Forecasting Model of Export and Import Value of Oil and Gas Using Gated Recurrent Unit Method

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Abstract

Indonesia's natural resources are abundant, including oil and gas. It is one of the countries active in international trade, including exports and imports. Oil and gas exports are a significant source of income for the country, encouraging economic growth. Oil and gas imports are very important to meet domestic energy needs, which continue to increase in demand. Increasing oil and gas imports can increase the trade balance, which can affect the country's economic stability if the value of imports exceeds the value of exports. Forecasting is a solution to overcome these problems by forecasting the value of oil and gas exports and imports. The gated recurrent unit (GRU) method is used for forecasting in this study because it has a simple computation and fairly high accuracy. The dataset used is monthly time series data from 1993 to 2023 from the website of the Badan Pusat Statistik (BPS). The MAPE results on the GRU model forecast the value of oil and gas exports and imports at 12.19% and 14.30%, respectively. The best average forecasting of export and import values obtained a MAPE of 13.38%.

Keywords: Forecasting Model, Oil and Gas Import Export Value, Deep Learning, Gated Recurrent Unit Model

I. INTRODUCTION

Information technology is not a difficult thing to get nowadays because it has entered all lines of life and provides many conveniences can also be felt in the economic field [1]. Technological developments that continue to impact the economic field positively encourage economic growth. The country's economic growth can increase national development and positively impact other fields [2]. Economic growth in a country can be obtained by conducting international trade, namely exports and imports. Exports are activities selling commodities in the country to other countries, while imports buy commodities from different countries for domestic needs [3]. International trade activities consist of export and import activities, which are generally categorized based on commodities with oil and gas and non-oil and gas types [4]. Oil and gas have become an energy source that is needed by the community because many sectors used by humans use oil and gas [5]. The high market demand for oil and gas commodities makes the government a policy maker, using forecasting of future export and import values to reduce the value of imports and increase the value of exports to maintain the country's economic stability. Forecasting is the science of making predictions on data, either estimates in the present or for the future, based on future events based on past time series [6]. Forecasting is done using data obtained within a certain period in a good sequence in the form of annual, monthly, weekly, daily, and hourly, referred to as a time-series dataset [7]. Forecasting helps minimize uncertain future risks. Forecasting is expected to provide positive results for the organization [8].

Indonesia is a country that has abundant natural resources, one of which is petroleum and natural gas (oil and gas) [5]. Oil and gas are essential commodities for meeting domestic energy needs and are a source of state revenue [9]. Oil and gas exports significantly contribute to state revenue and drive the country's economic growth [10]. Oil and gas imports are significant in fulfilling domestic energy needs. However, the increase in oil and gas imports can increase the trade balance deficit if the export value exceeds the export value, affecting the country's economic stability [5]. Therefore, a forecasting approach to the value of oil and gas exports and imports can greatly assist the government and oil and gas export and import industry players in making the right decisions regarding resource management, planning business strategies, and risk management.

Literature studies on previous research conducted forecasting using the Gated Recurrent Unit (GRU) method. One of them is a researcher [11] to predict the value of oil and gas imports with a MAPE value of 0.9999955%. The research [12] on predicting gold prices obtained accurate results with an MSE value of 0.111 and an RMSE of 0.334. The results of the researchers [13] to indicate the amount of drug use obtained an RMSE accuracy result of 13.020446. The research [14] results on predicting world crude oil prices get accurate results with a MAPE value of 2.25%. The results of the researchers [15] to predict the price of palm oil get the accuracy of MAPE 4.84%. Based on literature studies, no research using the Gated Recurrent Unit (GRU) method with a case study of forecasting the value of oil and gas exports and imports.

This research aims to develop a forecasting model using the GRU method for oil and gas export and import values and test the accuracy of the forecasting model. The GRU method is used in this research because it has advantages in the computational process, which is more straightforward than Long Short Term-Memory (LSTM). However, GRU has equal accuracy and effectively reduces the problem of vanishing gradient loss [12]. GRU is an enhanced Recurrent Neural Network (RNN) variant that can achieve optimal results [11]. GRU has cells containing two gates, the reset and update gates, and three activation functions. The lack of gates and functions will provide speed for processing large data, and it is designed to be better than LSTM for processing small datasets [12].

II. RESEARCH METHODOLOGY

Forecasting the value of oil and gas exports and imports using the Gated Recurrent Unit (GRU) method involves several processes visualized based on the flow in Figure 1.

