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OPTIMIZATION OF ARIMA RESIDUALS USING LSTM IN STOCK PRICE PREDICTION OF PT MEDCO ENERGI INTERNASIONAL TBK

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ABSTRACT

The capital market plays an important role in the economy by providing a means for companies to obtain capital and as a place to invest. Stocks are one of the popular investment instruments because their potential profits are attractive to investors. The stocks used in this study are PT Medco Energi Internasional Tbk (MEDC) shares. The purpose of this study is to obtain the optimal ARIMA-LSTM residual optimization model, how much the accuracy, and to predict Medco stock prices for the next 8-month period. The data used starts from January 4, 2021, to October 31, 2024, was obtained from the yahoofinance.com website. The ARIMA model, which is known to be effective in handling linear data, will be combined with LSTM. The use of residuals in the LSTM model can help LSTM capture patterns in the entire stock data so as to increase prediction accuracy. The research results obtained are the optimal ARIMA-LSTM optimization model, namely, ARIMA ([5,9],1,[5,9,11]) and LSTM with the best hyperparameter, namely, hidden layer 64, batch size 16, and learning rate 0.01. The accuracy of the ARIMA-LSTM optimization model is classified as very accurate, with a MAPE value of 0.3%. Medco Energi's stock price for the next 8-month period is predicted to increase from IDR1312 to IDR1430 or an increase of 9%.

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1. INTRODUCTION

The Indonesian market is a crucial component of the economy as a source of business capital and investment opportunities. Businesses can use investor modalities to achieve operational, expansion, or other needs. In addition, investors may make investments in the modal market to profit from depreciation or appreciation [1]. According to data from the Indonesian Central Securities Depository (KSEI), the number of available investors increased from 7.4 million in 2021 to 14.8 million in 2024 [2]. The Financial Services Authority (OJK), Indonesia Stock Exchange (IDX), Self-Regulatory Organization (SRO), and other stakeholders work together to increase the number of investors in the Indonesian capital market with an effective digitalization strategy to improve public financial literacy. IDX has organized various educational activities that have reached millions of participants, including the Capital Market School program and campaigns that have succeeded in attracting the interest of the younger generation, with the majority of new investors being under 40 years old. In addition, the development of digital infrastructure such as IDX Mobile and the expansion of the IDX Investment Gallery in various regions have further facilitated access to information and investment for the wider community [3].

Energy sector stocks, especially oil and gas, play a vital role in various fields such as the economy, transportation, and industry [4]. One of the companies engaged in the oil and gas sector is PT Medco Energi Internasional Tbk (MEDC). Medco has a market capitalization of IDR 32.17 trillion, making it the largest oil and gas company in Indonesia with extensive exploration areas not only in Indonesia but also in Thailand, Oman, Yemen, Tanzania, Libya, and Mexico. In addition, Medco has a sustainability commitment, along with the MSCI predicate increasing from BBB to A and being listed in the IDX LQ45 Low Carbon Leaders [5]. Stock prices are volatile, so investors must be careful in investing. Therefore, market analysis is needed to determine the right time to buy or sell stocks [6]. One way is to predict stock prices based on historical stock price data. Stock price data is time series data collected over time and consists of linear and nonlinear components [7]. The linear component reflects stable price changes, while the nonlinear component shows sharp fluctuations due to various factors. Causes an increase or decrease in stock prices, namely market news, changes in economic policy, and other external factors [8].

The Autoregressive Integrated Moving Average (ARIMA) is one statistical model used to analyze and predict linear and statistical time series data [9]. However, ARIMA's shortcomings in handling complex nonlinear data mean that the residuals that are produced frequently highlight data points that the model is unable to explain [10]. As a result, additional techniques like Long Short Term Memory (LSTM) are needed to increase prediction accuracy [11]. LSTM, as part of the Artificial Neural Network (ANN), excels in handling nonlinear data and is able to remember temporal relationships in sequential data with its internal memory mechanism [12]. ARIMA-LSTM optimization is carried out by utilizing ARIMA to capture linear patterns, while LSTM is used to model ARIMA residuals containing nonlinear patterns [13]. This combination also helps reduce bias in estimation, because LSTM can adjust the model to fluctuation patterns that cannot be captured by ARIMA. This makes it a more flexible solution in handling data with complex characteristics and unexpected pattern changes [14].

According to the research conducted by [15] on the prediction of the stock price in the Istanbul, Turkey index, ARIMA has a high level of accuracy when predicting the stock price movement, achieving a MAPE of 5.73%. On the other hand, research conducted by [16] compares the SVR, RNN, and LSTM methods for predicting future stock prices at the Nigerian Exchange Group (NGX). The study's findings indicate that LSTM is more accurate in predicting stock prices at a MAPE of 1.33%, compared to 2.17% for RNN and 3.40% for SVR. Further research conducted by [17] compares the ARIMA, LSTM, and ARIMA-LSTM optimizations in predicting the stock price on the Shanghai Stock Exchange. The study's findings indicate that the ARIMA-LSTM optimization model has the highest accuracy with a MAPE of 0.009%, compared to ARIMA 0.56% and LSTM 0.10%.

Although these studies demonstrate the potential of ARIMA-LSTM in improving stock price prediction accuracy, several research gaps remain. Most previous studies have been conducted on general market indices or foreign exchanges, while sector-specific studies in emerging markets such as Indonesia are still limited. Moreover, research rarely focuses on the energy sector, which is highly sensitive to global oil price fluctuations, geopolitical issues, and sustainability transitions. In addition, previous research has tended to emphasize technical accuracy, while practical implications for investors and industry stakeholders have not been deeply addressed. The choice of PT Medco Energi Internasional Tbk (MEDC) as a case study is therefore highly relevant, as it not only represents the largest oil and gas company in Indonesia but also faces global market challenges and sustainability demands. Based on these considerations, this study seeks to fill the gap by applying ARIMA-LSTM optimization for stock price prediction in MEDC, aiming to provide both methodological contributions to time series forecasting and practical insights for decision-making in the capital market.

