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SELECTING THE BEST MODEL FOR FORECASTING INDONESIA'S OIL AND GAS IMPORT VALUE USING ARIMAX AND ARIMAX-LSTM

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ABSTRAK

Prediksi nilai impor migas sangat penting bagi pemerintah untuk memutuskan kebijakan yang tepat di masa yang akan datang. Tujuan dari penelitian ini yaitu melakukan peramalan nilai impor migas Indonesia dengan mengikutsertakan variabel independen harga minyak mentah dunia, nilai tukar rupiah, dan inflasi. Metode yang digunakan yaitu dengan membandingkan model ARIMA (Autoregressive Integrated Moving Average), ARIMAX (ARIMA With Exogenous Variable), dan Hybrid ARIMAX-LSTM (ARIMA With Exogenous Variable Long-Short-Term Memory). Perbandingan model peramalan menggunakan MAPE (Mean Absolute Percentage Error). Hasil penelitian menunjukkan ARIMAX-LSTM (0,1,2) dengan variabel Harga Minyak Mentah dan Inflasi sangat baik memprediksi dan meramal nilai impor migas. Hasil peramalan menunjukkan peningkatan nilai impor migas pada periode Januari - September 2024 sebesar 3.03% dibandingkan total nilai impor tahun sebelumnya (Y-o-Y). Saran untuk penelitian selanjutnya yaitu perlunya pertimbangan penambahan variabel eksogen lain, penelitian lebih lanjut terkait optimasi hyperparameter, dan teknik validasi silang untuk meningkatkan akurasi prediksi dan mengukur kinerja model secara lebih terperinci.

ABSTRACT

In order for the government to make the best policy decisions going forward, it is critical to forecast the value of oil and gas imports. This study aims to anticipate Indonesia's oil and gas import value by taking into account the independent variables of inflation, rupiah exchange rates, and global crude oil prices. The ARIMA (Autoregressive Integrated Moving Average), ARIMAX (ARIMA With Exogenous Variable), and Hybrid ARIMAX-LSTM (ARIMA With Exogenous Variable Long-Short-Term Memory) are the methods that are compared. Mean Absolute Percentage Error, or MAPE, is a tool used to compare forecasting models. The outcomes demonstrated how well ARIMAX-LSTM (0, 1, 2) predicts and forecasts the value of oil and gas imports when combined with variables for inflation and crude oil prices. According to the forecasting results, the value of imports of gas and oil increased by 3.03% between January and September of 2024 when compared to the entire import value of the year prior (Y-o-Y). Other exogenous variable addition, additional research on hyperparameter tuning, and the use of cross-validation techniques to increase prediction accuracy and provide more precise measurements of model performance are other recommendations for future investigation.

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INTRODUCTION

Indonesia has a large potential for gas and oil. In particular, petroleum is one way to generate foreign cash in order to sustain the nation's development (Basundoro, 2017). The primary energy sources used in Indonesia to power the country's transportation and industrial sectors are gas and petroleum. Indonesia has a vital position in the global energy market due to its substantial deposits of gas and oil. In order to maximize financial gains and reduce negative environmental effects, the Indonesian government is working to create new technologies, increase the efficiency of resource exploitation, and manage these resources responsibly.

Indonesia has 4.2 billion barrels of oil reserves, according to Aspermigas data, and there are still a lot of untapped oil and gas areas (Putri, 2022). Furthermore, as of December 31, 2021, 42.93 trillion cubic feet (TCF) of natural gas were stored in Indonesia. With a 6,000 million standard cubic feet per day (MMSCFD) gas output, these reserves will last for approximately 19.6 years. Indonesia comprises 128 hydrocarbon basins, of which 20 have been produced, 27 have been drilled to identify possible reserves, 12 have been drilled but no reserves have been discovered, and 69 have not been drilled at all. According to Asmarini (2022), the Special Working Unit (SKK) of Oil and Gas, Indonesia still has a sizable amount of untapped oil and gas potential if these hydrocarbon basins can be thoroughly investigated and utilized. Furthermore, according to Atmaja et al. (2020), Indonesia's expenditures on infrastructure, capital, and human resources are not commensurate with the substantial potential of its oil and gas resources.

For Indonesia to develop, it is critical to forecast the supply and use of fuel, particularly gas and oil (Sa'adah et al., 2017). It is noteworthy that the country of Indonesia consumes more gas and oil than it produces. As a result, Indonesia's position on oil and gas has changed from net exporter to net importer. The Indonesian Ministry of Energy and Mineral Resources (MEMR) reports that the country's consumption of gas and oil in 2022 rose over 2021. According to reports, Indonesia will consume 1,585,000 barrels of oil and gas per day in 2022. Compared to 2021, when Indonesia's daily oil and gas consumption was 1,461,000 barrels, this consumption has grown. It is anticipated that Indonesia will continue to consume more gas and oil until

2050. According to projections from the BPPT Energy Outlook and the National Energy General Plan (RUEN), oil consumption in the New Renewable Energy (NRE) scenario is expected to be 1,016 million barrels in 2050, while production will be 70 million barrels.

Data from Consumer News and Business Channel Indonesia (CNBC) Indonesia and the Energy Institute (EI) show that Indonesia produced 57.7 billion cubic meters of natural gas and 644,000 barrels of oil per day in 2022. But according to reports, Indonesia consumed 1,585,000 barrels of oil per day in 2022. This demonstrates that Indonesia's output of oil and gas does not match the country's needs for these resources, meaning that Indonesia must continue to import these resources in order to meet its needs (Pangestu & Soesanto, 2023).

According to the Observatory of Economic Complexity, Indonesia will be the world's fourteenth-largest importer of refined oil in 2021. With $6.03 billion worth of refined oil exported to Indonesia at the time, Singapore was the biggest exporter. In the oil and gas industry, the net weight of oil product imports was consistently higher than the monthly total of crude oil and gas from August 2022 to August 2023 (BPS, 2023). While imports of oil products fell to 2136.8 thousand tons in August 2023 from the previous month, it was still the biggest amount compared to imports of gas and crude oil that same month. This is a result of the inability of crude and refined oil supplies to meet the demands of the Indonesian people.

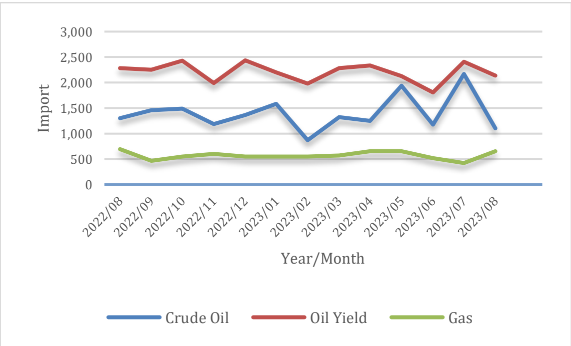

Figure 1. Imports of gas and oil from Indonesia. Source: BPS (processed data)

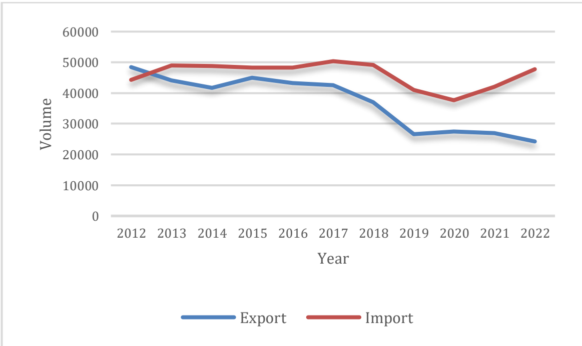

Figure 2. Volume of Oil and Gas Imports and Exports from Indonesia. Source: BPS (processed data)

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Imports and exports must be balanced to preserve economic equilibrium. Due to the abundance of basic raw materials, Indonesia is forced to export these raw materials because its industrial technology and products cannot compete with those of industrialized nations (Firmansyah & Indrajaya, 2019). According to information provided by the Directorate General of Oil and Gas, Ministry of Energy and Mineral Resources, the average price of crude oil in Indonesia fell by US$3.45 per barrel between October 2023 and September 2023, from US$90.17 per barrel to US$86.72 per barrel. The evolution of the conflict between Russia and Ukraine, the rise in COVID-19 cases in China, the economic downturn, and the maintenance of sanctions against Iran and Venezuela will all have a significant impact on crude oil prices in 2023, according to the Ministry of Finance, which published the fundamental macroeconomic assumptions of the State Budget. There's little doubt that the drop in crude oil prices will impact Indonesia's export prices.

