

Artificial Neural Network for Modelling Rainfall-Runoff

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ABSTRACT

The use of an artificial neural network (ANN) is becoming common due to its ability to analyse complex nonlinear events. An ANN has a flexible, convenient and easy mathematical structure to identify the nonlinear relationships between input and output data sets. This capability could efficiently be employed for the different hydrological models such as rainfall-runoff models, which are inherently nonlinear in nature and therefore, representing their physical characteristics is challenging. In this research, ANN modelling is developed with the use of the MATLAB toolbox for predicting river stream flow coming into the Ringlet reservoir in Cameron Highland, Malaysia. A back propagation algorithm is used to train the ANN. The results indicate that the artificial neural network is a powerful tool in modelling rainfall-runoff. The obtained results could help the water resource managers to operate the reservoir properly in the case of extreme events such as flooding and drought.

Keywords: Artificial neural networks, back propagation algorithm, rainfall-runoff modelling

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INTRODUCTION

Rainfall-Runoff modelling is significantly useful for the design and operation of various components of water resource projects like dams, barrages, water supply schemes etc. (Ghumman et al., 2011). Furthermore, the results of modelling could support hydrologists in decision-making in the face of bad predictions. It could, therefore, help water resource managers to prevent damage to private and public property as well as to avoid health and ecological dangers that can

result from flooding. Due to the great temporal and spatial variability of precipitation patterns, watershed characteristics and the number of parameters involved in the process of modelling and due to the presence of complex nonlinear relationships in the transformation of rainfall into runoff, the rainfall-runoff relationship is one of the most difficult hydrologic problems facing water resource managers (Wu & Chau, 2011; Young & Liu, 2014). Many approaches have been applied to estimate runoff, such as distributed physical-based models, stochastic models, conceptual models and black box models (Tingsanchali & Gautam, 2000; Bahremand & De Smedt, 2008; Bahremand & De Smedt, 2010). Conceptual modelling uses an approximation to forecast daily, monthly or seasonal stream flows in the long term. The Stanford Watershed Model (SWM) is an instance of conceptual modelling, which uses 20-30 variables for runoff forecasting (El-Shafie et al., 2011). Due to the numerous parameters and the high complexity of parameter interaction, the optimisation of model parameters is mostly applied by method of trial-and-error.

In order to overcome these difficulties, Artificial Neural Networks (ANNs) have been proposed. Indeed, they have recently received considerable attention as powerful computing systems in approaching hydrology problems due to their practical applications and ability to map the extremely complex and nonlinear systems among hydrological variables such as rainfall-runoff (Govindaraju, 2000; Wu & Chau, 2011). Since ANNs do not consider the physics of the problem, they are treated as black-box models; however, some researchers have recently reported that it is possible to detect physical processes in training ANN hydrologic models (Jain & Srinivasulu, 2004; Sudheer & Jain, 2004). Although there are extensive sorts of ANN algorithms, the main duty of all ANNs is to map a set of inputs into a set of outputs. ANNs are an information-processing system, which comprises many nonlinear interconnected elements called neurons (Srinivasulu & Jain, 2006). Researchers have investigated and concluded that ANNs gave better results when applied to problems that encountered noise or involved pattern generalisation, abstraction, diagnosis and recognition, and also in complex systems that do not have enough information or poor descriptions (Zhang & Govindaraju, 2000; Jain & Srinivasulu, 2004). In addition, ANNs can be used in situations when input data are insufficient or obscured by nature. It can be summarised that ANN approaches have the capability to map the patterns of the highly unknown input and output relationship and overcome the aforementioned difficulties. So, many researchers have used the ANN algorithm to discover the rainfall-runoff relationship due to its ability to generalise patterns in cases of ambiguous and insufficient data and to incorporate a complex model without enough knowledge or probability distributions. However, the conceptual models need numerous parameters for modelling, but all the required data are not available in many watersheds.

Another drawback of the conceptual method is using an approximation for prediction, which affects the accuracy of the results. In addition, the performance of the model is highly subjective and dependent on the user's knowledge, ability, understanding of watershed characteristics and skill in running the model. Although this type of modelling provides reasonable accuracy, its application is limited due to the aforementioned difficulties (Gökbülak et al., 2015). All these gaps can be covered by ANNs.