2. RESEARCH METHODS

2.1 Research Data

Among the data used is secondary data, namely the closing price of PT Medco Energi Internasional Tbk (MEDC) stock in the period from January 4, 2021, to October 31, 2024. The total number of data is 930 with 1 variable, namely close. The sample data that is utilized in this study are in accordance with Table 1 [18].

Table 1. Sample Data

No	Date	Close
1	04-01-2021	635
2	05-01-2021	635
…	…	…
930	31-10-2024	1.280

Data source: Yahoo Finance, 2024

2.2 Technical Research

Fig. 1 shows a flowchart illustrating the research process aimed at optimizing stock price prediction for Medco data using the ARIMA-LSTM approach. This diagram applies a structured integration of linear and nonlinear modeling techniques to improve prediction accuracy.

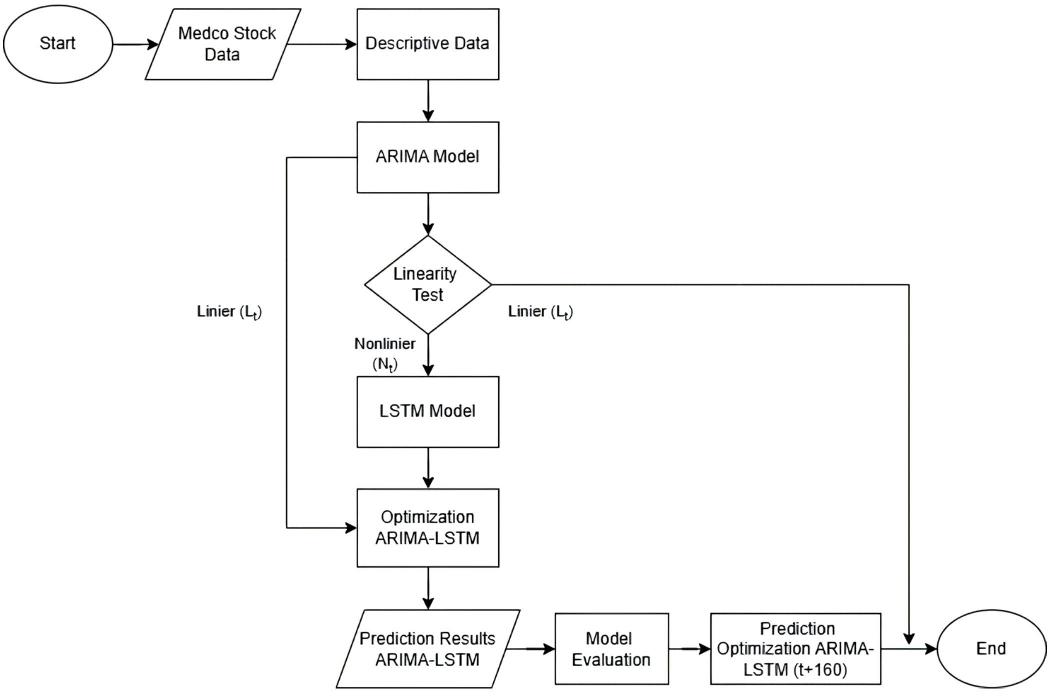


Figure 1. Flowchart Research

The study began with the collection of Medco stock data for descriptive analysis, such as identifying data patterns and their characteristics. Furthermore, the data is processed using an ARIMA model to determine the linear components in the time series data. After that, a linearity test is done to find out whether residual data (nonlinear components) cannot be modeled with ARIMA. If there are nonlinear components, the data is then analyzed using an LSTM model for analyzing complex nonlinear systems. After combining the ARIMA and LSTM prediction outputs into an ARIMA-LSTM optimization, the model is evaluated to determine the prediction accuracy. The final step is to predict stock prices for the next 8-month period or $(t + 160)$.

2.3 ARIMA Model

The Autoregressive Integrated Moving Average (ARIMA) model is a technique for time series prediction. This model is suitable for use in short-term predictions and has good forecast accuracy [19]. In ARIMA, there are three parts: Autoregressive (AR), Moving Average (MA), and Integrated (I) [20]. Autoregressive (AR) is a model where the value of the dependent variable influences the dependent variable. variable itself and can be formulated as in Eq. (1) [21]. However, according to research by [22], even if both assumptions are not fully satisfied, ARIMA prediction can still be carried out by selecting the model with the smallest AIC value as the basis for determining the best model.

$$Y_t = \emptyset_0 + \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \cdots + \emptyset_p Y_{t-p} - \varepsilon_t, \tag{1}$$

Moving Average (MA) is a model that measures the autocorrelation between error or residual values and can be formulated as in Eq. (2) [23].

$$Y_t = \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q}, \tag{2}$$

ARMA(p, q) is an acronym for Autoregressive Moving Average, which is a combined model combining AR(p) and MA(q), then can be formulated as in Eq. (3) [24].

$$Y_t = \emptyset_0 + \emptyset_1 Y_{t-1} + \cdots + \emptyset_p Y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q} \tag{3}$$

Autoregressive Integrated Moving Average (ARIMA) is a model for stationary data to produce accurate predictions. The ARIMA (p, d, q) model can be formulated as in Eq. (4) [25].

$$\phi_p(B)(1 - B)^d Y_t = \theta_0 + \theta_q (B)\varepsilon_t. \tag{4}$$

The next step is testing using the Akaike Information Criterion (AIC) to determine the model with the smallest AIC value. The model with the lowest AIC is chosen because it shows an optimal balance between complexity and accuracy, thus producing more representative residuals for further processing by the LSTM model [26]. The AIC calculation can be formulated in Eq. (5) [27].

$$AIC = -2\log(L) + 2k, \tag{5}$$

where L is the likelihood function of the data under the model and k is the total number of parameters in the model.

