International Journal of the Physical Sciences Vol. 6(8), pp. 1997-2003, 18 April, 2011
Available online at http://www.academicjournals.org/IJPS
DOI: 10.5897/IJPS11.314
ISSN 1992 - 1950 ©2011 Academic Journals

Full Length Research Paper

Performance of artificial neural network and regression techniques for rainfall-runoff prediction

A. El-shafie[1]*, M. Mukhlisin[1,2], Ali A. Najah[1] and M. R. Taha[1]

[1]Department of Civil and Structural Engineering, University Kebangsaan Malaysia, Malaysia.
[2]Department of Civil Engineering, Polytechnic Negeri Semarang, Indonesia.

Accepted 24 March, 2011

Different types of methods have been used in runoff prediction involving conceptual and empirical models. Nevertheless, none of these methods can be considered as a single superior model. Owing to the complexity of the hydrological process, the accurate runoff is difficult to be predicted using the linear recurrence relations or physically based watershed. The linear recurrence relation model does not attempt to take into account the nonlinear dynamic of the hydrological process. The Artificial Neural Network (ANN) is a new technique with a flexible mathematical structure that is capable of identifying complex non-linear relationships between input and output data when compared to other classical modelling techniques. Therefore, the present study aims to utilize an Artificial Neural Network (ANN) to predict the rainfall-runoff relationship in a catchment area located in a Tanakami region of Japan. The study illustrates the applications of the feed forward back propagation with hyperbolic tangent neurons in the hidden layer and linear neuron in the output layer is used for rainfall prediction. To evaluate the performance of the proposed model, three statistical indexes were used, namely; Correlation coefficient (R), mean square error (MSE) and correlation of determination (R^2). The results showed that the feed forward back propagation Neural Network (ANN) can describe the behaviour of rainfall-runoff relation more accurately than the classical regression model.

Key words: Rainfall-runoff, artificial neural network, linear regression.

INTRODUCTION

Hydrological modeling is a powerful technique of hydrologic system investigation for both the research hydrologists and the practicing water resources engineers involved in the planning and development of integrated approach for management of water resources. Prediction of runoff is one of the most useful hydrological systems. The prediction may be used to assess or predict aspects of flooding, aid in reservoir operation, or be used in the prediction of the transport of water born contamination (Jain, 1996). Rainfall-runoff models play an important role in water resource management planning and therefore, different types of models with various degrees of complexity have been developed for this purpose. Conceptual rainfall-runoff models usually incurporate interconnected physical elements with simplified forms and each element is used to represent a significant or dominant constituent hydrologic process of the rainfall-runoff transformation (O'Connor, 1997). Conceptual rainfall-runoff models have been widely employed in hydrological modeling. Some of the well-known conceptual models include the Stanford Watershed Model (SWM) (Crawford and Linsley, 1966), the Xinanjiang Model (Jain and Chalisgaonkar, 2000; Zhao, 1992; Zhao and Liu, 1995), the Soil Moisture Accounting and Routing (SMAR) Model [7, 8]. Although the modeling of runoff has been studied, many aspects of its dynamics are still unclear. The runoff dynamics is highly nonlinear and many useful statistical theories cannot be implemented.

River flow forecasting is an essential procedure that is necessary for proper reservoir operation. Accurate forecasting results in good control of water availability, refined operation of reservoirs and improved hydropower generation. Therefore, it becomes crucial to develop forecasting models for river inflow. Several approaches have been proposed over the past few years based on

*Corresponding author. E-mail: elshafie@vlsi.eng.ukm.my.

