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SEMI-DISTRIBUTED NEURAL NETWORK MODELS FOR STREAMFLOW PREDICTION IN A SMALL CATCHMENT PINANG

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Abstract

This paper applied an artificial intelligence methodology for streamflow prediction in a flash flood in Pinang catchment based on TOPMODEL input and output data sets. TOPMODEL is a semi-distributed rainfall runoff model widely used in numerous water resource applications. However, literature has indicated relative weakness in TOPMODEL performances in streamflow prediction. Thus, radial basis function neural network (RBF-NN) has been employed to improve the accuracy of streamflow prediction and then compared with TOPMODEL and multilayer perceptron neural network (MLP-NN) performances. Four years of daily hydro-meteorological data sets (for the period between 2007 to 2010) were used for calibration and validation analysis. The results have shown an improvement from 0.749 and -19.2 of the calibration period to 0.957 and 0.001, and from 0.774 and -19.84 of the validation period to 0.956 and -3.611 of Nash-Sutcliffe model (NS) and Relative Volume Error (RV_E), respectively. RBF-NN performance has been established to improve the daily streamflow prediction; however, the MLP-NN was better in contrast with the involved method in the study. It can be concluded that TOPMODEL performance showed a high ability to simulate the peaks compared with both AI methodologies.

Key words: flash flood catchment, Malaysia, radial basis function, streamflow prediction, TOPMODEL

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1. Introduction

Steamflow prediction is considered one of the main subjects of hydrological research (Awchi Taymoor, 2014). It is a very important issue in Malaysia, especially in flash flood areas such as the small Pinang catchment in Malaysia. In such areas, streamflow prediction is difficult due to its quick nature. The flash floods which results in significant loss of lives and property are caused by heavy rainfall pounding on such a small-sized area which is transformed quickly into runoff, in addition to the sloped area and small cross-section capacity of the river (Suliman et al., 2014). Rainfall runoff models are classified as physically based, conceptual or empirical models (Chow et al., 1988; Todini, 1988; Refsgaard and Knudsen, 1996). General classifications are basically built based on two factors, i.e. a) physical representation principles employed in models and b) parameterized information as well as simulated data set inputs to the model. Generally, rainfall runoff models have shown a high ability to provide basic streamflow pattern information (Güntner et al., 1999), which may further help to control and manage water resources, and help to predict the occurrence of floods in the future through enabling better preparation. Suliman et al. (2016) stated that an accurate rainfall runoff model is still a serious concern to most hydrologists and water resource engineers, as such a model is required to better enable streamflow prediction. Artificial Intelligence (AI) methods are well-known in solving such complex nonlinear

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rainfall runoff relationships as complex hydrological phenomenon, especially in tropical developing countries because of the limitation of required hydrological parameters and the scarcity of the spatial landform data (Abinashi et al., 2011; Mutua and Klik, 2007). AI methods may become alternatives for streamflow prediction (Kişi et al., 2012).

Artificial Intelligence (AI) modeling has become a popular technique for modeling complex precipitation discharge relationship (Dawson et al., 2005; Kueh and Kuok, 2018; Singh and Woolhiser, 200; Zhang et al., 2018), and is experiencing rapid development (Solomatine and Ostfeld, 2008). Among many non-parametric AI methods, multi-layered perceptron neural network (MLP-NN) and radial basis function neural networks (RBF-NN) are commonly utilized in rainfall runoff modeling. Irrespective of the parameters which reflect the system these methods have a proven ability to estimate the system model as a black box identification method based on a series of sample datasets. According to Solomatine (2005), the procedure for modeling a dynamic system through system identification approaches can be done by the following steps: state the problem; what result can be expected; input and output variable selection; choosing the specific software and algorithms; data preparation and pre-analysis; model calibration; model testing and finally model application and evaluation.

RBF-NN has been applied in the prediction of time series issues and flow forecasting (Awchi Taymoor, 2014; Harun et al., 2002; Irwan et al., 2007; Kumar et al., 2005; Lin and Chen, 2004). MLP-NN has been successfully applied for daily and hourly time series for flood forecasting (Wright and Dastorani, 2001), water level prediction (Patrick et al., 2002; Sulaiman et al., 2011), streamflow prediction (Bustami et al., 2007; Dastorani and Wright, 2001; Wang et al., 2006), rainfall estimation (Gosav and Tiron, 2012) and rainfall-runoff modeling (Agarwal and Sing, 2004; El-Shafie et al., 2011; Garbrecht, 2006; Gautam et al., 2000; Harun et al., 2002; Kumar et al., 2005; Rajurkar et al., 2002).

Kumar et al. (2005) presented a comprehensive evaluation of two types of ANN rainfall runoff model performance, MLP and RBF in terms of the characteristics of the predicted hydrographs and their uncertainty. The study concluded that the RBF model was trained better than MLP. Agarwal and Singh (2004) developed a rainfall runoff model using ANN with multi-layer back propagation. The objective was to simulate the rainfall runoff process using long term rainfall data to generate long term flow records at two different catchments of Narmada River in India. Irwan et al. (2007) applied RBF-NN at two different catchment areas located in Johor and Kedah, Malaysia for simulating the rainfall runoff relationship. Results indicated that RBF can predict runoff with minimum deviation compared to ANN method. Rajurkar et al. (2002) applied ANN methodologies for rainfall runoff modeling at a large catchment in Madhya Pradesh in India.

Multiple input-single output techniques (MISO) of ANN used to represent the rainfall runoff relationship during the monsoon flood event showed that MISO produced a high accuracy predict runoff. Sulaiman et al. (2011) designed an ANN model to test the accuracy of water level forecasts of Rantau Panjang station of Johor River, Malaysia. El-Shafie et al. (2011) employed ANN methods to predict runoff at the Tanakami region catchment, Japan. The application of feed forward back propagation was employed with hyperbolic tangent transfer function for the hidden layer and linear function for the output layer. It is found that the most important characteristic of ANN is the number of neurons in hidden layer. The result showed that ANN models are capable, useful and powerful tools to deal with complex processes which comprise the rainfall runoff relationship. MLP and RBF were adopted by Harun et al. (2002) to predict daily runoff as a response to daily rainfall at several rivers located in Selangor, Malaysia. The result showed that RBF method trained much faster and more accurately than MLP. It is also noted that the application of neural network methods are feasible in terms of rainfall-runoff modeling in Malaysia. Sahoo and Ray (2006) found that compared with RBF, MLP technique in daily flow prediction of a flash Hawaiian stream was superior.

