Monitoring Event-Based Suspended Sediment Concentration by Artificial Neural Network Models

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Abstract: This paper is concerned with monitoring the hourly event-based river suspended sediment concentration (SSC) due to storms in Jiasian diversion weir in southern Taiwan. The weir is built for supplying 0.3 million tons of water per day averagely for civil and industrial use. Information of suspended sediments fluxes of rivers is crucial for monitoring the quality of water. The issue of water quality is of particular importance to Jiasian area where there are high population densities and intensive agricultural activities. Therefore, this study explores the potential of using artificial neural networks (ANNs) for modeling the event-based SSC for continuous monitoring of the river water quality. The data collected include the hourly water discharge, turbidity and SSC during the storm events. The feed forward backpropagation network (BP), generalized regression neural network (GRNN), and classical regression were employed to test their performances. From the statistical evaluation, it has been found that the performance of BP was slightly better than GRNN model. In addition, the classical regression performance was inferior to ANNs. Statistically, it appeared that both BP (r^2=0.930) and GRNN (r^2=0.927) models fit well for estimating the event-based SSC in the Jiasian diversion weir. The weir SSC estimation using a single input data with the neural networks showed the dominance of the turbidity variable over water discharge. Furthermore, using the the ANN models are more reliable than classical regression method for estimating the SSC in the area studied herein.

Key-Words: -Artificial neural networks, river monitoring, suspended sediment concentration, turbidity, water discharge, modeling.

1 Introduction

River suspended sediment modeling is required to provide basic information on the water quality related to the river management problems. According to [1], information of suspended sediments fluxes of rivers is crucial for monitoring the quality of water. Studies have used the suspended sediment concentration for indicating water quality [2-4]. Water quality is extremely important, because constant access to good quality water is a condition necessary for life and economy activities. Beside the human life and economy activities, as indicated by [5], the sediment monitoring is essential for the sustainability of the biological resources. Sediment represents an important vector governing the transport and fate of nutrients [6, 7], trace and heavy metals [8], micropollutants [9] and pathogens [10, 11].

The sediments transportation monitoring required a good sample technique which is very lengthy and expensive [12, 13]. Correct estimation of sediment volume carried by a river is very important for many water resources projects. In the recent past, several studies focused on the understanding of sediment transport dynamics [14-16]. It has been demonstrated how the percentages of the different particle sizes in suspended sediment vary according to the hydraulic characteristics of the river and the climatic regime of the area [15]. It is therefore important to develop a model that can predict accurately the suspended sediments concentration from continuous water data set where typhoon and tropical storms exist such as Taiwan. According to [17] the relationship between water discharge, turbidity and suspended sediments concentration can be used for estimating continuously the water quality during the storm events. In the past, researchers have proposed several rating curves to

determine the average relationship between discharge, turbidity and rivers suspended sediment load based on the classical regression method [14, 18]. This method does not always fit well because of the complex relationship of the sediment process.
Artificial neural network (ANN) is a technique with flexible mathematical structure which is capable of identifying complex non-linear relationship between input and output data without detailed the nature of the internal structure of the physical process. The ANN is capable to model any arbitrarily complex nonlinear process that relates sediments load to continuous water discharge. According to [19], ANN is a massively parallel distributed information processing system based on concepts derived from research on the nature of human brains, and has many distinct advantages for hydrological modeling. ANNs are very common in hydrology science. The emergence of ANN technology has provided many promising results in the field of hydrology and water resources simulation [20-22]. The ANNs have been successfully employed in modeling a wide range of hydrologic processes, including streamflows [23], rainfall-runoff processes [24], groundwater flow and water quality [5] and erosion and sediment transport [4]. Study reported that, the ANN better performs the sediments yield loaded [25].
The above reviews modeled the sediment processes by using different neural networks. In this study, the generalized regression neural network (GRNN) and feed forward backpropagation network (BP) algorithms were employed. Study reported by [26] considers the GRNN as a worth technique in sediment modeling, which is one of the most challenging works in water resources engineering. GRNN approximates any arbitrary function between input and output vectors, drawing the function estimate directly from the training data. The employment of GRNN in river sediment load has been carried out in recent year. As well, the BP used in this study is one of the most popular and traditional feed forward networks which has been widely used in river sediment yield modeling [27, 28]. According to [29], ANNs generally were found to be superior to conventional statistical techniques in suspended sediment estimation.
The water discharge, turbidity and SSC data collected for most of the papers were daily or monthly time scaled. In this research, ANN was applied to hourly suspended sediments concentration collected manually during the storm events from July to October 2002 in Jiasian diversion weir in southern Taiwan. The issue of water quality is of particular importance to Jiasian area where there are high population densities and intensive agricultural activities. It was observed that no work has been mentioned in the literature related to the using of ANNs for SSC estimation in the Jiasian diversion weir. The main objective of this study is to evaluate the potential of ANNs model for the weir suspended sediment concentration estimation. The present study compares the performance of ANNs model for SSC estimation by using continuous hourly turbidity and water discharge as input data set collected from the Jiasian diversion weir in southern Taiwan.

