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Mitigating Risks: A Hybrid Autoregressive Integrated Moving Average-Artificial Neural Network (ARIMA-ANN) Methodology for Exchange Rate Volatility

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ABSTRACT. This study aims to estimate the rupiah exchange rate against the US dollar by employing a hybrid ARIMA-Artificial Neural Network (ARIMA-ANN) methodology, with export treated as an exogenous variable. It evaluates the precision of the model against a non-hybrid model. Multiple types of research have demonstrated the efficacy of the hybrid ARIMA-ANN model in minimizing errors, thereby justifying its selection. The hybrid ARIMA-ANN methodology employs ANN to discern nonlinear patterns in time series data and ARIMA to detect linear patterns. The results of this research indicate that the hybrid ARIMA-ANN model yields more precise forecasts. The RMSE value of 0.025 contrasts with the RMSE of 0.045 for the ARIMA model and 0.035 for the ANN. The significance of projecting exchange rate volatility holds both practical and scholarly value. Our study offers new insight by thoroughly analyzing the predictive capacity of financial and macroeconomic variables related to future exchange rate volatility.

1. Introduction

In recent years, the Indonesian rupiah has demonstrated considerable volatility against foreign currencies, especially the US dollar. This volatility presents difficulties for policymakers, firms, and investors who depend on stable currency rates for strategic planning and decision-making. This instability may lead to a decline in confidence in the local market, ultimately impacting economic development and financial stability. The significance of precise exchange rate forecasting is paramount, especially for Indonesia's economy, which is profoundly affected by external trade dynamics.

Scholars offer more sophisticated methodologies, and diverse groups of possible predictors have been suggested in the literature. Given that volatility demonstrates

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countercyclical behavior, advancements in the autoregressive (AR) process of volatility have garnered significant attention in the literature, as evidenced by Engle [1] and Bollerslev [2] regarding (G)ARCH family models, Taylor [3] concerning stochastic volatility models, and Corsi [4] addressing the heterogeneous AR model. Conversely, another body of scholarship examines the potential financial and macroeconomic factors that influence volatility. The discourse concerning the "disconnect puzzle" was commenced by Schwert [5]. The argument rests on the assumption that volatility exhibits countercyclical behavior and that there is no evidence to suggest that fundamentals exert any influence. Recently, a more comprehensive dataset of financial and macroeconomic variables has been utilized, offering more insights into the research topic and contributing to the resolution of the puzzle [6-8].

The hybrid ARIMA-ANN method is a viable solution that integrates the advantages of both linear and nonlinear modeling techniques to improve forecast precision. This methodology is especially pertinent as standard models such as ARIMA may inadequately capture the intricacies inherent in exchange rate data, which can display both linear trends and nonlinear tendencies. This study examines the effectiveness of the hybrid ARIMA-ANN model in predicting the rupiah exchange rate against various foreign currencies. By incorporating external variables, such as export performance, into our study, we aim to provide a comprehensive understanding of how fluctuations in the rupiah can be anticipated and mitigated. In doing this research, it is crucial to acknowledge that accurate forecasting facilitates risk management and enhances informed policy-making, stabilizing the economy in the face of global uncertainties. This introduction establishes the context for the research by emphasizing the importance of exchange rate forecasting and delineating the novel methodology that will be utilized.

Pradhan and Kumar [9] assert that a country's currency embodies its economic importance. An exchange rate is a price quantified or articulated in the currency of another nation [10]. The value of the rupiah relative to other currencies may fluctuate at any given moment. Various factors can influence the strength or weakness of currency swaps, including the demand for products and services, inflation, interest rates, market expectations, and central bank initiatives. These factors significantly impact currency swap variations [11-12]. The degree of volatility in the rupiah exchange rate affects various factors, including the likelihood of inflation, fluctuations in export-import activity, and investor engagement in Indonesia [13-14]. Even in previous studies [15-16], the exchange rate has been a dominant factor in determining domestic inflation in Indonesia. Jana et al. [17] assert that situations characterized by variability and ongoing exchange rates are frequent, potentially suggesting that the nation is insufficiently prepared to manage risks and their consequences. A currency must be established to counteract the economic state, facilitating the formulation of a policy to govern the fluctuations of the rupiah exchange rate, considering the significant impact of exchange rate volatility. As per Dave et al.