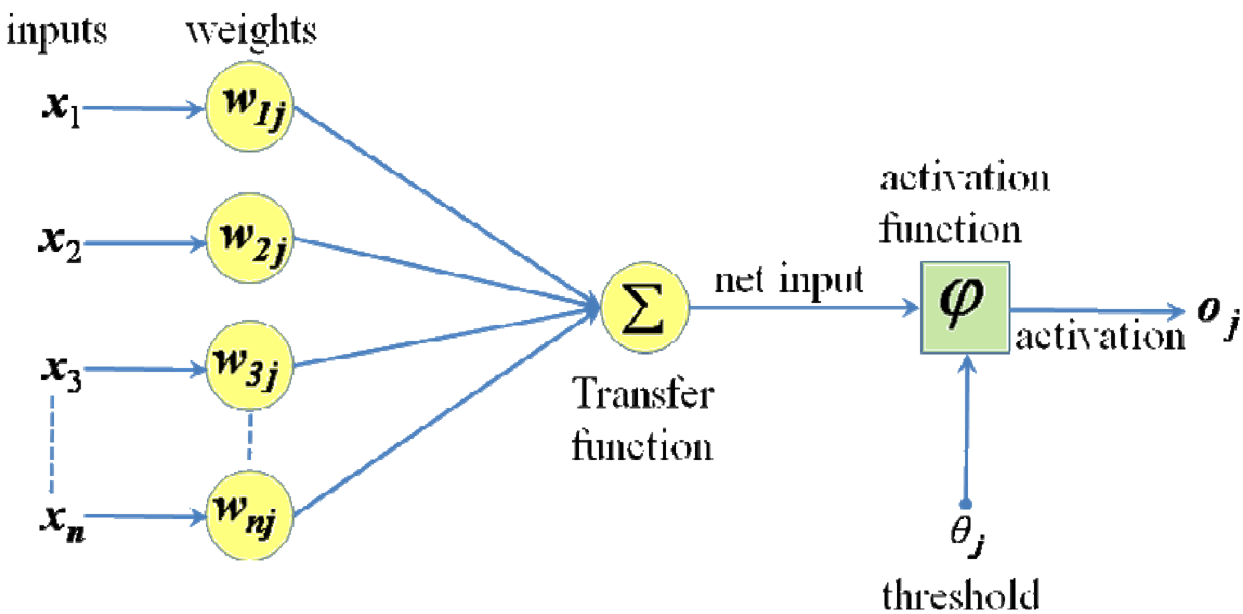


Figure 1. A typical multi-layer perceptron neural network architecture.

stochastic modeling or artificial intelligence (AI) techniques.

Artificial Neural Network (ANN) models have been used successfully to model complex non-linear input-output relationships in an extremely interdisciplinary field. The natural behavior of hydrological processes is appropriate for the application of ANN method. In recent years, ANNs have been used intensively for prediction and forecasting in a number of water-related areas, including water resource study (Najah et al., 2009; Ahmed et al., 2009; El-Shafie et al., 2007; 2008; 2009(a), 2009(b); 2010), prediction of evaporation (Sudheer et al., 2002), hydrograph simulator (Deka and Chandramouli, 2005; Lange, 1999), rainfall estimating (Hsu et al., 1999; Lin and Chen 2005; Luk et al., 2001). Hence, motivated by the successful applications in modeling non-linear system behaviors in a wide range of areas, this study demonstrated the application of Artificial Neural Network (ANN) to predict rainfall-runoff relationship in a catchment area located in a Tanakami region of Japan.

MATERIALS AND METHODS

Artificial Neural Network (ANN)

An artificial neural network (ANN) is tailored to mimic natural neural networks using a computing process (Haykin, 1999). Among many types of ANNs, the most widely used is the feed-forward neural network such as multi-layer perceptron (MLP) network with back-propagation training algorithm. The MLP is organized as layers of computing elements, known as neurons, which are connected between layers via weights. Apart from the input layer receiving inputs from the environment and the output layer generating the network's response, one or more intermediate hidden layers also exist.

Generally, forecasting models can be divided into statistical and physical based approaches. Statistical approaches determine the relationships between historical data sets, whereas physical based approaches model the underlying processes directly. MLP networks are closely related to statistical models and are the type of ANN most suited to forecasting applications (Rumelhart et al., 1986). When using ANNs for forecasting, the modelling philosophy employed is similar to that used in traditional statistical approaches. In both cases, the unknown model parameters (i.e. the connection weights in the case of ANNs) are adjusted to obtain the best match between the historical set of model inputs and the corresponding outputs.

