 2:

$H_0$: Non-oil and gas value is not affected by oil and gas value, $\mathrm{p} > \alpha$

$H_1$: Non-oil and gas value affected by oil and gas, $\mathrm{p} < \alpha$

The test results using Granger in Table 4 show that the value of non-oil and gas affects the value of oil and gas at the 12th lag, which means that $H_0$ hypothesis 1 is rejected. The second test result shows that the value of oil and gas affects the value of non-oil & gas at the 12th lag, which means that $H_0$ hypothesis 2 is rejected.

**Table 4.** Granger Causality Test Results

| Lag | Non-oil & gas does not cause oil & gas | | Oil & gas does not cause non-oil & gas | |
|---|---|---|---|---|
| | F-statistik | p-value | F-statistik | p-value |
| 1 | 0,1813 | 0,6705 | 0,2878 | 0,5920 |
| 2 | 0,7890 | 0,4551 | 1,0434 | 0,3533 |
| 3 | 1,7839 | 0,1498 | 1,6900 | 0,1688 |
| 4 | 1,3315 | 0,2577 | 3,8933 | 0,0041 |
| 5 | 1,2901 | 0,2577 | 3,1510 | 0,0085 |
| 6 | 1,6936 | 0,1215 | 2,4068 | 0,0271 |
| 7 | 1,4431 | 0,1869 | 2,4459 | 0,0185 |
| 8 | 1,2413 | 0,2739 | 2,3982 | 0,0158 |
| 9 | 1,4821 | 0,1529 | 2,5058 | 0,0087 |
| 10 | 1,8370 | 0,0533 | 2,3863 | 0,0096 |
| 11 | 1,6892 | 0,0743 | 2,8004 | 0,0017 |
| 12 | 1,7392 | 0,0575 | 2,7964 | 0,0012 |

Hypothesis 3:

$H_0$: Stationery data, $\mathrm{p} > \alpha$

$H_1$: Nonstationary data, $\mathrm{p} < \alpha$

The stationarity test using ADF to ensure data stationarity obtained the results shown in Table 5. The ADF test results for the $0^{th}$ oil and gas and non-oil and gas values show that both accept $H_0$ in hypothesis 3. After the first differencing stage, the ADF test results of oil & gas and non-oil and gas values are $H_0$ rejected, meaning that the oil and gas and non-oil and gas data have been stationary by differencing once.

**Table 5.** ADF Test Value

| Data | n-differencing | $p-value$ | Significant Level $(\alpha)$ | Conclusion |
|---|---|---|---|---|
| Oil & gas | 0 | 0,5053 | 0,05 | $p-value > \alpha$ |
| | 1 | 0,0 | | $p-value < \alpha$ |
| Non-oil & gas | 0 | 0,8519 | | $p-value > \alpha$ |
| | 1 | 0,0001 | | $p-value < \alpha$ |

For each ADF test with $H_0$ accepted, the differencing process is carried out iteratively n times until $H_0$ is rejected. The results of differencing the data are shown in Table 6.

**Table 6.** Differencing Result

| Date | Oil & gas | Oil & gas differencing | Non-oil & gas | Non-oil & gas differencing |
|---|---|---|---|---|
| 01/01/1993 | 864,3 | ... | 2 137,6 | ... |
| 01/02/1993 | 767,5 | -96.8 | 2 125,0 | -12.6 |
| 01/03/1993 | 892,2 | 124.7 | 2 116,3 | -8.7 |
| 01/04/1993 | 744 | -148.2 | 2 213,5 | 97.2 |
| 01/05/1993 | 888,3 | 144.3 | 2 229,7 | 16.2 |
| 01/06/1993 | 825,9 | -62.4 | 2 155,3 | -74.4 |
| 01/07/1993 | 847,3 | 21.4 | 2 178,4 | 23.1 |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| 01/08/2023 | 1 318,8 | 92.0 | 20 679,2 | 1043.8 |
| 01/09/2023 | 1 405,1 | 86.3 | 19 341,4 | -1337.8 |
| 01/10/2023 | 1 370,4 | -34.7 | 20 776,3 | 1434.9 |
| 01/12/2023 | 1 479,0 | 196.1 | 20 934,9 | 219.6 |

Determination of the optimum lag in the VAR model using the AIC method by selecting the smallest lag value. Based on Table 7, the optimum order is at lag 12.

