Levenberg-Marquardt Flood Prediction for Sungai Isap Residence

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***Abstract*— The flood can cause wide destroy to property and life because of the supreme corrosive force and can be highly damaging. In order to decrease the damages cause by the flood, an Artificial Neural Network (ANN) model has been established to predict flood in Sungai Isap, Kuantan, Pahang, Malaysia. This model is able to imitate same as the brain thinking process and avoid any influence to the predict judgment. This study proposed Levenberg-Marquardt (LM) back-propagation with two different ratios that is (80%: 10%: 10%) and (70%: 15%: 15%) for training sample, testing sample, and validation sample. The data collected in terms of temperature, precipitation, dew point, humidity, sea level pressure, visibility, wind and river level data were collected from January 2013 until May 2015. The results are shown on the basic of mean square error (MSE) and regression (R). The prediction by Levenberg-Marquardt with 80% training sample was shown better result compared with 70% training sample.**

***Index Terms*—Flood Prediction, Sungai Isap Residence, Artificial Neural Network, Levenberg-Marquardt**

I. Introduction

In 2014, it is reported as the worst flood hit Malaysia that caused 21 dead and 200,000 residents affected [1]. The factors that contributed to flood are heavy raining, high sea pressure, fast wind and river overflow in sea coast and lower land area. The floods affect the human or animal life, agriculture sector, building and its structure such as clean water supply. In the long term, the flood may affect the economic problems causing for example lasting in the limit period of time in a decrease in tourism sector, reconstruction costs, and insufficient food after the impact by flood.

The report from the Jabatan Pengairan Dan Saliran (JPS) Pahang, the flood that happened in Sungai Isap is caused by heavy rainfalls in Sungai Kuantan valley and came with large tides. Due to this, the flood has destroyed a big amount of properties and make the community live in discomfort. Figure 1 shows the maps with river flow Sungai Kuantan at Sungai Isap. That clearly sees the effect of flood at Sungai Isap is from the river, Sungai Kuantan. Sungai Isap is a previously swampy area and was developed into a residential area. This area has developed in more recent years, and was developed in phases which are first phase Perkampungan Sungai Isap 1, second phase Perkampungan Sungai Isap 2, third phase Perkampungan Sungai Isap Perdana, fourth phase Perkampungan Sungai Isap Uda Murni, and fifth phase Perkampungan Sungai Isap Jaya. The worst flood happened in 2013 inundated all areas of Sungai Isap as shown in Fig. 2.

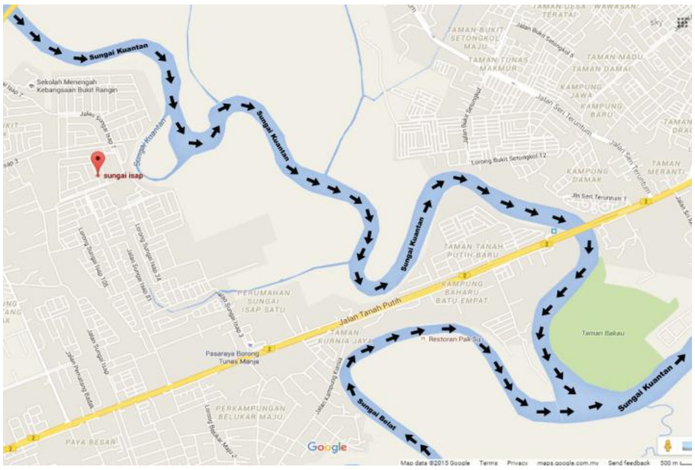

Fig. 1: Location of Sungai Isap town with river flow Sungai Isap, Kuantan (Google Maps View)


