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Hourly stream flow prediction in tropical rivers by multi-layer perceptron network

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ABSTRACT

Accurate stream flow (SF) prediction is considered among the basic requirements in dealing with several problems associated with the planning, designing and management of water resources and river systems. Multi-layer perceptron network (MLP), was employed to develop artificial intelligence-based models to predict the hourly SF in downstream areas from upstream water level and rainfall records in the Selangor River basin which is a paradigm of humid tropical rivers. Hourly SF, rainfall and water level records of a one-year period (2011) were applied to train and test the MLP-based models which comprise six different combinations of input variables. The developed models' performance was evaluated via the training, testing data set and overall data. The results of the performance evaluation criteria, i.e. correlation co-efficient (R) and mean absolute error (MAE) indicates that high prediction accuracy was attained. The best fit MLP model is M6-MLP with the highest R and lowest MAE. The R between the observed and predicted hourly SF by the M6-MLP model is 0.898 and 0.904, while the MAE is 10.922 and 10.83 for the training and testing data sets, respectively. The results demonstrate that the MLP technique is successfully applied with high accuracy for hourly SF prediction.

Keywords: Stream flow; Surface water hydrology; Prediction; Hydrological modeling; Artificial neural networks

1. Introduction

Different types of models have been applied to predict stream flow, and these can generally be classified into two main groups: knowledge-driven and data-driven based models. Each type has its specific set of advantages and disadvantages based on data availability and modeling conditions [1,2]. Several modeling approaches can be classified as data-driven based models, for instance statistical methods including linear and nonlinear regression models, artificial neural networks (ANNs), genetic algorithms (GAs), support vector machines (SVM) and fuzzy rule-based systems (FRBSs) [3–5].

In stream flow prediction and modeling, simple data-driven based models such as statistical models are not sufficient in modeling surface water hydrological systems like stream flow, since they are completely non-linear dynamic systems. In view of the mentioned complexity, there is a need to investigate more advanced models and approaches that can analyze and solve the complexity of stream flow systems even without fully reorganizing the system's physical and hydrological specifications [1]. For the aforementioned reasons, advanced data-driven based models such as ANNs are commonly reported in literature on hydrology, including stream flow prediction and modeling.

ANNs have been extensively applied in stream flow modeling and prediction for a multiplicity of objectives. For instance, Turan and Yurdusev [6] for river flow estimation from upstream flow records; Kentel [2] for estimation of monthly river flow and identification of input vectors susceptible to producing unreliable flow estimates; Bhadra, Bandyopadhyay [7] for rainfall-runoff modeling; Rakhshanehroo, Vaghefi [8] for flood forecasting in similar catchments; Besaw, Rizzo [9] for un-gagged stream flow

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prediction; Triana, Labadie [10] for stream-aquifer modeling; Edossa and Babel [11] for long-term stream flow forecasting in the Awash River Basin; Ethiopia, Sahu, Khatua [12] for prediction of discharge in straight compound open channel flow; Machado, Mine [13] for monthly rainfall–runoff modeling; Kisi, Ozkan [14] for modeling discharge-sediment relationships; Kisi, Ozkan [14] for forecasting river flow rate from the Melen Watershed, Turkey; and Wei, Yang [15] estimated and predicted river monthly flows.

In small river basins where the concentration time is less than one day, such as the Selangor River basin, the prediction of hourly stream flow is more practical than predicting daily or monthly stream flow. This is because the stream flow in small river basins may change dramatically within a few hours. Therefore, daily or monthly stream flow cannot adequately represent the real-time changes in hourly stream flow, something that is required in planning, designing and managing river systems and water resources.

The main objective of this paper is to develop a group of ANNs based models to predict the hourly stream flow in downstream areas from upstream water level and rainfall records in a humid tropical region. The Multi-Layer Perceptron network (MLP) are selected to be the modelling tool of this study.

Hourly records of stream flow, rainfall and water level for one year (2011) were used to develop the AI-based models. The hourly water level and rainfall data of upstream stations served as input variables while the hourly stream flow data of the downstream station acted as the output variable of the models. The models' performance was assessed on the basis of two performance evaluation criteria, including Correlation coefficient (R) and mean absolute error (MAE).

