Media Statistika

p-ISSN 1979 – 3693 e-ISSN 2477 – 0647
MEDIA STATISTIKA 18(1) 2025: 93-104
http://ejournal.undip.ac.id/index.php/media_statistika

FORECAST EVALUATION OF ARIMA AND ANFIS FOR INDONESIA'S MONTHLY EXPORT (2009-2024)

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DOI: 10.14710/medstat.18.1.93-104

Article Info:
Received: 19 August 2025
Accepted: 13 October 2025
Available Online: 17 October 2025

Keywords:
Export; Forecasting; Indonesia; Time Series
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Abstract: Indonesia's export sector is a key driver of economic growth, contributing significantly to foreign exchange, employment, and industrial development. Accurate forecasting of export trends is crucial for policymakers, economists, and businesses in shaping strategies and reducing risks. This study applies the Autoregressive Integrated Moving Average (ARIMA) model to forecast Indonesia's monthly export values from January 2014 to August 2024. Dataset has been divided into training (75%) and testing (25%) subsets, and the Box-Jenkins methodology was employed, including stationarity testing, identification via ACF and PACF plots, parameter estimation, and residual diagnostics. The optimal ARIMA(1,1,1) model achieved strong predictive performance in RMSE, MSE, and MAPE. To benchmark classical methods against modern approaches, ARIMA was compared with the Adaptive Neuro-Fuzzy Inference System (ANFIS). Results indicated that ARIMA delivered higher accuracy for this dataset, reaffirming the robustness of traditional models when data characteristics align with their assumptions. It has conducted prior research evaluation via 75%:25% holdout and rolling-actual back test. This research demonstrates that classical time-series models remain highly relevant in the era of artificial intelligence, emphasizing the importance of appropriate model selection in economic forecasting.

1. INTRODUCTION

Export activities, defined as the sale of goods or services across national borders, serve as a key indicator of a country's economic strength and global trade integration (Daniels, 2000; Rahmaningrum et al., 2021). In Indonesia, there are two kinds of exports which are oil and gas exports and non-oil and gas exports (Aisyah & Renggani, 2021). In addition, exports have a critical role in Indonesia's economic growth, contributing significantly to foreign exchange earnings, employment, and industrial development (Putri et al., 2023; Sultan et al., 2023). As a major player in global trade, Indonesia's export performance is influenced by various factors, including international demand, commodity prices, and exchange rate fluctuations (Ngatikoh, 2020). These complexities underscore the need for accurate and adaptive forecasting models to support strategic planning and policy formulation. Forecasting, particularly in the economic domain, is widely recognized as a fundamental tool for anticipatory decision-making and resource optimization (Karl et al., 2021; Petropoulos et al., 2022). Moreover, time-series forecasting has become an essential tool in economic and trade analysis, offering insights into future trends based on historical data (Kashpruk et al., 2023; Lim & Zohren, 2021).

There are several studies that conduct forecasting export in Indonesia. Implementation of Artificial Neural Network (ANN) method with backpropagation algorithm forecast palm oil export in Indonesia (Putri et al., 2023). Moreover, Dave et al. explored a hybrid model ARIMA-LSTM to forecast Indonesia exports (Dave et al., 2021). The hybrid model obtains the lowest error metrics among all tested models. Another study is examining non-oil gas export data in Indonesia (Bustami et al., 2023). The best model was employed to dataset which is exponential smoothing since has the lowest MAPE. In 2022, Ahmar et al. proposed forecasting model of oil and gas exports in Indonesia by using ARIMA Box-Jenkins (Ahmar et al., 2022). And ARIMA (0,1,1) has chosen as the best model as has AIC value of 2047.65. In addition, the classic box-jenkins method employed to forecast the quantity of oil and non-oil and gas export in Indonesia (Sinaga et al., 2023). Model (5,1,3) has the smallest MAPE of 8.142% so this model act to forecast the amount oil and gas and non-oil and gas exports in Indonesia. Furthermore, a study results show that Fuzzy Time Series, both with and without Markov Chain, provides better short-term forecasts with lower MAPE and MSE than the method without Markov Chain (Sri et al., 2019). Junita and Kartikasari in 2024 (Junita & Kartikasari, 2024) applied the NNAR method to forecast oil and gas exports, selecting it for its flexibility without assuming normality or white noise. The best model, NNAR(2,3), achieved a MAPE of 11.76%, indicating strong forecasting performance (Junita & Kartikasari, 2024).