These neural networks are commonly used in ecological studies because they are believed to be universal approximates of any continuous function. A neural network consists of at least three or more layers, which comprise an input layer, an output layer and a number of hidden layers, as shown in Figure 1. Each neuron in one layer is connected to the neurons in the next layer, but there are no connections between the units of the same layer. The number of neurons in each layer may vary depending on the problem. The weighted sum of the input components is calculated as follows (Freeman and Skapura, 1991):

$$Net_j = \sum_{i=1}^{n} W_{ij} + \theta_j \qquad (1)$$

where Net_j is the weighted sum of the jth neuron for the input data received from the preceding layer with n neurons, w_{ij} is the weight between the jth neuron and the ith neuron in the preceding layer, xi is the output of the ith neuron in the preceding layer and θj is the bias term of the jth neuron. The output of the jth neuron outj is calculated with a sigmoid function as follows:

$$out_j = f(Net_j) = \frac{1}{1 + e^{-Net_j}} \qquad (2)$$

The network is trained by adjusting the weights. The training process is done with a large number of training sets and training cycles (epochs). The main goal of the learning procedure is to find the optimal set of weights, which can ideally produce the correct output for the relative input. The output of the network is compared with the desired response to determine the error. The performance of the MLP is measured in terms of a desired signal and the criterion for convergence. For one sample, it is determined by the sum square error (SSE), expressed as follows:

$$SSE = \sum_{i=1}^{m} (T_i - out_i)^2 \tag{3}$$

Where Ti and outi are the desired (target) output and output of the neural network, respectively, for the ith output neuron, and m is the number of neurons in the output layer.

Performance criteria

To achieve desired optimal network model mean square error (MSE) correlation coefficient (R) and correlation of determination (R2) are used in current study. They are given by:

$$\mathrm{MSE} = \frac{\sum_{i=1}^{N}\left(\mathrm{Qt_i} - \widehat{\mathrm{Qt}}_i\right)^2}{\mathrm{N}} \tag{4}$$

$$\mathrm{R}^2 = 1 - \frac{\sum_{i=1}^{N}\left(\mathrm{Qt_i} - \widehat{\mathrm{Qt}}_i\right)^2}{\sum_{i=1}^{N}\left(\mathrm{Qt_i} - \bar{\mathrm{Qt}}_i\right)^2} \tag{5}$$

Where $\mathrm{Qt_i}$ and $\widehat{\mathrm{Qt}}_i$ denote actual value of flow and $\bar{\mathrm{Qt}}_i$ the mean of $\mathrm{Qt_i}$ values and N is the total number of data sets.

In the present study, the input and output variables are first normalized linearly in the range of 0 and 1, the normalization is done using the following equation:

$$\bar{X} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{6}$$

where $\bar{X}$ is the original data set is the standardized value of the input, X is the original data set, X_{min} and X_{max} are respectively, the minimum and maximum of the actual values, in all observations. The main reason for standardizing the data matrix is that the variables are usually measured in different units. By standardizing the variables and recasting them in dimensionless units, the arbitrary effect of similarity between objects is removed.

Study site description

In this study, the artificial rainfall test that has been done in the experimental slope is a completely bare slope located in Jakujo Rachidani of the Tanakami area, central Japan (35° N, 136° E) as shown in Figure 2. The basal area of the experimental slope is 30.1 m^2 with a slope length of 11.1 m and the mean gradient of 33.6°. The artificial rainfall applied within the area of 18 m^2 with a slope length of 4 - 5 m from the upper reach of the slope.

The catchment area is 0.18 ha with a mean slope gradient of 34.0°. The elevation ranges from 358 to 420 m above sea level. The soils are predominantly eroded, and consist of decomposed granite without an evident organic layer. Rainfall was measured in a forested catchment adjacent to the Jakujo Rachidani catchment. The ANN model was trained using the resulting runoff and rainfall each minute data from artificial rainfall test.

Rainfall simulator design

In this study, the artificial rainfall test was performed in collecting rainfall runoff data on November 10, 2001 (EX 1) and June 25, 2002 (EX2). The experimental test was provided by spray system consisting of an approximately 2 m high tower, two iron pipes equipped with nozzles spraying upward, a pump and three storage water tanks. The nozzle with pressure of 0.011 - 0.2 Mpa, supported with three storage water tank (500) and rainfall intensity, can be changed by turning off the valve attached to the pump (Table 1).

Data collection

The temporal changes of rainfall intensity were recorded by a tipping bucket type rain gauge placed on the boundary of the experimental slope. The total rainfall volumes were measured by eight milk packs with a surface area of 7.5 × 7.5 cm placed around the boundary.