2. Multi-layer perceptron networks (MLP)

In this study, multi-layer perceptron networks (MLP) which is one the ANNs techniques, is applied in hourly stream flow modeling. ANNs is an advanced data-driven modeling technique with a flexible mathematical structure making it proficient in modeling the non-linear and complex relations among the observed data sets without the need to fully physically recognize the natural systems [16]. The fundamental premise of ANNs is derived from the analogy of extremely simplified mathematical models of biological neural networks and is inspired by the brain's learning systems. ANNs has the capability to learn and generalize from historical data and previous examples to create meaningful explanations to problems [17,18].

MLP are the widely employed, feed-forward networks with unlimited numbers of hidden layers. The back propagation learning algorithm is the common learning rule for MLP. In MLP, the neurons are arranged in layers as illustrated in Fig. 1. The Fig. 1 presents a random sample of MLP containing three layers: an input layer with 4 input variables (4 neurons), one hidden layer with 7 neurons and an output layer with 1 output variable (1 neuron). Each neuron in the hidden, output layers, receives weighted inputs from all neurons in the previous layer. The active incoming vector is then forwarded through an activation function such as the sigmoid, linear, or cubic polynomial function, to the next layer. This means that each single neuron performs two actions. Initially, data from an external source is assimilated for the input layer, or from neurons in a previous layer for the hidden and output layers. Then, it creates an output dependent upon a prearranged activation function and sends it to the neuron in the next layer. This process in one neuron is comparatively non-complex; complications with MLP are eventually reached through contact and combinations between neurons in networks layers [16].

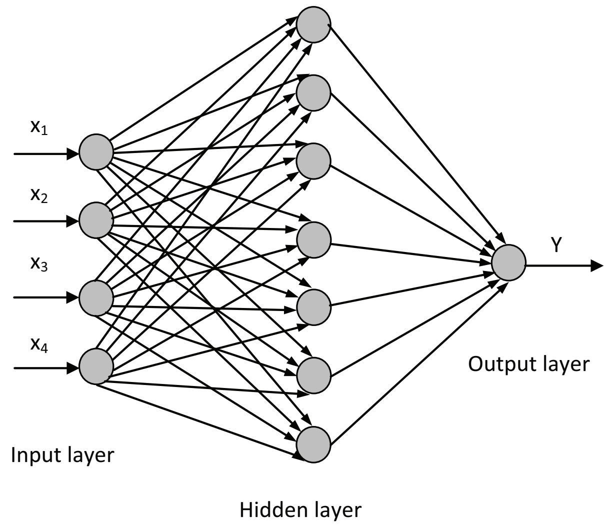


Fig. 1. Schematic diagram of MLP architecture.

As an example of a training process, consider a neuron in the hidden layer that receives signals from neurons in the input layer. The net input to the hidden neuron is the summation of the weighted inputs from the neurons in the input layer and is denoted by $O_{(in)}$.

$$I_{(in)} = w_1 x_1 + w_2 x_1 + w_3 x_3 + \ldots w_n x_n \tag{1}$$

x_i is the input vector, and N is the total number of data patterns. Then $I_{(in)}$ is proceeded by an activation function to produce the output V, $V = f\,(I_{(in)})$. For instance, the most common activation function is a sigmoid function, which is denoted as follows:

$$f(x) = \frac{1}{1+\exp(-x)} \tag{2}$$

This process is reiterated for all input vectors. At the end of a pass, via the whole training data set all the neurons modify their weights depending on the accumulated results of the difference between the observed and simulated data regarding each weight. These variations then change weight in order to make errors decay rapidly.

Considering w_m represents the value after iteration m of a weight w,then:

$$W_m = w_{m-1} + \Delta w_m \tag{3}$$

where Δw_m is the variation in weight w at the end of iteration m and is computed as follows:

$$\Delta w_m = -\varepsilon d_m \tag{4}$$

where ε is the factor guiding the rate of change in weights. d_m is given by:

$$d_m = \sum_{n=1}^{N} \left(\frac{\partial e}{\partial w_m}\right)_n \quad (5)$$

where N is the total number of data patterns, and e is the training output error [19].

