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A Comparison of Artificial Neural Networks for Prediction of Suspended Sediment Discharge in River- A Case Study in Malaysia

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***Abstract*—**Prediction of highly non linear behavior of suspended sediment flow in rivers has prime importance in the field of water resources engineering. In this study the predictive performance of two Artificial Neural Networks (ANNs) namely, the Radial Basis Function (RBF) Network and the Multi Layer Feed Forward (MLFF) Network have been compared. Time series data of daily suspended sediment discharge and water discharge at Pari River was used for training and testing the networks. A number of statistical parameters i.e. root mean square error (*RMSE*), mean absolute error (*MAE*), coefficient of efficiency (*CE*) and coefficient of determination (R^2) were used for performance evaluation of the models. Both the models produced satisfactory results and showed a good agreement between the predicted and observed data. The RBF network model provided slightly better results than the MLFF network model in predicting suspended sediment discharge.

***Keywords*—**ANN, discharge, modeling, prediction, suspended sediment,

I. INTRODUCTION

ALL rivers contain a large amount of sediments. In fact rivers can be considered as a body of sediments flowing along with flowing water. When a river approaches a hydraulic structure (i.e. dam, reservoir, barrages etc.), the sediments in the water settles down in reservoir and gradually deplete the reservoir capacity. Hence, river sediment flow information is important for designing different hydraulic engineering projects, assessment of water quality and sanitary engineering, etc. A number of techniques are available for time series analysis which assumes linear relationship between the variables. But in reality, the temporal changes in data exhibit a complex nonlinear behavior and accurate prediction is difficult. Hence, it requires a nonlinear model like artificial neural networks, which is able to capture the complex temporal variations in time series data. Artificial neural network (ANN) techniques have been successfully applied in various fields of engineering. In water resources engineering, ANN has been used successfully for forecasting flood discharge [1], for prediction of runoff from rainfall [2], river flow [3] and for modeling the runoff rainfall processes [4-5]. ANN also has been applied successfully for estimating and forecasting daily suspended sediments [6], modeling river sediment yield [7], estimation of reservoir sedimentation [8], and prediction of sediment concentration in rivers [9]. Alp and Cigizoglu [10] simulated suspended sediment load by two artificial neural networks using rainfall, flow and sediment data. They used rainfall and water discharge as model input parameter and suspended sediment load as output parameter. In the present study, only water discharge at the present time with two antecedent values has been used as model input parameters to predict suspended sediment discharge for the current time as the model output. The objective of this study is to compare predictive performance of Radial Basis Function (RBF) and Multi Layer Feed Forward (MLFF) neural networks for prediction of suspended sediments discharge in river using only time series data of water discharge data as input.

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II. ARTIFICIAL NEURAL NETWORK THEORY

ANN is a numerical modeling technique which is able to capture the complex non-linear relationships between input and output parameters. ANN contains several layers and each layer consists of a number of neurons. Generally, the first layer is known as input layer and the last layer in known as output layer while the intermediate layers are considered as hidden layers. There are different types of ANN but in the present study two types of ANNs are used. These are the Radial Basis Function (RBF) and Multi Layer Feed Forward (MLFF) networks. They are described briefly below.

A. Radial Basis Function Neural Network

Radial Basis Functions (RBF) networks were originally introduced by Broomhead and Lowe [11]. RBF neural networks (NN) has been successfully applied in various fields of water resources engineering i.e. runoff simulation [12], rainfall runoff modeling [13], water quality model calibration [14] etc. In the present study, a three layered (i.e. input, hidden and output layers) RBF neural network has been modeled. Previous studies [10] investigated that relationship between discharge and suspended sediments could be simulated by ANN from current water discharge, antecedent water discharge and antecedent rainfall data. Furthermore, [10] investigated different combinations of discharge and rainfall data with different antecedent conditions for estimation of suspended sediments. Previous studies by [6] and [7] have also adopted the similar practice for selection of appropriate inputs for neural networks. Generally, this knowledge is obtained from an examination of (i) the cross-correlation between time series of water discharge and suspended sediment discharge and (ii) auto-correlation between time series of water discharge and suspended sediment discharge data separately. Therefore, in the present study, appropriate number of input neurons was selected as three (1 current water discharge and 2 antecedent water discharge) based on the autocorrelation analysis performed by [15] between water discharge data for the Pari River. There are different types of radial basis functions which could be used in a RBFNN. The most common and popular RBF is the Gaussian function [16] and is used in this study. Maximum numbers of hidden neurons or radial basis functions are decided by making several trials. During trials with different predefined maximum number of hidden neurons in the training phase it was found that increasing the maximum number of hidden neurons beyond 100 did not improve the training accuracy significantly. Therefore, the maximum number of hidden neurons for the RBF network was selected to be 100. It is important to note that the training algorithm used for the RBF network in this study do not use the available maximum number of neuron in the hidden neuron at each iterative process, instead the RBF network starts with a single neuron in the hidden layer and increases the number of hidden neurons at successive iterations until the desired goal is reached or the maximum number of hidden neurons allocated are exhausted. Whereas in the MLFF network used in this study the number of neurons in the hidden layer are fixed too but the MLFF network uses all the available neurons in the hidden layer at each iterative step to reach the desired goal. Training parameter ‘spread’ was also decided by making trials with different value of spread. After a number of trials a spread value of 0.8 was found appropriate for the RBF model. Expected output from the model is only suspended sediment hence, there is only ones output neuron in the output layer.

