Artificial Neural Networks for Water Level Prediction Based on Z-Score Technique in Kelantan River

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Abstract—**In Malaysia, flood can happens annually anytime of the year in multitude of ways. This study aimed to predict water level at Jeti Kastam station (S6) in Kelantan River using an Artificial Neural Networks (ANN) as a modelling tool and validate the accuracy of the model. The Z-Score technique is applied to previous rainfall and water level data to all 6 stations along Kelantan River in identified the significant stations before the successful data resulted will fed to ANN model network. The ANN model was formulated to simulate water level using feedforward algorithm. Readings from 6 stations from rainfall stations showed that S1, S2, S3 and S6 code station while S1 and S2 for water level station were significant value based on Z-Score processing method. Total of 1095 data per station collected from January 2013 until December 2015 was used for training, validation and testing of the network model. Mean Square Error (MSE) and Regression analysis, R are calculated every node. The result showed that the 5 hidden nodes in hidden layer revealed that the regression, R for training, validation and testing were 0.9993, 0.9640 and 0.9989 respectively with MSE value was 2.14e-05. The result of prediction model has found to be suitable to predict flood model by training function feedforward optimization.**

***Index Terms*— Artificial Neural Network (ANN), Z-Score Technique, Water Level Prediction, Hidden Nodes, Mean Square Error (MSE)**

I. INTRODUCTION

A flood is a general discussion and temporary condition of partial in reduction of normally dry land areas from overflow of inland or tidal waters from the unusual and stream flow or runoff of surface waters from any source [1-3]. So, a flood is a natural disaster that can have far reaching effects on people and the environment [4]. Put simply, a flood is too much water in the wrong place [5]. Flooding occurs commonly from heavy rainfall when natural water resources do not have the capacity to convey excess water or in other word it depends to rainfalls, size area of land [6]. During floods roads, farms, houses, building, bridges, cars and property are destroyed [7, 8]. As a result, many people are killed or injured and also become homeless [7]. It usually takes years for affected communities to be rebuilt and business to go back to normal [9]. Water supply and electricity are disrupted even flooding brings a lot of diseases and infections [7, 8].

A flood early warning system is required for assembly and evacuation purpose [10]. The ability to predict water level helps people react and plan for upcoming flooding to avoid any disasters such as preventing deaths or property destruction [11]. Especially in paper [12], the state of Jakarta provided about 6-24 hours of evacuations period for early warning system. Rainfall is one of important climatic elements in agriculture [13]. However, rainfall actually has a relationship with water level in flooding events which is a heavy rain falling will increase water level [12]. As a result, the amount of stream flow will increase, water saturated ground and unusually high tides can leads to flood [6, 12]. Many researchers attracted in flood water level prediction since the accuracy of prediction flood water level is one the most important as an early warning system [14]. The eastern side of the peninsula of Malaysia especially Kelantan state, there's hardly a rainy season or monsoon basically happens starting from November to February every year[5, 15]. Kelantan river basin is the major river in Kelantan, Malaysia which is about 248 km long and drains an area of 13,000 km² occupying more than 85% of the land area [16]. Lebir, Gabis, Pergau and Nenggiri rivers are large tributaries of the Kelantan River [16]. Previous research [17], rainfall prediction become most important part and consideration of statistical and heuristic approaches are used for rainfall prediction. Thus, rainfall is one of main source of increasing water level in flooding [17].

Artificial Neural Networks (ANN) were introduced as an systematic and efficient tools of modelling and prediction can improves the model performance [18, 19].

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Some factors such as data pre-processing, the selecting of model input, a suitable network architecture and model validation are extremely important in ANN model development [18]. The ability of ANN model networks such as to determine the efficiency of generalization and provides a flexible approach for data pre-processing and good experience in successful simulation for prediction or modelling [10, 20, 21]. Feedforward neural network is one popular and simplest type of ANN model development [22]. Previous study [23], there are three variations of feedforward neural networks that influenced the accurate of performance in prediction and they are Backpropagation neural network, Radial Function Basis neural network and Optimization layer by layer neural network was studied in selection of suitable model.

Z-Score technique has ability in capable standardizing data in many range for provide the comparison among data under study by some experiments [24]. Therefore, Z-Score technique approach for microarray corrects data in different samples to identify the significant changes in gene expression [24, 25]. Typically, Z-Score has knowledge discovery from data which mean is sensitive to the data outliers, robust and efficient for data mining process [25]. Besides, Edward I.Altman founded the Z-Score in the year 1968 and the model has been well accepted as a financial crisis model to predict the probability of a firm to bankruptcy [26]. The paper study [27], proposed the combination of Z-Score and neural network in development the classification system of Forward Scattering Radar (FSR) vehicles. It showed that the evaluated of classification performance by different input data give the positive number of Z-Score and Z-Score value [27, 28]. Thus, the output shows the analysis of combination Z-Score method and neural network give the best performance in classification compared to combination method between K-nearest neighbour (KNN) and principle component analysis (PCA) [27]. This also was found in paper study [29], the significant chemical compounds of agarwood oils was identified by using Z-Score technique. Similar to the previous paper study, the chemical also have different abundances pattern well set as different input in Z-Score application [29]. The Z-Score will responsible in identified significant volatile compounds for determination of the qualities of agarwood oils either high or low quality [25, 29].

II. STUDY SITE AND DATA COLLECTION

A. Study Area

The study area is the catchment area of Kelantan river basin which is belongs to the state of Kelantan. The state of Kelantan is one of eleven states which are situated at the east in peninsular Malaysia. The Kelantan River traverses a total of length 248 km [16, 30]. The catchment area is about 13,000 km² in north-east Malaysia facing the South China Sea which occupying more than 85% of the state of Kelantan. Kelantan River has 4 main large tributaries, namely Galas,Lebir, Nenggiri and Pergau rivers [30]. Normally, the entire basin contains large areas of tropical forested mountains or limestone hills. However, the two major rivers, the Lebir and Galas rivers merge upstream of Kuala Krai to form the Kelantan River [16]. The downstream area is located in Kota Bharu with population density is exceeding 20,000 ppl/km² [30].

