Using Meta-heuristic Models for Simulation of Sediment Transport in Rivers

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Abstract

Two important characteristics of the hydrologic phenomena are their non-linear behaviour and uncertainty and ambiguity in their nature. So, as a hydrologic phenomenon, the sediment transport possesses a kind of uncertainty and ambiguity as well. Recently, use of Artificial Neural Networks (ANNs) and fuzzy sets in simulation and modelling of the systems with uncertainty has produced suitable results. In this research, for modelling and prediction of sediment transport of river flows, the Adaptive Neuro-Fuzzy Inference System (ANFIS) as a method based on the ANNs and fuzzy sets was used. Using several ANNs and ANFIS models for prediction of sediment load transport showed that using the river discharge in the current period and the river discharge and the sediment load in the previous period as the models nodes, yields the best results.

Keywords: Sediment transport, Neural network, Fuzzy sets, ANFIS

1 Introduction

Transport of solid materials by the rivers flow is one of the important subjects in river engineering. Due to the negative effects on the practical activities in river basin management, river structures, hydroelectric power plants, and in particular, loss of the useful volume of the dam reservoirs, sediment transport is of special importance in hydraulic engineering. Moreover, the sediment transport subject is now paid a great deal of attention from the environmental impacts viewpoint.

The phenomenon of erosion and sedimentation in rivers is one of the most complicated hydrodynamic problems which influences the operation of many hydraulic systems and is considered as one of the most acute problems in the operation of the water resources systems. This problem has been under more severe attention recently due to the environmental impact in particular in cases of transport of polluted sediments. Consequently, prediction of sediment load has been a subject of research for hydraulicians since a century ago.

Many formulae and methods have been developed and presented for the purpose of a more accurate estimation of the sediment load based on the analytic works and information obtained by field measurements. There has been a great discrepancy between the results of the predictions using different methods for different cases.

Sediment transport and the amount of sediment transported by the river from the watershed, is mainly influenced by the hydrologic parameters and the river flow characteristics. Considering the nature of the sediment transport phenomenon, use of the meta-heuristic methods for estimation of the sediment transported by the river flow could be of great help towards obtaining accurate results.

The Neural Network method has widely been used for this purpose and with sufficient data concerning the characteristics of sediments, characteristics of flow and sediment discharge, a suitable mean could be formed by which a reliable prediction of sediment load could be achieved as an alternative and a better solution. In this research, Neuro-Fuzzy concept was used as a mean for this purpose.

For evaluation of the capabilities of this model, its results were compared with those of the Neural Network model and the traditional sediment rating curve method. This comparison indicated more suitable prediction of the ANFIS method compared with that of Neural Network model and sediment-rating curve.

2 Brief Literature Review

Since the early nineties, there has been a rapidly growing interest among water scientists in applying the ANNs in different fields of water engineering such as rainfall-runoff modelling, stream flow and precipitation forecasting, water quality and ground water modelling, water management policy and so on.

Some of the applications of ANNs in hydrology could be mentioned as application of ANN for reservoir inflow prediction and operation (Jain et al., 1999), river stage forecasting using artificial neural networks (Thirumalaiah et al., 1998), back propagation in hydrological time series forecasting (Lachtermacher et al., 1994), performance of neural networks in daily stream flow forecasting (Birikundavyi et al., 2002), daily reservoir inflow forecasting using artificial neural networks with stopped training approach (Coulibaly et al., 2000), multivariate reservoir inflow forecasting using temporal neural networks (Coulibaly et al., 2001) and finally comparative analysis of event-based rainfall-runoff modelling techniques-deterministic, statistical, and artificial neural networks (Jain et al., 2003).

3 Basic Concept of Neural Network

Rosenblatt presented initially the ANNs as a computational method, as Perceptron nets and Widrow as ADALINE nets. The method is based on the complicated theory of parallel process of biologic neuron systems. The basic elements of an ANN are the artificial neurons, which may be referred to as nodes, units or processing elements. The input pattern to node is similar to a dendrite of a biological cell, which can be presented by a vector with N elements as:

$$X = (x_1, x_1, ..., x_N) \tag{1}$$

Now the scalar quantity S may be defined as:

$$S = \sum_{n=1}^{N} w_n . x_n = W^T . X \tag{2}$$

In which, $W = (w_1, w_2 ..., w_N)$, is vector of weights. The scalar S then enters a nonlinear transition function f, to yield output y. The function f often takes the form of sigmoid or hyperbolic tangent, the former is more common. The following relation defines the sigmoid function ,

$$y = f(S) = (1 + \exp(-s))^{-1} \tag{3}$$

The output y can either be the model result or be treated as an input to the next layer in multi-layer networks. Figure 1 shows a general neural network structure.

