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APPLICATION OF ARTIFICIAL NEURAL NETWORK ON FORECASTING EXCHANGE RATE OF RUPIAH TO US DOLLAR

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Abstract: *Neural network is one of the technologies in the field of Artificial Intellegence in which data pattern identification of the Rupiah forecasting system to US dollar can be done by the method of learning approach. Based on its learning ability, the neural network can be trained to study and analyze the past data patterns then find a formula or function that will correlate the past data pattern with desired output. This study aims to explain the mechanism of forecasting using artificial neural networks and to determine the neural network model in forecasting Rupiah against US dollar. The exerted software to create the exchange rate forecasting program is Matlab 7.0. The best model of simulation results shown in architecture with 10 input layers, 1 hidden layer with 2 hidden neurons, 1 output layer, backpropagation training algorithm, and bipolar sigmoid activation function. The results of calculations using artificial neural networks obtained MAE values Rp 45.74 in the data testing.*

Keywords:*Forecast, Exchange Rate, Artificial Neural Networks, Backpropagation Algorithm.*

INTRODUCTION

The exchange rate of rupiah is the price of the Rupiah towards other currencies. In other words, Rupiah is the valuation of one rupiah translated to the currency of other country (ex. Rupiah against US dollar, Rupiah against Yen, and so forth). Currency exchange rate data is acquainted as time series data. Time series data are chronologically successive observations of a variable. Time scope of observation is usually fixed, e.g. per hour, per day, per week, per month, and so on. Time series data are usually analyzed to find patterns of growth or change in the past that can be used to predict future patterns in accordance with the needs of business operations. Time series data analysis is useful for forecasting process and helps reduce errors in forecasting.

According to Siang (2005), artificial neural network is a processing system of information that has similar characteristics to biological neural networks. Artificial neural networks are formed as a generalization of mathematical models of biological neural network with the following assumptions:

a. Information processing occurs at many simple elements (neurons).

b. Signals transmitted between neurons through connectors.

c. Connector between neurons has its pertinent weight that will strengthen or weaken the signal.

d. To determine the output, each neuron uses activation function imposed on the summation of received inputs, then amount of output is compared with a threshold.

Backpropagation algorithm is one of artificial neural network algorithm. This algorithm utilizes network to get the balance between network ability in recognizingpatterns used during training and networkability in providing correct response to similar (but not equal) input pattern to another pattern used during training (Siang, 2005).

Basically, the backpropagation algorithm will move the weight with negative gradient direction. The basic principle of the backpropagation algorithm is to improve the network weights in the direction that makes the activation function to be decreased quickly.

This study aims to find out how to do the forecasting by using artificial neural networks and to determine the artificial neural network model which will be used to forecast Rupiah to US dollar. Software used for the exchange rate forecasting program in this research is Matlab 7.0.

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METHODOLOGY

Method used in this research is backpropagation artificial neural network. Backpropagation algorithm is an algorithm which is excellent in dealing with the introduction of complex patterns. This algorithm is a neural network algorithm that popular. Some examples of applications that involve the algorithm is data compression, computer virus detection, object identification, voice synthesis from text, forecasting, and others.

In artificial neural network architecture, response valueor *output*$\hat{y}$is calculated with :

$$\hat{Y}_{(k)} = f^o\left[\sum_{j=1}^{q}\left[w_{j(k)}^o f_j^h\left(\sum_{i=1}^{p} w_{ji}^h x_{i(k)} + b_j^h\right) + b^o\right]\right]$$

$$\hat{Y}_{(k)} = f^o\left[\sum_{j=1}^{q}\left[w_{j(k)}^o a_{j(k)}^h + b^o\right]\right]$$

$$\hat{Y}_{(k)} = w_{1(k)}^o a_{1(k)}^h + w_{2(k)}^o a_{2(k)}^h + \cdots + w_{p(k)}^o a_{p(k)}^h + b^o \quad \text{..........(1)}$$

where :

$$a_{j(k)}^h = f_j^h\left(v_{j(k)}^h\right) = \frac{1-e^{-\left[v_{j(k)}^h\right]}}{1+e^{-\left[v_{j(k)}^h\right]}} \quad \text{..........(2)}$$

$$\left(v_{j(k)}^h = \sum_{i=1}^{p} w_{ji}^h x_{i(k)} + b_j^h\right) \quad \text{..........(3)}$$

annotation :