3. Case study

The study area is the Selangor River basin, which is one of the main rivers in Malaysia. It is located in Selangor state, and covers an approximate area of 1960 km^2. The Selangor River streams about 110 km from the northeast to the southwest [20–22]. It is the main water resource for the states of Selangor and Kuala Lumpur whereabout 50% of water consumption is sourced from the Selangor River [23]. Fig. 2 presents a location map of the Selangor River basin in peninsular Malaysia as well as basin topographical maps.

The study area is regarded as a paradigm of rivers located in the tropical humid region of Southeast Asia. The Selangor River basin has a humid, tropical climate. The characteristic climate features are uniform temperatures with little variation year-round. On average, temperatures rise during daytime up to 32°C and drop to 23°C at night. The average annual rainfall varies between 2000 and 3000 mm annually throughout the basin. Evaporation ranges from 1600 mm to 1800 mm annually and the annual average of relative humidity is about 80% [24,25]. The average discharge of the Selangor River is 57 m^3/s, but seasonal rainfall variations cause flow to exceed 122 m^3/s or fall below 23 m^3/s about 10% of the time [26].

4. Methodology

The main issues that should be considered in developing ANNs-based models for stream flow prediction are data collection and analyses followed by selecting adequate model input and output variables. The variables of ANNs-based models for stream flow prediction depend on the estimation of lag time between upstream and downstream stations. Subsequently, the models' structure and training mechanism should be identified, and finally the developed models are assessed using performance evaluation criteria to select the best fit model that predicts hourly stream flow.

4.1. Data collection and analyses

The hydrological data were sourced from hydrological stations located along the Selangor River basin. There are two stations gauging stream flow (SF), seven stations gauging water level and more than thirty stations gauging rainfall.

Downstream stream flow data were extracted from the RantauPanjang gauging station, which is located downstream of the Selangor River. All major tributaries of the Selangor River join it before this particular station. Records of RantauPanjang station are considered the best stream flow indicator for the study area. The water level data were extracted from four upstream stations while rainfall data were extracted from other four upstream stations. The rainfall and water level gauging stations are located very close to each other, and the stations were selected based on data availability and modeling requirements. Fig. 3 presents the locations of the hydrological stations and flow paths between them in the Selangor River basin.

About 8753 patterns of hourly stream flow, water level and rainfall records representing a one-year period (2011) were used for modeling. The basic statistical characteristics of the data, such as minimum, maximum, mean, standard deviation and Skewness of hourly records of all stations employed are shown in Table 1. For each ANNs model, the modeling data was divided into three datasets: 50% for training (4387 patterns), 25% for validation (2193 patterns) and 25% for testing the models (2193 patterns).

The training dataset is utilized to train the models while the validation dataset is used in the early stopping of training process to prevent over-fitting and over training during the training step. The testing dataset serves to assess the performances of the AI-based models [27].

