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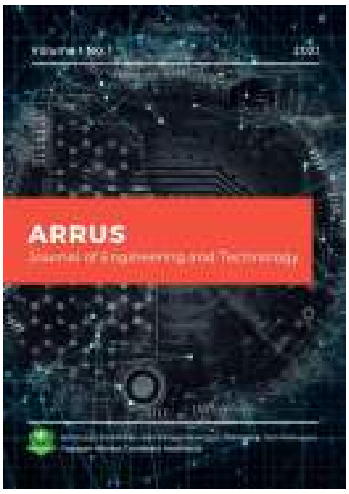

RESEARCH ARTICLE

Forecasting IDR Exchange Rate to USD Using Hybrid ARIMA – LSTM

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Abstract: Time series forecasting often involves both linear and nonlinear patterns, making the use of a single method less effective. This study aims to forecast the exchange rate of the Indonesian Rupiah (IDR) against the United States Dollar (USD) using a hybrid ARIMA–LSTM model. ARIMA is used to capture linear patterns, while LSTM is employed to model nonlinear residual components. The data used are weekly exchange rates from January 2020 to August 2025. Model performance is evaluated using Mean Absolute Percentage Error (MAPE). The results show that the hybrid ARIMA–LSTM model produces better forecasting accuracy compared to individual ARIMA and LSTM models, with the lowest MAPE value of 0.73%. This indicates that combining linear and nonlinear modeling approaches improves forecasting performance for complex time series data..

Keywords: ARIMA, Exchange Rate, Forecasting, LSTM, MAPE.

1. Introduction

Forecasting is one of the important techniques in data analysis used to estimate future values based on historical data. In time series analysis, the main objective of forecasting is to identify patterns in the data, such as trends, seasonality, and random fluctuations, so that they can be used to predict values in future periods accurately (Aswi & Sukarna, 2006). One of the most commonly used methods in time series forecasting is the Autoregressive Integrated Moving Average (ARIMA). The ARIMA model is known to have a good ability to capture linear patterns in time series data and is supported by a strong theoretical foundation. However, this model has limitations in handling nonlinear patterns that often appear in real-world data, especially economic and financial data which tend to be complex (Adhikari & Agrawal, 2013).

Along with technological advancements, Artificial Neural Network (ANN) methods have increasingly been used to overcome these limitations. One ANN model widely used in time series forecasting is Long Short-Term Memory (LSTM), which is a development of Recurrent Neural Network (RNN). LSTM has the ability to capture nonlinear patterns and long-term relationships in data, making it more flexible in modeling complex datasets (Sak dkk, 2014). Nevertheless, LSTM is not specifically designed to optimally model linear components, so in some cases its performance is not optimal when used as a standalone model..

Considering the advantages and limitations of each method, a hybrid approach combining ARIMA and LSTM becomes a potential solution. The hybrid ARIMA–LSTM model works by modeling the linear component using ARIMA, then modeling the residuals produced—which are assumed to contain nonlinear patterns—using LSTM. This approach allows the

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model to capture data characteristics more comprehensively, both in terms of linear and nonlinear aspects. Several previous studies have shown that the hybrid ARIMA–LSTM model is able to produce better forecasting accuracy compared to single models. This is evidenced by lower prediction error values, so the hybrid approach is considered more effective in handling complex time series data (Zhang, 2001).

One type of time series data that has such complex characteristics is exchange rate data. The exchange rate of the Indonesian Rupiah against the United States Dollar (USD) is an important indicator in Indonesia's economy because it affects various sectors, such as international trade, inflation, and investment (Mankiw, 2003). Exchange rate movements are highly fluctuating and are influenced by various factors, both domestic and global, so the data pattern is not only linear but also contains nonlinear components.

In recent years, the IDR exchange rate against USD has shown quite significant fluctuations, especially since the COVID-19 pandemic period until the global economic recovery period. This condition makes exchange rate forecasting increasingly challenging and requires methods capable of capturing the complexity of data patterns more effectively. Based on this, this study aims to apply the hybrid ARIMA–LSTM model in forecasting the IDR exchange rate against USD, as well as comparing the performance of the model with ARIMA and LSTM models separately. The results of this study are expected to contribute to the development of time series forecasting methods and serve as a reference in decision-making in the fields of economics and finance.