$\hat{Y}_{(k)}$ = the estimated value of the output variable

$x_{i(k)}$ = *p*numbers of input variables, (*i*=1,2,…,*p*)

k = data pairs index of *input-target*$\left(x_{i(k)}, y_k\right)$, *k* = 1,2,…, *n*

h = index of hidden layer

o = index of*output layer*

w_{ji}^h = weightof*i*th*input*towards*j*th*neuron*at*hidden layer*, (*j*=1,2,…,*q*)

b_j^h = bias of*j*th*neuron* at*hidden layer*

$w_{j(k)}^o$ = weight of*j*th*neuron*at *hidden layer* towards *neuron*at *output layer*

b^o = bias of *neuron*at *output layer*

f^o = activation functionat *neuronoutput layer*

f_j^h = activation functionat *neuronhidden layer*

RESULTS AND DISCUSSION

This study observed the fluctuation of rupiah against US dollar from January 1, 2007 until February 25, 2010 as research data. Data exchange is available in five-days cycle therefore the data amounted to 824. This period witnessed sharp fluctuations of exchange rate due to economic global crisis. There are 824 data formed into 774 datasets, with each dataset numbered to 50. In advance, each dataset is turned to stationary point by differencing. Then, each dataset's autocorrelation value is calculated and selected by taking 10 data with autocorrelation value that's closest to significant borderline (significance limits). Data on the lag (the previous value) which approaches the data limit affects the forecasting value significantly.

Here is an example of determining the model inputs for each dataset used in this research. The first step is testing autocorrelation in first dataset (the data to-1 to 50) without any differencing. The second step is differencing the dataset to enact the data into stationary. Autocorrelation value (ACF) in the data after first differencing can be seen in Table 1.

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Table 1. Autocorrelation Value in Exchange Rate Data After First Differencing

Lag	**ACF Value**	***Lag***	**ACF Value**	***Lag***	**ACF Value**	***Lag***	**ACF Value**	***Lag***	**ACF Value**
1	**-0.15396**	**11**	**0.1359**	21	0.023123	31	-0.02827	**41**	**-0.22558**
2	0.038459	12	-0.02754	22	0.036057	32	0.033671	42	0.068689
3	-0.03461	13	-0.02335	23	0.079645	33	0.106381	43	-0.09361
4	-0.0187	14	0.049851	24	-0.09299	34	-0.07827	44	-0.09051
5	-0.01381	**15**	**-0.14003**	25	0.06184	35	0.106234	45	-0.02835
6	-0.07449	16	0.084064	**26**	**0.133235**	36	-0.0381	46	0.02351
7	0.013295	17	-0.02326	27	-0.07387	37	0.082961	47	-0.04909
8	**-0.32906**	**18**	**-0.15231**	28	0.037716	38	-0.00765	48	0.100816
9	0.11272	19	-0.08573	29	0.044888	39	0.119341	49	0.01801
10	0.001178	20	-0.00145	30	-0.10161	40	-0.0254		

Autocorrelation values of lag 8, 41, 1, 18, 15, 11, 26, 39, 9 and 33 are the closestto significant boundary therefore the data on the lag is used as input data on the first row. The latest data from the first set of data is used as the target in the first row. The same step is done in the second set of data (the data to-2 up to 51), and so on through 774th dataset.

Table 2.*Input* and *Target* Model of Artificial Neural Network

No	***Input***										***Target***
	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	Y
1	9.6660	9.6635	9.6675	9.5663	9.5555	9.5585	9.5570	9.6605	9.5570	9.5580	9.6670
2	9.6605	9.6670	9630	9.5585	9.5585	9.6615	9.5585	9.5550	9.5580	9.7005	9.6690
3	9.6690	9580	9.6670	9.5590	9.6615	9.6695	9545	9.5555	9.5585	9.5570	9.7225
4	9.7225	9.5585	9.7000	9.5580	9.6630	9710	9.5455	9.5555	9615	9.6605	9.7110
5	9.7110	9.6675	9.6615	9705	9615	9.5570	9.5555	9.6630	9.5580	9.5585	9.7220
6	9.7220	9.6630	9.6670	9.5590	9.5590	9.5585	9.5570	9552	9.6615	9.5667	9.7220
7	9.6615	9.6690	9.7220	9.7110	9.5580	9.6605	9.5550	9.5575	9.6660	9.7005	9.6685
8	9.5570	9725	9.6660	9.6695	9.5590	9.5585	9.5665	9.6670	9.6635	9.5445	9.6630
9	9.7110	9.5585	9.6630	9.5580	9.7110	9.5663	9.7000	9.5665	9.5555	9.6690	9.6600
10	9.7220	9.6660	9.6670	9.5664	9.5552	9.5550	9.5570	9.6685	9.5663	9.6630	9.6615
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
774	9.8871	9.7225	9.7800	9.7992	9.8870	9.8821	9.6865	9.7880	9.8845	9.8840	9.8835

The third step is dividing the data into two parts, namely the training data and testing the data. Training data is about 699 and testing data is about 75.

