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OPTIMIZATION RAINFALL-RUNOFF MODELING FOR CIUJUNG RIVER USING BACK PROPAGATION METHOD

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Abstract -- *The rainfall-runoff model is required to ascertain the relationship between rainfall and runoff. Hydrologists are often confronted with problems of prediction and estimation of runoff using the rainfall date. In actual fact the relationship of rainfall-runoff is known to be highly non-linear and complex. The spatial and temporal precipitation patterns and the variability of watershed characteristics create a more complex hydrologic phenomenon. Runoff is part of the rain water that enters and flows and enters the river body. Rainfall-runoff modeling in this study using Artificial Neural Network, back propagation method and sigmoid binary activation function. This model is used to simulate single or long-term continuous events, water volume, making it very appropriate for urban areas. Back propagation is an inherited learning algorithm and is commonly used by perceptron with multiple layers to change the weights associated with neurons in the hidden layer. Back propagation algorithm uses output error to change the values of its weight in the backward direction. The location of the review is the Ciujung River Basin (DAS), the data used are rainfall and debit data of Ciujung River from 2011-2017. Based on training and simulation results, obtained R2 value: 2012 = 0,85102; 2013 = 0,78661; 2014 = 0,81188; 2015 = 0,77902; 2016 = 0,7279. on model 2 = 0,8724. On model 3 R2: January = 0,96937; February = 0,92984; March = 0,90666; April = 0,92566; May = 0,9128; June = 0,87975; July= 0,85292; August = 0,95943; September = 0,88229; October = 0,90537; November = 0,93522; December = 0,9111. with MSE (Mean Squared Error) of 0,0018479. The closer value of MSE to 0 and the value of R2 close to 1 then the better designed artificial neural network. If the data used for training more, the artificial neural network will produce a larger R2 value.*

Keywords: *Artificial Neural Network; Rainfall-runoff; Back propagation*

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INTRODUCTION

The rainwater that flows thin on the surface of the land will go into the trenches, then into the river. Surface runoff that flows rapidly exceeds the capacity of the flower will be flooded (Dou et al., 2017). Every year Indonesia is always experiencing a flood that causes a lot of losses.

Transforming rainfall into runoff is a difficult process to formulate, due to the large number of variables that are relevant, which change in both space and time. Evaluating this process with accuracy is what allows rational management of the different water uses, such as supply, irrigation, electric power generation, as well as forecasting of extreme flood events and dry periods. Generally mathematical models known as rainfall–runoff models perform the evaluation of this process (Quinteiro et al., 2018; Machado, 2011).

Watersheds are one of the mainland areas that are topo-graphically constrained by the ridges that accommodate and store rainwater that then channel into the sea through the main river. The area of the river is called the water tank area (DTA or catchment area). The rain will be discharge, so the rain-run-off relationship is linked to the characteristic of the watershed. Some methods that can be used as a method of calculating peak flood discharge is the synthesis unit hydrograph method and non-hydrograph. However, it takes a long time to analyze all available data, including long annual rainfall data, climate data, flow coefficient data and other data. With other constraints such as the possibility of human error (Booth & Konrad, 2017).

The author's analysis focuses more on the Ciujung-Rangkasbitung River. Ciujung River is located in the Cidanau-Ciujung-Cidurian Watershed (DAS). Ciujung River topography which is a plain area with a slope of 0.00016 - 0.0002 lies in the Rangkasbitung area towards the estuary and for the topography of the sloping towards the steep (mountainous area) lies on the Rangkasbitung area upstream towards the slope 0.00033 - 0.00042.

One component in the hydrological cycle is rainfall runoff. The component of rainfall runoff can be run-off (flow of surface) or larger flow like the flow of water in the river. Runoff is part of the rain water that enters and flows and enters the river body (Harun, 2002).

The rainfall-runoff model is required to ascertain the relationship between rainfall and runoff. Hydrologists are often confronted with problems of prediction and estimation of runoff using the rainfall date. In fact, the relationship of rainfall-runoff is known to be highly non-linear and complex. The spatial and temporal precipitation patterns and the variability of watershed characteristics create a more complex hydrologic phenomenon.

Rainfall-runoff models can be classified within several different categories (Adley et al., 2016; Wu & Chau, 2011). They can distinguish between event-based and continuous-simulation models, black-box versus conceptual versus process based (or physically based) models, lumped versus distributed models, and several others. It is important to note that the above classifications are not rigid - sometimes a model cannot be unequivocally assigned to one category. We will treat rainfall-runoff models by taking into consideration models of increasing complexity.

In previous studies it was observed that, in most cases, the ANNs are applied to shorter-term modelling or forecasting, with hourly or daily scales ((Bartoletti, N et al., 2018; Mehr & Nourani, 2017; Chau, 2017). There are few studies that have investigated the application of ANNs to longer-term modelling (Govindaraju & Rao, 2000). Asadi & Abbaszadeh (2013) states that among the daily, monthly and annual scales, the monthly rainfall–runoff relationship is probably the most difficult since it has to consider both short-term and long-term hydrological processes.

METHOD

Backpropagation algorithm was first formulated by Werbos and popularized by Rumelhart and Mccelland for use on artificial neural networks, and the algorithm was later adopted under the name Backpropagation. This algorithm is a supervised method and is designed for operations on multi-layer feed forward networks. Backpropagation using its performance index is Mean Squared Error.

This algorithm is used in regulatory applications because the training process is based on simple relationships. If the output is false, the weight of the weigh (*w*) is checked so that the error can be minimized, and the subsequent network response is expected to approach the target's corresponding result and to improve the weighing weight of the hidden layer.

Backpropagation training includes three phases, the advanced phase, the reverse phase, and the weight change phase. The advanced phase is the first phase of the input pattern is calculated forward from the insert layer to the output layer using the specified activation function. The second phase is the backward phase. Where this phase difference between the output network with the desired target is the error that occurred. The error is then propagated backwards and starts from a line directly related to the units in the output layer. The last phase or the third phase is the change of weight.

Phase I Forward Propagation

During this phase, the input signal (= xi) is propagated to a hidden layer using a predefined activation function. The output of each hidden layer unit (= zj) will then propagate forward again to the hidden layer above by using a predefined activation function. This is done so that it can produce network output (= yk).

