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Development of Generalized Feed Forward Network for Predicting Annual Flood (Depth) of a Tropical River

(Pembangunan Rangkaian Suapan ke Hadapan Menyeluruh untuk Meramalkan Banjir Tahunan (Kedalaman) Sungai Tropika)

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ABSTRACT

The modeling of rainfall-runoff relationship in a watershed is very important in designing hydraulic structures, controlling flood and managing storm water. Artificial Neural Networks (ANNs) are known as having the ability to model nonlinear mechanisms. This study aimed at developing a Generalized Feed Forward (GFF) network model for predicting annual flood (depth) of Johor River in Peninsular Malaysia. In order to avoid over training, cross-validation technique was performed for optimizing the model. In addition, predictive uncertainty index was used to protect of over parameterization. The governing training algorithm was back propagation with momentum term and tangent hyperbolic types was used as transfer function for hidden and output layers. The results showed that the optimum architecture was derived by linear tangent hyperbolic transfer function for both hidden and output layers. The values of Nash and Sutcliffe (NS) and Root mean square error (RMSE) obtained 0.98 and 5.92 for the test period. Cross validation evaluation showed 9 process elements is adequate in hidden layer for optimum generalization by considering the predictive uncertainty index obtained (0.14) for test period which is acceptable.

Keywords: Annual flood; artificial neural networks; cross validation; generalized feed forward; Johor River; predictive uncertainty

ABSTRAK

Pemodelan hubungan curahan hujan-aliran air di suatu kawasan tadahan adalah sangat penting dalam mereka bentuk struktur hidraulik, mengawal banjir dan menguruskan air ribut. Rangkaian neural tiruan (ANNs) dikenal pasti mempunyai keupayaan untuk memperaga mekanisme tak linear. Kajian ini bertujuan untuk membangunkan model rangkaian suapan ke hadapan menyeluruh (GFF) untuk meramalkan banjir tahunan (kedalaman) Sungai Johor di Semenanjung Malaysia. Untuk mengelakkan latihan berlebihan, teknik pengesahan silang telah dijalankan bagi mengoptimumkan model tersebut. Di samping itu, indeks ketidakpastian ramalan digunakan untuk melindungi daripada pemparameteran berlebihan. Algoritma latihan pentadbiran adalah perambatan balik terma momentum dan jenis tangen hiperbolik digunakan sebagai fungsi perpindahan bagi lapisan tersembunyi dan output. Hasil kajian menunjukkan bahawa seni bina yang optimum diperoleh melalui fungsi perpindahan linear tangen hiperbolik bagi lapisan tersembunyi dan output. Nilai Nash dan Sutcliffe (NS) serta punca min ralat kuasa dua (RMSE) memperoleh 0.98 dan 5.92 bagi masa ujian. Penilaian pengesahan silang menunjukkan 9 proses elemen adalah mencukupi dalam lapisan tersembunyi untuk pengitlakan yang optimum dengan mengambil kira ramalan indeks ketidaktentuan yang diperoleh (0.14) dalam masa ujian adalah diterima.

Kata kunci: Banjir tahunan; ketidakpastian ramalan; pengesahan silang; rangkaian neural tiruan; suapan ke hadapan menyeluruh; Sungai Johor

INTRODUCTION

Most of the hydrologic processes are nonlinear and represent a high degree of temporal and spatial variability. This poses challenges for accurate assessment and prediction of runoff, water level and contaminant concentrations. Moreover, changes in rainfall also lead to drought or flood and the subject of modeling the rainfall-runoff being essential (Wahidah & Kamarulzaman 2012). Hydrological models could provide a useful alternative for predicting and forecasting rainfall-runoff relationships (Jajarmizadeh et al. 2012a). Currently, hydrological models can be broadly grouped into three categories, namely empirical, deterministic and physical based (Jajarmizadeh et al. 2012b). Runoff or flood prediction follows two main modeling methods, namely conceptual (phenomenological) modeling and black-box modeling. Conceptual modeling employs some physical rules in mathematical formulation, whereas black-box models rely on an input-output description and seek to find the best relation of pattern (Elshorbagy et al. 2000).

