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NON-LINEAR AUTOREGRESSIVE NEURAL NETWORK WITH EXOGENOUS VARIABLE IN FORECASTING USD/IDR EXCHANGE RATE

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Abstract: In the history of economic development, the Rupiah exchange rate is considered one of the key factors in economic stability in Indonesia. Bank Indonesia' policies play an important role in the Indonesia's economy. The purpose of this study is to explore the relationship between time effect and the presence of exogenous variable that affect the response variable in the non-linear model. The methodological approach taken in this study is Nonlinear Autoregressive Exogenous Neural Network Method (NARX NN). NARX NN is a powerful method for forecasting of time series data and dynamic control problems. NARX NN method extracts generic principles from the past values of the time series to predict its future values so that can be used to forecast the Rupiah exchange rate to the dollar based on the BI rate variable. The obvious finding to emerge from this study are: 1) Feed Forward Neural Network (FFNN) with rprop+ training algorithm, the best model is FFNN (12-3-1). The best FFNN model applied to all BI 7-day (Reverse) Repo Rate data has an Adjusted R^2 of 98.8%; 2) Forecasting the USD/IDR exchange rate and its relation to the BI 7-day (Reverse) Repo Rate using the NARX NN series parallel model with the rptop+ training algorithm, obtained the best model NARX NN (13-4-1). The NARX NN model applied to all USD/IDR exchange rate data has an Adjusted R^2 of 96.19%; 3) Based on forecasting results for the next 6 periods, the USD/IDR exchange rate tends

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to experience a downward trend, meaning that the Rupiah exchange rate strengthens, while the BI 7-day (Reverse) Repo Rate increases.

Keywords: NARX NN; exchange rate; FFNN; BI 7-day.

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1. INTRODUCTION

Basically, the exchange rate is the price of a currency of one country against a currency originating from another country. Exchange rates can be assessed or expressed in the currency of another country. Exchange rate is also a comparison of values. That is, when there is an exchange between two currencies that are different from each other. Then in it will produce a comparison on the value or price of the currency. The exchange rate is also often referred to as the currency exchange rate. The exchange rate has an important role in terms of transactions, especially in export and import activities. The exchange rate is able to translate various prices into different currencies from other countries.

In addition, the exchange rate also has an important role in the foreign exchange market or commonly referred to as forex. In this foreign exchange market, there will be an exchange of currencies at an exchange rate that has been agreed upon by the various parties concerned. Exchange rates can also experience two kinds of changes in it, namely appreciation and depreciation. The meaning of appreciation in this case is an increase in currency against other foreign currencies. The appreciation will occur because of the very strong attraction between supply and demand in the foreign exchange market.

If the currency of another country experiences an appreciation of the currency of another country, it will cause export activities to become more expensive and import activities to become cheaper. While depreciation is a decrease in the value of the local currency against the currency of another country. If the local currency depreciates against currencies from other countries, it will cause export activities to become cheaper and import activities to become more expensive.

Bank Indonesia has a goal to achieve and maintain the stability of the value of the Rupiah.

In an effort to achieve this goal, since July 1, 2005, Bank Indonesia has implemented the Inflation Targeting Framework (ITF) monetary policy framework. The policy framework is considered in accordance with the mandate and institutional aspects mandated by the law. Within this framework, inflation is an overriding objective. Bank Indonesia continues to make various improvements to the monetary policy framework, in accordance with the changing dynamics and challenges of the economy, in order to strengthen its effectiveness. Based on the experience of the 2008/2009 global financial crisis, one of the important lessons that emerged was the need for sufficient flexibility for the central bank to respond to increasingly complex economic developments and the increasingly strong role of the financial sector in influencing macroeconomic stability. The global financial crisis that occurred in 2008/2009 required the central bank to stabilize the financial system and save the economy.