Rainfall intensity was measured by the tipping bucket, and then revised by the ratio or the total amounts of rainfall recorded by the tipping bucket to the mean value of total rainfall volumes collected by the milk packs. Water discharge was collected in a tank (width × length × height; 40 × 75 × 40 cm) at the outlet of the experimental slope, and runoff rates were recorded by passing runoff through a tipping bucket from the tank.

RESULTS AND DISCUSSION

The data in neural networks can be categorized into two sets: training sets and test sets. The training set is used to determine the adjusted weights and biases of a network. The test set is used for calibration, which prevents networks from being over trained. The general approach for selecting a good training set from available data series involves including all of the extreme events (that is, all possible minimum and maximum values in the training set).

In this study, the data were divided into two sets. The first set contained 70% of the data set used as the training set and the second test contained 30% of the data set used as the testing set. Moreover, one of the most important characteristics of ANN is the number of neurons in the hidden layer. If an insufficient number of neurons are used, the network will be unable to model the complex data and the resulting fit will be poor. On the contrary, if too many neurons are used, the training time may become excessively long and the network may over fit the data. In this study, the number of neurons needed in the hidden layers to achieve the precision criteria was generally determined by trial and error approach. The training of the ANN was performed with a variation of 1 - 20 neurons. In this study, 17 neurons were selected as the best number of neurons.