2 Material and Methods

2.1 Study Area

Jiasian diversion weir is located in Chishan River, southern part of Taiwan at 22 57’ 30” North latitude and 120 12’ 0” East longitudes (Figure 1). The Chishan River is a tributary of the Kaoping River which is a major river in Taiwan. The weir is built for supplying 0.3 million tons of water per day averagely for civil and industrial use. As industry and commerce in southern Taiwan are developing by leaps and bounds in recent years, demand for water is rising. Also, the weir is a continuation of the Nanhua reservoir which provides 0.8 millions tons of water per day. During the wet period, the surplus water of the Kaoping River is channeled into the Tsengwen Reservoir for allocation and storage. According to [30], the assessment of the drinking water quality in the Kaoping Rivers area is necessary. In this location, the average annual rainfall is 2794.4 mm with an abundance rainfall occurring in the wet season (May to October), conversely to the dry season (November to April). In the last fifty years, the total rainfall averages in dry and wet seasons were 235.9 and 2558.5 mm, respectively. Beside that, according to [31], the typhoon often raided island of Taiwan each year. It can be seen that the rainfall distribution at the location is unevenly distributed between the two seasons.

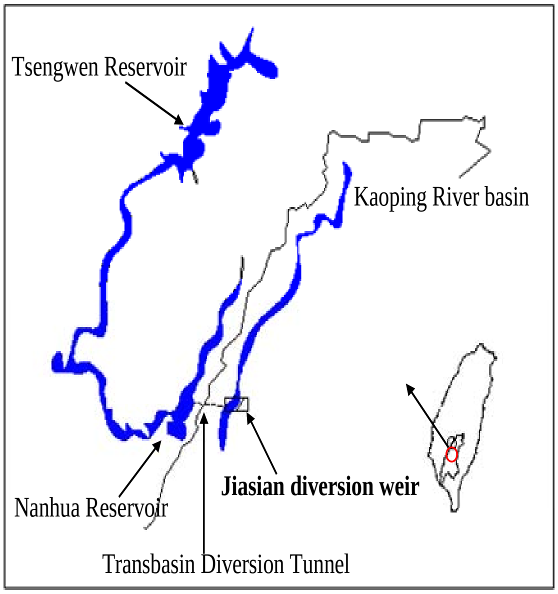

Figure 1. Sketch of the study area.

2.2 Data Collected

In this study, the hourly water discharge (cms), turbidity (NTU) and suspended sediments concentration (ppm) collected from July 18, 2002 to October 10, 2002. These hourly data were manually obtained during the storm events. The hourly sediment data have been collected because of the typical rainfall pattern and topography of the study area where most of the SSC is due to the typhoon storms. The water samples were analyzed by turbidimeter which applies a nephelometry technique that measures the level of light scattered by particles at right angles (90^o) to the incident light beam. The data set had a total of 1309 patterns and was divided between training, validation and testing to reach the best generalization. For preventing an overcome problem associated to the extreme values, the input and output data set were scaled in the range of [0 1] using the following equation [25].

$$Y_{norm} = \frac{Y_i - Y_{min}}{Y_{max} - Y_{min}} \quad (1)$$

where, Y_{norm} is the normalized dimensionless variable; Y_i is the observed value of variable; Y_{min} is the minimum value of the variable; and Y_{max} is the maximum value of the variable.

