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Prediction of Scour Depth around Inclined Bridge Piers Using Optimized ANFIS with GA

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ABSTRACT

Knowledge of the effective parameters and estimation of maximum scour depth around bridge piers has an important role in the safe design of bridges in rivers. With development of construction of structures, bridges with various geometries have been constructed such as inclined bridge piers group which has a complex scour process because of simultaneous effect of inclination of piers, foundation and sheltering of second piers. Therefore, most conventional approaches that are based on empirical method are unable to estimate scour dimension. One method to predict physical process whose effective parameters are related in a non-linear and complex manner is utilization of intelligent system. The aim of this research is to predict scour depth around the inclined bridge piers located on the rectangular foundation using optimized ANFIS parameters with GA, Matlab ANFIS and ANN with different hidden layers, activation function, and learning rules. Forty-eight sets of experimental data of scour around the inclined bridge piers were used for various flow condition foundation levels. To compare the results, R2 and RMSE were utilized. Analysis of results showed that Matlab ANFIS and ANN could predict the maximum scour depth with =0.976, RMSE=0.0530 and=0.99, RMSE=0.0359 at best configurations, respectively. Comparison of results indicated that optimization of ANFIS parameters improved the accuracy of prediction of desired parameters with=0.99, RMSE=0.0254.

1. Introduction

Flow around bridge piers generates large-scale turbulence in structures, resulting in the formation of horseshoe vortex, surface roller, and wake vortices. Due to 3-D complex flow field, local scour hole is formed around bridge piers. Because of the importance of estimation of maximum scour dimension, many studies have focused on various effective parameters. Results of previous works have shown that maximum scour hole reaches up to 2.4 pier diameter (Melville and Sutherland, 1988). However, as pier cross section is not uniform or is inclined, the maximum scour depth changes. In compound piers such as pier located on footing or cap which have become popular due to economical, geotechnical and constructional reasons, the prediction of scour is more complicated. Depending on top elevation of foundation, scour depth varies significantly. As top elevation of footing or foundation locate below the river bed and within maximum scour depth for uniform pier, the maximum scour depth decreases because of the reduction of horseshoe vortex power by collision on the top surface of foundation. Also, results have indicated that if top elevation of footing is near the bed or slightly above the bed, maximum scour depth increases significantly (Melville and Raudkivi, 1996; Melville and Sutherland, 1988; Breusers and Raudkivi, 1991; Jones et al., 1992; Vittal et al., 1994; Ataie-Ashtiani et al., 2010; Lu et al., 2011; Esmaeili Varaki et al., 2012).

Although numerous studies have been performed to estimate local scour around bridge piers, advancement in the technology of construction of structures have resulted in the design and construction of bridges with sophisticated geometry such as the inclined bridge piers group. Thus, there is not a single general reliable formula for the prediction of scour depth and length for all states. Process of scour at the mentioned bridge is more complicated since the inclined front pier toward upstream accelerates the intensity of horseshow vortex and acts as a shelter for the back pier. Experimental results of the effect of the top level elevations of foundation on the maximum scour depth at the inclined bridge piers group with rectangular cross section showed that when the foundation was located below the maximum scour depth per single pier, the scour depth would increase (Esmaeili Varaki et al., 2012).

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Because several parameters including hydraulic and geometric variables influence local scour around complex piers, there is a lack of reliable equations to estimate scour depth to cover most situations. An artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS) can provide a useful alternative for predicting the desired outputs when there is a non-linear relationship between the involving parameters. Artificial intelligent system is extensively applied in water science and engineering. Some examples related to local scour round bridge piers are estimation of scour depth around bridge piers using BNP (Lee et al., 2007), estimation of scour depth around bridge piers using neural network and neuro-fuzzy (Bateni et al., 2007), prediction of scour downstream of grade-control structure using neural network (Guvan and Gunal, 2008), ANFIS-based approach to predicting scour location of spillway (Azamathulla et al., 2008), estimation of current-induced scour depth around pile groups using neural network and ANFIS (Zounemat Kermani et al., 2009), scour depth prediction at bridge piers by ANFIS approach (Firat, 2009), ANFIS-based approach for scour depth prediction at piers in non-uniform sediments (Muzzammil and Ayyub, 2010), prediction of scour below submerged pipeline crossing a river using ANN (Azamathulla and Zakaria, 2011), prediction of pile group scour in waves using support vector machines and ANN, (Ghazanfari Hashemi et al., 2011), ANFIS-based approach to scour depth prediction at abutments in armored beds (Muzzammil and Alam, 2011), prediction of local scour depth at bridge piers under clear-water and live-bed conditions (Toth and Brandimarte, 2011), prediction of scouring around an arch-shaped bed sill using Neuro-Fuzzy model (Keshavarzi et al., 2012), bridge pier scour prediction by gene expression programming (Azamathulla et. al., 2012), prediction of equilibrium scour time around long abutments (Mohammadpour et al., 2012), estimation of current-induced pile groups scour using a rule-based method (Ghaemi et al., 2013), and estimation of abutment scour in clear-water and live-bed conditions by GMDH network (Najafzadeh et al., 2013). Comparison of results of intelligence systems may allow the prediction of the desired output with a suitable accuracy.

Fuzzy model systems with increase number of membership functions, number of IF-THEN rules to map inputs and outputs may generate the phenomenon of over-fitting, which reduces the generalizing property of the fuzzy model to predict the unforeseen data (Jamali et al., 2009). Therefore, it is important to use a method which can reduce the number of rules and its related parameters. The aim of this research is to predict the local scour depth around inclined bridge piers group using ANFIS system whose membership function parameters is optimized with genetic algorithm and the comparison of ANFIS and ANN with various learning rules and activation functions using MATLAB.