Next the network output (= yk) is compared to the target to be achieved (= tk). The tk-yk increment is an error occurring. If the error is smaller than the tolerance limit, then the weights in each line in the network will be modified to reduce the errors that occur.

Phase II Backward Propagation

Based on the error tk - yk calculated factor δk (k = 1,2, ..., m) used to distribute error in unit yk to all hidden units connected directly to yk, δk is also used to change the weights of lines directly related to the output unit.

Then, using the same method, we calculated the factor *δj* in each unit in the hidden layer as the basis for the weight change of all the lines coming from the hidden units in the lower layer. This is done until all δ factors in the hidden unit directly related to the input unit can be calculated.

Phase III Change Weight

After all the factors δ have been calculated, the weights of all lines are modified simultaneously. The change in the weight of a line is based on the *δ* of the overlying dilamere neuron. Example: the weight change of the line leading to the output layer is based on *δk* in the output unit.

All phases are repeated until the stopping conditions are met. The termination condition is the number of iterations or errors. Iterations will stop when the number of iterations has been met or exceeded the maximum limit set, or if the error is smaller than the tolerance limit that has been set.

In the backpropagation method, Matlab software is used. Matlab (Matrix Laboratory) is a numerical computing environment and a fourth-generation computer programming language. Developed by The Mathworks, Matlab allows the manipulation of matrices, plots of functions and data, algorithmic implementation, user scout creation, and interfacing with programs in other languages. Although numerically nuanced, a Toolbox that uses MuPAD's symbol machine, allows access to computer algebraic capabilities.
Many models of artificial neural networks use matrix or vector manipulation in their iterations. Matlab provides special functions for solving artificial neural network models. Usage only inputs the desired input, target, model, and parameter vectors (rate of understanding, threshold, bias, etc.).

The design of artificial neural system model that will be developed tailored to the application to be developed. To make predictions of river flow debit and rainfall runoff modeling that require relatively large data or input pattern, multilayer net with backpropagation method is a good choice.

Input Pattern

There are 3 Pattern of input / input used in research of artificial neural network is caused by 3 experiment of network architecture, that is:

a. The first model experiment, daily rainfall and discharge data per year.
b. The second model experiment, rainfall and debit data for 6 years from 2011-2016.
c. The third experiment, monthly rainfall and debit data for 6 years from 2011-2016.

Output Patterns

The expected outputs of the artificial neural system are:

a. Daily debit data per year.
b. Debit data of 2017.
c. Debit data per month of 2017.

Fig. 1 to Fig. 4 show the model of Arti Artificial Neural System Model.

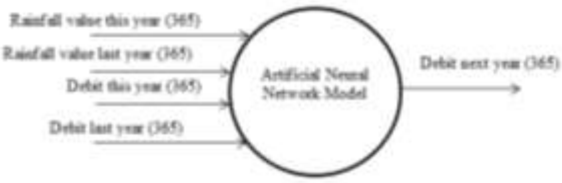


Figure 1. Diagram Block Model of Artificial Neural System Model 1

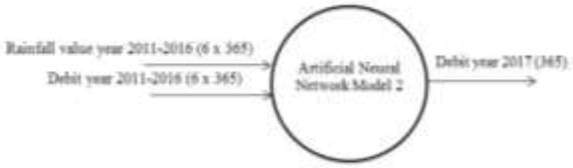


Figure 2. Diagram Block Model of Artificial Neural System Model 2

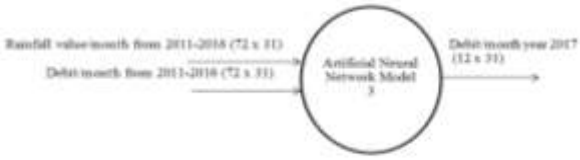


Figure 3. Diagram Block Model of Artificial Neural System Model 3

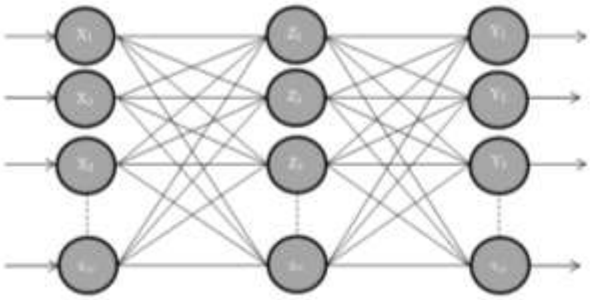


Figure 4. Artificial Neural System Architecture Model

The performance of the artificial neural system model is represented by MSE (Mean Square Error) which is a measure of the accuracy or ability of the neural system model to achieve the desired target value or value. The closer the value of MSE, the better the model of the artificial neural system.

To achieve faster convergence the developed model is set at the learning rate, the number of neurons in the hidden layer, the maximum epoch, and by changing the function of training or training functions (trainbgg, trainbr, traincgf, traincgp, traingd, traingdm, traingda, traingdx, trainlm, trainoss, trainr, trainrp, trainscg).

RESULTS AND DISCUSSION

The training function used in this research is Training Gradient Descent with Momentum & Adaptive LR (traingdx). This training function is chosen because it has a useful learning rate parameter for the learning speed parameter of the system or network. Each year's training is experimented by replacing the number of neurons in the hidden layer. Starting from 30, 50, 100, 200, 250. Here are the results of system training:

Model 1

Network training in 2012 using neurons 50 and lr 0.001 and the results are shown in Fig. 5 to Fig. 10.

Training regression value is 0.73689 means that 73 percent of the training data match with the target that should be reach.

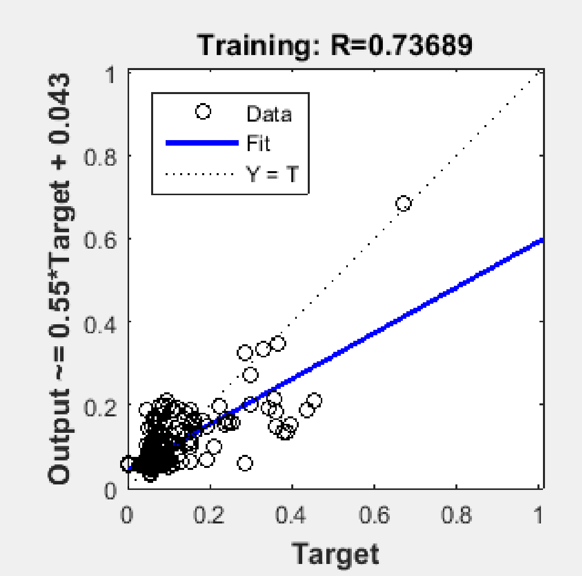


Figure 5. Regression Training Artificial Neural Network with 50 Neuron

Validation regression value is 0.94724 means that 94 percent data is validated, which is a good value to validation data.