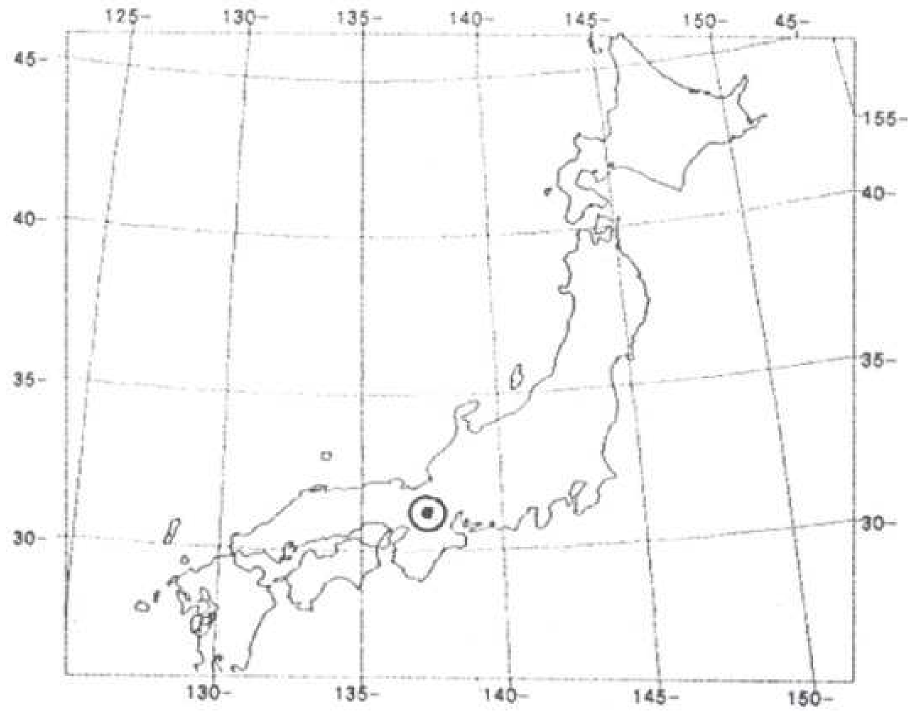


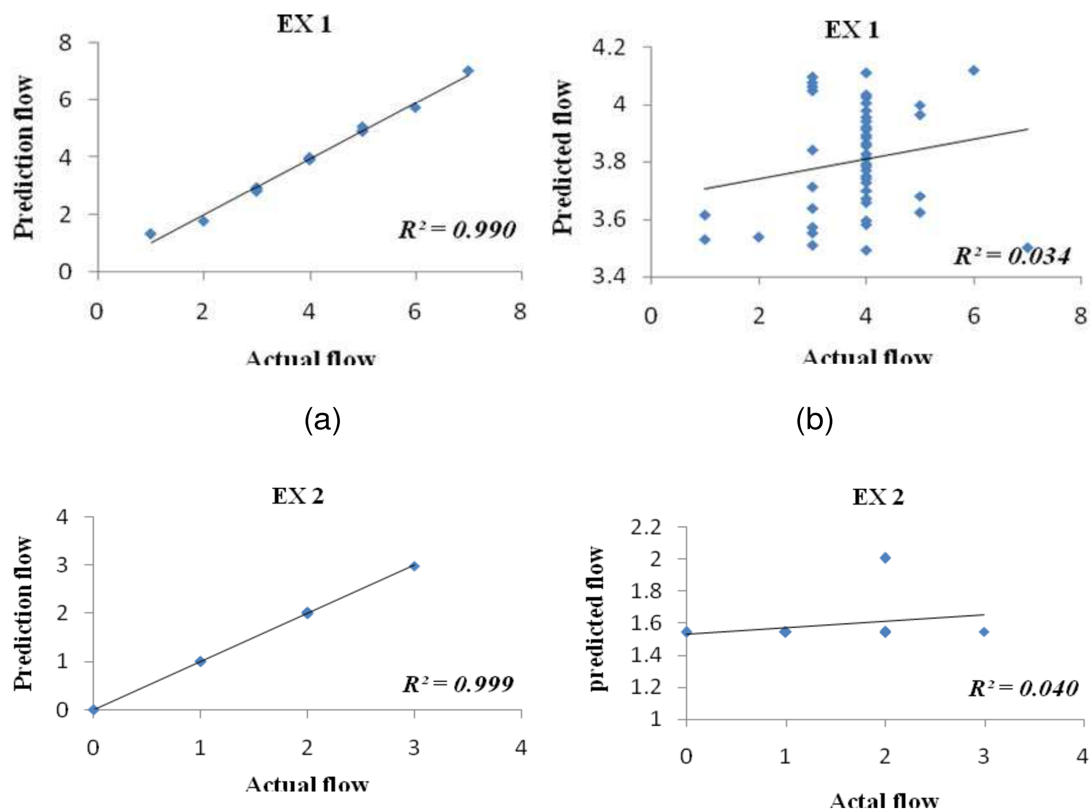
Figure 2. Location of Tanakami catchment, Japan.

Table 1. Summary of each experimental detail.

Details	EX 1	EX 2
Spraying system	Japan	Japan
Number of nozzle	8	6
Cone nozzle	B 1/4 HH-10	B 1/4 TT-SS+TG-2.8 W HH-10
Orifice diameter	3.18 mm	1.6 mm
Raindrop	2-3 mm diameter at 0.2 Mpa	1-2 mm diameter at 0.2 Mpa

The proposed architecture to predict runoff is tested after optimal parameters were select based on the procedure discussed in the previous paragraph. Figures 3, 4 and 5 illustrate the comparison between the predicted versus actual flow using 45° line of graph. The results show high accuracy in EX 2 compare to EX1. In addition the number of data in EX 2 is smaller than EX 1. It can be observed that ANN was more adequate than MLR for both phases. It is evident that the ANN is a new technique with a flexible mathematical structure that is capable of identifying complex non-linear relationships between input and output data when compared to other classical modeling techniques.

