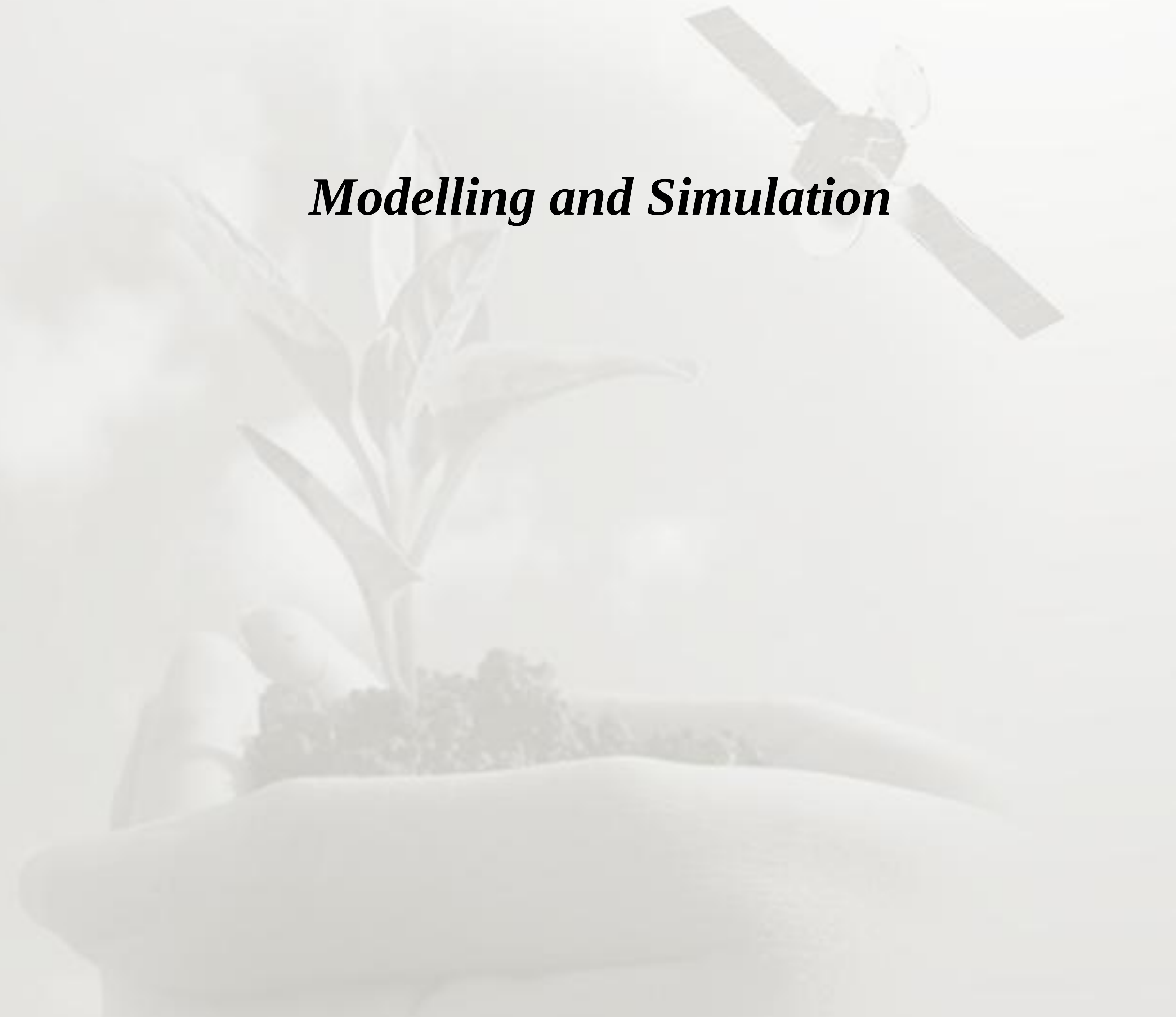
# *Modelling and Simulation*



# Heuristic Optimization Recurrent Neural Network Model to Predict Rainfall Based on *El-Nino Southern Oscillation* (ENSO) Variable.

