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Determining Local Scour Depth around the Cylindrical Pillars of Bridges Using Artificial Neural Network

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Abstract-One of the most important reasons of destruction of bridges especially in case of flooding is local scour around pillars. Determining the depth of local scour around bridges pillars has an important role in designing bridges against this destructive phenomenon. This phenomenon has been investigated by different researchers using various methods but the main problem of all these methods is that all of them need a predetermined mathematical equation for modeling this complicated phenomenon.

Existing equations for calculating the depth of scour have been all empirical up to now and the researchers in empirical proposed methods and formulas were likely to use two or more parameters in their relations and ignore some other ones.

The depth of scour in pillars has been investigated in this paper using an artificial neural network model. Artificial neural network which is formed from a neurons and smart structure following existing neurons in the mind of human being, tries to simulate intracellular behavior of neurons in the brain through mathematical defined functions. This network has three input, hidden and output layers. The best used artificial neural network in this research have respectively 5, 9 and 1 neurons in their layers.

After determining the mean of scour depth in pillars using network, target functions of MAE, RMSE and R2 have been used for comparison. Estimated values by model have been compared with some other methods (empirical formulas) and in order to determine the effectiveness of different parameters on the depth of scour, sensitivity analysis has been conducted that the results show that neural network model is one of the best methods for determining the depth of scour in pillars provided that it has adequate data to train network.

Keywords- *Cylindrical Pillars, Artificial Neural Network, Bridge*

I. INTRODUCTION

Control the flood is one of the most important problems in Hydraulic Engineering. Lots of studies have been conducted to enhance the hydraulic structures efficiency to dissipate the energy [1-5] and control the flood in rivers and channels with the structures or non-structures methods [6-7].The scour around pillars is one of the most important reasons of bridges destruction. Champiri et al. [8-9] reported some evaluation systems to classify scouring in different concrete and steel structures. Determining the depth of scour around pillars that is conducted using empirical equations has an important role in designing bridges against flooding. These equations have been obtained by different researchers and using various experiments and mainly through regression method. To determine exact rate of scour depth, many equations are used. Using neural network method in this paper, local scour around pillars has been compared with estimation equations of scour depth. Different parameters are considered in scour of pillars that include: 1-pillar width 2-pillar length 3- pillar shape 4-pillar angle to the direction of flow 5-the distance of pillars 6-the surface of pillar 7-pillar protection system 8-floating objects that are carried by flow [10]. A neural network is an idea for processing information that has been inspired by biological nervous system and processes information same as mind. Key component of this idea is new structure of information processing system. This system consists of many interconnected extraordinary processing components that act coordinately to each other to solve a problem [11].

Scour is in fact that very displacement of particles by flow from their initial establishing place to another place or in another word, stream bed and bank erosion caused by water flow, bed erosion in downstream of hydraulic structures because of high flow rate or bed erosion caused by creating local turbulent flows are known as scour.

It is mainly believed that scour has four phases: [12]

1. Initial phase
2. Development phase
3. Stabilization phase
4. Equilibrium phase

The first phase has high scour capacity and scour hole starts in this phase. The depth and dimensions of scour hole will develop in second phase. The changes trend of bed profile reduces in third phase. In this phase, the wall of scour hole downstream is changed tangibly. In fourth phase which is equilibrium one only the movements of particles might happen inside scour hole so that particles which have rolling movement won't exit scour hole. In this phase considering the conditions of flow, the movements of particles may even be stopped. The depth caused by bed erosion compared to initial bed is known as scour depth.

The pattern of flow around bridge's cylindrical pillar and downward flow and vortex systems around cylindrical pillars of bridge are shown in figures 1 and 2.

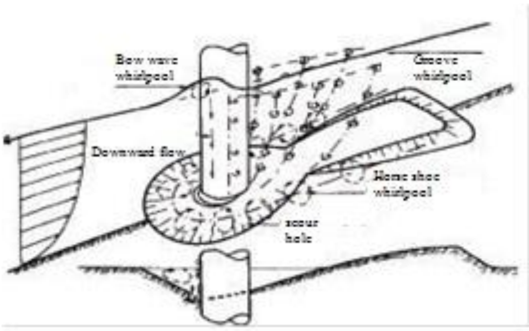

Figure 1. The pattern of flow around cylindrical pillar of bridge [13]

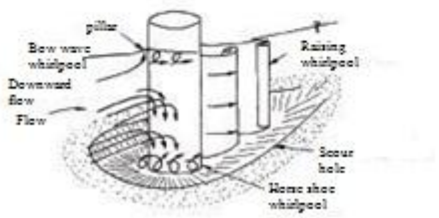

Figure 2. Downward flow and vortex systems around cylindrical pillar of bridge[13]

The basis of this research is on bridge scour and artificial neural network. The section and effective factors on this research should be first investigated. Then the factors which affect our study should be prominently considered. After that modeling is conducted similar to the approach has been applied previously in most of the modeling works to develop a comprehensive model [14-18]. Scour references are investigated and numerical simulation is compared with empirical relations. Also robust and comprehensive comparison between mathematical models and experiment have been performed which are noteworthy [19-24].