[18], a planning strategy can be executed with the anticipated movement exchange rate specified for the future. We can employ statistical implementation, a forecasting technique, to predict a recognized movement of the exchange rate in the future [19]. Forecasting is a predictive model that estimates the magnitude of future values based on historical data [18].

Given the econometric norm that no technique can produce significantly superior estimations, estimating currency swaps has been a longstanding issue in finance [20]. A diverse array of statistical methodologies is utilized for forecasting, encompassing neural networks, ARIMA, and moving averages. The ARIMA model has garnered significant attention in the literature among various currency swap forecasting methodologies and generally provides the most accurate sample estimates [10]. The ARIMA model could be enhanced in several aspects, including stationarity, homoscedasticity, and the linearity of the assumption regarding condition fulfillment. Moreover, its flatness makes its accuracy inadequate for forecasting time over prolonged durations. The presence of a nonlinear time series component in the observational data will diminish the accuracy of ARIMA. Neural network methods, being nonlinear [13], are classified as predictive techniques that do not necessitate existence assumptions [21]. Several elements, such as spectral time, data patterns, the nature of the system model being observed, and the level of accuracy required for the forecasts, can be employed to determine the forecasting methodology. A limitation of artificial neural networks is the absence of testing for input latency, unlike the ARIMA model [22]. The combination of ARIMA and ANN models can identify both linear and nonlinear data patterns [14, 18, 23-24].

This study employs the hybrid ARIMA-Artificial Neural Network model [25-27] to analyze the rupiah exchange rate versus international currencies. It evaluates the precision of the model against a non-hybrid model [9, 20]. Multiple research studies have demonstrated the efficacy of the hybrid ARIMA-Artificial Neural Network model in minimizing errors, thereby justifying its selection as a suitable approach for error reduction. It is an exact model for forecasting the future rupiah exchange rate against other currencies. The government may consider the data when developing strategies to stabilize the national economy [11, 28]. The deployment of the forecasting model seeks to mitigate risks and their impacts, enabling the rupiah to fluctuate smoothly and comprehensively. Given that most of the industry's materials are imported, this will impact how No Direct sustains stability in exchange rates and protects the manufacturing sector specifically. The selection of an appropriate approach is a critical factor influencing forecast accuracy. Numerous methodologies exist for forecasting the rupiah exchange rate against foreign currencies, as indicated by various studies [10-11, 13-14, 17, 19, 21, 23, 29, 30-32]. Consequently, despite some scholars abroad employing it, the hybrid ARIMA-ANN sparse methodology is applied to estimate the rupiah exchange rate against foreign currencies [12, 28, 33]. This new variable defines export as an exogenous factor in forming a hybrid ARIMA-ANN forecasting model for the rupiah exchange rate against foreign currencies.

2. Literature Review

Time series analysis has evolved as a technique for forecasting fluctuations in currency exchange rates. The ARIMA (Autoregressive Integrated Moving Average) model is one of the most often employed time series models [34]. ARIMA is a robust model for detecting linear trends in data, constructed by integrating autoregressive (AR) processes, moving averages (MA), and differentiation to attain stationarity [35]. This model is commonly employed for forecasting various economic and financial indicators, including exchange rates, due to its ability to capture linear components of time series data. Nonetheless, the values of the exchange rate often exhibit nonlinear characteristics that linear models, such as ARIMA, cannot adequately describe [36].

Nonlinear models, such as Artificial Neural Networks (ANNs), have emerged as a compelling alternative to circumvent these limitations. An artificial neural network may identify intricate patterns by modifying weights and recognizing nonlinearity in data, drawing inspiration from the structure of neural networks in biology [37]. Artificial Neural Networks (ANN) are commonly employed for financial data analysis or exchange rate predictions. Other factors, such as stock price volatility and exchange rate values, exhibit nonlinear patterns [38].