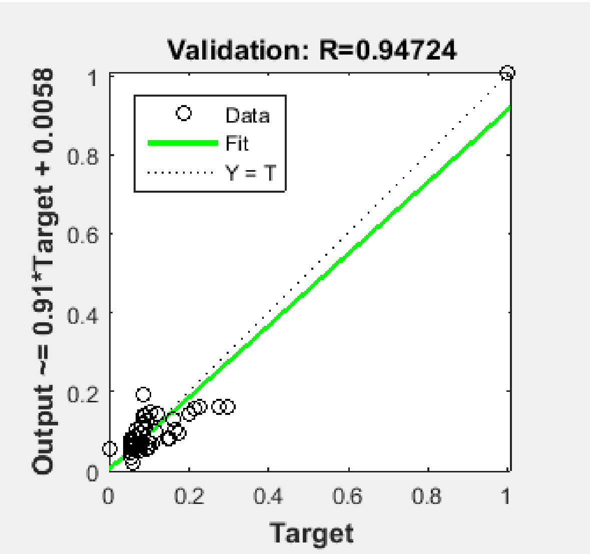


Figure 6. Regression Validation Artificial Neural Network with 50 Neuron

Test regression value is 0.9354 means that 93 percent data being simulated. Data needs to be simulated or tested to reach the target or output.

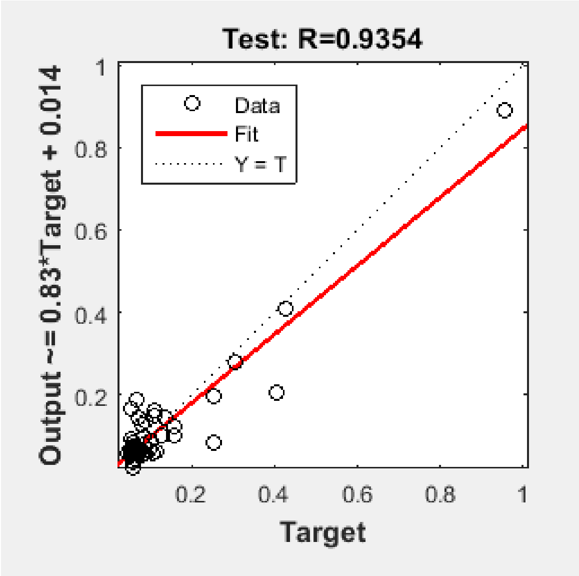


Figure 7. Regression Test Artificial Neural Network with 50 Neuron

All regression value is the average value of training, validation, and test. The value of the average of all regression is 0.85102 which is almost close to 1 and can give the best target match with the data from BBWS.

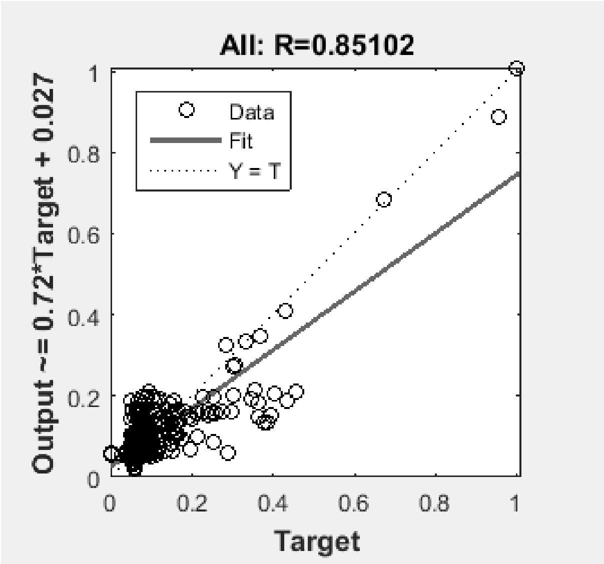


Figure 8. Total Regression Artificial Neural Network with 50 Neuron

Best validation performance shows the best mean squared error (MSE) in the most little epoch. The best MSE in this research is 0.0018479 which is almost close to 0.

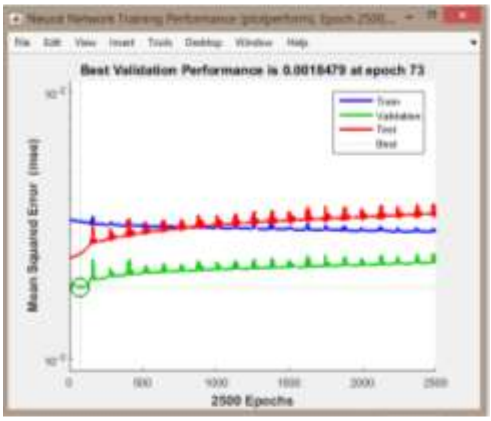


Figure 9. Best Performance Chart
(Best MSE 0.0018479)

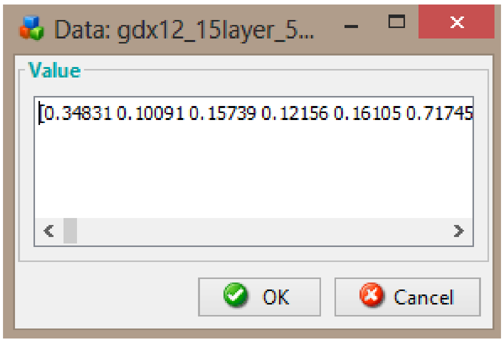
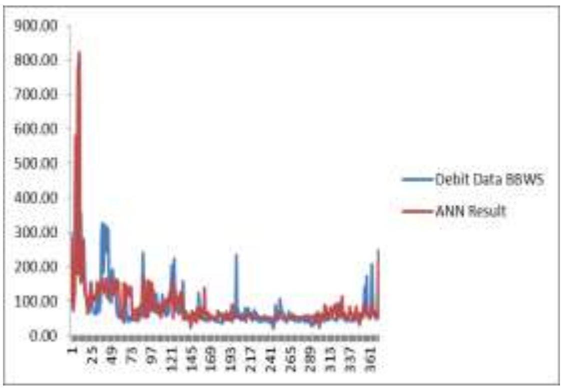


Figure 10. Output Value Prediction of year 2013

The predicted outcome is the prediction of the debit of 2013 with the input data of 2011 and 2012 which is shown in Fig. 5. The output data above need to normalized using the sigmoid binary transformation formula.