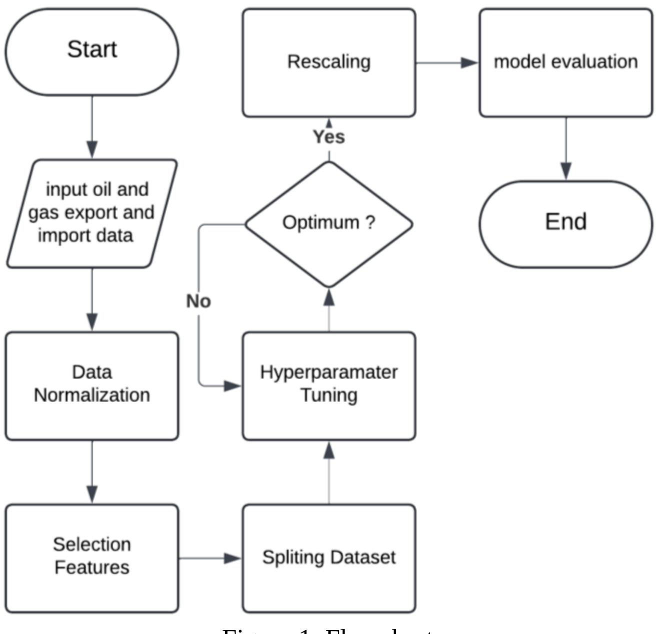

Figure 1. Flowchart

The initial step of the process in Figure 1 is to input data on oil and gas exports and imports. The next process is data normalization using the min-max scaling method to get a new value of 0 to 1. Next, features are selected to determine targets and attributes, and then the dataset is split into training and testing data. The following process is hyperparameter tuning to determine the Epoch, batch size, and neurons. After that, the optimization process using Adam is used if the forecasting is not optimal, then the hyperparameter tuning process is repeated if the results are optimal, and then the rescaling process is continued to restore the original value of the data. The last process is model evaluation using MAPE to determine forecasting accuracy.

A. Dataset

This study uses data obtained from the Badan Pusat Statistik (BPS). The data is a time series of oil and gas export and import values with historical data records for the period 1993-2023, as shown in Table 1.

Table 1. Oil and Gas Export and Import Value Data

Date	Export	Import
01/01/1993	864.3	113.2
01/02/1993	767.5	154.4
01/03/1993	892.2	112.1
01/04/1993	744.0	142.8
01/05/1993	888.3	153.8
01/06/1993	825.9	232.5
01/07/1993	847.3	108.2
01/08/1993	775.3	2,52.1
…	…	…
01/05/2023	1,308.6	3,135.1
01/06/2023	1,259.7	2,222.3
01/07/2023	1,226.8	3,132.1
01/08/2023	1,318.8	2,662.0
01/09/2023	1,405.1	3,328.6
01/10/2023	1,370.4	3,206.8
01/11/2023	1,282.9	3,488.7
01/12/2023	1,478.9	3,372.4

B. Data Normalization

The data that has been obtained will be normalized using the min-max method. Min-max normalization is one of the methods used for normalizing data by calculating data according to a certain scale between 0 and 1 [16]. Normalization Min-max data normalization can be calculated using Equation (1). Where variable X is the original data while variable $Xmin$ is the smallest data value and variable $Xmax$ is the largest data value.

$$X' = \frac{X - Xmin}{Xmax - Xmin} \quad (1)$$

C. Data Splitting

Splitting data is the process of dividing data into training data and testing data. Training data serves to train a model in learning the patterns contained in the data, while testing data is useful for seeing how well the model learns data patterns.

The division of training data and test data is one of the factors that can determine accuracy, so errors in determining the composition of the two types of data will affect the value of accuracy and precision [17]. This research divides the 60% training data and 40% testing data.

D. Gated Recurrent Unit Method

A gated recurrent unit (GRU) is one of the variations of a recurrent neural network (RNN) that was created to overcome the long-term dependency problem of RNN. GRU can remember long-term information like RNN. GRU also consists of recurrent processing modules [15]. GRU has fewer gates and was created to overcome the missing gradient problem in traditional RNN. GRU has two gates: the update gate and the reset gate. GRU has the advantage of processing small datasets due to the smaller number of gates than LSTM and is computationally less and ideal for limited computing resources [18]. Reset gate (R_t) in GRU is a gate to set the amount of information from the past time that should be forgotten through Equation (2) [19].

$$R_t = \sigma(W_{xr}.x_t + W_{hr}.H_{t-1} + b_r) \quad (2)$$

Update gate (U_t) is a gate that decides how much new information will be stored in the hidden state described in Equation (3).

$$U_t = \sigma(W_{xu} . x_t + W_{hu} . R_t \odot H_{t-1}) \quad (3)$$

Candidate's hidden state ($\widetilde{H_t}$) is the process of determining stored information from the past to produce a new forecast by calculating the reset gate and update gate using Equation (4).

$$\widetilde{H_t} = \tanh(W_{xh} . x_t + W_{hh} . R_t \odot H_{t-1} + b_h) \quad (4)$$