The purpose of this study was to develop an artificial neural network (ANN) model for simulation of daily runoff. So, the application of ANN methodology for modelling daily

runoff discharge of the Bertam River was investigated in this research. The Bertam River is the main river feeding the Ringlet reservoir in Cameron Highland, Malaysia. Since the Ringlet reservoir is a hydropower reservoir system, the results of the present study could help the managers to predict the future discharge to predict the future hydropower as well as to control the danger of flooding in times of extreme phenomena. In order to develop a rainfall-runoff model, three parameters, such as daily observed rainfall, daily observed stream flow and daily evapotranspiration data (estimated by Hargreaves-Samani equation) from 2003-2012 were used to train the network based on the back propagation learning rule. Afterwards, the performance of the developed ANN model in simulating the rainfall-runoff was assessed by four quantitative statistical indicators, such as the Nash-Sutcliffe Coefficient (E), Pearson Correlation of Coefficient (r), Root Mean Square Error (RMSE) and Mean Bias Error (MBE). The description of methods and the given results are described in detail in the following sections.

STUDY AREA AND DATA COLLECTION

The present research focused on the Cameron Highlands, Pahang, Malaysia. The Sultan Abu Bakar dam was constructed on the Bertam River in the district of Cameron Highland. The lake that was created from the construction of the dam is known as the Ringlet Reservoir (Figure 1).

The Ringlet Reservoir is nearly 3.2 km long and 0.4 km wide. It impounds the combined stream flow from Telom Tunnel and the Bertam River and other minor tributaries. The total Bertam catchment area is 159km². The principal aim of this research was to build a model for simulating the Bertam River stream flow coming into the Ringlet Reservoir. An average monthly inflow of the Bertam River is shown in Figure 2.

The data of rainfall, evapotranspiration and stream flow were collected to map the rainfall-runoff relationship. Daily rainfall and stream flow data were gathered from Tenaga Nasional Berhad Company. Evapotranspiration data were estimated by the Hargreaves-Samani equation, which needs the observed temperature data for estimation. The temperature data were collected from the nearest station into the reservoir (Table 1).

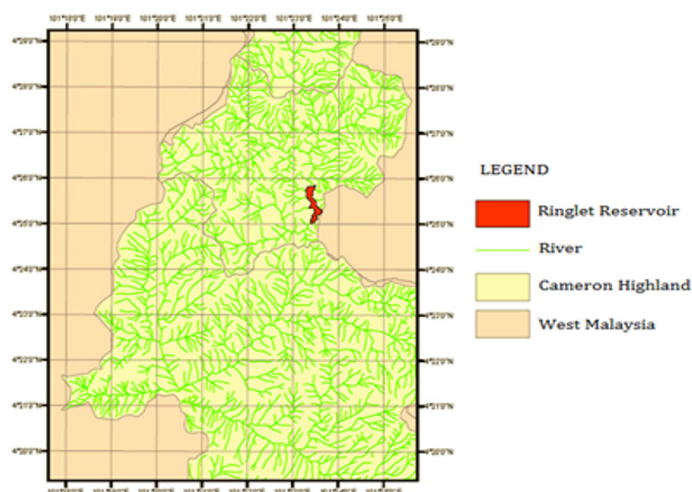


Figure 1. Location of Ringlet Reservoir in Cameron Highland, Malaysia.

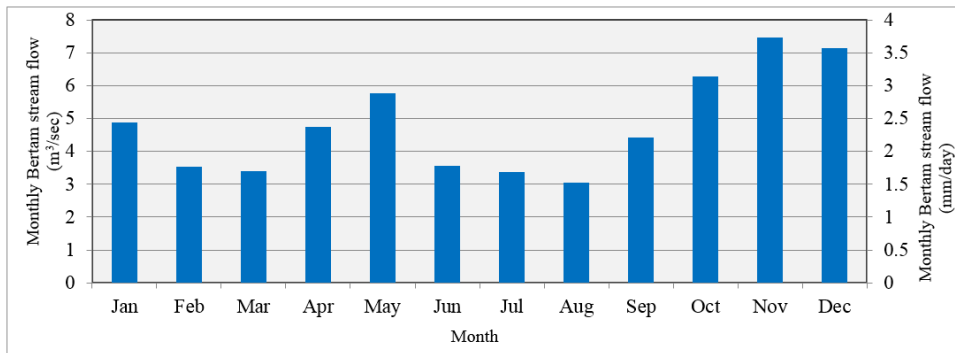


Figure 2. Average monthly inflow of Bertam River coming into Ringlet Reservoir.