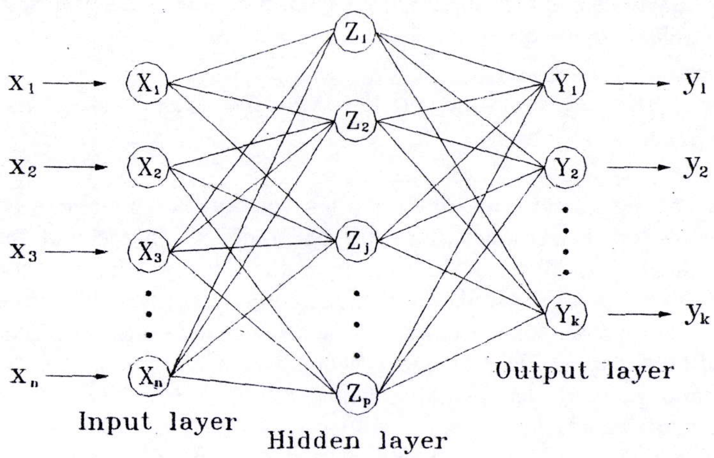

Figure 1: General structure of an ANN

As it is seen, each net has been formed by an input layer, one or more hidden layer, and an output layer. There are many algorithms developed for computing optimum weights; among them the back propagation algorithm has been used extensively. In this algorithm, first, nodes give small weights randomly, then, in a repetitive procedure, these weights are improved based on comparison between observed and computed outputs.

For the training algorithm the back propagation or delta rule scheme has been approved to be efficient in various problems. The same scheme has been employed in this study as the training algorithm. To select an appropriate network, root of mean square error (RMSE), and correlation coefficient of training and testing has been employed in this investigation.

4 Fuzzy Logic and Fuzzy Inference System

A fuzzy set {A} in the world space U is distinguished by a function $\mu_A(x)$ which takes values in the range [0,1]. So, a fuzzy set is the extension of classic set which allows the membership function to take any value in the range [0,1]. In the other word, a classic set could only take the two values of 0 and 1, while the membership function of a fuzzy set is a continuous function in the range [0,1].

In the classic logic, a sentence may be correct or incorrect. That is, the value of the correctness of a sentence is zero or one. The Fuzzy logic would extend the bi-value classic logic to the sentences the correctness of which could possess any value in the range of [0,1]. The process of mapping from one input data to an output one using the fuzzy logic is called the fuzzy inference.

This inference consists of membership function, fuzzy logic operators and the if-then rules. The main structure of an inference system is a model which converts the input characteristics to the input membership functions, the input membership functions to the rules, the basics to a set of output characteristics, the output characteristics to the output membership functions and the output membership functions to a simplified output value or a decision related to the output.

5 Application of the ANNs and the Neuro-Fuzzy Models in Sediment Transport

The amount of sediment transported by the river flow is a nonlinear mapping of the involved parameters in sediment transport phenomenon. In most of the hydrologic phenomena, due to the effects of different hydrologic factors. there exists a non-linear behaviour. In these cases, the applied statistical method usually is the regression curve.

However, due to the complexity and the non-linear nature of the phenomenon, this method is of no suitable efficiency and is accompanied by large errors. Nowadays, the artificial neural network has widely been used as a suitable tool for modelling phenomena in different fields of applied sciences.

One of the superiority of the neural networks is the recognition of the relation between input and output variables of a problem without considering the physics and the nature of the phenomenon under study. In this method, having data and information about the variables effective in the sediment transport phenomenon obtained from field measurements and using a suitable neural network, the behaviour governing the phenomenon could be assessed by training the network and it could then be used for prediction in the cases under study.

Apart from the non-linear behaviour of the hydrologic phenomena, the other characteristics of the phenomena are their uncertainty and ambiguity. The sediment transport phenomena possess also the characteristics of uncertainty and ambiguity due to the fact that it is strongly influenced by these hydrologic phenomena. Recently, the use of the fuzzy sets theory in modelling of the phenomena of uncertainty and ambiguity has given desirable results. Consequently, in this research, the Neural-Fuzzy model has been used for modelling sediment transport and for prediction of sediment load of the river flow.

6 The Case Study

The daily time series data of discharge and sediment concentration for the Qutnai River at the Porthill station was obtained. The number of data available for this station was 1691. In the neural network model, two time periods were designated as the training set and the testing set. In the Neuro-Fuzzy model three time periods were chosen as the training, the control set and the examination set. If Q_t and C_t are the discharge and sediment concentration at the time-step t, the following combinations were taken as input.