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*Abstract*— **Prediction of rainfall in the agricultural sector has now become a major requirement, as well as the selection of seeds, fertilizer and pest eradication. Information about the rainfall is very useful to farmers in anticipation of extreme events such as droughts and floods. Therefore, the model prediction of rainfall needed a fast and accurate prediction. This research employ a recurrent optimized heuristic neural network approach using El-Nino Southern Oscilation (ENSO) variable, namely Wind, SST, SOI and OLR to forecast regional monthly rainfall. Three optimized heuristic learning algorithms are applied in recurrent Elman, i.e gradient descent adaptive learning rate with various parameter values, gradient descent adaptive learning rate & momentum with various parameter values, and resilient backpropagation with various parameter values. The best forecasting rainfall for leap 0 is resilient backpropagation algorithm application which is obtaining 77% maximum $R^2$ with RMSE 138,52. While the best forecasting rainfall for leap 1 is resilient backpropagation algorithm application which is obtaining 84,8% maximum $R^2$ with RMSE 125. Our result on leap 0 is better than previous approach which employing neural network standard backpropagation.**

***Keywords—rainfall, ENSO, regional monthly rainfall, recurrent neural network, optimized heuristic learning algorithm***

## I. INTRODUCTION

Prediction of rainfall in the agricultural sector has now become a major requirement, as well as the selection of seeds, fertilizer and pest eradication. Information about the rainfall is very useful to farmers in anticipation of extreme events such as droughts and floods [12]. Therefore, the model prediction of rainfall needed a fast and accurate prediction.

The model of rainfall prediction that has been implemented rarely use variable of *El-Nino Southern Oscilation* (ENSO) as neural network data input whereas the ENSO variable made quite big impact on rainfall throughout Indonesian territory. The previous study had been done by using only temperature and rainfall data as neural network data, the result was not satisfied enough. Some of the previous study are the application of *Principal Component Regression* [5] method resulted in $R^2$ of 63,16% whereas using neural network standar back propagation [9] resulted in $R^2$ of 74,02% dan neural network standar back propagation [1] resulted in $R^2$ of 48,179%. Considering the matter above, the study on this field is still worthy and need to be done in order to obtain the more accurate rainfall prediction model.

This study will use neural network *recurrent* which is heuristically optimized to identify ENSO variable pattern against rainfall prediction. The applied ENSO variable data are: *wind, Southern Oscillation Index* (SOI), *Sea Surface Temperatur* (SST) dan *Outgoing Long Wave Radiation* (OLR)

Heuristic optimization is a development of performance analysis on *gradient descent standard* algorithm which consists of three learning algorithms that are: *gradient descent adaptive learning rate*, *gradient descent adaptive learning rate & momentum* serta *resilient backpropagation.*

### *A.The Objective and the Benefit of Study***.**

The objective of this study is to develop the *recurren* neural network *t* model which is heuristically optimized for rainfall prediction based on ENSO variable.

### *B. Scope***.**

a. The applied model is limited to neural network Recurrent Elman.
b. Learning optimization that is conducted by using heuristic technique namely *gradient descent adaptive learning rate*, *gradient descent adaptive learning rate* & *momentum* as well as *resilient backpropagation.*
c. The rainfall data obtained from Balai Penelitian Agroklimat & Hidrologi (BALITKLIMAT) Bogor and this study source ENSO data from International Institution such as National Weather Service Center for Environmental Prediction Climate (NOAA).
d. The input data only consist of ENSO variable and rainfall data target so that the other influenced factors of rainfall are not taken into account.

## II. THE ARTIFICIAL NEURAL NETWORK RECURRENT ELMAN

Recurrent neural network is a network which accommodate output network to become an input of the network again in order to result in the next network output. The recurrent network Elman consists of one or more hidden layer. The first layer has the weight that is obtained from the input layer every layer will receive weight from the previous layer. This network usually uses the activation function of sigmoid bipolar for the hidden layer and linear function (*purelin)* for the output layer. Unlike backpropagation, this Elman network has activation function that can be in the form of any function both continue and discontinue. Delay that is happened in the connection between the input layer and the first hidden layer in the previous time (t-1) can be used in the current time (t) [6]. The unique of the recurrent neural network is the feedback connection which conveys interference information (noise) at the previous input that will be accommodated to the next input [2].