Simulation

Weights initialization in artificial neural network should be determined before starting the training process. During the training process, the weight value will continue to change until the network target is met where the the maximum iteration is reached or stopping error is fulfilled (Nuraeni, 2009). Initialization ofearly weight in this study was drawn at random by the network.

Simulation models are made with trial and error to produce the best model. The best model is obtained by simulation with the value of learning rate (α), epoch, momentum (μ), and varied number of hidden neurons. The model which produces the smallest MAE value is the best model.

Learning Rate Determination

Learning rate parameter (α) ranges between 0 and 1. The value of learning rate that will be used in forecasting is the value of learning rate that produces the smallest MAE. Used training function is *the gradient descent with adaptive learning rate* (traingda). This function will improve the weights based on gradient descent with adaptive learning rate.

Learning rate determination is conducted on a hidden neuron of artificial neural network model, 20 epochs with variations of learning

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rate.Simulation resultshows that the smallest MAE value obtained when the value of αequals 0.6. Furthermore, the value of the learning rate is used to simulatethe models with varied number of epochs.

Epoch Number Determination

Backpropagation algorithm can not provide certainty about how the many epoch must be passed to reach the desired condition. To anticipate this, the training process can be stopped by limiting the number of epochs. In determining the amount of the epoch, a hidden neuron of artificial neural network model is simulated, α = 0.6, with the *traingda* training function of varied number of epochs. The simulation result shows the optimum epoch number is 600 with a value of Rp. 56.7663 MAE.

Momentum Determination

The addition of the momentum value (μ) is intended to avoid drastic weight change when the data is very different from the others (outliers). Parameter momentum (μ) value ranges between $0 \leq \mu \leq 1$. The momentum value that will be used in forecasting is the momentum value which produces the smallest MAE. Used training function is *gradient descent with momentum* and *adaptive learning rate (traingdx)*. This function will improve the weights based on gradient descent with adaptive learning rate and momentum. The simulation result shows that the smallest MAE value is obtained when the value of μ = 0.7 with a value of MAE Rp. 57.9929. MAE value after the addition of the momentum is greater than the value of MAE in previous models. In other words, the model with the addition of the momentum has not been able to produce a better model. Then, simulation models are conducted with varying number of hidden neurons by using *traingda* training function.

Number of Hidden Neurons Determination

The architecture of artificial neural network in a hidden layer can theoretically identify any pair between the input and the target with specified level of accuracy. The network is enlarged by increasing the number of hidden neurons. The simulation result shows the optimum number of hidden neurons, which is 2 neurons with MAE value of Rp. 45.7663.

Best Model

The best artificial neural network model simulation results obtained with the following parameters:

- Learning rate value (α) : 0,70
- Number of *epoch(s)* : 600
- Number of *hidden neuron(s)* : 2
- Training Function : *gradient descentwith adaptive learning rate* (*traingda*)
- Architecture : 10-2-1
  which means that the model uses 10 input variables in the input layer, 2 neurons in the hidden layer, and an output layer.

Comparison of forecasted values and actual values in the training data with the best testing model data is shown in Figure 1 and 2. In the training process, it's obtained the value of MAE Rp 152.69 while in the process of testing the obtained value is about MAE Rp 45.74.