Typically, a fine sandy soil and paddy soil is found in the extreme east and west of downstream area[31]. Kota Bharu is the capital city of the state of Kelantan and the river estuary is situated about 15 km north Kota Bharu. Figure 1 shows the map of Kelantan River. The Kelantan river basin system flows northward passing through the several populated cities along Kelantan River including Kuala Krai, Tanah Merah, Pasir Mas and Kota Bharu before it goes into South China Sea. Kota Bharu sub catchment also is one of the major flood-prone areas in Kelantan River Basin [30]. Generally, the water level river affected by the tide when flooding occurs in this sub catchment due to tide events from the South China Sea during high tide. The Kelantan River basin is classified as a tropical climate and there is significant rainfall throughout the year [31].

The average annual rainfall is 2500 mm which occurs during monsoon season starting November until February. However, the mean annual temperature at Kota Bharu approximately 27.5 °C with means relative humidity of 81%. In this study, there are a total of six stations of rainfall and water level stations were used for data samples collection. The stations namely Kuala Koh (S1), Tualang (S2), Kuala Krai (S3), Kusial (S4), Dataran Air Mulih (S5) and Jeti Kastam (S6) will be the stations which provide both rainfall and water level data as it located at the outlet of the Kelantan River basin.

B. Data Collection

For hydrological data analysis, data obtained from Department of Irrigation and Drainage, Malaysia (DID). The sampling time for the water level data is one hour per data as set up and is a standard operating procedure (SOP) by DID. Hydrological data are records of natural phenomena i.e. rainfall and water level river. DID has set up a network of hydrological stations to collect data and the data collected are processed and stored in a database for easily located and retrieved when needed. Therefore, the averages of daily and hourly hydrological data were used in analysis for all six stations only for a period of approximately 3 years from 2013 until 2015.

Selection of the appropriate station regarding flood prone area is useful in prediction of water level. The data samples were collected period is from 1/1/2013 to 31/12/2015 and only one data per day were used for analysis. The average of daily rainfall and water level data were used for same period. In year 2013 to 2015, a total of 6,570 data samples from six rainfall stations and a total of 6,570 data samples from six water level stations were used in Z-Score analysis. As a result, only 4 stations were identified as significant value from rainfall stations and 2 stations were identified from water level stations. They are S1, S2, S3 and S6 station from rainfall stations while S1 and S2 from water level stations. As set the S6 station as focused location for water level prediction. The data samples of rainfall (mm) from S1, S2, S3 and S6 stations and data samples of water level (m) from S1 and S2 were set as input. The data samples of water level (m) from S6 set as output to predict the river water level. As recommended by [26], the Z-Score value belongs to positive value and greater than zero value for rainfall and water level parameter will be categorize as significant value. After the experimental using Z-Score technique, the data from the most significant stations were fed to MLP network model for model developed in flood modelling.

Fig.1: Six hydrology stations in Kelantan River Basin (S1 to S6).

III. METHODOLOGY

A. Z-Score Technique

The Z-Score is selected as a feature extraction technique or tool to extract the best feature contained in dataset in identifying the significant value. The knowledge of the Z-Score function in standardizing and normalizing dataset is important for an understanding of identifying the significant data value. According to Z-Score principle, there are positive and negative values of Z-Score obtained. It is show that the positive values of Z-Score indicating the score is above the mean. It represents the significant data. Hence, the negatives values of Z-Score indicating the score is below the mean which act as insignificant data. Besides, positive and negative score also reveal the number of standard deviations that the score is either above or below the mean [27].

First we tested the data from S1 to S6 which is the water level and rainfall stations along Kelantan River. The main purpose of using the Z-Score technique for data selection in identification is to evaluate which stations will contribute more to the improvement of water level prediction performance in term of climatic classification the accuracy (%). The standard Z-Score, Z calculation is programmed using MATLAB software version R2015a.

The values of Z-Score can be either positive or negative values. Based on the statistical theory, Z-Score can be determined by using equation (1) [27, 29, 32].

$$z = \frac{x - \mu}{\sigma} \quad \ldots (1)$$

Where x is the value of data, μ as mean of all values in the data set and σ is standard deviation of data.

In Z-Score normalization, the data is scaled to a fixed range usually 0 to 1due to end up with smaller standard deviations which can suppress the effect of outliers. As a result, the significant values which are positive or equal to zero of Z-Score values can be determined as input to ANN analysis. The hydrological data in year 2013 until year 2015 is provided by Department of Irrigation and Drainage Malaysia (JPS) [33].

B. Artificial Neural (ANN) Network Model

A simply definition of Artificial Neural Network (ANN) is defines a mathematical model for the simulation of a network of biological neurons. ANN operates like human brain process which is a soft – computing tool that can learn patterns and predicts [20]. In this study, this

ANN model is developed using feedforward net mat lab script function. Matlab R2015a which is the software automatically optimized the network via several default parameters. The parameters are; algorithm is Levenberq - Marquadt , epoch is 1000 and 5 unit in hidden layer.

In order to set up an experimental in ANN, the architecture of the ANN and the training algorithm was important elements to define. The most commonly used ANN architecture is feedforward neural network (FFN). FFN was the simplest type of ANN that comprise of the three layers of neurons mainly; input layer, hidden layer and output layer [20, 34]. Input layer is responsibility in receiving the information, input signals, data inputs or measurements from the external environment where these inputs are usually normalized with the limit value generated by the activation function. The hidden layer are consists of neurons which are responsible in perform computations and transfer information from the input nodes to the output nodes. The output layer is also consists of neurons and responsible for computation and transferring information from the networks to the final network which result from the processing performed by the neurons in the previous layers [35].

In this study, the feedforward neural network (FFN) was applied in build a prediction model network due to its simplicity and ideal candidates for performing approximation of nonlinear input-output relationships [36]. However, feedforward network consist of two types of back propagation which are the single layer perceptron and multi-layer perceptron (MLP) network model.