After making predictions using ARIMA to obtain the predicted value of the linear component $(\hat{L}_t)$, it can be continued to find the ARIMA residual value [28]. Based on the equation to obtain the value of the nonlinear component (N_t), namely the ARIMA residual, which will be used as input in the LSTM model, can be formulated as in Eq. (6) [29].

$$N_t = Y_t - \hat{L}_t, \tag{6}$$

where N_t is the t-th ARIMA residual, Y_t is the t-th time series data, $\hat{L}_t$ is the ARIMA prediction result at time t.

2.4 Liniearity Test

The data linearity test is conducted to determine whether there are nonlinear components in the data [30]. The ARIMA residual data that has been obtained will be tested using the terasvirta test and can be formulated as in Eq. (7) [31]. The following are the hypotheses of the Terasvirta test:

H_0: Residuals do not contain nonlinear patterns,

H_1: Residuals contain nonlinear patterns.

$$F_{Statistic} = \frac{\frac{SSR_0 - SSR_1}{m}}{\frac{SSR_1}{n - p - 1 - m}}, \tag{7}$$

where $F_{Statistic}$ is F value calculated for hypothesis testing, SSR_1 is sum of squared residuals for linear models, SSR_1 is sum of squared residuals for nonlinear models, m number of additional parameters in the nonlinear model, n number of observed data, p number of parameters in the initial linear model.

2.5 Normalization

Data in the dataset contains values with unequal ranges [32]. This can impact the results of data analysis calculations; therefore, data normalization is needed. Data normalization is a method for changing the data range value to between 0 and 1 [33]. The calculation of min-max scale normalization can be formulated as in Eq. (8) [34].

$$N' = \frac{N_t - N_{min}}{N_{max} - N_{min}}, \tag{8}$$

where N' is a normalized residual, N_t is residual at time t, N_{min} is the minimum residual, N_{max} is the maximum residual.

2.6 Hyperparameter Tuning Grid Search

Hyperparameter tuning using grid search is a method of testing hyperparameter combinations that uses a grid configuration [35]. The grid search method will search for all possibilities by preparing a grid, which is then evaluated to obtain the hyperparameter combination with the best value among all grids [36]. This process provides a comprehensive approach to finding the most optimal hyperparameters without missing any combination [37].

2.7 LSTM Model

LSTM is a model created to solve the vanishing gradient problem. In addition, LSTM can be used to process various types of data, namely text, video, and time series data. This method is designed to process data sequences [38]. LSTM is very suitable for handling data with nonlinear characteristics [39].

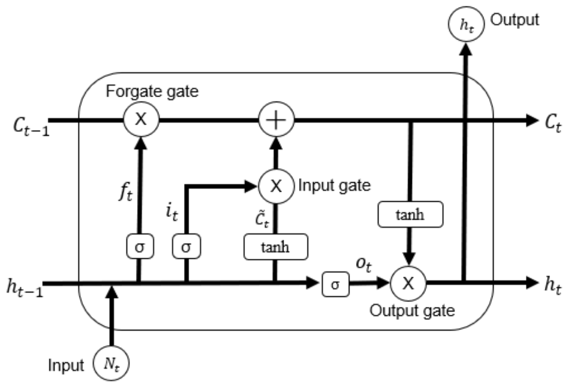


Figure 2. Architecture of LSTM

In LSTM, there are two activation functions: a sigmoid function and a tanh function [40]. The sigmoid activation function has a function to produce output from 0 to 1. While the tanh activation function can be called a hyperbolic tangent, and has a value between -1 to 1. The equations of the sigmoid and tanh activation functions can be seen in Eqs. (9) and (10) [41].

$$\sigma(x) = \frac{1}{(1 + e^{-x})}, \tag{9}$$

$$tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}, \tag{10}$$

where, σ sigma is the sigmoid activation function, x is the input data and e is Euler's constant.

LSTM has 3 gates, the first is the forget gate (f_t) which determines which information needs to be removed from the cell state. The formula of the forget gate can be seen in Eq. (11) [42].

$$f_t = \sigma\left(W_f \cdot [N_t, h_{t-1}]\right) + b_f, \tag{11}$$

where f_t is the forget gate, σ is the sigmoid activation function, W_f is the weight of the forget gate, h_{t-1} is the output before time t, N_t is residual at time t, and b_f is the bias of forget.

The second gate is the input gate, which has a function to select new information to be stored in the cell state. The input gate has a sigmoid layer and a tanh layer. The input gate can be formulated in Eq. (12) and the candidate gate in Eq. (13) [43].

$$i_t = \sigma(W_i \cdot [N_t, h_{t-1}]) + b_i\ , \tag{12}$$

$$\tilde{C}_t = tanh(W_c \cdot [N_t, h_{t-1}]) + b_c, \tag{13}$$

where i_t is the gate input, σ is the sigmoid activation function, W_i is the gate input weight, h_{t-1} is the previous hidden state, N_t is the residual at time t, b_i is the gate input bias, $\tilde{C}_t$ is the candidate gate, $tanh$ is the tanh activation function, W_c is the cell state weight, and b_c is the cell state bias.

Cell state has a function to update the value in the previous cell state with the new cell state value. The update process is carried out by. Cell state calculations can be formulated in Eq. (14) [44].