Table 1
Weather Data Used as LARS-WG Input

Station	Climate parameters	Longitude	Latitude	Altitude (m)	Source
Kajiklim Habu	Daily precipitation	101° 23' E	4° 25' N	1101.46	Tenaga Nasional Berhad
Cameron Highland	Daily min and max temperatures	101° 22' E	4° 28' N	1545	Meteorological Department

Evapotranspiration Estimation Method

In this research, the Hargreaves-Samani (HS) equation was employed to estimate the amount of evapotranspiration (ET_0) at the reservoir (Lima et al., 2013; Raziei & Pereira, 2013). The required data for the HS method are only the observed minimum temperature (T_{min}) and maximum temperature (T_{max}) for the estimation of daily evapotranspiration (mm/day), which is expressed as:

$$ET_0 = 0.0135 K_{Rs} R_a (T_{max} - T_{min})^{0.5} (T_a + 17.8) \tag{1}$$

In this equation, 0.0135 is a constant, which converts American units to the international system of units. K_{Rs} is the adjustment coefficient of radiation. In the typical version of HS, the value of K_{Rs} is equal to 0.17. R_a is called extraterrestrial radiation, which will be explained in detail in the next section. T_{min} , T_{max} , T_a are minimum, maximum and average daily air temperature (°C), respectively (Hargreaves & Allen, 2004).

Extraterrestrial radiation (R_a). The extraterrestrial radiation (R_a) for each day of the year and for various latitudes is estimated from the solar declination, solar constant and the time of the year (Raes & MUNOZ, 2008). So, for a certain latitude, the R_a is constant for each day of every year. The R_a formula is expressed as follows:

$$R_a = (24 * 60 / \pi) G_{sc} d_r [w_s \sin(\alpha) \sin(\phi) + \cos(\alpha) \cos(\phi) \sin(w_s)] \tag{2}$$

In this equation, R_a = extraterrestrial radiation ($\text{MJ m}^{-2} \cdot \text{Day}^{-1}$); G_{sc} = solar constant ($0.0820 \text{ MJ m}^{-2} \text{ min}^{-1}$); d_r = inverse relative distance Earth-Sun; w_s = sunset hour angle (rad); α = latitude (rad); φ = solar declination (rad). The unit of latitude (α) is in radians, which has a positive sign for the northern hemisphere and negative sign for the southern hemisphere. The conversion equation from decimal degrees to radians is given by:

$$[\text{Radians}] = (\pi/180)[\text{decimal degrees}] \quad [3]$$

The inverse relative distance Earth-Sun and solar declination is expressed by:

$$d_r = 1 + 0.003 \cos[(2\pi/365)J] \quad [4]$$

$$\varphi = 0.409 \sin[(2\pi J/365) - 1.39] \quad [5]$$

In these equations, J is the number of days in any year (from 1 January to 31 December).

In order to compute the evapotranspiration based on the Hargreaves-Samani equation, minimum and maximum temperature data were collected from Cameron Highland station, and extraterrestrial radiation was calculated as a function of day and latitude. The latitude of the reservoir is 4.42.

Artificial Neural Networks Procedure

Artificial Neural Networks (ANNs) are information-processing systems that imitate the functions of the human brain. The ANN structure comprises a number of processing elements, which are called neurons, and the interconnections between the neurons are called weights (Kisi et al., 2013). In the architecture of ANN, neurons are classified in groups, and are called layers. The neurons in one layer have connections to those neurons in adjacent layers, but not to those in the same layer. The strength of the connection between two neurons in adjacent layers is known as their weight (Lake et al., 2009). Most of the developed ANN models use three layers: input, hidden and output layers. The input layer is the layer where the data import to the network, data processing is done in the hidden layer, and the output layer is where the results of imported data are generated. Overall, ANN models can be either 'feed forward' or feedback networks. The feed forward network is selected for use in this study. Based on this network, the information from the input layer passes into the output layer in the forward direction only. An important stage in developing an ANN model is its training to determine the weight matrix in order to learn the relationship between the data introduced. There are two principal types of training mechanisms: supervised and unsupervised. A supervised training method needs an external teacher or a guide to be involved throughout the training process. The main objective of this training is to minimise the error at the output layer by searching for a strong connection from generated outputs that are equal or close to the targets. The most popular supervised training method employed in the sciences and engineering for the training of the feed forward ANN is called the back propagation method (Srinivasulu & Jain, 2006). Back propagation is part of a gradient descent method used to train the ANN model. ANN has a parallel processing system that interconnects the neural computing elements. The system architecture is illustrated in Figure 3 (Shirke et al., 2012).