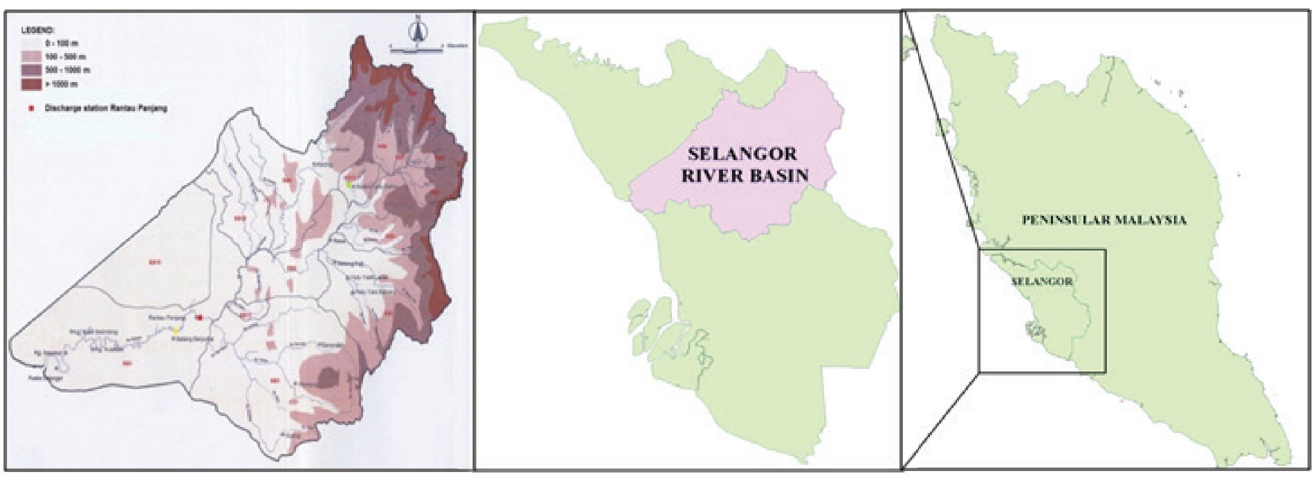


Fig. 2. Location and topography maps of the Selangor River basin.

4.2. Models development

4.2.1. Determination of models variables

Determining adequate input and output variables, is considered one of the most important issues in the development of AI-based models. In stream flow prediction models, model variable selection is commonly based on prior knowledge of the river basin's hydrology, which provides initial indication of potential inputs and outputs [28]. Stream flow in tropical rivers can be characterized as the function of several influential variables, such as rainfall, water level and the river's physical characteristics [29]. In this paper, the main objective is to predict the hourly stream flow in the downstream area of a tropical river from upstream water level and rainfall records. Thus, hourly records of water level and rainfall from upstream stations are used as input variables, while hourly records of stream flow data from a downstream station serve as the output variable. Eq. (6) presents the relationship between stream flow and the influential variables:

$$Sf_t = f\left(X_{(t)}\right) + e \tag{6}$$

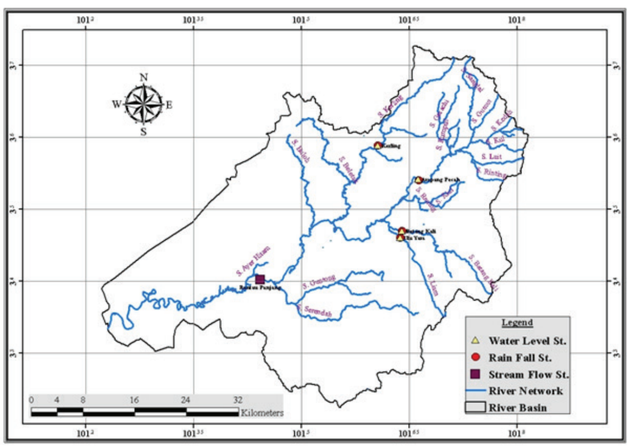


Fig. 3. Location of hydrological stations in the Selangor River basin.

where *Sf(t)* represents the stream flow, *X(t)* is the input vector, which includes the input variables, i.e. rainfall and/or water level, and *e* is the random error.

There are three scenarios in selecting the model input and output variables. The first scenario is to use the rainfall data from upstream stations as input variables; the second scenario is to use the water level data from upstream stations as input variables; and the third scenario is to use both water level and rainfall data from upstream stations as input variables. Two input vectors were applied for the three scenarios. One is with the single antecedent record of upstream stations, and the second is with the average of the antecedent records from the upstream stations. For the six input vectors, the antecedent single record of stream flow from the downstream station is used as another input variable to predict stream flow at the downstream station for ahead period equal to the lag time between the upstream stations and downstream station. The final selection of input variables for the six input vectors depends on the lag time estimation between the upstream and downstream stations.

4.2.2. Lags between the model variables

Determining the input variables for the hourly stream flow prediction with ANNs-based models includes finding the antecedent water level and rainfall records that have a major effect on predicted stream flow [30]. In this study, it was estimated by calculating the correlation co-coefficient corresponding to 24 different time lags between the antecedent hourly water level and rainfall records of upstream stations which represent the input variables and hourly stream flow data records from the downstream station which represents the output variable.

