

Hybrid ANFIS Model for Predicting Scour Depth using Particle Swarm Optimization

M. H. Jannaty^{1*}, A. Eghbalzadeh² and S. A. Hosseini¹

¹Department of Technical and Engineering, Tehran Science and Research Branch, Islamic Azad University, Tehran, Iran; hemenjannaty@iausdj.ac.ir, abbas_hoseyni@srbiau.ac.ir

²Civil Engineering Department, Advanced Research Institute for Water and Wastewater, Razi University of Kermanshah, Iran; eghbalzadeh@gmail.com

Abstract

During recent years, data mining and machine learning techniques have been developed in various fields for building intelligent information systems. However, few of the presented methods possess online support capabilities or sufficient flexibility to use large and complicated data sets. For this reason, the present study implemented the Particle Swarm Optimization (PSO) technique to predict scour depths by obtaining appropriate parameters for the neural network model and fuzzy inference system. The test was conducted based on samples obtained from 188 pier scour depths presented by the United States Geological Survey (USGS). The empirical results showed that, due to its minimum Root Mean Square Error (RMSE), the presented model was preferable to the ANFIS model. Moreover, the proposed model produced better solutions than FDOT and HEC-18 equations. The momentum method was implemented to accelerate learning by teaching for increasing the accuracy of short-term predictions.

Keywords: Field Data, PSO-ANFIS, Scour Depth, Single Pier

1. Introduction

Bridge piers and abutments are weakened due to water erosion caused by river currents, and this can lead to structural failure in bridges. Such structural failure would require huge costs for repairing or replacing the bridge and it can also lead to loss of life. Scouring near bridge piers and abutments during high water (flooding) periods is the major cause of bridge failure⁹. Design and maintenance of bridge piers must be based on the maximum scour depth during severe flooding. The maximum predicted scour depth must be applied when designing bridge Pier foundation.

The term “scour” is defined here as settlement of ground due to water erosion below an assumed natural surface or other agreed datum. Scour is a natural phenomenon and the main cause for concern in alluvial flows. Scour is also a problem in any waterway with an erodible bed. Scour around bridge piers can be caused by one or a combination of the following three components:

- Local Scour: Erosion caused by internal turbulence in the flow (e.g., vortexes around the piers).
- Contraction Scour: Erosion resulting from acceleration of water flow due to decreased flow section area at the bridge.
- General Scour: Erosion caused by natural processes in the river. This kind of scour takes several years and occurs in any water canal even in the absence of a bridge.

Although the above components are not completely independent, they are nevertheless assessed separately during the design phase to calculate the total scour depth at the bridge site. Many empirical relations have been developed for calculating contraction scour and local scour at bridge sites. Some of these equations are introduced below.

Ahmad¹, Chitale⁶, and Blench⁵ extracted their equations by making measurements at irrigation canals in India. These equations were to be used for describing the conditions

*Author for correspondence

which could stabilize the existing sediments. However, these equations somehow underestimate local scour.

Larsen (1963) presented a solution for local and contraction scour at rectangular piers. Larsen showed that local scour depth remained independent of contraction scour depth as long as the scour hole in the neighbor pier had not started overlapping. For sand, the normal scour whole width to flow depth ratio has been observed at about 2.75. Colorado State University (CSU) developed an equation for circular piers using laboratory data³.

The data obtained by Chabert and Engelder (1956) and CSU (Chen et al., 1966) were subsequently selected. These data were used by Chen et al. (1969) for extracting the Chen equation. The HEC-18 equation was modified in time and is currently used for estimating scour depth in simple piers.

The equation for highways and railways proposed by Gao et al. (1993) was used in China for more than 20 years. This equation was developed using local scour data obtained at bridge piers in China, including 137 data in live beds and 115 data in clear water. The equation was tested before 1964 using field data. Many equations have been developed from field data, including those proposed by Froehlich (1988), Ansari and Qadar (1994). Froehlich equation was obtained from data fitting at 83 bridge measurement sites in the United States and elsewhere.

Through fitting more than 100 piers scour depth field measurements obtained from 12 different sources and several countries (including 40 measurements from India), Ansari and Qadar (1994) obtained an envelope equation. They also compared their field scour depths with those obtained by Larsen (1963), Breusers (1965) and Breusers and Raudkivi (1991).