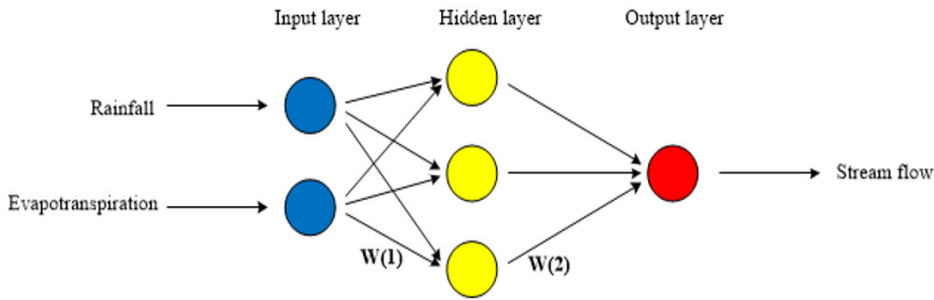


Figure 3. Architecture of back propagation ANN model.

The many neurons (also known as ‘nodes’) of the ANN process the information. The signals are transferred by employing the connecting links. These links have associated weights, which will be multiplied by the incoming signal (input). Furthermore, the output signal is determined using activation functions to the net input. There are different learning mechanisms, which help the ANN to discover knowledge (Kohonen, 2012).

In the ANN structure, each layer comprises several nodes. The layers are interconnected by associated weights. Each node in the input layer ($k=1,2,\dots,m$) disseminates the input signal to the hidden layer. Any hidden node ($i=1,2,\dots,n$) calculates its weighted input signals according to:

$$U_{ink} = b_i + X_k W_{ki} \tag{6}$$

In this equation, W_{ki} is an associated weight between input layer node (k) and output layer node (i), X_k is an input signal and b_i is the weight for any bias. Later, the current formulation will be used to apply the activation function in order to calculate the output signal from any input signal according to:

$$U_i = f(U_{ink}) \tag{7}$$

The neurons go through an activation function to generate the result. The system, therefore, needs continuous-transfer functions in order to determine the output of neurons based on its input. The most common transfer functions are identity functions, binary functions, binary sigmoid (Logistic) functions and binary sigmoid (Hyperbolic Tangent) functions. In the present research, the sigmoid function is used (Ehret, 2014). This transfer function is a continuous, differential and monotonically increasing function, which is typically employed in back propagation network. Later, the signal transmits from the second to third layer and the error is transmitted from the output layer back to the earlier layers. This process is called back propagation because the output error goes back to the input nodes in order to revise the weights.

ANN learning process. The learning process is a procedure that modifies the network weights and biases. The duty of the learning process is to train the network system to do some tasks. There are three different learning rules: supervised learning, unsupervised learning and reinforcement learning. In the current research, supervised learning is used.

The system will be trained based on the training data to map the relationship between input-output. When the inputs are imported to the network, the outputs will be compared with

the targets. In this step, the learning rule is employed to modify the weights and biases of the system in order to decrease the difference between the outputs and targets.

ANN training procedure. An ANN is used to discover the relationship between the input and output data. Several techniques can be employed to assign a strength connection among data sets. One method is to set the weights based on prior knowledge. This method cannot be applied for some models due to lack of information and knowledge. A neural network is an efficient way to overcome these difficulties. In this technique, the network will be trained by teaching patterns and letting it adjust its weights and biases based on the learning rules. The problem still exists of how to adjust the associated weights from the input layer to the hidden layer. In order to solve this problem, the back propagation learning rule is used. Based on the back propagation, the errors for the elements of the hidden layer are specified by back-propagating the errors from the elements of output layer. The weights of the network are adjusted by minimising the error between the target and computed outputs. The network weights are continuously revised until the minimum error is obtained (Nayak et al., 2013; Kisi et al., 2013). As a result, training pairs are chosen from the training set, and the network computes the outputs according to the inputs used for the training pair. The obtained result from the network is then compared with the outputs by the training pair. According to this result, the weights add biases to all neurons, modified by a coefficient is based on the discrepancy between actual output and calculated output (errors), the derivation of the sigmoid function and actual output. The amount of neuron weight adjustment depends largely on the learning rate (α), which is a single coefficient that is multiplied by all adjustments. A small learning rate does not allow the network to learn and therefore, it will capture a local minimum, meaning it will not discover more precise weights. However, large learning rates produce extremely poor network results. Therefore, selecting the proper learning rate is very important before starting ANN training (Shirke et al., 2012).