2. Literature Review

2.1. *Forecasting*

Forecasting is a method used to estimate future values based on available historical data. In the context of data analysis, forecasting not only aims to predict values but also to understand the patterns underlying the data. Forecasting in time series is conducted by utilizing the relationships between observations in previous periods. In the field of economics, forecasting is very important because it can be used as a basis for strategic decision-making, such as policy planning, risk management, and market trend analysis (Aswi & Sukarna, 2006).

2.2. *Time Series Analysis*

Time series analysis is a statistical method used to analyze data collected sequentially over certain time intervals. Time series data have the main characteristic of temporal dependence, meaning that values at a given time are influenced by values in previous periods. The main objective of time series analysis is to identify patterns such as trends, seasonality, and cycles, and to utilize them for forecasting. This approach is widely used in various fields, including economics, finance, and environmental studies (Aswi & Sukarna, 2006).

2.3. *Autoregressive Integrated Moving Average (ARIMA)*

The Autoregressive Integrated Moving Average (ARIMA) model is one of the classical methods in time series analysis used to model data based on linear patterns. This model consists of three main components: Autoregressive (AR), Integrated (I), and Moving Average (MA). The AR component describes the relationship between current values and previous values, the I component represents the differencing process to achieve stationarity, and the MA component describes the relationship between current errors and previous errors. The general form of the ARIMA model can be written in the following equation (Box et al., 2016):

$$\emptyset_p(B)(1-B)^d Y_t = \theta_q(B)\varepsilon_t$$

According to (Box et al., 2016), ARIMA is effective for data that have linear patterns and meet stationarity assumptions. However, this model has limitations in capturing nonlinear patterns that often appear in complex data.

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2.4. *Long Short-Term Memory (LSTM)*

Long Short-Term Memory (LSTM) is a development of RNN designed to overcome the vanishing gradient problem. LSTM uses a special structure in the form of a memory cell and three types of gates, namely the input gate, forget gate, and output gate, which function to regulate the flow of information in the network. According to (Sak et al., 2014), LSTM is capable of capturing long-term relationships and nonlinear patterns more effectively compared to standard RNN. Therefore, LSTM is widely used in forecasting complex time series data.

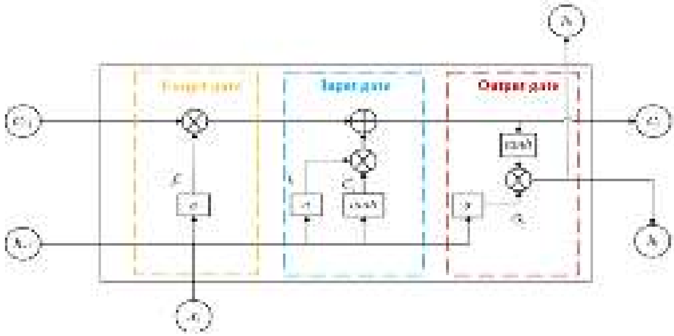

Figure 1. Structure of Long Short-Term Memory (Jin et al., 2023)

2.5. *Hybrid ARIMA – LSTM Model*

The hybrid ARIMA–LSTM model is an approach that combines statistical and machine learning methods to improve forecasting accuracy. In this model, ARIMA is used to model the linear component of time series data, while LSTM is used to model residuals that contain nonlinear patterns. According to (Zhang, 2001), this hybrid approach is able to overcome the limitations of each method when used separately. By combining both models, it is expected to obtain more accurate and robust forecasting results..

2.6. *Model Accuracy Evaluation*

Model accuracy evaluation is an important stage in forecasting analysis to assess the performance of the model used. One commonly used measure is Mean Absolute Percentage Error (MAPE), which measures the average percentage error between actual values and predicted results. According to (Chang et al., 2007), a smaller MAPE value indicates better model accuracy. MAPE is the absolute value of the percentage error relative to the average data, so the equation is obtained as follows:

$$\text{MAPE} = \frac{\sum_{t=1}^{n} \left| \frac{x_t - f_t}{x_t} \right|}{n} \times 100\%$$

2.7. *Exchange Rate*

Exchange rate is the price of one currency relative to another currency. In an open economy, exchange rates play an important role because they affect international trade, investment flows, and economic stability. According to (Mankiw, 2003), exchange rate changes can take the form of appreciation or depreciation, which indicate the strengthening or weakening of the domestic currency, respectively. High exchange rate fluctuations indicate economic instability and present challenges in the forecasting process, thus requiring methods capable of accurately capturing data patterns.