2.3 Artificial Neural Networks

2.3.1 Feed forward backpropagation

The most commonly used ANN in hydrological predictions is the feed forward network with the BP training algorithm [24]. Feed forward backpropagation is a supervised learning technique used for training artificial neural networks. BP has been widely used in approximating a complicated nonlinear function. The neural network structure in this study possessed a three-layer learning network consisting of an input layer, a hidden layer and an output layer. Adjustable weights are used to connect the nodes between adjacent layers and optimized by training algorithm to get the desired classification results [32]. Figure 2 shows the typical configuration for a BP used in this study.

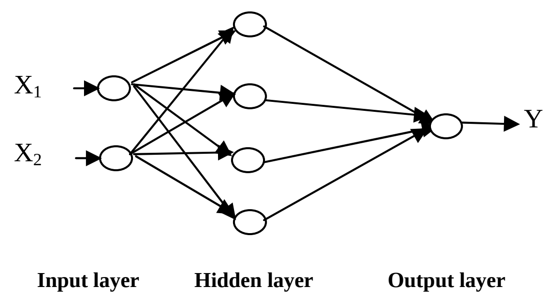

Figure 2. Structure of BP neural network Selected.

The mathematical equation of each layer may be written as following:

$$Y_o = \Phi(\sum W_{io} X_i - \theta_o) \quad (2)$$

where Y_o is the output of the neuron o, W_{io} is the weight increments between i and o, X_i is the input signal generated for neuron i, θ_o is the bias term associated with neuron o, and the nonlinear activation function Φ is assumed to be a sigmoid function as $\Phi(x) = 1/(1+e^{-x})$ for the continuous and differential process.

2.3.2 Generalized regression neural network

Generalized regression neural network (GRNN) can be treated as a normalized radial basic function network in which there is a hidden unit centered at every training case. These radial basic function units are usually probability density functions such as the Gaussian. By definition, the regression of a dependent variable Y on an independent X estimates the most probable value for Y, given X and a training set. The regression method will produce the estimated value of Y with a minimized root mean square error (RMSE). Figure 3 shows a schematic diagram of generalized regression neural network architecture. The number of input units in input layer depends on the total number of the observation parameters. The first layer is connected to the pattern layer and in this layer each neuron presents a training pattern and its output. The pattern layer is connected to the summation layer. The summation layer has two different types of summation, which are a single division unit and summation units. The summation and output layer together perform a normalization of output set. In Figure 2 and 3, X_1, X_2 and Y represent the turbidity (T), water discharge (Q) and suspended sediment concentration (SSC), respectively.

Suppose that $\mathrm{f(X,Y)}$ represents the joint probability density function of a vector random variable X (input), and a scalar random variable Y (output). The most probable predicted value of Y which is also conditional mean of Y given X (regression of Y on X) is expressed by:

$$\mathrm{E(Y/X)} = \hat{\mathrm{Y}}(\mathrm{X}) = \frac{\int_{-\infty}^{+\infty} \mathrm{Y f(X,Y) dY}}{\int_{-\infty}^{+\infty} \mathrm{f(X,Y) dY}} \quad (3)$$

The density function can be estimated from the training set using the Parzen's nonparametric estimator [33]:

$$\mathrm{f(X,Y)} = \frac{1}{n(2\pi)^{\frac{p+1}{2}}\sigma(p+1)} \sum_{i=1}^{n} \mathrm{e}^{-\mathrm{d}(\mathrm{X},\mathrm{X}_i)} \mathrm{e}^{-\mathrm{d}(\mathrm{Y},\mathrm{Y}_i)} \quad (4)$$

Where $\mathrm{d}(\mathrm{X},\mathrm{X}_i) = \sum_{j=1}^{p}[(\mathrm{X}_j - \mathrm{X}_{i_j})/(\sigma_j)]^2$ and $\mathrm{d}(\mathrm{Y},\mathrm{Y}_i) = [(\mathrm{Y}-\mathrm{Y}_i)/(\sigma_y)]^2$ the number of training patterns and the number of independent variables are denoted n and p, respectively. The density function $\mathrm{f(X,Y)}$ is therefore estimated by a weighted sum of the "Kernel function"[34]. The parameter σ represent the smoothing parameter the width of the "Kernel function".