*A. Inisialisasi Nguyen-Widrow.*

This initialization generally accelerates learning process compare to random initialization [4].

Nguyen-Widrow initialization is defined as the following equation:

a. Calculate the value of multiple factor β

$$\beta = 0.7\ p^{1/n} \tag{1}$$

Where:

β = multiple factor.

n = the *neuron* number of input layer.

p = The neuron number of The hidden layer

b. For each hidden unit (j=1, 2... p):

Calculate $v_{ij}$ (old) namely random figure between -0.5 and 0.5 (or between -γ and γ).

c. Calculate: $\| v_j \|$

The weight renewal $v_{ij}$ (old) to be $v_{ij}$ (new) namely:

$$v_{ij}\,(old) = \frac{\beta\, v_{ij}\,(old)}{\| v_j\,(old) \|} \tag{2}$$

a. Set bias :

$B_{1j}$ = the random figure between a – β up to β.

*B. The prediction Accuracy*

The prediction accuracy of a regression model can be viewed through its determination coefficient ($R^2$) and *Root Mean Square Error* (RMSE). The value of i $R^2$ indicates proportion of the total quadrate which can be explained by the variety source of free variable, whereas RMSE indicates the amount of estimation value deviation against its actual value. $R^2$ is quadrate of correlation between observation vector value y and estimation vector value $\hat{y}$ [10].

*C. Heuristic Learning Optimization*

In the *backpropagation neural network* there is heuristic technique optimization namely algorithm learning has function to accelerate learning process and constitute a development of some performance analysis on *steepest (gradient) descent standard algorithm*. Three algorithms of heuristic technique optimization [6] that are frequently used:

*D. Gradient Descent Adaptive Learning Rate.*

This heuristic technique improves weight based on *gradient descent* with the adaptive learning rate/speed. In *gradient descent standard*, during learning process, the learning rate (α) will continue has constant value. If the learning rate is too high, the algorithm will become unstable. On the contrary, if the learning rate is too low, the algorithm will need very long time to reach convergence. In fact the optimal learning value rate will continuously change during learning process along with the change of the performance function value. In *gradient descent adaptive learning rate*, the learning rate value will be changed during learning procces to keep this algorithm always stable during learning process. The performance of neural network is calculated based on the network output value and learning error. In every epoh, the new weights are calculated by means of the existing learning rate. Then the performance of new neural network is calculated. If the comparison of performance in new neural and old neural exceeds the maximum of performance increase (*max_perf_inc*), then the new weight will be ignored, and the learning rate value will be reduced by multiply it to parameter of learning rate decrease (*lr_dec)*. Conversely, If the comparison of performance in new neural and old neural less than the maximum of performance increase, then the weights value will be retained, and the learning value will be increased by means of multiply it to parameter of learning rate increase (*lr_inc)*.

*E. Gradient Descent Adaptive Learning Rate and Momentum.*

This heuristic technique improves weight based on *gradient descent* with the learning rate which has adaptive characteristic and use momentum (*mc*).

Momentum is a constant which influence weight change and has value between 0 and 1. If *mc* = 0 the weight change will be influenced only by *gradient* and if *mc* = 1 then the weight change will same as the previous weight change. This heuristic technique steps are:

*F. Resilient Backpropagation*

The neural network that is built by *multilayer* structure usually use activation function of *sigmoid.* This activation function will bring the input with unlimited range value to the output with limited range value, namely between 0 and 1. One of the sigmoid functions characteristic is its gradient will be almost zero if the given input is very much. *Gradient* which is almost zero imply the low of weight change. If the change of weights is not enough, the algorithm will really slow in approaching its optimum value [6].

R*esilient backpropagation* algorithm try to eliminate the great effect of partial integral by means of only use its integral sign and ignore the amount of integral value. The integral sign will determine the direction of weights improvement. The amount of every weight change will be determined by some factor that is managed in parameter of weight increase (*delt_inc)* or parameter of weight decrease (*delt_dec).* If the gradient of performance function change from one iteration to iteration, the weight will be decreased by *delt_dec* and if the gradient of performance function does not change its sign, the weight will be increase by *delt_inc*. If the gradient of performance function = 0, then the weight change will be the same as previous weight change.