2. Material and Methods

2.1. Dimensional analysis

Parameters effective on the local scour around complex piers include the pier and foundation geometry, flow characteristic and bed sediment features which can be expressed as the following functional relationship using dimensional analysis:

$$f_1\left(\frac{y}{D_*}, \frac{d_s}{D_*}, \frac{L_u}{D_*}, \frac{L_f}{D_*}, \frac{T}{D_*}, \frac{D}{D_*}, \frac{Z}{D_*}, \frac{U}{U_c}, Fr, \frac{D}{D_{50}}, \sigma_g, \alpha, \beta, \frac{t}{t_e}\right) = 0 \quad (1)$$

in which y = flow depth; d_s = maximum scour depth, L_u and L_f = extensions of pile cap upstream of and sides of the pier, respectively; T = thickness of the pile cap; D = pier width or diameter; D_* = foundation width; Z = foundation elevation relative to bed level; U and U_c = mean velocity of approach flow and critical flow velocity for sediment inception of motion, respectively; Fr = Froude number of approach flow; D_{50} = mean sediment size; σ_g = geometric standard of sediment sizes; α and β = angle of attack of approach flow with the pier axis and angle of inclination of pier with the vertical plane, respectively; t and t_e = time from beginning of the experiment and time to equilibrium, respectively.

The large number of parameters makes it difficult to consider all of them in limited experiments. Therefore, some of the mentioned parameters, i.e. L_u/D_*, L_f/D_*, T/D_*, α, β, and σ_g are constant. Also, the effect of $D/D_{50} > 50$ on d_s was not significant (Melville and Sutherland, 1988). Finally, Eq. (1) may be reduced to:

$$\frac{d_s}{D_*} = f_2\left(\frac{y}{D_*}, \frac{U}{U_c}, \frac{Z}{D_*}, Fr, \frac{t}{t_e}\right) \quad (2)$$

2.1. Experimental setup and procedure

Experiments were carried out in a glass-sided rectangular recirculating flume 8.6 m in length, 0.92 m in depth, and 1 m in width. The compound bridge piers geometry had a scale of 1/190 of 8th bridge of Ahvaze, Iran (see Fig. 1.a and b). It consisted of two rectangular piers with the width of 3.5 cm and the length of 2.5 cm mounted on footing with the width of 10 cm and the length of 16 cm. The value of scale of the bridge pier, i.e. the ratio of flume width to pier diameter, should be greater than 6.25 to ensure that scour dimension would not be affected by flume (Raudkivi and Ettema, 1983). Ratios for pier and foundation are 26 and 10, respectively. The piers and foundations that were embedded in the middle of the recess with the length of 1.5 m and the depth of 0.3 m was located 5 m downstream of the flume entrance to ascertain approach flow to be a fully developed. The recess was filled with uniform sand of d=0.6 mm. Also, upstream and downstream of recess was formed with sand of d_{50} of 1 mm.

Before performing main part of the experiments, it was essential to determine velocity of inception of motion. Several experiments were conducted for various flow

depths and velocities. Finally, the inception of motion velocity was determined as 0.22 m/s. The comparison of results showed a good agreement with empirical equation and shield's diagram.

The scour process is time-consuming. Therefore, it is important to determine equilibrium time in all investigations about this phenomenon. We used Raudkivi and Ettema (1983)'s criteria according to which equilibrium time is obtained when scour depth is less than 1 mm for consecutive hours.

