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Original Article

Non-stationary exchange rate prediction using soft computing techniques

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Abstract

Soft computing is widely used as it enables forecasting with fast learning capacity and adaptability, and can process data despite uncertainties and complex nonlinear relationships. Soft computing can model nonlinear relationships with better accuracy than traditional statistical and econometric models, and does not make much assumptions regarding the data set. In addition, soft computing can be used on nonlinear and nonstationary time series data when the use of conventional methods is not possible. In this paper, we compare estimates of the nonstationary USD/IDR exchange rates obtained by three soft computing methods: fuzzy time series (FTS), the artificial neural network (ANN), and the adaptive-network-based fuzzy inference system (ANFIS). The performances of these methods are compared by examining the forecast errors of the estimates against the real values. Compared to ANN and FTS, ANFIS produced better results by making predictions with the smallest root mean square error.

Keywords: nonstationary, time series, forecasting, soft computing

1. Introduction

One widely used statistical modeling approach in various areas of research is time series forecasting. Time series forecasting was initially performed using statistics based methods, including linear autoregression (AR) and autoregressive moving average (ARMA) type models (Fan & Yao, 2003), due to their flexibility in modeling time series data with stationary processes. The Box–Jenkins method and its extensions apply only to stationary time series. However, most time series data, especially in economics, contain trend elements that are nonstationary. These methods have been widely used, but have limitations in capturing nonstationary time series and weaknesses in modeling time series data that tends to be nonlinear.

Over the past few decades, artificial neural networks (ANN) have provided tools for supervised machine learning, such that can represent data relationships also in time series data. Compared to other approaches, ANN have better adaptive abilities, training performance, and the ability to pattern match nonstationary signals (De Gooijer & Hyndyman, 2006). Unlike traditional computing, soft computing techniques can estimate and provide solutions to real life issues. Fuzzy logic, genetic algorithms, ANN, machine learning, and expert systems provide the basis of soft computing, which is a group of methods that can process data well despite the presence of uncertainties, inaccuracies, and partial truths.

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ANN can find solutions to nonlinear problems that are challenging for classical models to solve. ANN have been used for various applications in time series forecasting, including the fields of finance, economics, energy systems, earthquakes, and weather. This is because an ANN requires no prior assumptions about the nonlinear forms (Park & Sandberg, 1991). Some studies have used ANN and their extensions for applications, such as De Groot and Wuertz (1992), Grudnitski and Osburn (1993), Kuan and Liu (1995), Yee and Haykin (1999), Kodogiannis and Lolis (2002), and Smola and Scholkopf (2004).

Although the ANN can successfully resolve many problems, they have some weaknesses and limitations, including being a black box technique (Xu & Xue, 2008), overfitting, and getting stuck in local minima during training. One artificial intelligence technique under development today is an expert system implemented using fuzzy logic. Fuzzy expert systems can process large volumes of data while also being very supple, being able to adjust to changes and uncertainties that accompany a problem and to model complex nonlinear functions. Fuzzy time series is one of the applications in forecasting. In complex systems, the application of fuzzy logic is usually difficult and it requires a lot of time to determine the appropriate membership rules and functions.

In ANN, the processing steps are very long and complicated. Fuzzy logic does not have the ability to learn and adapt, and although ANN can learn and adapt, they do not have the reasoning abilities of fuzzy logic. Therefore, models have been developed that combine these two techniques, known as hybrid systems, one of which is the adaptive neuro fuzzy inference system (ANFIS) (Jang, 1993). The ANFIS method has all the advantages of fuzzy inference systems and of ANN. It has a fast learning capacity, can deal with nonlinear structures, is adaptable, and requires no expert knowledge (Şahin & Erol, 2018).

The ANFIS has been successfully applied to various cases and fields and in recent years has focused on modeling time series data, including works by Alakhras (2005), Alizadeh, Rada, Balagh, and Esfahani (2009), and Fahimifard, Homayounifar, Sabouhi, and Moghaddamnia (2009), Atsalakis, Skiadas, and Braimis (2007), Atsalakis, *et al*. (2007), Xu and Xue (2008), Cheng and Wei (2010), Wei, Chen, and Ho (2011), Mordjaoi and Boudjema (2011), Wang, Chang, and Tzeng *et al*. (2011), Tarno, Subanar, Rosadi, and Suhartono (2013), Savić, Mihajlović, Arsić, and Živković, (2014), Ashish (2011), Lei & Wan (2012), Prasad, Gorai, and Goyal (2016); and Mihalache and Popescu (2016). These studies have shown that the ANFIS method is reliable and accurate in time series prediction.