The role of the financial system is getting bigger in the economy, so the impact of financial system instability is becoming more significant. This is reflected in the high cost of rescue and the impact of the 2008/2009 global financial crisis. This raises awareness of the importance of the central bank's role in maintaining financial system stability. A new dimension since the global financial crisis has been the development of the central bank's role in maintaining financial system stability in an integrated manner with the mandate to achieve price stability. In relation to the inflation targeting strategy, Bank Indonesia announced an inflation target for a certain period in the future. In order to strengthen the effectiveness of monetary policy transmission, on August 19, 2016 Bank Indonesia set the BI 7-day (Reverse) Repo Rate (BI 7DRR) as the policy interest rate that represents a signal of monetary policy response in controlling inflation in line with the target. The use of BI 7DRR as the benchmark interest rate is part of the monetary policy reformulation carried out by Bank Indonesia. Previously, Bank Indonesia used the BI Rate as the benchmark interest rate equivalent to 12-month monetary instruments. Through the determination of BI 7DRR as the reference interest rate, the tenor of the instrument is shortened, which is equivalent to a 7-day monetary instrument, so it is hoped that it will accelerate the transmission of monetary policy and direct inflation in line with its target.

The ultimate goal of monetary policy is to maintain and maintain the stability of the value of the Rupiah, one of which is reflected in a low and stable inflation rate. To achieve this goal, Bank Indonesia set the BI-7 Day Reverse Repo Rate (BI7DRR) policy rate as the main policy instrument to influence economic activity with the ultimate goal of achieving inflation. This process or transmission from the decision of the BI-7 Day Reverse Repo Rate (BI7DRR) to the achievement of the inflation target through various channels and requires time (time lag).

The data in this study include the relationship between time effect and the presence of exogenous variables that affect the response variable in the non-linear model. Based on the explanation above, the purpose of this study is to apply an approach method that can be used to forecast the Rupiah exchange rate to the dollar based on the BI rate variable, namely Nonlinear Autoregressive Exogenous Neural Network Method (NARX NN).

2. PRELIMINARIES

The data for this study is secondary data regarding monthly historical data of USD/IDR exchange rate and the BI 7-day (reverse) repo rate from January 2017 to July 2021. The data of USD/IDR exchange rate was obtained from the investment website (https://www. investing.com/) and BI 7-day (reverse) repo rate data from the Bank Indonesia website (https://www.bi.go.id/id). In Non-linear Autoregressive Exogenous Neural Network analysis, data on the rupiah exchange rate against the dollar are used as the main variable and the BI 7-day (reverse) repo rate data is used as the exogenous variable. The analysis was performed using the R software.

Artificial Neural Network (ANN) or generally referred to as a Neural Network is an information processing system that has properties like biological neural networks [3]. Neural networks are the right solution for modeling with nonlinear relationships. This method is structured so that repeated learning data patterns can be explored and adjusted so that they can be used for forecasting without paying attention to the initial data pattern. Nonlinear Autoregressive Exogenous Neural Network (NARX NN) is one of the developments of The Neural Network method which is a non-linear regressive method that the function used Neural Network (NN) in predicting time series data in which additional exogenous variables are in place to make more accurate estimates [4].

The NARX model sets the current value of the dependent variable (***Y***) with the past value or the current value of the independent variable (***X***) and the past value of the dependent variable (*Y*) in relation the NARX model can be written as follows:

(1) $$y_t = f(y_{t-1} + y_{t-2} + \cdots + x_t + x_{t-1} + x_{t-2} + \cdots) + \varepsilon_t,$$

It is known that ***y*** as the response variable and the main observed variable and ***x*** as the predictor variable is the exogenous variable that explains the response variable. Information from the predictor variable along with the past value of the response variable is used to predict the current value of the response variable. Measurement noise or model uncertainty is given by a random variable $\boldsymbol{\varepsilon}$. The *f* function is a nonlinear function that can be a neural network function, wavelet, and others.

There are two network architecture models in NARX NN, namely a *parallel model that* is a *recurrent neural network* (RNN) and a *serial-parallel model that* is a *feed-forward neural network* (FFNN). In this study, the *serial-parallel model architecture is* used*,* in which the future value of $y(t)$ is predicted from the current and past values of $x(t)$ and the actual value of $y(t)$ time series [5].