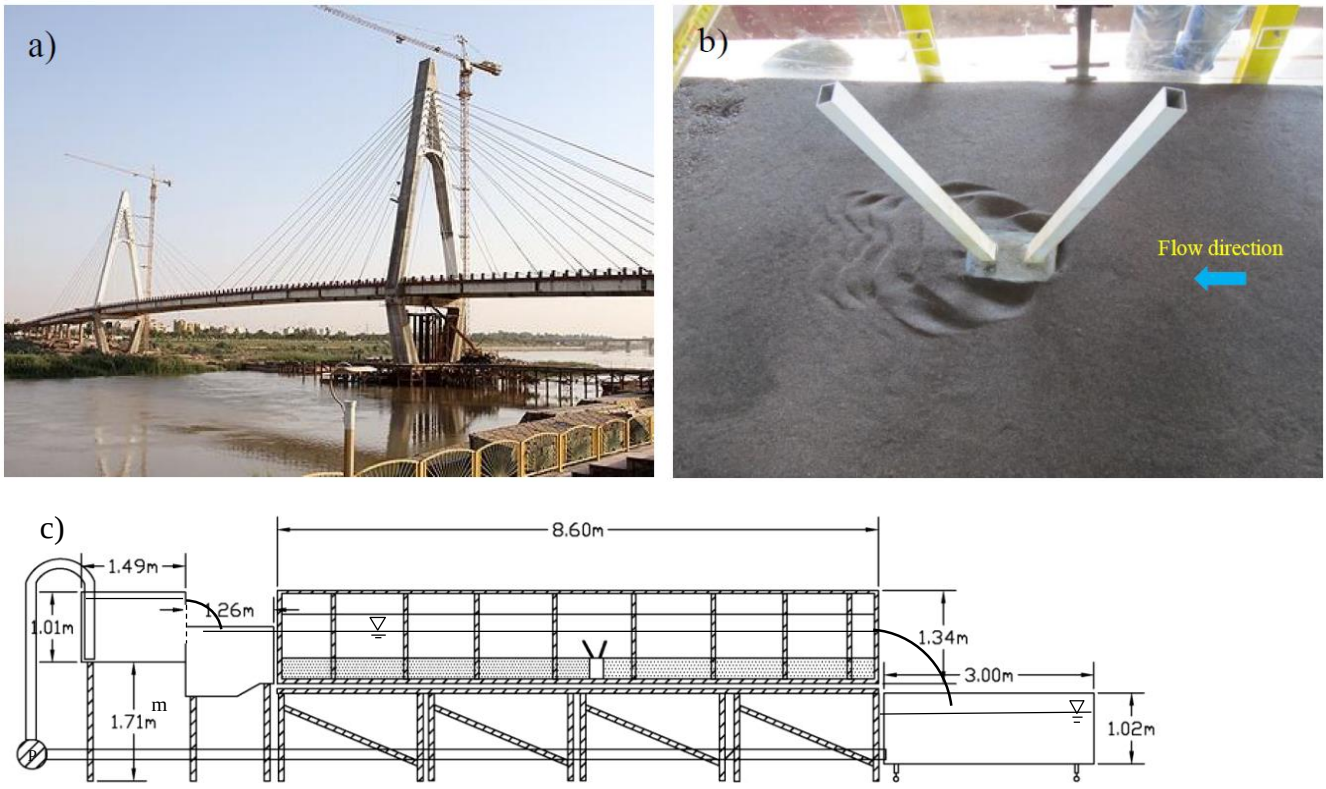


Figure. 1. a) 8th bridge of Ahvaze, **b)** experimental model of inclined bridge piers group, and **c)** sketch of experimental flum

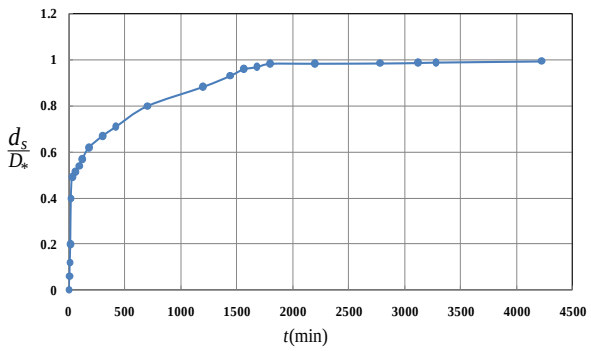


Figure. 2. Temporal variations of scour depth under $y/D_*=1$, $U/U_C=0.95$ and $Z/D_*=0$

Long experiment under $y/D_*=1$, $U/U_C=0.95$ and $Z/D_*=0$ was conducted for 72 hours and the depth of scour was measured using point gage with 0.1 mm accuracy. Finally, equilibrium time was determined as 25 hours (Fig. 2).

Totally, 48 sets of experiments were performed to study the effect of top level elevation of footing, *Z*, flow velocity and depth (see Table 1).

Table 1. Hydraulic and geometric parameters of experiment

Q (l/s)	U/U_C	y/D_*	Z/D_*	Number of experiment
11-58	0.5, 0.6, 0.8 and 0.95	1, 2 and 3	0	12
11-58	0.5, 0.6, 0.8 and 0.95	1, 2 and 3	1	12
11-58	0.5, 0.6, 0.8 and 0.95	1, 2 and 3	-0.5	12
11-58	0.5, 0.6, 0.8 and 0.95	1, 2 and 3	-1	12

2.3. Optimized ANFIS architecture

The ANFIS is a multilayer feed-forward network consisting of a set of TSK-type fuzzy IF-THEN rules that can be used in modeling to map inputs to outputs. The formal definition of such identification problem is to find a function, $\hat{f}$, so that it can be approximately used instead of the actual one, f. For example, an ANFIS with *n* input, one output and *M* data sets can be written as:

$$y_i = f(x_{i1}, x_{i2}, x_{i3}, \ldots\ldots, x_{in}) \quad (i = 1, 2, 3, \ldots\ldots, M) \tag{3}$$

The problem is now to determine an ANFIS that minimizes the error between the actual and predicted output, $\hat{y}_i$, that is:

$$\hat{y}_i = \hat{f}(x_{i1}, x_{i2}, x_{i3}, \ldots\ldots, x_{in}) \quad (i = 1, 2, 3, \ldots\ldots, M) \tag{4}$$

$$\sum_{i=1}^{M} [f(x_{i1}, x_{i2}, x_{i3}, \ldots\ldots, x_{in}) - y_i]^2 \rightarrow \min \tag{5}$$

To do this, a set of linguistic TSK-type fuzzy IF-THEN rules is designed to approximate $\hat{f}$ by f using *M* data set of n-input-single-output data (x_i, y_i) $(i = 1, 2, 3, \ldots\ldots, M)$. The fuzzy rules embodied in such ANFIS models can be conveniently expressed using the following generic form:

$$Rule_1: \; IF\ x_1\ is\ A_1^{(j_1)}\ AND\ x_2\ is\ A_1^{(j_2)}\ AND\ \ldots,\ x_n\ is\ A_1^{(j_n)}\ THEN\ y = \sum_{i=1}^{n} w_i^1 x_i + w_0^1 \tag{6}$$

in which, $j_i \in (1,2,\ldots,r)$ and $W^1 = \{w_1^1, w_2^1, \ldots\ldots, w_n^1, w_0^1\}$ are the parameter sets of the consequent of each rule. The entire fuzzy set in x_i space is given as:

$$A^{(i)} = \left\{ A^{(1)}, A^{(2)}, A^{(3)}, \ldots, A^{(r)} \right\} \tag{7}$$