The estimator $\mathrm{f(X,Y)}$ is asymptotically unbiased and consistent [35]. An interpretation of the probability estimate $\mathrm{f(X,Y)}$ is that it assigns sample probability of width σ for each i th value of X and Y. The indicated integration yields the following:

$$\hat{\mathrm{Y}}(\mathrm{X}) = \frac{\sum_{i=1}^{n} \mathrm{Y}_i e^{-\mathrm{d}(\mathrm{X},\mathrm{X}_i)}}{\sum_{1=i}^{n} e^{-\mathrm{d}(\mathrm{X},\mathrm{X}_i)}} \quad (5)$$

The predictor (5) is a weighted sum over all the training patterns. It is directly applicable to problems involving numerical data. Each training pattern is weighted exponentially according to its Euclidean distance to the unknown pattern x and also according to the smoothing factors. This predicator was mapped into a neural network, which includes four layers: input layer, pattern layer, summation layer and output layer.

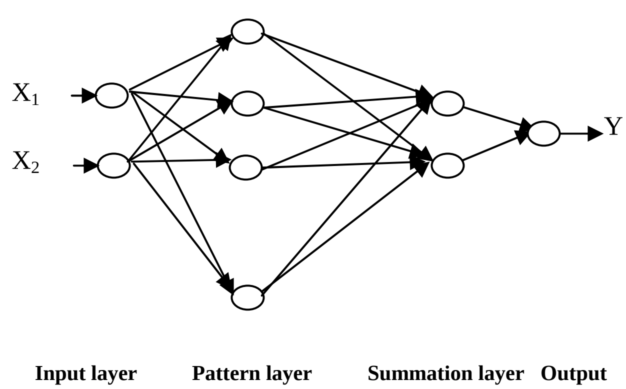

Figure 3. Schematic diagram of GRNN architecture.

2.3 Models Evaluation

The classical procedure between water discharge, turbidity and SSC reported by several studies [36-38] may be written as following:

$$Y_s = aX^b \tag{6}$$

where Y_s represents suspended sediment concentration, X is turbidity or water discharge, and a and b are the constants.

The performances evaluations were based on the root mean square errors and the square value of coefficient of correlation (r) between estimated and observed SSC. The root mean square error was used to test the statistical significant between estimates and observed SSC which can be expressed as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} d_i^2}{N}} \tag{7}$$

where d_i is the difference between *i*th estimated and *i*th SSC observed values and N is the number of observations.

The coefficient of correlation has been used for further analysis to evaluate the performance of estimation model. It is defined as follows:

$$r = \frac{\sum_{i=1}^{N}(X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{N}(X_i - \overline{X})^2 \sum_{i=1}^{N}(Y_i - \overline{Y})^2}} \tag{8}$$

Where X_i and $\overline{X}$ are the observed and its average values; Y_i and $\overline{Y}$ are the estimated and its average values; N is the number of observations.

3 Discussion of Results

The neural networks were fed with turbidity (T) and water discharge (Q) data selected as the independent input variables. The suspended sediment concentration (SSC) was used as a dependent output variable for the networks. In general, the training, validation and testing are the fundamental steps of neural network process. The training data set is used to train a neural network by minimizing the error of the data set during the training. The validation data set is used to find the neural network performance. Then, the test set is used for checking the overall performance of a trained and validated network. The networks were tested using different input and output values that were not given for training previously. For the Feed forward back propagation (BP) the data have been divided in three sets, training (60%), validation (30%) and testing (10%). The determination of the number of nodes in the hidden layers providing the best training results was the initial process of the training procedure. Hence, various numbers of nodes in a hidden layer were tried for the BP algorithm. However, the generalized regression neural network (GRNN) does not require an iterative training procedure as the BP model. GRNN was carried out by trying different smoothing parameters in order to obtain the best performance. Table 1 shows the networks performance during the training stage for BP and GRNN. The configuration with 2 inputs (turbidity and water discharge), 4 hidden nodes and unique output (SSC) denoted as BP (2 4 1) provided the best performance during the training stage, i.e. highest r^2 (0.977). For the generalized regression neural network, the structure GRNN (2, 0.01, 1) with 2 inputs, smoothing parameter 0.01 and 1 input gave the highest r^2 (0.958) during the training stage.

For the testing period, the network performances comparison results were given in Table 2. BP (2 4 1) configuration for the testing period compared with the observed SSC gave better

Table 1: Performances of BP and GRNN during the training period.

ANN configuration	Model input	Nodes in hidden layer	r^2
FFBP (2 4 1)	Q, T	4	0.977
FFBP (1 2 1)	T	2	0.929
FFBP (1 2 1)	Q	2	0.883
GRNN (2, 0.01, 1)	Q, T	-	0.958
GRNN (1, 0.01, 1)	T	-	0.934
GRNN (1, 0.01, 1)	Q	-	0.896

Table 2: Performance of BP and GRNN during the testing period.