II. DIFFERENT TYPES OF NEURAL NETWORKS

Considering the type of learning, neural networks are divided into two categories:

- Supervised learning
- Unsupervised learning (self-organizing network)

In supervised learning, existing samples are proposed to the network and network output is compared with desired output. In each training repetition, the size of error between network output and expected output is calculated and used for calculating internal parameters of network including the weights and fixed values. Calculating parameters will be repeated according to a particular algorithm of learning till minimum error is obtained. To use this type of training desired output is required to be able to train network and judged the learning of network using that. The networks which use supervised learning are mainly used in unclear equations such as relationship between dependent and independent variables in a prediction problem.

In unsupervised learning (self-organizing learning), there is no external trainer or criticizer for supervising learning process [14]. In this type of training, existing data are proposed to the network and based on closeness or similarity of data, the network divides them in different clusters. Output clusters of a self-organizing network can be used as an input for a network with supervised training. Different algorithms are used for unsupervised training of networks such as Kohonen and Boltzmann learning.

III. BUILDING ARTIFICIAL NEURAL NETWORK AND ESTIMATING ITS CAPACITY TO DETERMINE EQUILIBRIUM SCOUR DEPTH

Effective parameters on the depth of local scour of pillar were first determined to build network. Effective parameters of selected input include: pillar diameter, average diameter of aggregate, depth of flow, average velocity of flow, critical velocity of flow. Output parameter is the rate of local scour depth in pillar.

The range of input and output data is as table 1.

After selecting effective input and output parameters, the next step is choosing the number of layers or hidden layers and the number of neurons in these layers. For fast training of network and simplicity for practical function, one hidden layer has been selected. Mean absolute error value (MAE) against the number of neurons was obtained as the minimum error in the number of neuron 9 for hidden layer (figure 3). The number of training course (epoch) was 603 that the value of MAE was obtained as 0.00351 (figure 4).

Whole data includes 191 sets of data that have been obtained through experiments by different people. Network was trained using 160 sets of data and with training network for investigating the capability of network, the values of RMSE, MAE and R2 were calculated as follows:

$$RMSE = \sqrt{\frac{\sum_{k=1}^{N}(t_k - y_k)^2}{N}} \tag{1}$$

$$R^2 = 1 - \frac{\sum_{k=1}^{N}(t_k - y_k)^2}{\sum_{k=1}^{N}(t_k - \overline{t_k})^2} \tag{2}$$

$$MAE = \frac{1}{N}\sum_{k=1}^{N}\left|t_k - y_k\right| \qquad (3)$$

In which t_k is target output, y_k is obtained output of network, $\overline{t_k}$ is the mean of target output and N is the number of training pairs [25-26].

TABLE I. THE RANGE OF INPUT AND OUTPUT DATA IN NETWORK

	Parameter	Training data (160 sets of data)			Test data (31 sets of data)		
		Minimum	Mean	Maximum	Minimum	Mean	Maximum
Input parameters	pillar diameter	10	158.83	1000	16	150.6	600
	average diameter of aggregate	0.24	1.78	7.8	0.41	1.77	5.35
	depth of flow	0.046	137.41	600	0.051	128.78	600
	average velocity of flow	0.17	0.552	19	0.175	0.395	1.032
	critical velocity of flow	0.194	0.468	1.252	0.295	0.458	0.801
Output parameter	the rate of local scour depth	10	114	440	17	111.21	216

When the obtained answer of network reaches acceptable level, the network was tested using 31 remained data sets that the network wasn't trained for them. To select test data, it has been noticed that these data should be located in the range of training data. If the network is trained more than usual, although it might give better answer for training data but predicting network for tests data will be weaker. This is known as over fitting or over training mode. To control this mode, the errors are controlled in each phase and compared with the errors of previous phase. Also in each phase of training network, the capability of network will be also tested with the set of test data. Obtained results for training and test data are shown in later figures. A comparison has been mentioned between the answers obtained from network and real ones in figure 5. It is seen that the network has been able to well propose the answers near to real ones for training data.