These fuzzy sets are assumed to have a Gaussian shape defined on the domains $[-\alpha_i, +\beta_i]$ and $[-\alpha_i, +\beta_i]$. In this way, the domains are appropriately selected so that all the fuzzy sets are complete, that is, for any $x_i \in [-\alpha_i, +\beta_i]$, there exists $A^{(j)}$ in Eq.(6) such that the degree of membership function is non-zero, i. e., $\mu_{A^{(j)}}(x_i) \neq 0$. Each fuzzy set $A^{(j)}$ $(j = \{1,2,\ldots,r\})$ is represented by Gaussian membership functions in the form as below:

$$\mu_{A^{(j)}}(x_i) = Gaussian\ (x_i, c_j, \sigma_j) = \exp\left(-\frac{(x_i - c_j)^2}{2\sigma_j^2}\right) \tag{8}$$

where c_j and σ_j are adjustable parameters and optimally selected by GA. The architecture of ANFIS consists of five layers (see Fig. 3). The model is briefly defined in the next paragraph (Bateni. et. al., 2007).

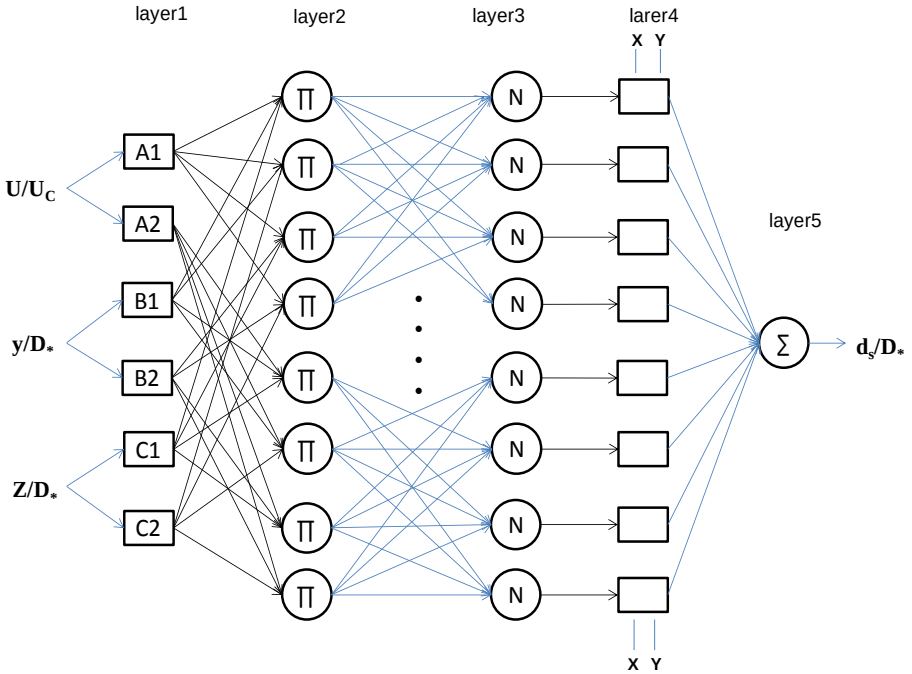


Figure. 3. ANFIS structure for two-input Sugeno fuzzy model with eight rules to predict scour depth

Layer 1: this layer is known as an input layer. Each node *i* of this layer generates membership values of an input variable using defined membership function. The node output $Q_{l,i}$ for two input and membership functions is expressed by:

$$Q_{l,i} = \mu_{A_i}(x) \quad for \quad i = 1,2 \tag{9}$$

$$Q_{l,i} = \mu_{B_{i-2}}(y) \quad for \quad i = 3,4 \tag{10}$$

in which x and y are input to the i-node, and A_i and B_i are linguistic labels characterized by appropriate membership functions $\mu_{A_i}(x)$ and $\mu_{B_i}(x)$, respectively.

Layer 2: the nodes in this layer are not adaptive and fixed. Each node in this layer estimates the value of the consequent of each rule (w_i) by applying the AND operator. w_i means the degrees to which the antecedent part of a fuzzy rule is satisfied and it shapes the output function for the rule. Thus, the outputs $Q_{2,i}$ of this layer are the multiplication of the incoming signals from layer 1:

$$Q_{2,i} = w_i = \mu_{A_i}(x) \times \mu_{B_i}(y) \qquad i = 1,2 \tag{11}$$

Layer 3: The nodes of this layer are also fixed nodes. Each node in this layer estimates the ratio of the ith w_i in inference layer to the sum of all the rules' firing strengths. The output of each node in this layer is given by the following equation.

$$Q_{3,i} = \overline{w}_i = \frac{w_i}{\sum_{i=1}^{N} w_i} \qquad i = 1,2 \tag{12}$$

in which, N is number of node in each layer.

Layer 4: All the nodes in this layer are adaptive nodes. The output of each node in this layer is computed as

$$Q_{4,i} = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i) \tag{13}$$

Where f is a linear function of input variables. p_i, q_i and r_i are linear parameters in the then-part of fuzzy if–then rules, and are called consequent parameters.

Layer 5: This layer aggregates the qualified consequents to produce an output as:

$$Q_{5,i} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{14}$$

In this ANFIS structure, Layer 1 has modifiable parameters related to the input membership function. The parameters in this layer are called premise parameters. Layer 4 also has three modifiable parameters (p_i, q_i and r_i) pertaining to the first order polynomial. These parameters are called consequent parameters. The architecture of the ANFIS model of this research is shown in Fig. (3).

