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Research Article

SIMULATION DEPTH OF BRIDGE PIER SCOURING USING ARTIFICIAL NEURAL NETWORK AND ADAPTIVE NEURO –FUZZY INFERENCE SYSTEM

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ABSTRACT
Bridges are among the most important river-related structures. They are considered as the communication keys. Floods ruin bridges each year exactly when they are significantly demanded. One of the most significant factors making bridges ruined is scouring around bridge pier. Although construction tools and structures have been developed, the number of bridges ruined due to scouring is ever-increasing. Depth of bed erosion relative to initial depth is called scouring depth. Current research has been done on 44 bridges located in different states of the U.S.A artificial neural network and multi-layer Perceptron model are tested using posterior algorithm and adaptive neuro-fuzzy inference system (ANFIS). Results have shown that artificial neural network outperforms ANFIS in simulation of depth of bridge pier scouring.

Keywords: *Scouring, Bridge Pier, Neuron Network, Adaptive Neuro-Fuzzy Inference System (Anfis)*

INTRODUCTION
One of the most important factors making bridges ruined is scouring around bridge pier. Therefore, to avoid or reduce the effect of scouring, it is necessary to identify its mechanism. Beds composing of Granite take a long time for erosion while sand beds reach to the maximum scouring depth in a short time. In addition to ground and river composition which is one of the most effective factors, hydraulic factors play an important role in erosion also. Bed and canal erosion due to water flowing is called downstream erosion. Erosion of hydraulic constructs due to intensive water-flow or due to local turbulent water-flow is called scouring. Depth of bed erosion relative to initial depth is called scouring depth. In this section, researches done on scouring around bridge pier using artificial neural network and ANFIS is presented briefly. Ramezani *et al.,* (1389) estimated the depth of local scouring of bridge pier with the aid of artificial intelligence. The optimized results were related to RBF model in training phase and related to ANFIS, FFBP and RBF in testing phase.

Artificial intelligence develops the accuracy of estimation of scouring depth of bridge pier compared with regression methods. Precise and reliable designs are possible only with the help of artificial intelligence method. Kanaani *et al.,* (1391) used ANFIS whose input parameters were optimized using genetic algorithm. Results indicated that ANFIS optimized with genetic algorithm would perform better. It could predict the maximum depth of scouring of 0.992 with R^2 and of 0.02396 with RMSE. Hosseinnejad *et al.,* (1391) developed a model for estimating the depth of scouring with the help of artificial neural network. Results of the mentioned model were compared with experimental results and real data. Artificial neural network increased the accuracy of estimation of depth of scouring. It offered a more reliable evaluation f depth of scouring than experimental relations. Ghazanfari *et al.,* (1388) showed that results of SVM are of higher accuracy compared with ANN.

Accuracy of these two methods is higher than experimental relations. Shahradfar *et al.,* (1387) compared results of three valid methods for estimating the depth of scouring with the results of an optimized artificial neural network model. They used real statistics for the mentioned comparison. Results indicated that ANN is of high speed and of great accuracy. It offers better results than other models. Khosravi *et al.,* (1390) studied the possibility of usage of multi-layer Perceptron network (MLP) to estimate the maximum depth of scouring around three drops including drops with half-circle, winged and vertical walls. Accuracy of artificial neural network in estimating the depth of scouring around drops with vertical walls is higher than the other drops.

MATERIALS AND METHODS

Artificial Neural Networks

According to applicability, different types of neural network have been developed. Multi-layer Perceptron networks are among usable networks in engineering domains. A model with Multi-layer Perceptron networks includes input, hidden and output layers (figure 1). Each layer has one or more neurons so that the performance of neurons is similar to that of human brain. Training of artificial neural network means calculating weights of different connections. To train artificial neural networks, different algorithms including posterior, coupled gradient and radial principal function algorithms are used. Selection of algorithm depends on learning speed and accuracy of network. Posterior algorithm includes two main paths. The first path is called forward path on which input vector enters MLP network. Effects distribute into output layer through middle layer. Output vector formed on output layer provides real response for MLP. In this path, parameters are constant and unchanged. The second path is called backward on which parameters are changed and adjusted. Adjustment is done based on error correction principles. Error signal is formed in output layer. Error vector is the difference between desired and real responses. Error distributes into network through network layer when backing from output layer. The mentioned distribution is against weighted connection path of neurons; therefore, the word posterior is selected to explain network behavioral correction.