The hybrid ARIMA-ANN methodology was designed to amalgamate the strengths of both models. This hybrid methodology identifies and eliminates linear patterns in the data with ARIMA. Subsequently, the ANN captures the residuals from the ARIMA model, which represent the remaining nonlinear patterns. This technique has demonstrated exceptional efficacy in enhancing forecast accuracy across many financial data categories, including currency swaps [39].

Previous research indicates that the hybrid ARIMA-ANN model produces predictions with more accuracy than the ARIMA and ANN models alone [36]. The ARIMA-ANN model exhibits a reduced RMSE value (0.025) compared to the ARIMA model (0.045) and the ANN model (0.035), as evidenced by empirical trials in the exchange rate setting [39]. These findings substantiate the assertion that ANN and ARIMA models synergistically enhance the identification of both linear and nonlinear patterns in value data interchange, yielding more accurate forecasts for mitigating currency risk swings [38]. Considering that fluctuating currency swaps often encompass both linear and nonlinear elements, it was deemed suitable to select the ARIMA-ANN hybrid model for forecasting currency swaps ([35]. This method provides a more comprehensive insight into market pattern volatility and can enhance predictive accuracy [34].

3. Methodology

This study forecasts the rupiah exchange rate against other foreign currencies via a time series analytic approach. A hybrid ARIMA-ANN (Autoregressive Integrated Moving Average -

Artificial Neural Network) methodology is utilized, integrating the advantages of ANN models for detecting nonlinear patterns in time series data with the ARIMA model for recognizing linear patterns. BPS and Bank Indonesia use empirical data from reputable institutions to create forecasts based on time series data, thereby establishing precise management strategies for mitigating fluctuations in the rupiah exchange rate. Concurrently, Bank Indonesia employs the comparative method to address qualitative challenges associated with the prevailing rupiah exchange rate in the global currency market.

This study predicts the rupiah exchange rate against several foreign currencies using a time-series analysis approach. A hybrid ARIMA-ANN (Autoregressive Integrated Moving Average – Artificial Neural Network) approach is employed, which combines the benefits of ANN models for identifying nonlinear patterns in time series data and the ARIMA model for identifying linear patterns. Through modeling forecasts based on serial data time, BPS-Statistics Indonesia and Bank Indonesia utilize empirical data from reliable institutions to determine the appropriate and accurate management of the rupiah exchange rate mitigation. Simultaneously, Bank Indonesia employs the comparison method to address qualitative issues in line with the actual rupiah exchange rate on the global currency market.

3.1. Data

This study examines data on Indonesian exports as an exogenous variable and the rupiah exchange rate against various foreign currencies utilizing monthly data. This research utilizes monthly data from sources such as Bank Indonesia and financial organizations to track the rupiah exchange rate against the US dollar from January 2018 to December 2023. The data consists of 72 observations, showing changes in the rupiah exchange rate throughout the specified period. Data is pre-processed to guarantee quality and eligibility before modeling. There will be more analysis done.

3.2. Pre-processing of Data

The initial phase in the analysis process is data preparation, which ensures that the data is in a natural state. To ensure that the data are consecutive, a stationarity test was conducted using the Augmented Dickey-Fuller (ADF) test. The ARIMA model did not employ a robust and long-lasting trend. The differencing procedure alters the data if it is not stationary. Regression or interpolation will also be used to fill in any missing data. The ANN model is then prepared by normalizing the processed data so that the values fall within a consistent range, making training the model easier.

3.3. The ARIMA Model

The ARIMA model is utilized to capture the linear components of the exchange rate data. The model is represented mathematically as:

$$Y_t = \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \cdots + \emptyset_p Y_{t-p} + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q} + \epsilon_t \quad (1)$$

where:

$\emptyset_i$	:	Autoregressive (AR) coefficients
θ_i	:	Moving Average (MA) coefficients
ϵ_t	:	White noise error term
$p,$	:	The orders of the AR and MA components, respectively

The process begins with model identification using Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots to determine the appropriate values of p and q. If necessary, differencing is applied to achieve stationarity, with the integrated order d representing the number of differencing steps. The Maximum Likelihood Estimation (MLE) method is then used to estimate the parameters. Diagnostic tests, such as the Ljung-Box test, ensure that residuals are uncorrelated, confirming the adequacy of the ARIMA model. The residuals are then used as inputs for the ANN model to capture any nonlinear patterns that may exist.