**Table 7.** Optimal Lag Determination

| Lag | AIC |
|---|---|
| 1 | 23,96 |
| 2 | 23,57 |
| 3 | 23,52 |
| 4 | 23,51 |
| 5 | 23,50 |
| 6 | 23,50 |
| 7 | 23,52 |
| 8 | 23,51 |
| 9 | 23,50 |
| 10 | 23,49 |
| 11 | 23,48 |
| 12 | 23,46 * |

The parameter estimation results of the VAR$_{(12)}$ model using OLS with a lag of 12 obtained the Equation $Y_{1t}$ for the VAR model of oil & gas export value and $Y_{2t}$ for the VAR model of non-oil & gas export value.

$$Y_{1\mathrm{t}} = -7{,}813 + -0{,}228, Y_{11} + 0{,}028, Y_{21} + -0{,}515, \mathrm{Y}_{12} + 0{,}048, Y_{22} + -0{,}002, Y_{13}$$
$$+0{,}017, Y_{23} + -0{,}6, Y_{14} + 0{,}016, Y_{24} + -0{,}106, Y_{15} + 0{,}092, Y_{25} + -0{,}047, Y_{16}$$
$$+0{,}057, Y_{26} + -0{,}07, Y_{17} + 0{,}023, Y_{27} + -0{,}115, Y_{18} + -0{,}007, Y_{28} + -0{,}043, Y_{19}$$
$$+0{,}056, Y_{29} + -0{,}022, Y_{110} + -0{,}004, Y_{210} + -0{,}125, Y_{111} + -0{,}019, Y_{211}$$
$$+0{,}052, Y_{121} + 0{,}013, Y_{212} + \varepsilon$$

$$Y_{2t} = 98{,}691 + 0{,}839, Y_{11} + -0{,}685, Y_{21} + 0{,}854, Y_{12} + -0{,}34, Y_{22} + 0{,}455, Y_{13}$$
$$+ - 0{,}244, Y_{23} + 0{,}416, Y_{14} + -0{,}193, Y_{24} + -0{,}192, Y_{15} + -0{,}035, Y_{25} + 0{,}164, Y_{16}$$
$$+ - 0{,}096, Y_{26} + 0{,}354, Y_{17} + -0{,}089, Y_{27} + 0{,}001, Y_{18} + -0{,}056825, Y_{28} + -0{,}054, Y_{19}$$
$$+ - 1{,}0141, \mathrm{Y}_{29} + 0{,}294, \mathrm{Y}_{110} + -0{,}132, \mathrm{Y}_{210} + -0{,}457, \mathrm{Y}_{111} + 0{,}041, \mathrm{Y}_{211}$$
$$+0{,}271, \mathrm{Y}_{112} + 0{,}275, \mathrm{Y}_{212} + \varepsilon$$

After the parameter estimates are generated, the next step is to test the forecasting of the VAR$_{(12)}$ model obtained in Table 8.

**Table 8.** VAR Model Testing Results

| Lag | MAPE | |
|---|---|---|
| | Oil & gas | Non-oil & gas |
| 12 | 18,4% | 32,1% |

The test results of each VAR model obtained a MAPE value of 18.4% for oil & gas exports and a MAPE value of 32.1% for non-oil & gas exports. Based on Table 3, the oil & gas VAR model is considered good, and the non-oil & gas VAR model is considered sufficient.

b. LSTM Method

The preprocessing stage in the LSTM model after splitting the dataset is data normalization. The normalization results of Indonesia's oil & gas and non-oil & gas export value datasets are shown in Table 9.

**Table 9.** Data Normalization Results

| Date | Oil & gas | Non-oil & gas |
|---|---|---|
| 01/01/1993 | 0,0979148 | 0,01818083 |
| 01/02/1993 | 0,07085756 | 0,01720353 |
| 01/03/1993 | 0,10571333 | 0,01652873 |
| 01/04/1993 | 0,06428891 | 0,02406788 |
| 01/05/1993 | 0,10462321 | 0,02532441 |
| ⋮ | | |
| ⋮ | | |
| 01/08/2023 | 0,22495528 | 1,456328 |
| 01/09/2023 | 0,24907759 | 1,35256385 |
| 01/10/2023 | 0,23937835 | 1,46385939 |
| 01/11/2023 | 0,21492062 | 1,45912803 |
| 01/12/2023 | 0,2697339 | 1,47616093 |

The results of the LSTM model forecasting test using MAPE are shown in Table 10. Tests were performed recursively by performing hyperparameter tuning with the candidate parameters shown in Table 1 with an overall number of model epochs of 100, optimizer madam, and using random weights and biases.