3. Research Method and Materials

This study uses a quantitative approach by utilizing secondary data in the form of the exchange rate of the Indonesian Rupiah (IDR) against the United States Dollar (USD). The data used are weekly data obtained from the Investing.com website, covering the observation period from January 2020 to August 2025. The selection of weekly data aims to capture

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exchange rate movement patterns more stably compared to daily data, while still being able to represent short-term dynamics.

The analysis begins with data exploration to understand the initial characteristics of the data, including trends and fluctuations. Next, the data are divided into two parts: training data (80%) and testing data (20%). This division is carried out to evaluate the model's ability to perform forecasting on data that have not been used during the training process.

Modeling is conducted using the hybrid ARIMA–LSTM approach. In the first stage, the ARIMA model is used to model the linear component of the time series data. Before modeling, a stationarity test is performed using the Augmented Dickey-Fuller (ADF) test to ensure that the data meet stationarity assumptions. If the data are not stationary, differencing is applied until stationarity is achieved. Next, ARIMA model identification is performed by analyzing the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots, and selecting the best model based on the Akaike Information Criterion (AIC).

After obtaining the best ARIMA model, the next step is to extract residuals from the model. These residuals are assumed to contain nonlinear patterns that cannot be captured by ARIMA. Therefore, the residuals are then used as input for Long Short-Term Memory (LSTM) modeling. Before being used in the LSTM model, the residual data are normalized using Min-Max Scaling to improve model training performance.

The LSTM model is built using a neural network architecture capable of capturing long-term relationships in the data. The training process is conducted by determining parameters such as the number of neurons, epochs, and batch size. After the LSTM model is trained, predictions are made on the residuals to obtain the nonlinear component of the data. The final stage is constructing the hybrid model by combining predictions from the ARIMA model and residual predictions from the LSTM model. This combination produces the final prediction that is expected to represent both linear and nonlinear patterns simultaneously. Model performance is evaluated using Mean Absolute Percentage Error (MAPE), where a smaller value indicates better accuracy.

4. Results and Discussion

4.1. *Descriptive Data Analysis*

Initial analysis was conducted to understand the characteristics of the IDR/USD exchange rate data during the observation period. The data show significant fluctuations with an increasing trend during certain periods, especially at the beginning of the COVID-19 pandemic. This indicates the presence of complex dynamics in exchange rate movements.

Tabel 1. Descriptive Statistucs of IDR/USD Exchange Rate

	N	Min	Max	Mean	Standard Deviation
Nilai Tukar	296	13,565	16,830	15.117	742

Based on Table 1, the exchange rate has a relatively wide range, indicating high volatility during the observation period.

4.2. *Pemodelan ARIMA*

At this stage, modeling is performed using ARIMA to capture linear patterns in the data. The results of the Augmented Dickey-Fuller (ADF) test show that the data are not stationary, so first-order differencing is applied until the data become stationary.

Model identification is conducted through ACF and PACF plot analysis, resulting in several candidate models. The best model is selected based on the Akaike Information Criterion (AIC), resulting in the most optimal ARIMA model to represent the linear data pattern.

$$Z_t = 1{,}0962\, Z_{t-1} - 0{,}0962\, Z_{t-2} - 0{,}1427\, Z_{t-3} + \varepsilon_t$$

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4.3. LSTM Modeling

Residuals obtained from the selected ARIMA model, namely ARIMA (2, 1, 0), are then used as input in LSTM modeling. These residuals are assumed to contain nonlinear patterns that cannot be captured by ARIMA. Residuals are calculated using the following formula.

$$e_t = y_t - \widehat{y_t}$$

Where is y_t is the actual and $\widehat{y_t}$ is the ARIMA predicted value.