The aim of this study was to identify and compare the performances of three soft computing forecasting techniques, including ANN, fuzzy time series, and ANFIS for predicting foreign exchange rates. The main reason for using these techniques is that they can model nonlinear relationships more successfully and accurately than traditional statistical and econometrical models, and do not require any assumptions about the data set (Pabuçcu, 2017). In this study, the exchange rate used was the USD/IDR exchange rate. Estimates of exchange rates can be used to generate profit through speculation on the foreign exchange market. The rest of this paper is organized as follows: in section 2, we describe the materials and methods used in this paper. In section 3, we present case studies using a large volume of economic data to compare the performances of soft computing forecasting methods. In section 4, we draw our conclusions and offer guidelines for future research.

2. Materials and Methods

2.1 Data used

The data set used for this study was the IDR exchange rate against the USD. The data were obtained from the website www.bi.go.id. We used 850 daily data of exchange rates from May 3, 2014 until October 29, 2018 to predict the exchange rate of the IDR against the USD for the next period. The selection of the data period is based on the consideration that during this period there were fluctuations in the exchange rate of the IDR against the USD, which could indicate non-stationarity of the data. There is no missing data in the data set. The process of identifying data shows that the data is not stationary. Because the data used in this analysis are only a single time series without exogenous variables, ARIMA method was used to help determine the input variables for the NN and ANFIS methods. In this case the determination of input variables was to use significant lag obtained from the ARIMA model identification stage.

2.2 Artificial Neural Network

The three factors that determine the reliability of an ANN are the network architecture, training algorithms, and the activation function (Fausett, 1994). ANN have good time-series forecasting ability, whereby the outcomes or the results of several steps ahead in time can be predicted. ANN does so by capturing temporary patterns in the data in the form of memory or past memories implanted in the model.

In this research, we used multi-layer perceptron network architectures, which consist of input, hidden and output layers (Rumelhart, Hinton, and Williams, 1986). Network output is the predicted value for a dependent variable y, and is written as a function $f(x,w)$ with input data $X=[x_1,\ldots,x_p]$ and network parameters w (weights). The architecture has the following network functions

$$f(x,w)=\sum_{j=1}^{q}\beta_j\,\psi\Big(\sum_{i=1}^{p}\gamma_{ij}\,x_i\Big),$$

where $w=[\beta_1\,\beta_2\ldots\beta_q\,\gamma_{11}\,\gamma_{12}\ldots\gamma_{pq}]'$ are the weights or parameters in the ANN model. The nonlinearity in the function $f(x,w)$ is obtained through use of an activation function. The sigmoid logistic function was used as activation function in the input layer and the purelin function in the hidden layer. The training process used backpropagation algorithm. In this stage, each output unit compared the calculated activation with the target value, to compute the error sum $E=\frac{1}{2}\sum_{k=1}^{n}\left(y_k-\hat{y}_k\right)^2$.

The error from the model is also used as an index of the success in approximating the target function by the ANN model. The training problem in the ANN can be formulated as an error minimization problem using equation

$$E(w)=\frac{1}{2}\sum_{i=1}^{p}\left(y_{(k)}-f_s^o\left[\sum_{j=1}^{q}w_{sj}^o\ f_j^h\left(\sum_{i=1}^{p}w_{ji}^h\ x_{i(k)}\right)\right]\right)^2,$$

where *w* is a vector,

$$w=\left\{w_{ji}^h, w_{sj}^o : i=1,2,\dots,p;\ j=1,2,\dots,q;\ s=1,2,\dots,m\right\}.$$

2.3 Fuzzy time series (FTS)

In contrast to classical set theory, which states that an object is either a member or not a member in a set with a clear binary membership (crisp), the fuzzy set theory allows for a degree of membership of an object in the set and the transition of membership in stages ranging between 0 and 1, or in the interval [0,1]. A fuzzy set is defined as a set of objects *x* with each object having a membership function "μ" that is also called the truth value. If $Z_{i,t}$ is a set of objects, $Z_{i,t} = (Z_{1,t}, Z_{2,t}, \dots, Z_{m,t})$ and its members are expressed as *Z*, then the fuzzy set from *A* in *Z* is a set with a pair of members or can be stated as $F = \{(Z, \mu_F(Z)) | Z \in Z_{i,t}\}$, where F is the fuzzy set and $\mu_F(x)$ is the degree of membership of *Z* in *F*. A fuzzy membership function is one that maps data input points into membership values. Several functions are commonly used as membership functions, including triangular, trapezoidal, and Gaussian that is used in this study. A fuzzy inference system (FIS) is a computational structure built using fuzzy set theory, the fuzzy if–then rules, and fuzzy reasoning. According to Jang (1993), an FIS consists of five sections i.e. a rule base, a database, decision-making units, fuzzification, and defuzzification.