The FFN network model in this study was optimized through the variation of nodes in hidden layers. The node is varied from one to ten. The node that result the lowest MSE and high accuracy was selected to determine the best ANN model. In other hand, Levenberg - Marquadt was used as a training algorithm accompanied by 1000 defaults. The ratio for training, validate and testing data set is 70%, 15%, 15%, respectively. The criterion used was Mean Square Error (MSE) and the Coefficient Regression (R) for training, validation and testing dataset. The FFN network model learns in a supervised manner. A few steps for water level prediction as follow:

i. The data consists of 2 inputs of water level (m) from S1 and S2 stations and 4 inputs of rainfall (m) from S1, S2, S3 and S6 stations and 1 output (water level (m) from S6 station) is normalizing the range of 0 to 1 because of different data and different magnitude value.
ii. The normalize data is dividing to training, validation and testing dataset with the ratio of 0.7:0.15:0.15 respectively.
iii. Training requires a set data of training data and the weight is the network is adjusted until the desired input-output mapping occurs.
iv. The FFN network model was employed using Matlab software using Levenberg - Marquadt Algorithm (LM) default.
v. The hidden nodes in hidden layer were varied from 1 to 10.
vi. Mean Square Error (MSE) is computed for each nodes.
vii. The regression, R for training network is performed to check the closeness or fit between the observed and predicted data.
viii. Autocorrelation functions are applied to determine whether exist correlation in the difference between the measure value and predicted value water level.
ix. Cross correlation function are applied to check the dynamic of water level whether there is correlation between error and input. Error is describes as differentiation value between measure and predicted value of water level.

III. RESULT AND DISCUSSION

All the networks were tested for the water levels data from all stations and the resulting water levels which is predicting water levels were compared with measured water levels. The Z-Score method is applying in identifying the significance stations of hydrological stations. A Z-Score is preferred to identify the significance stations because it is the most basic standard score since a score is a unit distance between two limits and it is useful in educational management as it gives an accurate definition of the score especially in data analysis.

There are 4 stations of rainfall stations show the significant data due to Z-Score value while 2 stations of water level stations show the significant data resulted from Z-Score analysis. There are S1, S2, S3 and S6 station showed the significant data then S1 and S2 from water level station. The Z-Score values represent the positive or greater than zero indicates the score above the mean. The Z-Score value represent the negative or less than zero indicates the score below the mean which act as insignificant data. In addition, positive and negative score also reveal the number of standard deviations that the score is either above or below the mean. The only significant data will be applied as input into FFN model network for development. Table I and II tabulate the Z-Score and mean value for water level and rainfall stations in 2013 to 2015 at Kelantan River.

TABLE I
RESULT OF Z-SCORE VALUES FOR WATER LEVEL STATIONS IN 2013 TO 2015 AT KELANTAN RIVER

Water Level Station	Z-Score Value, b	Mean Value, bb	Significant
S1	1.7397	0.8385	Yes
S2	0.4297	0.582	Yes
S3	-0.0409	0.4899	No
S4	-0.4735	0.4052	No
S5	-1.1385	0.275	No
S6	-0.5164	0.3968	No

*As recommended by [37], the *Zi* value is equal or above than 0.00 is identified as significant

TABLE II
RESULT OF Z-SCORE VALUES FOR RAINFALL STATIONS IN 2013 TO 2015 AT KELANTAN RIVER

Rainfall Station	Z-Score Value, *b*	Mean Value, bb	Significant
S1	1.-231	0.3995	Yes
S2	0.8841	0.393	Yes
S3	0.1262	0.3575	Yes
S4	-1.0015	0.3057	No
S5	-1.416	0.2865	No
S6	0.3841	0.3699	Yes

*As recommended by [37], the *Zi* value is equal or above than 0.00 is identified as significant

Then, using the FFN network model was fed to develop for prediction water level in flood modelling at Jeti Kastam Station (S6) whose learning algorithms used in their training process. This method attribute uses Levenberg Marquadt (LM) used for the training, validation and testing of the proposed metrics concept using via Matlab software, R2015a.

Levenberg-Marquardt optimization algorithm is used as a learning tool for feedforward neural network to predict the water level output. The networks takes normalize input in a range [0, 1] for standardize magnitude value of input output data value. The network is trained the data for 10 iteration with 5 hidden nodes, 7 inputs and 1 output. 70% of the whole data is used to train the neural network while 15% of the data is used as validation data and 15% of the data is used as testing data. Mean square error, MSE of the network is calculated as it fitness function. MSE of the function is found to be 1.05e-04 for the training data. The response of the neural network is shown in Figure 3.