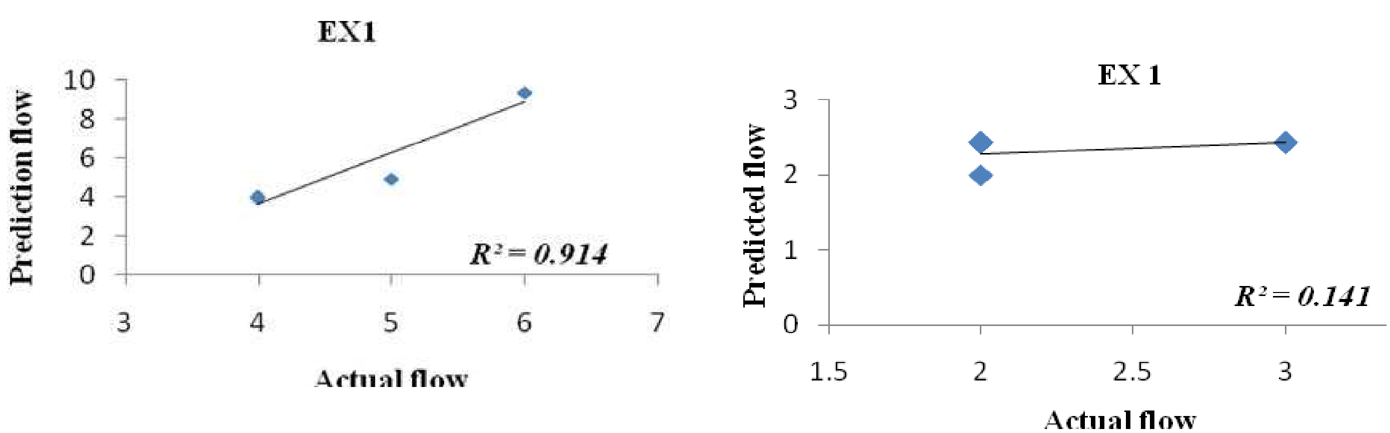
The correlation coefficient (R), mean square error (MSE) and correlation of determination (R^2) computed for training and testing data sets used for the two phases are presented in Table 2. Examining Table 2 carefully, it can be observed that ANN was more adequate than MLR, where R was determined to be (EX1 = 0.99, 0.95; EX2 = 0.99, 0.99) for the training data set and testing set respectively when utilized ANN while, R was determined to be (EX1 = 0.18, 0.49; EX2 = 0.2, 0.37) for the training data and testing set respectively when utilized MLR. These results figured out that the ANN model could effectively capture non-linearity in the input/output mapping than the MLR. However, the methodology of ANN model development for rainfall-runoff relationship has proved its efficacy, it should be emphasized that there are no structured methods today to identify what network structure can be best approximate the function, mapping the inputs to outputs. In addition, pre-processing for the data is essential step for runoff prediction model and required more survey and analysis that could lead to better accuracy in their application. Moreover, the optimal selection of the key parameter still required to be achieved by augmenting the ANN model with other optimization model such as genetic algorithm or particle swarm optimization methods. Therefore, further



(a) (b)

(c) (d)

Figure 3. The performance ANN and MLR for two phases during the training process: (a) ANN-EX1; (b) MLR-EX1; (c) ANN-EX2; (d) MLR-EX2.



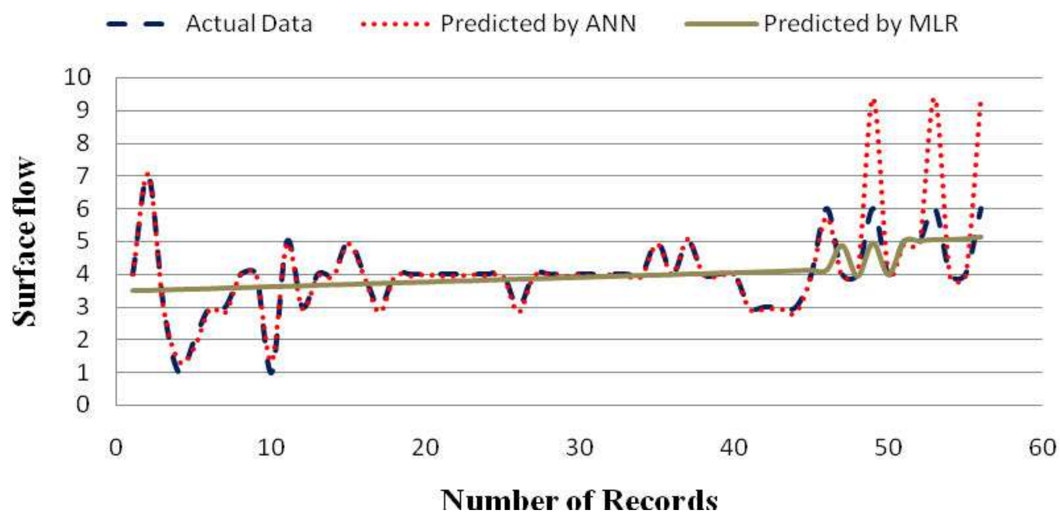
(a) (b)

Figure 4. The performance ANN and MLR for one phase during the testing process: (a) ANN-EX1; (b) MLREX1.