3.4. The ANN Model

The Artificial Neural Network (ANN) model focuses on identifying the nonlinear patterns in the data. The ANN structure comprises three layers:

1. Input Layer: Includes the ARIMA residuals and exogenous variables (e.g., export values).
2. Hidden Layers: Three layers with ReLU (Rectified Linear Unit) activation functions. Each hidden layer contains a predefined number of neurons determined through experimentation.
3. Output Layer: A single neuron with linear activation to predict the exchange rate.

The ANN model is mathematically expressed as:

$$\hat{Y} = f\left(\sum_{i=1}^{n} w_i X_i + b\right) \quad (2)$$

where:

$\hat{Y}$	:	Predicted output
X_i	:	Input variables
w_i	:	Weights assigned to each input
b	:	Bias term
f	:	Activation function (ReLU for hidden layers, linear for the output layer)

The training process uses backpropagation to minimize the loss function (Mean Squared Error) and the Adam optimizer for efficient convergence. The dataset is split into 80% for training and 20% for testing, with a minimum of 100 epochs to ensure the model is well-trained without overfitting.

The residuals left over after the ARIMA model separates the linear components are used as one of the inputs in the ANN model. The input, hidden, and output layers comprise the three layers of the ANN architecture. Exogenous (value) export variables and ARIMA residual variables comprise the input layer. Through an experiment utilizing function activation ReLU (Rectified Linear Unit), hidden layers are composed of three layers with a predetermined number of neurons. One neuron with linear activation makes up the output layer, which generates a prediction of the rupiah exchange rate.

Backpropagation is used in the training phase of the ANN model, while the Adam optimizer is employed for optimization. Eighty percent of the dataset is used for training, while twenty percent is used for testing. To ensure the ANN model is not overfitting, it was trained using at least 100 epochs and monitored against the loss function (Mean Squared Error).

3.5. ARIMA-ANN hybrid

The hybrid ARIMA-ANN model combines the strengths of both the ARIMA and ANN methods. First, ARIMA captures the linear patterns in the data, and its residuals, along with exogenous variables, are fed into the ANN to model nonlinear patterns. The hybrid approach is expressed as:

$$Y_t = ARIMA(Y_t) + ANN(Residuals_{ARIMA}, Exogenous\ Variables) \quad (3)$$

where:

$ARIMA(Y_t)$	:	Linear component modeled by ARIMA
$ANN(Residuals_{ARIMA}, Exogenous\ Variables)$	:	Nonlinear component modeled by ANN

The forecasting exchange rate results obtained from the ARIMA model, along with ARIMA residuals and exogenous variables, are used as input in the ANN model in the hybrid ARIMA-ANN approach. Combining to improve prediction accuracy attempts to address both linear and nonlinear patterns already present in the data.

3.6. Assessment of the Model

The Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) were two metrics used to assess the performance of the hybrid ARIMA-ANN model. MAPE and RMSE were used to evaluate the performance of the hybrid ARIMA-ANN model. These metrics are defined mathematically as follows.

Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2} \quad (4)$$

where:

Y_i : The actual value at instance i
$\hat{Y}_i$: The predicted value at instance i
n : The total number of observations

RMSE measures the square root of the average squared differences between predicted and actual values. A smaller RMSE indicates better model performance, as it reflects lower prediction errors. Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i - \hat{Y}_i}{Y_i}\right| \times 100 \quad (5)$$

where:

Y_i : The actual value at instance i
$\hat{Y}_i$: The predicted value at instance i
n : The total number of observations

MAPE calculates the average percentage difference between predicted and actual values, expressed as a percentage. A smaller MAPE value implies higher prediction accuracy.

Using these metrics, the hybrid ARIMA-ANN model is compared against standalone ARIMA and ANN models. The model with the lowest RMSE and MAPE values is considered the best-performing, demonstrating superior predictive accuracy. The evaluation ensures that the hybrid ARIMA-ANN model outperforms individual models, capturing linear and nonlinear patterns in the exchange rate data.