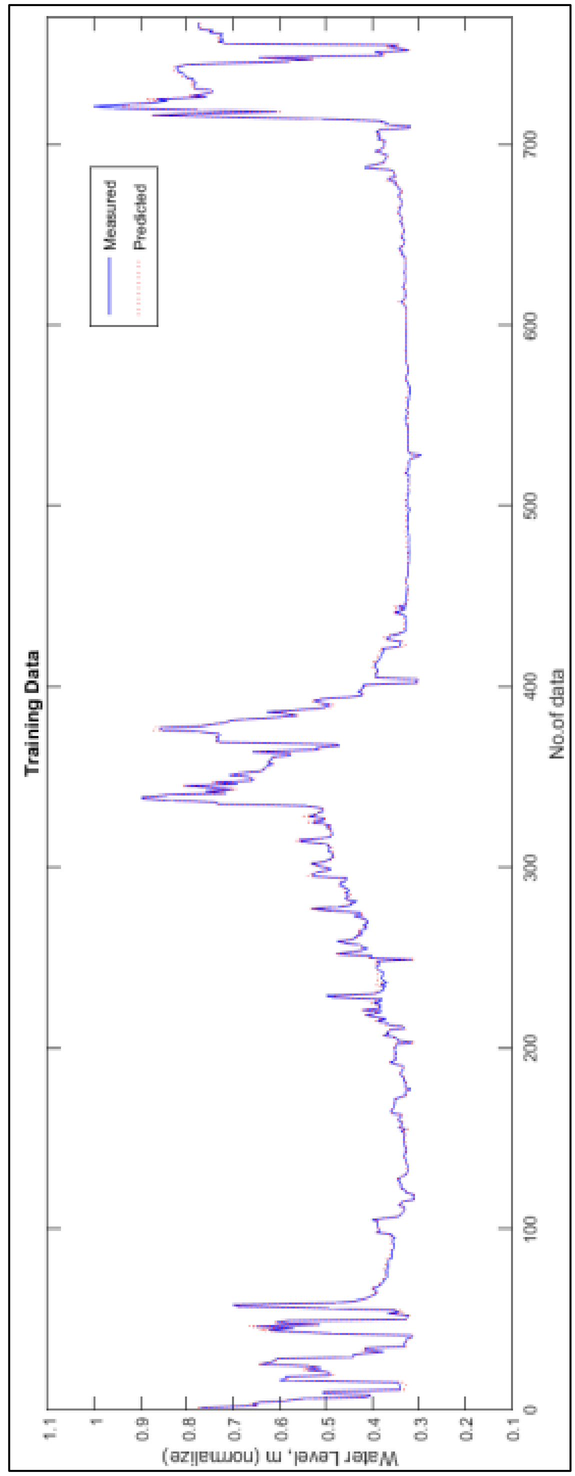

Fig.3: Neural Network response for training data

The response of neural network for validation data is shown in figure 4. The neural network response for the data is plotted and MSE is found to be 3.37e-05.

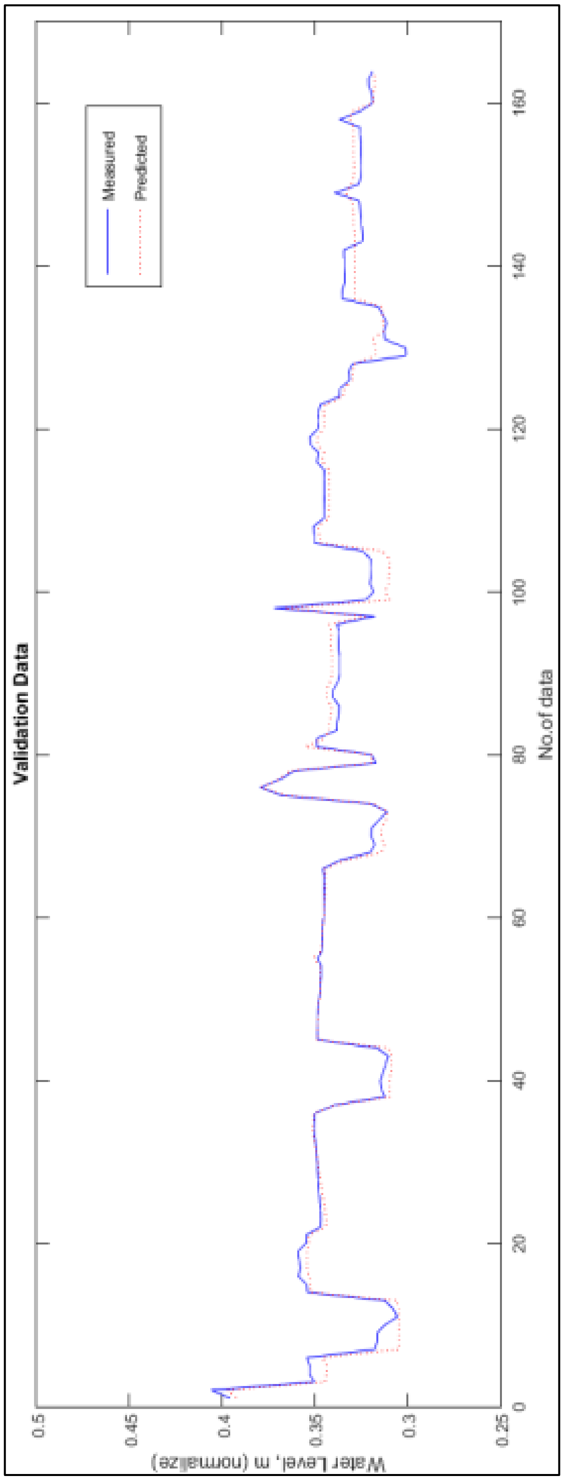

Fig.4: Neural Network response for validation data

The response of neural network for testing data is shown in figure 5. MSE of the network is found to be 8.08e-05 and the response of the neural network is shown in figure 5.