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t\ , \tag{14}$$

where C_t is cell state, f_t is the forget gate, C_{t-1} is the previous candidate gate, i_t is the input gate, and $\tilde{C}_t$ is the candidate gate.

The output gate determines the output value of the cell state by selecting the part to be output through the sigmoid layer. Next, the output is multiplied by the result of the tanh layer to ensure compliance with the previous decision. The output gate is shown in Eq. (15) and the hidden gate in Eq. (16) [45].

$$O_t = \sigma(W_o \cdot [N_t, h_{t-1}]) + b_o, \tag{15}$$

$$h_t = O_t \cdot tanh(C_t), \tag{16}$$

where O_t is the output gate, σ is the sigmoid activation function, W_o is the weight of the output gate, h_{t-1} is is the previous hidden state, N_t is residual at time t, b_o is the bias of the output gate, h_t is a hidden gate at time t, $tanh$ is the tanh activation function, and C_t is the cell state.

2.8 Denormalization

After the prediction results are obtained, denormalization must be done before determining the accuracy of the prediction findings by changing the data to its original scale. Denormalization can be formulated as in Eq. (17) [46].

$$\hat{N}' = N'(N_{max} - N_{min}) + N_{min}, \tag{17}$$

where $\hat{N}'$ is the denormalized prediction results, N' is a prediction, N_{min} is minimum residual, N_{max} is the maximum residual.

2.9 Optimization ARIMA-LSTM

ARIMA-LSTM optimization is a combination of statistical and machine learning methods, where ARIMA is effective for linear data, and LSTM excels in handling nonlinear data [47]. In the first stage, ARIMA is used to model linear components, while the residuals obtained are modeled with LSTM to handle nonlinear components [48]. The prediction results from ARIMA and LSTM are then combined according to the equation formulated in Eq. (18) [49].

$$\hat{Y}_t = \hat{L}_t + \hat{N}_t \tag{18}$$

where $\hat{Y}_t$ is the predicted value of ARIMA-LSTM optimization at time t, $\hat{L}_t$ is ARIMA predicted at time t, $\hat{N}_t$ is the predicted value of LSTM at time t.

2.10 MAPE

Model evaluation using Mean Absolute Percentage Error (MAPE) aims to measure the accuracy of the prediction results [50]. The smaller the MAPE value, the more accurate the model used [51]. The calculation of the MAPE value can be formulated as in Eq. (19) [52].

$$MAPE = \frac{\sum_{t=1}^{n} \left| \frac{Y_t - \hat{Y}_t}{Y_t} \right|}{n} \times 100\% \quad (19)$$

Based on Table 2, the MAPE value is divided into four categories. First, the MAPE value of less than 10% is included as a very accurate prediction, then the MAPE between 10-20% is included as a good prediction. The MAPE between 20-50% is included in the decent prediction category, and the MAPE above 50% is included in the inaccurate prediction category [53].

Table 2. MAPE Value Range

MAPE Range	Category Prediction
< 10%	Prediction is Very Good
10 - 20%	Prediction is Good
20 - 50%	Prediction is Fair
> 50%	Prediction is Bad

3. RESULTS AND DISCUSSION

3.1 Descriptive Data

Data description has the purpose of providing a general analysis of statistics of PT Medco Energi Internasional Tbk (MEDC) stock price data. Data description includes various important information, such as minimum, maximum, mean, and standard deviation values that help understand data patterns. This information is presented in detail in Table 3 to facilitate further analysis and interpretation.

Table 3. Descriptive Data

Year	Mean	Std. Deviation	Max	Min
(2021-2024)	924.82	329.33	1665	434
2021	591.58	84.50	760	434
2022	748.07	230.08	1190	462
2023	1128.43	200.56	1665	840
2024	1312.68	91.74	1620	115

Table 3 above shows descriptive statistics of PT Medco Energi's stock price from 2021 to 2024, with an overall average of IDR 924.82, a maximum value of IDR 1665, and a minimum of IDR 434. In 2021, the stock price was relatively stable with an average of IDR 591.58 and a standard deviation of IDR 84.50, while in 2022, it increased with an average of IDR 748.06 and higher volatility indicated by a standard deviation of IDR 230.08. In 2023, it recorded an average of IDR 1128.43 with a standard deviation of IDR 200.58, reflecting a more dynamic price movement. In 2024, the stock price fluctuated with an average of IDR 1312.68, a maximum value of IDR 1620, and a lower standard deviation of IDR 91.74. Overall, the stock price experienced an upward trend with volatility that varied each year.

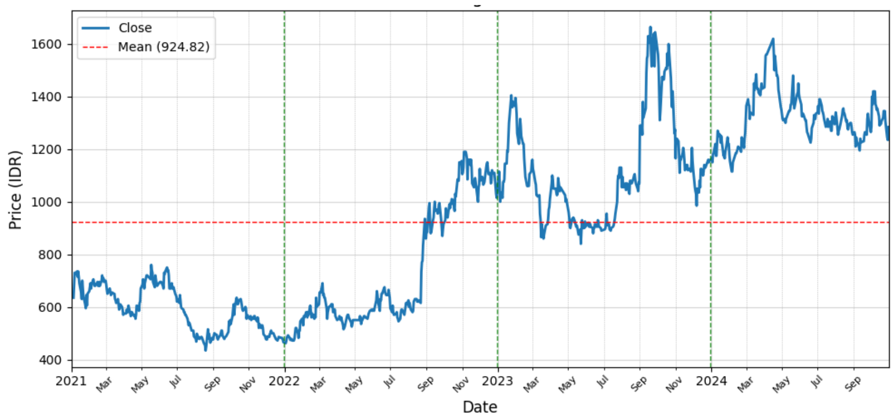


Figure 3. Medco Energi Stock Price
(Source: *Data processing results from Python*)