B. Multilayer Feed Forward Neural Network

Multilayer feed forward (MLFF) neural network with standard back propagation algorithm is the most commonly used neural network type. In the present study, the MLFF network used consists of three layers (i.e. input, hidden and output layer). In the input layer similar to the RBF network three neurons were used for the MLFF network. The number of neuron in the hidden layer was obtained by trial and error. From trial and error method [17] the number of neurons in the hidden layer was established to be three. Only suspended sediment discharge is the expected as output from the model, hence, only one neuron in the output layer was used. Mustafa et al. [15] proposed that Levenberg Marquardt (LM) training algorithm is ideal for training MLFF neural network for predicting suspended sediment discharge. Therefore, the LM training algorithm was selected for training the MLFF neural network.

III. Data Source And Study Area

Time series data of daily water discharge and suspended sediment discharge at Silibin station of Pari River in Perak state, Malaysia was used in this study. Five year data (1993-1998) was acquired from Department of Irrigation and Drainage (DID), Ministry of Natural Resources and Environment, Kuala Lumpur, Malaysia. Time series data from January 6, 1993 to March 3, 1997 was used for training and from March 4, 1997 to October 24, 1998 was used for testing the models. The Pari River station at Silbin is about 37 m above mean sea level and has a catchment area of 245 km^2. About 60% of the catchment is mountainous whereas rest of the area is relatively flat with some undulating landscape. The thickness of the soil varies throughout the area.

IV. DATA NORMALIZATION

The network training process could be speeded up by preprocessing the input and target data before training [18]. In this study the, input and target data was preprocessed to scale the data between the range -1 and 1 using the following equation;

$$X_p = 2 * \frac{(x_p - x_{\min})}{(x_{\max} - x_{\min})} - 1 \qquad (1)$$

Where X_p is the normalized value and x_p is the original value while x_{min} and x_{max} are the minimum and maximum values in the data, respectively. After training and testing results are achieved, the output values were de-normalized by multiplying with the corresponding normalization factor to get the output in the original scale of the data. The algorithms for the neural network models (RBFNN and MLFFNN) were implemented using neural network toolbox in MATLAB with programming codes.

V. Performance Evaluation Criteria

The performance of both models was evaluated using different statistical measures. The performance evaluations measures included in this study are root mean square error (*RMSE*), mean absolute error (*MAE*) and Nash and Sutcliffe coefficient of efficiency (*CE*), expressed by the following equations;

$$RMSE = \left[\frac{1}{N} \sum_{n=1}^{N} (z_n - y_n)^2 \right]^{1/2} \qquad (2)$$

$$MAE = \frac{1}{N} \sum_{n=1}^{N} (z_n - y_n) \qquad (3)$$

$$CE = 1 - \frac{\sum_{n=1}^{N} (z_n - y_n)^2}{\sum_{n=1}^{N} (z_n - \bar{z})^2} \qquad (4)$$

Where z_n and y_n are the observed and predicted values, respectively, $\bar{z}$ is the mean of observed values and N is the total number of observations used for error computation.

Ideally, the value of *RMSE* and *MAE* should be zero and *CE* should be one.

VI. Results And Discussion

Two different types of neural networks (RBF and MLFF) have been used to predict suspended sediments in Pari River. In both the models number of neurons in input layer and output layer are same (i.e. three and one respectively). Generally, neural network training is stopped by predefined error level known as goal or on completion of predefined number of epochs. In this study both criteria were followed, either the maximum numbers of epochs are reached or goal is achieved. In both the models predefined error or goal was defined as 0.001. In RBF, adaptive learning procedure was followed. In which number of hidden neurons act as number of epochs or iterations and thus, maximum number of hidden neurons or epochs was defined as 100. In MLFF network maximum numbers of epochs was defined as 2000. Fig. 1 show the comparison of observed and predicted suspended sediment discharge during testing stage of the RBF neural network. The RBF model learned precisely the nonlinear pattern of suspended sediment discharge during the training and produced generalization during testing stage of the network. The observed and the predicted suspended sediment discharge values are close to each other. The difference between observed and predicted values can be visualized clearly at points 1 and 2 marked in Fig. 1. This examination reveals that RBF model has followed the exact pattern of suspended sediment data and there is only a little difference between observed and predicted values. Similar pattern is also observed when MLFF neural network was used (Fig. 2). The inspection at points 1 and 2 (Fig. 1 and Fig. 2) presents that both RBF and MLFF neural networks predicted the suspended sediments very closely, even in RBF model the predicted and observed values are overlapped. However, both models followed the nonlinear pattern in the data and predicted the values very close to the observed data. Previous attempts by [10] on suspended sediment prediction from rainfall and river flow data using RBF and MLFF neural networks showed some negative prediction values for suspended sediment discharge. However, in this study time series of river discharge and sediment discharge data was used for training the models and no negative prediction values for suspended sediment discharge was observed.