Melvil (1997) proposed a justifiable physical method for estimating local scour depth at bridge piers based on an extended set of laboratory data obtained by Oakland University and other studies. In this method, a number of factors (K factors) were used to determine the various parameters influenced by scour. The values of K factors would be determined from the respective envelope fitting curves. This is an inherently conservative method.

A number of articles have been published where scour depth is obtained using alternative methods such as artificial neural networks^{4,7,10}. Whereas this method is capable of presenting proper predictions for certain ranges of data, it is more or less prone to over fitting.

In accordance with the dynamic and complicated nature of the real world, intelligent information systems

also require complicated methods. Such systems must be able to learn and deal with different data types and acquire knowledge through interacting with their environment. Studies have shown that the most popular neural network models are the trained multi-layer perception algorithm, Back Propagation Neural Networks (BPNN), and radial function based networks^{2,8}. However, these are not suitable for online learning. These models are generally implemented for a fixed-size structure with limited ability to use new data. Moreover, accessing the previous data would require processing of new data which can be unacceptably time consuming. In addition, these models often experience other problems including difficulty in selecting the initial optimum structure, inability to access the minimum local (data), and producing irrelevant descriptions regarding the method used for obtaining results. As a result, explaining the decision making process based on the constructed network output would be difficult or impossible.

A review of previous studies and increasing online learning reveal the following problems: 1. the traditional ANN methods act as a black box and the rules extracted from them are not easy to understand. 2. The machine learning and data mining methods do not offer online support and lack the flexibility required for handling complicated data sets. To solve these problems, the PSO-ANFIS model was proposed. This model can make possible adaptive learning through combining the ANFIS model with incremental fuzzy clustering and other particle swarm based techniques. In addition, the particle swarm technique can be used to obtain the optimum membership function parameters.

2. Previous Research and Methodology

2.1 Adaptive Neuro-fuzzy Inference System (ANFIS)

First introduced by Lotfizadeh, Fuzzy Logic (FL) and Fuzzy Inference Systems (FIS) can be used for decision making based on incomplete or vague data. Fuzzy logic expresses models or knowledge using IF-THEN statements.

The key to the fuzzy inference method is recognizing the rules. Two problems arise in this regard: 1. there is no standard method for converting human knowledge and experience into a rule. 2. There is no way of regulating membership functions for minimizing output errors and

maximizing performance of the model. In this study, the ANFIS method was used to obtain the FIS.

First proposed by Jang, ANFIS is based on multi-layer networks and acts like an FIS minimized through implementing the back propagation error technique. ANFIS acts similarly to both the neural network and fuzzy logic. In the neural network and FL methods, the input passes through the input layer (via the input membership function) and the output is shown in the output layer (via the output membership function).

For further discussion, we assume the ANFIS model to be an FIS comprising two inputs (x and y) and one output (f) (Figure 1). An IF-THEN rule involving a two-fuzzy set can be expressed as:

Rule 1: IF x is A_1 And y is B_1 , then $f_1 = p_1x + q_1y + r_1$

Rule 2: IF x is A_2 And y is B_2 , then $f_2 = p_2x + q_2y + r_2$ (1)

The node $O_{k,i}$ is shown at the i-th position in the k-th layer, and the node functions on the same layer of the same family of functions are as follows: Layer 1 is the input layer and each node i on this layer is a square node with a membership function (Equation 2).

$$O_{1,i} = \mu A_i(x) \quad \text{for } i = 1, 2 \quad (2)$$

$O_{1,i}$ is the membership function for A_i . The input membership function is a Gaussian membership function (Equation 3) with maximum and minimum values of 1 and 0 respectively. The reason for this is that, according to empirical results, this distribution provides better and more reasonable predictions for scour depth and is more stable.

$$\mu A_i(x) = e^{-\frac{(x-c)^2}{2\sigma^2}} \quad (3)$$

In the above relation, C is the mean and σ is the variance of the membership function. Each node in Layer

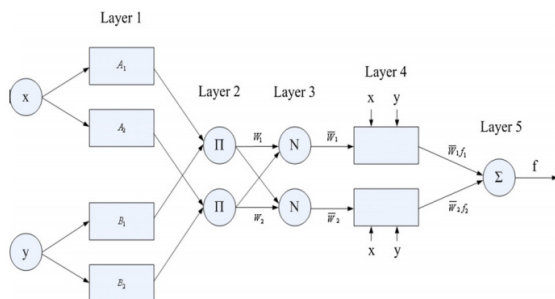


Figure 1. An FIS including two inputs and one output.