Here are the steps of the NARX NN analysis [6]:

1. Split data based on the series of Rolling Origin Cross Validation (ROCV). The data is divided into 20% for test data and 80% for train data.
2. Formation of the network architecture:
   - Neuron input: Past value of the exogenous variable itself
   - Hidden level: 1 hidden level is enough
   - Hidden neurons: determined by trial and error
   - Neuron output: 1 neuron *output* for case prognosis

3. Normalize the variable data using the *min-max* scaling technique with the following formula:

   (2) $$y_i' = a + \frac{(y_i - y_{min})(b-a)}{y_{max} - y_{min}}$$

   y_i' : Data value after normalization

   y_i : original data value

   y_{min} : Minimum value of the original data

   y_{max} : Maximum value of the original data

   a : minimum range value

   b : maximum range value

4. The training and testing process

   The training and testing process is carried out to obtain the optimal model that will produce the minimum error. The backpropagation algorithm is used to carry out the training process. One of the development versions of the backpropagation algorithm is resilient backpropagation (rprop). The Rprop algorithm is used in this study because it is adaptive learning with faster convergence than backpropagation [7]. The rprop algorithm is divided into two parts, namely rprop without weight backtracking(rprop-) and rprop with weight backtracking (rprop +). For the rprop + algorithm, when the sign of the partial derivative changes, the size of the weight is reduced directly by the size of the weight change in the previous iteration. The rprop + algorithm was chosen in the training process of this research.

5. Model evaluation

   The results of the training and testing process must be evaluated in order to obtain specification model with certain hidden neuron tha generate minimal errors. To evaluate the model in the forecast process using the Rolling Origin Cross Validation (ROCV) method. the error value is calculated from each roll using the mean absolute percentage error (MAPE). The MAPE equation is as follows:

   (3) $$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \times 100\%$$

   calculated value of *Adjusted R* which shows how good the models are in forecasting. The *Adjusted* R^2 equation is as follows:

(4) $$Adjusted\ R^2 = 1 - (1 - R^2)\frac{T-1}{T-k-1}$$

6. Forecast of exogenous variables

   Prediction of the exogenous variables can be done using a forecasting method that fits with the characteristics of the variables. In this study, the prediction was performed using FFNN. Since the value of the forecast results is still within the normalization interval, which is in the range from 0 to 1, a denormalization is necessary in order to obtain the true forecast value. The denormalization formula is as follows.

   (5) $$y_i = [y_i' \times (y_{max} - y_{min})] + y_{min}$$

   y_i : forecast result

   y_i' : forecast result in normalized form

   y_{max} : maximum value of the original data

   y_{min} : minimum value of the original data

7. Prediction of the main variables

   The NARX NN model with the smallest error size according to the model scoring results is used to predict the main observed variables. Variable forecasting is done using all actual data *Y* and all combined data *X*. Since the value of the forecast results is still within the normalization interval, which is in the range from 0 to 1, a denormalization is necessary in order to obtain the true forecast value.

3. MAIN RESULTS

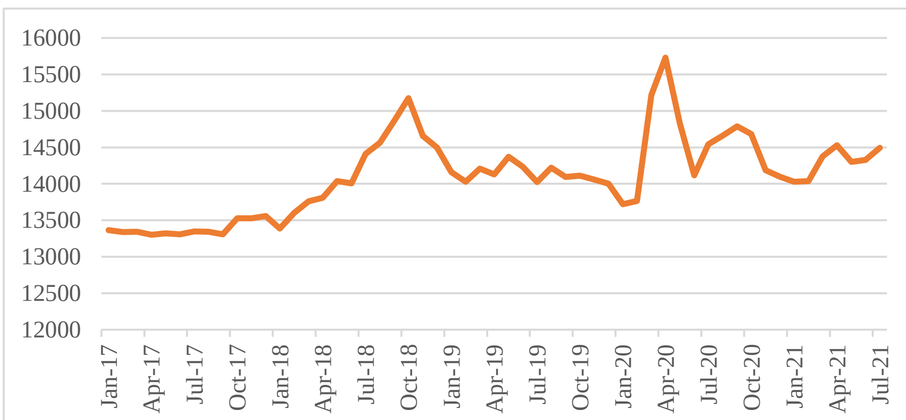
3.1 Descriptive Analysis

Before forecasting the process, a descriptive analysis of the variable data of the Rupiah exchange rate against the dollar and the BI 7-day (reverse) repo rate is performed to obtain exploratory descriptions and information. The results of the descriptive analysis are shown in the table below.