Another comparison in daily streamflow estimation by Sudheer and Jain (2003) found large deviation from the observed data sets for MLP technique against RBF. Awchi (2014) investigated and evaluated MLP and RBF flow forecasting at two tributaries of Tigris River in Northern Iraq. In comparison, MLP technique performance was superior to RBF in monthly data-based flow forecasting. In this study, two types of artificial intelligence (AI) methodologies have been investigated for streamflow prediction of the main river in a flash flood tropical catchment of Penang Island. These methodologies are MLP-NN and RBF-NN to create an accurate model utilizing the inputs and output of a semi distributed TOPMODEL, which had been applied in a previous study by Suliman et al. (2014). Consequently, evaluating applicability through examination of the performance improvement of MLP-NN and RBF-NN in streamflow simulation is explored and then compared with TOPMODEL. This study might be useful as one of essential component of warning system against flash flood to serve the safety of Penang the most economically developed region in Malaysia.

2. Material and methods

2.1. Study area

The flash flood of tropics Pinang basin located in the northern part of Penang Island is investigated. It has size of 34 km^2 (Fig. 1) with mean annual rainfall ranging from (1800-3000) mm, its geographical coordinates are 100º 14' to 100º 19' E longitude and 5º 21' to 5º 26' N latitude.

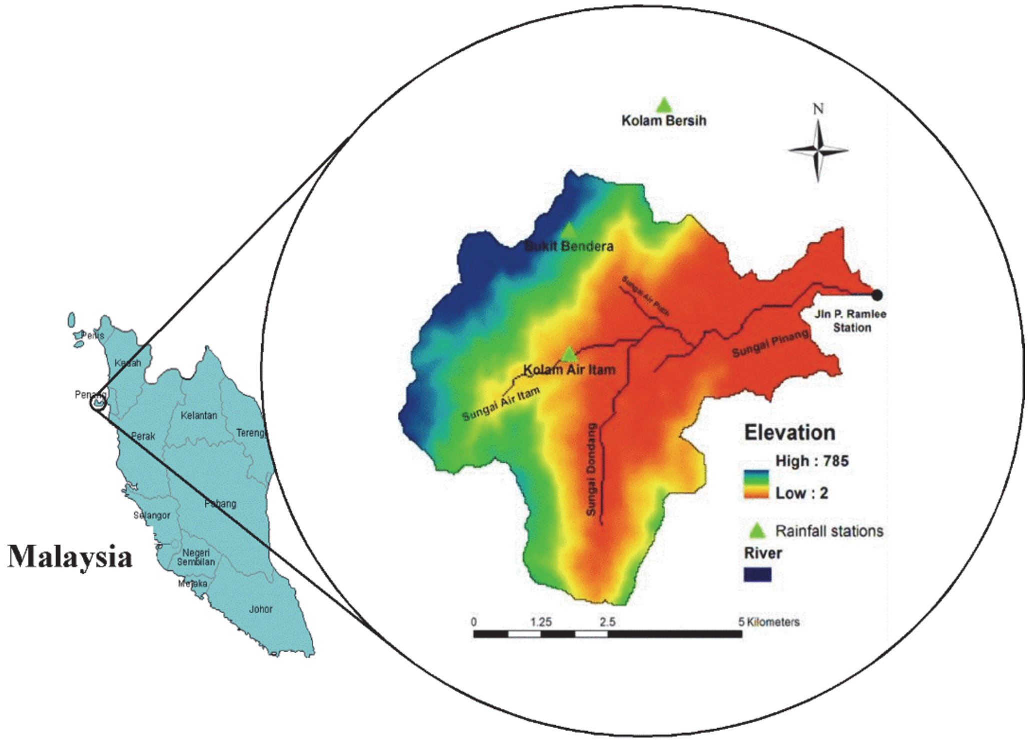


Fig. 1. Pinang catchment, Malaysia

Table 1. Statistics of datasets used for TOPMODEL, are involved for RBF-NN and MLP-NN

Statistics	***Overall datasets***		***Calibration***		***Validation***	
	Q	***R***	***Q***	***R***	***Q***	***R***
Minimum	0.00	0.00	0.00	0.00	0.00	0.00
Maximum	0.02	0.12	0.02	0.12	0.02	0.11
Mean	0.0049	0.0077	0.0048	0.0078	0.0051	0.0076
Median	0.0047	0.0014	0.0045	0.0019	0.0049	0.0008
StdV.	0.00131	0.01486	0.00120	0.01415	0.00141	0.01555
Skewness	2.467	3.479	2.315	3.584	2.521	3.389

Daily hydro-meteorological datasets (inputs and outputs) were collected from Department of Irrigation and Drainage (DID), Malaysia. The catchment outlet, the gauging station of Jalan P.Ramlee, is where the discharge dataset is measured. The water level datasets for year 2007-2010 were provided to be used for calibration and validation processes. The three stations, Kolam Bersih, Bukit Bendera, and Kolam Air Itam, were used for rainfall calculation to provide TOPMODEL input as shown in Fig. 1. Based on the required potential datasets for TOPMODEL, Table 1 shows the statistics as entire, training and validation of discharge (Q) and Rainfall (R) of Pinang River.

2.2. TOPMODEL

TOPMODEL application at small basins was recommended as stated by Beven et al. (1984). TOPMODEL is represented based on three interconnected layers are root zone, unsaturated zone and saturated zone (Fig. 2). The infiltration Q occurs after the maximum storage ($SRmax$) is filled at root zone. This zone contributes to the surface runoff at saturation condition. Evaporation at the potential rate is allowable till the store become empty.

In gravity drainage, an incremental leakage rate with a constant through time Qv is taking place from this zone to the third storage which is not saturated and can be given by $\sum A_i Q_{vi}$ where, A_i is the contributing area weighted by the TI distribution (Romanowicz, 1997).

Evaporation from this zone is assumed at potential rate and the falling will become an overland runoff flow at the saturated area. TOPMODEL assumptions are reported by Beven, (1997) suggest that as the local surface topographic slope can be similar to the local hydraulic gradient, an exponential relationship between the declines of transmit-ability with depth and recharge through the catchment with quasi steady-state condition is assumed to be uniform. The relationship of the saturated zone with the subsurface drainage Q_b and the steady distribution of the soil moisture deficit based on the TI, see (Beven et al., 1994) for more detailed description of the TOPMODEL. This study focuses on the development of the AI-NN models within Matlab environment to train the TOPMODELs' input and output data sets.