However, from 2013 to 2022, Indonesia's import volume of oil and gas exceeded its export volume, and the country's export volume showed a declining tendency, according to BPS statistics on oil and gas import and export volume. As a result, Indonesia's imports and exports of gas and oil were out of balance. A deficit in Indonesia's trade balance may result from this imbalance. Trade balance and economic growth are in sync. According to Blavasciunaite et al. (2020), there is a negative correlation between economic growth and the decline or deficit of the trade balance. One of the primary causes of the slowdown in the rate of economic growth can be long-term trade deficits (Awan & Mukhtar, 2019). Additionally, it is argued that, over time, the trade balance also benefits the GDP, foreign direct investment, and currency rates. This indicates that these three factors diminish when the trade balance is negative.

International trade theory states that a genuine devaluation or depreciation of the home currency will increase the cost of imports while lowering the cost of exports, necessitating an improvement in the trade balance in the end (Arize et al., 2017). Bosupeng et al. (2023) state that in developing nations, depreciation shocks have a beneficial short- and long-term impact on the trade balance due to exchange rate volatility. However, Ahmed et al. (2023) looked at the connection between inflation and the trade balance as shown by crude oil prices. Therefore, in comparison to other shocks, changes in the price of crude oil react to an increase in inflation the quickest.

The government relies on precise forecasts of gas and oil imports and exports to decision-making on budget distribution, inflation control, and the development of proactive economic policies. These estimations are pivotal in effectively managing both revenues and expenses, providing valuable insights into the nation's financial requirements, and projecting expenditures associated with the oil and gas sector. Accurate predictions empower the government to respond adeptly to market fluctuations, ensuring the stability of the national economy.

As a quantitative method of making future predictions, forecasting naturally depends on historical data (Rahayu & Nurdiansyah, 2022). Forecasting is divided into two categories: qualitative and quantitative, depending on the methodology. Time series and regression are the two categories under which quantitative forecasting techniques fall. Time series analysis is employed for many reasons, such as understanding the relationship between variables, researching that relationship, and pinpointing control mechanisms (Hanifah & Kartiasih, 2018; Hawari & Kartiasih, 2017; Ningsih & Kartiasih, 2019; Wardah, 2016). A time series comprises four primary pattern components, arranged chronologically: cycles, trends, seasonality, and horizontal patterns (Garini & Anbiya, 2022). Multivariate data can also benefit from the use of time series analysis in addition to univariate data. The Box Jenkins method, also known as ARIMA, is one of the most widely used time series modeling techniques for forecasting.

The function of variable Y and other independent variables at time t influences the factors that affect the dependent variable Y then. The ARIMAX model is used to forecast data with several independent variables. Exogenous variables are introduced as predictor variables that have an impact on the dependent variable Y in the ARIMA method, which is an extension of the Box-Jenkins ARIMA method (Wen et al., 2023). Intervention analysis and outlier instances can be handled by the ARIMAX model, which is an extension of the ARIMA model (Anggraeni et al., 2015). Since the value of oil and gas imports is heavily influenced by some other factors, including crude oil prices, the demand for oil and gas, and the volume of oil and gas produced, the

ARIMAX model is appropriate for predicting the value of oil and gas imports for the upcoming periods. This is predicated on the time series data's structure, which can include both linear and nonlinear structures simultaneously (Anggraeni et al., 2015).

Many studies have employed ARIMAX and Long-Short Term Memory (LSTM) models to forecast while accounting for the non-linear elements included in time series data. With a much greater degree of accuracy than models like GP (Gaussian Process Regression) and BPNN (Back Propagation Neural Network), Huang et al. (2019) predicted China's CO2 emissions using LSTM. Wu and Lin (2019) used LSTM to effectively predict the air quality index with success. The LSTM-ARIMA hybrid model was successfully employed by Dave et al. (2021) to predict Indonesia's future export volume, assisting the Indonesian government in developing economic strategies. By integrating the ARIMA and LSTM models, Fan et al. (2021) successfully and precisely projected well production, which is essential for prolonging well life cycles and improving reservoir recovery. The CNN-LSTM and CNN-GRU methods using Skip-Connection are the new hybrid models that Kim & Jang (2023) used to improve the accuracy of oil price prediction. The study did note, however, that developing more accurate prediction models based on time-series data requires using a multivariate approach and creating computationally efficient models with skip connections. This is because relying solely on one data source is ineffective for predicting long-term changes in oil prices.

This study compares the hybrid ARIMAX-LSTM and ARIMAX methods to determine which is the better forecasting model for Indonesia's oil and gas import value. The research is based on previously conducted research that addresses the selection of the best model and research limitations. In contrast to earlier studies, the Dave et al. (2021) study uses multiple data sets, including the independent variables of inflation, rupiah exchange rates, and world crude oil prices, to create a forecasting model. This study's contribution is to test the hybrid ARIMAX-LTSM and ARIMAX models in combination by analyzing the error the model produces to identify a model that yields a higher accuracy value. The value of Indonesia's future imports of gas and oil is predicted by this research, which can help the government make decisions about import and export regulations for these resources. Through comprehension of the oil and gas industry's patterns and forecasts, the government can enhance its readiness to tackle intricate economic issues in the future.

The government of Indonesia can use this research's unique features to inform policy decisions for the import and export of gas and oil. To identify an accurate forecasting model, this study compares the hybrid ARIMAX-LSTM method with the ARIMAX model. Prior studies by Dave et al. (2021), Wu and Lin (2019), Huang et al. (2019), Fan et al. (2021), and Wu and Lin (2019) combined hybrid ARIMA and LSTM approaches to obtain an effective model for forecasting in different sectors, but they only employed the ARIMA model without exogenous variables. Furthermore, no one has used this form of forecasting in the Indonesian oil and gas import industry. Because other variable factors must be considered as supporting variables to anticipate the value of oil and gas imports, the ARIMAX method approach is crucial.

LITERATURE REVIEW

Mineral wax, also known as ozokerite, bitumen, and asphalt produced during the mining process, are examples of petroleum, which is a byproduct of natural processes that results in hydrocarbons in liquid or solid phases under atmospheric pressure and temperature; coal and solid hydrocarbon deposits obtained from activities unrelated to the oil and gas industry are not included in this (Minister of Energy and Mineral Resources Regulation No. 29 of 20). Natural processes are responsible for the formation of hydrocarbons under atmospheric pressure and temperature, as well as the gas phase that results from the extraction of oil and gas (Government Regulation Number 93 of 2021).