Fig. 2 : Sungai Isap flood on December 2013

In the last decades, Artificial Neural Network (ANN) has been widely used to flood prediction. Although ANN models may be computationally intensive, the evolution in high speed computer has promoted their application. The ANN can be used for predicting because of having the capability of examining and determining the historical data used for prediction [2]. ANN flood prediction and modeling widely used in Malaysia for Johor River basin Kelang River, and Sungai Batu Pahat [3–7], The researcher employed various ANN models such as Exogenous Input (NARX), Extended Kalman Filter (EKF), Back-Propagation Neural Network (BPN) and Elman Neural Network (ENN). Based on reference [3–7], all results showed good predicted of flood with the real records. Other than that, ANN flood prediction and modeling widely used in other country for upper Serpis Basin (Spain), Wardha River (India), Danjiangkou Reservoir (China), Pinios River (Greece), Arno River (Italy), and Nysa Klodzka River (Poland) [8–13]. The researcher explored using PCTR-BENIARRES (***P**redicción de **C**recidas en **T**iempo **R**eal – **B**eniarrés*), Time Lagged Recurrent Neural Network, General Recurrent Neural Network, Optimal Subset Regression (OSR), Back-Propagation Neural Network (BPNN) Adaptive Linear Neuron Network (ADALINE), Elman Network, Black-Box Type Runoff Simulation Model, and Radial-Basis Function Neural Network. From the reference [8–13], all results show good accuracy of flood predict. The researcher agrees that their result could be used to help for planning and development infrastructure to decrease flood occurred [3]. Based on the literature, it was found no specific algorithm to solve all flood predictions.

This study utilizes the advantages of ANN with Levenberg-Marquardt with two different ratios that is (80%: 10%: 10%) and (70%: 15%: 15) for training sample, validation sample, and testing sample for flood prediction at Sungai Isap.

II. Methodology

ANN is an intelligent process model that inspired biological nervous systems, for an example brain process [14]. This is caused by this network try to model the capabilities of the human brain. ANN is being widely used in many fields of study. World first ANN with neuron is created at 1943 with the ANN has grown faster after the first ANN training algorithm introduced in 1958 [15]. For the past decade, ANN used a theoretically change to the statistical model. A systematic methodological flow chart of the study is presented in Fig. 3.

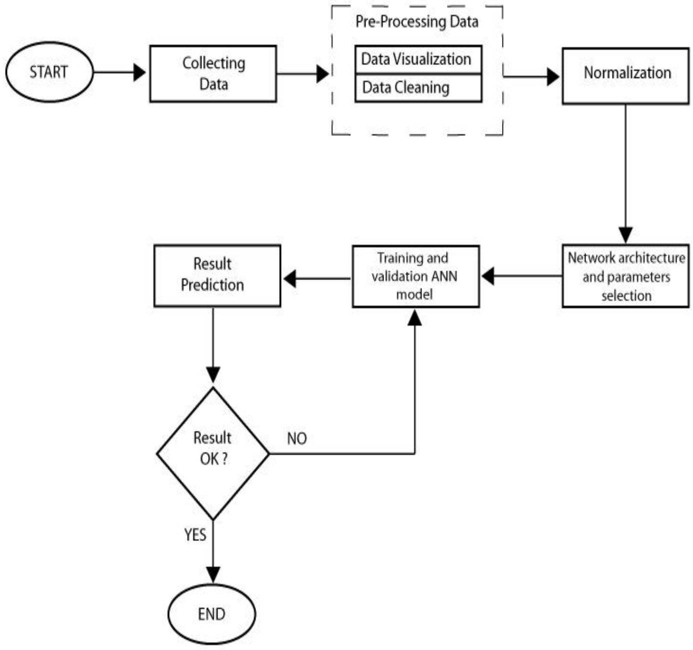

Fig. 3: Methodological flow chart

A. Data Collection

Flood conditioning factor data set was constructed by factors is temperature, precipitation, dew point, humidity, sea level pressure, visibility, wind and river level from January 2013 until May 2015. The river level and precipitation data collect from Jabatan Pengairan & Saliran (JPS) Pahang and temperature, dew point, humidity, sea level pressure, visibility, wind is collected from the website (www.wunderground.com).

B. Data Visualization

Data Visualization is a method that shows the data in pictorial or graphical format with many researcher uses for representing their charts to faster and easily understanding the information from the data [16].