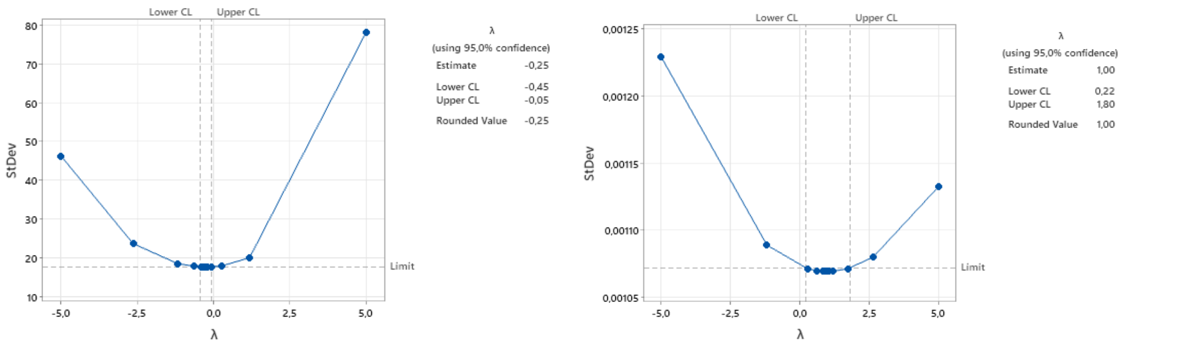
Visualization in Fig. 3 shows the movement of PT Medco Energi Internasional Tbk (MEDC) stock prices from early 2021 to October 2024. The stock price was relatively stable in 2021 to mid-2022 in the range of IDR 430–IDR 760 due to the post-COVID-19 economic recovery. A significant spike occurred from July 2022 to March 2023, reaching IDR 1400, influenced by the Russia-Ukraine war, which disrupted global oil supplies. An increase occurred again in September 2023 to October 2023 due to reduced oil production by Saudi Arabia, while in early 2024, the price jumped to IDR 1600 due to Iran-Israel tensions. However, after the ceasefire between Iran and Israel, the stock price fell gradually until October 2024 to IDR 1285.

3.2 Proportion Data

After the data is described, then continued with data division. The division is very important because it affects the prediction results. In this study, the division is done by dividing the data into 80% train data and 20% test data used to predict stock prices from the original data.

3.3 ARIMA Model

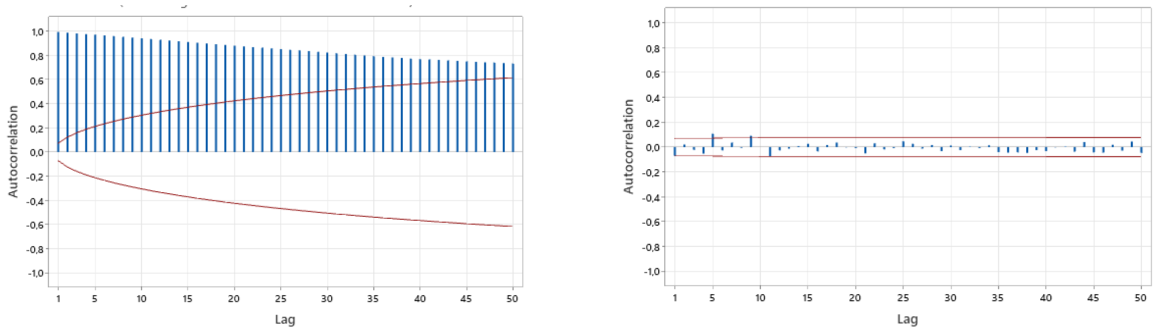
The first step in the ARIMA model is to perform a stationarity test. This is done because stationarity is an important requirement in time series analysis in the ARIMA model, where a series is considered stationary if the variance and mean are constant over time. Here is the Box-Cox test to test stationarity in the variance as shown in Fig. 4 (a) and Fig. 4 (b). Then the results of the ACF plot to test stationarity in the mean as shown in Fig. 5 below.



(a) Indicating Whether Variance Stabilization is needed **(b) Showing the Effect of Transformation on Data Distribution**

Figure 4. Plot Box-Cox Test of Close (a), Plot Box-Cox Test of Trans (b)
(Source: *Data processing results from Minitab)*

In Fig. 4 (a)**,** it can be seen that the closed data produces a rounded value or λ of -0.25, which means that the data is not stationary to the variant, so a transformation is carried out. Then Fig. 4 (b) shows the result of the transformation producing a rounded value or λ of 1, so the data is stationary to the variant.



(a) **(b)**

Figure 5. Plot ACF Before Differencing (a), Plot ACF After Differencing (b)
(Source: *Data processing results from Minitab)*

From Fig. 5 (a), it can be said that the data is not stationary because all the blue lines at each lag are outside the confidence limits (red lines), the correlation between current data and previous data is very significant, so differencing is needed. Then, in Fig. 5 (b), the data have been stationary in the mean because the blue lines have been around the mean.