Graph 1 shows the comparison of prediction of Artificial Neural Network with BBWS debit data 2013 and the comparison between BBWS Debit Data and ANN Result.



Graph 1. Comparison Debit of BBWS Data and ANN Result Model 1

The next training generates the following R^2 values: Year 2013 = 0.78661, Year 2014 = 0.81188, Year 2015 = 0.77902 and Year 2016 = 0.7279.

Model 2

In the next experiment, the input data used more. Data of debit and rainfall from 2011-2016 serve as input and debit data of 2017 targeted. Output to be generated in the form of daily discharge data for one year. The parameter data are Hidden layer: 20, Neuron: 50 and lr: 0.01.

Training regression value is 0.82948 means that 82 percent of the training data match with the target that should be reach.

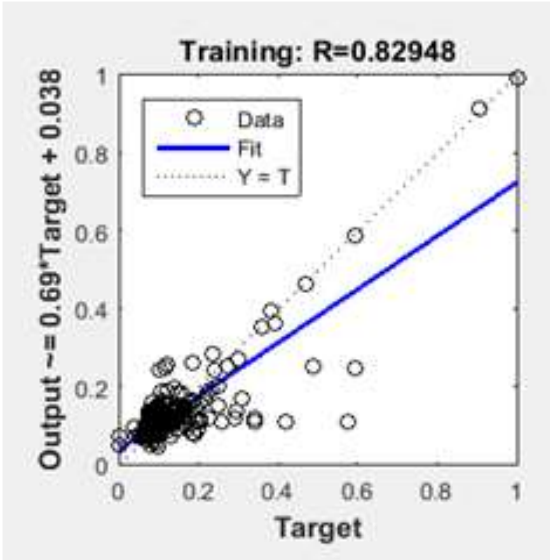


Figure 11. Regression Training Artificial Neural Network with 50 Neuron

Validation regression value is 0.92382 means that 92 percent data is validated. Which is a good value to validation data.

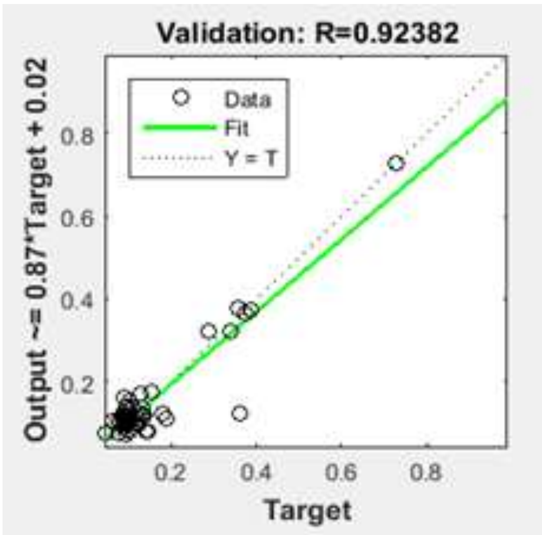


Figure 12. Regression Validation Artificial Neural Network with 50 Neuron

Test regression value is 0.85416 means that 85 percent data being simulated. Data needs to be simulated or tested to reach the target or output that we want.

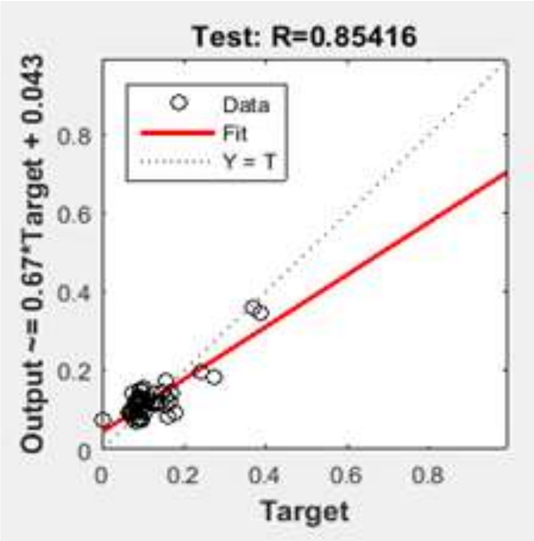


Figure 13. Regression Test Artificial Neural Network with 50 Neuron

All regression value is the average value of training, validation, and test. The value of the average of all regression is 0.8724 which is almost close to 1 and can give the best target match with the data from BBWS.

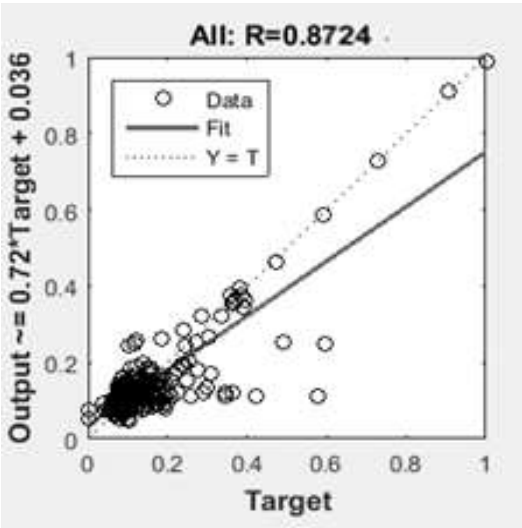


Figure 14. Total Regression Artificial Neural Network with 50 Neuron

Best validation performance shows the best mean squared error (MSE) in the most little epoch. The best MSE in this research is 0.0015552 which is almost close to 0.