Table 1. Descriptive statistics of USD/IDR Exchange Rate and BI 7-day (reverse) Repo Rate

Variable	Minimum	Q1	Median	Mean	Q3	Maximum
Rupiah (IDR) to USD rate	13301	13662	14097	14099	14452	15730
BI 7-day (reverse) repo rate	0.03500	0.04250	0.04750	0.04714	0.05250	0.06000

Table 1 shows the minimum, maximum, average, quantile 1, median, and quantile 3 values for the two variables. The lowest exchange rate of the Rupiah against the dollar is Rp. 13.301 and the highest is Rp. 15.730. The average exchange rate of the Rupiah against the dollar for 55 periods is Rp. 14,099. The lowest value of BI 7DRR is 3.5% and the highest value 6%. The average value of BI 7DRR is 4.71%. The following is a graph of the data for the two variables from January 2017-July 2021.

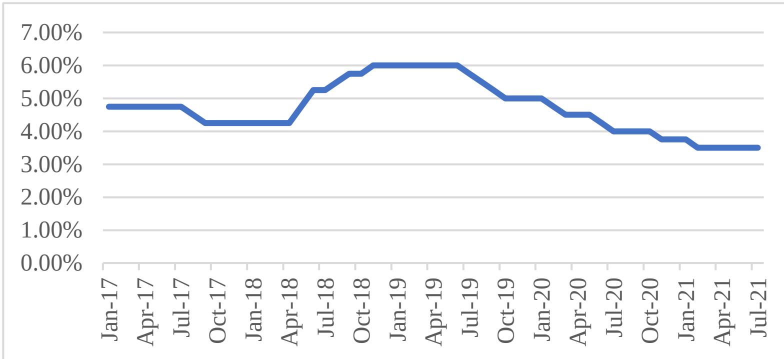


Source: https://www.investing.com

Figure 1. Line chart of USD/IDR Exchange Rate for the period January 2017 - July 2021

Figure 1 shows that the Rupiah's exchange rate against the dollar fluctuates every month. There was an upward trend from January to October, after that the graph began to decline until January 2020. From March to April 2020 there was a very significant increase in the exchange rate. The highest value of the Rupiah exchange rate against the dollar was recorded on March 23, 2020, when the value of the Rupiah experienced unexpected volatility due to economic uncertainty during the COVID-19 outbreak. The next figure as an illustration of BI 7-Day (Reverse) Repo

Rate on January 2017-July 2021.



Source: https://www.bi.go.id/id

Figure 2. Line chart of the 7-Day (Reversed) BI Repo Rate period January 2017 - July 2021

Similar to the Rupiah exchange rate, the BI 7-day (reverse) repo rate is influenced by economic uncertainty. From May 2019 to January 2021, BI 7DRR recorded a downward trend. From February to July 2021, BI 7DRR tends to stagnate at 3.5%.

3.2 Linearity Test

The linearity test was conducted to test the specification of the model relationship between the main variable ($\boldsymbol{Y}$) and the exogenous variables ($\boldsymbol{X}$). If the model of the data does not meet the linearity assumption, the NARX NN method is an appropriate time series data analysis technique that is used to overcome the nonlinearity relationship. So, a linearity test will be carried out with the Ramsey RESET test statistic with the following process:

Hypothesis:

H_0: $a_1 = a_2 = \cdots = a_k = 0$ (There is no misspecification in the model or the model is linear)

H_1: $a_k \neq 0$ At least one equal sign is invalid (there is an incorrect specification in the model or a non-linear model)

Test Statistics: Ramsey RESET Test

$$\text{RESET} = \frac{[(\hat{e}'\hat{e} - \hat{u}'\hat{u})/\, p^*]}{[(\hat{u}'\hat{u})/(n-k)]}$$

RESET	p-value
4.4233	0.01692

Test criteria: **Reject H_0** if p-value ≤ α, in other cases accept; p-value = 0.01692 <0.05 = alpha then H_0 discarded rejected.

Conclusion: Since the p-value is smaller than α, H_0 rejected, it means that the model misspecification (the model is not linear).