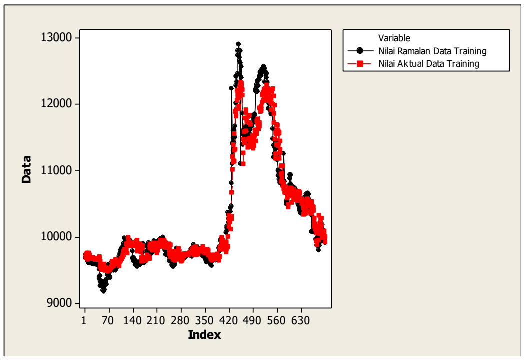

Figure 1. Results Comparison of Artificial

Neural Network Forecasting Model with Actual Data on Training Data

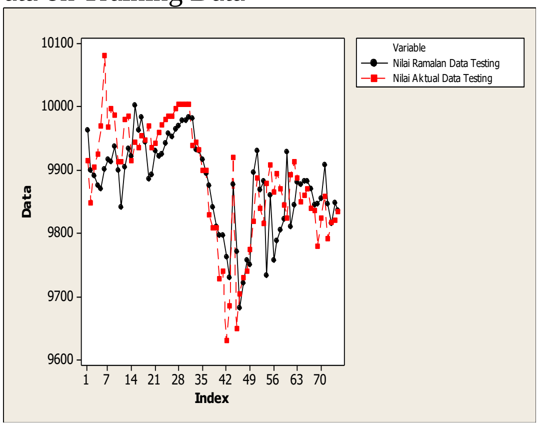

Figure 2. Results Comparison of Artificia

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Neural Network Forecasting Model with Actual Data on the Data Testing

Equation of Artificial Neural Network Model

Once the best network architecture is formed and final weights are obtained, then the equation(1) to forecast the rupiah towards the US dollar is :

$$\hat{Y}_{(k)} = w^{o}_{1(k)} a^{h}_{1(k)} + w^{o}_{2(k)} a^{h}_{2(k)} + b^{o}$$

$$\hat{Y}_{(k)} = -0{,}8263 a^{h}_{1(k)} + 0{,}8775 a^{h}_{2(k)} + 0{,}6477 \quad \text{....................................(4)}$$

where :

$$a^{h}_{1(k)} = f^{h}_{1}\left(v^{h}_{1(k)}\right) = 2\left(\frac{1}{1+e^{-\left[v^{h}_{1(k)}\right]}}\right) - 1 = \frac{1-e^{-\left[v^{h}_{1(k)}\right]}}{1+e^{-\left[v^{h}_{1(k)}\right]}}, \text{ dengan}$$

$$v^{h}_{1(k)} = -0{,}2832X_{1(k)} - 0{,}4374X_{2(k)} - 0{,}1556X_{3(k)} - 0{,}3991X_{4(k)} - 0{,}3608X_{5(k)} - 0{,}1023X_{6(k)} - 0{,}0819X_{7(k)} - 0{,}125X_{8(k)} + 0{,}3248X_{9(k)} + 0{,}3988X_{10(k)} + 1{,}9344$$

$$a^{h}_{2(k)} = f^{h}_{2}\left(v^{h}_{2(k)}\right) = 2\left(\frac{1}{1+e^{-\left[v^{h}_{2(k)}\right]}}\right) - 1 = \frac{1-e^{-\left[v^{h}_{2(k)}\right]}}{1+e^{-\left[v^{h}_{2(k)}\right]}}, \text{ dengan}$$

$$v^{h}_{2(k)} = 0{,}9334X_{1(k)} + 0{,}1811X_{2(k)} + 0{,}1926X_{3(k)} - 0{,}1506X_{4(k)} - 0{,}1093X_{5(k)} + 0{,}0847X_{6(k)} + 0{,}014X_{7(k)} - 0{,}028X_{8(k)} - 0{,}0077X_{9(k)} - 0{,}0509X_{10(k)} + 0{,}147$$

CONCLUSION

Based on the results of this study can be summarized as follows :

1. Step forecasting of the rupiah against the US dollar as follows :
   a. The determination o the input model of the data set having the autocorrelation value closest to the significant boundary.
   b. Data sharing training and testing.
   c. Selection of artificial neural network parameters.
   d. Determination of the best neural network model that has the smallest MAE (Minimum Absolute of Error)
   e. Use of the best neural network model for forecasting the rupiah against US dollar
2. The best forecasting model of rupiah against the dollar US with backpropagation training algorithm as follows :
   a. Value of learning rate (α) : 0,70
   b. Epoch number : 600
   c. Number of hidden neuron : 2
   d. Training functions : *gradient descentwith adaptive learning rate* (*traingda*)
   e. Architecture : 10-2-1, it can be interpreted that the model uses 10 input variables on the input layer, 2 pieces of neuron on the hidden layer and 1 output
3. The results of calculations using artificial neural networks obtained MAE values respectively Rp 45.74 in the data testing.

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