There are two main concepts involved within ANFIS networks design, namely, the parametric and the structural identification problems. Some authors present a hybrid method which uses genetic algorithms (GA) and singular value decomposition (SVD) method to optimally design the Gaussian membership functions of antecedents, c_j and σ_j, and the vector of linear coefficients of consequents, respectively (Jamali et al., 2009). The SVD method is a robust technique to solve linear optimization problems especially if the system of linear equations has a singular value. In this research, the SVD method was used to estimate consequent parameters of TSK. The objective function is minimization of RMSE which can be defined as:

$$RMSE = \sqrt{\sum_{i=1}^{M} \frac{(y_{i(Model)} - y_{i(Actual)})^2}{M}} \tag{15}$$

In which M is the number of data set of input layer.

The incorporation of GA into the design of such ANFIS models starts with representing the $N = n + 1$ real-value parameters of c_j and σ_j as a string of concatenated substrings of binary digits. Thus, each such a substring represents the fuzzy partitioning of antecedents of fuzzy rules embodied in such ANFIS models in binary coded form. In order to optimize the system, the initial population is generated randomly. At the next step, values are converted to integer number and objective function is calculated for each chromosome. A population of 100 individuals with a crossover probability of 0.8 and mutation probability of 0.1 was used in 100 generations. After determination of GA parameters, for three inputs and two membership functions, 2^3=8 rules were generated.

Furthermore, to evaluate MATLAB software to predict the maximum scour depth around the inclined bridge piers group, initial fuzzy inference system (FIS) generator including GENFIS1, which produces grid partitioning of the input space, GENFIS2, which produces subtractive clustering of the input space and GENFIS3, which generates fuzzy inference system using c-means (FCM) clustering to produces the input space were used.

2.2. Artificial neural networks

The most important features of the ANN are its abilities to learn, to associate, and to be error tolerant. Nonlinearity is a natural characteristic of neural networks when nonlinear activation functions are used. The method is nonparametric and therefore useful when the form of nonlinearity in the data is not known. Neural networks generally consist of a number of interconnected processing elements or neurons.

The design of any neural network architecture, basically, involves the following three steps:

1. Choosing the appropriate neurons' function (transfer function).

2. Basic decision about the amount of neurons to be used in each layer.

3. Selecting the amount of hidden layers.

The number of neurons in each layer depends on the complexity of the target/desired function. If there are not enough neurons in each layer, the outputs will not be able to fit all the data points (under-fitting). On the other hand, if there are too many neurons in each layer, oscillations may occur between data points (over-fitting). Therefore, an architectural study must be conducted in order to find the most appropriate architecture for this project by trial and error. However, each node multiplies every input by its interconnection w_i weights and then adds the sum of the products to a bios number. At the next step, the sum

of the products passes through a transfer function to generate the results. There are different transfer functions. A Tangent hyperbolic function can be presented as:

$$\mathrm{Net_j} = \sum \mathrm{w_{ij}x_i} + \mathrm{b_i} \quad (16)$$

$$\mathrm{y}_j = \mathrm{f}(\mathrm{Net_j}) = \frac{\mathrm{e}^{(\mathrm{Net}_j)} - \mathrm{e}^{-(\mathrm{Net}_j)}}{\mathrm{e}^{(\mathrm{Net}_j)} + \mathrm{e}^{-(\mathrm{Net}_j)}} \quad (17)$$

After comparing the obtained results with the target values, the errors would be calculated and by using the back propagation algorithm, the entire weights would be corrected. This process will be continued until either errors are less than a specified value or the number of training epochs reaches the favorite repetition. At this stage, ANN is considered as trained. An example of a feed forward neural network to be trained for estimation of scour depth is shown in Fig. 4.

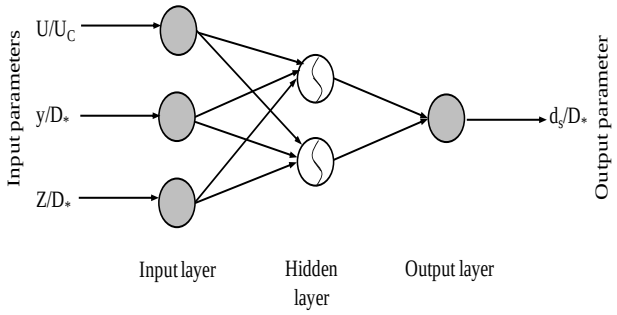


Figure. 4. An ANN structure for prediction of the maximum scour depth

In this research, different transfer function including Linear, Tanh (Tangent hyperbolic), Sigmoid, DNNA (Digital Neural Network Architecture) and Sine were employed to predict scour depth around the inclined bridge piers group. Learning rules were Delta-rule, Quick-prop, DBD (Delta-Bar-Delta), Max prop, Ext-DBD (Extended Delta-Bar-Delta) and Normalize Cumulative Delta. Hidden layers of 1 and 2 and neurons of 2 to 10 at each layer were studied using NeuralWorks Pro. II/PLUS Software Package.

3. Results

To evaluate the developed optimized ANFIS and ANN models, a total of 48 sets of scour data as listed in Table 1 were used. Among them, 36 data sets were used as training data and 12 data sets were employed as testing data. Evaluation of the predicted results of models was based on correlation coefficient, R^2, which presents the degree of association between predicted and actual experimental data and root mean square error, *RMSE*, which can be written as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(O_i - p_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O}_i)^2} \quad (18)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(O_i - p_i)^2}{n}} \quad (19)$$

where, O_i and p_i are actual data and network output for *i*th output, respectively, $\bar{O}_i$ is the average of actual data of outputs and *n* is the total number of data sets. Next section presents the results of ANN models and optimized ANFIS.