C. Data Cleaning

The factor data (raw data) of the 8 factors have some missing data, so the SPSS software is used to finds back those missing data, this method is called as data cleaning. Data Cleaning included the discovery and excision or correction of errors [17]. If there are incomplete datas and then is either replaces, modified or deleted the data. Data cleaning process need careful consideration because the influence the results. Cleaning data need always checks and treatment of missing responses will be done Statistical Product and Service Solution (SPSS) software will consistency check and treatment of missing responses that cleaning [18].

D. Normalization

Because of different data and different magnitude value, the samples need to be scaled in 0-1 using normalization. Normalization is a method that adjusts the value measurement due to the different scale to a collaborative scale and frequently before averaging. Normalization also refers as complex adjustments where the purpose is to bring the whole probability assigned adjusted values into alignment. Equation (1) is a formula for normalization.

$$X' = \frac{X - X\min}{X\max - X\min} \tag{1}$$

where X' is the scaled value, X is the sample value, $X\min$ and $X\max$ are the minimum value and maximum value.

E. Training Algorithm

ANN training quantity iteratively adapting the weights of a neural network until the connection weights determine an input and output that function that near the relationship between input and output structure of a given training data set. In this research, Levenberg-Marquardt back-propagation used for execution the concept and the lowest MSE the best results. The results in [2,19,20,21], that show Levenberg-Marquardt is better that other training algorithm and the main reasons this paper. Levenberg-Marquardt back-propagation network training function is a Levenberg-Marquardt optimization that updates according to the weight and bias values and faster training algorithm for network of moderate size compare to other algorithms. Levenberg-Marquardt also highly recommended as a first-choice manages algorithms cause it does not require more memory and more time for training. Other than that, it also reduces feature for use when the sample data is large.

The program MATLAB with Neural Network Toolbox is a strong tool for prediction. The Neural Network Toolbox function to develop feed forward back-propagation model. This tool allows importing, creating, using, export neural network and data, and change parameters (number of neurons, learning rate, number of hidden layers, transfer function and performance functions). The structure of an ANN is created by weight between neuron, transfer function, and learning laws. The transfer function is used to control the generations of output in neurons. Learning laws are used to determine the relative weights for input to the neuron. In a feed-forward network, the weighted connections feed activations only in the forward direction from an input layer to the output layer.

F. Neurons

Neurons manipulate logical parallelism and the information is sent from later to serial operations. If too few neurons will direct affect the network performance and next will outcome in under-fitting and too many neurons the network is over-fitting. For this research, the number of neurons is set by ranging from 10 neurons until 200 neurons.

G. Layer

A layer is a group that set up by neurons and a group of later can set up a network. The ANN model usually got input layer, a hidden layer, and output layer. In this paper, using the single layer with prepares adequate hidden neurons in a single layer.

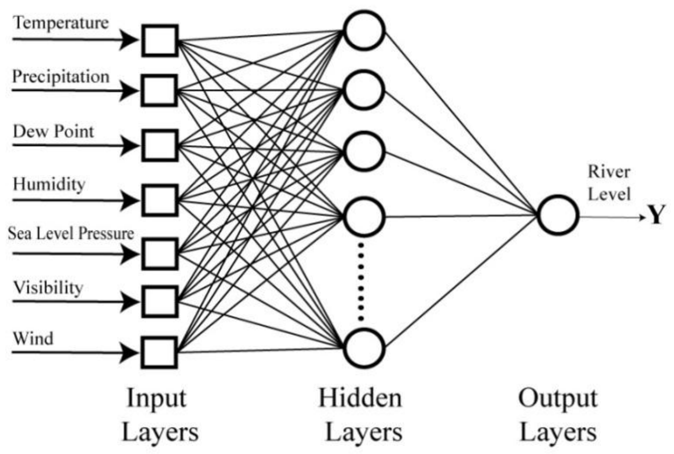

Fig. 4: Structure of a feed-forward ANN model

H. The Best Function

To define the best structure, different number of neurons in hidden layers is testing [22]. Mean Squared Error (MSE) and Regression (R) is frequently used to execute the performance evaluation. MSE defines as the average squared difference between observed output values from ANN and targets introduced in the training samples.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(t_i - a_i)^2 \tag{2}$$