## III. METHOD

*A. Data Collection*

The data that are used in this study:

a. Data ENSO

This Data obtained from NOAA with data range domain of ENSO within Nino-3,4 area, namely: 5° LU - 5° LS and 90° BB - 150° BB that recorded for 83 months.

b. Rainfall Data
The rainfall data which is used in this study are the average rainfall in Bongan Bali area with data range domain 08° 33' 05" S and 115° 05' 48"E on the 124 altitude. The study sources the rainfall which are consist of 83 months recorded data from BALITKLIMAT Bogor.

*B. Research Method*

The study preceded by indentifying ENSO variables and its impact on the rainfall within Indonesia territory. Having identifying the previous studies concerning rainfall prediction, evidently the method which have been used and the study result mainly regarding the achieved prediction accuracy (see figure 1)

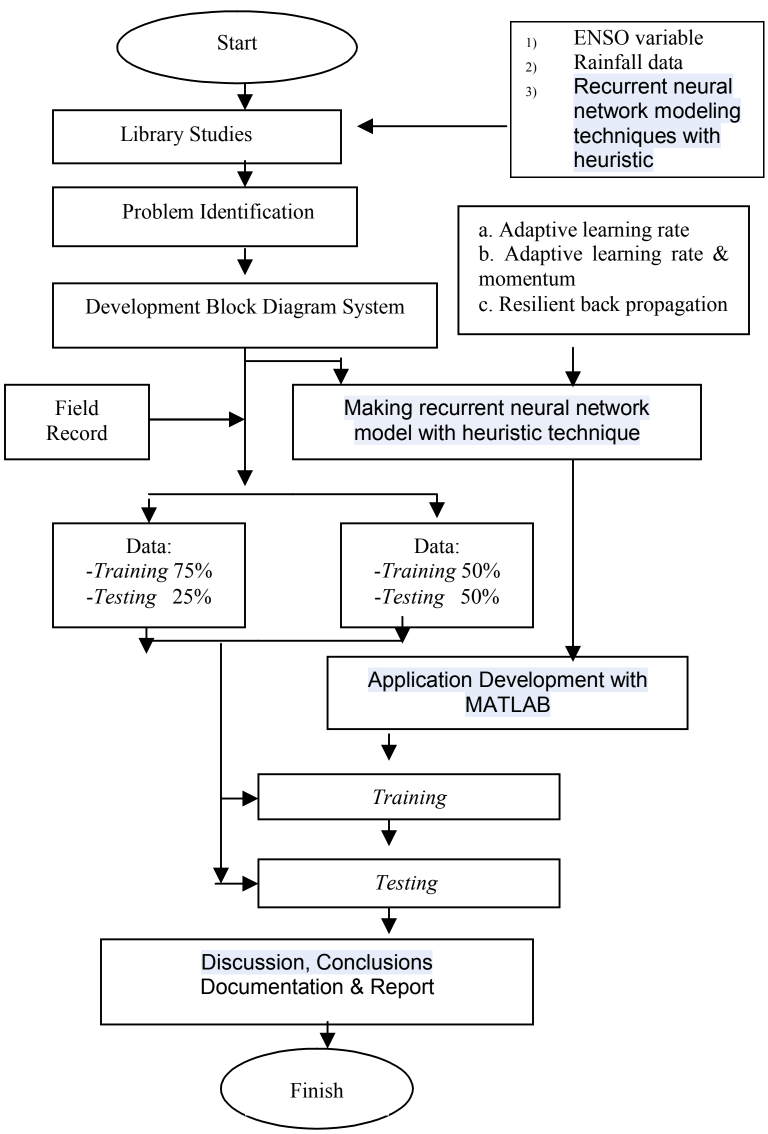


Figure 1. Research Method

*C. The Study Stage*

The study will examine the model of the heuristically optimization neural network recurrent for rainfall prediction based on ENSO variables.