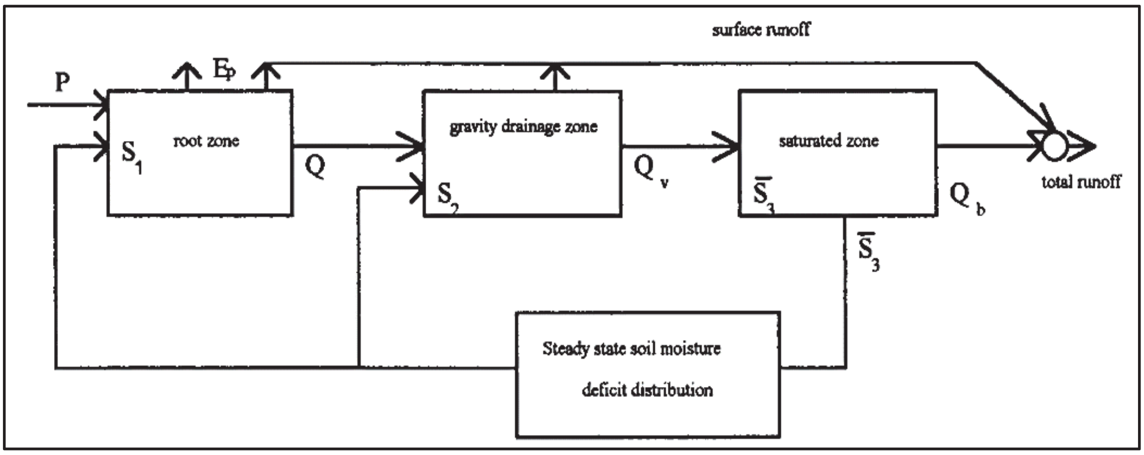


Fig. 2. TOPMODEL scheme represents the three zones (Romanowicz, 1997)

2.3. AI Methodologies and adopted method

AI methodologies are flexible structures modeled mathematically to be capable of identifying complex non-linear relationships (Mokhtari et al., 2013) such a rainfall runoff without understanding the nature of the phenomena. RBF-NN and MLP-NN as common artificial intelligence methodologies are used to supervise the networks. RBF-NN is the neural network modeling method adopted in this study. It is a feed forward neural network containing three layers, one of each input, hidden and output layers (Piotrowski et al., 2006). The hidden layer contains a number of nodes as well as the centers (weight vector) as internal parameters. The performance of RBF is based on the selection of centers, particularly how to conduct selection in the presence of a huge number of parameters. The MLP-NN model structure investigated in a previous study also contained a three layer structure with one input, one hidden and one output layer. Fig. 3 illustrates the architecture design of the RBF-NN and MLP-NN.

Investigation of the parameters (scaling parameters and centers) and the weights between the hidden layer and the output layer are the two stages to find best-fit train of RBF-NN. Learning and training RBF-NN is known by finding the weights and centers based on the inputs and outputs of the network. These processes are used to adjust the weight values through trial and error. In addition, the objective is to minimize the error between the simulated and the observed. Numerous learning algorithms can be employed within Matlab environment. One of the common nonlinear transfer functions of RBF-NN used to rule the nodes is Gaussian. This transfer function is decreased with distance from the center. It is assumed to be an approximation with the effect owned by data points at the center. In RBF network, the Euclidean (r_j) which is the radial distance between the radial centers (Y^j) = ($w_{1j}, w_{2j}, \dots, w_{mj}$) and the datum vector y= ($y_1, y_2, \dots, y_m$) is given according to Irwan et al. (2007) Eqs. (1-4) etc.

$$r_j = (y - Y^j) = \left[\sum_{i=1}^{m}(y_i - w_{ij})^2\right]^{\frac{1}{2}} \quad (1)$$

After applying a specific transfer function, it can be given by:

$$\Phi(r_j) = \phi(y - Y^j) \quad (2)$$

where Φ represent the transfer function used is Gaussian can be given by:

$$\Phi = exp\left(-\frac{\|X - Y^j\|^2}{\sigma}\right) \quad (3)$$

where X represents any input variable, σ is a value to be optimized during training period. The final stage at the output layer ($k=1$), the linear combination of the weights given as:

$$y^k = w_o + \sum_{j=1}^{n} c_{kj}\,\phi_{(rj)} = w_o + c_{kj}\phi\,(\|y - Y^j\|) \quad (4)$$

Fig. 4 shows the training algorithm for RBF-NN which has been adopted to train MLP-NN. It includes the input layer which contains two inputs (TOPMODEL inputs) represented by $x(t)$, and $y(t)$ is the TOPMODEL output which was considered as input to train the RBF-NN model based on the illustrated algorithm. First, the TOPMODEL prediction method is used to find the optimal configuration of each delay time and number of neurons (Suliman et al., 2017). The data sets from the calibration period (2007-2008) were used to train the RBF-NN model. Next, the trained model is validated using the years (2009-2010). However, model efficiency was calculated for all processes using three factors which are Nash Sutcliffe (NS) (Nash and Sutcliffe, 1970), Relative Volume Error (RV_E) (Janssen and Heuberger, 1995) and Relative Error (RE) Eqs. (5-7) respectively.

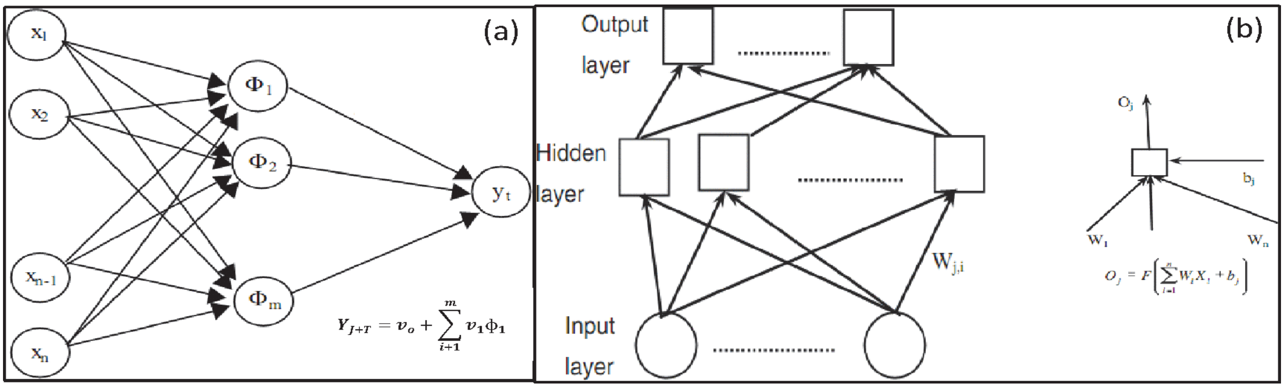


Fig. 3. (a) RBF-NN model structure, (b) MLP-NN structure with single hidden layer and schematic diagram of the neuron (Awchi, 2014)