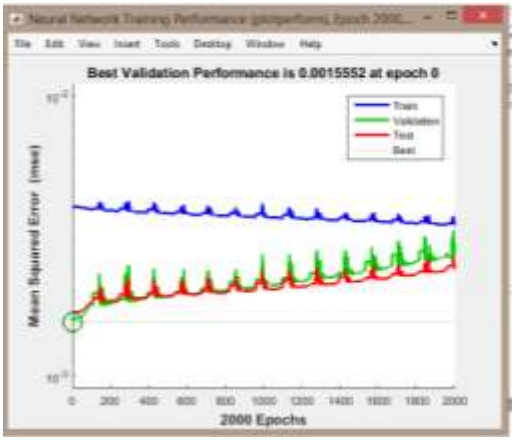


Figure 15. Best Performance Chart (Best MSE 0.0018479)

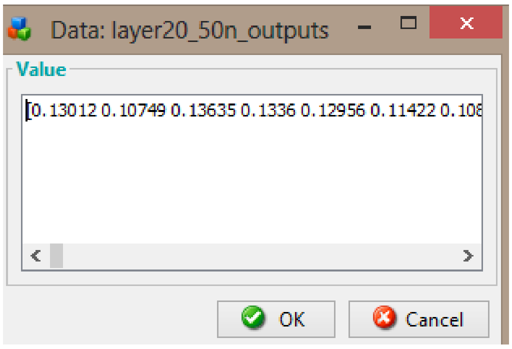
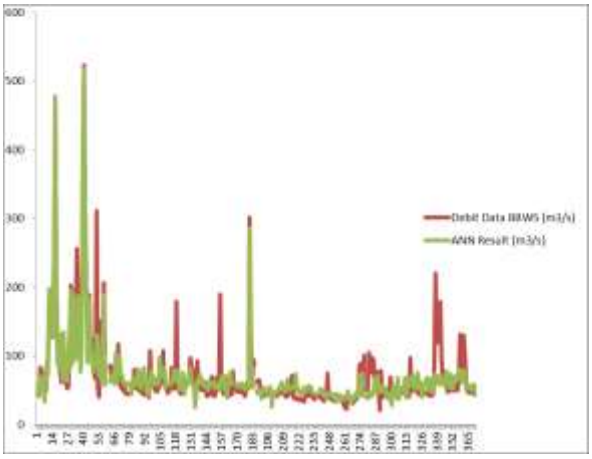


Figure 16. Output Value Prediction of year 2013

The predicted outcome is the prediction of the debit of 2017 with the input data of 2011-2016 which is shown in Fig. 6. The output data above need to normalized using the sigmoid binary transformation formula. The Graph 2 shows the comparison of prediction of Artificial Neural Network with BBWS debit data 2017and the comparison between BBWS Debit Data and ANN Result.



Graph 2. Comparison Debit of BBWS Data and ANN Result Model 2

Model 3

The data used is the year 2011-2017. In this third experiment, researchers took more data input. 2011-2016 rainfall and discharge data are used as input and debit data of 2017 used as targets. Artificial neural network training is done monthly. The parameters data are Hidden layer: 20, Neuron: 50, lr: 0.01 dan Epoch: 2000.

Training regression value is 0.90912 means that 90 percent of the training data match with the target that should be reach.

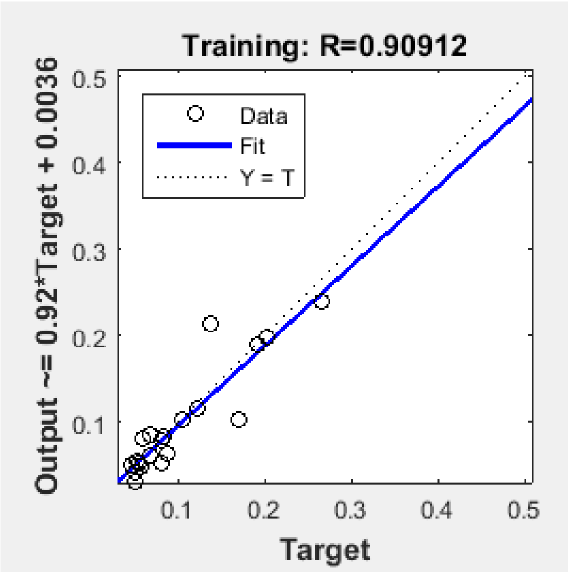


Figure 17. Regression Training Artificial Neural Network with 50 Neuron

Validation regression value is 0.99762 means that 99 percent data is validated. Which is a good value to validation data.

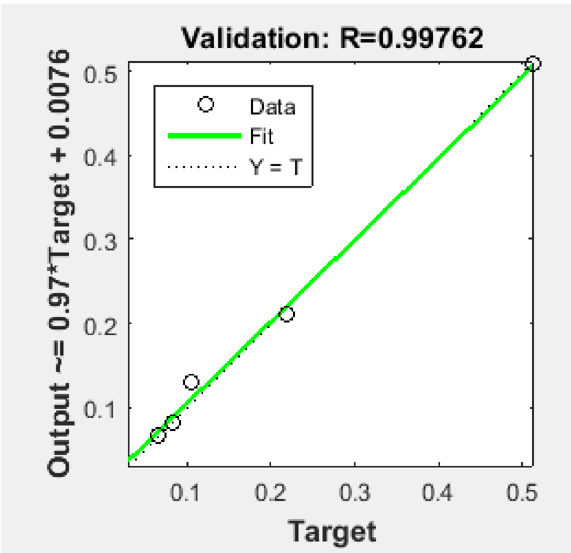


Figure 18. Regression Validation Artificial Neural Network with 50 Neuron

Test regression value is 0.97263 means that 97 percent data being simulated. Data needs to be simulated or tested to reach the target or output that we want.