The beginning stage, every data group will undergo initialization process using Nguyen-Widrow method. The number of neuron and hidden layer are determined by preliminary experiment in trial & error technique and refers to previous studies. On next stage, the following experiment is conducted:

- The first step conducting learning against the fourth of ENSO variables and rainfall as a target, by using the first data group that is 75% of training data and 25% of testing data.
- The second step conducting learning against the fourth of ENSO variables and rainfall as a target, by using the second data group that is 50% of training data and 50% of testing data.

Every data group with the composition mentioned above is used to perform experiment against the different leap variation that are leap = 0, 1, 2, dan 3.

- *Leap* 0 the rainfall prediction on the same month.
- *Leap* 1 the rainfall prediction on the next one month.
- *Leap* 2 the rainfall prediction on the next two months.
- *Leap*3 the rainfall prediction on the next three months.

Every experiment will be iterated 20 times with the purpose to gain the average $R^2$ and RMSE with the smallest standard deviation. The value of $R^2$ and RMSE in every combination is located on the certain interval value (minimum and maximum). The result of experiment on this study is focused on comparison of the neural network accuracy prediction that is resulted in $R^2$ maximum and RMSE minimum.

## IV. THE RESULT AND DISCUSSION

*A. The Composition of Training Data and Testing Data*

The composition of training and testing data has great influence to the prediction accuracy of neural network. As explained in methodology, the data is divided into two experiment data groups, namely the first data group, 75% training data (62 months) and 25% testing data (21 months) and the second data group namely 50% data (42 months) used for training and 50% data (41 months) used for testing data.

*B. The Experiment Result of the First Data Group*

In the first experiment, the ENSO variable that are *wind*, SOI, SST and OLR as *input* and rainfall as a target. The experiment result for this data group as follow:

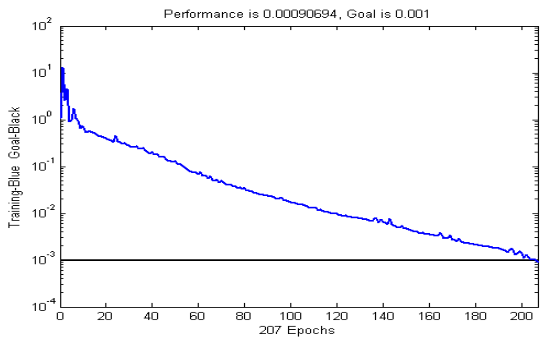


Figure 2. The number of the best epoch in neural network *recurrent resilient backpropagation* for the first group data with *leap* 0

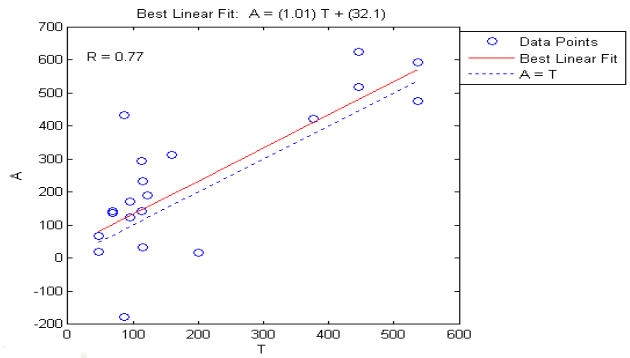


Figure 3. The best correlation of neural network *recurrent resilient backpropagation* for the first data group with leap 0

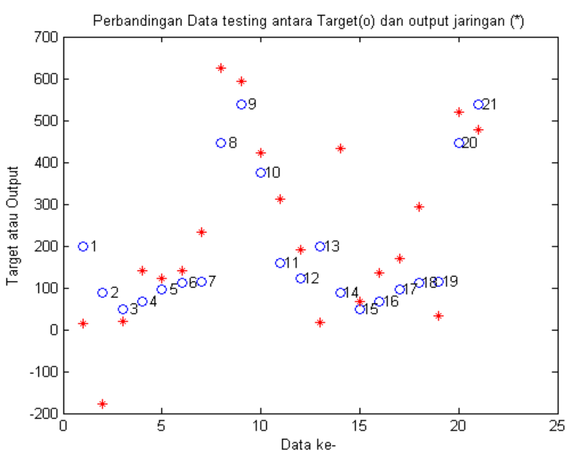


Figure 4. The best prediction value (*output*) and the best actual value of neural network *recurrent resilient backpropagation* for the first data group leap 0