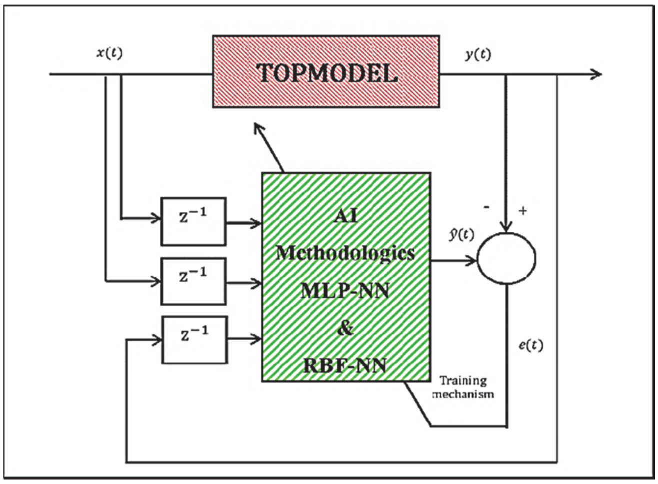


Fig. 4. AI-NN training algorithm to calibrate TOPMODEL's data sets

$$NS = 1 - \frac{\sum_{i=1}^{n} (Q_{sim,i} - Q_i)^2}{\sum_{i=1}^{n} (Q_i - \overline{Q})^2} \quad (5)$$

$$RV_E = \left[\frac{\sum_{i=1}^{n} Q_{sim,i} - Q_{obs}}{\sum_{i=1}^{n} Q_{obs}} \right] * 100\% \quad (6)$$

$$RE = \frac{1}{N} \sum_{t=1}^{N} \frac{Q_{sim} - Q_{obs}}{Q_{obs}} \quad (7)$$

where n is the total number of time steps, Q_{obs}, Q_{sim}, $\overline{Q}_{obs}$, $\overline{Q}_{sim}$ are observed and simulated discharges and their means, respectively.

3. Results and discussion

3.1. Calibration and validation periods

The extracted input and output based on TOPMODEL using daily data sets of years 2007-2008 were involved in order to train TOPMODEL-RBF-NN. The algorithm (NEWRB) provided by Matlab toolbox was used in this regard. Minimizing the deviation compared with the observed data is the algorithm target for training processes. Specified inputs and output, the neurons to be added between displays, maximum number of neurons and the default goal are required for training. TOPMODEL-RBF-NN has a fixed number of layers; however, only parameter used for sensitivity analysis is the spread factor. A large spread value means several neurons are required to fit a fast-changing function and vice versa. The training is conducted after specifying the input and output sets, the default goal equaled (zero), maximum number of neurons and the neurons to be added between displays. On that basis, the calibration and validation processed results of TOPMODEL-RBF-NN are presented in Table 2 and 3.

All created models from changing the spread factor values were evaluated at training and calibrating periods. TOPMODEL-RBF-NN shows a high performance over all trained models. In this regard, all created TOPMODEL-RBF-NN models are used for validation processes. The spread factor is then set to that which gives the best performance. The relationship between NS and RV_E efficiencies with different spread factors are illustrated. Both processes have shown good and approximate results in terms of NS and RV_E, making it difficult to choose the optimal configuration for TOPMODEL-RBF-NN. From Table 4 it can be seen that the optimal configuration featured a spread factor of 0.7. All other trained models indicated satisfactory values to be trained and verified. Fig. 5 and 6 illustrated the final result from the new simulation improvement compared with the original TOPMODEL simulation from previous study (Suliman et al., 2014) and TOPMODEL-MLP-NN from (Suliman et al., 2017). Overall performance of both periods compared to that found during the application of the new method shows a high ability to be matched with the observed streamflow as shown in Table 4. The model is then considered to be well performed. But, performance of modeling tends to underestimate high streamflow simulation for both calibration and validation periods of each TOPMODEL-RBF-NN and TOPMODEL-MLP-NN as shown in Fig. 7.

3.2. Peak flow Examination

The investigation of peak flows in water planning and management issues is essential. RBF-NN prediction performance which was adopted in this study is explored and compared to TOPMODEL and MLP-NN from previous studies (Suliman et al., 2014; Suliman et al., 2017).

In this regard, flows of 12 and 14 representing calibration and validation periods, respectively, comprise the 26 maximum flows of the observed data set. Fig. 8 shows the peaks selected from observed data set for calibration period and the predictions of TOPMODEL, TOPMODEL-MLP-NN as well as the TOPMODEL-RBF-NN involved in this study. Generally, Fig. 8 reveals that the predictions are contrary compared with the observed. It is also shown that TOPMODEL and TOPMODEL-MLP-NN peak predictions are very close to each other unlike TOPMODEL-RBF-NN, which shows some weakness.

Over all models, the underestimation of peak predictions obviously appeared at peak numbers (1, 4-10) reflecting a weakness to meet the observed peaks. The RE predictions for the 12 peaks were 28.3 %, 26.5 % and 42.1 % for TOPMODEL, TOPMODEL-MLP-NN, and TOPMODEL-RBF-NN, respectively. On the other hand, in Fig. 9 is shown the peaks selected from observed data set for validation period and the predictions of TOPMODEL, TOPMODEL-MLP-NN as well as the TOPMODEL-RBF-NN. It is shown that TOPMODEL peak predictions are relatively very close to the observed peaks. TOPMODEL-RBF-NN performed better at peaks number (2-6) compared with TOPMODEL-MLP-NN, which was the best for the rest of the peaks.