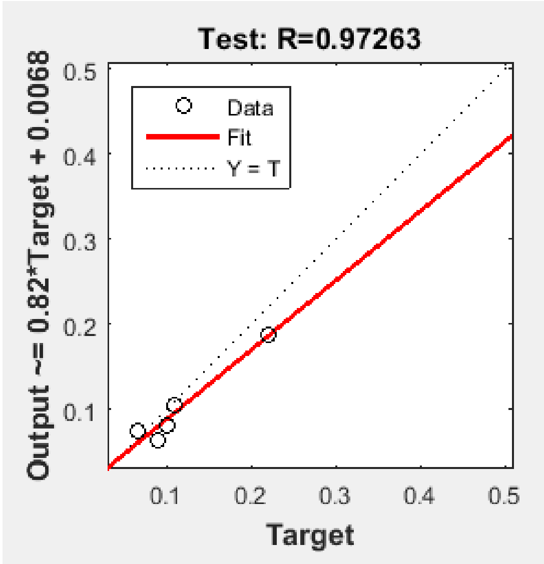


Figure 19. Regression Test Artificial Neural Network with 50 Neuron

All regression value is the average value of training, validation, and test. The value of the average of all regression is 0.96937 which is almost close to 1 and can give the best target match with the data from BBWS.

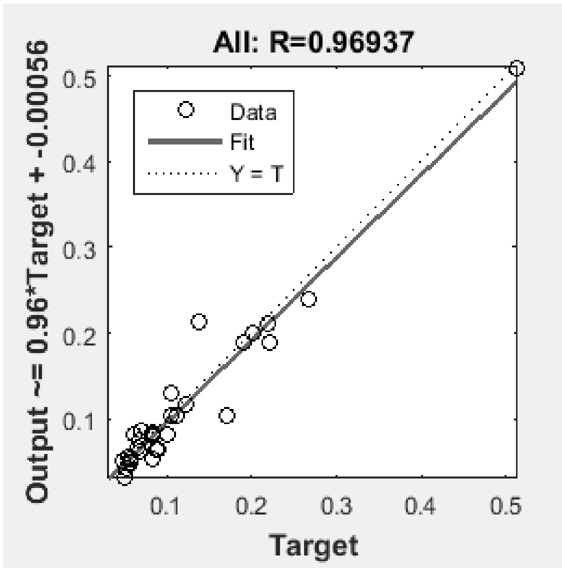


Figure 20. Total Regression Artificial Neural Network with 50 Neuron

Best validation performance shows the best mean squared error (MSE) in the most little epoch. The best MSE in this research is 0.00015053 which is almost close to 0.

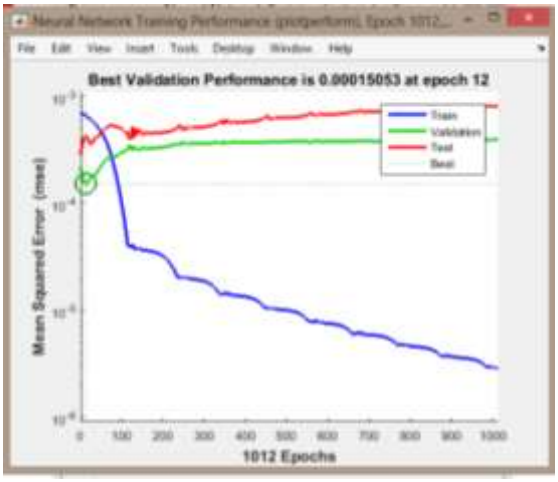


Figure 21. Best Performance Chart (Best MSE 0.0018479)

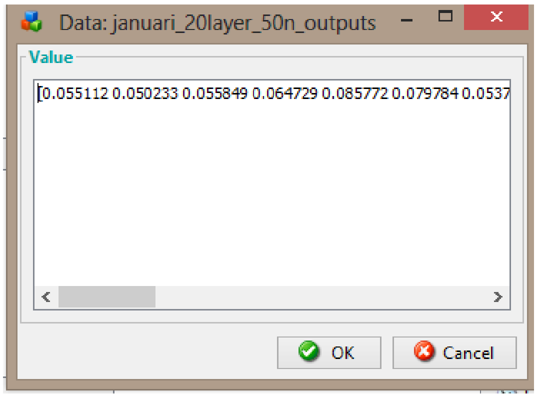


Figure 22. Output Value Prediction of year 2013

From the above graph obtained value of R^2:
Training = 0.90912
Validation = 0.99762
Testing = 0.97263
All = 0.96937
And also get the best MSE value of 0.00015053 on Epoch / Iteration 12. Comparison of artificial neural network output and BBWS data are listed in Table 1.

The graph shown in January for example, the next month will be resume without graph and table.

February
value of R^2:
Training = 0.87554
Validation = 0.99985
Testing = 0.93799
All = 0.92984
And also get the best MSE value of $2.6771e^{-0.5}$ on Epoch / Iteration 0.

Table 1. Comparison of artificial neural network output and BBWS

January		
Date	**BBWS Data**	**Output JST**
1	50.89	49.86
2	46.38	43.83
3	51.57	49.60
4	59.77	82.70
5	79.20	63.71
6	73.67	75.91
7	49.62	51.92
8	28.08	47.06
9	38.52	47.32
10	77.40	76.79
11	96.38	102.17
12	184.16	186.75
13	175.00	176.49
14	95.30	158.32
15	197.02	126.92
16	221.72	246.02
17	469.02	472.90
18	174.34	203.84
19	107.74	112.86
20	74.61	92.74
21	75.15	76.79
22	69.79	62.06
23	49.21	75.91
24	57.19	62.88
25	59.55	81.51
26	61.46	60.69
27	44.63	52.70
28	75.67	55.59
29	120.23	96.79
30	194.07	202.66
31	95.72	96.48

March
value of R^2:
Training = 0.81337
Validation = 0.91424
Testing = 0.9968
All = 0.90666
And also get the best MSE value of $7.1328e^{-0.5}$ on Epoch / Iteration 0.

April
value of R^2:
Training = 0.88726
Validation = 0.75606
Testing = 0.98041
All = 0.92566
And also get the best MSE value of 0.00026736 on Epoch / Iteration 79.

May
value of R^2:
Training = 0.87855
Validation = 0.99974
Testing = 0.98342
All = 0.9128
And also get the best MSE value of $1.953e^{-0.5}$ on Epoch / Iteration 0.

June
value of R^2:
Training = 0.80271
Validation = 0.99362
Testing = 0.81891
All = 0.87975
And also get the best MSE value of 0.00047175 on Epoch / Iteration 0.

July
value of R^2:
Training = 0.74261
Validation = 0.97587
Testing = 0.99663
All = 0.85292
And also get the best MSE value of 0.000234 on Epoch / Iteration 136.