The obtained answers of neural network have been compared with experimental answers for training data in figures 6 and 7. Considering these figures, the network has been able to predict good answers for local scour depths of bridges' pillars.

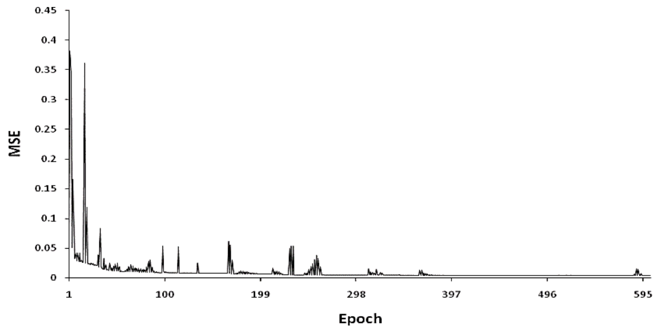

Figure 4. The value of MAE against the number of training course (epoch)

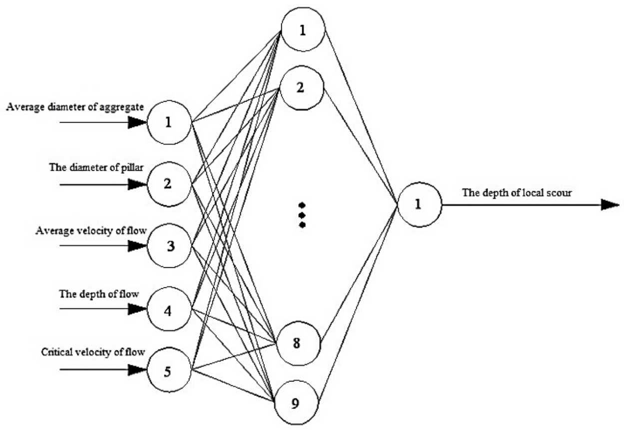

Figure 3. Neural Network

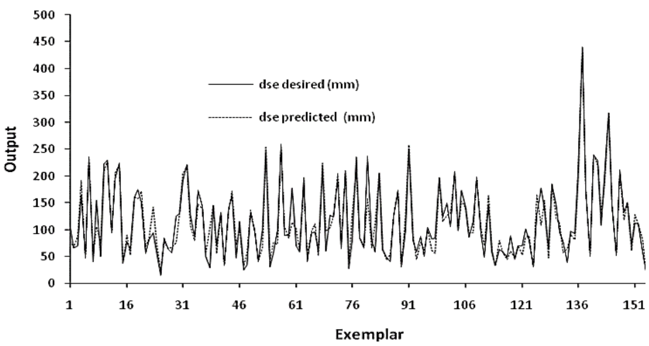

Figure 5. Comparing the answer of network with experimental answer for training data

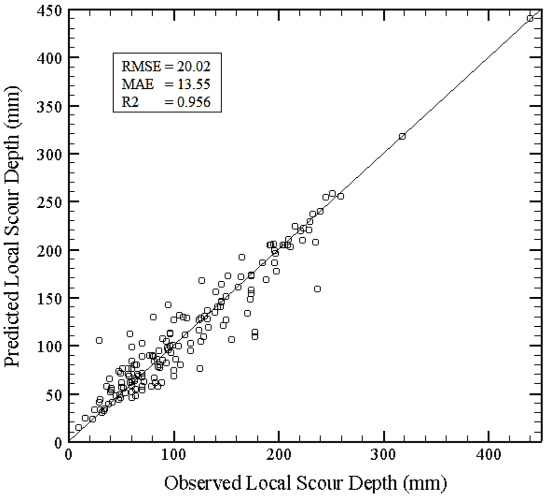

Figure 6. Comparison of artificial neural network with real ones for training data

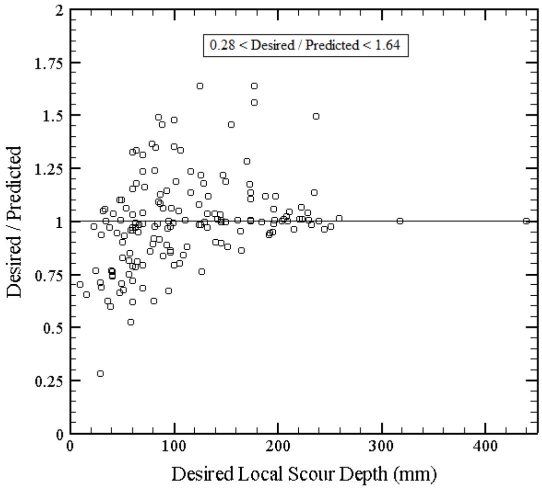

Figure 7. The ratio of experimental answer to the answer of network for training data

Now that we could build network well for training data, the capability of trained network for data which network hasn't seen them can be investigated. Here 31 sets of data remained have been used for testing the network. Figures 8, 9 and 10 show that the network can have good prediction which indicate the capability of trained network in predicting the depth of local scour in pillars.