3.3 Formation of The NARX NN Model

In this study, the actual data on the Rupiah exchange rate against the dollar will be transformed using the inverse square root function to stabilize the variance. The Rupiah exchange rate data that has been transformed as the main variable (Y) and the BI 7-day (Reverse) Repo Rate (BI 7DRR) data as the exogenous variable (X) are used to form the NARX NN model. The data processing process begins by dividing the data on the Rupiah exchange rate against the dollar into training data and testing data, while all BI 7DRR data is used as input in the training of the NARX NN model. In this study, there are 20% of the total data was used as testing data, which was 11 data. The distribution of data on the Rupiah exchange rate against the dollar is carried out according to a series of ROCV procedures. The following is an illustration of a series of training data (blue) and testing data (green).

Rolling to-		
1	1 2 3 44	45
2	1 2 3 45	46
3	1 2 3 46	47
4	1 2 3 47	48
5	1 2 3 48	49
6	1 2 3 49	50
7	1 2 3 50	51
8	1 2 3 51	52
9	1 2 3 52	53
10	1 2 3 53	54
11	1 2 3 54	55

Figure 3. Distribution of USD/IDR Exchange Rate data

The next stage after splitting data is the formation of NARX NN network architecture response variable. In this study, the *input* for predicting the Rupiah exchange rate against the dollar is the past value of the Rupiah exchange rate against the dollar and the current value of the BI 7DRR. The previous value of the Rupiah exchange rate against the dollar used 12 lags because the data interval is monthly data, that mean Y_t is influenced by $Y_{t-1}, Y_{t-2}, \ldots, Y_{t-12}$. So, the number of input neurons used is 13 neurons, consisting of $Y_{t-1}, Y_{t-2}, \dots, Y_{t-12}$ and X_t. The number of hidden layers used is 1 layer. The number of hidden neurons is determined by trial and error, where the best number of neurons is the number of neurons that produces the smallest error value. The number of output neurons used is 1 neuron because there is only one output, namely the Rupiah exchange rate against the dollar.

Table 2. NARXN NN Network architecture of USD/ IDR

Input neurons	13 neurons, consisting of: *Lag* 1 to 12 from USD/IDR exchange rate and Current value of BI 7DRR
Hidden layer	1 layer
Hidden neurons	1, 2, 3, 4, 5, 6, 7 neurons (*trial and error*)
Output neurons	1 neuron

After forming the network architecture, the next step is the process of training, testing, and evaluating the model. Before entering the training stage, the data on the Rupiah exchange rate against the dollar were normalized using the min-max scaling technique with values a=-0.8 and b=0.8.

The training process in this study uses the *RPROP + algorithm* and includes an activation function. The *tanh* activation function is used in the hidden layer, while the linear activation function is used in the output layer. The training and testing process is repeated in each roll as shown in Figure 3.3 (ROCV method). In addition, the evaluation of the model is carried out by calculating the MAPE value in each network architecture with certain hidden neurons with the following results.

Table 3. The Error Sizes of NARX NN Model of USD/IDR Exchange Rate

Architecture	**Hidden neurons**	**MAPE test**
Input neurons = 13 Hidden Layer = 1 Neuron output = 1	1	4.112845
	2	3.431055
	3	3.224370
	4	3.668823
	5	3.010813
	6	3.736860
	7	3.029802

Table 3 shows that the network architecture with the minimum MAPE value is a network architecture with 13 input neurons, 1 hidden layer, 4 hidden neurons and 1 output neuron or can be written as a NARX NN model (13-5-1). The following is a visualization of the comparison between the results of the training and test process prediction with the ROCV method for the variable Y.