In this research, we used the fuzzy time series (FTS) proposed by Chen, which involves several steps.

1. Define the universe of discourse in intervals of equal length.
2. Define fuzzy sets in the universe of discourse.
3. Perform fuzzification of the historical data by identifying associations between the fuzzy sets defined in the previous step and the values in the dataset.
4. Identify fuzzy relationships that were established based on the fuzzified historical data of exchange rate. If the time series of year *t-1* is fuzzified as A_k and year *t* as A_q, then the fuzzy relationship is denoted as $A_k \rightarrow A_q$.
5. Establish fuzzy logical relationship groups (FLRGs), whereby if the same fuzzy set is related to more than one set, then the right side is merged.
6. Defuzzify the forecasted output as follows: if the fuzzified exchange rate of *F*(*t-1*) is assumed to be A_j, then according to the principle put forward by Poulsen (2009), the forecasted output of *F*(*t*) is determined by computing the midpoint of interval u_i. From the results of the interval-midpoint calculation, obtain the predicted value for each data. Then, compare the predicted value with the actual observed value to obtain the error. Using this interval-midpoint method, the root mean square error (RMSE) is obtained.

2.4 Adaptive neuro fuzzy inference system (ANFIS)

The ANFIS architecture is practically the same as that in Sugeno's fuzzy-rule-based model. Assume that the fuzzy inference system consideration has two inputs *x* and *y*. The form of the first-order Sugeno model with two fuzzy if–then rules is as follows

Rule 1: if x is A_1 and y is B_1 then $f_1 = p_1x + q_1y + r_1$

Rule 2: if x is A_2 and y is B_2 then $f_2 = p_2x + q_2y + r_2$

The ANFIS network used consists of five layers (Jang, Sun & Mizutani, 1997) as follows.

Layer 1*:* Fuzzification layer. Every node i is an adaptive node to the parameters of activation in this layer with a node function $O_{1,i} = \mu_{Ai}(x)$, for i = 1,2 or $O_{1,i} = \mu_{Bi-2}(y)$, for i = 3,4 where x, y are the input to node i and A_i, B_i, are linguistic labels. In other words, $O_{1,i}$ is the membership grade of a fuzzy set *A* (A_1, A_2, B_1, B_2). The degree of membership given by the input membership function is the output of each neuron. The membership function for *A* can be any appropriate parameterized membership function such as the generalized bell membership function that is expressed as $\mu_A(x) = \frac{1}{1+\left|\frac{x-c_i}{a_i}\right|^{2b}}$ where {a, b, c} is the parameter set referred as premise parameters.

Layer 2*:* A fixed neuron is referred to as the firing strength of a rule, which is the product of all entries, i.e., $O_{2,i} = w_i = \mu_{Ai}(x).\mu_{Bi}(y)$, $i = 1,2$ and typically uses the AND operator and every neuron represents the *i*-rule.

Layer 3*:* Each neuron in the form of a fixed neuron (N), called the normalized firing strength, is the calculated ratio of the first firing strength (w_i) to the sum of the overall firing strengths in the second layer, i.e., $O_{3,i} = \bar{w}_i = \frac{w_i}{w_1+w_2}, i = 1,2.$

Layer 4*:* A neuron that is adaptive to an output, as $O_{4,i} = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i), i = 1,2$ with $\bar{w}_i$ is the normalized firing strength in the previous layer, with p_i, q_i, and r_i being the consequent parameters.

Layer 5*:* A single neuron (Σ) is the sum of all outputs from the fourth layer, as $overall\ output = O_{5,i} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$.