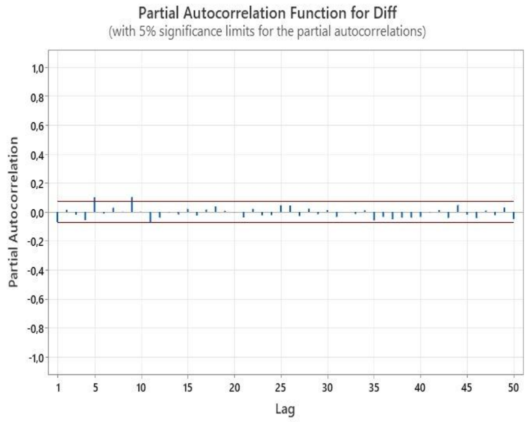


Figure 6. Plot PACF
(Source: *Data processing results from Minitab)*

The next step is to identify the temporary model with the aim of finding the most appropriate model based on the plot ACF in Fig. 5 (b) and plot PACF in Fig. 6. The results of the identification of the ACF and PACF plots of the ARIMA model obtained temporary estimates are ARIMA (1,1,1), ARIMA (1,1,0), ARIMA (0,1,1), ARIMA ([5,9],1,[5,9,11]), ARIMA (9,1,[5,9,11]), and ARIMA ([9,11],1,[1,9,11]).

Table 4. Parameters Estimation

Models	Parameters	Estimate	*p*-value	Criteria	AIC
ARIMA (1,1,1)	MA [1]	-0.263	0.583	Not Significant	7266.85
	AR [1]	-0.070	0.482	Not Significant	
ARIMA (1,1,0)	AR [1]	-0.064	0.081	Not Significant	7265.46
ARIMA (0,1,1)	MA [1]	0.059	0.106	Not Significant	7265.69
ARIMA ([5,9],1,[5,9,11])	MA [5]	-0.382	0.000	Significant	7247.24
	MA [9]	0.593	0.000	Significant	
	MA [11]	0.048	0.036	Significant	
	AR [5]	-2.292	0.000	Significant	
	AR [9]	0.676	0.000	Significant	
ARIMA [9,11],1,[1,9,11])	MA [1]	0.061	0.009	Significant	7251.42
	MA [9]	0.671	0.000	Significant	
	MA [11]	0.266	0.000	Significant	
	AR [9]	0.724	0.000	Significant	
	AR [11]	0.161	0.018	Significant	
ARIMA ([1,9],1,[1,9,11])	MA [1]	0.287	0.000	Significant	7250.79
	MA [9]	0.646	0.000	Significant	
	MA [11]	0.075	0.017	Significant	
	AR [1]	0.208	0.000	Significant	
	AR [9]	0.709	0.000	Significant	

After estimation and significance test were conducted on Table 4, three models were obtained that met the requirements, namely ARIMA ([5,9],1,[5,9,11]), ARIMA (9,1,[5,9,11]), and ARIMA ([9,11],1,[1,9,11]). Of the 3 models, ARIMA ([5,9],1,[5,9,11]) was chosen because it has the smallest AIC value.

Then, by conducting a white noise test and a normality test, the results were obtained $p-\text{value} = 0.0754 > \alpha(0.05)$ and Q = 11.50 > 3.841 do not meet the white noise requirements. So, it is concluded that we reject H_0 so that ARIMA ([5,9],1,[5,9,11]) does not meet the white noise assumption. Based on the Kolmogorov-Smirnov test above, the results are KS value = 0.0899 > $KS_{(0.05,743)} = 0.0495$ and p-value = 0.01 < 0.05, so it is decided to fail to reject H_0 which means the residual is not normally distributed. Based on the results of the white noise test and the normality test, ARIMA ([5,9],1,[5,9,11]) does not meet both requirements. However, because this study uses ARIMA-LSTM optimization, the assumption can be violated, so that ARIMA ([5,9],1,[5,9,11]) can be used to make predictions. Then, for the ARIMA equation ([5,9],1,[5,9,11]) to make predictions can be formulated as follows.

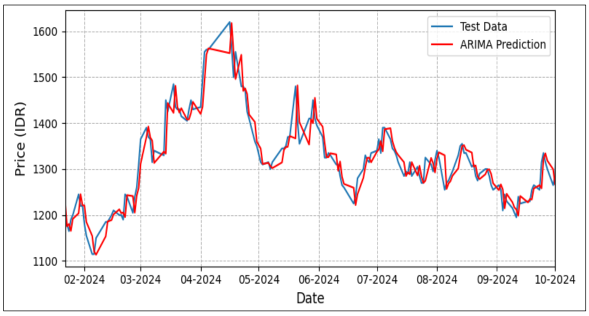
$$Y_t = Y_{t-1} - 0.292Y_{t-5} - 0.292Y_{t-6} + 0.676Y_{t-9} - 0.676Y_{t-10} + \varepsilon_t - 0.3822\varepsilon_{t-5} + 0.593\varepsilon_{t-9} + 0.048\varepsilon_{t-11}.$$

The results of Medco Energi stock price predictions using the ARIMA model ([5,9],1,[5,9,11]) are shown in Table 5.

Table 5. ARIMA Prediction Results

Date	Close	ARIMA Prediction
2021-01-04	635	-
2021-01-05	635	635.69
2021-01-06	685	635.69
…	…	…
2024-10-30	1285	1249.46
2024-10-31	1280	1234.76

Visualization in Fig. 7 (a) shows that this model is quite good at capturing the general pattern of price fluctuations. Meanwhile, Fig. 7 (b) is a comparison of actual stock prices for January 2021 to October 2024 and the ARIMA prediction results. In general, the ARIMA model is able to predict stock prices from actual data, but there are quite large differences. The difference between actual and predicted data becomes more apparent as the end of the period approaches.



(a)

(b)

Figure 7. Plot Test Data Vs ARIMA Prediction (a), Plot Actual Data Vs ARIMA Prediction (b)
(Source: *Data processing results from Python)*

After obtaining the ARIMA prediction results used to model the linear component (L_t), the next step is to calculate the residual or (N_t) from the ARIMA prediction. ARIMA residuals can be obtained by calculating the mismatch between actual data and ARIMA prediction results, as shown in Table 6.