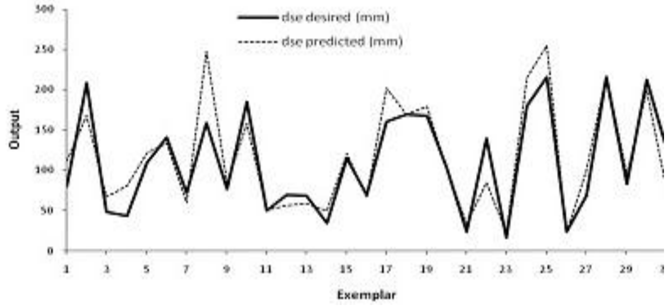

Figure 8. Comparing the answer of network with experimental answer for training data

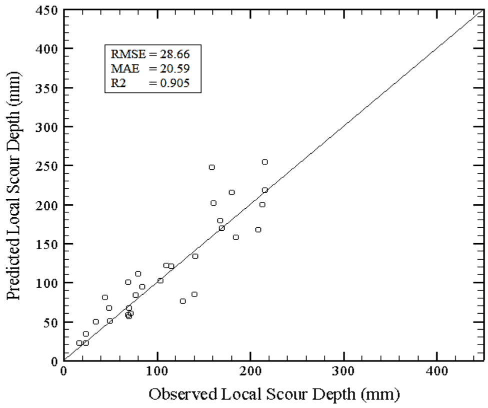

Figure 9. Comparing the answer of artificial neural network with real answer for test data

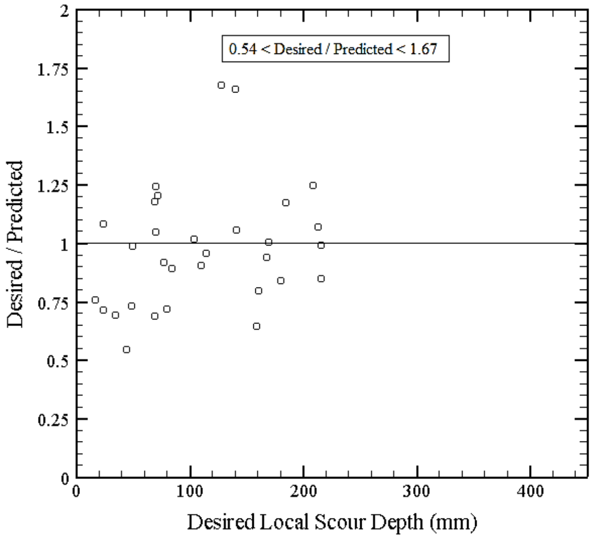

Figure 10. The ratio of experimental answer to network answer for test data

IV. THE COMPARISON OF NETWORK'S ANSWERS WITH EMPIRICAL FORMULAS

Trained network was used for predicting the depth of local scour of pillars in previous section. The built network with existing empirical formulas will be compared for predicting the depth of local scour of pillars. Figures 11, 12 and 13 as well as table 2 have proposed a comparison between obtained answers of network with empirical formula.

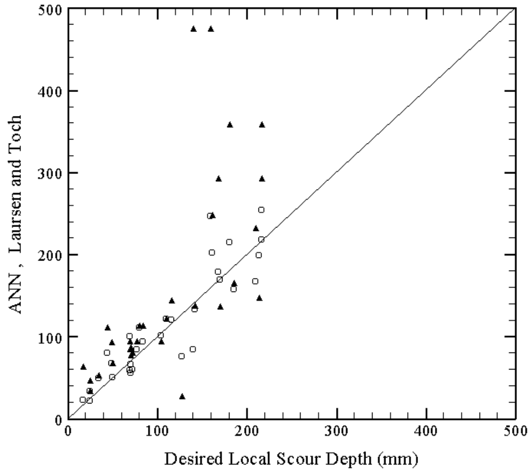

Figure 11. The comparison of network prediction with empirical formula (Laursen and Toch)