Table 2. Results of calibration period based on different Spread factor

SPREAD FACTOR	*NS*	*RV_E*	*SPREAD FACTOR*	*NS*	*RV_E*
0.1	0.959	-1.3E-05	1.1	0.957	7.37E-06
0.2	0.958	1.05E-06	1.2	0.957	1.05E-05
0.3	0.958	4.79E-05	1.3	0.957	1.63E-05
0.4	0.957	-1.4E-06	1.4	0.957	-2.9E-06
0.5	0.958	0.00011	1.5	0.957	1E-06
0.6	0.957	4E-05	1.6	0.957	1.84E-05
0.7	0.957	6.42E-06	1.7	0.957	1.17E-06
0.8	0.957	7.84E-06	1.8	0.957	-1.4E-05
0.9	0.957	3.86E-06	1.9	0.957	1.97E-07
1	0.957	4.66E-06	2	0.957	5.6E-06

Table 3. Results of validation period based on the same Spread factor from calibration period

SPREAD FACTOR	*NS*	*RV_E*	*SPREAD FACTOR*	*NS*	*RV_E*
0.1	0.162	-0.09883	1.1	0.956	-0.03619
0.2	0.936	-0.0452	1.2	0.956	-0.03621
0.3	0.938	-0.046	1.3	0.956	-0.0362
0.4	0.950	-0.04009	1.4	0.956	-0.03658
0.5	0.943	-0.04211	1.5	0.956	-0.0365
0.6	0.949	-0.03834	1.6	0.956	-0.03652
0.7	0.956	-0.03611	1.7	0.955	-0.03663
0.8	0.955	-0.03705	1.8	0.956	-0.03666
0.9	0.956	-0.03623	1.9	0.955	-0.03676
1	0.956	-0.03618	2	0.955	-0.03667

Table 4. Results obtained from calibration and validation processes

Model	*TOPMODEL*		*TOPMODEL-RBF-NN*		*TOPMODEL-MLP-NN*	
Periods	*Calibration*	*Validation*	*Calibration*	*Validation*	*Calibration*	*Validation*
	2007-2008	2009-2010	2007-2008	2009-2010	2007-2008	2009-2010
NS	0.749	0.774	0.957	0.956	0.978	0.975
RV_E	-19.2	-19.84	0.001	-3.611	0.364	-0.029

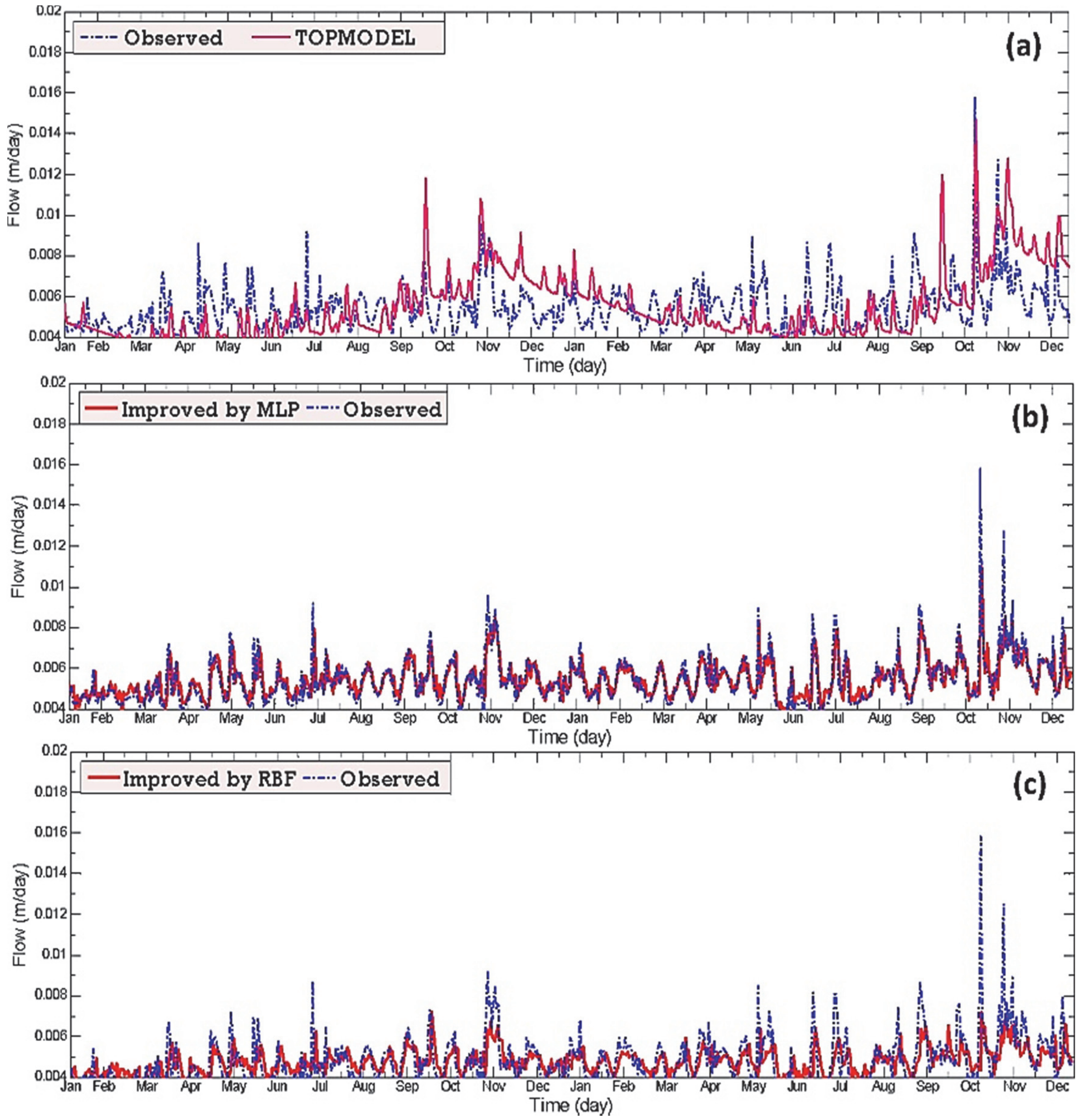


Fig. 5. Simulated and observed discharge for calibration period, 2007-2008, a) Original TOPMODEL simulation from (Suliman et al., 2014) b) Improved TOPMODEL simulation by MLP-NN model training algorithm to calibrate TOPMODEL's datasets c) Improved TOPMODEL simulation by RBF-NN model training algorithm to calibrate TOPMODEL's datasets

The RE predictions for the 14 peaks were 12.8 %, 37.1 % and 42.7 % for TOPMODEL, TOPMODEL-MLP-NN, and TOPMODEL-RBF-NN, respectively. In contrast, RE values were reduced and increased in the validation period for TOPMODEL and TOPMODEL-MLP-NN, respectively, and approximated in case of TOPMODEL-RBF-NN. The overall RE was 19.9 %, 32.2 % and 42.4% for TOPMODEL, TOPMODEL-MLP-NN, and TOPMODEL-RBF-NN, respectively. It is obvious the TOPMODEL performance was the best in predicting of peaks than the involved AI methodologies.

4. Conclusions

A new algorithm for improving flash flood stream flow prediction in the most economically developed tropical Pinang catchment was presented. Accurate prediction is required for planning and management of sustainable water resources. In this paper, the potential of using TOPMODEL-RBF-NN involving TOPMODEL inputs and output dataset requirements is explored.