According to Presidential Regulation No. 32 of 2022, the act of bringing products into the customs area is known as importation. The BPS defines imports as the entry of goods and services that nationals buy from citizens of other nations, resulting in the national economy's outflow of foreign exchange. As per the Ministry of Finance's Income Tax Article 22, import value is comprised of the whole amount utilized for determining import duties, cost insurance and freight (CIF), and additional levies applied in compliance with customs legislation concerning imports.

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Because Indonesia depends so heavily on oil imports to meet its domestic energy needs, changes in the price of crude oil around the world have a significant impact on the value of Indonesia's oil imports. As a result, when world crude oil prices rise, so does the value of Indonesia's oil imports (Firmansyah & Indrajaya, 2019). The production, consumption, and policies implemented to continue achieving people's welfare are also impacted by changes in the price of crude oil globally (Andriani et al., 2018).

Setyorani (2018) elucidated that a positive trend in the rupiah exchange rate was observed when export values declined. Additionally, his research revealed a substantial short- and long-term association between the exchange rate and exports. Financial and macroeconomic stability are correlated with exchange rate flexibility (Ghosh et al., 2015). However, depending on whether the nation exports or imports significant commodities, tiny open economies will be impacted by the global cycle differently, one of which is brought on by exchange rate changes (Alstadheim et al., 2021). Because price elasticity and exchange rate volatility are typically highly significant, the research findings by Zhang et al. (2023) support the idea that these two factors influence import demand. However, T. Sari & A. Rauf (2018) distinguished between two correlations involving imports and inflation. Excessive demand and fluctuations in the cost of products and services are the causes of the first. Second, it is brought on by a lack of things to produce and distribute, which lowers the usual normal demand—in this case, imports.

The development of precise forecasting models for different energy and national economic strategies has been the focus of multiple studies. To provide early warning about excessive power consumption for utilities by formulating the generation, transmission, and distribution of electric energy, Xiong et al. (2023) applied a long-short-term memory method based on a hybrid model based on VMD and Deep TCN with Self-Attention Mechanism on forecasting. Their experimental results showed that the proposed model significantly improved prediction accuracy in terms of evaluation metrics compared to other contrasting models.

METHODS

Data

The secondary data that was used includes 165 monthly period data points with four data points: the value of Indonesia's imports of gas and oil (in US dollars), the percentage of inflation, the rupiah exchange rate (in thousand rupiah), and the global crude oil prices (in US dollars) throughout January 2010 to September 2023. Data on import values and inflation were sourced from the website of the Central Statistics Agency (BPS). The Bank Indonesia website provides information on the rupiah's exchange rate concerning the US dollar (USD). Data on global crude oil prices can be found on the website id.investing.

Methodology

In the research process illustrated in Figure 1, the initial step involves integrating import values for gas and oil into time series data to evaluate stationarity. Should the data prove non-stationary, a cycle of differentiation and stationarity testing ensues, culminating in the construction of an ARIMA model once stability is achieved. Subsequently, an ARIMAX model is developed, considering every possible combination of variable X. To identify the optimal ARIMAX model, each iteration undergoes significance tests and residual analysis. The following step entails assessing the accuracy of both ARIMA and ARIMAX models using test data, with a focus on achieving a Mean Absolute Percentage Error (MAPE) value below 10%. If the MAPE remains relatively high (>10%), an alternative approach is employed—integrating the ARIMAX model with Long-Short Term Memory (LSTM) deep learning to address non-linear components and enhance accuracy. The final phase includes evaluating the correctness of the hybrid model and projecting oil and gas import values for the upcoming timeframe, aligning with the study's objectives.

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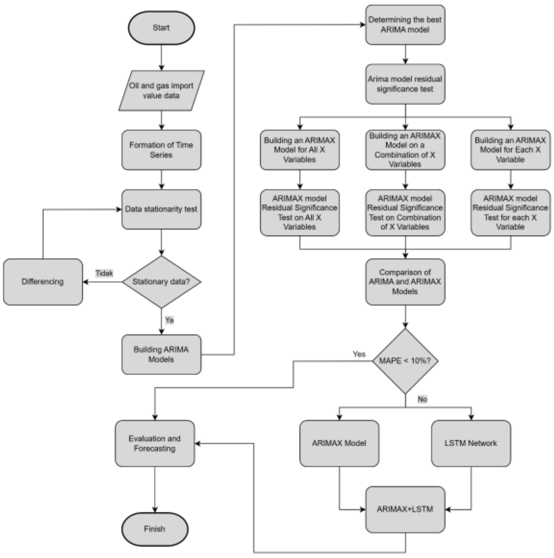

Figure 3. Research stage flow

Stationarity

The statistical characteristics of a process that yields time series that remain constant across time are known as stationarity (Kartiasih et al., 2012). The time series is regarded as stationary if each variable's mean, variance, and covariance remain unaffected by time (Kartiasih & Setiawan, 2020; Laura et al., 2023; Pertiwi et al., 2023). A time series' stationarity can greatly influence its forecasting characteristics and behavior; incorrectly putting the time series into the stationary form might produce erroneous findings (Greunen et al., 2014).

Autocorrelation Function (ACF)

The degree of similarity of the linear relationship between values of the same variable over different periods is shown by the autocorrelation coefficient. This autocorrelation is comparable to or equal to the Pearson correlation for bivariate data. The link between the autocorrelation and its lag is known as the autocorrelation function (ACF), since ρ_k is a function of k. In a time series, the autocorrelation function (ACF) specifies how data points are averaged with earlier data points (Box, Jenkins, & Reinsel, 1994).

$$\rho_k = \frac{\sum_{t=k+1}^{n} (Y_t - \underline{Y})(Y_{t-k} - \underline{Y})}{\sum_{t=k+1}^{n} (Y_t - \underline{Y})^2}$$

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Partial Autocorrelation Function (ACF)

When the impact of additional time lags 1, 2, 3,..., k-1 is eliminated, partial autocorrelation (PACF) is utilized to calculate the degree of correlation between Y_t them Y_{t-k} (Makridakis et al., 1997). In the Box-Jenkins model, one often used method for model identification is the partial autocorrelation plot (Box et al., 1994).

Correlogram

A correlogram uses the Autocorrelation Function (ACF) to determine whether a time series of data is stationary. This function aids in the explanation of a stochastic process involving the correlation between closely spaced nearby data points. A correlogram graphic facilitates fast and simple visualization of the ACF (Makridakis et al., 1997). Non-stationary correlogram-characterized data typically do not decline quickly as k grows. On the other hand, even as k increases, data with stationary correlograms typically does not drop quickly.

Augmented Dickey-Fuller (ADF)

Unit root tests are a popular method these days to check if time series data is stationary. Dickey and Fuller's (1979) Augmented Dickey-Fuller test served as the model for this assessment. The Dickey-Fuller test is a unit root test that verifies the null hypothesis in the model equation $y_t = c + \beta t + \alpha y_{t-1} + \phi \Delta Y_{t-1} + e_t$ that α=1 (α is the coefficient of the first leg of Y). The ADF test incorporates higher-order regressive processes into the model, extending the Dickey-Fuller test equation. This is the ADF model's equation:

$$y_t = c + \beta t + \alpha y_{t-1} + \phi \Delta Y_{t-1} + \phi \Delta Y_{t-2} + \ldots + \phi \Delta Y_{t-p} + e_t$$

ADF Hypothesis:

H_0: Unit Root Exists (Data is not stationary.)