However, the body of literature on export forecasting in Indonesia has been growing and employing various techniques such as Artificial Neural Networks (ANN), hybrid ARIMA-LSTM, NNAR, and exponential smoothing. There remains a lack of empirical studies that isolate and rigorously evaluate the standalone performance of the traditional ARIMA model on comprehensive national export data. Most existing studies either focus narrowly on specific commodities or emphasize hybrid model performance, leaving a gap in understanding how well ARIMA alone can capture broader export dynamics. In addition, the Adaptive Neuro-Fuzzy Inference System (ANFIS) combines the robust of fuzzy logic and neural networks, handling it to effectively capture intricate patterns in historical data (Eliwa et al., 2024; Samanta et al., 2021).

The objective of this research is to determine the most suitable ARIMA configuration for export data, evaluate its predictive accuracy, compare the forecasted result with ANFIS model, and offer insights that can aid in formulating strategic trade policies and economic decisions. ARIMA (Autoregressive Moving Average) methods are among the most powerful approaches in the statistical methods which can identify means (Chodakowska et al., 2021). Furthermore, since 1970, the ARIMA model has become a reliable and adaptable method among forecasting systems (Ledolter, 1979). ARIMA model is the most popular accepted time series (Kaur et al., 2023). Known for its ability to model complex patterns in univariate time-series data, ARIMA is widely used for economic forecasting due to its simplicity and effectiveness. The empirical evidence prefers that ANFIS not merely provides superior out-of-sample accuracy compared to traditional linear models but also offers significant advantages in forecasting volatile trade series (Salimi-Badr, 2024).

2. LITERATURE REVIEW

2.1. Autoregressive Integrated Moving Average (ARIMA)

The Box-Jenkins technique, or ARIMA for short, is an acronym for Autoregressive (AR) Integrated (I) Moving Average (MA) (Rhanoui et al., 2019). The three parameters (p, d, and q) define an ARIMA model, such as:

a. p is defined as the number of autoregressive terms [AR(p)]
b. d is defined as the order of differencing required to achieve stationarity [I(d)]
c. q is defined as the number of moving averages [MA(q)]

The formula of ARIMA model can be presented in the following Equation (1) (Zhang, 2003):

$$y_t = \theta_0 + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q} \tag{1}$$

where y_t is called as the actual data at time step t, ε_t is called as the random bias at time step t, ϕ_i and θ_j are called as the coefficient, p and q are referred to as integers, these represent the model order and are designated as polynomials for autoregression and moving averages, respectively.

2.2. The Adaptive Neuro-Fuzzy Inference System (ANFIS)

The Adaptive Neuro-Fuzzy Inference System (ANFIS) is a hybrid model that combines neural networks and fuzzy logic, widely implemented for tasks such as prediction, classification, and control in numerous fields (Septiarini et al., 2020; Septiarini & Musikasuwan, 2018b; Tabbussum & Dar, 2021). Recent advancements have focused on enhancing ANFIS's performance through parameter optimization and simplification methods (Qiao et al., 2023). Additionally, parameter optimization techniques using Gaussian mixture models and multilayer perceptrons have improved ANFIS's robustness in any tasks, achieving significant accuracy improvements and reduced training times (Jabeen et al., 2023). The protocol of ANFIS has 5 layers (Tarno et al., 2019; 2018) that can be written as follow:

Layer 1: The first layer consists of adaptive nodes, each controlled by a single-parameter activation function.
Layer 2: Each second-layer node is fixed, and its output equals the product of its incoming signals.
Layer 3: The third layer consists of fixed nodes that compute each rule’s firing strength relative to the aggregate across rules.
Layer 4: The fourth layer comprises adaptive nodes, with each node’s output controlled by its fitted parameters.
Layer 5: Every node in the fifth layer is fixed, returning the sum of all incoming inputs.