In the experiment with the first data group, the best result obtained when using *resilient backpropagation algorithm*. For *leap* 0, when *delt_inc* value is increased from 1,5 to 1,7 and *delt_dec* value is decreased from 0,6 to 0,4 the result is the $R^2$ maximum value increase rise from 54,4 to 56,2 indicate increasing amounting to 1,8 whereas the RMSE value decrease from 206,7 to 198,82. When *delt_inc* value remain 1,7 and *delt_dec* value is increased from 0,4 to 0,6 result in the maximum $R^2$ value increase from 56,2 to 77 indicate increasing amounting to 20,8 whereas the RMSE value decrease from 198,82 to 138,52. This is the best result in the experiment of the first data group with *leap* 0 by the value composition delt_inc 1,7 and delt_dec 0,6. The number of epoh for the best result is presented in Figure 4. The conformity correlation of network *output* with target has value of 0, 77 or 77% as presented in Figure 5. The comparison of prediction value (*output*) and actual value (target) is presented in Figure 6, showing some point (*output*) already approach to some circle (target). The matter can be signified that some prediction value already approach to its actual value. The best result occurs if the point and circle located at the same position.

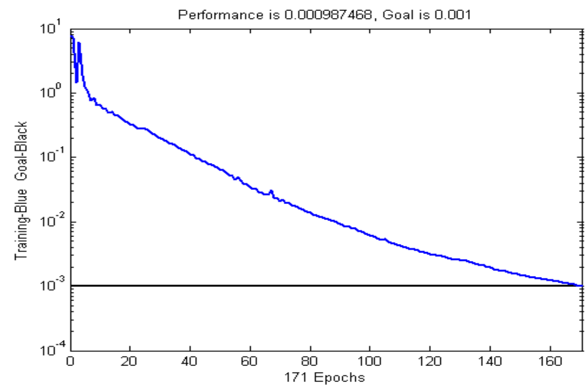


Figure 5. The number of the best of neural network *recurrent resilient backpropagation* for the first data group with *leap* 1

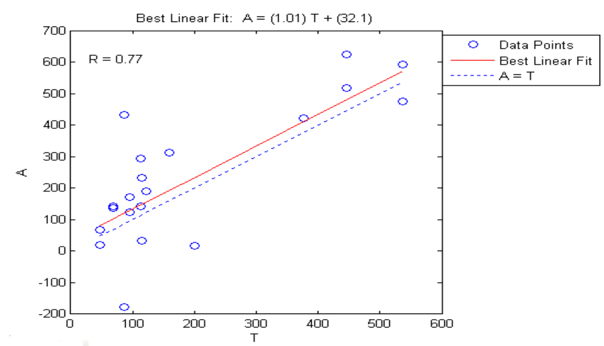


Figure 6. The best correlation of neural network *recurrent resilient backpropagation* for the first data group with leap 1

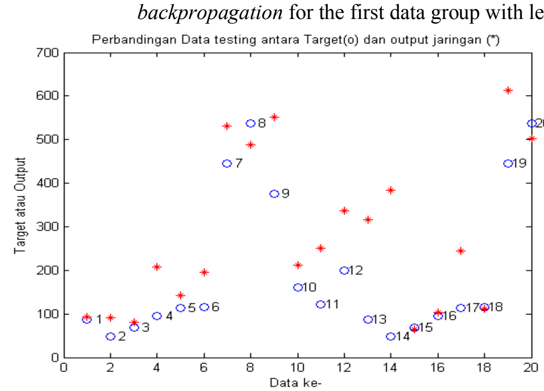


Figure 7: The best prediction value (*output*) and the best actual value (*target*) of neural network *recurrent resilient backpropagation* with the first data group *leap* 1.

In the experiment with leap 1, 2 and 3, the best prediction result is obtained at *leap* 1. The resulted maximum $R^2$ value is 84,8% within the $R^2$ interval value between 28,5 and 84,8 with RMSE value is 125 within RMSE interval value between 125 321,52. The best result of experiment for this *leap* 1 is obtained by composition value delt_inc 1,7 and delt_dec 0,4 as presented by Figure 7, Figure 8 and Figure 9. Considering the result of experiment using this first group data, the best rainfall prediction occurs at *leap* 1.