H_1: No Unit Root (Stationary data)

ARIMA Model

Yule, Slutsky, Walker, and Yaglom developed the ideas behind autoregressive (AR) and moving average (MA) models (Chen et al., 2014). The ARMA model and differencing are combined in the ARIMA model. The ARMA and ARIMA models are contrasted as follows:

ARMA Model:

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$(1-\phi_1 B-\phi_2 B^2 - \ldots - \phi_p B^p) y_t = (1+\theta_1 B+\theta_2 B^2 + \ldots + \theta_q B^q) e_t$

ARIMA Model: $(1-\phi_1 B-\phi_2 B^2 - \ldots - \phi_p B^p)(1-B)^d y_t = (1+\theta_1 B+\theta_2 B^2 + \ldots + \theta_q B^q) e_t$

Economic time series forecasting has found success with the ARIMA model, a well-liked linear model (Wang et al., 2013). Because of their strong economic ties, the ARIMA model is thus ideally suited for predicting things like the value of imports of gas and oil.

ARIMAX Model

Exogenous variables for predictor variables that can have an impact on the dependent variable Y are added to the Box-Jenkins ARIMA development process to create ARIMAX (Wen et al., 2023). In this model, other independent variables at time t, as well as the function of the variable Y at time t, influence the factors that affect the dependent variable Y at time t. The following mathematical model describes the general form of the ARIMAX model.

$$Y_t = c + \beta_1 X_{1,t} + \cdots + \beta_p X_{p,t} + \phi_1 Y_{t-1} + \cdots + \phi_p Y_{t-p} + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t$$

where Y_t is the observation value at time t, β_p is the parameter for the independent variable, ϕ_p is the model's autoregressive component's parameter, θ_q is the moving average component's parameter, and ε_t is the period t error. (Vicente Amekauma & Essi, 2016)

Long-Short-Term Memory (LSTM)

The feedback-enhanced recursive neural network design of Long-Short Term Memory (LSTM), which can handle complete sequences as well as individual data points, offers a solution to long-term reliance (Manowska et al., 2021). The LSTM model's neural network is made up of three layers: an input layer, a hidden layer, and an output layer. According to Somu et al. (2020), the LSTM's interconnected memory blocks enable the model to handle sequential data while learning long-term dependencies. Consequently, the LSTM model may converge more quickly and increase the precision of estimating the import values of gas and oil.

ARIMAX-LSTM

ARIMAX and LSTM models are combined to create the suggested model. Using a deep learning LSTM model named ARIMAX-LSTM, volatility prediction is carried out using the residue of the best ARIMAX model. Stated differently, the residual series of the ARIMAX model is modeled by the LSTM model, which is then utilized to train non-linear trends (Fan et al., 2020). The suggested model's primary goal is to determine the ideal input lag for deep learning applications to maximize results. The prediction result (Yt) of the hybrid ARIMAX-LSTM is obtained by combining the linear part (L_t) with the non-linear part (N_t) (Milenković et al., 2023).

$$Y_t = L_t + N_t$$

Ljung Box Test

A statistical study called the Ljung-Box test is used to identify the autocorrelations in a set of time series that deviate from zero. Because it looks for general randomness rather than testing it on individual lags, this test is a portmanteau. In the ARIMA (p,d,q) model, the residual independence is tested using the Ljung-Box test.

H_0: $r_1 = r_2 = \ldots r_k = 0$ (no residual correlation between lags)

H_1: $\exists r_k = 0$ (there is at least one residual correlation between lags)

$$Q = n(n+2)\sum_{k=1}^{h} -\frac{\widehat{\rho_k^2}}{n-k}$$

where n is the number of samples, h is the number of lags chosen for the test sample, and $\widehat{p_k}$ is the autocorrelation value for the lag-k. The model is appropriate for predicting $Q > \chi_{(\alpha,k-1)}$ rejects, which indicates that the errors lack autocorrelation.

Model Evaluation

The goal of forecasting techniques is to approximate values using past data to generate forecast results with the best possible outcomes in the future. The model's goodness and the accuracy of the forecasted results are utilized in the model evaluation process to gauge the model's forecasting performance. The Akaike Information Criterion, or AIC, is used to evaluate how good a model is. The optimal value for the model in terms of parameter estimation is thought to be the AIC value, which is determined using the probability density function's log likelihood value. The formula can be used to get the AIC value.

$$AIC = -2l + 2p$$

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The number of parameters is indicated by, while the value of l represents the log likelihood. Mean Absolute Percentage Error (MAPE) can be used to compute the predicted results' accuracy assessment in the interim. By figuring out the percentage difference between the actual data and the forecasted data that results, MAPE, or the error rate, is determined. If the resulting MAPE value is less than 10%, the forecasting model is considered very good (Margi & Pendawa, 2015). The formula below is the mathematical formula for calculating MAPE.

$$MAPE = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{X_t - F_t}{X_t}\right|$$

F_t is the forecasted outcome for the t period, X_t is the actual data, and the value of n represents the quantity of data. The optimal model to employ as a forecasting model will be identified by comparing the models' AIC and MAPE values.

RESULTS

Initial Data Exploration

Stationarity testing is the initial stage in modeling. The real-time series data of the import values of gas and oil from January 2010 to September 2023 is visualized in Figure 4. It is believed that the data is not steady based on how the real data is visualized. Next, with a correlogram, an ACF plot is created to determine the stationary hypothesis. The correlogram of the real data on the import value of gas and oil from January 2010 to September 2023 is visualized in Figure 5.

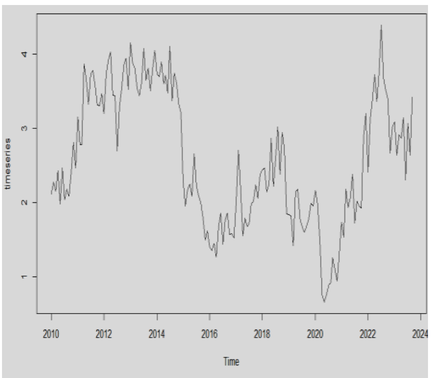

Figure 4. Value of Imported Oil and Gas (January 2010–September 2023)

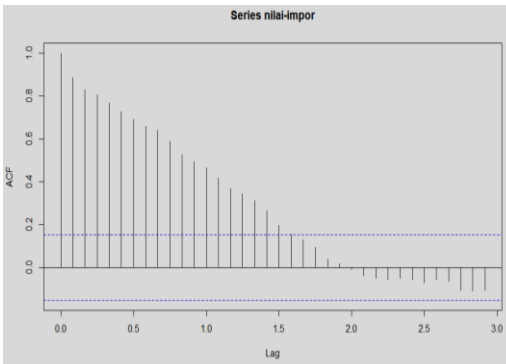

Figure 5. ACF of Real Data on the Import Value of Oil and Gas

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Figure 5's correlogram indicates that the real import value data for gas and oil from January 2010 to September 2023 is not stationary. The p-value is 0.41 based on the unit root test of the actual data on oil and gas import value from January 2010 to December 2023. The result exceeds the significance level (α) of 0.05. In that example, it can be demonstrated that the time series data has a unit root value or that the real data on oil and gas import values is not stationary at the 5% significance level. As a result, it might be said that the data is not level or stationary. Therefore, to obtain stationary data, differencing is done.