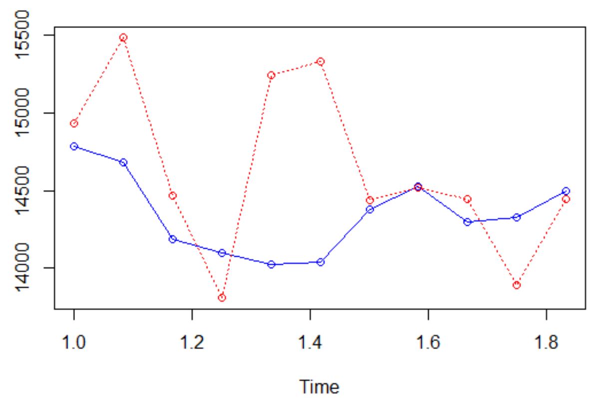


Figure 4. Graphically Comparison of Training Process Result with USD/IDR Exchange Rate Data

The visualization of the network architecture of the NARX NN model (13 - 5 - 1):

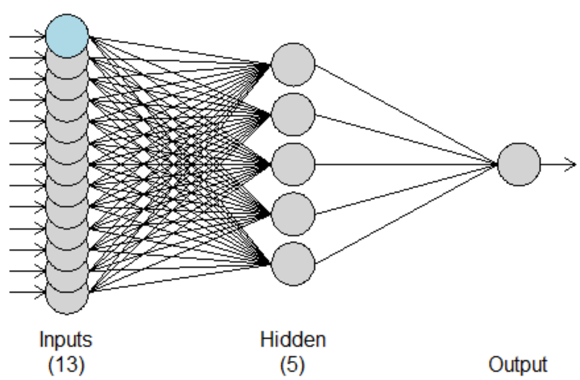


Figure 5. The Network Architecture of the NARX NN model (13 - 5 - 1)

Next, the NARX NN model (13-5-1) is applied to all data and used to predict the Rupiah exchange rate against the dollar (see the figure 4 below). In this study, BI 7DRR becomes an exogenous variable that affects the exchange rate of the Rupiah against the dollar. Therefore, in order to get the results of the forecast of the exchange rate of the Rupiah against the dollar, it is necessary to forecast BI 7DRR first.

3.4 Prediction of Exogenous Variable (X)

In BI-7DRR exogenous variable forecasting, it is done using Feed Forward Neural Network with the same steps as in sub-chapter 3.3. BI-7DRR splitting data is carried out as shown in Figure 3. Furthermore, the FFNN network architecture was developed for BI 7DRR forecasting as follows:

Table 4. FFNN Network architecture of BI 7DRR

Input neurons	12 neurons, that is Lag 1 to 12 from BI 7DRR
Hidden layer	1 layer
Hidden neurons	1, 2, 3, 4, 5, 6, 7 neurons (trial and error)
Output neurons	1 neuron

After the network architecture is formed, the next step is the process of training, testing, and evaluating the model. Before entering the training stage, the data of BI 7DRR were normalized using the min-max scaling technique with values a=-0.8 and b=0.8.

With the same training and testing stages as in sub-chapter 3.3, the results of trial and error for the BI 7DRR model network architecture are as follows:

Table 5 The Error Sizes of FFNN Model of BI 7DRR

Architecture	**Hidden Neurons**	**MAPE test**
Input neurons = 12 Hidden Layer = 1 Neuron output = 1	1	3.601063
	2	3.172344
	3	3.394337
	4	4.194512
	5	3.694808
	6	5.404346
	7	5.511159

Table 5 shows that the network architecture with the minimum MAPE value is a network architecture with 12 input neurons, 1 hidden layer, 2 hidden neurons and 1 output neuron or can be written as a FFNN model (12-2-1). The visualization of the network architecture of the FFNN model (12 - 2- 1):

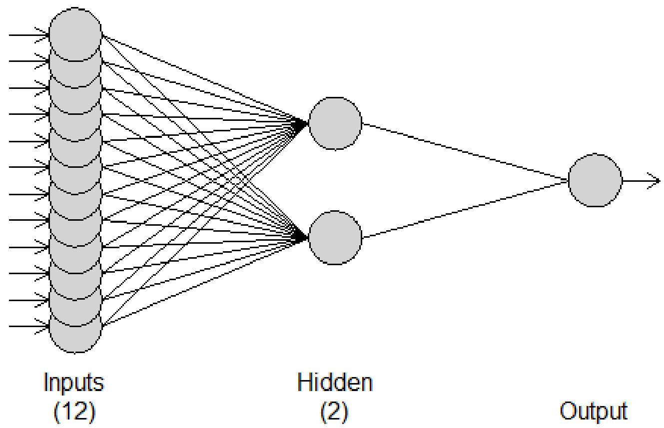


Figure 6. The Network Architecture of the FFNN model (12 - 2- 1)

The following is a visualization of the comparison between the results of the training and test process prediction with the ROCV method for the *X* variable.