1) Q_{t-1}, Q_t and C_{t-1}
2) Q_{t-2}, Q_{t-1}, Q_t and C_{t-1}
3) Q_{t-2}, Q_{t-1}, Q_t, C_{t-2}, C_{t-1}

The Neural Works software was used for the neural network modelling. Neuro-fuzzy modelling was carried out using the ANFIS which is part of the fuzzy package of MATLAB software, The ANFIS or Adaptive Neuro-Fuzzy Inference System is capable of modelling a series of input data-output including the fuzzy output and input. So, ANFIS, in a general view, is a combination of the artificial neural networks and the fuzzy sets theory.

In order to determine the time range of teaching and examination sets in the neural network model, 76 percent of the Porthill data was allocated to the training set and 25 percent of the data was allocated to the testing set. In the neuro-fuzzy model, 7 percent of the data was allocated to the training set, 12 percent of the data was allocated to the control set and 12 percent of the data was allocated to the testing set.

6.1 Development of the Artificial Neural Network

In this research, for suitable organization of the networks and achieving the best possible solution (the answer closest to the field data), different examinations were carried out. These examinations were in the form of change of the number of the neurons of the hidden layer, change of the weights of the layers, change of the momentum coefficient, change of the rate of the learning and then choosing the network which gave the closest answer to the field data. For comparison and analysis of the results, the parameters root mean square error (RMSE) and regression coefficient were used. The results of the training and testing of the network of the Porthill station are presented in tables 1 to 4.

Table 1: Selected networks for the first state model

Network	Number of node in each layer					RMSE	Regression coefficient	
	Input	Hidden 1	Hidden 2	Hidden 3	Output		Training set	Testing set
1*	3	5	0	0	1	149.74	0.909	0.857
2	3	3	2	0	1	158.075	0.891	0.855
3	3	2	4	0	1	156.73	0.893	0.856
4	3	4	5	0	1	157.33	0.894	0.849
5	3	5	5	0	1	163.46	0.886	0.842
6	3	6	5	0	1	158.318	0.893	0.845
7	3	7	4	0	1	158.16	0.896	0.844
8	3	7	6	0	1	157.1	0.894	0.852
9	3	2	2	2	1	151.93	0.909	0.844

Table 2: Selected network for the second state model

Network	Number of node in each layer					RMSE	Regression coefficient	
	Input	Hidden 1	Hidden 2	Hidden 3	Output		Training set	Testing set
1	4	3	0	0	1	147.75	0.918	0.852
2	4	4	0	0	1	148.18	0.915	0.856
3	4	3	2	0	1	150.267	0.914	0.848
4	4	6	2	0	1	148.72	0.915	0.854
5	4	2	3	0	1	147.5	0.920	0.843
6*	4	5	6	0	1	146.48	0.928	0.853
7	4	2	2	2	1	148.42	0.916	0.856

Table 3: Selected Network for the third state model

Network	Number of node in each layer					RMSE	Regression coefficient	
	Input	Hidden 1	Hidden 2	Hidden 3	Output		Training set	Testing set
1	5	1	1	0	1	162.2	0.884	0.84
2	5	2	1	0	1	151.76	0.913	0.831
3	5	2	3	0	1	148.84	0.913	0.850
4	5	5	3	0	1	158.06	0.892	0.845
5	5	2	1	1	1	150.15	0.913	0.843
6	5	3	1	1	1	153.59	0.918	0.813
7*	5	5	3	1	1	149.03	0.919	0.854
8	5	3	4	2	1	149.44	0.913	0.854

Table 4: Selected ANN models for the first, second and third states

State	No. of input	RMSE	Regression coefficient	
			Training set	Testing set
1	3	149.74	0.909	0.857
2	4	146.48	0.928	0.853
3	5	149.03	0.919	0.854

6.2 Development of the Neuro-Fuzzy model

The Neuro-Fuzzy model is a combination of the artificial neural networks and the fuzzy inference system. This combination is a mean for optimum selection of the membership function parameters. So, the membership function parameters of input and output variables are assumed as the neural network weights and are optimized. The requirement of a proper function of the ANFIS model is the availability of sufficient and effective number of data in order to optimize the membership function parameters with regard to the teaching and control data.

The ANFIS model is capable of extracting the hidden knowledge of information with high degree of nonlinearity. So, application of this model in the phenomena with complicated structure could very much be useful. In teaching by the ANFIS model, it should be noted that the number of rules of the fuzzy inference system should be such that the related fuzzy principles station would be complete.