From the Eq. 2 that n is size of the sample set, a_i is the ANN observed output, and t_i is the corresponding target output. The (R) is defined as the correlation between the targets and output. When R=1, is meant a close relationship, vice versa R=0, there is random relationship. Smaller network weights and fewer effective parameters simplify the network size to avoid the training data overfitting caused by over-complex network structure, it also can improve the generalization of neural network in practical application

The Gradient Decent with Momentum Weight and Bias Learning Function was chosen for Adaption Learning Function for neural network (7-1-1: 7 input, 1 hidden layer, and 1 output) is shown in Fig. 4 structure of feed-forward ANN model and observed to be the best adaptive learning function as it shows results with minimum MSE [2]. Tan-Sigmoid Transfer Function is the best choice for hidden layers over Linear Transfer Function and Log Sigmoid Transfer Function because of its very fast learning rate and sensitivity towards change number of samples and neurons. Other than that, results bring the conclusion that Tan-Sigmoid function gives the best predictions for ANN architecture in terms of goals, epochs and comparison with the target data [23].

I. Training, Verifying, and Testing

In this paper, 2 different ratios are used that is for first ratio training 80% of input data from January 2013 until May 2015 were applied to training network. In verifying part, the program will stop of the calculation when 10% data are applied to determine the network structure work that was not used in training. Verifying data have checked in a different sequence of training and continued when the number of error reduced in the verifying. The last 10% data will apply to the process after the training process and verifying process finish. For second ratios are (70% Training: 15% Validation: 15% Testing). The Levenberg-Marquardt training algorithms are used to train the network and the corresponding configuration parameters are as shown in Table I.

TABLE I
The training algorithm configuration parameters

Configuration Parameters	LM
Maximum number of epochs to train	1000
Epochs between displays	25
Performance goal	0
Maximum time to train in seconds	Infiniti
Minimum performance gradient	1e-07
Maximum validation failures	6
Initial μ	0.001
μ decrease factor	0.1
μ increase factor	10
Maximum μ	1e+10
Learning rate	N/A

III. Results and Discussion

ANN architecture attributes use Levenberg-Marquardt for the training and testing of the proposed metrics concept. Table II captures the architecture and ANN attributes used in the experiment, Table III is the result of mean square error (MSE).

TABLE II
Architecture and ANN attributes

Network Type	Feed-Forward Back-Propagation (FFBP)
Training Function	Levenberg-Marquardt
Adaptive Learning Function	LEARNGDM
Performance Function	MSE
Number of Layer	01
Number of Neurons	10,20,30,40,50,60,70,80,90,100,110,120, 130,140,150,160,170,180,190,200
Transfer Function	Tan-Sigmoid
Epochs	1000

The lowest MSE is the better ANN attributes in maintainability prediction, from the Table III and Table IV the result with the lowest MSE is at Table III Result MSE with ratio (80%: 10%: 10%) is 0.0019231 using Levenberg-Marquardt with 120 neurons is the best of ANN attributes.

TABLE III
Result MSE (80:10:10)

Neurons	MSE	Neurons	MSE
10	0.0031911	**110**	0.0070726
20	0.0049203	**120**	0.0019231
30	0.0062713	**130**	0.0028143
40	0.0042255	**140**	0.0029577
50	0.0034647	**150**	0.0031299
60	0.0075899	**160**	0.0034169
70	0.0025577	**170**	0.0021680
80	0.0021512	**180**	0.0030842
90	0.0078860	**190**	0.0030574
100	0.0033275	**200**	0.0035297

TABLE IV
Result MSE (70:15:15)

Neurons	MSE	Neurons	MSE
10	0.0047377	**110**	0.0020686
20	0.0080938	**120**	0.0040221
30	0.0027311	**130**	0.0040819
40	0.0032440	**140**	0.0029030
50	0.0075195	**150**	0.0022756
60	0.0036020	**160**	0.0043467
70	0.0029161	**170**	0.0055751
80	0.0020988	**180**	0.0039078
90	0.0089303	**190**	0.0043990
100	0.0035220	**200**	0.0027019