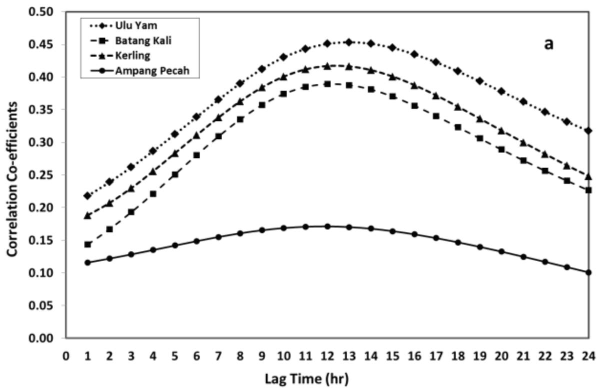
The correlation analysis was conducted based on hourly antecedent records from 0 to 24 h. The correlation co-efficient results for the water level and rainfall stations are presented in Fig. 4. This figure indicates that the highest correlation for the water level stations is at 12 h and for the rainfall stations at 17 h. The correlation co-efficient is generally weak and can be explained by the highly complex relation between water level and rainfall, and stream flow, as well as by the influence of other hydrological parameters on stream flow. Although the correlation co-efficient is generally weak, it is very useful to select the input variables from the stream flow ANNs-based models.

Table 1
The hydrological stations and statistical characteristics of the data used

Station	Function	Latitude	Longitude	Mean	Min.	Max.	Std. Dev.	Skewness
RantauPanjang	SF (m^3/s)	03 24 10.0	101 26 35.0	60.35	23.94	294.64	39.00	2.04
Ulu Yam	RF (mm/h)	03 27 38.4	101 38 14.4	32.24	30.56	35.49	0.49	–0.78
Batang Kali	RF (mm/h)	03 28 11.7	101 38 23.3	32.42	27.03	34.71	0.78	–4.55
Kerling	RF (mm/h)	03 35 18.1	101 36 22.8	44.18	43.93	45.61	0.12	2.64
AmpangPecah	RF (mm/h)	03 32 25.4	101 39 48.3	50.16	49.61	50.89	0.15	0.97
Ulu Yam	WL (m)	03 27 38.4	101 38 14.4	0.16	0.00	19.33	0.73	11.85
Batang Kali	WL (m)	03 28 11.7	101 38 23.3	0.24	0.00	22.67	0.91	10.90
Kerling	WL (m)	03 35 18.1	101 36 22.8	0.25	0.00	25.33	1.06	11.70
AmpangPecah	WL (m)	03 32 29.1	101 39 44.4	0.24	0.00	28.00	1.08	12.85

Depending on lag time estimation and based on the three scenarios for selecting the models' input and output variables, six variable combinations of variables were selected to model and predict hourly stream flow. The input and output variables of the ANNs models are shown in Table 2.

$Sf_{(t+12)}$ represents 12 h ahead of stream flow at RantauPanjang station, $Rf_u(t)$ represents single records of hourly rainfall at Ulu Yam, $Rf_{u(t)}$ represents the average of three antecedent records of hourly rainfall at Ulu Yam, $Wl_u(t)$ represents a single record of water level at Ulu Yam, and $Wl_u(t)$ represents the average of three antecedent records of hourly rainfall at Ulu Yam.



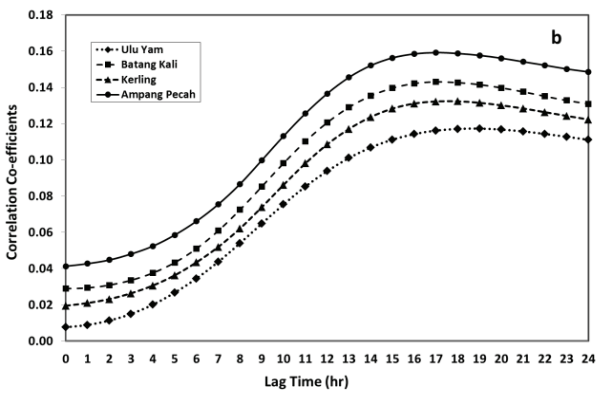


Fig. 4. Correlation co-efficient between hourly stream flow records of downstream station and hourly records of upstream station: (a) Water level station, and (b) Rainfall station.