Neural networks have been greatly employed in hydrological simulations (Altunkaynak 2007; Can 2002). Neural networks are mainly semi-parametric regression estimators that have large potential for modeling hydrologic processes in a basin (Senthil Kumar et al. 2005). ASCE (2000a, 2000b) and Maier and Dandy (2000) present a comprehensive review on the application of ANNs in hydrology. Moreover, Bowden et al. (2005) comprehensively reviewed the available methods for development of neural networks in water resources management. Despite numerous neural networks studies for predicting hydrological phenomena, this subject remains popular due to its potential for improvement from time to time (Agarwal et al. 2006; De Vos & Rientjes 2005; Kişi et al. 2012; Rajurkar et al. 2004; Xu et al. 2008).

Shamsudin et al. (2011) applied various forms of multi-layer feed-forward neural network (MLFFNN) for flow estimation in eight catchments. They studied five neuron transfer functions and the results showed that when the logistic function is employed as the neuron transfer function, the estimation of MLFFNN has the optimum results for daily time scale forecast. El-Shafie and Noureldin (2011) investigated the performance of generalized versus non-generalized neural network model for flow estimation. They found that generalized neural network (GNN) model outperforms non-generalized neural network. El-Shafie et al. (2012) further evaluated dynamic versus static neural network for rainfall estimation in Malaysia. They applied one neural network and two different static neural networks. The results of their study showed that dynamic model is the most promising model for rainfall forecasting. This study examines the suitability of applying neural network for predicting annual flood of Johor River in Peninsular Malaysia. The study aimed to develop GFF network for predicting flood by applying cross validation technique as optimization procedure during training and finding the role of data division for training/cross validation and test on result of generalization. Indeed, this study has been motivated by previous research in southern part of Malaysia by importance of flood events (Jamaludin Suhaila et al. 2010).

GENERALIZED FEED FORWARD (GFF) NETWORK

Generalized Feed Forward (GFF) network is the generalization of multi layers perceptron in which connections are capable to move over one or more layers. A GFF theoretically resolves the problems that an MLP can resolve, but GFF often resolves the problems in an efficient manner (Kişi 2008). GFF has two significant characteristics. First, its processing elements (PEs) are nonlinear and second, they are heavily interconnected in a way that one element of a layer feeds all other elements of the next layer (Kişi 2009, 2007, 2006). Consequently, the utility of the GFF network is implied in its capability to send activities forward through passing layers. The final outcome is that the training process of the layers nearer to the input becomes more efficient (ASCE 2000a). Details of neural network training can be found in Sorayya et al. 2012.

MATERIALS AND METHODS

We collected 45 years river flow record of Johor River, measured at the Rantau Panjang gauging station (Figure 2, 01° 46' 50''N and 103° 44' 45''E) but there were 10 years missing data in discharge gauges during 1965-2010 period. Johor River is located in the southeast of Peninsular Malaysia, covering a total catchment area of 2700 km^2. The climate of the study area is tropical with mean annual rainfall of 2470 mm, mean air temperature of 28.5°C and mean relative humidity of 85%.

The development of neural network is ordinal that includes gathering of data, pre-processing data, selecting the network, normalizing, training the network and lastly evaluating the results (Dawson & Wilby 1998). Moreover, as Tokar and Johnson (1999) put, the quality and quantity of data are of prime importance in modeling by ANNs. In the current study, annual precipitation (mm) and annual flood depth (mm) from 1965-2010 were used by removing the missing data. The input variables were then divided in three sections such as training, cross-validation and test. Every GFF network includes the following components; transfer function, training algorithm, attributed elements such as step size and momentum coefficient. For computation of every neuron output, as Tokar and Johnson (1999) put, a transfer function needs to be determined. One of the commonly employed transfer functions in hydrological