2.3. Model Evaluation

The Root Mean Square Error (RMSE), a crucial measure of the model's forecasting accuracy, is used in this study to evaluate the model. By taking the square root of the average of the squared differences between the expected and actual values, RMSE calculates the standard deviation of the residuals, also known as prediction errors (Calanca, 2014). MSE squares the difference between actual and predicted values to penalize greater errors more severely (Rachmawati & Gunawan, 2020). Forecasting accuracy is expressed as a percentage using MAPE, making it simple to interpret across datasets (Lemoine & Kapnick, 2024). This assessment guarantees that the chosen forecasting model produces accurate projections appropriate for guiding trade and economic policy decisions. To evaluate the forecasting performance of each model, several evaluation metrics were computed. These metrics are widely used in time series forecasting to capture different aspects of model accuracy. The following four criteria were adopted in the following Equation (Apriliyanti et al., 2023; Chicco et al., 2021; Munandar et al., 2022; Pratiwi et al., 2025):

$$MSE = \frac{1}{m}\sum_{i=1}^{m}(X_i - Y_i)^2 \quad (2)$$

$$RMSE = \sqrt{MSE} \quad (3)$$

$$MAPE = \frac{1}{m}\sum_{i=1}^{m}\left|\frac{X_i - Y_i}{y_i}\right| \quad (4)$$

where x_i is defined asthe forecasted i^{th} value, y_i is the actual i^{th} value, and m is the amount data.

3. MATERIAL AND METHOD

3.1. Data Management

The Indonesia export data is obtained from https://www.bps.go.id/id/ which is collected from January 2009-August 2024. The total data is 188 monthly data as shown in Figure 1. In this study, the data set will be divided into two groups namely training and testing set. According to a study (Septiarini & Musikasuwan, 2018a), the optimal ratio of splitting dataset is 75% : 25%, for 141 training data and 47 testing data,. All models are trained on the same data partition and evaluated on the identic evaluation metrics. Furthermore, the plot of time series export data indicate fluctuation along the time set. Thus, it is needed the transformation in order to adjust the stable data set which is differencing process. Another reason is that ARIMA process is implemented on a stationary series (Rhanoui et al., 2019). Figure 2 depicts a stationary series of Indonesia export.

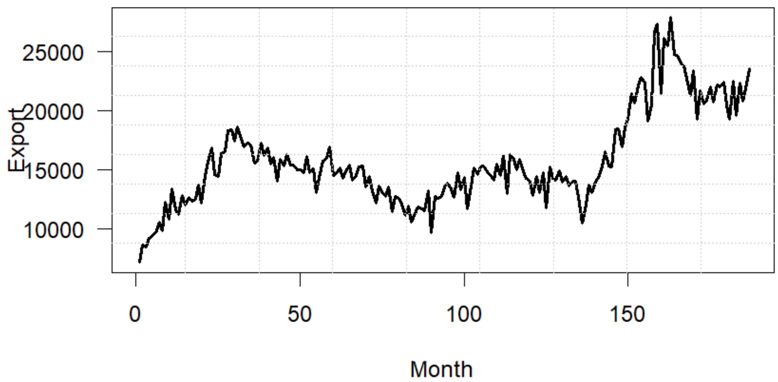


Figure 1. The Plot of Time Series Export Data

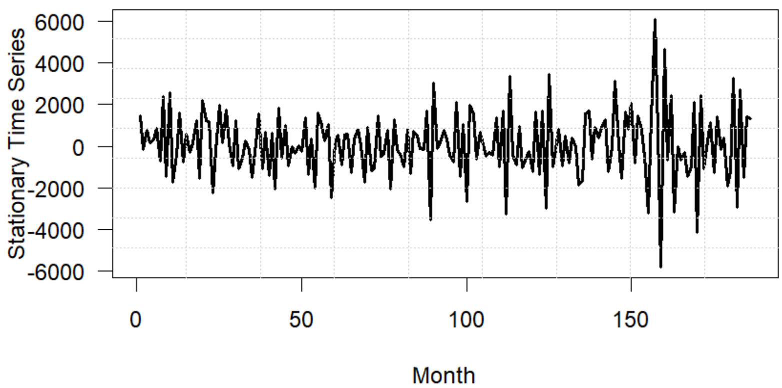
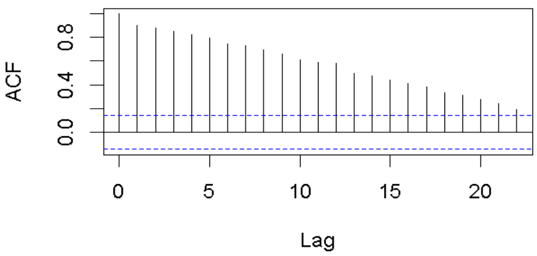


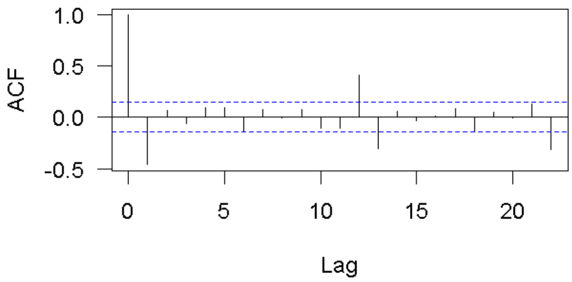
Figure 2. Time Series Plot after Differencing Transformation

Figure 1 displays the monthly time series of Indonesia's export values over approximately 15 years. The plot shows clear non-stationary behavior with an overall upward trend, periodic fluctuations, and increased volatility around the 150th month. These characteristics justify the use of time series modeling techniques, particularly ARIMA, which requires data transformation to achieve stationary before forecasting.