4.2.3. Models structure identification

After selecting the appropriate combinations of input and output variables for the six models, the structure of the three modeling techniques should be determined to begin the modeling processes. To develop the ANN-based model, the neural network specifications including network structure, connection scheme and weight range should be selected. The number of layers and number of neurons per layer often specify the network framework. Next, the neuron specifications, meaning the activation function and its range, should be determined followed by system dynamics and training algorithm selection.

Each neural network should include three layers: input, hidden and output layers. The input layer is composed of input data and the output layer comprises the model output. The hidden layer includes the activation function to provide nonlinearities for the network and it can be one or more layers with an unlimited number of neurons.

So far, there is no scientific approach to selecting the ideal number of hidden layers and neurons. The optimal number of neurons is identified using a trial and error process by developing many ANNs-based models and evaluating them. The optimum number of hidden layers in ANNs-based models is influenced by several elements, such as the numbers of input variables, the number of data cases, the complexity of the process to be modeled, the amount of noise in the training data, the type of ANNs-based model and the type of training algorithm and activation function.

4.3. Models training

Once the structure of the ANNs-based model has been established, the conditions to stop the training processes should be fixed prior to beginning training. Some of the conditions that control training are: maximum number of iterations, maximum time of training, target performance which specifies the tolerance between observed and predicted stream flow, and minimum learning rate.

Generally, ANNs-based model training includes the following steps. Input variable records are inserted into the input layer, then weighted and passed on to the hidden layer. The neurons in the hidden layer create outputs by applying an activation function to the sum of the weighted input values. Next, the outputs of the hidden layer are weighted by the connections between the hidden and output layers. The desired results are finally produced in the output layer.

Table 2
The input and output variables of the AI models

Model	Inputs	Output	No. input variables
M1	$Rf_{u(t)}, Rf_{b(t)}, Rf_{k(t)}, Rf_{a(t)}, Sf_{(t)}$	$Sf_{(t+17)}$	5
M2	$Rf_{u(t)}, Rf_{b(t)}, Rf_{k(t)}, Rf_{a(t)}, Sf_{(t)}$	$Sf_{(t+17)}$	5
M3	$Wl_{u(t)}, Wl_{b(t)}, Wl_{k(t)}, Wl_{a(t)}, Sf_{(t)}$	$Sf_{(t+12)}$	5
M4	$Wl_{u(t)}, Wl_{b(t)}, Wl_{k(t)}, Wl_{a(t)}, Sf_{(t)}$	$Sf_{(t+12)}$	5
M5	$Wl_{u(t)}, Wl_{b(t)}, Wl_{k(t)}, Wl_{a(t)}, Rf_{u(t-5)}, Rf_{b(t-5)}, Rf_{k(t-5)}, Rf_{a(t-5)}, Sf_{(t)}$	$Sf_{(t+12)}$	9
M6	$Wl_{u(t)}, Wl_{b(t)}, Wl_{k(t)}, Wl_{a(t)}, Rf_{u(t-5)}, Rf_{b(t-5)}, Rf_{k(t-5)}, Rf_{a(t-5)}, Sf_{(t)}$	$Sf_{(t+12)}$	9

The ANNs-based models reach optimum learning by having the interconnected weights continuously modified until there is good accord between the model output and observed output. The residuals between observed and predicted stream flow represent the ANNs-based model error.

4.4. Performance evaluation criteria

Model performance was assessed on the basis of two performance criteria: correlation co-efficient (R) and mean absolute error (MAE). R is a statistical technique that indicates the strength and direction of a linear relationship between two variables [31]. R was used to check the level of agreement between the observed and predicted hourly stream flow. R^2 describes how much of the variance between the two variables is described by the linear fit. There are different modes of calculating the correlation co-efficient, but the most widely used is the Pearson correlation co-efficient (R). It is obtained by dividing the covariance of the two variables by the product of their standard deviations, as described in the following equation.

$$R = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{7}$$

where n is the number of pairs of data, and x and y are the variables.