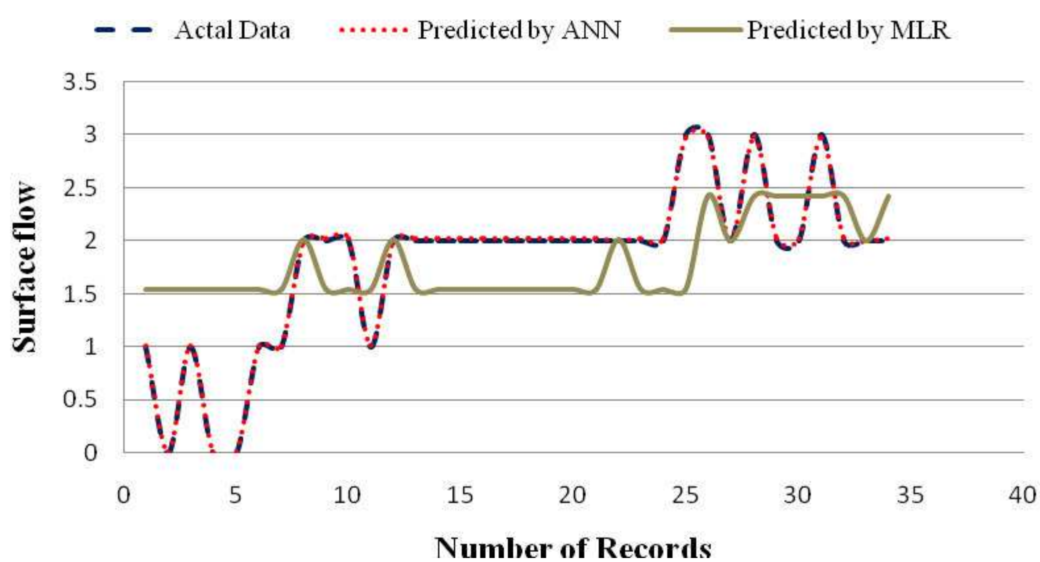
discussion on the effect of augment the ANN model with optimization model for specific applications is beyond the scope of this study.

Conclusion

The Artificial Neural Network (ANN) models show an



(A)



(B)

Figure 5. Comparison of ANN, MLR models and actual flow for phase (A) EX1 and (B) EX2.

Table 2. Statistical accuracy measures of this network model at testing and training in EX1 and EX2.

Phase	Model	Process	MSE	R	R2
EX1	ANN	Training	8.38E-05	0.9967	0.99
		Testing	6.70E-04	0.9564	0.9147
	MLR	Training	1.0369	0.1854	0.034
		Testing	0.1736	0.4906	0.2407
EX 2	ANN	Training	6.12E-05	0.9995	0.999
		Testing	2.24E-04	0.9978	0.999
	MLR	Training	0.5841	0.2011	0.04
		Testing	0.2454	0.3757	0.1411

appropriate capability to model hydrological process. They are useful and powerful tools to handle complex problems compared with the other traditional models. In this paper, ANN model was developed to predict rainfall-runoff relationship in a catchment area located in a Tanakami region of Japan. ANN structure has been designed and trained using the MATLAB Neural Network Toolbox. The results and comparative study indicate that the artificial neural network method is more suitable to predict runoff than classical regression model MLR. This result shows that it is difficult to produce a reliable model with conventional modeling approaches due to the high variance and inherent non-linear relationship of rainfall-runoff and the complexity of the hydrological process. The proposed approach can be a very efficient tool and useful alternative for the computation of rainfall-runoff relationship.

In fact in the current research, the comparison analysis might not be sufficiently performed as long as the architecture of the ANN differs than the ARMA model. Therefore, for future research an enhancement for the current ARAM model would be proposed to be relatively similar to ANN model in order to carry out the comparison analysis in tolerable manner. Indeed, there is a potential for enhancing the classical ARMA model. In spite of the comparative analysis carried out in this study showed that the proposed neural network model significantly out-performed the ordinary ARMA model, better formulation of ARMA model might lead to successful forecasting skills. As a result from the correlation analysis, an identification and simulation techniques based on a periodic ARMA (PARMA) model to capture the inter-relation between rainfall-runoff behavior could be developed. In addition to the correlation analysis, there are a certain principles that should be considered while developing the PARMA model including the marginal distribution of the process, the long-term dependence of the process, and the linearity in lagged in the rainfall-runoff process.