Figure 2 shows the time series plot of Indonesia’s export data after first-order differencing. The transformation was applied to remove trend components and achieve stationary, a key requirement for ARIMA modeling. The resulting series fluctuates around a constant mean with relatively stable variance, indicating that the data is now suitable for further time series analysis and model identification. Furthermore, the Augmented Dickey–Fuller (ADF) test result concluded that the time series after differencing is stationary, as shown by the test statistic of −5.2697 and a p-value of 0.01, which is below the 0.05 significance level. This means the null hypothesis of a unit root is rejected, suggesting that the data does not exhibit a trend or varying variance over time.



(a)



(b)

Figure 3. ACF Plot (a) Before Differencing, (b) After Differencing

Figure 3(a) illustrates the autocorrelation function (ACF) plot of the original export time series data. The slow decay pattern of the ACF values indicates strong trend components and non-stationary, which violates the assumption required for ARIMA modeling. Figure 3(b) presents the ACF plot after first-order differencing. The autocorrelations drop sharply and lie mostly within the 95% confidence bounds, confirming that the differenced series is stationary and appropriate for ARIMA model identification and estimation.

3.2. Model Construction ARIMA

There are three main steps to construct ARIMA model (Box et al., 2015):

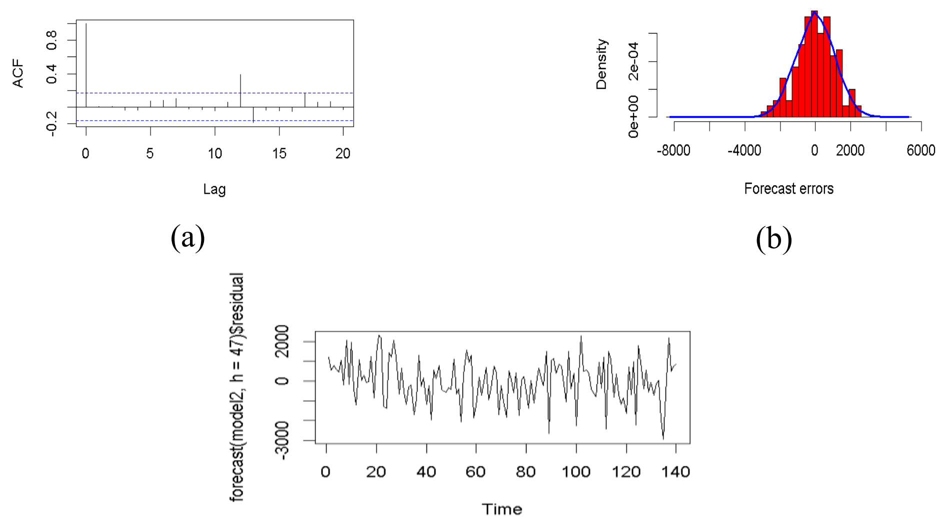
a. Identification
Figure 4 displays the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. Unless otherwise stated, these plots are computed on the first-differenced training data used for model identification. Figure 4(a) shows the Autocorrelation Function (ACF) plot of the differenced series, where significant spikes are present only at the first lag, and the remaining lags fall within the 95% confidence bounds. This pattern is indicative of a Moving Average (MA) process of order 1. Figure 4(b) displays the Partial Autocorrelation Function (PACF) plot, which shows a significant spike at lag 1 and minor insignificant values at subsequent lags. This suggests the presence of an Autoregressive (AR) component of order 1. Figure 3 depicts the level series for descriptive purposes only and model identification relies on the differenced series in Figure 4.

b. Estimation
The second step of ARIMA model is parameter estimation which has been analyzed by using R Version 4.5.0 program. And model estimation obtained ARIMA (1,1,1).

c. Diagnosis checking
The last step focused on the verification of model relevance. Moreover, 47 predicted values are covered by the diagnostic checking deal. Figure 5 shows that the predicted error appears to fit a normal distribution with zero mean and constant variance. And it can be stated that estimated model is appropriated approach.