3.1. 3.1. Evaluation of ANN configurations for prediction of the maximum scour depth

Table 2 shows the results of the best prediction of scour depth for different learning rules and transfer function. Assessment of results of the Delta-rule learning rules showed that the best transfer function was Tanh having two hidden layers and six neurons which could be able to predict scour depth with R^2 = 0.99, RMSE = 0.0359 and repetition of 19,000. Evaluation of results of the Quick-prop learning rules showed that the best transfer function was Sine having two hidden layers and 10 neurons which could predict scour depth with R^2 = 0.96, RMSE = 0.0646 and repetition of 25,000.

Comparison of results of the DBD learning rules showed that the best transfer function was Tanh having one hidden layer and 10 neurons which could predict scour depth with R^2 = 0.94, RMSE = 0.0743 and repetition of 100,000.

Evaluation of results of the Max prop learning rules showed that the best transfer function was Sine having two hidden layers and 10 neurons which could predict scour depth with R^2 = 0.83, RMSE = 0.115 and repetition of 100,000. Furthermore, as seen in Table 2, ANN could not predict output with transfer functions Sigmoid and DNNA.

Assessment of results of the Ext-DBD learning rules showed that the best transfer function was Sine having one hidden layer and 8 neurons which could predict scour depth with R^2 = 0.97, RMSE = 0.0585 and repetition of 8,000.

Comparison of results of the DBD learning rules showed that the best transfer function was Tanh having one hidden layer and 10 neurons which could predict scour depth with R^2 = 0.94, RMSE = 0.0743 and repetition of 100,000.

Table 2. Statistical performance of ANN's configuration for prediction of the scour depth

Learning rules	Transfer function	Number of hidden layer	Number of neuron at each layer	RMSE	R^2	Repetition
Delta-rule	Linear	1	6	0.1273	0.85	9000
Delta-rule	Tanh	2	6	0.0359	0.99	19000
Delta-rule	Sigmoid	2	10	0.0772	0.94	69000
Delta-rule	DNNA	1	2	0.0929	0.91	6000
Delta-rule	Sine	2	4	0.0410	0.98	66000
Quick-prop	Linear	1	10	0.1304	0.8	14000
Quick-prop	Tanh	2	4	0.0665	0.96	54000
Quick-prop	Sigmoid	2	2	0.1115	0.84	25000
Quick-prop	DNNA	1	4	0.0876	0.91	93000
Quick-prop	Sine	2	8	0.0646	0.96	25000
DBD	Linear	1	10	0.1382	0.77	2000
DBD	Tanh	1	10	0.0743	0.94	100000
DBD	Sigmoid	1	8	0.1202	0.82	100000
DBD	DNNA	1	6	0.1265	0.76	100000
DBD	Sine	2	10	0.0767	0.94	100000
Max prop	Linear	2	2	0.1263	0.77	5000
Max prop	Tanh	2	6	0.1196	0.83	11000
Max prop	Sigmoid	*	*	*	*	*
Max prop	DNNA	*	*	*	*	*
Max prop	Sine	2	10	0.1150	0.83	100000
Ext-DBD	Linear	1	6	0.1349	0.78	2000
Ext-DBD	Tanh	1	8	0.0692	0.96	8000
Ext-DBD	Sigmoid	1	4	0.0728	0.95	100000
Ext-DBD	DNNA	1	10	0.0982	0.91	18000
Ext-DBD	Sine	2	8	0.0585	0.97	21000
Normalize Cumulative Delta	Linear	2	6	0.1351	0.8	4000
Normalize Cumulative Delta	Tanh	1	10	0.0960	0.91	16000
Normalize Cumulative Delta	Sigmoid	2	2	0.1120	0.85	28000
Normalize Cumulative Delta	DNNA	1	2	0.1007	0.88	32000
Normalize Cumulative Delta	Sine	2	8	0.0637	0.96	21000

Assessment of results of the Ext-DBD learning rules showed that the best transfer function was Sine having one hidden layer and 8 neurons which could predict scour depth with R^2 = 0.97, RMSE = 0.0585 and repetition of 8,000.

Comparison of results of the Cumulative Delta learning rules showed that the best transfer function was Tanh having one hidden layer and 10 neurons which could predict scour depth with R^2 = 0.96, RMSE = 0.0637 and repetition of 21,000.

In Fig. 5, a comparison of the predicted and experimental data was shown for the best models at each learning rules. As a conclusion, among the different learning rule, Delta-rule had the best performance. Also, transfer functions Tanh and Sine exhibited the best performance in predicting the desired output.