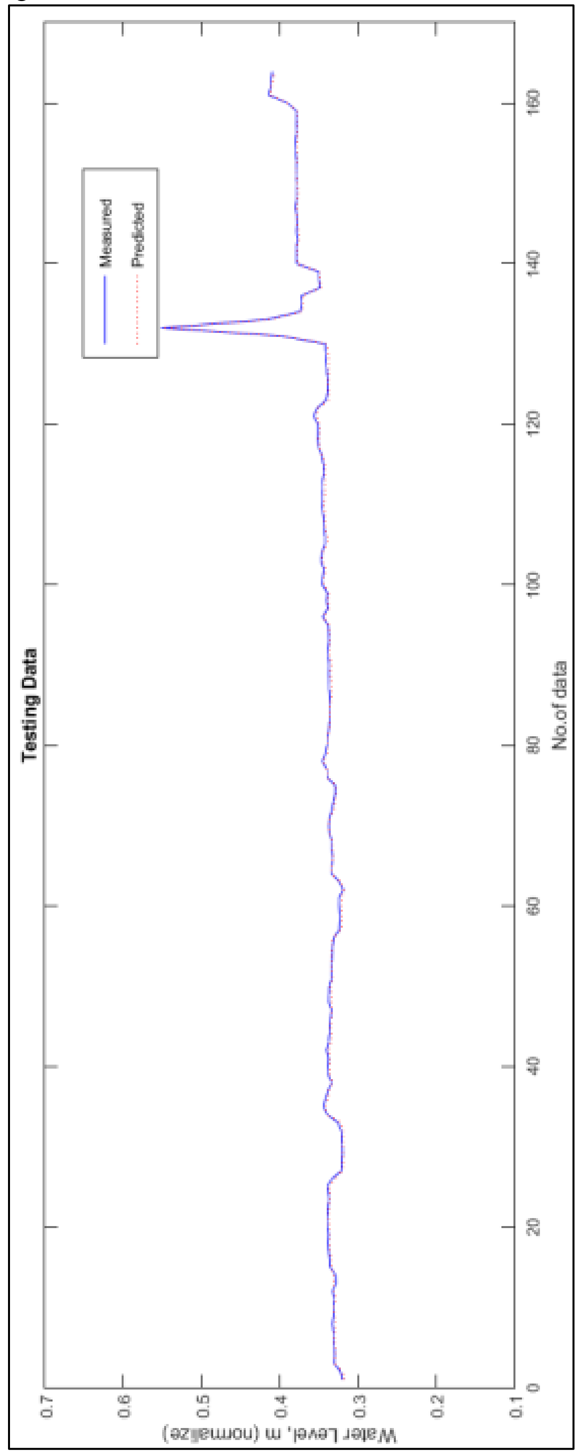

Fig.5: Neural Network response for testing data

As can be seen in Table III, MSE finding was the results at the response of the neural network in hidden nodes variation from one to ten to find the lowest MSE. Therefore, the lowest MSE was 2.45e-05 for FFN model with five hidden nodes in hidden layer. The result showed the MSE of training, validation and testing.

TABLE III
MSE VALUES OF TRAINING, VALIDATION AN TESTING

Hidden Nodes	Mean square error, MSE			
	Training	Validation	Testing	All
1	1.05E-04	3.37E-05	8.08E-05	9.04E-05
2	6.84E-05	2.36E-05	7.23E-05	6.23E-05
3	5.94E-05	3.35E-05	6.71E-05	5.66E-05
4	1.18E-05	1.44E-05	1.85E-04	3.82E-05
5*	2.94E-05	2.30E-05	3.79E-05	2.45E-05
6	1.18E-05	1.84E-05	1.07E-04	2.71E-05
7	2.80E-05	2.60E-05	2.57E-04	6.21E-05
8	1.92E-05	2.63E-05	9.42E-05	3.16E-05
9	1.66E-05	1.27E-05	5.44E-05	2.73E-05
10	1.21E-05	1.73E-05	1.65E-04	3.57E-05

Note: * is the smallest MSE

The Regression, R of the network is found for training, validation and testing data and it is closes to 1 which is signifies a very good linear regression correlation. According to the result, the regression correlation between measured and predicted data exactly fulfilled the criteria of regression. Table IV tabulates the regression, R of training, validation and testing for hidden nodes in hidden layer variation from one to ten to find the suitable number that yields very close to 1 of regression correlation. The regression, R value was 0.9992 for FFN model with five hidden nodes has been show in table below.

TABLE IV
THE REGRESSION, R VALUES OF TRAINING, VALIDATION AND TESTING

Hidden Nodes	Regression			
	Training	Validation	Testing	All
1	0.9977	0.9400	0.9918	0.9971
2	0.9984	0.9680	0.9926	0.9980
3	0.9986	0.9422	0.9905	0.9983
4	0.9997	0.9768	0.9736	0.9988
5	0.9993	0.9640	0.9989	0.9992
6	0.9997	0.9689	0.9874	0.9991
7	0.9993	0.9663	0.9643	0.9981
8	0.9995	0.9634	0.9833	0.9990
9	0.9997	0.9789	0.9931	0.9990
10	0.9997	0.9722	0.9733	0.9986

Autocorrelation plot is purposely applied to determine whether exist correlation in prediction residuals. There is a slight failed in autocorrelation especially during lags 1 to lags 3. This occurred due to a slight correlation appear between errors in the data for training and validation. However, this dispute was overcome by the majority pass in autocorrelation function (ACF) from lags 4 to lags 20. Furthermore, it also supported by the 100% pass in cross-correlation function (CCF). In regression analysis, the difference between measured water level value and the predicted water level value is called residual. Cross-correlation graph is plot to check whether there is correlation between prediction residual and input. This mean that the dynamics of the model is considered good if this model pass both correlation tests. In this research, FFN model is valid within 0.05 error value or 95% of confidence limit which is represented in Figure 6 to Figure 7 for autocorrelation and Figure 8 to Figure 10 for cross-correlation function. Figure 6 and Figure 7 showed the autocorrelation plot of training, validation and testing data.

Figure 6 shows the autocorrelation function (ACF) plots of training, validation and testing data for lower panel. The lag is shown along the horizontal and the autocorrelation is on the vertical. The lines indicated bounds for statistical significance. For the first graph represents an autocorrelation function of residuals for training data used ANN model. This plot shows that lag 1, 2 and 3 have been failed in correlation test. The second graph show the autocorrelation function of residuals for validation data used ANN model. The apparent in this plot has failed in correlation test at lag 1,2,3,4 and 5. The third graph shows the autocorrelation function of residuals for testing data used ANN model. The only at lag 1 shows that the correlation test has been failed.

Figure 7 shows the autocorrelation function (ACF) plots of training, validation and testing data for higher panel. For the first graph represents an autocorrelation function of residuals for training data used ANN model. This plot shows that lag 1, 2, 3 and 4 have been failed in correlation test. The second graph show the autocorrelation function of residuals for validation data used ANN model. The apparent in this plot has failed in correlation test at lag 1, 2 and 3. The third graph shows the autocorrelation function of residuals for testing data used ANN model. The only at lag 1 shows that the correlation test has been failed.

Figure 8 to Figure 10 showed the cross-correlation function (CCF) plot of training, validation and testing data. All graph plots included training, validation and testing showed that the no correlation coefficients have been detected. The entire of correlation test also within range bound. As a result, this is a good CCF for residual and input.