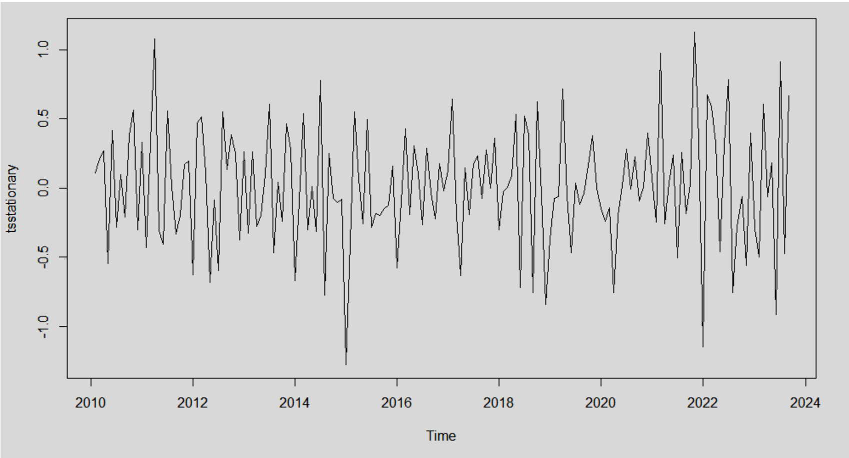

Figure 6. Data Plot Following Oil and Gas Import Value Differencing from January 2010 to September 2023

Stationarity

After differencing, it can be presumed that the import value data for gas and oil is stationary. The p-value is 0.01 based on unit root data testing following the differentiation of oil and gas import values from January 2010 to December 2023. The value is less than the 0.05 significance level (α). That is, it can be demonstrated that the time series data or the data on the import values of oil and gas after differencing is stationary, with a significance level of 5%. Therefore, the data can be said to be stationary at the initial difference.

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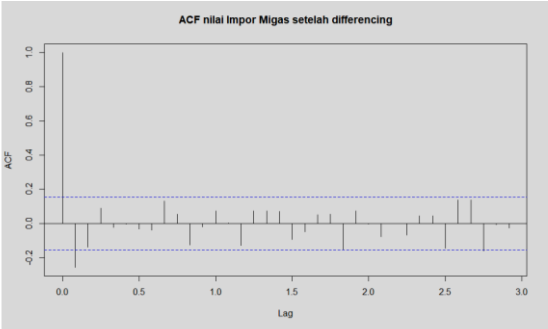

Figure 7. ACF Data of Oil and Gas Import Value after Differentiating

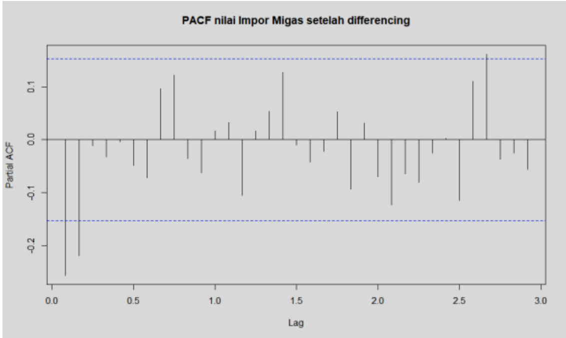

Figure 8. PACF Data of Oil and Gas Import Value after Differentiating

ARIMA

Following the initial difference's achievement of stationarity, the data is processed and added to the ARIMA model. For the prospective ARIMA models, ARIMA(0,1,1), ARIMA(0,1,2), ARIMA(1,1,1), and ARIMA(1,1,2), Table 1 displays the parameter estimates for each model. We may conclude that the models that become the chosen ARIMA model candidates are ARIMA (0,1,1) and ARIMA (0,1,2). The p-value results demonstrate that all variables for the ARIMA(0,1,1) and ARIMA(0,1,2) models are significant at the 5 percent level.

Table 1. ARIMA Model Parameters

Model	Variables	Estimate	Standard Error	z-value	p-value
ARIMA(0,1,1)	MA(1)	-0.3114	0.0992	-3.1365	0.0017
ARIMA(0,1,2)	MA(1)	-0.2563	0.0887	-2.8882	0.0038
	MA(2)	-0.1731	0.0919	-1.8824	0.0397
ARIMA(1,1,1)	AR(1)	0.3604	0.1868	1.9295	0.0536
	MA(1)	-0.6420	0.1487	-4.3162	0.0000
ARIMA(1,1,2)	AR(1)	-0.3919	0.4836	-0.8102	0.4178
	MA(1)	0.1301	0.4734	0.2749	0.7833
	MA(2)	-0.2852	0.1315	-2.1683	0.0301

Table 2 displays the AIC values for each of the four potential ARIMA models. The model with the lowest AIC value—one that includes all of the model's significant variables—will be chosen based on the AIC value. Table 2 demonstrates that the ARIMA (0,1,2) model has the lowest AIC value, with an AIC value of 115.345. As a result, the best model to utilize for additional modeling was determined to be the

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ARIMA(0,1,2) model. The Ljung-Box test is used to make sure the model is free of autocorrelation. To check for white noise residuals, this is done.

Table 2. ARIMA Evaluation Model

Model	AIC
ARIMA(0,1,1)	**116.565**
ARIMA(0,1,2)	**115.345**
ARIMA(1,1,1)	116.069
ARIMA(1,1,2)	117.048

Using the Ljung-Box method to evaluate the autocorrelation of the ARIMA residuals, the resulting x-squared indicator value is 0.17585, or a p-value of 0.675. Since the resulting p-value exceeds the significance level of 0.05, H0 is not rejected. Therefore, it can be demonstrated that the generated residuals satisfy the independence and randomness requirements or that the model obtained is sufficient at a significance level of 5%. The form of the equation found for the ARIMA(0,1,2) model is as follows:.

$$y_t = y_{t-1} + e_t - 0.2563e_{t-1} - 0.1731e_{t-2}$$

where y_t is the observation value in period t, y_{t-1} is the observation value in 1 period before t, e_{t-1} is the error in 1 period before t, e_{t-2} is the error in 2 periods before t, and e_t is the error in period t. The model prediction results are then presented in graphical form. Based on the graph in Figure 9, it can be seen that the resulting model predicts test data like a straight line.

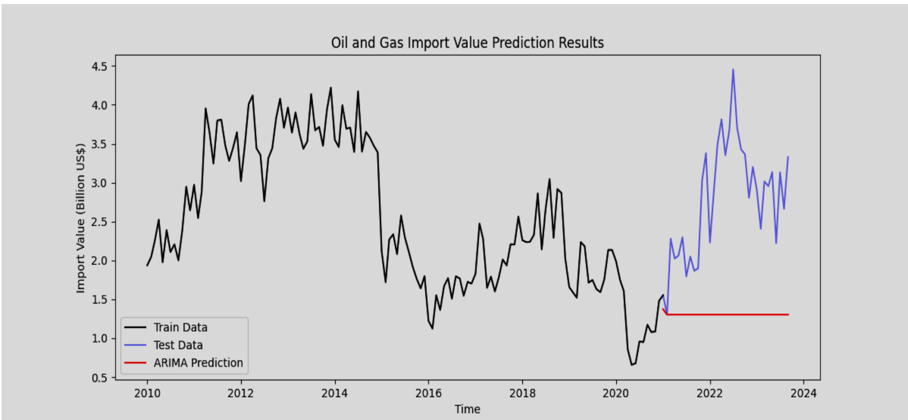

Figure 9. Training Data, Test Data, and Prediction Data of Oil and Gas Import Value for January 2010–September 2023 ARIMA Model (0,1,2)

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ARIMAX

This study uses ARIMAX, an extension of the ARIMA model that makes use of exogenous variables that are hypothesized to have an impact on the value of imports of gas and oil. Inflation, rupee currency rates, and crude oil prices are the exogenous variables that are considered.