The results compared to TOPMODEL performance have shown to improve streamflow prediction. Based on NS and RV_E the results range from 0.749 and -19.2 to 0.957 and 0.001 of calibration period, and from 0.774 and -19.84 to 0.956 and -3.611 for the validation period, respectively. It was proven that the TOPMODEL-MLP-NN still has the ability to provide more accurate prediction than the TOPMODEL-RBF-NN.

Moreover, the results have shown underestimation in streamflow predictions. This paper has also investigated the overall comparison of TOPMODEL, TOPMODEL-MLP-NN and TOPMODEL-RBF-NN and concluded that the TOPMODEL is superior in peak flow prediction.

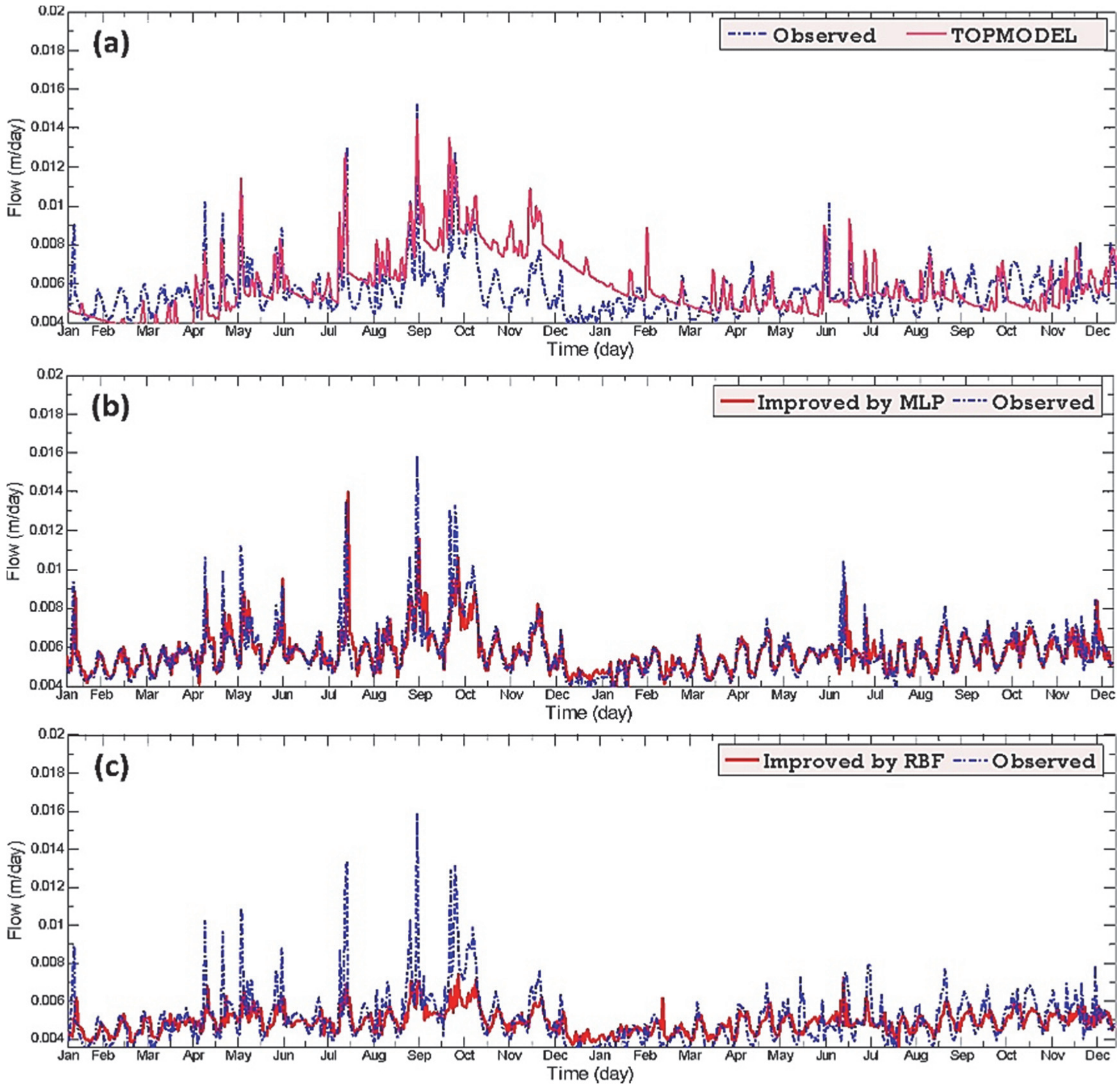
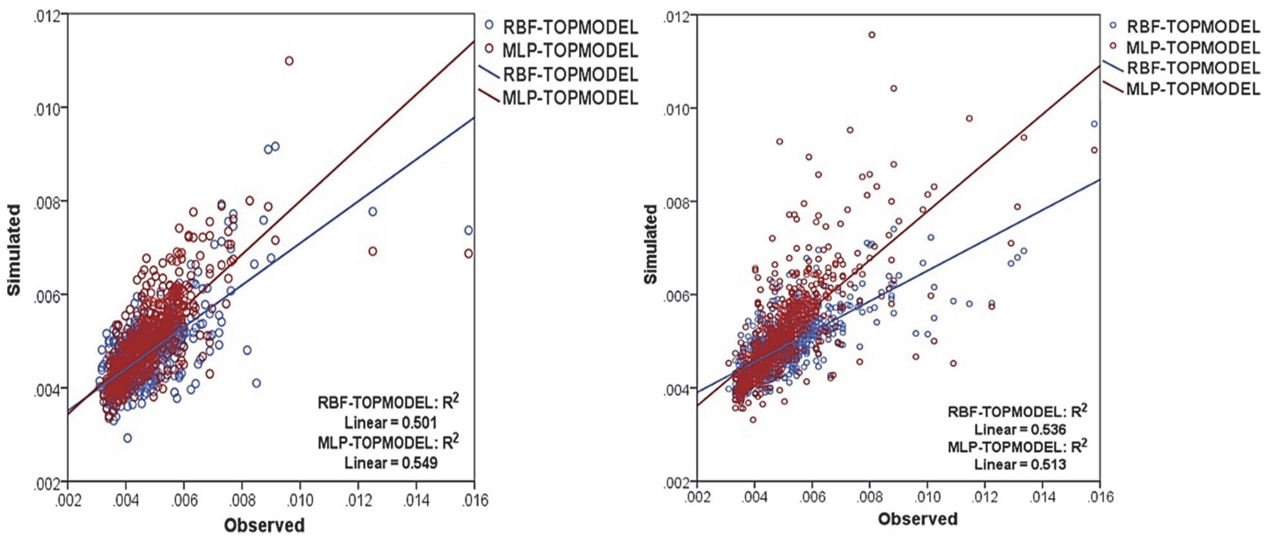