In Fig. 5 show that the graph best training performances is 0.0019231 MSE is considered better result that compare to [2] with 6.58 MSE, [24] with 2.75 MSE, [20] with 1.1 MSE, [25] with 0.30265, and [21] with 0.01185 MSE. Fig. 5 show the graph plot solid line represents independent train, dash line is represents test, the dash dot-dot line represent the validation, and the dot-dot line represents best value for this training. In Fig. 6, shows the regression (R) graph with training, validation, test, and all data. The dotted line in the graph shows the $Perfect\_result - outputs = targets$ and the solid line represent best fit linear regression between the target and the output for Fig. 6 (a) is training data regression, Fig. 6 (b) is validation data regression, Fig. 6 (c) is test data regression, and Fig. 6 (d) is all data regression. The regression (R) is represented the relation between the targets and the outputs that if R=1, meaning that is an accurate linear relationship between targets and outputs. Vice versa if R=0, there is no linear relationship between targets and outputs.

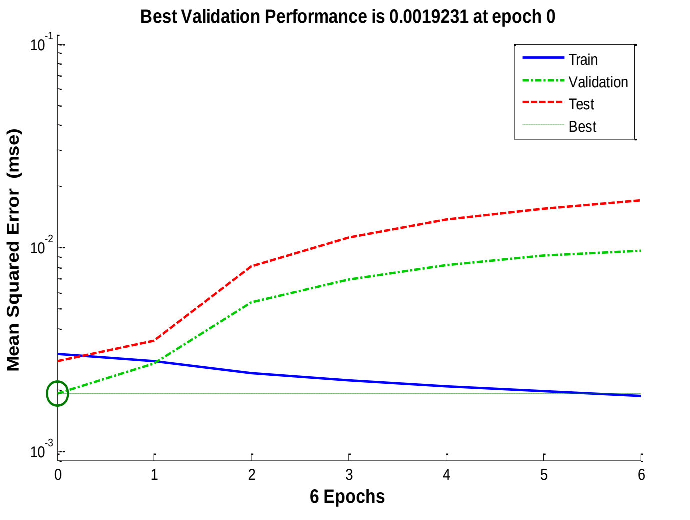

Fig. 5: Best training performance with Levenberg-Marquardt using 120 neurons

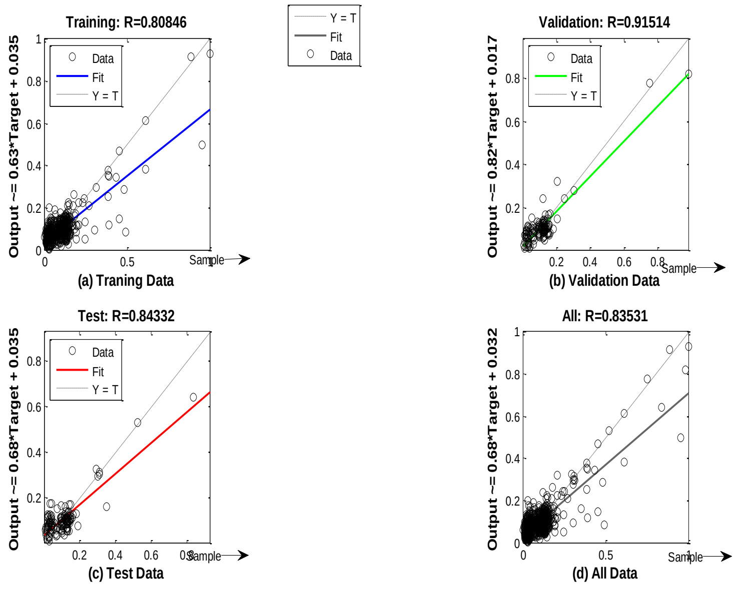

Fig.6 : ANN regression result Levenberg-Marquardt (a) Training data regression (b) Validation data regression (c) Test data regression (d) All data regression

The training data are giving good result with R for training is 0.80846 with Ourput~=0.63^Target+0.035 at Fig. 6 (a), R for validation is 0.91514 with Output~=0.82^Target+0.017 at Fig. 6 (b), R for test is 0.84332 with Output~=0.68^Target+0.035 at Fig. 6 (c), and R for All is 0.83531 with Output~=0.68^Target+0.032at Fig. 6 (d). The graph is very important that can to show clearly some of that data points are poor fits. After the training proses finish, the graph in Fig. 7 shows the results of prediction data and the actual data are shown in the graph. The solid line represents the actual data and the dash line shows the prediction data in Fig. 7. The perfect way to clearly see the comparison of actual data and predict data is used graph method.