(a) (b)

Figure 4. Plot (a) ACF, (b) PACF of the First-differenced Training Series (Jan 2009–Aug 2024)



(a) (b)

(c)

Figure 5. (a) ACF Plot for Forecasting Error, (b) Histogram for Forecasting Error, (c) Time Series Plot Forecasting Error

Figure 5 presents diagnostic plots to evaluate the adequacy of the selected ARIMA model. Figure 5(a) depicts most autocorrelations lie within the 95% confidence bounds, indicating that the residuals behave like white noise and no significant autocorrelation remains unmodeled. In addition, Figure 5(b) displays the distribution of forecast errors is approximately normal and centered around zero, suggesting that the model residuals are symmetrically distributed. And Figure 5(c) illustrates the residuals fluctuate randomly around zero without discernible patterns, confirming the assumption of homoscedasticity and no model misspecification.

3.3. Model Construction ANFIS

This study implemented a Sugeno-type ANFIS on the first-differenced export series using the same 75:25 train–test split as ARIMA. Figure 6 illustrates the ANFIS architecture which inputs are consist of the last four monthly lags and each input uses five Gaussian membership functions. Furthermore, the rule base comprises 200 fuzzy rules while the output node is constant. Parameters are trained with the standard hybrid algorithm (least-squares for consequents, backpropagation for premises) for 100 epochs, with early stopping by validation loss.

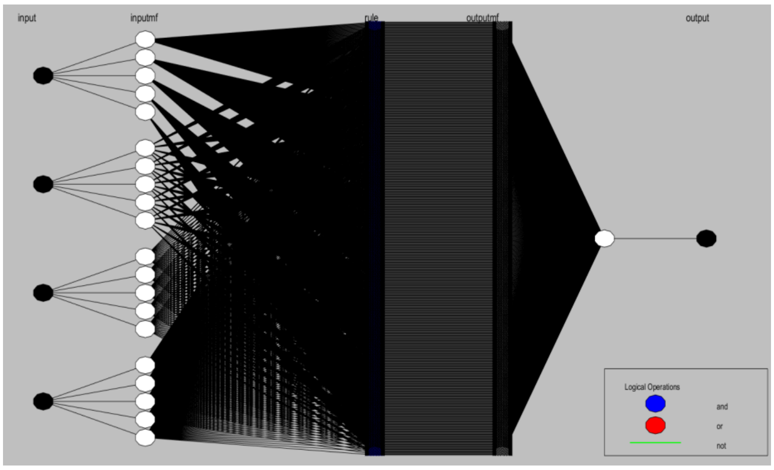


Figure 6. The Architecture of ANFIS Model

4. RESULTS AND DISCUSSION

The implementation of ARIMA model for forecasting Indonesia exports has been obtained that is depicted in Figure 7. The plot illustrated a small different between forecasted and actual value. Furthermore, the forecasting results are from January, 10 2020 until January, 8 2024 that will be evaluated by using RMSE, MSE, and MAPE. In addition, comparing the performance of ARIMA with ANFIS (Adaptive Neuro-Fuzzy Inference System) model will be discussed in this study. Table 1 represents the evaluation value of ARIMA and ANFIS model for testing data.

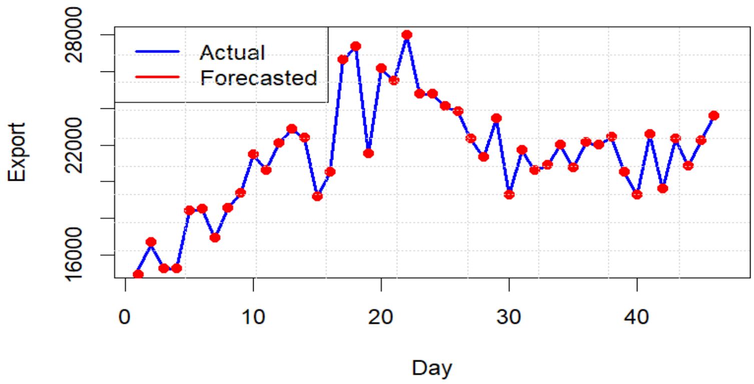


Figure 7. The Plot of ARIMA Forecasting Results

Figure 7 displays the ARIMA model forecasting results for Indonesia's export values over a 47-day horizon. The red line represents predicted export values, showing an overall stable pattern with moderate fluctuations. The forecast indicates a short-term upward trend followed by a stabilization phase, suggesting that export performance is expected to maintain consistency in the near term. These results demonstrate the ARIMA model's capability in capturing the underlying trend and seasonality within the export data.