Table 3. Estimates of the ARIMAX Model Parameters for Every Variable X

Model	Variables	Estimate	Standard Error	z-value	p-value
ARIMAX(0,1,2) with Crude Oil Price	MA(1)	-0.4986	0.0880	-5.6647	0.0000
	MA(2)	-0.2331	0.0877	-2.6569	0.0078
	Crude Oil Price	0.0303	0.0039	7.7049	0.0000
ARIMAX(0,1,2) with Exchange	MA(1)	-0.2689	0.0895	-3.0029	0.0026
	MA(2)	-0.1813	0.0934	-1.9392	0.0524
	Exchange	-0.1078	0.1124	-0.9589	0.3376
ARIMAX(0,1,2) with Inflation	MA(1)	-0.2426	0.0895	-2.7100	0.0067
	MA(2)	-0.1613	0.0960	-1.6801	0.0929
	Inflation	0.1638	0.0610	2.6818	0.0073
ARIMAX(0,1,2) with Crude Oil and Exchange Price	MA(1)	-0.4977	0.0881	-5.6442	0.0000
	MA(2)	-0.2288	0.0885	-2.5837	0.0097
	Crude Oil Price	0.0310	0.0041	7.5256	0.0000
	Exchange	0.0486	0.0817	0.5952	0.5517
ARIMAX(0,1,2) with Crude Oil Price and Inflation	MA(1)	-0.4888	0.0889	-5.4935	0.0000
	MA(2)	-0.2322	0.0895	-2.5932	0.0095
	Crude Oil Price	0.0299	0.0038	7.7144	0.0000
	Inflation	0.1518	0.0562	2.6967	0.0079
ARIMAX(0,1,2) with Exchange and Inflation	MA(1)	-0.2517	0.0904	-2.7841	0.0053
	MA(2)	-0.1683	0.0975	-1.7260	0.0843
	Exchange	-0.0784	0.1114	-0.7040	0.4814
	Inflation	0.1599	0.0614	2.6022	0.0092
ARIMAX(0,1,2) with All Variables X	MA(1)	-0.4874	0.0892	-5.4634	0.0000
	MA(2)	-0.2231	0.0907	-2.4602	0.0138
	Crude Oil Price	0.0309	0.0040	7.6412	0.0000
	Exchange	0.0715	0.0825	0.8671	0.3859
	Inflation	0.1559	0.0560	2.7816	0.0054

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The purported parameters of each model for variable X—crude oil prices, rupiah exchange rates, and inflation—are shown based on the findings in Table 3. These findings demonstrate that the ARIMA(0,1,2) model can be strongly influenced by the random variables of inflation and crude oil price, but not by the random variable of exchange. The model that omits the random variable exchange is the one that was selected, as indicated by the p-value values, which also indicate that the model is significant at the 5 percent significance level.

Table 4 demonstrates that, out of all the models that could be created with substantial exogenous factors influencing the model, the ARIMAX (0,1,2) Crude Oil Price & Inflation model is the best model because it generates the minimum AIC value of 73.48. The Ljung-Box test is used to evaluate the residuals for white noise to demonstrate the absence of autocorrelation in the chosen model.

Table 4. ARIMAX Model Evaluation

Model	AIC
ARIMAX(0,1,2) Crude Oil Price	**78.59**
ARIMAX(0,1,2) Exchange	116.25
ARIMAX(0,1,2) Inflation	**110.18**
ARIMAX(0,1,2) Crude Oil Price & Exchange	80.23
ARIMAX(0,1,2) Crude Oil Price & Inflation	**73.48**
ARIMAX(0,1,2) Exchange & Inflation	111.69
ARIMAX(1,1,2) all variables X	74.70

The autocorrelation of ARIMA residuals was tested using Ljung-Box, and the findings show that the p-value, when converted to an x-squared indicator value, is 0.9784, or 0.0007. Because the resulting p-value above the significance level of 0.05, H0 is not rejected. Therefore, it may be demonstrated that the model developed is sufficient or that the residuals have satisfied the conditions of independence and randomness at a significance level of 5%. A p-value of 0.9784 was obtained from the Ljung-Box test findings, which is higher than the significance level of 0.05. It is possible to deduce from the test results that either the model developed is sufficient or the residuals have complied with the independence and randomization assumptions. The derived equation for the ARIMAX (0,1,2) Crude Oil Price and Inflation model has the following form.

$$y_t = y_{t-1} + 0.0299X_{1,t} + 0.1518X_{2,t} - 0.4888e_{t-1} - 0.2322e_{t-2} + e_t$$

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where y_t is the observation value in period t, y_{t-1} is the observation value in 1 period before t, $X_{1,t}$ is the price of crude oil in period t, $X_{2,t}$ is inflation in period t, $e_{t-1}$is the error in 1 period before t, e_{t-2} is the error in 2 periods before t, and e_t is the error in period t. The model prediction results are then presented in graph form. Based on the graph in Figure 10, it can be seen that the resulting model predicts the test data looks quite good, namely following the pattern but not too fit with the test data so that it still has a large enough error.

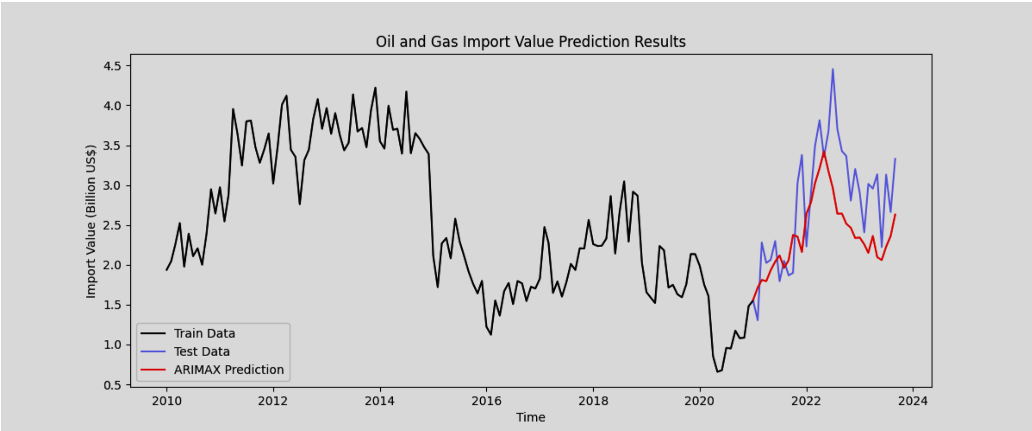

Figure 10. Training Data, Testing Data, and Predicted Data of Oil and Gas Import Value for January 2010 - September 2023 ARIMAX (0,1,2) Oil Price and Inflation

Best Model Selection

By contrasting the magnitude of the forecasted results with the actual data, the optimal model may be chosen. The MAPE of the two model approaches—ARIMA (0,1,2) and ARIMAX (0,1,2)—for oil prices and inflation for test data—which represents 20% of the data from January 2021 to September 2023—will be compared in the Table 5.