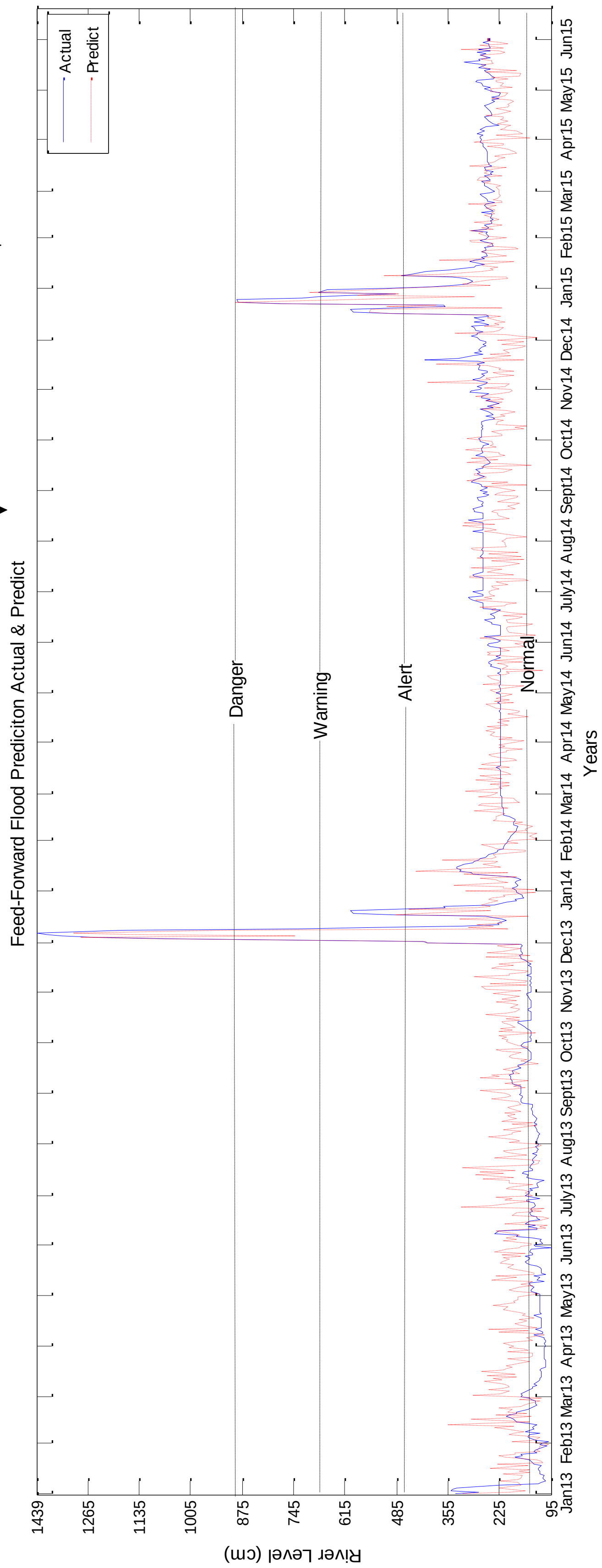

Fig. 7:ANN Feed Forward Flood Prediction Actual & Predict

IV. CONCLUSION

Artificial Neural Network ANN method is used for this project aimed to develop a good prediction result on flood prediction. In order to show the performance Levenberg-Marquardt back-propagation method, sample data from Jan 2013 until May 2015 data has been used. The best results are achieved in ratio (80%; 10%; 10%) with 120 neurons at MSE is 0.0019231, using Levenberg-Marquardt back-propagation. The prediction done successfully u with Training R=0.80846, Validation R=0.91514 and Test R= 0.84332 and All R=0.83531. On the other hand, ANN method has proven to produce satisfying results for flood prediction.

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