*C. The Experiment Result of the Second Data Group*

First experiment use ENSO variable that are *wind*, SOI, SST and OLR sebagai *input* as well as rainfall as target. The experiment result for this data group is as follow:

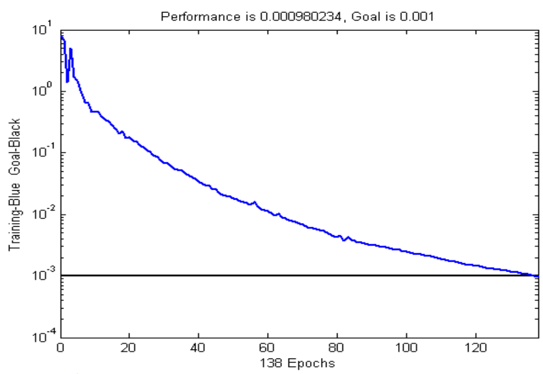


Figure 8. The number of the best epoch neural network *recurrent resilient backpropagation* resulted by the second data group with *leap* 0

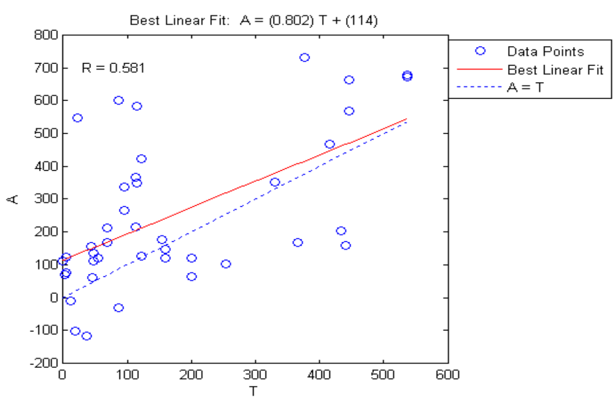


Figure 9. The best Correlation of neural network *recurrent resilient backpropagation* resulted by the second data group with *leap* 0

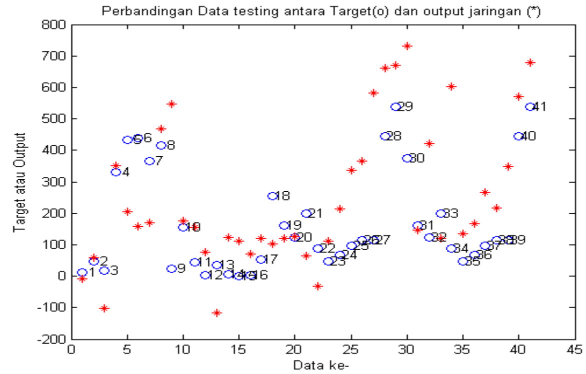


Figure 10. The best prediction value (*output*) and actual value (*target*) of neural network *recurrent resilient backpropagation* resulted by the second data group *leap* 0.

In experiment with the second data group, the best result obtained when using *resilient backpropagation* algorithm. At *leap* 0, when *delt_inc* value is increased from 1,5 to 1,7 and *delt_dec* is decreased from 0,6 to 0,4 the result are $R^2$ value rise from 45 to 58,1 indicate increase amounting to 13,1. The RMSE value increase from 198, 63 to 201, 63. This result is the best at *leap* 0 with the composition value *delt_inc* 1,7 and *delt_dec* 0,4 .