Fig. 6. Simulated and observed discharge for validation period (a) Original TOPMODEL simulation from (Suliman et al., 2014), (b) Improved TOPMODEL simulation by MLP-NN model, (c) Improved TOPMODEL simulation by RBF-NN model training algorithm to calibrate TOPMODEL's datasets



(a) (b)

Fig. 7. Scatter plot of observed versus simulated flows of TOPMODEL-RBF-NN and TOPMODEL-MLP-NN: (a) for calibration period, (b) for validation period

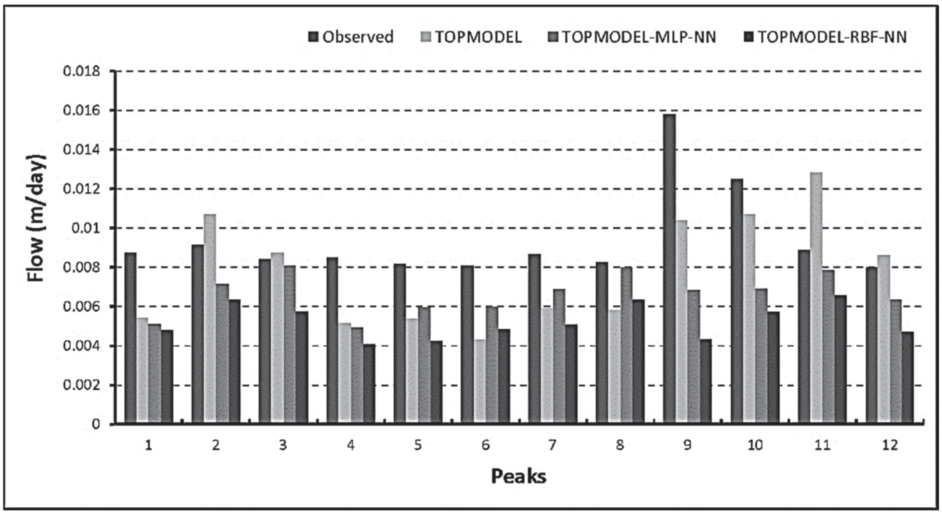


Fig. 8. Selected maximum peaks of TOPMODEL, TOPMODEL-MLP-RBF-NN predictions for calibration period

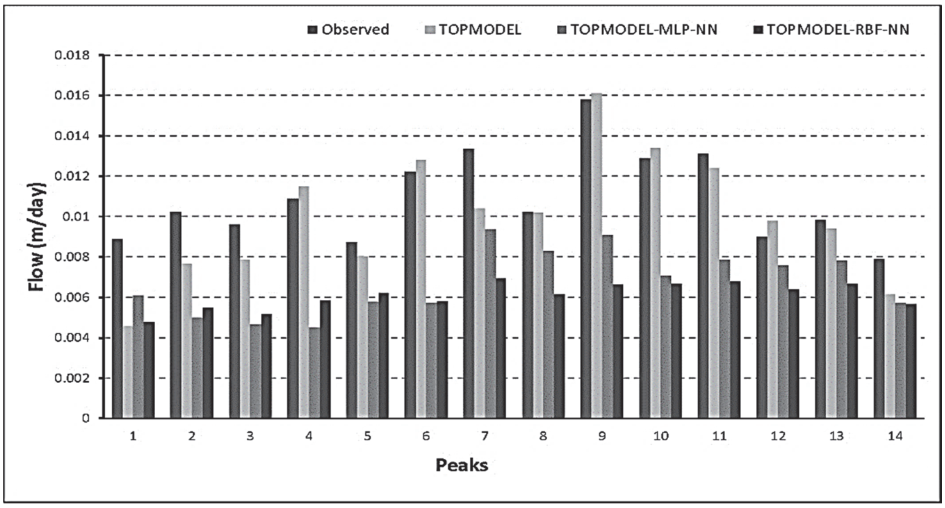


Fig. 9. Selected maximum peaks of TOPMODEL, TOPMODEL-MLP-RBF-NN predictions for validation period

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References

Abinashi S., Raghunath J., Dhruba B., Reda A.I.A., Veer R. S., Byong-Hun J., (2011), Applicability of TOPMODEL in the catchments of Nepal: Bagmati River Basin, *Geosystem Engineering*, **14**, 180-190.

Agarwal A., Singh R.D., (2004), Runoff modelling through Back Propagation Artificial Neural Network with Variable Rainfall-Runoff Data, *National Institute of Hydrology*, **18**, 285-300.

Awchi Taymoor A., (2014), River discharges forecasting in Northern Iraq Using Different ANN Techniques, *Water Resources Management*, **28**, 801-814.

Beven K.J., Kirkby M.J., Schofield N., Tagg A.F., (1984), Testing a physically-based flood forecasting model (TOPMODEL) for three U.K. catchments, *Journal of Hydrology*, **69**, 119-143.

Beven K., Quinn P., Romanowicz R., Fisher J., Lamb R., (1994), TOPMODEL and GRIDATB, A users guide to the distribution versions (94.01), Technical Report TR110/94, Lancaster University Centre For Research On Environmental Systems and Statistics, Lancaster, England.

Beven K.J., (1997), *Distributed Hydrological Modelling: Applications of the TOPMODEL Concept*, John Wiley and Sons Ltd., Chichester, U.K.

Bustami R., Bessaih N., Bong C., Suhaili S., (2007), Artificial Neural Network for precipitation and water level predictions of Bedup River, *International Journal of Computer Science*, **34**, 228-239.

Chow V., Maidment D., Mays L., (1988), *Applied Hydrology*, McGraw Hill, New York.

Dastorani M.T., Wright N.G., (2001), *Application of Artificial Neural Networks for Ungauged Catchment Flood Prediction,* Floodplain Management Association Conference, San Diego, CA.

Dawson C.W., See L.M., Abrahart R.J., Wilby R.L., Shamseldin A.Y., Anctil F., Belbachir A.N., Bowden G., Dandy G., Lauzon N., (2005), *A Comparative Study of Artificial Neural Network Techniques for River Stage Forecasting*, Proc. of IEEE International Joint Conference on Neural Networks, Montreal, 2666-2670.