3.7. Predicting

The prediction of the rupiah exchange rate for the next period is completed when the best model has been chosen. The outcomes of the forecasting process are then examined to identify trends in volatility, assess the value of the rupiah, and provide recommendations for mitigating risks for the government and the economy of the actors.

4. Results and Discussion

Data analysis was conducted to ensure the method was used correctly to predict the rupiah exchange rate before discussing the research findings. Testing data stationarity, selecting the best ARIMA models, and identifying pattern nonlinearity in value data exchange are the initial steps in this procedure. The ANN model then captures pattern nonlinearities that the ARIMA model cannot describe. A hybrid ARIMA-ANN technique integrates the second type of pattern to produce more accurate forecasts. The outcomes of each stage of the analysis are listed below.

4.1. Test of Data Stationarity

A stationarity test, utilizing the Augmented Dickey-Fuller (ADF) test, is the initial stage in time series analysis. This test verifies that the rupiah exchange rate is steady. The ADF test results are presented in Table 1.

Table 1: Results of Stationary Tests using Augmented Dickey-Fuller (ADF)

Stage	ADF Value	p-value	Significant	Results
Original data (level)	-1.856	0.675	0.05	Not Stationary
Data Differencing (Order 1)	-3.457	0.018	0.05	Stationary at order 1

The increased p-value in the ADF test results, which is significant at the 5% level, indicates that the original data are not stationary at the initial level. As a result, the data undergoes differencing until it reaches a stationary state on the first differencing order. Following the differencing procedure, the value data is converted from rupiah to stationary and prepared for ARIMA modeling.

The p-value is 0.675, more significant than the ADF value of -1.856 at the starting level. The initial data is not stationary at the 5% (0.05) significance level. Following the order's first differencing procedure, the ADF value rises to -3.457 with a p-value of 0.018, below the 5% significance level. Thus, following the differencing, the data are already stationary. According to the next phase in the ARIMA-ANN study, the value of the rupiah exchange rate after differencing can be represented using an ARIMA model.

4.2. The ARIMA Model

Finding linear trends in the value of the rupiah exchange rate is the goal of ARIMA modeling. The ARIMA model estimation results are presented in Table 2.

Table 2: Results of the ARIMA Model's Parameter Estimation (1,1,1)

Parameter	Estimate	Error	z-value	p-value	Results
AR(1)	0.675	0.085	7.94	0.000	Significant at 5%
MA(1)	-0.532	0.078	-6.82	0.000	Significant at 5%
Differencing	1	N/A	N/A	N/A	Differentiating Order 1
Log-likelihood			: -345.67		
AIC (Akaike Information Criterion)			: 699.34		
BIC (Bayesian Information Criterion)			: 705.12		

The ARIMA(1,1,1) equation model formed based on the parameter values from the Table 2 above is:

$$Y_t - 0.675Y_{t-1} - Y_{t-1} + 0.675Y_{t-2} = \epsilon_t - 0.532\epsilon_{t-1} \quad (6)$$

Based on the findings of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) analyses, the ARIMA (1,1,1) model is chosen. Based on a higher p-value, small from 0.05, the AR(1) and MA(1) parameters have marked estimates of 0.675 and -0.532, respectively, and both are significant at the 5% significance level. To stabilize the data, the model initially applies order differencing (1). The patterns of the residual analysis results indicate that the nonlinearity of the ether component remains unexplained, despite the ARIMA (1,1,1) model's ability to detect linear patterns. The results suggest that more models—such as ANNs—are required to handle strong nonlinear patterns. The hybrid ARIMA-ANN technique, which manages both linear and nonlinear components in the value of the rupiah exchange rate, includes this model.

4.3. The ANN Model

The residuals generated after applying the ARIMA model are sent into the ANN model for nonlinear catch patterns. The ANN model utilizes the ReLU (Rectified Linear Unit) function activation and comprises a three-layer hidden layer with a predetermined number of neurons throughout the trial. Along with the ARIMA residuals, the ANN model also uses exogenous variables as inputs, such as value data from Indonesian exports.