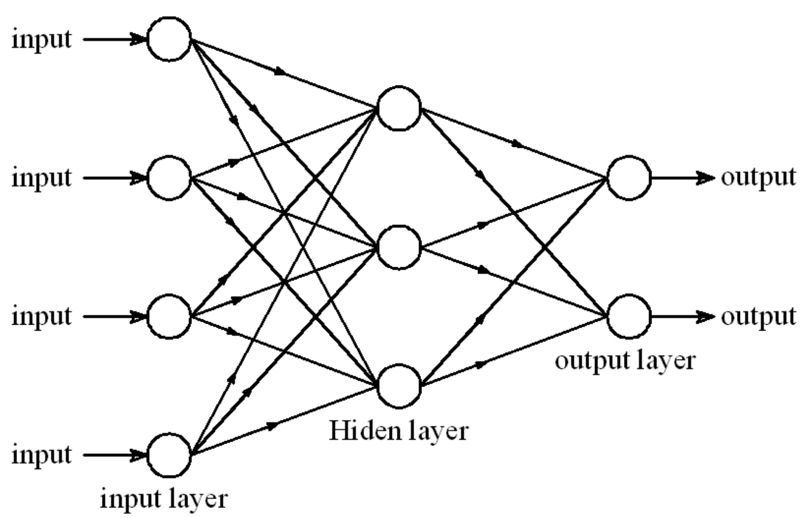


Figure 1: MLP Network

In neural network, a part dataset (70%) indicating possible conditions is used for network training. The remaining (30%) is used for testing network performance. The point in selecting data is that vast range of data is used. To choose testing data, it is tried not to include the maximum and minimum values. Additionally, two training and testing datasets should be close to each other in terms of mean and standard deviation to make them similar. Data should be normalized before entering network i.e. to use sigmoid hidden threshold function; input data should be normalized before training normal neural network so that data is converted to numbers between 0 and 1. Output of the mentioned function is also between 0 and 1. Form of input data plays an important role on network learning. For inputs close to zero or one, neuron weights are of the minimum change because in this condition, processor operator works slowly. Entering raw data leads to slow and inaccurate network performance. To avoid this problem and to make data value equal for network, Normalization is done based on:

$$X_n = \left[\frac{x - x_{Min}}{X_{max} - X_{min}}\right]$$

Where,

X represents observed data.

Xmin and Xmax are the minimum and maximum of data respectively.
Xn indicates normalized data.
After selection of testing and training datasets, neuron network is designed. To train network, MATLAB is used.

Adaptive Neuro-fuzzy Inference System

Fuzzy logic introduced against classic logic is a powerful tool to solve the problems related to complex systems which are hard to understand. Also, it is used to solve the problems related to conclusion, decision making and inference. Choosing an appropriate approach for system modeling depends on the degree of system complexity. Also, it is in a reverse relation with the amount of knowledge and cognition we have of that system. Totally, information related to a fuzzy system is used as a membership function in all theories and applications. Membership function determines how much a fuzzy system is fuzzy. Fuzzy inference system is based on if-then based on which a relation is developed between input and output variables. Therefore, FIS is considered as a prediction model when input and output data are of high uncertainty. In this case, classic prediction methods such as regression are not able to model uncertainty. Generally, a fuzzy system has the ability to compile human knowledge in the form of rules and principles. Ultimately, after administering a fuzzy system, a rule base similar to what human skills provide, will be available. Rules such as if-then explain system behavior. Sometimes, it is hard for us to identify rules and principles and we are not able to write these rules easily, but we know that we have some desirable inputs and outputs. To show it by a fuzzy system, it should be treated as a neuron network. Parameters of fuzzy system should be changed based on data. Finally, a combination of neuron and fuzzy systems called Adaptive neuro-fuzzy inference system (ANFIS) is obtained. ANFIS is a fuzzy system providing us with qualitative expression ability.