The ARIMAX (0,1,2) Oil Prices and Inflation model, with a MAPE of 17.89%, is judged to be the best model based on the MAPE comparison of the two model methods, namely ARIMA (0,1,2) and ARIMAX (0,1,2) Oil Prices and Inflation for test data, or 20% of the data used to train the model. This indicates that there will be an average 17.89% discrepancy between the estimated and actual values of oil and gas imports from January 2021 to September 2023. This demonstrates that the predicting variance of the ARIMAX (0,1,2) Oil Price and Inflation model is 17.89%.

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Table 5. MAPE Evaluation for Testing Data

Time	Actual Data	ARIMA (0,1,2)	APE	ARIMAX (0,1,2) Crude Oil Price & Inflation	APE
01-2021	1.5518	1.3721	11.5793	1.5605	0.5608
02-2021	1.3043	1.3026	0.1255	1.7125	31.2990
03-2021	2.2791	1.3026	42.8431	1.8095	20.6008
04-2021	2.0234	1.3026	27.3797	1.7948	11.2972
…	…	…	…	…	…
06-2023	2.2223	1.3026	41.3822	2.0592	7.3386
07-2023	3.1321	1.3026	58.4092	2.2258	28.9339
08-2023	2.6620	1.3026	51.0645	2.3605	11.3230
09-2023	3.3286	1.3026	60.8645	2.6297	20.9959
		MAPE	**49.1085**	MAPE	**17.8871**

The ARIMAX (0,1,2) Oil Price and Inflation model is determined to be sufficiently accurate in predicting and forecasting data on oil and gas import values based on the summary shown in Table 5. The test data MAPE of 17.89%, however, this is higher than 10%. It is believed that in terms of forecasting and projecting the value of imports of oil and gas, it still falls short of the good category. As a result, it is suggested that the ARIMAX-LSTM model be used to accurately estimate and predict the values of oil and gas imports. To capture non-linear components, the ARIMAX-LSTM model is a variation of the ARIMAX using an LSTM technique.

ARIMAX-LSTM

The LSTM method is used by the hybrid ARIMAX-LSTM model to simulate non-linear errors produced by ARIMAX. Table 6 displays the setup of the hybrid ARIMAX-LSTM (0,1,2) Oil Price and Inflation mode for test data. The number of hidden layers in the LSTM and the number of epochs conducted must be increased due to the configuration being utilized, which adapts to the data quantity of 165 data. Training results using the ARIMAX-LSTM model can reduce the ARIMAX model's MAPE to less than 10%, allowing this hybrid model to enhance the final model.

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Table 6. ARIMAX-LSTM Model Configuration

ARIMAX Model	ARIMAX-LSTM Configuration				
	LSTM			MAPE	
	Number of cells in the hidden layer	Number of Epochs	Batch Size	Train	Test
ARIMAX(0,1,2)	32	200	32	9.58%	8.01%

Following hybrid ARIMAX-LSTM modeling, the models' MAPE comparison for training data—that is, 80% of the data used to train the model—is between ARIMAX (0,1,2) Oil Prices & Inflation and ARIMAX-LSTM (0,1,2) Oil Prices & Inflation. The time frame for the training data is January 2010–December 2020. To get the APE (average percentage error) number for each observation at the time, prediction data and actual data are compared. The MAPE of the two model will be compared in the following for test data, which is 20% of the data.

Table 7. MAPE Evaluation for Testing Data

Time	Actual Data	ARIMAX (0,1,2) Crude Oil Price & Inflation	APE	ARIMAX-LSTM (0,1,2) Crude Oil Price & Inflation	APE
01-2021	1.5518	1.5605	0.5608	1.7049	9.8691
02-2021	1.3043	1.7125	31.2990	1.6264	24.6956
03-2021	2.2791	1.8095	20.6008	1.9682	13.6384
04-2021	2.0234	1.7948	11.2972	2.0092	0.6986
...	...	...	...	...	...
06-2023	2.2223	2.0592	7.3386	2.6680	20.0558
07-2023	3.1321	2.2258	28.9339	2.9859	4.6646
08-2023	2.6620	2.3605	11.3230	3.0284	13.7655
09-2023	3.3286	2.6297	20.9959	3.2968	0.9537
		MAPE	**17.8871**	MAPE	**8.0137**

With a MAPE of 8.01%, the ARIMAX-LSTM (0,1,2) Oil Prices & Inflation model is determined to be the best model based on the comparison of the two model approaches that were used. This indicates that there will be an average 8.01% difference between the estimated and actual values of oil and gas imports from January

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2021 to September 2023. This demonstrates that the prediction variation for the ARIMAX-LSTM (0,1,2) Oil Price and inflation model is 8.01%.

The form of the ARIMAX-LSTM(0,1,2) Crude Oil Price and Inflation model equation obtained is as follows

$$y_t = y_{t-1} + 0.0299X_{t-1} + 0.1518X_{t-2} - 0.4888e_{t-1} - 0.2322e_{t-2} + e_t + N_t$$

where y_t is the observation value in period t, y_{t-1} is the observation value in 1 period before t, $X_{1,t}$ is the price of crude oil in period t, $X_{2,t}$ is inflation in period t, e_{t-1} is the error in 1 period before t, e_{t-2} is the error in 2 periods before t, e_t is the error in period t, and N_t is the non-linear component resulting from the LSTM model. The model prediction results are then presented in the form of a graph. Based on Figure 11, it can be seen that the resulting model predicts the test data looks quite good, namely following the pattern but not too fit with the test data so that it still has a large enough error.

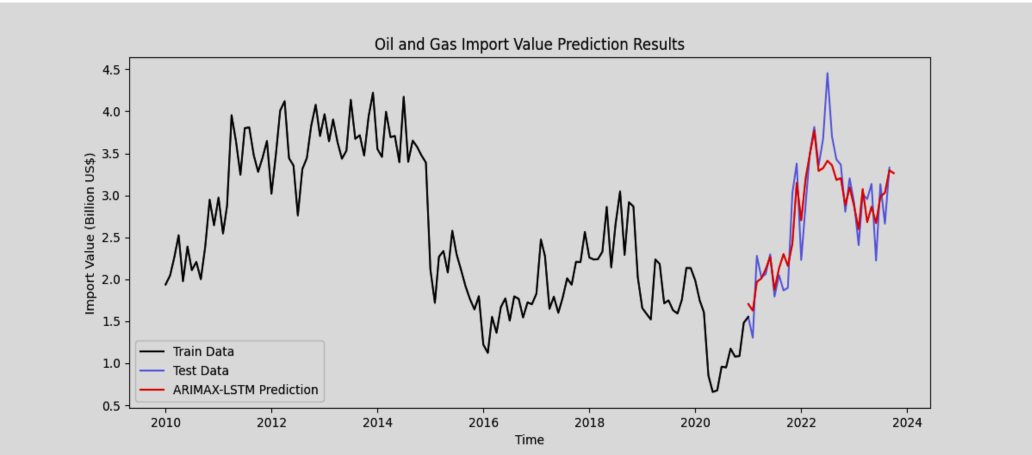

Figure 11. Training Data, Testing Data, and Predicted Data of Oil and Gas Import Value for January 2010 - September 2023 ARIMAX-LSTM (0,1,2) Model Oil Price and Inflation

The ARIMAX-LSTM (0,1,2) Oil Price and Inflation model is proven to be highly effective in predicting and forecasting oil and gas import value data based on the MAPE summary of the model for training and test data. This is as a result of the test data's 8.01% MAPE and the training data's 9.58% MAPE both being less than 10%. This is regarded as having forecasted and predicted oil and gas import value data to the outstanding category.