ACKNOWLEDGEMENTS

This research was supported by the research grant for the first author from University Kebangsaan Malaysia UKM-GUP-PLW-08-13-308 and (01-01-02-SF0570) grant from the Ministry of Science, Technology and Innovation (MOSTI) of Malaysia. In addition, this work was supported by grant from the Ministry of Science, Technology and Innovation (MOSTI) of Malaysia (01-01-02-SF0570).

REFERENCES

Ahmed AN, Elshafie A, Karim O, Jaffar O (2009). Evaluation the efficiency of Radial Basis Function Neural Network for Prediction of water quality parameters. Eng. Intelligent Syst., 17(4): 221-231.

Crawford NH, Linsley RK (1966). Digital Simulation in Hydrology: Stanford Watershed Model IV, Technical Report 10-Department of Civil Engineering, Stanford University, Stanford, CA.

Deka P, Chandramouli V (2005). Fuzzy neural network model for hydrologic flow routing. J. Hydrol. Eng., 10(4): 302–14.

El-Shafie A, Reda TM, Noureldin A (2007). A Neuro-Fuzzy Model for Inflow Forecasting of the Nile River at Aswan High Dam. Water Res. Manage., 21(3): 533-556.

El-Shafie A, Noureldin AE, Taha MR, Basri H (2008). Neural network model for Nile River inflow forecasting based on correlation analysis of historical inflow data. J. Appl. Sci., 8 (24): 4487-4499.

El-Shafie A, Alaa EA, Noureldin A, Mohd RT (2009a). Enhancing Inflow Forecasting Model at Aswan High Dam Utilizing Radial Basis Neural Network and Upstream Monitoring Stations Measurements. Water Res. Manage., 23(11): 2289-2315.

El-Shafie A, Najah AA, Karim O (2009b). Application of neural network for scour and air entrainment prediction. International Conference on Computer Technology and Development. Art. no., 5360151: 273-277

El-Shafie A, Noureldin A (2010). Generalized versus non-generalized neural network model for multi-lead inflow forecasting at Aswan High Dam. Hydrol. Earth Syst. Sci. Discussions, 7(5): 7957-7993

Haykin S (1999). Neural Networks: Comprehensive Foundation. Upper Saddle River, N.J, USA: Prentice-Hall.

Hsu KL, Gupta HV, Gao X, Sorooshian S (1999). Estimation of physical variables from multichannel remotely sensed imagery using a neural network: application to rainfall estimation. Water Resour. Res., 35(5): 1605–18.

Jain MK (1996). GIS based rainfall, runoff modeling for Hemavathi Catchment. NIH Report CS/AR-22/96-97, National Institute of Hydrology, Roorkee.

Jain SK, Chalisgaonkar D (2000). Setting up stage-discharge relations using ANN. J. Hydrol. Eng., 5(4): 428-433.

Lange NT (1999). New mathematical approaches in hydrological modeling an application of artificial neural networks. Phys. Chem. Earth (B), 24(1–2): 31–35.

Lin GF, Chen LH (2005). Application of an artificial neural network to typhoon rainfall forecasting. Hydrol. Process, 19: 1825–37.

Luk KC, Ball JE, Sharma A (2001). An application of artificial Neural networks for rainfall forecasting. Math. Comput. Modell., 33: 683–93.

Najah A, Elshafie A, Karim OA, Jaffar O (2009). Prediction of johor river water quality parameters using artificial neural networks. Euro. J. Sci. Res., 28(3): 422-435.

O'Connor KM (1997). Applied hydrology Ideterministic. Unpublished Lecture Notes. Department of Engineering Hydrology, National University of Ireland, Galway.

Rumelhart DE, Hinton GE, Williams RJ (1986). Learning representations by backpropagating errors. Nature, 323: 533–536.

Sudheer KP, Gosain AK, Rangan DM, Saheb SM (2002).Modelling evaporation using an artificial neural network algorithm, Hydrol. Process. lfi, 3189-3202.

Zhao RJ (1992). The Xinanjiang model applied in China. J. Hydrol., 135: 371-381.

Zhao RJ, Liu XR (1995). The Xinanjiang model. In: Singh, V.P. (Ed.), Computer Models of Watershed Hydrology. Water Resources Publications, Littleton, CO.