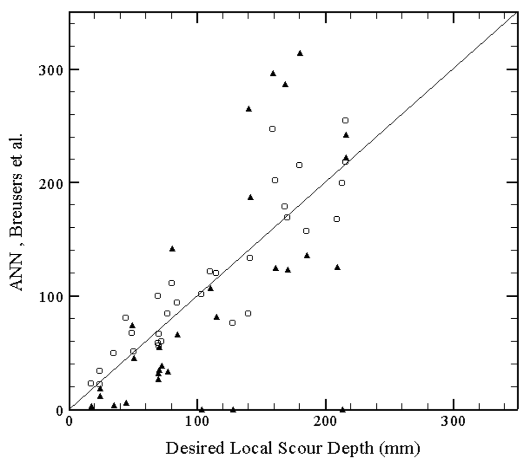

Figure 12. The comparison of network prediction with empirical formula (Breusers et al)

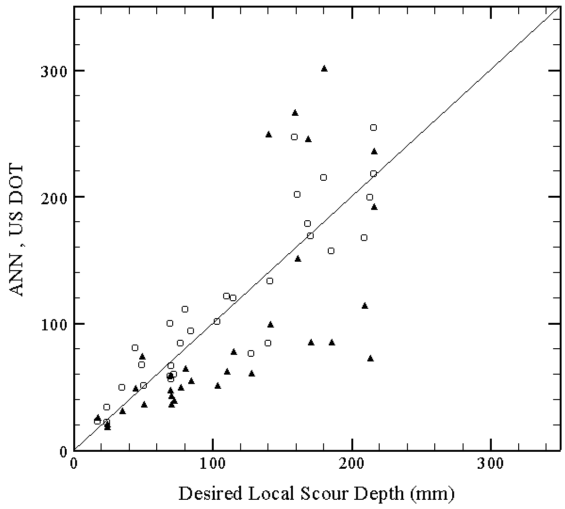

Figure 13. The comparison of network prediction with empirical formula (US DOT)

TABLE II. THE COMPARISON OF PREDICATION CAPABILITY OF ARTIFICIAL NEURAL NETWORK WITH EMPIRICAL FORMULAS

	Min	Mean	Max	MAE	RMSE	R^2
Experimental answer (desired)	17.000	111.213	216.000	0.000	0.000	1.000
ANN	22.190	116.289	254.466	20.595	28.657	0.905
Laursen & Toch (1956)	26.888	158.521	475.453	62.382	102.290	-1.725
Breusers et al. (1977)	-32.006	98.759	313.684	56.5	77.446	-0.562
US DOT (1993)	18.698	96.689	301.387	45.044	59.606	0.075

V. SENSITIVITY ANALYSIS OF EFFECTIVE PARAMETERS

After building, training and testing network and ensuring the accuracy of built artificial neural network, now the effect of every single one of input parameters in output value of network that is the value of local scour depth of pillars is investigated. Considering figure 14, pillar diameter is the most important factors in the value of local scour depth of pillar.

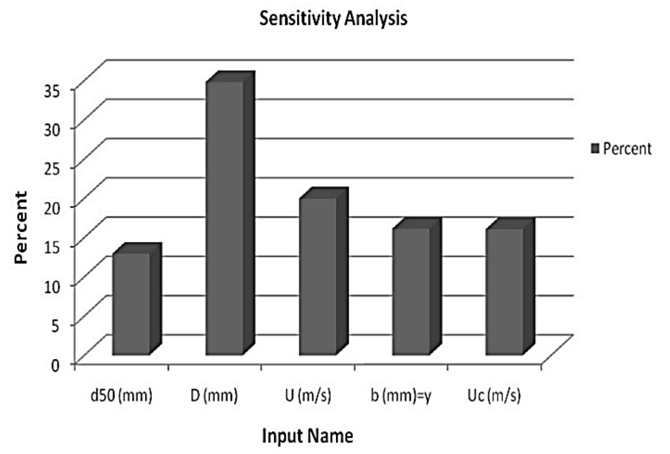

Figure 14. The percentage of effect of effective parameters on the local scour depth of pillar

In figures 14 and 18, the trend of changes in local scour depth of pillar has been shown with every single one of input parameters.

Considering figure 14 that shows changes of local scour depth of pillar with average diameter of aggregate, it can be concluded that by increasing the diameter of aggregate, the rate of local scour will be more but this trend goes on to an extent and after that this trend will reduce, this trend can be justified considering the weight of aggregate and the rate of contacting with water. So it can be said that after reaching maximum scour mode, whatever the size of sediment gets more, the depth of local scour of pillar reduces.