**Table 10.** Accuracy of LSTM Model Scheme

| Batch size | Activation | Neuron | MAPE | |
|---|---|---|---|---|
| | | | Oil & gas | Non-oil & gas |
| 8 | tanh | [10,10,20] | 6,87% | 18,00% |
| | | [50,50,100] | 9,02% | 19,63% |
| | rel | [10,10,20] | 10,20% | 35,52% |
| | | [50,50,100] | 9,12% | 24,60% |
| | sigmoid | [10,10,20] | 8,35% | 29,85% |
| | | [50,50,100] | 10,63% | 29,46% |
| 16 | tanh | [10,10,20] | 7,72% | 24,91% |
| | | [50,50,100] | 7,88% | 15,17% |
| | rel | [10,10,20] | 6,38% | 21,49% |
| | | [50,50,100] | 7,85% | 17,86% |
| | sigmoid | [10,10,20] | 21,86% | 35,45% |
| | | [50,50,100] | 7,43% | 26,23% |
| 32 | tanh | [10,10,20] | 6,23%* | 17,48% |
| | | [50,50,100] | 6,40% | 17,18% |
| | rel | [10,10,20] | 7,10% | 8,18%* |
| | | [50,50,100] | 6,97% | 23,24% |
| | sigmoid | [10,10,20] | 20,76% | 63,55% |
| | | [50,50,100] | 11,03% | 32,91% |

Based on Table 10, the LSTM model for the best oil & gas obtained a MAPE value of 6.23% with the architecture of the number of batch sizes 32, activation tanh, and neurons as many as [10,10,100]. The best non-oil & gas LSTM model obtained a MAPE value of 8.18% with an architecture of the number of batch sizes 32, activation relu, and neurons of [10,10,20]. Based on Table 3, the architecture of the oil & gas and non-oil & gas LSTM model is categorized as very good. The best average hyperparameter scheme for the model architecture is the number of batch sizes 32, activation relu, and neurons [10,10,20] with a total MAPE value of 7.64% with each MAPE value of oil & gas 7.10% and non-oil & gas 8.18%.

c. Method Comparison

The development of a forecasting model using the VAR method from the resulting parameter estimates with the optimal number of lags of 12 obtained an oil & gas MAPE value of 18.4% and a non-oil & gas MAPE value of 32.1%. Based on Table 3 the LSTM method produces the worst model with an oil & gas MAPE value of 21.86% and non-oil & gas MAPE of 63.55%. The best LSTM model obtained an oil & gas MAPE value of 6.23% and a non-oil & gas MAPE of 8.18%.

## CONCLUSION

Based on the forecasting model for Indonesia's oil & gas and non-oil & gas export values using the VAR and LSTM methods. The results of Granger causality testing state that the value of oil & gas and non-oil & gas exports affect each other. The results of developing a VAR model with an optimum number of lags of 12, the oil & gas VAR model obtained a MAPE value of 18,4%, and the non-oil & gas VAR model obtained a value of 32,1%. The best LSTM model development results obtained an accuracy value of 6,32% for the oil & gas model and MAPE 8,11% for the non-oil & gas model. The accuracy results for each model are 12,08% for oil & gas and 11% for non-oil & gas.

The comparison of the two models concluded that the LSTM method uses simpler stages than the VAR method because it can develop time series forecasting models on nonstationary data without conducting stationarity tests, so no repeated differencing process is required. However, these simpler stages prove from the test results that the LSTM model obtained the best performance compared to the VAR model on the architecture with the number of epochs 100, optimizer madam, number of batch sizes 32, activation relu, and neurons [10,10,20] for the case of forecasting the value of Indonesian oil & gas and non-oil & gas exports with relatively few historical data records. The disadvantages of the LSTM model are that it is a black box so it is difficult to understand the mathematical calculations of forecasting in LSTM cells, and the LSTM method takes a long time to perform hyperparameter tuning to produce an optimal forecasting model.

Suggestions from this research are to develop forecasting models using the VAR and LSTM methods for large historical data records, as well as integrate forecasting models in web-based and mobile applications so that they are easily accessible to policymakers and investors to help the decision-making process in the future.

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