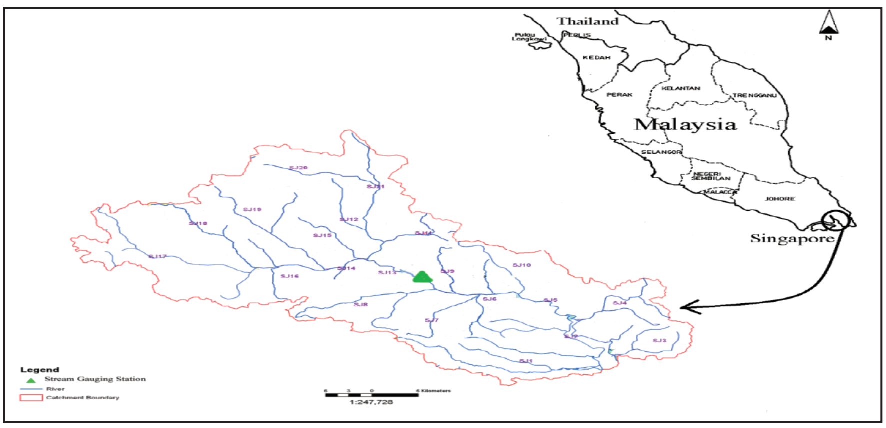


FIGURE 1. Map of Johor River in south of Peninsular Malaysia

neural networks is hyperbolic tangent function which has been suggested for GFF networks (Rezaeian Zadeh et al. 2010). In this study, it has been applied the tangent hyperbolic and linear tangent hyperbolic functions to develop GFF for neurons in hidden and output layers. Table 1 shows 16 scenarios that have been developed by considering the transfer function possibilities in hidden and output layers. Then division of data for train/cross-validation and test periods has been examined by choosing 70% training and 30% testing data as well 50% for both train and test.

Before application of input-output, the network variables require data scaling. The input data need to be normalized due to unusual data behavior or limitations of the transfer function output (Srivastava et al. 2006). While using the tangent hyperbolic as a transfer function, the data were scaled in the range of -1 to +1 according to suggestion of Nayebi et al. (2006). The tangent hyperbolic transfer function is given in (1):

$$f(x_i, w_i) = \tanh\left[x_i^{lin}\right], \tag{1}$$

where $x_i^{lin} = Bx_i$ is the scaled and offset activity inherited from the linear computation. Linear tangent hyperbolic replaces the intermediate portion of the tan hyperbolic by a line of slope b, making it a piecewise linear approximation of the tan hyperbolic as given in (2) (Menhaj 2010):

$$f\left(x_i, w_i\right) = \begin{cases} -1 & x_i^{lin} \quad < 1 \\ 1 & x_i^{lin} \quad > 1 \\ x_i^{lin} & else \end{cases} \tag{2}$$

The employed training algorithm was back propagation with momentum term. The procedure includes determination of gradient and weight change (Bishope 1995; Jain et al. 1996). The hydro-meteorological data for the development of GFF network was divided into three sections; training section constituted 60% of the data set, cross validation section (10% of the training data) and test/validation section (30% of the data) as suggested by Parasuraman et al. (2006) and Wu et al. (2005). The number of hidden layers and the number of nodes in these layers were determined by trial and error (ASCE 2000a, 2000b; Maier & Dandy 2000).

During the learning pattern recognition, error on the training dataset usually decreases with every iteration (epoch) in a way that the computation can proceed from the optimum number of training steps. In addition, similarly, cross validation data set error initially decreases during training but then begins to increase. Training at this point should be stopped. Once an optimum number of training is obtained, there is no need to continue the learning process (Nourani & Kalantar 2010). If learning process is permitted to progress further, overtraining occurs and usually the model results in weak generalization (Srivastava et al. 2006).

Evaluation of the model results was performed by following guidelines in Senthil Kumar et al. (2005). A multi-criteria assessment can be performed through three different evaluation procedures. The Nash-Sutcliffe (NS) and root mean square error (RMSE) were considered as statistical indices (Tombul & Ersin 2006; Wu et al. 2005). NS measures the performance of a hydrological model with value in the range of [-∞, 1]. Values of NS between 0.6 and 0.8 suggest moderate to good fit, more than 0.8 indicate a good fit and one a perfect fit. RMSE measures the agreement between the observed and simulated data. The predictive uncertainty index (PU) of the ANN is assessed with the noise-to-signal ratio index (Senthil Kumar et al. 2005). Evaluation of PU index protect over parameterization in neural networks. More information is available in