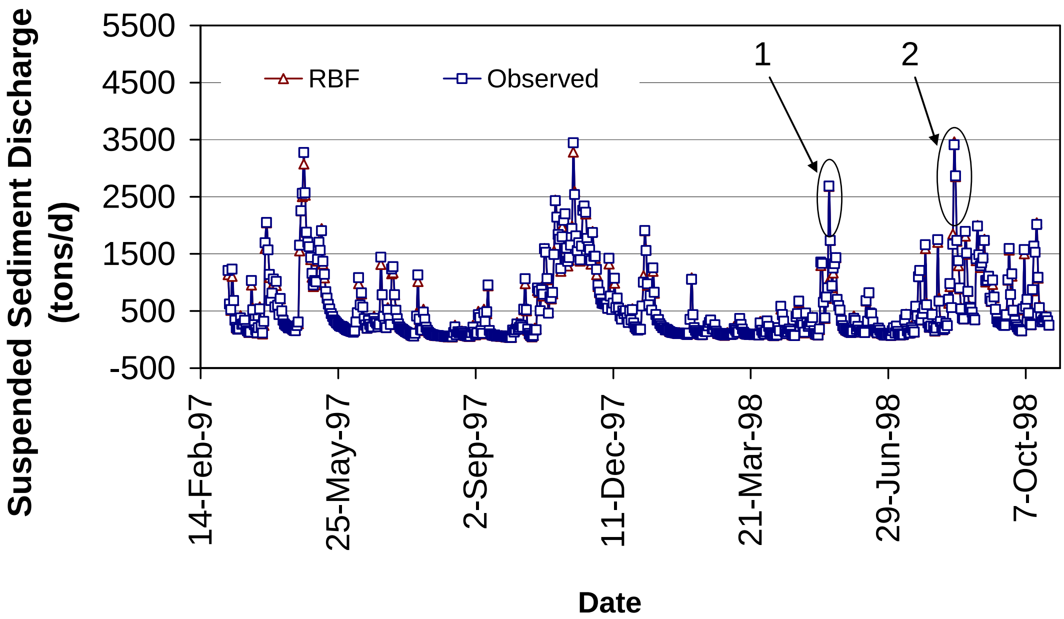

Fig. 1 Comparison between observed and predicted suspended sediments discharge obtained using RBF Neural Network

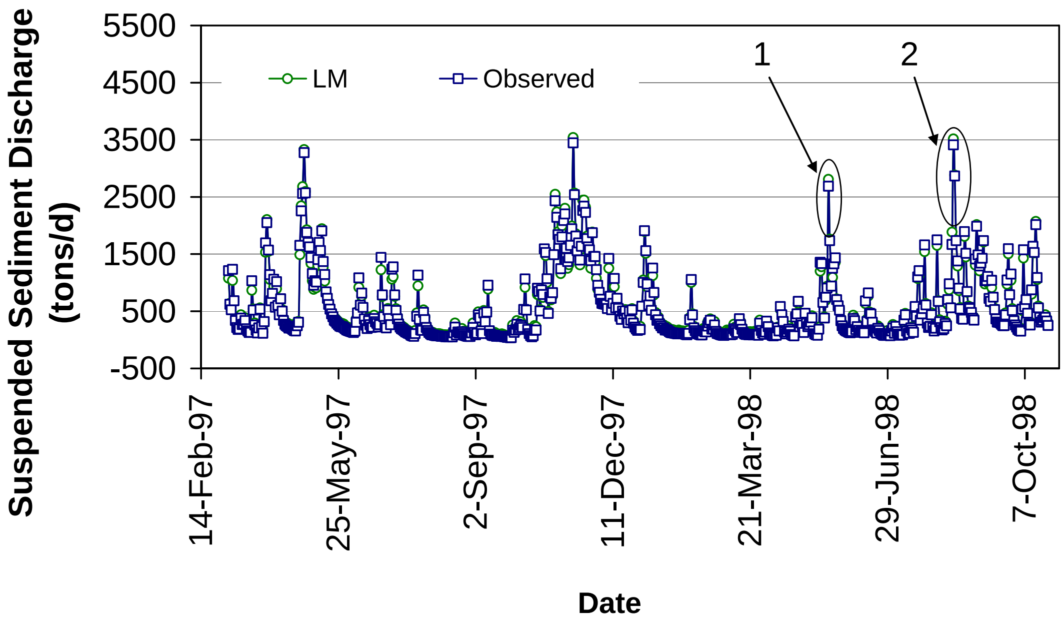

Fig. 2 Comparison between observed and predicted suspended sediments discharge obtained using MLFF Neural Network