ANN configuration	Model input	RMSE	r^2
FFBP (2 4 1)	Q, T	0.0227	0.930
FFBP (1 2 1)	T	0.0245	0.915
FFBP (1 2 1)	Q	0.0651	0.524
GRNN (1, 0.01, 1)	Q, T	0.0225	0.927
GRNN (2, 0.01, 1)	T	0.0237	0.919
GRNN (1, 0.01, 1)	Q	0.0597	0.558

estimates results by its lowest RMSE (0.0227) and highest r^2 (0.930). In this configuration the network has two inputs, hourly turbidity and water discharge for estimating the event-based SSC. Using this configuration, it can be seen from Figures 4a (plot) and b (scatter) a good agreement between estimated and observed SSC when turbidity and water discharge are used together as input. Conversely, using only one input in the same configuration, the performance of BP was reduced as shown in the Table 2 for both training and testing period. It could be observed that, using a single input with BP algorithm less performs the suspended sediment concentration estimation. BP algorithm may not lead to good generalization properties for the network when the input data are limited [21]. Although the single input less performs, it has been observed that, the performances were higher for turbidity (RMSE=0.0245, r^2=0.915) than water discharge (RMSE=0.0651, r^2=0.524) during the testing period. Accordingly, the turbidity seems to be a dominant variable over the water discharge for the suspended sediment concentration estimation for Jiasian diversion weir. For GRNN, during the testing period, the configuration GRNN (2, 0.01, 1) provided the best performances (RMSE=0.0225, r^2=0.927) as shown in Table 2. The GRNN network performing comparisons between observed and estimated suspended sediment concentration during the testing period are presented in Figures 5. Figures 5a and b show the plot and scatters of estimated and observed SSC during the testing period, respectively when T and Q are used as the network input. Similarly to BP, using a single turbidity or water discharge as input variable with GRNN, decrease the performance of the neural network model. The performances evaluated during the testing period were RMSE=0.0237, r^2=0.919 when the turbidity was used as a single input, and RMSE=0.0597, r^2=0.558 for the water discharge.

Further observation showed that the turbidity is a dominant parameter over the water discharge for the event-based SSC estimation in the weir. According to [39], other factors which are not included as inputs in the networks could explain this poor performance of water discharge. Studies done by [40, 41] denoted that human activity related to land surface disturbance increase the suspended sediment flux. Data analysis of hydrological processes of the watershed reveals that the water quality parameters are mostly affected by weather forces and land use of the watershed [42]. It is generally assumed that the human activities increase the rivers sediment concentration in the extensive urbanized and industrialized areas [5, 43].

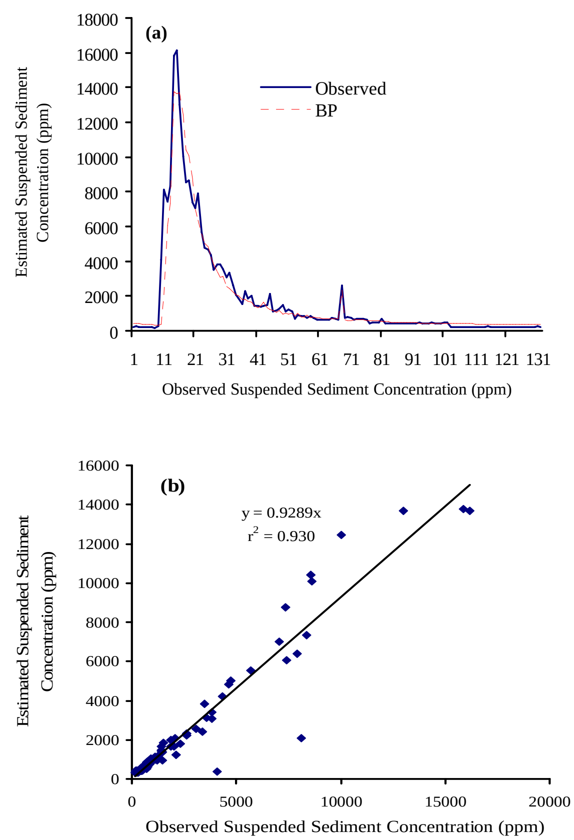

Figure 4. Suspended sediment concentration estimated by BP for the testing period using T and Q as input variables.