When the premise parameter is obtained, the final output will be a linear combination of the consequent parameters (Jang, Sun & Mizutani, 1997), namely

$$\begin{aligned} f &= \frac{w_1}{w_1+w_2}f_1 + \frac{w_2}{w_1+w_2}f_1 \\ &= \bar{w}_1(p_1x + q_1y + r_1) + \bar{w}_2(p_2x + q_2y + r_2) \\ &= (\bar{w}_1x)p_1 + (\bar{w}_1y)q_1 + (\bar{w}_1)r_1 + (\bar{w}_2x)p_2 + \\ &\quad (\bar{w}_2y)q_2 + (\bar{w}_2)r_2, \end{aligned}$$

which is linear. Hybrid algorithms will set consequent parameter forward and premise parameter backward. Consequent parameters are estimated using least-squares regression. In the reverse step, the signal error propagates backwards, and the premise parameters are corrected using the gradient descent method. The procedure for the hybrid learning ANFIS method in this study followed Jang *et al*. (1997).

2.5 Forecasting accuracy

No one can ensure that a forecasting model built with a variety of different procedures will fit data correctly. In this study, we used the RMSE to evaluate the forecasting accuracy. RMSE is used to measure the estimated error of the model and is expressed in terms of the root of the average squared error.

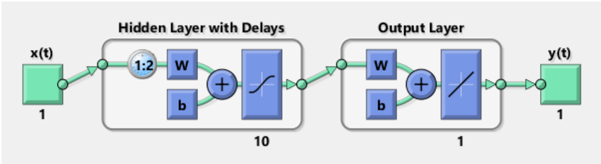
The formula for determining the RMSE is $\sqrt{\frac{\sum(Z_t-\hat{Z}_t)^2}{n}}$. We used the RMSE to compare several estimation models for the same time series. A model with a lower RMSE is preferred, which indicates that it is more suitable for, or closer to the existing data, and tends to have comparatively small predictive error variances. Figure 2 explains the design model that was built for each method used in this study until the best method is obtained to predict the exchange rate of the IDR against the USD.

3. Results and Discussion

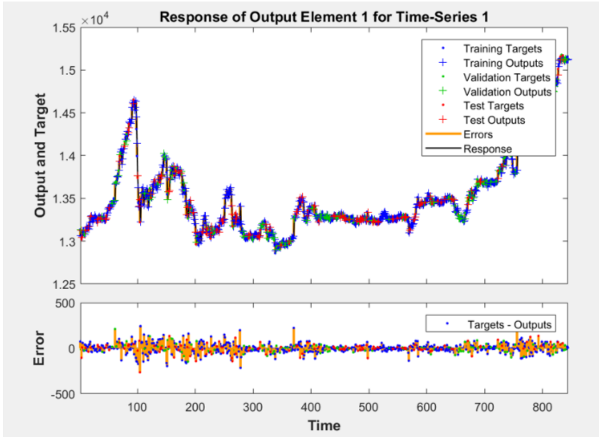
In this paper, we conducted empirical research to test the performances of ANN, FTS, and ANFIS models in predicting exchange rates. We also compare these three soft computing techniques with ARIMA as a statistical model. The results of the analysis of the soft computing methods are given below.

3.1 Artificial neural network

Input determination in ANN is the same as in ANFIS. Because the data used here are not stationary, the determination of input data used in this problem was a historical value with a significant lag of the first differentiation ARIMA process. The significant lags were of 3, 4, and 5 steps in inputs and the target data was the next period data. We validated and tested the data



(a)



(b)

Figure 2. (a) The best ANN structure with 1 inputs and 1 output; (b) Graph of inputs, targets, and errors versus time