Table 6. Residuals ARIMA

Actual Data	ARIMA Prediction	Residuals ARIMA
635	-	-
635	635.69	-0.69
685	635.69	49.30

Actual Data	ARIMA Prediction	Residuals ARIMA
…	…	…
1285	1249.46	-14.46
1280	1234.76	50.23

3.4 Linearity Test

The next step is to conduct a linearity test to check whether there are nonlinear components or not using the terasvirta test according to the equation. The test criteria are to reject $\boldsymbol{H_0}$ if $\boldsymbol{F_{statistics}} > \boldsymbol{F_{(\alpha, m(n-p-1-m))}}$ or $\boldsymbol{p}$-value $< \boldsymbol{\alpha}$. The test results obtained 3.07 > 2.37 or 0.016 < 0.05 then reject $\boldsymbol{H_0}$ which can be concluded as nonlinear residuals.

3.5 LSTM Model

After the residual data is processed, normalization is continued with min min-max scaler. Then the formation of a time series in the LSTM model from residual data ($\boldsymbol{N_t}$), is based on the ARIMA model lag error to be used as input data and target data. Based on the equation obtained above, the ARIMA lag errors are 5, 9, and 11. Therefore, the LSTM input data used is $\boldsymbol{t-5}$, $\boldsymbol{t-9}$ and $\boldsymbol{t-11}$, while the target data starts from $\boldsymbol{t = 12}$. The time series formation pattern is shown in Table 7.

Table 7. Time Series Formation

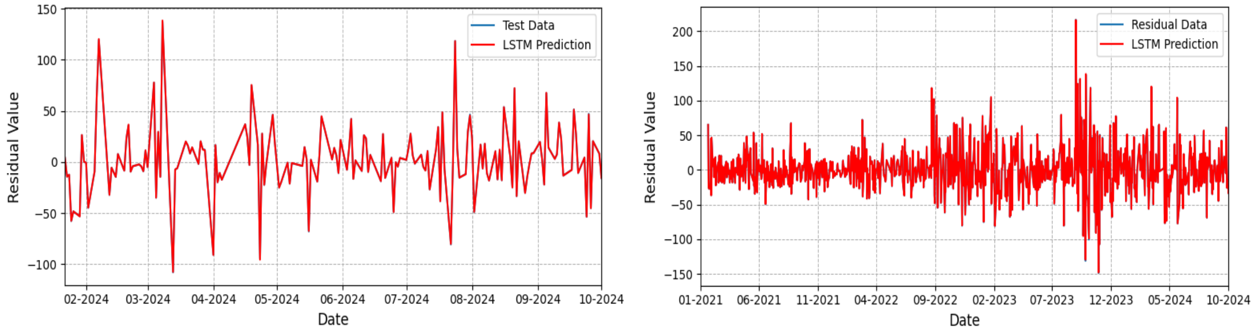
$\boldsymbol{N_{t-5}}$	$\boldsymbol{N_{t-9}}$	$\boldsymbol{N_{t-11}}$	$\boldsymbol{\widehat{N}_{t=12}}$
0.350	0.307	0.585	0.585
0.451	0.329	0.338	0.338
…	…	…	…
0.425	0.412	0.229	0.229
0.472	0.296	0.367	0.367
0.483	0.229	0.544	0.544

After the formation of the time series, the next step is hyperparameter tuning grid search with hyperparameters tested, namely hidden layer (32, 64, 128), batch size (16, 32, 64), and learning rate (0.1, 0.01, 0.001). Below is Table 8, which displays the results of hyperparameter tuning.

Table 8. Hyperparameter Tuning Grid Search Results

Hidden Layer	Batch Size	Learning Rate	MAPE (%)	MAPE Average (%)
	16	0.001	1.06	
		0.01	0.22	
		0.1	0.39	
	32	0.001	1.26	
32		0.01	0.38	2.24
		0.1	0.54	
	64	0.001	14.86	
		0.01	0.43	
		0.1	1.03	
	16	0.001	1.17	
		0.01	**0.08**	
		0.1	1.98	
	32	0.001	2.28	
64		0.01	0.66	2.67
		0.1	0.55	
	64	0.001	10.14	
		0.01	0.41	
		0.1	0.56	
	16	0.001	1.20	
		0.01	1.19	
		0.1	17.76	
	32	0.001	0.81	
128		0.01	1.21	3.91
		0.1	4.66	
	64	0.001	5.41	
		0.01	0.82	
		0.1	2.15	

The best hyperparameter configuration obtained was a hidden layer of 64, a batch size of 16, and a learning rate of 0.01 with a very small MAPE value of 0.08%. The LSTM prediction results using the best hyperparameters are shown in Fig. 8 (a) and Fig. 8 (b) below. It can be said that the LSTM prediction results are very good because they are able to capture characteristics of the residual data.



(a) (b)

Figure 8. Plot Test Data Vs LSTM Prediction (a), Plot Residual Data Vs LSTM Prediction (b)
(Source: *Data processing results from Python)*

3.6 Optimization ARIMA-LSTM

ARIMA-LSTM optimization prediction is obtained by combining ARIMA prediction results and LSTM prediction results. The visualization of ARIM-LSTM optimization prediction results is shown in Fig. 9 below. By optimizing ARIMA residuals, more accurate Medco Energi stock price prediction results are obtained because the model is able to capture almost all data patterns and characteristics.