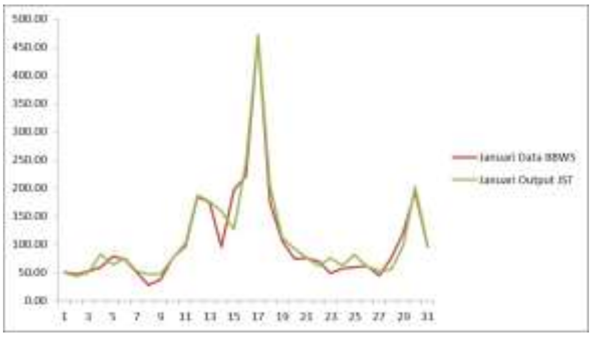
August
value of R^2:
Training = 0.99903
Validation = 0.9432
Testing = 0.96129
All = 0.95943
And also get the best MSE value of 0.0021232 on Epoch / Iteration 1952.

September
value of R^2:
Training = 0.86593
Validation = 0.73381
Testing = 0.91866
All = 0.88229
And also get the best MSE value of 0.00039394 on Epoch / Iteration 29.

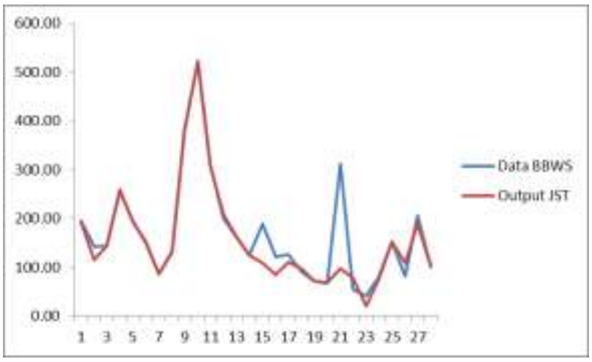
October
value of R^2:
Training = 0.84226
Validation = 0.99998
Testing = 0.98546
All = 0.90537
And also get the best MSE value of $1.7529e^{-0.5}$ on Epoch / Iteration 25.
November
value of R^2:
Training = 0.8974
Validation = 0.98185
Testing = 0.95892
All = 0.93522
And also get the best MSE value of 0.00018248 on Epoch / Iteration 0.

December
value of R^2:
Training = 0.87276
Validation = 0.98705
Testing = 0.99128
All = 0.9111
And also get the best MSE value of 0.00029682 on Epoch / Iteration 0.

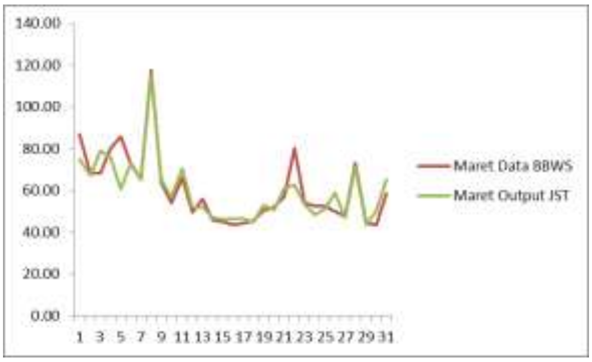
The comparison graph from January until December will be shown in Graph 3 – Graph 14.



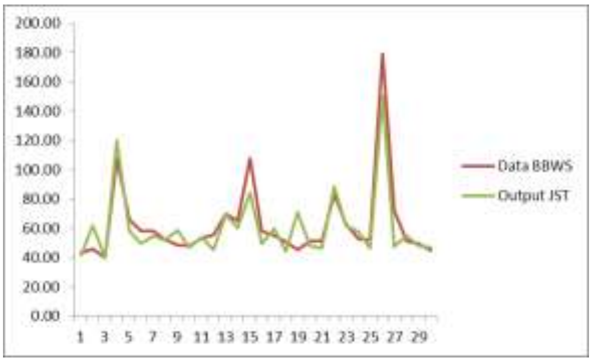
Graph 3. Comparison Debit of BBWS Data and ANN Result Model 3 on January



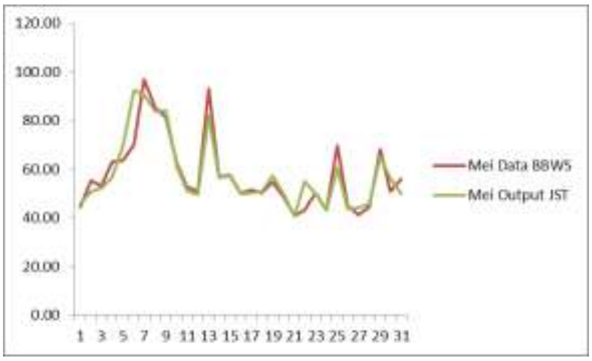
Graph 4. Comparison Debit of BBWS Data and ANN Result Model 3 on February



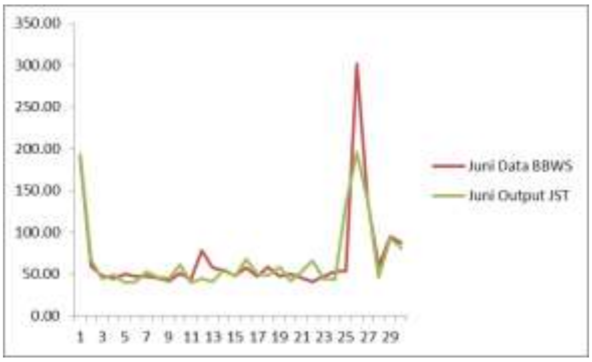
Graph 5. Comparison Debit of BBWS Data and ANN Result Model 3 on March



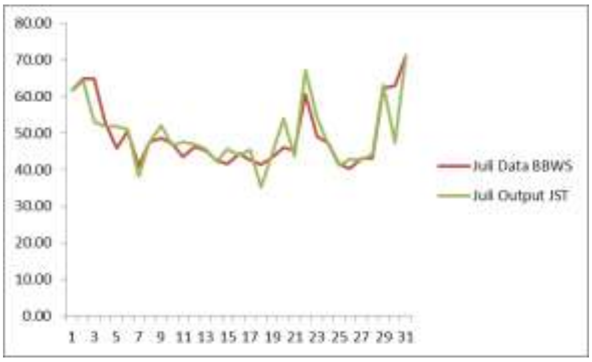
Graph 6. Comparison Debit of BBWS Data and ANN Result Model 3 on April