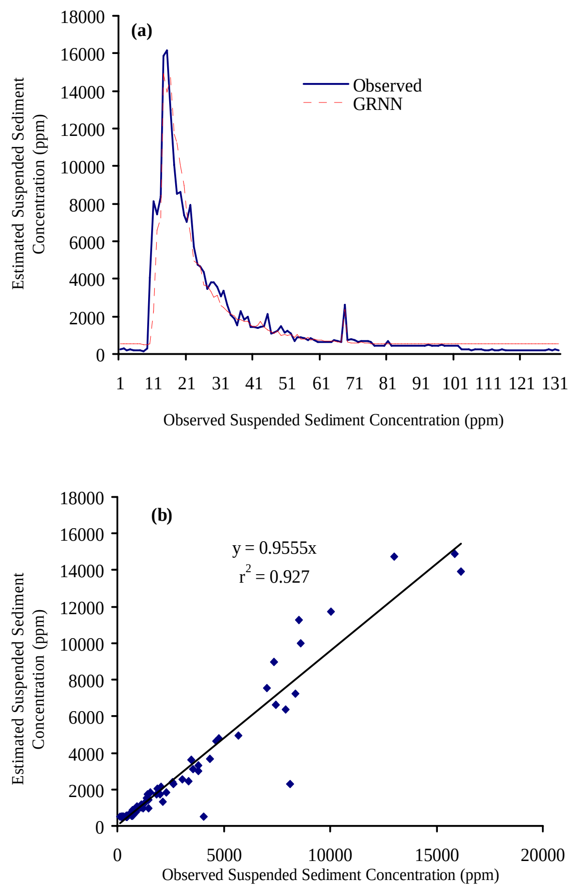

Figure 5. Suspended sediment concentration estimated by GRNN for the testing period using T and Q as input variables.

The human activities could increase the suspended flux independently to the water discharge. This could explain the poor relationship between water discharge and suspended sediments concentration recorded at the weir. It could be conclude that from this study, by using a single input variable decrease the performance of the neural networks.

By comparing the performance of ANN with the classical linear regression method, ANN could provide the highest performance for event-based suspended sediment concentration estimation. The relationship from classical method for turbidity versus SSC, and water discharge versus SSC were r^2 (0.890) and r^2 (0.455), respectively. Studies reported that, ANN could provide an estimate closer to observed suspended sediment concentration than the classical linear regression method [23, 29, 44]. Previous Report done by [41] demonstrated from the daily suspended sediment concentration simulation that, the modeling of sediment concentration in a river is possible through the use of ANN. The predictive accuracy of the ANN model was found to be better for modeling sediment transport [45]. According to [42], the performance of the BP was found to be superior to conventional statistical and stochastic methods in continuous flow series forecasting. The superiority of ANNs over the conventional method in the reviewed prediction study can be attributed to their capability to capture the non-linear dynamics and generalize the structure of the whole data set [46]. Clearly, using the ANNs for sediment modeling is more reliable than the other methods in the weir studied herein.

4 Conclusions

In this study, the applicability of artificial intelligence techniques is investigated in the jiasian diversion weir in southern Taiwan. This study showed the ability of the feed forward back propagation (BP) and the generalized regression neural networks to model the event-based suspended sediment concentration in Jiasian diversion weir. The performances of the models and observations were compared and evaluated based on their performance in training and testing sets. Both BP and GRNN perform better than the conventional linear regression method. It was observed from the results of this study, that, the performances of the networks were higher when turbidity and water discharge were used together as an associate input. Using a single input decreases the network performances. In addition, the turbidity seems to be a dominant variable on water discharge for the event-based suspended sediment concentration estimation for Jiasian diversion weir. Other factors such as human activities, which are not included as inputs in the networks could explain the poor relationship between water discharge and SSC recorded at the weir. The human activities could increase the suspended flux independently to the water discharge. It could be conclude clearly that by using the ANNs for modeling the sediment in the weir studied herein is more reliable than the other methods.

5 Acknowledgments

The authors like to express thier sincer thanks to the South Region Water Resources Office, WRA, MOEA, for the financial support to this study. In addition, the authors wish to acknowledge the National Pingtung University of Science and Technology for providing the facility needed during this study.

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