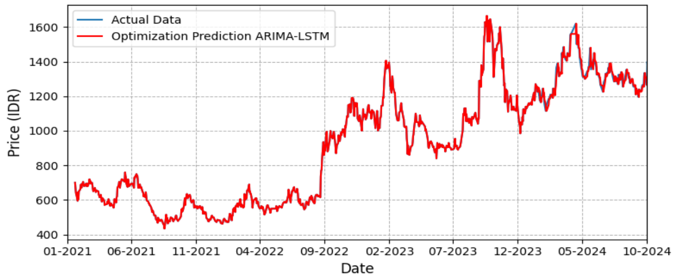


Figure 9. Plot Actual Data Vs Optimization ARIMA-LSTM
(Source: *Data processing results from Python)*

3.7 Evaluation Models

Next, compare the results of each prediction model, ARIMA, LSTM and ARIMA-LSTM optimization to find out how accurate the model is in predicting Medco Energi stock prices as shown in Table 9.

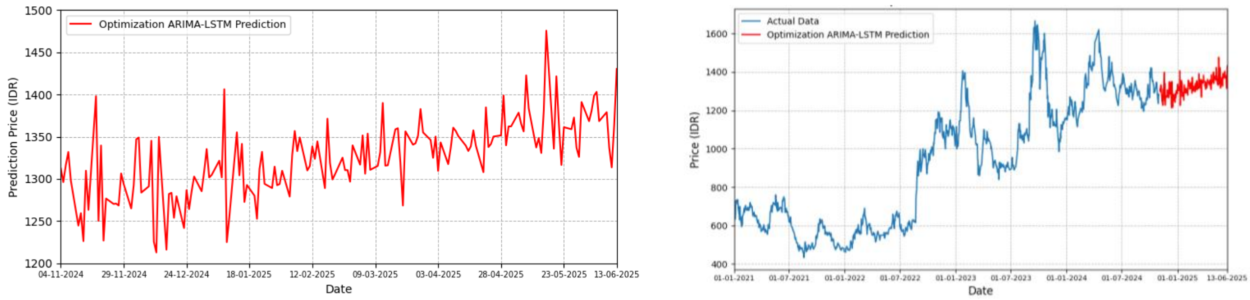
Table 9. Compare MAPE Value

Model Prediction	MAPE Value
ARIMA	2.5%
LSTM (ARIMA residual data)	2.6%
LSTM (actual data)	1.8%
ARIMA-LSTM Optimization	0.3%

Based on Table 9, it can be said that the results of ARIMA-LSTM optimization prediction are able to improve the results of ARIMA prediction alone without optimization. With an ARIMA MAPE value of 2.5%, it decreases when ARIMA-LSTM optimization is carried out to 0.3%.

3.8 Prediction 8 Months Forward

ARIMA-LSTM optimization prediction for the next 8 months or $(\boldsymbol{t+160})$ is needed because during this period, it is able to capture relevant market fluctuations more accurately, given the rapidly changing market dynamics. 8-month predictions provide stock price predictions that can be applied as a reference for making investment planning decisions. Visualization of the prediction results is shown in Fig. 10.



(a) **(b)**

Figure 10. **(a) Optimization ARIMA-LSTM $(t + 160)$, (b) Actual Data and Optimization ARIMA-LSTM $(t + 160)$**
(Source: *Data processing results from Python)*

Based on the visualization in Fig.10 above, between actual data and the ARIMA-LSTM optimization prediction $(t + 160)$, it can be seen that after experiencing an increase and a decrease in prices from early January 2024 to the end of October 2024, the ARIMA-LSTM optimization prediction $(t + 160)$ has increased, approaching the highest price in 2024.

The ARIMA-LSTM optimization model in this study still has shortcomings because outlier detection has not been carried out, and exogenous variables have not been added. Research by [54] shows that outlier detection can reduce errors by up to 50.3%, while research by [55] shows that adding exogenous variables such as inflation and world crude oil prices can reduce errors by up to 83.6%. Based on these two findings, it is proven that outlier detection and the addition of exogenous variables can increase prediction accuracy.

In practice, these findings imply that while the ARIMA-LSTM model can capture stock price trends with reasonable accuracy, prediction risks remain due to unaccounted outliers and external factors. Investors are therefore advised to complement predictive models with fundamental indicators such as inflation and global commodity prices. For the capital market industry, this study highlights the potential to develop more reliable forecasting systems by integrating macroeconomic variables, enabling more effective investment strategies.

4. CONCLUSION

From the analysis that has been done, the stock price prediction of PT Medco Energi Internasional Tbk (MEDC) through ARIMA residual using LSTM shows that the ARIMA-LSTM optimization approach produces very good predictions with a MAPE value of 0.3%. This advantage shows that linear and non-linear optimization in the ARIMA-LSTM model can effectively capture complex patterns in stock data. Then it is predicted that there will be an increase in stock prices in the next 8 months, from IDR 1312 on November 1, 2024, to IDR 1430 on June 13, 2025, or an increase of 9%.

Author Contributions

Achmad Fachril Yusuf Ababil: Conceptualization, Methodology, Data curation, and Initial Drafting. Abdulloh Hamid: Formal Analysis, Software, Visualization, Funding, and Writing - Review and Editing. Hani Khaulasari: Investigation, Resources, Project Administration, and Validation. Dian Candra Rini Novitasari: Supervision, Validation, Funding Acquisition. Wika Dianita Utami: Writing - Original Draft, Supervision. All authors reviewed and approved the final manuscript.

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Declarations

This research is carried out jointly according to the division of tasks of each one, without any conflict of interest between authors.

Declaration of Generative AI and AI-assisted Technologies

AI-assisted technology (ChatGPT) was used to support light paraphrasing and sentence restructuring for clarity. The authors confirm that the underlying ideas, arguments, data analyses, and conclusions are original and were not generated by AI. All AI-assisted edits were critically reviewed and validated by the authors.

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