The last step is to calculate the hidden state (H_t), which depends on the update gate and the candidate's hidden state using Equation (5).

$$H_t = U_t \odot H_{t-1} + (1 - U_t) \odot \widetilde{H_t} \quad (5)$$

Where variable x_t is the hidden state at the previous time t and the H_{t-1} variable is the hidden state at the previous time $t-1$. Reset gate and update gate using sigmoid function (σ). In the update gate, the candidate's hidden state and hidden state use component-wise multiplication ($\odot$). In the reset gate variable W_{xr} and variable W_{hr} are the weight parameters and b_r variable is the bias parameter. While at the update gate, the W_{xu} and W_{hu} variable is the weight parameters and b_u variable is the bias parameter. The candidate's hidden state uses the hyperbolic tangent function (tanh), while the W_{xh} and W_{hh} variables is the weight parameters and b_h variable is the bias parameter.

E. Mean Absolute Percentage Error

One method of calculating accuracy for forecasting models is using MAPE. The resulting calculation is the average percentage error value between actual and forecast values. MAPE is used to compare the same method on different series or compare different methods. Accuracy results are obtained by estimating the model in absolute form as the average error [20]. MAPE can be calculated using the Equation (6).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{A_i - F_i}{A_i}\right| \times 100\% \quad (6)$$

Where variable A_i the actual value and variable F_i is the predicted value, while the variable n is the number of periods. The smaller the MAPE result, the more accurate the forecasting model. The results and criteria of MAPE can be seen in Table 2 [14].

Table 2. MAPE criteria

MAPE Result	Criteria
<10%	Excellent
10% - 20%	Good
20% - 50%	Fair
50%>	Poor

III. RESULTS AND DISCUSSION

In previous studies, there were several studies related to oil and gas exports and imports. Researcher [11], the dataset used is data on the value of oil and gas and non-oil and gas imports for the period January 2000 - June 2022. Researcher [2], the dataset used is data on the value of exports and imports of oil and gas and non-oil and gas imports for the period January 1993 - December 2020. Researcher [10], the dataset used is data on the value of oil and gas exports for the period January 1993 - December 2021.

This study uses a time series dataset for the period 1993-2023, which is shown in Figure 2. Based on data on the value of oil and gas exports and imports from January 1993 to December 2023, it can be seen that the highest value of oil and gas exports was in August 2011, with a value of USD 4,091.6 and the lowest value was in April 1998 with a value of USD 514 with an average value of oil and gas exports of USD 1,472.9. Meanwhile, the highest oil and gas import value was USD 4,455.3 in July 2022, and the lowest value was USD 1,616.6.

The pre-existing data will be processed to normalize the data using min-max to get a value of 0 to 1. Data that has been normalized using the min-max process can be seen in Table 3.

In previous studies, several researchers used dataset-sharing schemes to divide training data and testing data. Research [11] uses training and testing data at 60:40, 70:30, and 80:20. Researcher [2] used training and testing data at 40:60, 50:50, 60:40, 70:30, and 80:20. Research [10] uses 60% training data and 20% testing data.

This research uses 372 data divided into 60% training data, or 148 data, and 40% testing data, or 223 data. Data splitting can be seen in Figure 3. The training data starts from January

1993 to August 2011, and the testing data from September 2011 to December 2023.

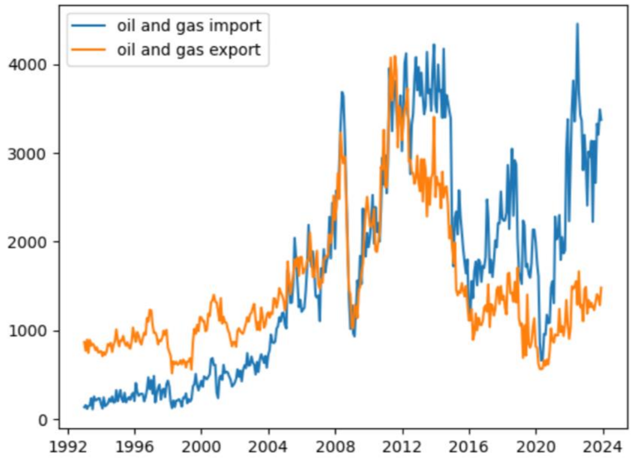

Figure 2. Oil and Gas Export and Import Data

Table 3. Data Normalization

Date	Export	Import
01/01/1993	0.097915	0.005521
01/02/1993	0.070858	0.010628
01/03/1993	0.105713	0.000897
01/04/1993	0.064289	0.007957
01/05/1993	0.104623	0.010490
…	…	…
01/08/2023	0.224955	0.587472
01/09/2023	0.249078	0.740816
01/10/2023	0.239378	0.712797
01/11/2023	0.214921	0.777645
01/12/2023	0.269706	0.750891