Before the training process, residuals are normalized using Min-Max Scaling. The LSTM model is then trained to capture nonlinear patterns in the data. The LSTM prediction results for residuals are then added back to the ARIMA prediction results to obtain the final predicted value:

$$Y_t = L_t - N_t$$

The results show that LSTM model is able to follow the residual pattern well, thus improving ARIMA prediction results.

4.4. Hybrid ARIMA – LSTM Model

The hybrid model is formed by combining ARIMA predictions as the linear component and LSTM predictions as the nonlinear component. This approach allows the model to capture data patterns more comprehensively.

Tabel 2. Model Peformance Comparison

Model	MAPE
ARIMA	0,72 %
LSTM	0,81 %
Hybrid ARIMA–LSTM	0,70 %

Based on Table 2, the hybrid ARIMA–LSTM model produces the smallest MAPE value compared to other models. This indicates that the combination of linear and nonlinear methods improves forecasting accuracy. A visual comparison of the three models can be seen in Figure 2.

Figure 2. Comparison of Actual and Predicted Values for All Methods

From the graph, it can be seen that the hybrid ARIMA–LSTM prediction line is closest to the actual data. This model successfully combines the strength of ARIMA in capturing linear trends and the strength of LSTM in recognizing nonlinear fluctuations.

5. Conclusion

The hybrid ARIMA–LSTM method has been proven to provide the best forecasting results compared to single models, with a MAPE value of 0.70%. This model is effective in capturing both linear and nonlinear patterns, making it suitable for complex time series data such as exchange rates.

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References

Adhikari, R., & Agrawal, R. . (2013). An Introductory Study on Time Series Modeling and Forecasting Ratnadip Adhikari R. K. Agrawal. ArXiv Preprint ArXiv:1302.6613, 1302.6613, 1–68.

Aldi, M. W. P., Jondri, & Aditsania, A. (2018). Analisis dan Implementasi Long Short Term Memory Neural Network Untuk Prediksi Harga Bitcoin. E-Proceeding of Engineering, 5(2), 3548–3555.

Ardesfira, G., Zedha, H. F., Fazana, I., Rahmadhiyanti, J., Rahima, S., & Anwar, S. (2022). Peramalan Nilai Tukar Rupiah Terhadap Dollar Amerika Dengan Menggunakan Metode Autoregressive Integrated Moving Average (Arima). Jambura Journal of Probability and Statistics, 3(2), 71–84.

Aswi, & Sukarna. (2006). Analisis Deret Waktu Aplikasi dan Teori. Andira Publisher.

Benamirouche, H., & Moussi, O. E. (2017). FORECASTING ALGERIA'S NATURAL GAS PRODUCTION USING A BASIC AND GENERALIZED HUBBERT MODEL. September.

Fahmuddin, M., & Rais, Z. (2021). Model hibrida dekomposisi-arima untuk peramalan inflasi di Kota Makassar. VARIANSI: Journal of Statistics and Its Application on Teaching and Research, 3(2), 97-101.

Box, G. E. P., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2016). Time Series Analysis Forecasting and Control. In Sustainability (Switzerland) (Fifth Edit, Vol. 11, Issue 1). Wiley.

Budiman, H. (2016). Analisis Dan Perbandingan Akurasi Model Prediksi Rentet Waktu Support Vector Machines Dengan Support Vector Machines Particle Swarm Optimization Untuk Arus Lalu Lintas Jangka Pendek. Systemic: Information System and Informatics Journal, 2(1), 19–24.

Chang, P. C., Wang, Y. W., & Liu, C. H. (2007). The development of a weighted evolving fuzzy neural network for PCB sales forecasting. Expert Systems with Applications, 32(1), 86–96.

Che, Z., Purushotham, S., Cho, K., Sontag, D., & Liu, Y. (2018). Recurrent Neural Networks for Multivariate Time Series with Missing Values. Scientific Reports, 8(1), 1–12. https://doi.org/10.1038/s41598-018-24271-9

Dave, E., Leonardo, A., Jeanice, M., & Hanafiah, N. (2021). Forecasting Indonesia Exports using a Hybrid Model ARIMA-LSTM. Procedia Computer Science, 179(2020), 480–487.