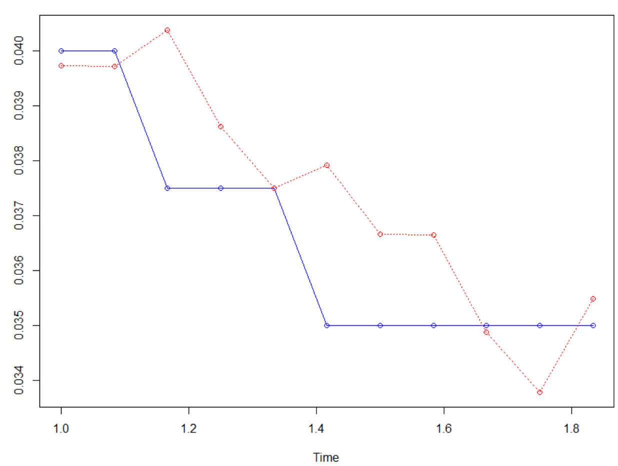


Figure 7. Graphically Comparison of Training Process Result with USD/IDR BI 7DRR Data

The FFNN (12-2-1) model is applied to all BI 7DRR data. From FFNN model obtained the value of Adjusted R^2 is 98,25%. Figure 6 below is a plot between the actual data and the predicted data from the FFNN model (12-2-1) for all BI 7DRR data. The forecast period for BI 7DRR data (***X***) is at least as long as the forecast period for data on the exchange rate of the Rupiah against the dollar (***Y***). In this study, forecasts are made for the next 6 periods.

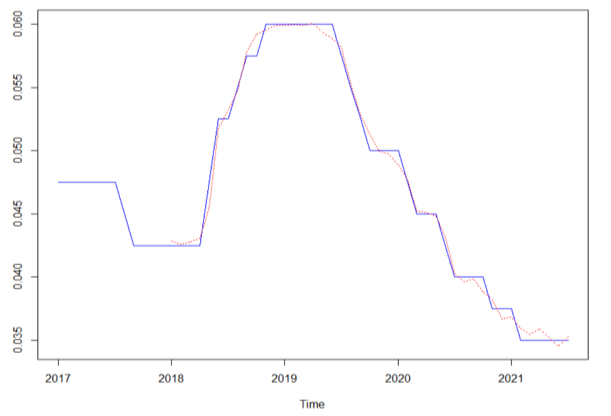


Figure 8. Graphs of Actual and Predicted Values for all BI 7DRR data

The forecast results from BI 7DRR for the next 6 months are as follows:

Table 6. BI 7DRR forecast results

Period	Forecast	In percent
August 2021	0.03692686	3,692%
September 2021	0.03767240	3.767%
October 2021	0.03922826	3,922%
November 2021	0.04259032	4,259%
December 2021	0.04854249	4,854%
January 2022	0.05228220	5.228%

Forecast results from BI 7DRR are combined with actual data from BI 7DRR to obtain combined data for 61 periods, namely 55 periods of actual data and 6 periods of forecast results from BI 7DRR. The combined data is then used as exogenous variable input to predict the Rupiah exchange rate against the dollar using the best NARX NN model.

3.5 Prediction of The Main Variable (Y)

In subsection 3.3, the process of forming the NARX NN model was performed and the best

NARX NN model (13-5-1) was obtained, which is used to compute the exchange rate data of the Rupiah against the dollar with the combined BI 7DRR data as exogenous variable. The NARX NN model, which is applied to all USD/IDR exchange rate data, has an Adjusted R^2 of 96. 39%. The following is a graph between the actual data and the predicted data of the NARX NN model (13-4-1) for all data relating to the exchange rate of the Rupiah to the dollar.