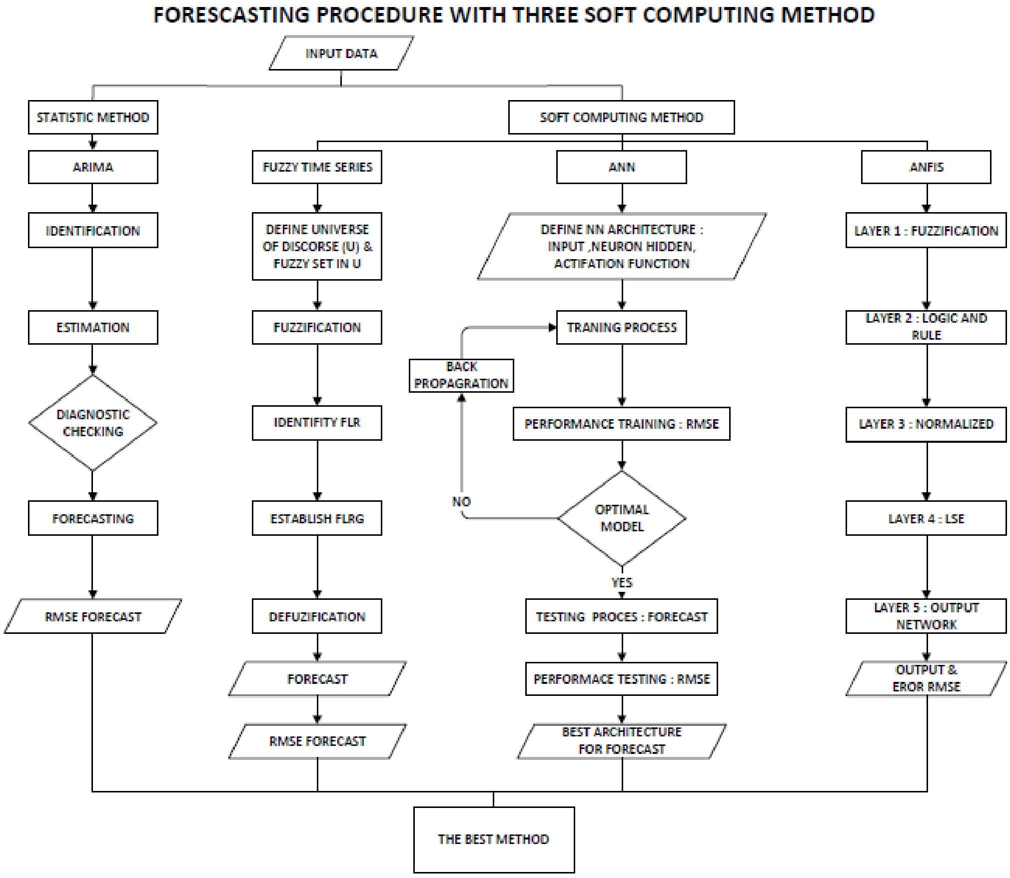


Figure 1. Design of forecasting with soft computing method

using some observational data outside the training data. The data were divided into three sets with 70% used for training, 15% for validation, and 15% for testing. The network architecture was a one-hidden-layer feedforward network, with a sigmoid transfer function in the hidden layer, and a linear transfer function in the output layer. The Levenberg-Marquard method was used as training algorithm. We can see in Table 1 that the forecasts of the exchange rates by ANN are the best when using Z_{t-3} as an input variable, which yielded the smallest RMSE values, 52.036 for training and 54.818 for testing. Figure 2 shown the architecture of the best ANN model and a graph of inputs, targets, and errors versus time for the best architecture.

3.2 Fuzzy time series

In this research, we used six steps of the Chen FTS with simple arithmetic operations that reduces the unnecessarily high computational overhead.

Step 1: Define the universe of discourse U in into seven intervals of equal length.

The universe of discourse U is defined as [$D_{min} - D_1$, $D_{max} + D_2$] with D_{min} = 12861 and D_{max} = 15177. D_1 and D_2 are positive numbers, with D_1 = 61 and D_2 = 73. Then, U = [12800, 15250] is partitioned into u_1 = [12800, 13150], u_2 = [13150, 13500], u_3 = [13500, 13850], u_4 = [13850, 14200], u_5 = [14200, 14550], u_6 = [14550, 14900], and u_7 = [14900, 15250].

Step 2: Define fuzzy sets A_i in the universe of discourse interval. Denote a linguistic value of exchange rate represented by a fuzzy set with $1 \leq i \leq 7$, i.e. A_1 = very high, A_2 = high, A_3 = high enough, A_4 = average, A_5 = quite low, A_6 = low, and A_7 = very low. The membership value of a fuzzy set A_i is 0, 0.5, or 1 determined by

$$A_1 = \frac{1}{u_1} + \frac{0.5}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0}{u_7}$$
$$A_2 = \frac{0.5}{u_1} + \frac{1}{u_2} + \frac{0.5}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0}{u_7}$$
$$A_3 = \frac{0}{u_1} + \frac{0.5}{u_2} + \frac{1}{u_3} + \frac{0.5}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0}{u_7}$$
$$A_4 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0.5}{u_3} + \frac{1}{u_4} + \frac{0.5}{u_5} + \frac{0}{u_6} + \frac{0}{u_7}$$
$$A_5 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \frac{0.5}{u_4} + \frac{1}{u_5} + \frac{0.5}{u_6} + \frac{0}{u_7}$$
$$A_6 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0.5}{u_5} + \frac{1}{u_6} + \frac{0.5}{u_7}$$
$$A_7 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0.5}{u_6} + \frac{1}{u_7}$$

Step 3: Fuzzify the historical data in accordance with its highest degree of membership.