Model development. In the present research, an ANN was developed to map the rainfall-runoff relationship. The more factors used, the more accurate results were obtained. Three types of data were therefore gathered: rainfall, evapotranspiration and stream flow. The input layer comprised two layers (rainfall and evapotranspiration) and the stream flow constituted the output layer.

The whole data set was divided into two subsets, including the training set and testing set. Seventy per cent of the data was used for training and the remaining 30 per cent comprised the testing set. In the training sets, the adjusted weights and biases of the network were determined, and the test set was employed to prevent the networks from being over-trained. The overall idea in selecting a good training set from the available data series was to have extreme events (including all minimum and maximum values in the training sets).

Another factor, which is one of the most significant characteristics of ANNs, is the number of neurons in the hidden layers. If the number of neurons is insufficient, the network cannot configure the complex data set and the obtained results will be a poor fit. Conversely, if the number of neurons is too high, the time required for network training will be long, and the network might over-fit the data (Rodríguez-González et al., 2011). In the present research, the number of neurons was determined by trial and error. The best result was obtained using 10 neurons. The proposed architecture was developed in order to predict the Bertam River runoff coming into the Ringlet Reservoir. The obtained results give valuable information to water

resource managers to operate the reservoir efficiently and protect the system from extreme events such as flooding.

Model evaluation. The performance of the developed ANN model in simulating the rainfall-runoff was assessed by four statistical evaluation measurements: the Nash-Sutcliffe Coefficient (Riad et al., 2004), Pearson Correlation of Coefficient (r), Root Mean Square Error ($RMSE$) and Mean Bias Error (MBE) (Riad et al., 2004). $RMSE$ and MBE statistics evaluate the efficiency of the model in terms of its ability to predict data from a calibrated model. The other statistics E and r quantify the effect of the ANN model in capturing the dynamic, complex and nonlinear rainfall-runoff processing. These statistical criteria are calculated according to the following equations

Nash-Sutcliffe Coefficient (E)

$$E = 1 - \frac{\sum_{i=1}^n (X_{obs,i} - X_{model,i})^2}{\sum_{i=1}^n (X_{obs,i} - \bar{X}_{obs,i})^2} \tag{8}$$

(Correlation Coefficient (r))

$$r = \frac{\sum_{i=1}^n (X_i - \bar{X}_i) \cdot (Y_i - \bar{Y}_i)}{\sqrt{\sum_{i=1}^n (X_i - \bar{X}_i)^2 \cdot (Y_i - \bar{Y}_i)^2}} \tag{9}$$

Root Mean Square Error ($RMSE$)

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (X_{obs,i} - X_{model,i})^2}{n}} \tag{10}$$

Mean Bias Error (MBE)

$$MAE = \frac{\sum_{i=1}^n (X_{model,i} - X_{obs,i})}{n} \tag{11}$$

In these equations, the parameters $X_{model,i}$ and $X_{obs,i}$ are simulated and observed values, respectively and $\bar{X}_{obs,i}$ is the mean value of observed data and n is the number of samples. Furthermore, X_i and Y_i are the input and output values of the ANN model respectively and \bar{X}_i and \bar{Y}_i are the mean values of input and output data, respectively.

RESULTS AND DISCUSSION

An ANN was developed using three types of data: rainfall, evapotranspiration and stream flow. The available data covering the duration of 10 years (2003-2012) were employed in this research. The imported data used to build the ANN model were taken from the Bertam River catchment, Malaysia. The daily rainfall data were collected from the nearest station (Kajiklm Habu station) to the Ringlet reservoir, and daily evapotranspiration data were estimated by the Hargreaves-Samani equation. Another required data set was stream flow, which was taken

from the Bertam River catchment and constituted the output layer. The units of stream flow were converted from m³/sec into mm/day and then used in the model. This conversion was made due to improve the network performance. The number of neurons and hidden layers was determined by trial and error. The results indicated that ANN could give the best output by using 10 neurons and three hidden layers.

A number of statistical measurements were calculated to evaluate the network performance in both training and test sets (Table 2). The Nash-Sutcliffe coefficient was used to specify the predictive power of the hydrological models, which obtained 0.77 in training sets and 0.74 in testing sets. These results show that the constructed network had an acceptable predictive power. The correlation coefficient is a measure of the strength and direction of the linear relationship between two or more variables. The results indicate that the ANN model had good ability to capture the relationship between input/output in both training and test sets. RMSE and MBE are frequently-used measures of the differences between values (sample values) predicted by a model and the values actually observed, and in this model the differences were found to be negligible. Overall, the evolution measurements illustrate the ability of the ANN as a predictor to simulate the observed data. The results indicate that the ANN model has good ability to capture the nonlinearity of input/output in both training and test sets. It could, therefore, be used as a predictor to simulate the rainfall-runoff model.