Devi, A., & Hendikawati, P. (2024). Prediksi Kurs Rupiah Terhadap Dolar dengan MenggunakanModel Long-Short Term Memory. Prisma, 7, 882–891

Hsu, D. (2017). Multi-period Time Series Modeling with Sparsity via Bayesian Variational Inference. 1–14.

Jin, Y. C., Cao, Q., Wang, K. N., Zhou, Y., Cao, Y. P., & Wang, X. Y. (2023). Prediction of COVID-19 Data Using Improved ARIMA-LSTM Hybrid Forecast Models. IEEE Access, 11, 67956–67967.

Junaidi, J., Mandasari, S., Franciska, Y., Fahmi, A., & Rosnelly, R. (2022). Implementasi Jaringan Syaraf Tiruan Menggunakan Algoritma Backpropagation Dalam Meramalkan Kebutuhan Handsanitizer Di Pemerintah Kota Medan. Journal of Science and Social Research, 5(3), 671.

Karno, A. S. B. (2020). Analisis Data Time Series Menggunakan LSTM (Long Short Term Memory) Dan ARIMA (Autoregressive Integrated Moving Average) Dalam Bahasa Python. Ultima InfoSys : Jurnal Ilmu Sistem Informasi, XI(1), 1–7.

Krugman, P. R., Obstfeld, M., & Melitz, M. J. (2012). International Economics Theory & Policy Ninth Edition.

Mahfuzh, M. F., & Yuliantari, R. V. (2022). Analisis Penerapan Artificial Neural Network Algoritma Propagasi Balik untuk Meramalkan Harga Saham pada Bursa Efek Indonesia. Journal of Applied Electrical Engineering, 6(1), 1–3.

Mankiw, N. G. (2003). Pengantar Ekonomi (W. C. Kristiaji (ed.); Second). Erlangga.

Masri dan Hadi, A. H. (2016). Nilai Tukar Dan Kedaulatan Rupiah. Sosio-E-Kons, 8(1), 62–71.

https://doi.org/10.35877/jetech4899

ISSN : 2776-7914 (Print) / 2807-3045 (Online)

Maysarah, N. R., Widyarto, L., Pb, C. E., Suhendra, I., & Anwar, C. J. (2023). Analisis Pengaruh Hubungan Inflasi Dan Nilai Tukar Rupiah Di Indonesia. Jurnal Ilmiah Wahana Pendidikan, 9(16), 623–629.

Mustamu, R., Rumlawang, F. Y., & Lesnussa, Y. A. (2018). Aplikasi Korelasi Spearman Untuk Menganalisis Hubungan Antara Stres Kerja Dengan Kepuasan Kerja Pegawai Berdasarkan Gender (Studi Kasus : Dinas Perhubungan Kota Ambon). Al-Khwarizmi: Jurnal Pendidikan Matematika Dan Ilmu Pengetahuan Alam, 3(1), 83–92.

Qiu, J., Wang, B., & Zhou, C. (2020). Forecasting stock prices with long-short term memory neural network based on attention mechanism. PLoS ONE, 15(1), 1–15.

Sak, H., Senior, A., & Beaufays, F. (2014). Long Short-Term Memory Based Recurrent Neural Network Architectures for Large Vocabulary Speech Recognition. Cd.

Samosir, K., Arka, S., Langsung, I. A., Makro, G., Tukar, S. N., Regresi, A., & Berganda, L. (2024). Fluktuasi Nilai Tukar Rupiah Atas Dolar AS. 7, 10431–10441.

Sánchez Mesa, J. A., Galán, C., & Hervás, C. (2005). The use of discriminant analysis and neural networks to forecast the severity of the Poaceae pollen season in a region with a typical Mediterranean climate. International Journal of Biometeorology, 49(6), 355–362.

Syahram, E. F., Effendy, M. M., & Setyawan, N. (2021). Sun Position Forecasting Menggunakan Metode RNN – LSTM Sebagai Referensi Pengendalian Daya Solar Cell. Jurnal JEETech, 2(2), 65–77.

Wang, W., Bin, M., Wing, G., Chen, Y., & Xu, Y. (2024). A Hybrid ARIMA-LSTM Model for Short-Term Vehicle Speed Prediction.

Zhang, P. G. (2001). Time Series Forecasting Using A Hybrid ARIMA and Neural Network Model. Neurocomputing, 50, 159–175.