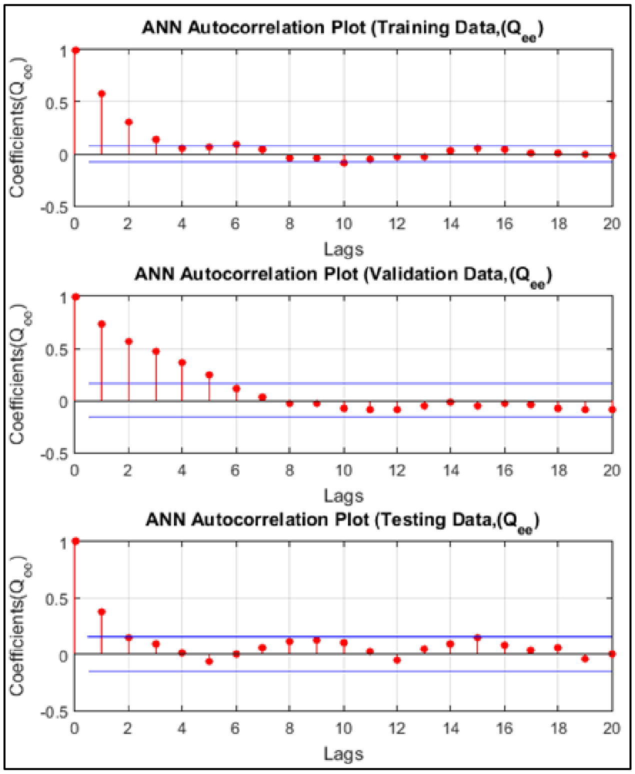

Fig.6 Autocorrelation Plot of Training, Validation and Testing Data ANN Prediction Model (1/2)

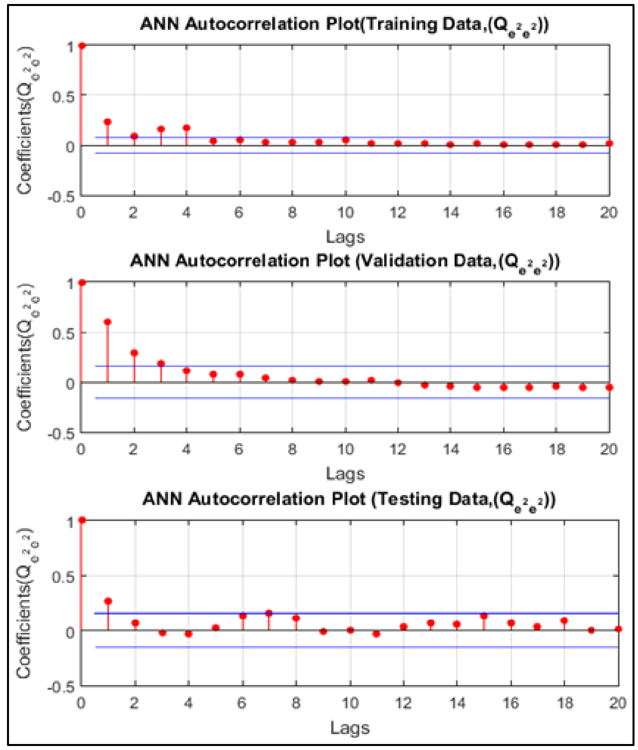

Fig.7 Autocorrelation Plot of Training, Validation and Testing Data ANN Prediction Model (2/2)

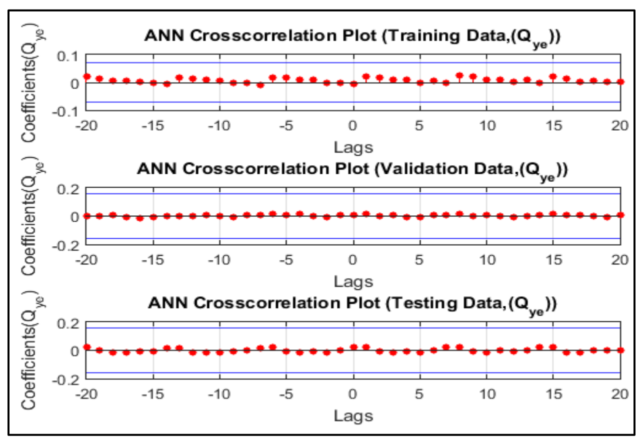

Fig.8 Cross-correlation Plot of Training, Validation and Testing Data ANN Prediction Model (1/3)

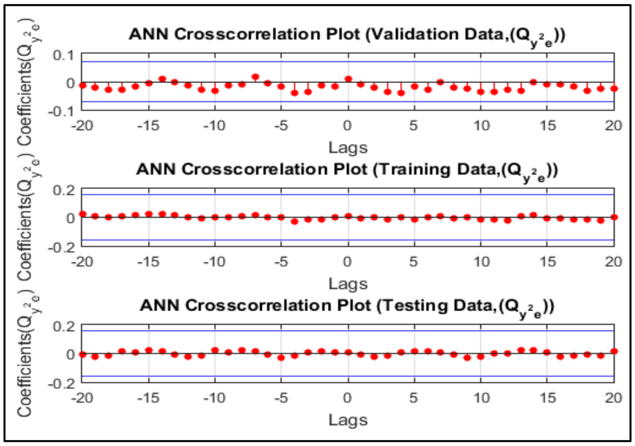

Fig.9 Cross-correlation Plot of Training, Validation and Testing Data ANN Prediction Model (2/3)

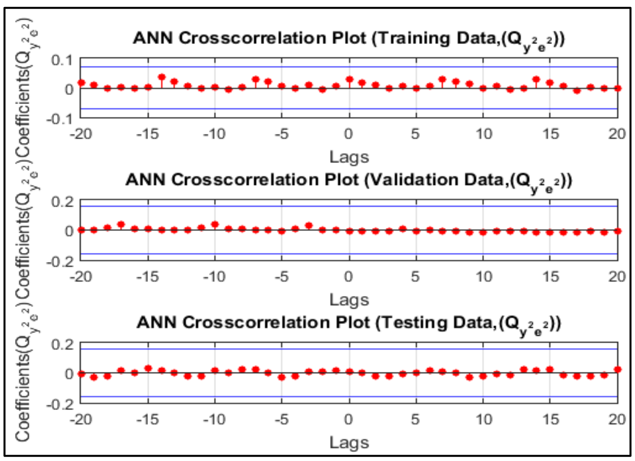

Fig.10 Cross-correlation Plot of Training, Validation and Testing Data ANN Prediction Model (3/3)