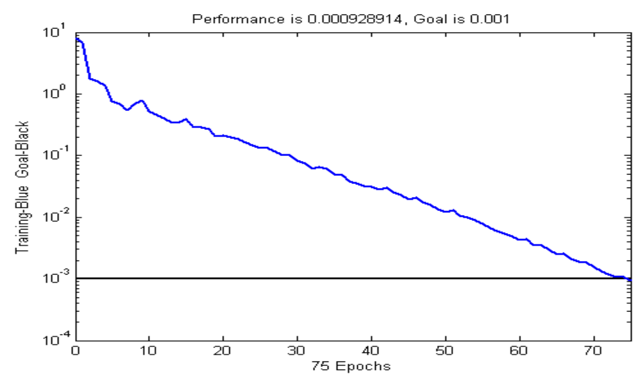


Figure 11. The number of the best epoch neural network *recurrent resilient backpropagation* resulted by the second data group at *leap* 1

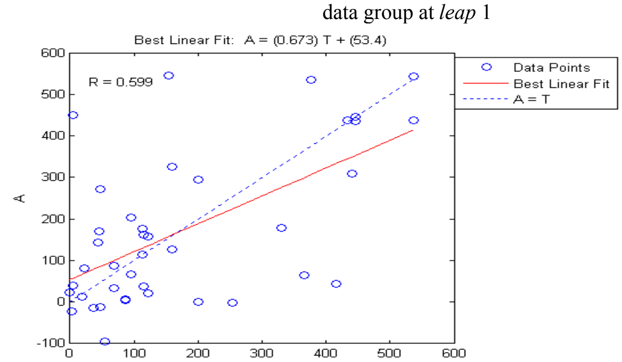


Figure 12. The best correlation of neural network *recurrent resilient backpropagation* resulted by the second data group at *leap* 1

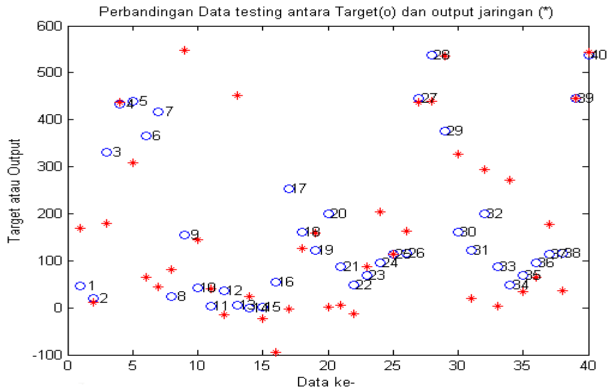


Figure 13. The best prediction value (*output*) and actual value (target) of neural network *recurrent* in the second data group *leap* 1.

Among *leap* 1, 2 and 3, the best graphic prediction is obtained at *leap* 1, when the *delt_inc* value is increased from 1,5 to 1,7 and *delt_dec* value is decreased from 0,6 to 0,4 resulted in the decreasing of the maximum $R^2$ value from 59,5 to 56,3 whereas the RMSE value rise from 156,46 to 169,77. When *delt_inc* value remain 1,7 and *delt_dec* is increased from 0,4 to 0,6 resulted in the increasing maximum $R^2$ value from 56,3 to 59,9 within $R^2$ interval value between 19,5 and 59,9 whereas the RMSE value decrease from 169,77 to 155,29 within RMSE interval value 155,29 up to 282,97. This is the best result for the experiment of the second data group at *leap* 1 with the value composition *delt_inc* 1, 7 and *delt_dec* 0,6 as presented in Figure 11 , Figure 12 and Figure 13.

## V. CONCLUSIONS

### *A. Conclusions*

a. The heuristically optimization neural network *recurrent* can be applied in the rainfall prediction based on ENSO variable with the adequate accuracy level.

b. The best heuristically optimization technique in this research is *resilient backpropagation* algorithm.

c. The best rainfall prediction at *leap* 0 resulted in the maximum $R^2$ value 77%, at *leap* 1 resulted in the maximum $R^2$ 84,8%, *leap* 2 resulted in the maximum $R^2$ 75,5%, and at l*eap* 3 resulted in the maximum $R^2$ 54,1%.

d. Composition of 75% training data & 25% testing data resulted in the maximum $R^2$ maksimum higher than Composition of 50% training data and 50% testing data.

### *B. Needs for further research*

This study still needs further research. The things probably need to be developed as follow:

a. There can be further study that is trying to use the other learning algorithm which is probable to increase the prediction accuracy level of neural network *recurrent.*

b. The further research needs the development of the variable number instead of ENSO variable, such as wind direction and other parameter that has possibility correlation with rainfall.

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