In a perfectly increasing linear relationship circumstance, R is +1; however, r is –1 in a perfectly decreasing linear relationship instance. R values between +1 and –1 indicate the strength degree of the linear relationship between the variables and r = 0 signifies no linear relationship between the variables.

MAE was applied to evaluate the residual or the differences between observed and predicted stream flow. Theoretically, the minimum value of MAE is zero, meaning that the model represents a perfect fit something not easy to achieve. There is no maximum MAE value. The following equation describes MAE.

$$MAE = \frac{\sum_{i=1}^{n}\left|X_{o,i} - X_{m,i}\right|}{n} \tag{8}$$

Where X_m is predicted by a model and X_o is observed data.

5. Results and discussion

Six ANNs-based models with different input variable combinations were selected to predict hourly stream flow at Rantau Panjang station. Three of the models used single, prior record of the upstream stations while the other three models used the average of three previous records of upstream stations with the highest correlation co-efficient. The model structures are presented in Table 2.

Six models with various input variable combinations were trained and developed using MLP. The developed models' performance was evaluated via the training data set, testing data set and overall data performance. The results of the performance evaluation criteria, i.e. R and MAE of the MLP models, are presented in Table 3.

Table 3
The performance values of MLP models

Model	Training data set		Testing data set		Overall data	
	R	MAE	R	MAE	R	MAE
MLP-M1	0.869	11.550	0.874	12.039	0.873	11.823
MLP-M2	0.880	11.771	0.882	12.163	0.877	11.741
MLP-M3	0.886	12.088	0.882	11.640	0.881	11.991
MLP-M4	0.881	11.897	0.893	11.578	0.883	11.913
MLP-M5	0.889	11.052	0.894	11.586	0.890	11.352
MLP-M6	0.898	10.922	0.904	10.839	0.895	11.025

A comparison of the performance evaluation for the six MLP models can be seen in Fig. 5. Clearly, the best fit MLP model is M6-MLP with the highest R value and lowest MAE value for the training and testing data sets. The R between the observed and predicted hourly stream flow by the M6-MLP model is 0.898 and 0.904, while the MAE is 10.922 and 10.83 for the training and testing data sets, respectively.

Fig. 6 shows the correlation between the observed and predicted hourly stream flow by the M6-MLP model, (a) training data set, and (b) testing data set. The observed and predicted hourly stream flow of the training and testing data sets seem to be in good accord with R^2 0.806 and 0.917, respectively. In Fig. 7, a comparison between the observed and predicted hourly stream flow by M6-MLP for September 2013 can be seen. Acceptable agreement between the observed and predicted hourly stream flow is apparent.

6. Conclusions

In this paper, the ability of MLP to predict hourly stream flow in downstream are as using upstream water level and rainfall records in a humid tropical area was explored.

The hourly records of stream flow, rainfall and water level for one year (2011) were applied to train and test the ANNs-based models. Hourly water level and rainfall data from upstream stations were used as input variables, while the hourly stream flow data from the downstream station served as the output variable of the models. The models' performance was assessed on the basis of two performance evaluation criteria, including Correlation coefficient (R) and mean absolute error (MAE). The best fit model for predicting hourly stream flow was determined based on the testing data sets' performance evaluation.

The performance evaluation of the ANN-based models suggests that M6 with 9 input variables achieved the best performance out of all models. The correlation between the observed and predicted hourly stream flow using the MLP-M6 for both training and testing data sets seemed to be in good accord. A comparison between the observed and predicted hourly stream flow by MLP-M6 for September 2013 shows good accord between the observed and predicted hourly stream flow. The results of performance evaluation criteria R and MAE of the MLP-M6 suggest that the MLP technique performs very well in hourly stream flow prediction.