Step 4: Identify fuzzy relationship based on the fuzzified historical data shown in Table 2.

Step 5: Establish fuzzy logical relationship groups (FLRGs) with rules that if a fuzzy set is related to more than one set, then the right side is merged. Table 3 shows an overview of the relationship groups obtained.

Step 6: Defuzzify the forecasted output and determine the forecasted output of $F(t)$ by the midpoint value for interval u_i as shown in Table 4. Based on these results, we obtained the predicted values for 850 observational cases and compared them with the actual observation values, and obtained the RMSE of 100.9058 for training and 87.4171 for testing.

Table 1. Forecasting result by ANN with various input variables

Input		Training	Validation	Testing
Z_{t-3}	MSE	2,707.77823	2,257.23712	3,005.10338
	RMSE	52.03632	47.51039	54.81882
	R	0.99415	0.99591	0.99352
Z_{t-4}	MSE	2315.93664	2,979.22778	3,541.69751
	RMSE	48.12418	54.58230	59.51216
	R	0.99479	0.99444	0.99370
Z_{t-5}	MSE	2,749.22911	2,769.00386	3,283.84253
	RMSE	52.43309	52.62133	57.30482
	R	0.99439	0.99434	0.99261
Result by ANN with multi input variable				
Z_{t-1}, Z_{t-2}	MSE	2,514.48632	2,275.50572	4,481.67324
	RMSE	50.14467	47.70226	66.9453
	R	0.99468	0.99574	0.99194
Z_{t-1}, Z_{t-2}, Z_{t-3}	MSE	2,778.3497	4,600.31423	3,172.7210
	RMSE	52.71005	67.82562	56.32691
	R	0.99466	0.99139	0.99497
Z_{t-1}, Z_{t-2}, Z_{t-3}, Z_{t-4}	MSE	2,218.04894	3,532.7056	3,230.84301
	RMSE	47.09617	59.43657	56.84051
	R	0.99540	0.99183	0.99447
Z_{t-3}, Z_{t-4}	MSE	2,674.0895	2,824.6328	3,757.1836
	RMSE	51.7116	53.1473	61.2959
	R	0.99459	0.99387	0.99273
Z_{t-3}, Z_{t-5}	MSE	2,329.03574	2,460.20758	3,804.03285
	RMSE	48.26	49.6	61.6768
	R	0.99557	0.99502	0.98927
Z_{t-4}, Z_{t-5}	MSE	2,375.60245	3,423.68815	3,136.995
	RMSE	48.7402	58.5123	56.0089
	R	0.99521	0.99292	0.99417

Table 2. Fuzzy set relationships

$A_1 \to A_1$	$A_1 \to A_2$	$A_2 \to A_1$
$A_2 \to A_2$	$A_2 \to A_3$	$A_3 \to A_3$
$A_3 \to A_4$	$A_4 \to A_4$	$A_4 \to A_5$
$A_5 \to A_4$	$A_5 \to A_5$	$A_5 \to A_6$
$A_6 \to A_6$	$A_6 \to A_5$	$A_4 \to A_3$
$A_3 \to A_2$	$A_6 \to A_7$	$A_7 \to A_7$

Table 3. FLRG's

Group	FLRG's
Group 1	$A_1 \to A_1$ $A_1 \to A_2$
Group 2	$A_2 \to A_1$ $A_2 \to A_2$ $A_2 \to A_3$
Group 3	$A_3 \to A_3$ $A_3 \to A_4$ $A_3 \to A_2$
Group 4	$A_4 \to A_4$ $A_4 \to A_5$ $A_4 \to A_3$
Group 5	$A_5 \to A_4$ $A_5 \to A_5$ $A_5 \to A_6$
Group 6	$A_6 \to A_6$ $A_6 \to A_5$ $A_6 \to A_7$
Group 7	$A_7 \to A_7$

3.3 Adaptive neuro fuzzy inference system

As proposed by Wei *et al*. (2011) the procedures for applying the ANFIS model for forecasting involve the following stages.