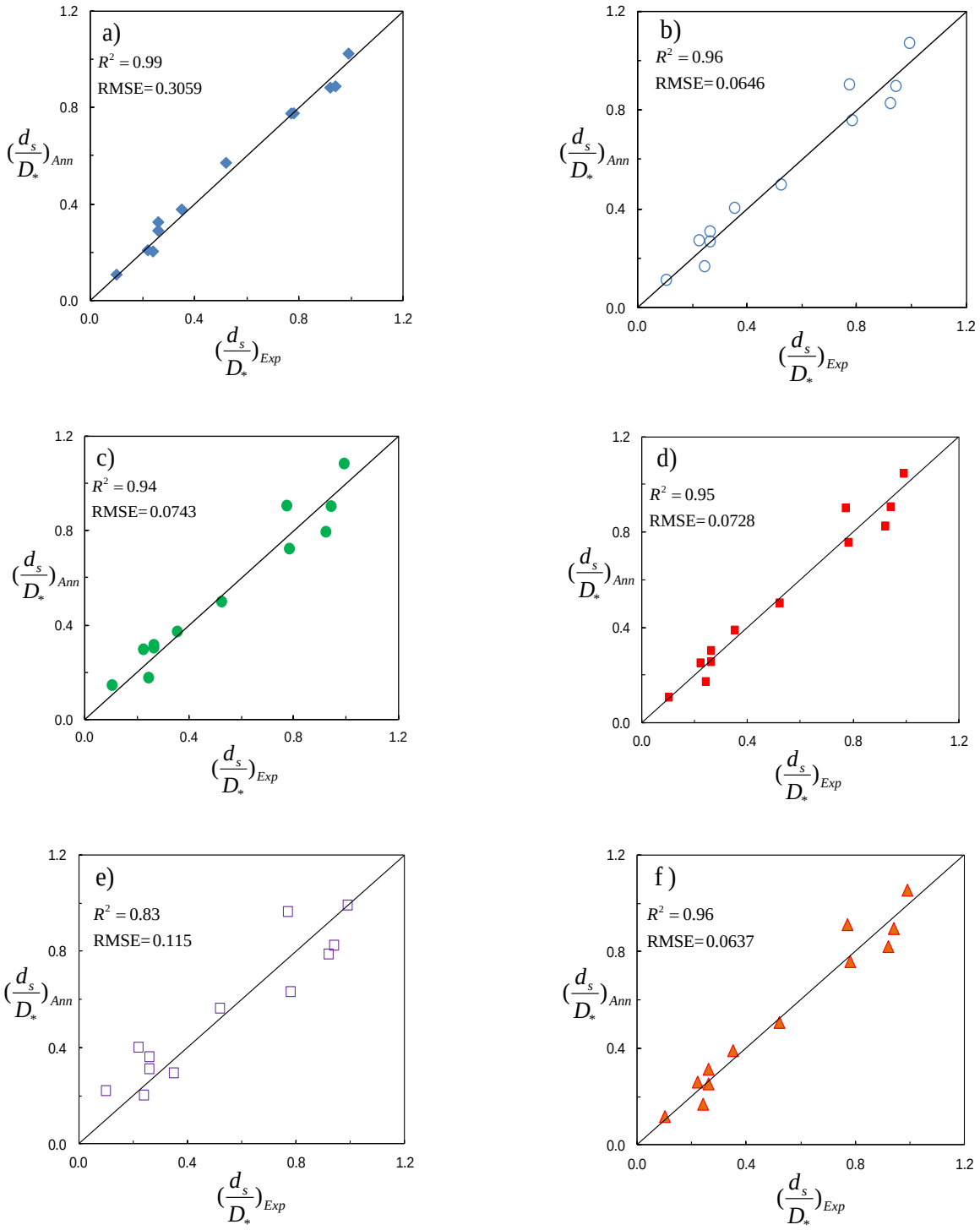


Figure 5. Comparison of ANN configurations results with experimental data
a) Delta-rule, **b)** Quick-prop, **c)** DBD, **d)** Ext-DBD, **e)** Max prop, and **f)** Normalize Cumulative Delta

3.2. Evaluation of the Matlab ANFIS to predict the maximum scour depth

Results of GENFIS 1 of Matlab ANFIS for 4 membership functions including Gaussian, Triangular, Bell and Trapezoidal curves and two and three membership functions for each input values are presented in Table 3 and Fig 6a. Comparison of results showed that the Gaussian membership function with two membership functions had the best performance to predict the desired output.

Table 3. Statistical performance of GENFIS 1 configurations for the prediction of the maximum scour depth.

Type of membership functions	Number of membership functions	R^2	RMSE	Type of data
Gaussian	2	0.994	0.0223	Training
		0.976	0.053	Test
	3	1	0	Training
		0.891	0.1046	Test
Triangular	2	0.994	0.0239	Training
		0.973	0.0568	Test
	3	1	0	Training
		0.975	0.1335	Test
Bell	2	0.994	0.0239	Training
		0.779	0.0533	Test
	3	1	0	Training
		0.830	0.1334	Test
Trapezoidal	2	0.993	0.0248	Training
		0.973	0.0531	Test
	3	1	0	Training
		0.745	0.1623	Test

Results of GENFIS 2 of Matlab ANFIS are presented in Table 4 and Fig 6b. GENFIS 2 generates an initial FIS for ANFIS by first applying subtractive clustering on the data set. GENFIS 2 accomplishes this by extracting a set of rules that models the data behavior. The rule extraction method first uses the subclust function to determine the number of rules, antecedent membership functions and then linear least squares estimation to determine each rule's consequent equations. Comparison of results showed that optimum radius, the range of influence from the cluster center for each input and output dimension, would be 0.5 for the best prediction of desired output.

Results of GENFIS 3 of Matlab ANFIS is presented in Table 5 and Fig 6c. The rule extraction method of GENFIS3 includes applying FCM function to determine the number of rules and membership function for antecedents and consequents. Comparison of results indicated that five clusters had the best performance in predicting the desired outputs.

Table 4. Statistical performance of GENFIS 2 configurations for the prediction of the maximum scour depth

Influence radius	0.5	0.45	0.40	0.35	0.30	0.25	0.20	0.15	0.10
R^2	0.870	0.859	0.805	0.809	0.824	0.823	0.813	0.831	0.812
RMSE	0.1170	0.1273	0.1415	0.1383	0.1326	0.1328	0.1376	0.1298	0.1391
Influence radius	0.95	0.90	0.85	0.80	0.75	0.70	0.65	0.60	0.55
R^2	0.910	0.919	0.903	0.684	0.496	0.456	0.576	0.723	0.853
RMSE	0.1494	0.1442	0.1678	0.2707	0.3073	0.3105	0.2463	0.1777	0.1276

Table 5. Statistical performance of GENFIS 3 configurations for the prediction of the maximum scour depth