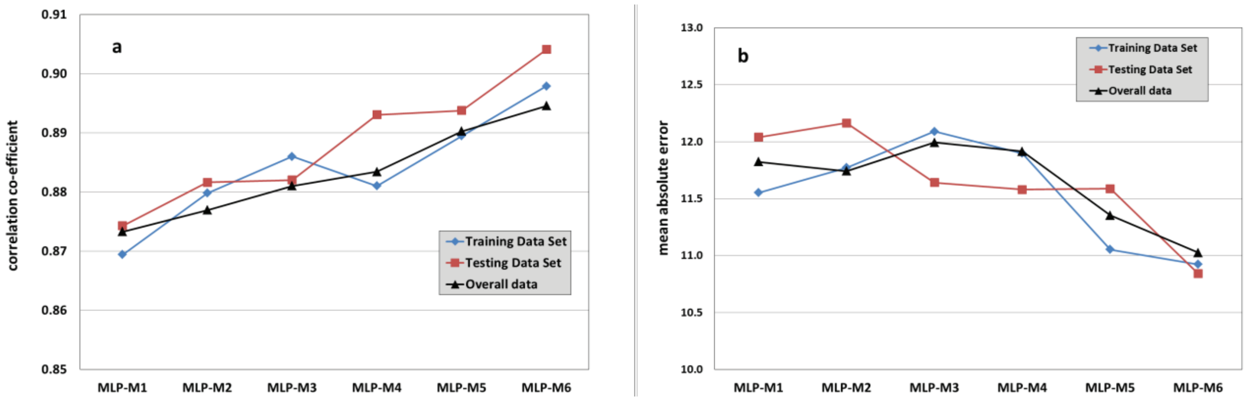


Fig. 5. Performance values of MLP models: (a) correlation co-efficient and (b) mean absolute error.

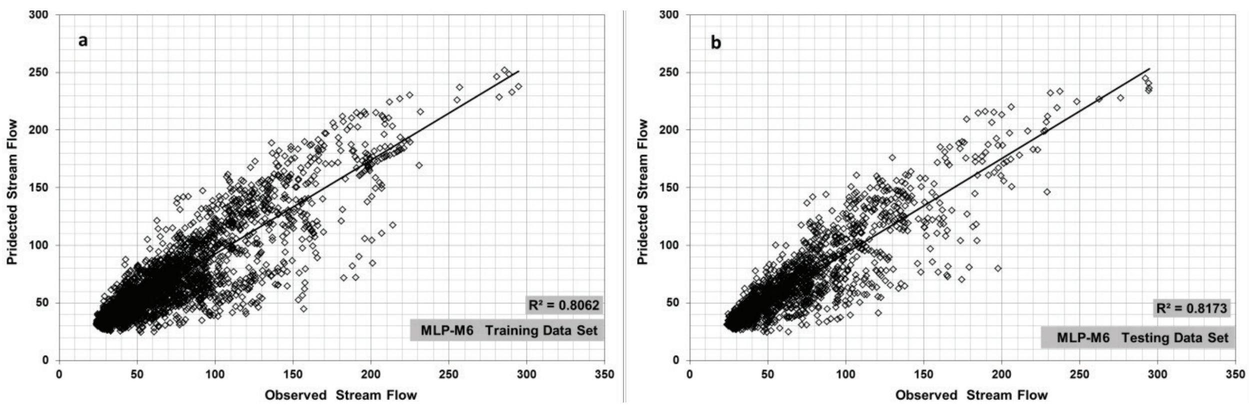


Fig. 6. Correlation between the observed and predicted hourly stream flow by M6-MLP model: (a) training data set, and (b) Testing data set.

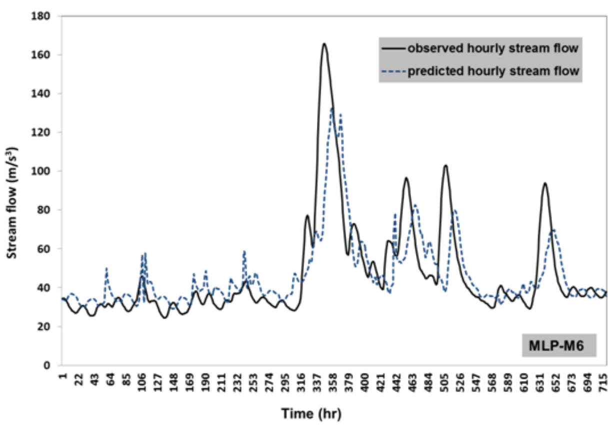


Fig. 7. Comparison between the observed and predicted hourly stream flow using the M6-MLP model.

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