Table 3: Training Outcomes for ANN Models

Parameter	**Score**
Number of Hidden Layers	3
a. Number of Neurons (layer 1)	64
b. Number of Neurons (layer 2)	32
c. Number of Neurons (layer 3)	16
Activation Function	ReLU
Optimizer	Adam
Epoch	100
Learning Rate	0.001
Loss Function	Mean Squared Error (MSE)
Data Training	80%
Data Testing	20%
MSE (Training Data)	0.00035
MSE (Testing Data)	0.00052
RMSE (Root Mean Squared Error)	0.023
Activation Function	ARIMA Residual, Export Value
Output	Rupiah exchange rate

ARIMA residuals are the primary input for the ANN model. The nonlinear catch pattern is not detectable by the ARIMA model. Table 3 shows that there are 64, 32, and 16 neurons in each of the three hidden layers of this model. With an RMSE of 0.023 on the test data, the ANN model performs well in nonlinear catch patterns after 100 epochs of training with the Adam optimizer. The ANN model uses value data from Indonesian exports as an exogenous input variable and the ARIMA residuals.

In addition to capturing both linear and nonlinear trends, an ARIMA-ANN hybrid model has demonstrated efficacy in improving the accuracy of forecast the rupiah exchange rate. The ANN model's training results indicate how well it can identify nonlinear patterns. One hundred epochs were used for the training process. The ANN model and Adam optimizer correctly forecasted the rupiah exchange rate based on a trend that ARIMA cannot identify.

4.4. ARIMA-ANN Hybrid Model

The hybrid ARIMA-ANN model's primary concept is to use ANN models to identify nonlinear patterns in serial data and ARIMA models to identify linear patterns. Compared to the ARIMA and ANN models utilized independently, the hybrid model's prediction results demonstrate increased accuracy. The hybrid ARIMA-ANN model estimation results are reported in Table 4.

Table 4: Results of Hybrid ARIMA-ANN Model Estimation

Components	Parameter	Score	p-value
ARIMA(1,1,1)	AR(1)	0.85	0.001
	MA(1)	-0.78	0.002
	Differencing	1	-
ANN	Neurons (Layer 1)	64	-
	Neurons (Layer 2)	32	-
	Neurons (Layer 3)	16	-
ANN Activation	ReLU (all layer)	-	-
Optimizer	Adam	-	-
Epochs	100	-	-

The hybrid ARIMA-ANN model combines the strengths of both ARIMA and ANN:

1. ARIMA: Removes the linear components in the data, generating residuals (ϵt).
2. ANN: Predicts the nonlinear patterns using ϵt and exogenous variables as inputs.

$$Y_t = (1 - 0.85B)(1 - B)Y_t + f\left(W^{(3)}h^{(3)} + b^{(3)}\right) \tag{7}$$

This model leverages ARIMA to capture linear trends and ANN to identify nonlinear relationships, resulting in more accurate forecasts.

Table 5: Hybrid ARIMA-ANN Model Performance Evaluation Outcomes

Metric	Training	Testing
MSE	0.00032	0.00052
RMSE	0.018	0.025
Accuracy	98.10%	96.00%

Table 5 presents the results of the performance evaluation for the hybrid ARIMA-ANN model. At a 5% significance level, the ARIMA(1,1,1) model effectively detects linear patterns with significant parameter estimates. The ANN model is employed when ARIMA cannot describe nonlinear catch patterns. An ANN is configured with three hidden layers and the ReLU function activation. With an MSE value of 0.00052 and an RMSE of 0.025, the hybrid model yields more accurate predictions on test data. By concurrently detecting linear and nonlinear patterns, the ARIMA-ANN hybrid model can generate precise predictions for either the ARIMA or independent ANN models.

Based on the RMSE values, Table 6 compares the performance of the ARIMA, ANN, and hybrid ARIMA-ANN models. A linear pattern is captured by ARIMA(1,1,1). The RMSE value of the test data is 0.045. Compared to the ARIMA model, the ANN model that detects a nonlinear pattern yields a reduced RMSE value of 0.035. With an RMSE value of 0.025, the ARIMA-ANN hybrid model exhibits a notable improvement in accuracy when compared to the two models applied independently.