On the other hand, due to the considerable computation volume in the verification and optimization of the parameters in the ANFIS model, creation and teaching a fuzzy inference system with the minimum number of fuzzy principles is vital. One of the effective means for this purpose is the use of clustering methods. In these methods, processing the input and put data, the collection of these data are divided based on their distances from each other and the closer data are located in the gathered data collections of clusters.

The number of the fuzzy principles would be a direct function of the number of the selected clusters. Each cluster is introduced by its centre and its influence area. The bigger the influence area of the clusters, the less would be the number of them and the number of the fuzzy principles.

In this research, carrying out trial and error on the indicator parameter of the clusters size, it was tried to gain the best model. It is necessary to note that with reduction of the influence area of the clusters, although the number of the fuzzy principles increases, it would not result in a better ANFIS model. So, it is vital to close the number of principles (clusters size) such that both errors related to the training and control data in different repetitions of the training process would eventually be descending and would simultaneously be minimized.

Also, it should be noticed that increase in number of repetitions in the process of training would not necessarily result a reduction in the error in training and control data and it is possible that after a number of repetition, the values of the errors would be ascending, oscillating or divergent. So, although, the error of the training data would reduce, the increase in the error of the control data would result in an increase in the error of the ANFIS model. The results of the trading, control and examination by the ANFIS model at the Porthill station are presented in tables 5 to 8.

Table 5: Selected ANFIS models for the first state

Model	Cluster area	RMSE	Regression coefficient		
			Training set	Control set	Testing set
1*	0.28	122.25	0.926	0.867	0.868
2	0.31	122.076	0.928	0.861	0.860
3	0.14	124.461	0.929	0.856	0.821

Table 6: Selected ANFIS models for the second state

Model	Cluster area	RMSE	Regression coefficient		
			Training set	Control set	Testing set
1*	0.44	119.1	0.939	0.865	0.859
2	0.43	117.3	0.948	0.878	0.767
3	0.21	120.63	0.940	0.840	0.851

Table 7: Selected ANFIS models for the third state

Model	Cluster area	RMSE	Regression coefficient		
			Training set	Control set	Testing set
1*	0.15	126.57	0.930	0.824	0.840
2	0.14	129.24	0.925	0.845	0.834
3	0.19	129.66	0.927	0.827	0.835

Table 8: Selected ANFIS models for the first, second and third states

Model	Cluster area	RMSE	Regression coefficient		
			Training set	Control set	Testing set
1	3	122.25	0.926	0.867	0.868
2*	4	119.1	0.939	0.865	0.859
3	5	126.57	0.930	0.842	0.840

6.3 The Sediment Rating Curve of the Porthill Station

Based on the input and output data of the Porthill station and fitting a power curve on these data, using the EXEL software, the following relation was obtained as the sediment rating curve

$$Q_s = 0.0176Q^{1.5867} \tag{4}$$

In this equation Q_S is the sediment load and Q is the discharge. It should be noted that the above relation has been obtained by fitting a curve on the training data and it should be examined and evaluated for the testing data. The final comparison of the results of the Neuro-Fuzzy model and Artificial Neural Network with those of the sediment rating curve mode was carried out using the regression coefficient and the root mean square error parameters which is presented in table 9.

Table 9: Comparison of the ANN, ANFIS, and the sediment rating curve models results

Model	RMSE	Regression coefficient		
		Training set	Control set	Testing set
ANFIS	119.1	0.939	0.865	0.859
ANN	146.48	0.928	0.853	0.853
SRC	231.02	0.706	0.701	0.701

7 Conclusions

Using several ANNs and ANFIS models for prediction of sediment load transport at the Porthill station, the following results were obtained:

- Prediction of sediment load based on the sediment rating curve method leads to a relatively high errors. In this model the regression coefficient, *R*, (as a tool for comparison) was obtained as 0.706.
- Using the river discharge in the current period and the river discharge and the sediment load in the previous period as three nodes in the ANNs models in the best network yields 0.909 for the regression coefficient, *R*. Adding the discharge data in two previous period yields for this coefficient the value of 0.928 which considerably improves the prediction. However adding the sediment load in two previous period yields 0.919 for the regression coefficients.
- The same trend was observed in the ANFIS model in which the best results were obtained in the second state models. However, the model is more accurate than the ANNs model, with the value of 0.939 for the regression coefficient, *R*.
- Based on the results presented in table 9, the answer to the problem from the ANNs model and the ANFIS model are considerably better than that given by the rating curve method. Comparison of between RMS error and regression coefficient parameters for ANNs and ANFIS models indicates superiority of the ANFIS model.

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