El-Shafie A., Mukhlisin M., Najah A. A., Taha M. R., (2011), Performance of artificial neural network and regression techniques for rainfall-runoff prediction, *International Journal of the Physical Sciences*, **6**, 1997–2003.

Garbrecht J.D., (2006), Comparison of three alternative ANN designs for monthly rainfall-runoff simulation, *Journal Hydrologic Engineering*, **11**, 502-505.

Gautam M.R., Watanabe K., Saegusa H., (2000), Runoff analysis in humid forest catchment with Artificial Neural Networks, *Journal of Hydrology*, **235**, 117-136.

Gosav S., Tiron G., (2012), Artificial Neural Network built for the rainfall estimation using a concatenated database, *Environmental Engineering and Management Journal*, **11**, 1383-1388.

Güntner A., Uhlenbrook S., Seibert J., Leibundgut C., (1999), Multi-criterial validation of TOPMODEL in a mountainous catchment, *Hydrological Processes*, **13**, 1603-1620.

Harun S., Kassim A.H., Nor Ahmat N.I., (2002), *Rainfall-Runoff Modelling Using Artificial Neural Network*, 2nd World Engineering Congress, Kuching.

Irwan A.N., Harun S., Kassim A.H., (2007), Radial basis function modeling of hourly stream flow hydrograph, *Journal of Hydrologic Engineering*, **12**, 113-123.

Janssen P.H.M., Heuberger P.S.C., (1995), Calibration of process-oriented models, *Ecological Modelling*, **83**, 55-66.

Kişi O., Nia A.M., Gosheh M.G., Tajabadi M.R., Ahmadi A., (2012), Intermittent streamflow forecasting by using several data driven techniques, *Water Resources Management*, **26**, 457-474.

Kueh S.M., Kuok K.K., (2018), Forecasting long term precipitation using cuckoo search optimization neural network models, *Environmental Engineering and Management Journal*, **17**, 1283-1292.

Kumar A.P.S., Sudheer K.P., Jain S.K., Agarwal P.K., (2005), Rainfall-runoff modeling using artificial neural networks: comparison of network types, *Hydrological Processes*, **19**, 1277-1291.

Lin G., Chen L., (2004), A non-linear rainfall-runoff model using radial basis function network, *Journal of Hydrology*, **289**, 1-8.

Mokhtari M., Busu I., Mokhtari H., Zahedi G., Sheikhattar L., Movahed M., (2013), Neural Network and Multiple Linear Regression for Estimating Surface Albedo from ASTER Visible and Near-Infrared Spectral Bands, *Earth Interactions*, **17**, 1-20.

Mutua B.M., Klik A., (2007), Predicting daily streamflow in ungauged rural catchments the case of Masinga catchment Kenya, *Hydrological Sciences Journal*, **52**, 292-304.

Nash J.E., Sutcliffe J.V., (1970), River flow forecasting through conceptual models, Part I: A discussion of principles, *Journal of Hydrology*, **10**, 282-290.

Patrick A.R., Collins W.G., Tissot P.E., Drikitis A., Stearns J., Michaud P.R., Cox D.T., (2002), *Use of the NCEP MesoEta Data in a Water Level Predicting Artificial Neural Network*, Proc. of 19th Conf. on weather Analysis and Forecasting, San Antonio, Texas.

Piotrowski A., Napiorkowski J.J., Rowinski P.M., (2006), Flash-flood forecasting by means of neural networks and nearest neighbor approach - a comparative study, *Nonlinear Processes in Geophysics*, **13**, 443-448.

Rajurkar M.P., Kothyari U.C., Chaube U.C., (2002), Artificial neural networks for daily rainfall–runoff modeling, *Hydrological Sciences Journal*, **47**, 865-877.

Refsgaard J.C., Knudsen J., (1996), Operational validation and intercomparison of different types of hydrological models, *Water Resources Research*, **32**, 2189-2202.

Romanowicz R., (1997), A MATLAB implementation of TOPMODEL, *Hydrological Processes*, **11**, 1115-1129.

Sahoo G.B., Ray C., (2006), Flow forecasting for a Hawaii stream using rating curves and neural networks, *Journal of Hydrology*, **317**, 63-80.

Singh V., Woolhiser D., (2002), Mathematical modeling of watershed hydrology, *Journal of Hydrologic Engineering*, **7**, 270–292.

Solomatine D.P., (2005), *Data-Driven Modelling and Computational Intelligence Methods in Hydrology*, In: *Encyclopedia of Hydrological Sciences*, Andersen M.G., (Ed), **1**, John Wiley & Sons, New York.

Solomatine D.P., Ostfeld A., (2008), Data-driven modelling: some past experiences and new approaches, *Journal of Hydroinformatics*, **10**, 3-22.

Sudheer KP, Jain SK. (2003), Radial basis function neural network for modelling rating curves, *Journal of Hydrologic Engineering*, **8**, 161-164

Sulaiman M., El-Shafie A., Karim O., Basri H., (2011), Improved water level forecasting performance by using optimal steepness coefficients in an artificial neural network, *Water Resources Management*, **25**, 2525-2541.

Suliman A.H.A., Gumindoga W., Katimon A., Darus I. Z. Mat, (2014), Semi-distributed rainfall-runoff model for streamflow simulation utilizing ASTER DEM in tropical areas, *Sains Malaysiana*, **43**, 9.

Suliman A.H.A., Katimon A., Darus I. Z. Mat, Shahid S., (2016), TOPMODEL for Streamflow Simulation of a tropical catchment using different resolutions of ASTER DEM: optimization through Response Surface Methodology, *Water Resources Management*, **30**, 3159-3173.

Suliman A.H.A., Darus I. Z. Mat, Katimon A., (2017), gis-based Rainfall-Runoff Neuro model for streamflow prediction, *International Review of Civil Engineering*, **8**, 235-240

Todini E., (1988), Rainfall-runoff modelling past, present and future, *Journal of Hydrology*, **100**, 341-352.

Wang W., Van Gelder P.H.A.J.M., Vrijling J.K., Ma J., (2006), Forecasting daily streamflow using Hybrid ANN Models, *Journal of Hydrology*, **324**, 383-399.

Wright N.G., Dastorani, M.T., (2001), *Effects of River Basin Classification on Artificial Neural Networks Based Ungauged Catchment Flood Prediction*, 3rd Int. Symp. on Environmental Hydraulics, Phoenix, Arizona.

Zhang M.Y., Wang K.L., Liu H.Y., Luo W.., Wang J., Yue Y.M., (2018), Factors affecting the pattern of vegetation carbon density in a karst region in northwest Guangxi, China, *Environmental Engineering and Management Journal*, **17**, 1657-1666.