A goodness of fit test is a probability test that can employed for the distribution model verification. Note that unimodal distributions can also know as bell-shaped with only one peak of residuals for training data. The second histogram represents a normal distribution with one peak. The peak is symmetric with well-behaved tails for residuals of validation data. . Ideally these curve-fit errors or residuals should be normally distributed. The third histogram represents a skewed distribution to the right. It means that distribution is positively skewed. Briefly, the residual of testing data valued greater than zero. The distribution of the residual is roughly symmetric showed in histogram analysis in Figure 11 as below.

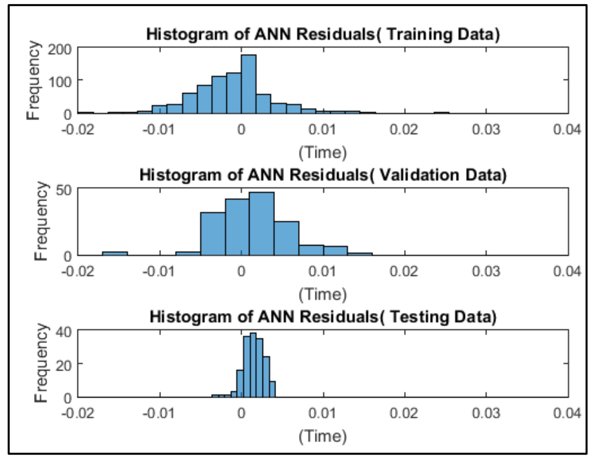

Fig.11 Histogram of ANN Residuals

IV. CONCLUSION

This research finding as confirmed that the technique of Z-Score has been successfully applied as a feature extraction in identified the significant data of rainfall and water level stations. In the result reported that the data give the positive number or greater than zero value of Z-Score present better performance FFN model analysis. It is conclusive that the combination between the technique of Z-Score and FFN for model development should be used to improved the accuracy of water level prediction system performance at Jeti Kastam (S6) station. As a result, the finding in this study is important for the implementation of the ANN model rapid in prediction field.

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REFERENCES

[1] D. Komori, S. Nakamura, M. Kiguchi, A. Nishijima, D. Yamazaki, S. Suzuki, *et al.*, "Characteristics of the 2011 Chao Phraya River flood in central Thailand," *Hydrological Research Letters,* vol. 6, pp. 41-46, 2012.

[2] A. A. Latif and N. H. Arshad, "A review of flood management governance framework in malaysia and selected countries," in *Information Technology and Multimedia (ICIMU), 2014 International Conference on*, 2014, pp. 178-183.

[3] H. Linke, D. Karimanzira, T. Rauschenbach, and T. Pfutzenreuter, "Flash flood prediction for small rivers," in

Networking, Sensing and Control (ICNSC), 2011 IEEE International Conference on, 2011, pp. 86-91.

[4] R. Adnan, A. M. Samad, Z. M. Zain, and F. A. Ruslan, "5 hours flood prediction modeling using improved NNARX structure: case study Kuala Lumpur," in *System Engineering and Technology (ICSET), 2014 IEEE 4th International Conference on*, 2014, pp. 1-5.

[5] E. Chiang, Z. Zainal, A. Narayana, and K. Seetharamu, "Potential Of Renewable Wave And Offshore Wind Energy Sources In Malaysia," 2003.

[6] S. S. Maidin, M. Othman, and M. N. Ahmad, "Information Sharing in Governance of Flood Management in Malaysia: COBIT Based Framework," in *IT Convergence and Security (ICITCS), 2014 International Conference on*, 2014, pp. 1-5.

[7] N. W. Chan, "Impacts of Disasters and Disaster Risk Management in Malaysia: The Case of Floods," in *Resilience and Recovery in Asian Disasters*, ed: Springer, 2015, pp. 239-265.

[8] S. Shafiaia and M. S. Khalidb, "Flood Disaster Management in Malaysia: A Review of Issues of Flood Disaster Relief During and Post-Disaster," *The European Proceedings of Social & Behavioural Sciences EpSBS,* 2016.

[9] M. J. Purvis, P. D. Bates, and C. M. Hayes, "A probabilistic methodology to estimate future coastal flood risk due to sea level rise," *Coastal engineering,* vol. 55, pp. 1062-1073, 2008.

[10] M. R. M. Romlay, M. M. Rashid, and S. F. Toha, "Development of Particle Swarm Optimization Based Rainfall-Runoff Prediction Model for Pahang River, Pekan," in *2016 International Conference on Computer and Communication Engineering (ICCCE)*, 2016, pp. 306-310.

[11] M. Tayyab, J. Zhou, X. Zeng, and R. Adnan, "Discharge Forecasting By Applying Artificial Neural Networks At The Jinsha River Basin, China," *European Scientific Journal, ESJ,* vol. 12, 2016.

[12] A. P. Anindita, P. Laksono, and I. G. B. B. Nugraha, "Dam water level prediction system utilizing Artificial Neural Network Back Propagation: Case study: Ciliwung watershed, Katulampa Dam," in *2016 International Conference on ICT For Smart Society (ICISS)*, 2016, pp. 16-21.

[13] K. D. HARTOMO and E. WINARKO, "WINTERS EXPONENTIAL SMOOTHING AND Z-SCORE, ALGORITHMS FOR PREDICTION OF RAINFALL," *Journal of Theoretical & Applied Information Technology,* vol. 73, 2015.

[14] R. Adnan, F. A. Ruslan, A. M. Samad, and Z. M. Zain, "Flood water level modelling and prediction using artificial neural network: Case study of Sungai Batu Pahat in Johor," in *Control and System Graduate Research Colloquium (ICSGRC), 2012 IEEE*, 2012, pp. 22-25.