TABLE 1. Developed scenarios of GFF for Johor River

Number	Network	Hidden Layer	Output Layer	Train/Cross-validation	Test
1	GFF1	Tangent Hyperbolic	Tangent Hyperbolic	70%(1965-1996)	30%(1997-2010)
2	GFF-1-1	Linear Tangent Hyperbolic	Linear Tangent Hyperbolic	70%(1965-1996)	30%(1997-2010)
3	GFF-1-2	Tangent Hyperbolic	Linear Tangent Hyperbolic	70%(1965-1996)	30%(1997-2010)
4	GFF-1-3	Linear Tangent Hyperbolic	Tangent Hyperbolic	70%(1965-1996)	30%(1997-2010)
5	GFF2	Tangent Hyperbolic	Tangent Hyperbolic	70%(1979-2010)	30%(1965-1979)
6	GFF-2-1	Linear Tangent Hyperbolic	Linear Tangent Hyperbolic	70%(1979-2010)	30%(1965-1979)
7	GFF-2-2	Tangent Hyperbolic	Linear Tangent Hyperbolic	70%(1979-2010)	30%(1965-1979)
8	GFF-2-3	Linear Tangent Hyperbolic	Tangent Hyperbolic	70%(1979-2010)	30%(1965-1979)
9	GFF3	Tangent Hyperbolic	Tangent Hyperbolic	50%(1965-1986)	50%(1987-2010)
10	GFF-3-1	Linear Tangent Hyperbolic	Linear Tangent Hyperbolic	50%(1965-1986)	50%(1987-2010)
11	GFF-3-2	Tangent Hyperbolic	Linear Tangent Hyperbolic	50%(1965-1986)	50%(1987-2010)
12	GFF-3-3	Linear Tangent Hyperbolic	Tangent Hyperbolic	50%(1965-1986)	50%(1987-2010)
13	GFF4	Tangent Hyperbolic	Tangent Hyperbolic	50%(1987-2010)	50%(1965-1986)
14	GFF-4-1	Linear Tangent Hyperbolic	Linear Tangent Hyperbolic	50%(1987-2010)	50%(1965-1986)
15	GFF-4-2	Tangent Hyperbolic	Linear Tangent Hyperbolic	50%(1987-2010)	50%(1965-1986)
16	GFF-4-3	Linear Tangent Hyperbolic	Tangent Hyperbolic	50%(1987-2010)	50%(1965-1986)

Senthil Kumar et al. (2005) for predictive uncertainty (PU) calculation. Indeed using cross validation and PU index help to reduce over training and over parameterization of neural networks.

RESULTS AND DISCUSSION

It is important to apply the relevant input variables to ensure the accuracy of the model output. Due to keep logically physically meaning of model development correspond precipitation has been used for flood prediction in annually modeling. Figure 2 shows RMSE and NS values for 16 developed scenarios. Development of 16 scenarios show the importance of data division (train/test) and significance of using transfer functions in hidden and output layers to better learning and boosting pattern recognition phenomena. The purpose of carrying out various scenarios by heuristic method was to increase generalization and discover lowest error for flood prediction. Figure 2 shows the architectures with linear tangent hyperbolic in output layer (GFF-1-1,GFF-3-1,GFF-1-2,GFF-4-2,GFF-4-1,GFF-2-1) which have the lowest error (RMSE). As a result, it was found that GFF-1-1 has the most optimum generalization for flood prediction.

Training the networks showed that better generalization was found for application of linear tangent hyperbolic for both hidden and output layers as neurons transfer function. Figure 3 shows mean square errors (MSE on normalized data) in training and cross validation data set for architecture GFF-1-1 which is 9 neurons in hidden layer. Moreover, PU index has been calculated for train and test 0.21 and 0.14 which both of them are under unity and acceptable for GFF-1-1.

The performance of the model was assessed based on the procedures suggested by World Meteorological Organization WMO (1975). Both graphical and non-graphical evaluation methods were performed. The non-graphical evaluation methods used are RMSE and NS. The values of NS, and RMSE for the calibration period were 0.98 and 4.45, respectively. The corresponding values for test period were 0.98 and 5.92. NS shows inspiring values for the training and testing phases. The trend analysis (Figures 4 and 5) suggest that the simulated data have agreement with the observed flood. In total, the flood values were well predicted during the test period. The reason can be considered the variety flood values in train/cross validation period that has been involved in Johor River. The small discrepancies for generalization can be due to the structure of GFF network. Mutlu et al. (2008) suggested that further evaluations such as using more input variables might improve the performance of the model but modeler should consider the time and cost. More recently, Singh et al. (2012) found that multi layer perceptron has successfully predicted low and medium values of monthly sedimentation but not for high values. Usually, the failure to capture flood value could possibly be overcome by having a longer data set for training. According to Ghumman et al. (2011), short data sets and poor data quality are common problems in generalization of neural networks. In this study, the result of flood prediction is promising in annually scale according statistical analysis and graphical presentation.