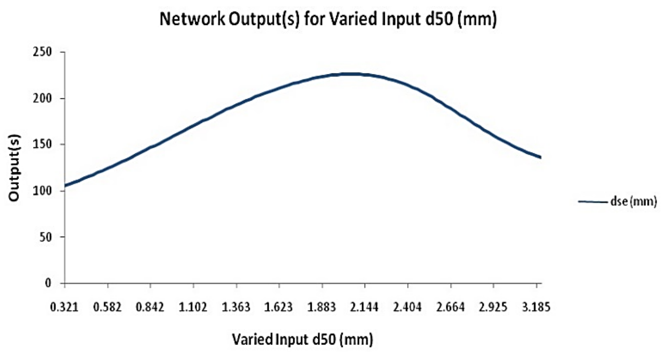

Figure 15. The way of changes in depth of local scour of pillar with average diameter of aggregate

The way of changes of local scour depth of pillar with the diameter of pillar which is the most important factor has been shown in figure 16. It is seen that by increasing the diameter of pillar, the value of scour will also increase.

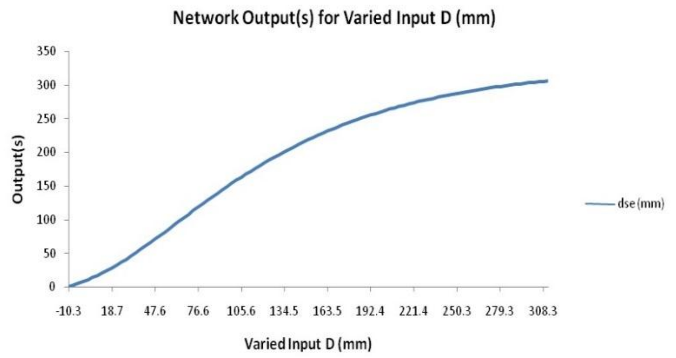

Figure 16. The way of changes in depth of local scour of pillar with pillar diameter

Figures 17 and 18 respectively show the trend of changes of local scour depth of pillar with average velocity of flow and critical velocity of flow. It is seen that by increasing average velocity of flow scour depth flow will also increase and it seems that when the ratio of average velocity to critical velocity is 1, the maximum rate of scour has happened and because taken sedimentary from upstream gets high, the power of filling will get more than power of pulling and scour depth will gradually reduce. If average velocity is very more than critical velocity, scouring starts again and that is because pulling power again becomes more than filling power. Of course this subject is realized when there is live bed. In case water is clear, after maximization of scour depth, because no sedimentary has been carried from upstream, there won't be reduction in the depth of scour anymore.

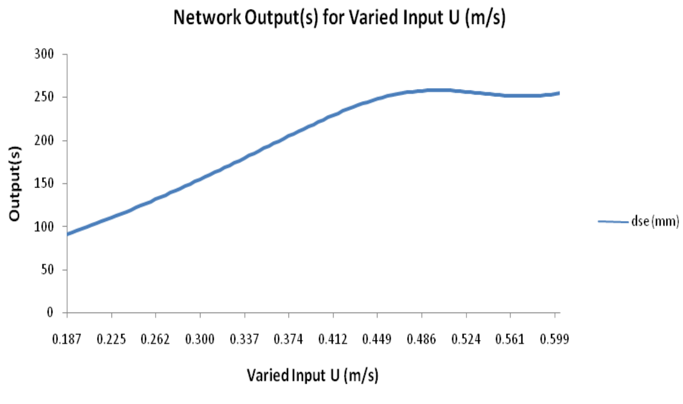

Figure 17. The way of changes in depth of local scour of pillar with average velocity of flow

Figure 18 shows the process of changes local scour depth of pillar with critical velocity that should be studied beside figure 18. It is seen that by increasing the value of critical velocity of flow, the value of scour depth will decrease till when the value of average velocity ratio to critical velocity becomes 1 that in this case the value of critical velocity won't have any effect on the value of scour depth.