Table 4. FLRG's with forecast exchange rate use interval midpoint

Group	FLRG's	Interval midpoint	Forecasted enrollment
Group 1	$A_1 \rightarrow A_1, A_2$	12975, 13325	13150
Group 2	$A_2 \rightarrow A_1, A_2, A_3$	12975, 13325, 13675	13325
Group 3	$A_3 \rightarrow A_2, A_3, A_4$	13325, 13675, 14025	13675
Group 4	$A_4 \rightarrow A_3, A_4, A_5$	13675, 14025, 14375	14025
Group 5	$A_5 \rightarrow A_4, A_5, A_6$	14025, 14375, 14725	14375
Group 6	$A_6 \rightarrow A_5, A_6, A_7$	14375, 14725, 15075	14725
Group 7	$A_7 \rightarrow A_7$	15075	15075

1. Preprocessing original data and determining the input variables using 850 observations of daily data for the IDR exchange rate to the USD, and divide to 680 as training data and 170 as testing data. The same steps as for ANN are used to determine ANFIS inputs. The data were processed using ARIMA before the data were forecasted with ANFIS. From significant lags in the autocorrelation and partial autocorrelation functions, the model was identified as ARIMA (1,1,0) with significant lags of 3, 4, and 5. With reference to the study of Tarno *et al*. (2013), some tentative models that were offered include ARIMA ([3,4],1,0), ARIMA ([3, 5],1,0), ARIMA ([4,5],1,0), and ARIMA ([3,4,5],1,0).
2. Defining and partitioning of input variables based on ARIMA ([3,4,5],1,0) model for the preprocessed data. We selected lag-3, lag-4, and lag-5 of the AR model as input variables for ANFIS. In this study, the input variables of ANFIS we used were a combination of significant lags such as lag-3 and lag-4 (Z_{t-3}, Z_{t-4}), lag-3 and lag-5 (Z_{t-3}, Z_{t-5}), lag-4 and lag-5 (Z_{t-4}, Z_{t-5}), and lag-3, lag-4, and lag-5 (Z_{t-3}, Z_{t-4}, Z_{t-5}). We classified the selected input variables into three clusters and determined the membership functions using trimf, trapmf, and gaussmf. The simulation picture is given in Figure 3.
3. Setting the type of membership function for input variables. The first-order Sugeno method is used to set the membership for the output variables and a linear equation is used for the input variables.
4. Generating the fuzzy if–then rules by using a linear Sugeno model for the three membership functions.
5. Training the parameters of the fuzzy inference system with hybrid algorithms that will set the consequent parameters forward using least-squares and the premise parameters backward and corrected using the gradient descent method.
6. Forecasting the training data from 24 different models and the RMSEs are calculated. Table 5 shows the empirical study result of the IDR exchange rate against the US dollar using ANFIS method.

We chose the model with the smallest RMSE values in the training and testing data as the optimal model. Table 5 shows that the smallest RMSE values for the training and testing processes were obtained when using ANFIS with two input variables Z_{t-3} and Z_{t-5} that yielded RMSE of 52.2245 for training and 51.5684 for testing.

From the empirical study we can summarize the result for the best model of each method in Table 6. Analysis and forecasting using the ARIMA as a statistical model has been carried out and provided the best model ARIMA ([2,3],1,0) with RMSE training (in sample) 55.523 and RMSE testing (out sample) 71.5945, as seen in Table 7. The results show that in this case ARIMA provides more accurate forecasting than the fuzzy time series method. However, ARIMA did not show better forecasting results when compared to ANN and ANFIS. The ANFIS model performed slightly better than ANN and FTS. The ANFIS with two input variables produced more accurate results than the best ANN method. The determination that ANFIS gave more accurate results than ANN and FTS was based on the fact that the RMSE value was smaller, although the difference was not very significant.