Table 2
Statistical Evaluation Measurements of the Ringlet Reservoir

Model Evaluation	Training Set	Test Set
Nash-Sutcliffe Coefficient (<i>E</i>)	0.77	0.74
Correlation Coefficient (<i>r</i>)	0.88	0.86
Root Mean Square Error (<i>RMSE</i>)	0.17	0.17
Mean Bias Error (<i>MBE</i>)	0.001	0.004

The comparison between daily observed (actual) and simulated (predicted) Bertam river stream flow data from 2003-2012 was calculated and shown in Figure 4. The coefficient of determination (R^2) is the measurement that indicates the goodness fit of a model or represents how well data fit a statistical model. This measurement can vary from 0 to 1. The closest value to 1 shows the strongest fit between observed and simulated data. The R^2 result was found to be 0.76 in this model, which is an acceptably good result.

Furthermore, the linear regression between observed stream flow (Y) and the simulated stream flow (X) was found, and the best line fit for simulation period (2003-2012) was determined (Eq. 12). This equation shows the general relationship between observed and predicted values. This equation can be used to validate the predicted value. For example, for predicting stream flow, observed rainfall and evapotranspiration data should be imported to the constructed model and the model should then be run to give the predicted (modelled) stream flow. After determination of the modelled stream flow value (X), Eq (11) can be used to modify this value for a more accurate stream flow (Y) reading.

$$Y=0.9921X \quad [11]$$

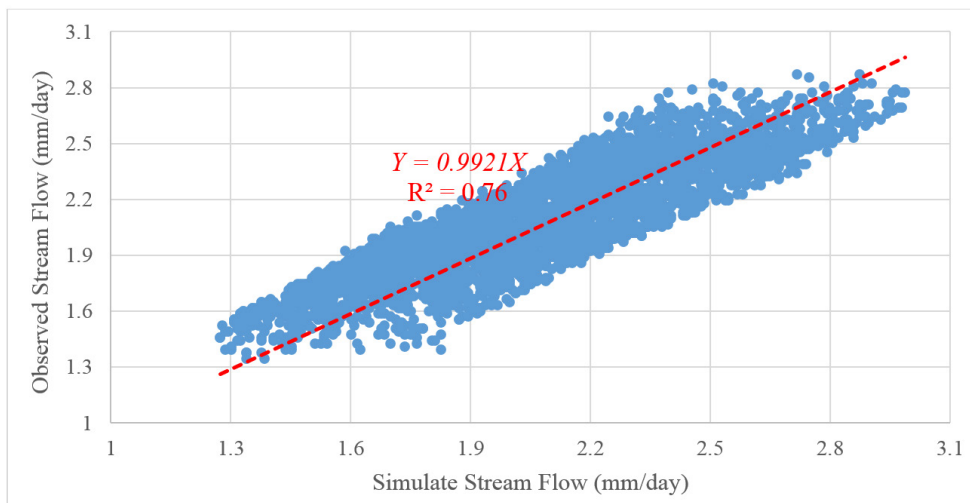


Figure 4. Comparison between daily observed (actual) and simulated (predicted) Bertam River runoff from 2003-2012.

CONCLUSION

In the present research, an Artificial Neural Network (ANN) was used to predict daily river runoff as a function of daily evapotranspiration and rainfall for the Bertam river stream flow coming into the Ringlet Reservoir in Cameron Highland, Malaysia. The back propagating learning rule was employed to train the network. The performance of the developed model was then evaluated by statistical evaluation measurements, such as the Nash-Sutcliffe Coefficient (E), Pearson Correlation of Coefficient (r), Root Mean Square Error (RMSE) and Mean Bias Error (MBE). The results indicated that ANN could capture the nonlinearity of rainfall-runoff modelling very well with 76% predictive power for simulation in hydrological models. The given results provide valuable information, which could help water resource managers to predict future stream flow into the reservoir, especially in extreme phenomena in order to mitigate the danger of damage. To improve the predictive power of the ANN model, it is recommended to include in the future other environmental factors as assessed parameters, such as deforestation, agricultural activities and land use.

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