Evaluating Performance of the Two Models

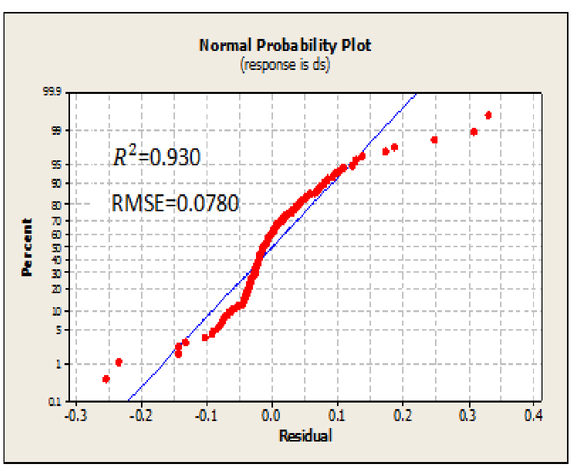
To evaluate efficiency and performance of each network and to investigate ability of that network for simulating, different measures are used. In the current research, root mean square error (RMSE) and determination coefficient (R2) are used:

$$RMSE=\sqrt{\frac{\sum_{i=1}^{N}(O_i-t_i)^2}{N}}$$

$$R^2=1-\frac{\sum_{i=1}^{N}(O_i-t_i)^2}{\sum_{i=1}^{N}(O_i-\overline{O}_i)^2}$$

Result Analysis

Figures 2 and 3 are representing measured real values and simulated values of depth of scouring around bridge pier using the ANFIS and artificial neural network models.



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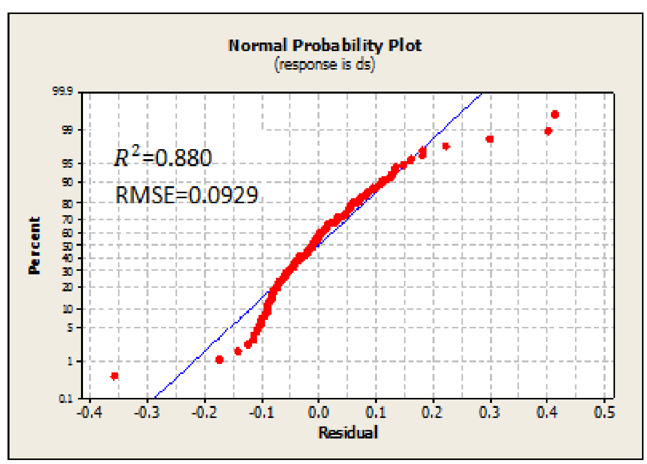

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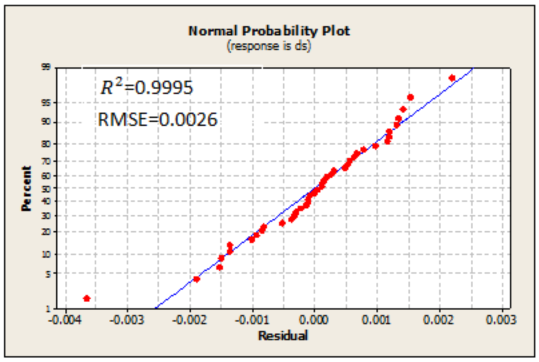
Figure 2: Scour depth comparison of observed and simulated neural fuzzy inference model

Figure 2 is related to ANFIS model. The best selected models have R2 value of 0.930 and RMSE value of 0.0780 and R2 value of 0.880 and RMSE value of 0.0929.

Figure 3 represents artificial neural network model. The best selected models have R2 value of 0.9995 and RMSE value of 0.0026, R2 value of 0.9998 and RMSE value of 0.00191 and R2 value of 0.9998 and RMSE value of 0.0072.