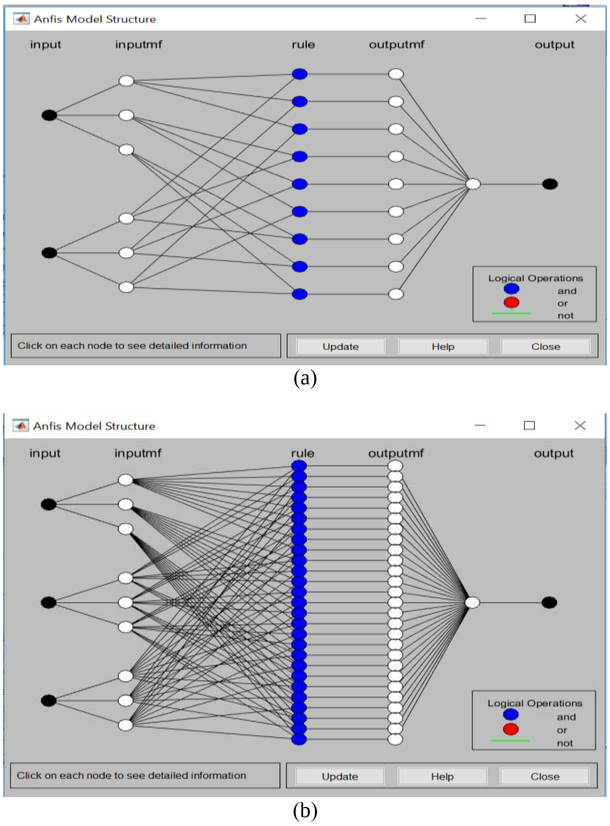


Figure 3. (a) ANFIS structure with 2 inputs and 1 output; (b) ANFIS structure with 3 inputs and 1 output

4. Conclusions

The motivation for using soft computing methods in forecasting is that these methods can process data effectively despite the presence of uncertainties and nonlinear

Table 5. Forecasting result by ANFIS with various input variables

Input	MFs	Cluster	Method	RMSE	
				Training	Testing
Z_{t-3}, Z_{t-4}, Z_{t-5}	trimf	[3,3,3]	Backpropagation	82,5948	72,8321
	trapmf			87,3081	129,2026
	gaussmf			83,0463	75,1087
	trimf	[3,3,3]	Hybrid	50,8023	196827,3146
	trapmf			51,0135	85,9292
	gaussmf			48,2663	248,2964
Z_{t-3}, Z_{t-4}	trimf	[3,3,3]	Backpropagation	73,3421	64,1772
	trapmf			79,5133	75,7797
	gaussmf			75,0583	65,6896
	trimf	[3,3,3]	Hybrid	52,0624	6621,633
	trapmf			53,2740	55,6646
	gaussmf			50,2066	67,5796
Z_{t-3}, Z_{t-5}	trimf	[3,3]	Backpropagation	90,7002	72,0004
	trapmf			81,6555	76,76
	gaussmf			79,7156	59,2506
	trimf	[3,3]	Hybrid	55,6630	2501,8429
	trapmf			53,8468	51,5925
	gaussmf			52,2245	51,5684
Z_{t-4}, Z_{t-5}	trimf	[3,3]	Backpropagation	92,5212	80,5952
	trapmf			98,7666	91,2154
	gaussmf			94,9179	87,8064
	trimf	[3,3]	Hybrid	74,2191	343001,425
	trapmf			76,8761	74,2635
	gaussmf			71,7821	166,2882

Table 7. Forecasting with ARIMA

Model	Variable Coeff (Prob.)	R^2	SSR	AIC	SBC
ARIMA(1,1,0)	AR(1): 0.0394 (0.03)	0.0013	0.0117	-8.1267	-8.1134
ARIMA([2],1,0)	AR(2): 0.0566 (0.0238)	0.00295	0.01166	-8.1283	-8.1150
ARIMA([3],1,0)	AR(3): 0.0862 (0.0007)	0.00715	0.01165	-8.1325	-8.1192
ARIMA([1,3],1,0)	AR(1): 0.0350 (0.0567) AR(3): 0.0843 (0.0009)	0.0084	0.01159	-8.1308	-8.1108
ARIMA([2,3],1,0)	AR(2): 0.0528 (0.0416) AR(3): 0.0837 (0.0017)	0.0992	0.01158	-8.1324	-8.1124
ARIMA(2,1,0)	AR(1): 0.0371 (0.0599) AR(2): 0.055 (0.0426)	0.0043	0.0117	-8.1268	-8.1068

Table 6. RMSE forecasting with ARIMA and three soft computing methods

Method	RMSE	
	Training (in sample)	Testing (out sample)
ARIMA([2,3],1,0)	55.5230	71.5945
ANN	52.0363	54.8188
Fuzzy Time Series	100.9058	87.4171
ANFIS	52.2245	51.5684

relationships, they have a rapid learning capacity, and are adaptable. In this study, we compared forecasts of the IDR\USD exchange rate using FTS, ANN, and ANFIS approaches to deal with nonstationary data. The results show that the soft computing methods are more powerful than the traditional statistical method (ARIMA). ANFIS gave the most accurate results over ARIMA, ANN and FTS, because it gives the smallest RMSE, although the difference was not very significant. In this case, to obtain a more accurate ANFIS formula, in future research we will strive to improve the ANFIS model by using several alternative approaches in data preprocessing, to determine input variables to get better forecasting results.

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