The robustness of the model was also evaluated by performing residuals analysis with the assumptions of homoscedasticity and normality. Homoscedasticity deals with the assumption that the dependent variable has similar magnitude of variance across the range of values of an independent variable. The residuals were calculated by subtracting the simulated from the observed flood. In an

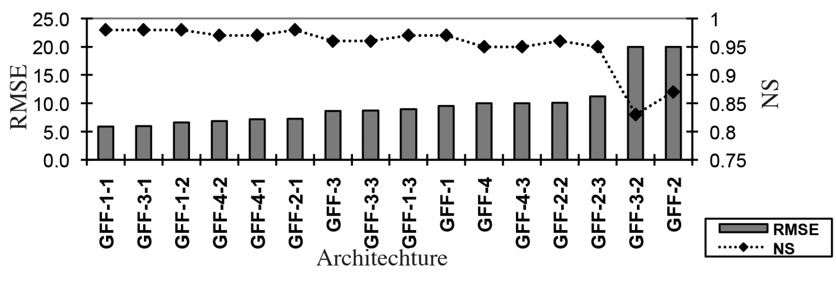
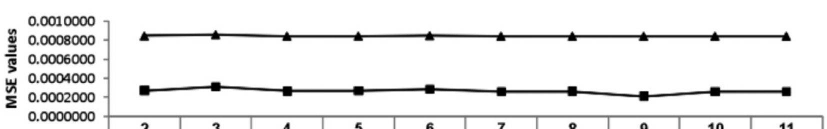


FIGURE 2. Presentation of RMSE and NS values for 16 scenarios of GFF development



	2	3	4	5	6	7	8	9	10	11
Training	0.000844	0.000857	0.000842	0.000843	0.000847	0.000842	0.000842	0.000841	0.000842	0.000842
Cross Validation	0.000272	0.000309	0.000265	0.00027	0.000284	0.000262	0.000263	0.000212	0.000262	0.000258

Number of neurons in hidden layer — Training — Cross Validation

FIGURE 3. MSE values against number of neurons in GFF-1-1 network

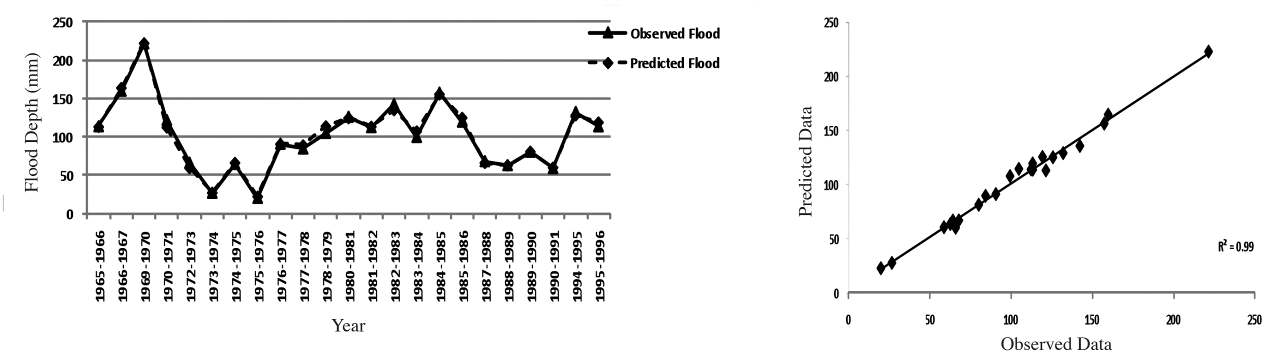


FIGURE 4. Observed and simulated flood (mm) trend analysis and 1:1 plot of observed and simulated flood for training data set (1965-1996)