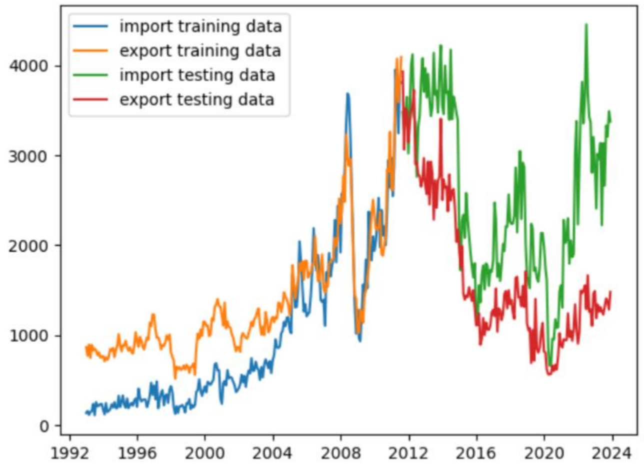

Figure 3. Training Data and Testing Data

The tuning hyperparameters used in this research are batch size, Epoch, and neuron. In this study, 30 model experiments were conducted by combining hyperparameter tuning. At the final stage, all models that have been tested will evaluate the model using MAPE. The forecasting results and accuracy can be seen in Table 4.

Table 4. GRU Forecasting Results

Batch Size	Epoch	Neuron	MAPE	
			Export	Import
8	50	50,50,100	15.60%	15.16%
		100,100,200	13.23%	27.03%
		200,200,300	16.79%	16.79%
	100	50,50,100	15.24%	18.31%
		100,100,200	12.98%	17.28%
		200,200,300	13.58%	19.18%
16	50	50,50,100	14.69%	14.87%
		100,100,200	13.96%	15.20%
		200,200,300	14.42%	14.56%
	100	50,50,100	13.36%	17.44%
		100,100,200	13.16%	16.48%
		200,200,300	13.79%	15.49%
32	50	50,50,100	13.16%	14.40%
		100,100,200	13.25%	14.44%
		200,200,300	15.23%	14.51%
	100	50,50,100	14.96%	14.94%
		100,100,200	13.20%	15.24%
		200,200,300	12.89%	15.78%
64	50	50,50,100	12.19%	14.99%
		100,100,200	14.30%	14.47%
		200,200,300	12.54%	14.51%
	100	50,50,100	12.51%	14.56%
		100,100,200	13.31%	17.09%
		200,200,300	13.06%	14.59%
128	50	50,50,100	12.85%	15.26%
		100,100,200	12.25%	15.11%
		200,200,300	12.45%	14.30%
	100	50,50,100	13.07%	15.35%
		100,100,200	12.86%	14.47%
		200,200,300	12.82%	14.38%

Based on Table 4, it is known that the best GRU forecasting results for export values obtained a MAPE value of 12.19% by using the number of batch sizes 64, epoch 50, and neurons 50,50,100, and the worst results of forecasting oil and gas export values obtained a MAPE value of 16.79% by using batch size 8, epoch 50, and neurons 200,200,300. The best oil and gas import value forecasting results get a MAPE value of 14.30% using a batch size of 128, epoch 50, and neurons 200,200,300, and the worst value of oil and gas import value forecasting gets a MAPE of 27.03% using a batch size of 8, epoch 50, and neurons 100,100,200. As for the average value of the best oil and gas export and import value forecasting, it gets a MAPE value of 13.38% with a batch size of 128, epoch 50, and neurons 200,200,300.

IV. CONCLUSION

Based on the forecasting model of oil and gas export and import values in Indonesia using the GRU method. The best results for predicting the value of oil and gas exports get a MAPE value of 12.19% with a batch size of 64, epoch 50, and neurons 50,50,100. As for the best results of forecasting the

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value of oil and gas imports, the MAPE value is 14.30% with a batch size of 128, epoch 50, and neurons 200,200,300. The results of all MAPE accuracy tests for forecasting the value of oil and gas exports and imports are summed up for each scheme and then divided by 2 to get the average value. Calculation of the average value of each scheme is done to determine the best scheme for forecasting the value of oil and gas exports and imports. The best value obtained produces an average MAPE of 13.38% with a hyperparameter scheme of 128 batches, 50 epochs, and 200,200,300 neurons.

Based on the results of this study, it can be concluded that the gated recurrent unit (GRU) method for forecasting the value of oil and gas exports and imports gets good MAPE result criteria in forecasting with a relatively small amount of data, namely 372 data on the value of oil and gas exports and imports.

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