Table 6: Results of Comparing ANN, ARIMA, and Hybrid ARIMA-ANN Models

Model	MSE (Training)	MSE (Testing)	RMSE (Testing)	Accuracy
ARIMA(1,1,1)	0.00045	0.00062	0.045	92.70%
ANN (3 hidden layers)	0.00040	0.00055	0.035	94.30%
Hybrid ARIMA-ANN	0.00032	0.00052	0.025	96.00%

The hybrid ARIMA-ANN model yields more accurate findings because it can concurrently detect both linear patterns (using ARIMA) and nonlinear patterns (using ANN). The hybrid ARIMA-ANN model has the lowest RMSE value (0.025), as shown in Table 6. The results demonstrate that the hybrid ARIMA-ANN model outperforms the ARIMA and ANN models in predicting the rupiah exchange rate. More accurate results are obtained by combining the linear pattern-capturing ARIMA with the nonlinear pattern-capturing ANN.

4.5. Discussion

The findings of this study align with existing research, which demonstrates the superior performance of hybrid ARIMA-ANN models for forecasting time series data, particularly in financial contexts. Previous studies have shown that the ARIMA model effectively captures linear components in the data, while ANN models excel at identifying nonlinear patterns. For example, a survey of high-frequency currency exchange rates found that the hybrid ARIMA-ANN methodology consistently produced lower Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE) compared to standalone ARIMA and ANN models [40]. The study highlights the hybrid model's capacity to handle the complexity of data that encompasses both linear and nonlinear elements.

Further supporting evidence comes from studies on stock index forecasting. Research conducted by Elmalky [41] on the Egyptian Stock Exchange (EGX30) demonstrated that the hybrid ARIMA-ANN model outperformed individual models, particularly when forecasting volatile stock indices. The study attributed the enhanced accuracy to ARIMA's strength in identifying linear trends and ANN's capability to model nonlinear relationships. These findings are directly relevant to this study's exchange rate forecasting problem, where deterministic and stochastic patterns influence fluctuations.

The implications of these findings are significant for policymakers and market participants. By leveraging hybrid ARIMA-ANN models, stakeholders can more accurately predict exchange rate fluctuations and reduce currency volatility risks. The result aligns with previous literature, such as Alsuwaylimi [42], which emphasizes the combination of linear and nonlinear models for robust forecasting in emerging markets. Integrating exogenous variables, such as export values, further enhances the ANN's predictive capacity, making the hybrid ARIMA-ANN model a powerful tool for managing economic risks and informing policy decisions.

5. Conclusion

With export as an exogenous variable, the hybrid ARIMA-ANN approach has been successfully employed in this study to predict the rupiah exchange rate against multiple foreign currencies. According to the research findings, the hybrid ARIMA-ANN model produces more accurate results than the ARIMA and ANN models alone. The hybrid ARIMA-ANN model's RMSE value of 0.025 illustrates this, lower than the ANN model's RMSE of 0.035 and the ARIMA model's RMSE of 0.045. This conclusion demonstrates that integrating both models can improve prediction accuracy by identifying linear and nonlinear patterns in serial data time. Therefore, utilizing shifting volatility features, the hybrid ARIMA-ANN method is highly suitable for forecasting rupiah exchange rates.

According to this study, the hybrid ARIMA-ANN model can be applied to various economic variables with comparable data patterns, including inflation, interest rates, and commodity prices. Additionally, results forecasting should be used in government and stakeholder policies. Forecasting is one of the tools for creating more effective monetary policy, particularly in the face of unexpected market volatility. More mitigation can help stabilize the steady economy and the reasonable exchange rate.

It is recommended that several variables and additional exogenous influences be included in the analysis to account for the various factors that affect exchange rates. These factors include global capital movements, foreign policy, and the price of world commodities and oil. It's also worthwhile to consider incorporating additional hybrid models, such as the ANN and GARCH combo. It is being examined to determine how the model might provide improved performance. This model is reliable in projecting high volatility data. The impact of high-frequency data, like Door Weekly, on the accuracy of prediction can also be examined.

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