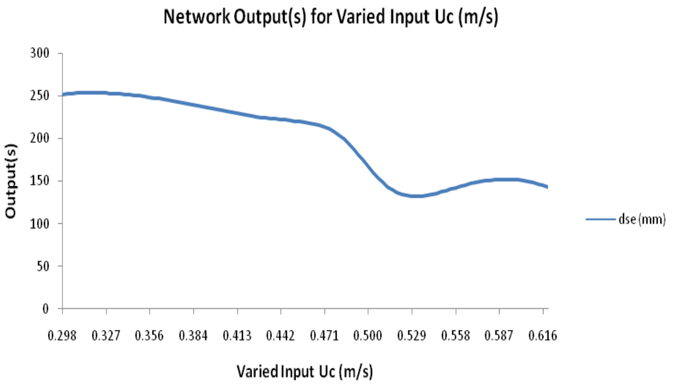

Figure 18. The way of changes in depth of local scour of pillar with critical velocity of flow

Figure 19 also shows the way of changes in depth of local scour of pillar with depth of flow that has had ascending process that is whatever the depth of flow is more, the value of scour will be more.

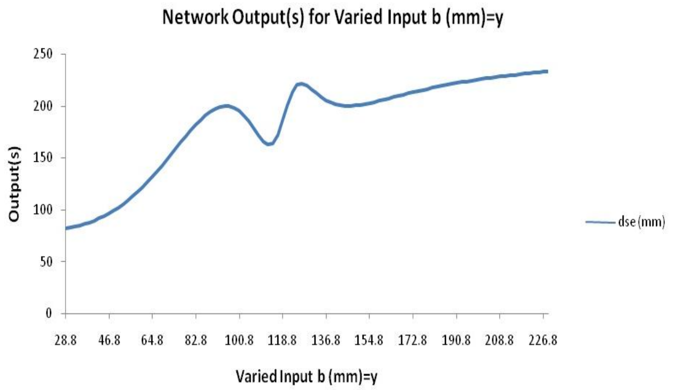

Figure 19. The way of changes in depth of local scour of pillar with depth of flow

VI. BUILDING NETWORK AND TESTING THAT FOR DEPTH OF LOCAL SCOUR DEPENDING ON TIME

For building network in this mode also, first effective parameters on depth of local scour of pillar was determined at the mode of depending on time. Effective parameters of selected input include: the diameter of pillar, average diameter of aggregate, depth of flow, average velocity of flow, critical velocity of flow, time, the time of reaching the depth of equilibrium scour and equilibrium local scour. Output parameter is also the arte of local scour in the time mode of pillar. The range of input and output data is as table 3.

After choosing effective parameters of input and output, the next step is selecting the number of layers or hidden layers and the number of neurons in these layers. To train network rapidly and simplicity for practical function, a hidden layer has been chosen. The value of mean absolute error (MAE) against neurons was obtained as the minimum error in the number of neuron 13 for hidden layer (figure 20).

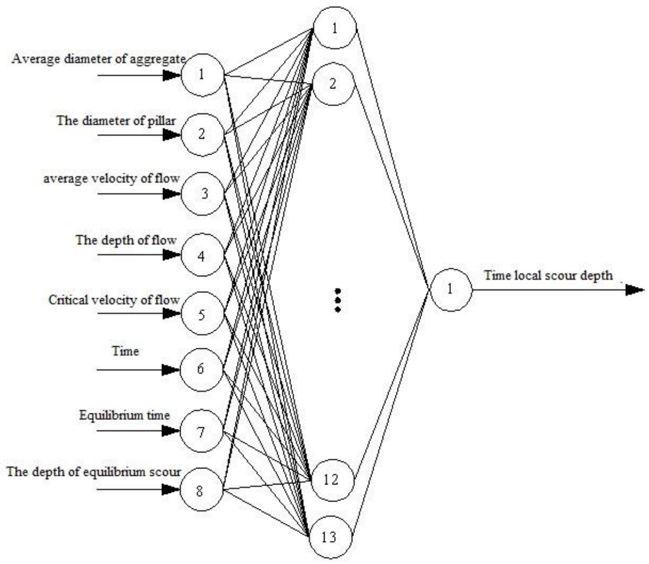

Figure 20. Arranging neurons in the built network

Obtained results for trained and tested network have been shown in figures 21 to 24.