Statistical index	Type of data	Number of cluster							
		2	3	4	5	7	10	15	20
R^2	Training	0.907	0.964	0.963	0.977	0.969	0.999	1	1
	Test	0.853	0.930	0.941	0.958	0.749	0.793	0.849	0.832
RMSE	Training	0.0942	0.0587	0.0597	0.0442	0.0183	0.0099	0.0	0.0
	Test	0.1228	0.0885	0.0821	0.0659	0.1654	0.1574	0.1268	0.1345

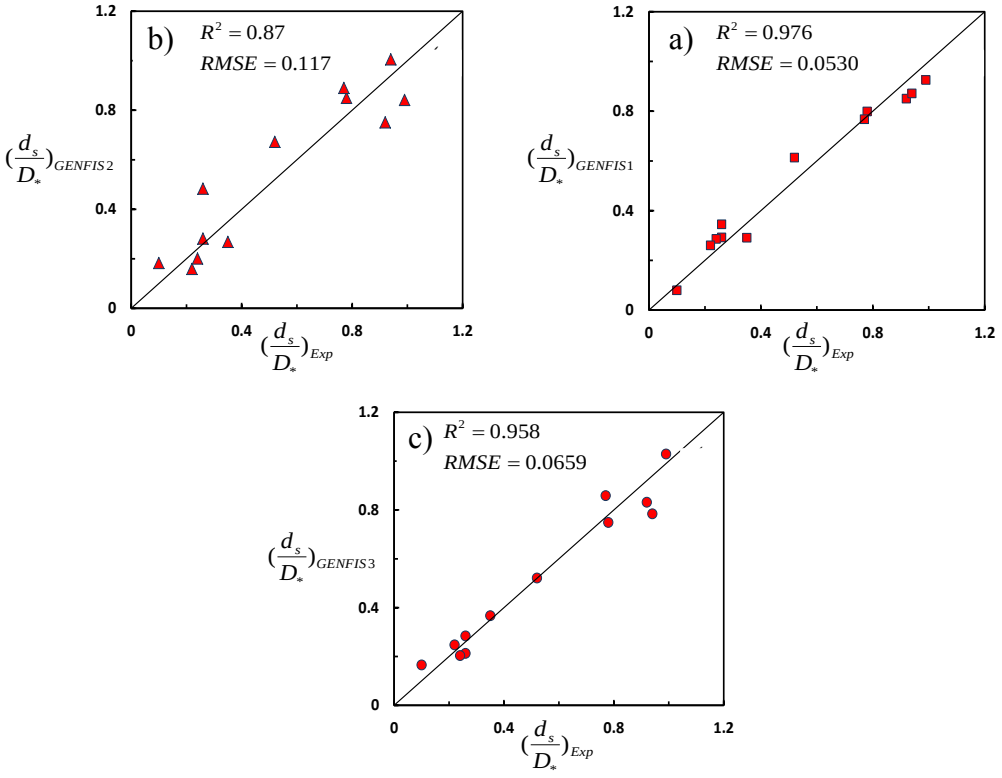


Figure 6. Comparison of the Matlab ANFIS to predict the maximum scour depth **a)** GENFIS1, **b)** GENFIS2 and **c)** GENFIS3

3.3. Evaluation of the Optimized ANFIS to predict the maximum scour depth

Results of optimized ANFIS by GA are presented in Table 6 and Fig 7. Comparison of results showed that optimization of ANFIS parameter could improve the accuracy of prediction from RMSE = 0.0356 to 0.0253 for training data and from 0.0559 to 0.0254. Evaluation of prediction scour indicated that optimization of ANFIS parameter with GA could improve the accuracy of prediction from RMSE = 0.0401 to 0.0318 for training data and from 0.0545 to 0.0357. Fig. 8 compares the predicted results with experimental data.

Table 7. Comparison of optimized ANFIS and AFNIS to predict scour depth

Model	Type of data	scour depth	
		RMSE	R^2
Optimized ANFIS	Training data	0.0240	0.99
	Testing data	0.0254	0.99

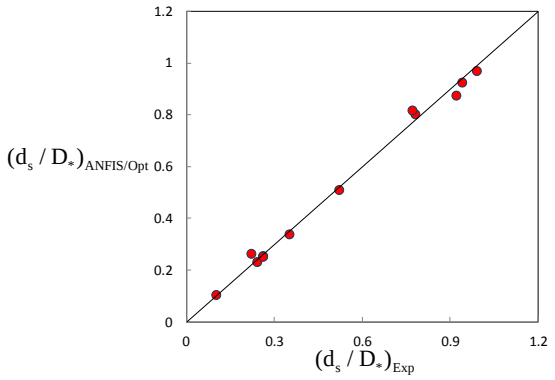


Figure 7. Comparison of predicted scour depth results with optimized ANFIS

4. Conclusion

This research investigated the performance of ANN with different learning rules, transfer functions and hidden layer configuration and optimized adaptive neuro-fuzzy inference system for estimation of scour depth around inclined bridge piers group. Comparison of results showed that the best learning rules to predict scour depth is Delta-rule which had R^2 = 0.99 and RMSE = 0.0359. Furthermore, transfer function of Tanh has better performance to predict scour depth. Evaluation of ANFIS prediction results indicated that optimization of ANFIS could increase the accuracy of results considerably in comparison with both MATLAB toolbox ANFIS and all configurations of ANN. In addition, the comparison of MATLAB toolbox ANFIS with the best configuration of ANN showed that artificial neural networks have better performance in predicting scour depth. The results of the study are encouraging and suggest that an optimized adaptive neuro-fuzzy approach is a powerful tool to model scour depth around inclined bridge piers group.

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