Model Evaluation

With training data MAPE of 9.58% and test data MAPE of 8.01%, ARIMAX-LSTM (0,1,2) Oil Prices and Inflation is found to be the best model based on the comparison of MAPE measurements between ARIMA (0,1,2), ARIMAX (0,1,2), and ARIMAX-LSTM (0,1,2) Oil Prices and Inflation. Data visualization of prediction outcomes using test data that is almost identical to the test data supports this. Figure 12 compares the prediction results for test data from various models and shows that the ARIMAX-LSTM model produces predictions that are more accurate than those from other models because it can identify patterns and tends to be more fit with the test data itself, resulting in a smaller error.

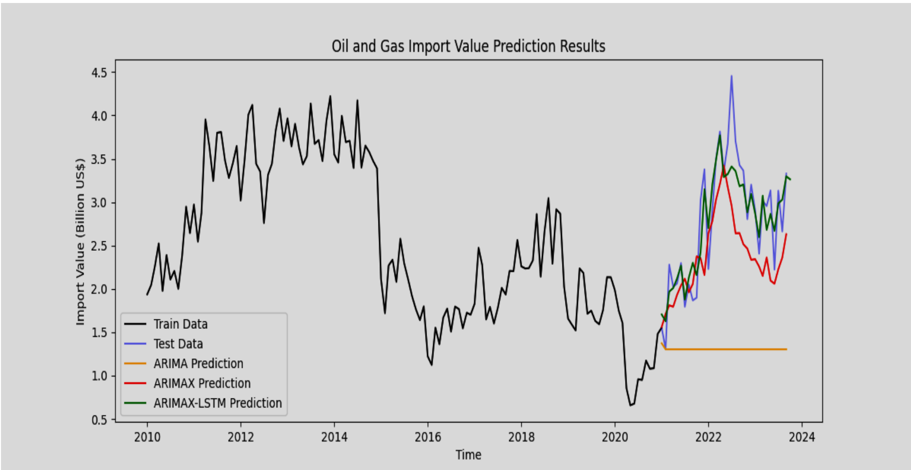

Figure 12. Training Data, Testing Data, and Comparison of Prediction Data of Oil and Gas Import Value for January 2010 - September 2023 ARIMA Model (0,1,2), ARIMAX (0,1,2), and ARIMAX-LSTM (0,1,2) Oil Price and Inflation

Forecasting Results

Forecasting for the following twelve (12) months, from October 2023 to September 2024, may be done using the best model found, which is hybrid ARIMAX-LSTM (0,1,2) crude oil prices and inflation. This model is shown in Table 10 and in Figure 13. This model's prediction can track the actual data trend from the prior time frame. According to the predicted findings, imports of gas and oil would be valued less between December 2023 and June 2024 and more between July 2024 and September 2024. In comparison to the total import value of the prior year (Y-o-Y), the total import value grew by 3.03% overall during the January through September 2024 period. Rising global crude oil prices and anticipated increases in inflation in the upcoming months might be the cause of the rise in the value of oil and gas imports the

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following year. This rise is also the effect of rising fuel subsidies driving up demand for gas and oil, which in turn raises community use of fuels.

Table 10. Forecasting Results of ARIMAX-LSTM (0,1,2) Model Oil Prices & Inflation for the Period October 2023 to September 2024

Time (Month-Year)	Oil and Gas Import Value (Billion Rupiah)
10-2023	3.2634
11-2023	3.1326
12-2023	3.0174
01-2024	3.0175
02-2024	2.9304
03-2024	2.8250
04-2024	3.0368
05-2024	2.7708
06-2024	2.7759
07-2024	2.9009
08-2024	3.0284
09-2024	3.2969

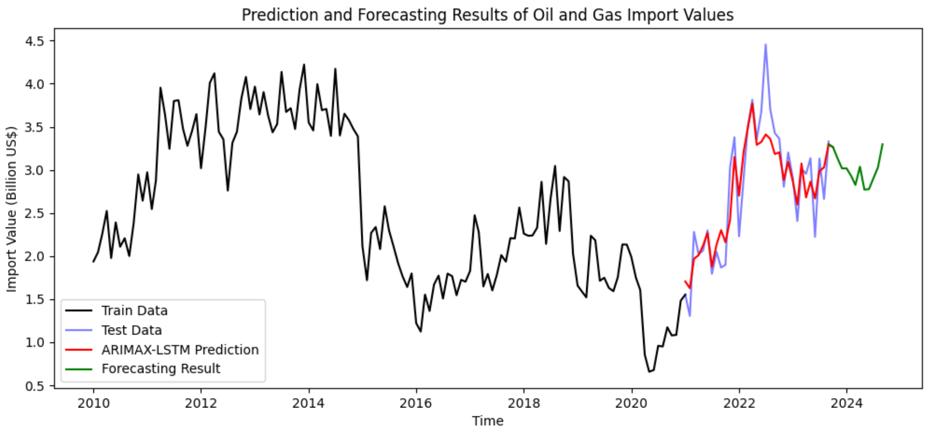

Figure 13. Forecasting Results of Oil and Gas Import Value Model ARIMAX-LSTM (0,1,2) Crude Oil Prices and Inflation for the Period October 2023 - September 2024

CONCLUSION AND SUGGESTION

In comparison to the ARIMA and ARIMAX models, the study leads to the conclusion that the hybrid ARIMAX and LSTM techniques can estimate and forecast the value of oil and gas imports extremely well. Using exogenous factors such as world crude oil prices and inflation, the ARIMAX-LSTM (0, 1, 2) model performs the best when it comes to forecasting and predicting the value of oil and gas imports.

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The total import value for the period January–September 2024 increased by 3.03% compared to the total import value in the previous year (Y-o-Y). This increase in import value can be attributed to the results of forecasting the value of oil and gas imports using the ARIMAX-LSTM (0, 1, 2) model using the exogenous variable World Crude Oil Prices. The decision to raise imports may have been influenced, notwithstanding the small increase, by changes in the dynamics of the international oil market or by a rise in the demand for gas and oil globally. This is also consistent with Indonesia's growing need for gas and oil, as seen by the country's growing reliance on oil-based transportation and other growing necessities. This is also consistent with Indonesia's growing need for gas and oil, as seen by the country's growing reliance on oil-based transportation and other growing necessities.

The government needs to be quite concerned about the outcomes of the forecasting process on the value of oil and gas imports, as they indicate a shift in energy consumption. In this instance, the government should support and encourage the measures that stimulate the use of renewable energy. This can include policies that encourage investment in more environmentally friendly energy sources, tax breaks, and aid with subsidies. Given how the world's energy consumption is changing, Indonesia may find it challenging to become dependent on imports of gas and oil and even to increase the value of those imports. To lessen reliance on gas and oil, the government must promote energy source diversity.

Because it captures both linear and non-linear impacts on the value of oil and gas imports, the ARIMAX-LSTM (0, 1, 2) model is a very effective tool for forecasting the value of oil and gas imports when used in conjunction with the exogenous variable World Crude Oil Prices. A future study should take into account the inclusion of additional exogenous variables, such as international trade policies, geopolitical circumstances, or other indicators pertinent to the energy industry, that might impact imports of oil and gas. To increase prediction accuracy, an additional study on hyperparameter tuning in the ARIMAX-LSTM model may be done. Additionally, techniques like cross-validation or temporal validation can be employed to assess the model's performance in greater detail.

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