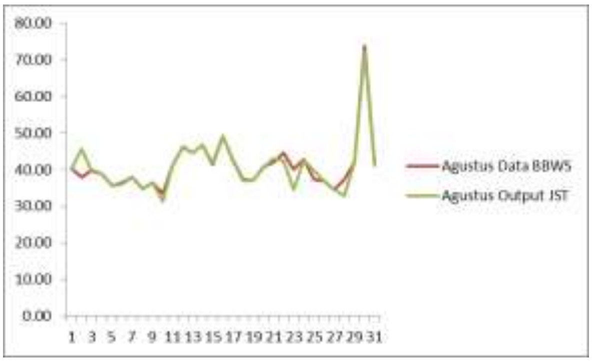
Graph 7. Comparison Debit of BBWS Data and ANN Result Model 3 on May



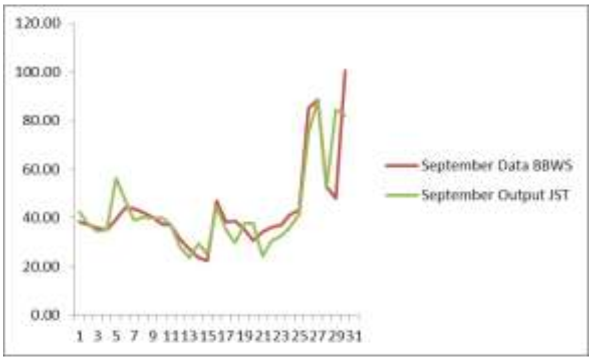
Graph 8. Comparison Debit of BBWS Data and ANN Result Model 3 on June



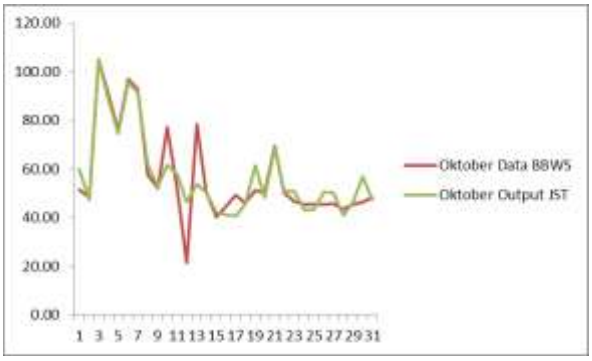
Graph 9. Comparison Debit of BBWS Data and ANN Result Model 3 on July



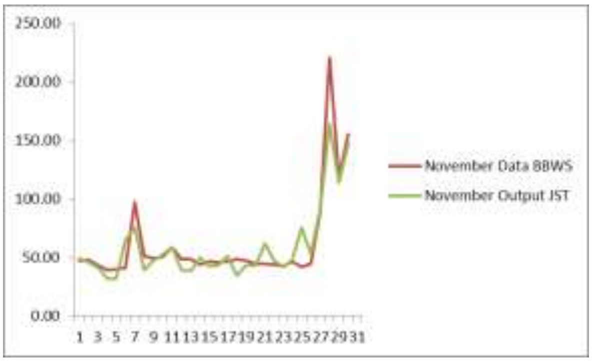
Graph 10. Comparison Debit of BBWS Data and ANN Result Model 3 on August



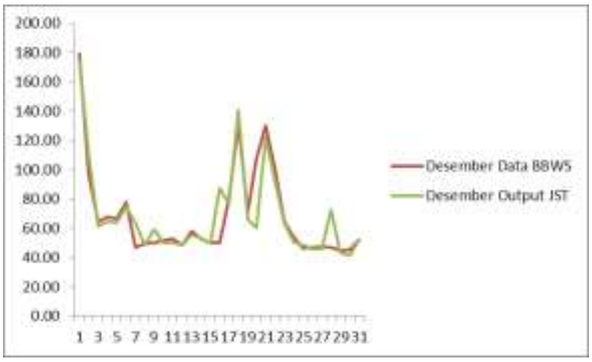
Graph 11. Comparison Debit of BBWS Data and ANN Result Model 3 on September



Graph 12. Comparison Debit of BBWS Data and ANN Result Model 3 on October



Graph 13. Comparison Debit of BBWS Data and ANN Result Model 3 on November



Graph 14. Comparison Debit of BBWS Data and ANN Result Model 3 on December

A comparison of R (All) values for all neural network models are listed in Table 2.

CONCLUSION

From the design result of artificial neural network which is designed, got the following conclusion. The value of R^2 in Model 1, in 2012 and 2014 has a high correlation, while in 2013, 2015, and 2016 has enough correlation, with R^2: 2012 = 0.85102; 2013 = 0.78661; 2014 = 0.81188; 2015 = 0.77902; 2016 = 0.7279. Then, the value of R^2 in Model 2 has a high correlation with the value R^2 = 0.8724. The value of R^2 in Model 3 has a high correlation with a higher R^2 value than Model 1 and Model 2. January = 0.96937; February = 0.92984; March = 0.90666; April = 0.92566; May = 0.9128; June = 0.87975; July = 0.85292; August = 0.95943; September = 0.88229; October = 0.90537; November = 0.93522; December = 0.9111.

It also be stated that the more input data for training and learning process, then the value of R^2 will be greater and closer to the value of 1. The number of neurons and hidden layers is done by trial and error to produce the desired value.

Table 2. a comparison of R (All) values for all neural network models

Model 1	R (All)	Correlation	R (All) Model 2	Correlation	Model 3	R(All)	Correlation
2012	0.85102	High	0.8724	High	January	0.96937	High
2013	0.78661	Enough			February	0.92984	High
2014	0.81188	High			March	0.90666	High
2015	0.77902	Enough			April	0.92566	High
2016	0.7279	Enough			May	0.9128	High
2016	0.7279	Enough			June	0.87975	High
2016	0.7279	Enough			July	0.85292	High
2016	0.7279	Enough			August	0.95943	High
2016	0.7279	Enough			September	0.88229	High
2016	0.7279	Enough			October	0.90537	High
2016	0.7279	Enough			November	0.93522	High
2016	0.7279	Enough			December	0.9111	High

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