The observed and predicted suspended sediment data obtained using RBF neural network and MLFF neural network are shown in Fig. 3 and Fig. 4 respectively. The agreement between the plots of observed and predicted suspended sediments obtained using RBF and MLFF suggest that both types of ANN are comparable and appropriate to predict time series of suspended sediment discharge from water discharge (i.e. current water discharge and antecedent water discharge values). However, RBF model results produced slightly better coefficient of determination (R^2=0.997, Fig. 4) than MLFF model (R^2=0.992, Fig. 3).

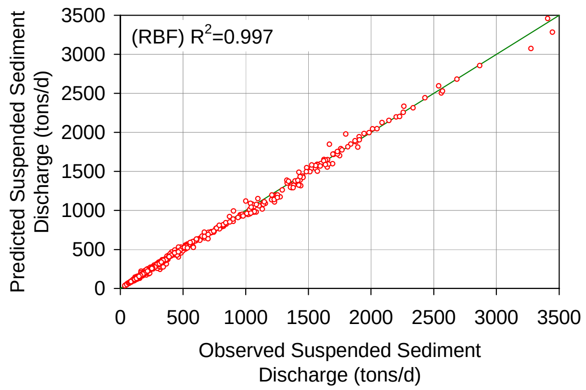

Fig. 3 Comparison between observed and predicted suspended sediments discharge using RBF Neural Network

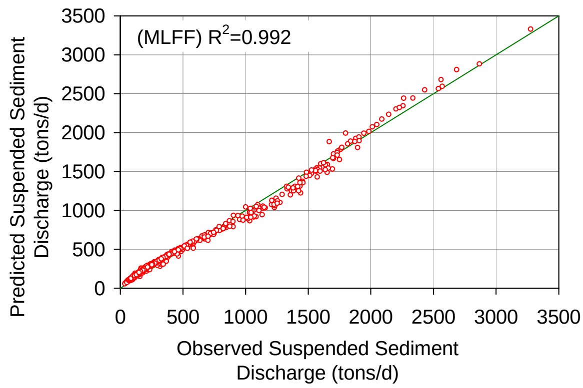

Fig. 4 Comparison between observed and predicted suspended sediments discharge using MLFF Neural network

A comparative analysis in terms of statistical measures *RMSE*, *MAE* and *CE* during training and testing stages of both ANN models is summarized in Table 1. During training stage, RBF model produced less error and better efficiency (*RMSE*= 23.72, *MAE*= 12.02 and *CE*=0.999) than MLFF model (*RMSE*= 49.46, *MAE*= 38.19 and *CE*= 0.996). Similar trend was found during testing stage, where RBF model also performed slightly better (*RMSE*= 30.86, *MAE*= 17.64 and *CE*= 0.997) than MLFF model (*RMSE*= 58.62, *MAE*= 48.73 and *CE*= 0.990).

TABLE I
COMPARISON OF PREDICTIVE PERFORMANCE OF RBF AND MLFF NETWORKS

Performance Measures	RBF		MLFF	
	Training	Testing	Training	Testing
RMSE	23.72	30.86	49.46	58.62
MAE	12.02	17.64	38.19	48.73
CE	0.999	0.997	0.996	0.990

All the results reveal that performance of both the models in all cases is very close to each other. Both models captured well the complex behavior of suspended sediments. Furthermore, RBF neural network required much more hidden neurons (100) than MLFF networks. However, during both training and testing stages, RBF network produced slightly better performance than MLFF network.

VII. CONCLUSIONS

The time series of suspended sediment discharge has been predicted from the time series of water discharge data at Pari River using two types of neural network. The study also compared the performance of RBF and MLFF neural network in learning the behavior of suspended sediments in rivers. The performance of the RBF and MLFF neural network models are found comparable. However, RBF neural network model showed slightly better performance than MLFF neural network model. The configuration used for both networks are appropriate to capture the highly dynamic behavior of suspended sediments. The study also showed that both RBF and MLFF networks can be modeled for prediction of suspended sediment discharge by using only water discharge data (i.e. excluding rainfall data).

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