Table 1. The Evaluation Values

	ARIMA	ANFIS
RMSE	2,183.36	13,199.55
MSE	4,767,059	174,228,160.80
MAPE	0.08	19.24

Once ARIMA model has been implemented to forecast Indonesia export. In this study, ARIMA model as a classic forecasting model will be compared with artificial intelligence which is ANFIS model. Moreover, based on studies, all results presented are analyzed on the common 75:25 split (Septiarini et al., 2020, 2021). Training data is implemented to construct the model and testing data set will be put as inputs to obtained the forecasted results. According to Figure 6, it can be described that ARIMA model can propose the forecasted values close to the actual observation. In addition, evaluation metrics of ARIMA model is smaller than ANFIS model. Modern method cannot guarantee to perform better than classical method. And the classical method also cannot guarantee to perform better than modern method. Thus, it is necessary to manage and examine the dataset in order to get forecasting method properly.

This study makes a significant contribution to the forecasting literature within the context of macroeconomics, particularly in relation to national exports in developing countries. It reaffirms the validity of the Autoregressive Integrated Moving Average (ARIMA) model as a classical method in economic time-series forecasting. Despite its long-standing use (Box et al., 2015), ARIMA remains relevant in the modern era, even amid the growing dominance of artificial intelligence-based approaches (Lim & Zohren, 2021). The comparative analysis of ARIMA and the Adaptive Neuro-Fuzzy Inference System (ANFIS) presented in this study enriches the methodological discourse in forecasting research. The finding that ARIMA yielded a lower RMSE than ANFIS suggests that model complexity does not necessarily equate to higher predictive accuracy (Rhanoui et al., 2019). This aligns with the view of (Petropoulos et al., 2022), who argue that the choice of forecasting method should be informed by the characteristics of the data rather than a preference for advanced technologies. Accordingly, this study enhances our understanding of the conditions under which traditional statistical models remain highly effective. It also offers empirical insights for similar research in developing country contexts, where data limitations and technological constraints are often prevalent.

From a practical standpoint, this study offers extensive implications for policymakers and stakeholders in the export sector. Accurate forecasting results provide data-driven support for strategic decision-making in foreign trade policy, which is crucial given the significant role of exports in driving Indonesia's economic growth (Ngatikoh, 2020). The ability to project export values with precision enhances the effectiveness of national economic planning and policy formulation. Institutions such as the Ministry of Trade, Statistics Indonesia (BPS), and Bank Indonesia may utilize the ARIMA model's output to design fiscal and monetary policies that are more adaptive to global economic dynamics. As export fluctuations are often driven by international demand and commodity price volatility (Ngatikoh, 2020), predictive modelling based on historical data becomes an essential tool for export diversification and foreign exchange stabilization. Moreover, for export-oriented enterprises, accurate short-term forecasting supports planning across production, distribution, and logistics, while enabling better risk mitigation amid market uncertainties. This, in turn, strengthens the international competitiveness of Indonesian products (Hasmarini & Murtiningsih, 2017). By providing a forecasting approach that is both replicable and easily implementable using statistical software such as R, the study also contributes to enhancing technical capacity among economic analysts and policy practitioners at both regional and national levels.

5. CONCLUSION

This study focused on forecasting Indonesia's export trends using the ARIMA time series model and comparing its predictive performance with the ANFIS model. The dataset was divided into training (75%) and testing (25%) sets to ensure objective model evaluation.

The results demonstrated that ARIMA provided more accurate predictions than ANFIS, as indicated by lower RMSE values on the test dataset. These findings suggest that classical statistical models like ARIMA remain effective for export forecasting, particularly when the data exhibit linear temporal patterns. The outcome of this study may support policy makers and government stakeholders in making informed decisions related to trade planning and economic strategy. Furthermore, the study emphasizes the importance of selecting an appropriate time horizon and proportion of training-testing data to build reliable forecasting models. Future research is encouraged to explore different data partitioning strategies, include longer time series, and assess the influence of model complexity, particularly by combining traditional and machine learning approaches to enhance predictive performance.

ACKNOWLEDGMENT

The authors also wish to express their gratitude to the reviewers for their valuable feedback.

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