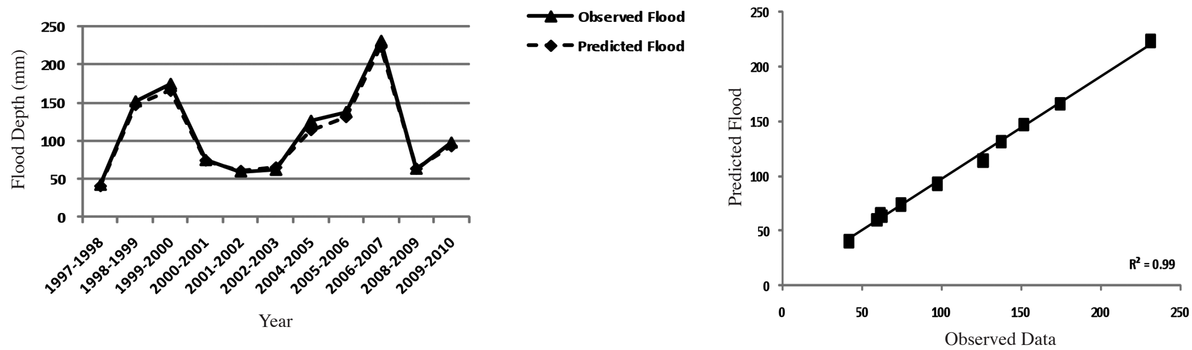


FIGURE 5. Observed and simulated flood (mm) trend analysis and 1:1 plot of observed and simulated flood for test data set (1997-2010)

ideal situation, the residuals have to follow homoscedastic behavior. A positive value means overestimation and negative value means underestimation of the flood. Figure 6 shows the residual plots for training and testing periods, respectively. As shown in Figure 6, the residual errors for training period are randomly dispersed, indicating that the assumption of homoscedasticity is complied. However, the flood was under estimated during the testing period and the residual errors are not randomly distributed. The largest error was associated with the flood in water-year 2004-2005. In this regard, Senthil Kumar et al. (2005) reported that generally neural network is less effective in capturing flows in perfect manner in test period.

CONCLUSION

In this study, GFF was used for predicting flood of Johor River in Peninsular Malaysia. Predictive uncertainty index

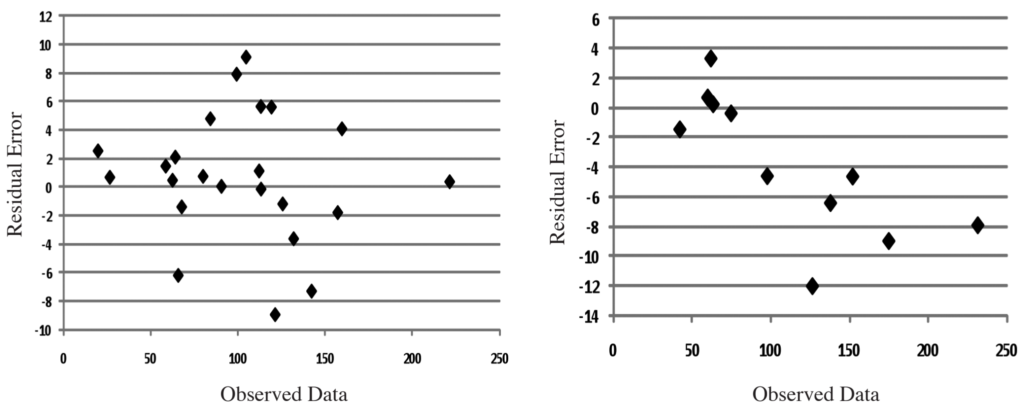


FIGURE 6. Plots of residual error (simulated minus observed) against observed flood depth (mm) for train and test periods

and cross-validation were used for developing optimum architecture. Generally, the networks with using linear tangent hyperbolic for hidden and output layers was found better architecture in GFF in comparison with those involved hyperbolic tangent. This study shows that GFF structure is promising for learning pattern recognition in annually time scale and tropical regions with short data. We emphasize that the quality and quantity of data is crucial for reliable prediction of flood using ANNs such as GFF. The future studies can examine the applicability of GFF neural network in predicting finer scale data such as daily and monthly for tropical rivers. It is also interesting to incorporate other climatic data such as relative humidity, temperature and solar radiation.

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