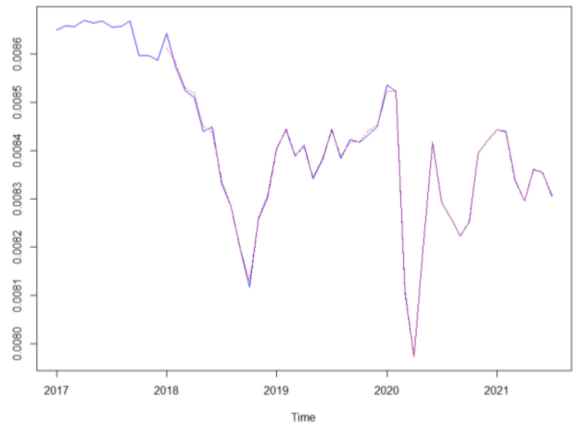


Figure 9. Graphs of Actual and Predicted Values for USD/IDR data

Then, the Rupiah exchange rate against the dollar will be forecasted for the next 6 periods. Forecasting is carried out using all actual data on the Rupiah exchange rate against the dollar and the combined BI 7DRR data. The results of the forecasting of the Rupiah against the dollar for the next 6 periods are as follows.

Table 7. Forecast results of USD/IDR Exchange Rate

Period	**Forecast**
August 2021	14450.01
September 2021	14532.82
October 2021	14747.02
November 2021	14457.69
December 2021	14102.59
January 2022	14209.62

The following is a combined representation of the forecast results for the Rupiah versus the dollar and the BI 7-day (reversed) repo rate.

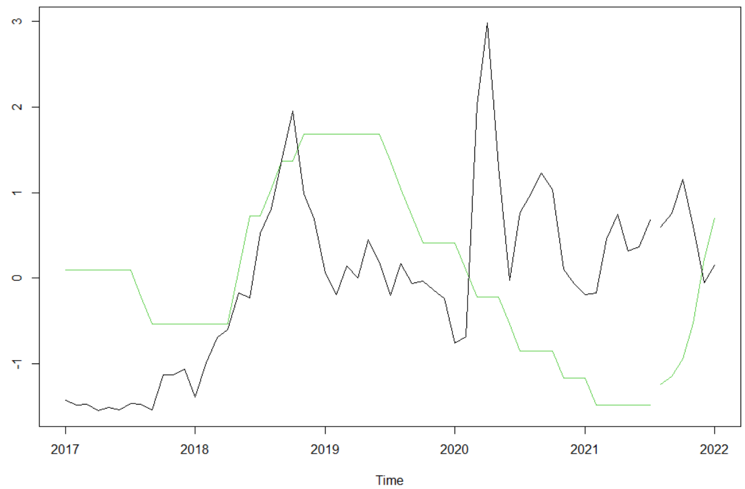


Figure 10. USD/IDR Exchange Rateand BI 7-day (reverse) Repo Rate Forecast Result

Figure 8 shows that the results of the BI 7-day (Reverse) Repo Rate forecast have increased, where the higher interest rates will encourage capital inflows thereby increasing the supply of foreign exchange in the country. As a result, the exchange rate of the domestic currency, such as the Rupiah, will strengthen. This is indicated that the results of the forecasting of the Rupiah exchange rate against the dollar which is experiencing has downward trend, meaning that the Rupiah exchange rate is strengthening.

To conclude the study, the result identifies as below:

- To forecast the USD/IDR exchange rate (Y) using the NARX NN method, it is necessary to forecast the BI 7-day (Reverse) Repo Rate as an exogenous variable (X) first. By using Feed Forward Neural Network (FFNN) with rprop+ training algorithm, the best model is FFNN (12-3-1). The best FFNN model applied to all BI 7-day (Reverse) Repo Rate data has an Adjusted R^2 of 98.25%. The combination of the forecast results with the actual BI 7DRR data is used as an input variable in forecasting the USD/IDR exchange rate.
- Forecasting the USD/IDR exchange rate and its relation to the BI 7-day (Reverse) Repo Rate using the NARX NN series parallel model with the rptop+ training algorithm, obtained the best model NARX NN (13-5-1). The NARX NN model applied to all USD/IDR exchange rate data has an Adjusted R^2 of 96.39%.

- Based on forecasting results for the next 6 periods, the USD/IDR exchange rate tends to experience a downward trend, meaning that the Rupiah exchange rate strengthens, while the BI 7-day (Reverse) Repo Rate increases.

CONFLICT OF INTERESTS

The author(s) declare that there is no conflict of interests.

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