According to models, results simulated by artificial neural network are better than that simulated by ANFIS. Accordingly, it is concluded that artificial neural network performs better in simulating the depth of scouring around bridge pier than ANFIS.



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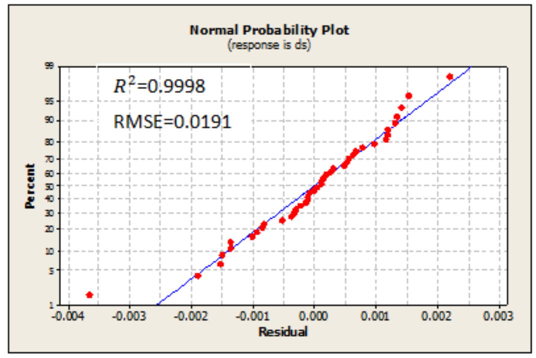

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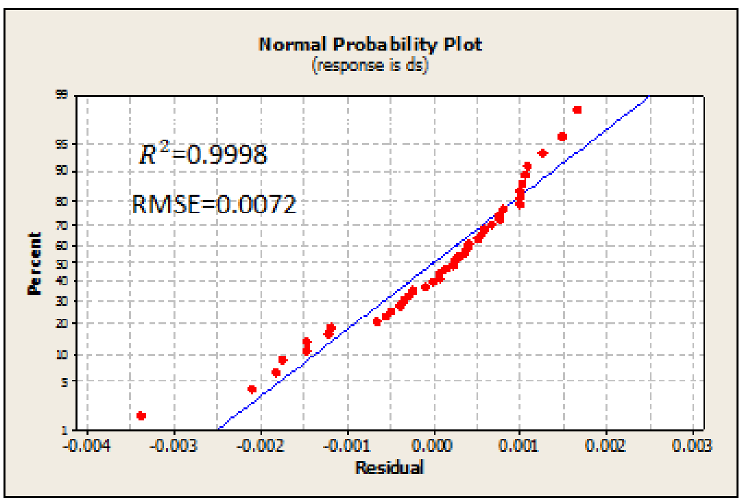

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Figure 3: Scour depth comparison of observed and simulated by artificial neural network

In table (1), statistical parameters obtained from simulation results are given with ANFIS. As seen, according to statistical parameters, the second row including DS-D50-V-Y-B shows better results than the other simulation models.

In table (2), statistical parameters of simulation results are given with artificial neural network models. As seen, according to statistical parameters, MLP29 model including DS-V-B shows better results than the other simulation models.

Table 1: Adaptive neuro-fuzzy inference system models (ANFIS)

RMSE		Number of mfs	Epochs	Mf type	Parameter	Row
0.0929	**0.880**	**3**	**40**	**gaussmf**	**ds-b**	**1**
0.0780	**0.930**	**3 3 3 3**	**30**	**trapmf**	**ds-d50-v-y-b**	**2**

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Table 2: Artificial neural network models

RMSE	R^2	TRAINING	The output layer	Second hidden layer		The first hidden layer		Number of layers	model	parameter	Row
		R	Function of stimulus	Number of neurons	Function of stimulus	Number of neurons	Function of stimulus				
0.0191	0.9998	0.99945	purelin	3	tan sig	4	tan sig	3	MLP 16	ds-y	1
0.0026	0.9995	0.99974	purelin	-	-	2	log sig	2	MLP 17	ds-D50-b	2
0.0072	0.9998	0.99964	purelin	-	-	2	log sig	2	MLP 29	ds-v-b	3

Conclusion

This research investigates 44 bridge located in different states of the U.S.A After training network, different model are obtained among which MLP29 with R2 value of 0.9998 and RMSE value of 0.0027 shows better results than the other simulation models. Also, results obtained from ANFIS and neuron system with R2 value of 0.9300 and RMSE value of 0.0780 are available. Consequently, compared with ANFIS, neural network is a useful and accurate tool to predict depth of scouring around bridge pier.

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