[15] C. C. Wing, "Managing flood problems in Malaysia," *Buletin Ingeniur,* 2005.

[16] I. Hafiz, L. M. Sidek, H. Basri, K. Fukami, M. N. Hanapi, L. Livia*, et al.*, "Integrated flood analysis system (IFAS) for Kelantan river basin," in *Telecommunication Technologies (ISTT), 2014 IEEE 2nd International Symposium on*, 2014, pp. 159-162.

[17] Gunawansyah, T. H. Liong, and Adiwijaya, "Prediction and anomaly detection of rainfall using evolving neural network to support planting calender in soreang (Bandung)," in *2017 5th International Conference on Information and Communication Technology (ICoIC7)*, 2017, pp. 1-6.

[18] S. Rani and F. Parekh, "Predicting reservoir water level using artificial neural network," *International Journal of Innovative Research in Science, Engineering and Technology,* vol. 3, pp. 14489-14496, 2014.

[19] H. R. Maier and G. C. Dandy, "Neural networks for the prediction and forecasting of water resources variables: a review of modelling issues and applications," *Environmental modelling & software,* vol. 15, pp. 101-124, 2000.

[20] S. H. Elsafi, "Artificial Neural Networks (ANNs) for flood forecasting at Dongola Station in the River Nile, Sudan," *Alexandria Engineering Journal,* vol. 53, pp. 655-662, 9// 2014.

[21] M. H. Beale, M. T. Hagan, and H. B. Demuth, "Neural network toolbox™ user's guide," in *R2012a, The MathWorks, Inc., 3 Apple Hill Drive Natick, MA 01760-2098,, www. mathworks. com*, 2012.

[22] T. Hayashida, I. Nishizaki, S. Sekizaki, and M. Nishida, "Structural optimization of neural networks and training data selection method for prediction," in *Computational Intelligence and Applications (IWCIA), 2014 IEEE 7th International Workshop on*, 2014, pp. 171-176.

[23] V. Karri and T. Kiatcharoenpol, "Prediction of internal surface roughness in drilling using three feedforward neural networks - a comparison," in *Neural Information Processing, 2002. ICONIP '02. Proceedings of the 9th International Conference on*, 2002, pp. 1890-1894 vol.4.

[24] C. Cheadle, M. P. Vawter, W. J. Freed, and K. G. Becker, "Analysis of microarray data using Z score transformation," *The Journal of molecular diagnostics,* vol. 5, pp. 73-81, 2003.

[25] N. Ismail, M. H. F. Rahiman, M. N. Taib, M. Ibrahim, S. Zareen, and S. N. Tajuddin, "Identification of significant compounds of agarwood incense smoke different qualities using Z-Score," in *Signal Processing & Its Applications (CSPA), 2015 IEEE 11th International Colloquium on*, 2015, pp. 203-207.

[26] K. Yu-hong and L. Xiang, "Research on financial distress prediction of China real estate public companies based on Z-Score model," in *Management Science and Engineering (ICMSE), 2011 International Conference on*, 2011, pp. 1166-1173.

[27] N. F. Abdullah, N. E. A. Rashid, Z. I. Khan, and I. Musirin, "Analysis of different Z-score data to the neural network for automatic FSR vehicle classification," in *IET International Radar Conference 2015*, 2015, pp. 1-5.

[28] N. F. Abdullah, N. E. A. Rashid, K. A. Othman, and I. Musirin, "Vehicles classification using Z-score and modelling neural network for forward scattering radar," in *Radar Symposium (IRS), 2014 15th International*, 2014, pp. 1-4.

[29] N. Ismail, M. H. F. Rahiman, M. N. Taib, N. A. M. Ali, M. Jamil, and S. N. Tajuddin, "Classification of the quality of agarwood oils from Malaysia using Z-score technique," in *System Engineering and Technology (ICSET), 2013 IEEE 3rd International Conference on*, 2013, pp. 78-82.

[30] E. D. P. Perera and L. Lahat, "Fuzzy logic based flood forecasting model for the Kelantan River basin, Malaysia," *Journal of Hydro-environment Research,* 2014.

[31] A. Yusoff, N. M. Din, S. Yussof, and S. U. Khan, "Big data analytics for Flood Information Management in Kelantan, Malaysia," in *2015 IEEE Student Conference on Research and Development (SCOReD)*, 2015, pp. 311-316.

[32] C. C. Lai, C. F. Jhan, and W. S. Wang, "Digital image watermarking using DCT and z-score transform," in *2010 International Conference on Machine Learning and Cybernetics*, 2010, pp. 2933-2937.

[33] K. S. A. D. a. Sekitar. (2016, 20 APRIL). *Jabatan Pengairan Dan Saliran Malaysia, Kementerian Sumber Asli Dan Alam Sekitar*. Available: http://infobanjir2.water.gov.my/

[34] S. K. Vyas, Y. P. Mathur, G. Sharma, and V. Chandwani, "Rainfall-Runoff Modelling: Conventional regression and Artificial Neural Networks approach," in *2016 International Conference on Recent Advances and Innovations in Engineering (ICRAIE)*, 2016, pp. 1-6.

[35] M. Rashid, K. Kamal, T. Zafar, Z. Sheikh, A. Shah, and S. Mathavan, "Energy prediction of a combined cycle power plant using a particle swarm optimization trained feedforward neural network," in *2015 International Conference on Mechanical Engineering, Automation and Control Systems (MEACS)*, 2015, pp. 1-5.

[36] F. Li, J. M. Zurada, Y. Liu, and W. Wu, "Input Layer Regularization of Multilayer Feedforward Neural Networks," *IEEE Access,* vol. 5, pp. 10979-10985, 2017.

[37] S. Lias, Z. H. Murat, N. Sulaiman, and M. N. Taib, "IQ Index using Alpha-Beta correlation of EEG power spectrum density (PSD)," in *2010 IEEE Symposium on Industrial Electronics & Applications (ISIEA)*, 2010, pp. 612-616.