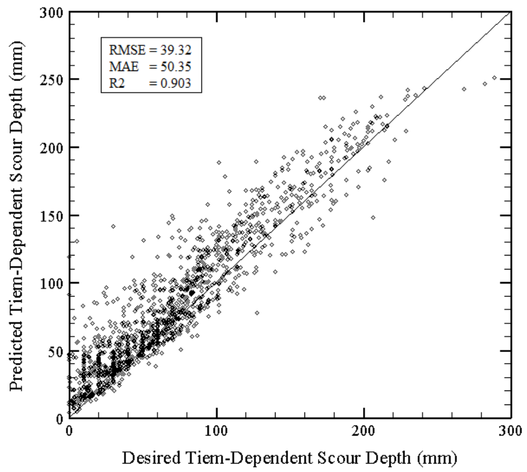

Figure 21. The comparison of artificial neural network answer with real answer for training data

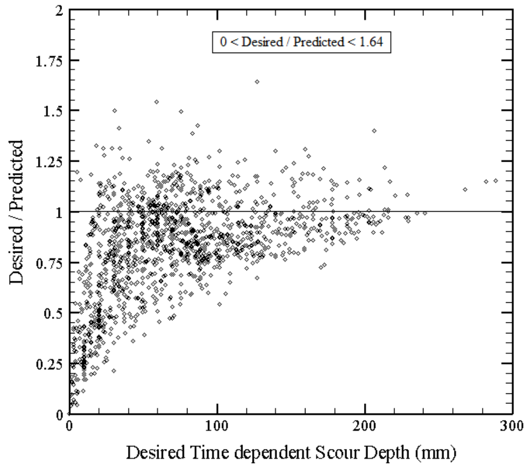

Figure 22. The ratio of experimental answer to the answer of network for training data

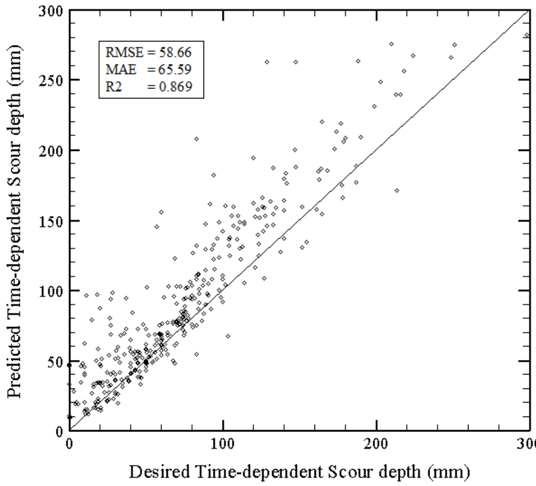

Figure 23. The comparison of artificial neural network answer with real answer for test data

VII. CONCLUSION

Artificial neural network method with error propagation algorithm has been used in this paper for simulation and prediction of pillar local scour depth in equilibrium mode and time dependent. Mentioned network was first trained by the help of experimental data then the rate of scour depth was predicted by mentioned network that following results have been obtained:

1- The mean of pillar local scour depth in equilibrium mode that was estimated by artificial neural network model is equal to 116.289 millimeter.

2- Error percentage of mentioned model in estimating the depth of local scour has been shown below which shows that model has low relative error.

RMSE=0.286

MAE=0.205

3- The correlation coefficient of measured data and estimated values is R2=0.956. Whatever coefficient R2 is closer to 1, the result will be more accurate.

4- The table below represents the comparison of estimated values by neural network model with some methods that have been used up to now:

5- Sensitivity analysis of effective parameters show that pillar diameter is the most important parameter for determining the depth of pillar's scour.

6- The other effective parameters respectively include: average velocity of flow, depth of flow, critical velocity and the diameter of aggregate.

7- Network MLP/BP (Multi-layer perceptron) showed that it is able to predict the depth of local scour in training process through an appropriate accuracy and input data with very low and measurable number in any laboratories and understandable for most of civil engineering engineers.

8- The network predicts scour behavior with high accuracy in the range of training data.

9- Generally, it can be said that technique of neural network MLP/BP has acceptable ability for predicting the depth of local scour in pillars. It is reminded that advanced mathematical models also have many weaknesses in this case.

10- Based on mentioned information, it can be said that if trained network above is used for predicting the behavior of a hydraulic structure, obtained values will be really close to the reality compared to existing empirical formulas.

VIII. RECOMMENDATIONS FOR FUTURE STUDIES

Some steps were taken into improving the prediction of hydraulic structures through this paper, but it was only a hint from the use of different prediction methods in investigating pillar's hydraulic behavior that of course more works are required in this case. Some of future researches that can be conducted in future will be mentioned here:

- Using other networks with different activity functions such as RBF for predicting shear behavior
- Doing sensitivity analysis with the effects of other parameters such as the characteristics of aggregation (size and shape of aggregate) in trained network
- Using more experimental data for improving the process of prediction and generalizing to bigger ranges

- Using other smart systems such as adaptive neuro-fuzzy inference system, like the work which has been done by Bardestani et al. [27] or machine learning by Sajjadi et al. [28] to predict the depth of local scour of bridges' pillar.

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