2 is a circle labeled Π (norm operator). The input signal coefficients are obtained from the following equation:

$$O_{2,i} = w_i = \mu A_i(x) \times \mu B_i(y) \quad \text{for } i = 1, 2 \quad (4)$$

Each node in Layer 3 is labeled with a circle. The weights along this route are normalized (Equation 5).

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2} \quad \text{for } i = 1, 2 \quad (5)$$

Each node i enters the node function in Layer 4 (Equation 6). The parameters in this layer refer to the respective results.

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i (p_i + q_i + r_i) \quad (6)$$

Where p_i , q_i , and r_i are parameters. In this layer, a circle node is labeled as a sigma element. The total output is calculated as the sum of the input signals (Equation 7).

$$O_{5,i} = \sum \bar{w}_i f_i = \frac{\sum_{i=1} w_i f_i}{\sum_{i=1} w_i} \quad (7)$$

2.2 Particle Swarm Optimization (PSO)

The PSO method is a population-based random optimization method inspired by the social behavior of birds and fish, which was developed by Eberhart and Kennedy (1995). PSO is very similar to evolutionary computation techniques like GA. However, unlike GA, it does not involve evolutionary operators such as crossover and mutation. The potential solution in PSO is obtained by flying through the problem space following optimum particles. The value of each particle is determined through the optimum evaluation function and the flying speed of that particle. The searched optimum value is the social information contained between individual particles.

Each particle i represent the candidate with the current best value and position, demonstrated as p_{best} . A particle in the total population as neighbors has a global best position of g_{best} . All the particles can share information regarding the search space. The current velocity of the i-th particle in dimension D during the k-th iteration is

$$V_{id}^{k+1} = w^k V_{id}^k + C_1 rand_1 (P_{id}^k - x_{id}^k) + C_2 rand_2 (P_{gd}^k - x_{id}^k) \quad (8)$$

In the above equation, $r()$ is a random function in the [0,1] interval. C_1 and C_2 are positive constants representing individual and social training factors, respectively. W is the inertial weight. Velocity is limited to the interval $[-V_{max}, V_{max}]$ where V_{max} is a predefined boundary

value. The new position of a particle is obtained from the following formula:

$$x_{id}^{k+1} = x_{id}^k + V_{id}^{k+1} \quad (9)$$

Particle velocity is updated based on the best previous position of the particle and the best previous positions of its counterparts. The PSO is the only evolutionary algorithm which does not implement the Survival of the Fittest principle.

2.3 Methodology

A hybrid ANFIS model was constructed based on 188 scour depth data listed by the USGS. In the ANFIS model, the clustered parameters were optimized and the membership function parameters were optimized using the PSO method. This section discusses the separation and scaling of data, selection of variables, and dimensional analysis of the PSO-ANFIS model.

2.3.1 Separation and Scaling of Data

The data used in this study were extracted from the USGS database. The scour data presented were collected from 33 sites (Table 1). The drainage area of the bridge pier scour sites included an area of 166 to 157212 square kilometers and the slope at each site was within the 0.0001-0.0029 m/m range. The bed material in most sites comprised sand and/or gravel. The random separation method was used to separate 70 percent of the samples as training samples and 30 percent as test samples.

2.3.2 Selection of Variables

Variable selection was used to determine the candidates included in the input vector for predicting scour depth. The effects of the pier, fluid, floor sedimentation, and turbulent flow factor used for determining scour depth y_s can be obtained in the form of the following function:

$$\frac{y_s}{D} = f_1 \left(Fr, \frac{h}{D}, \frac{d_{50}}{D} \right) \quad (10)$$

Where d_{50} is the average size of bed sediments, h is the upstream water head, D is the pier width, and Fr is the Froude number at bridge upstream. The four variables d_{50} , h , D , and V (velocity at upstream of pier) are selected as input variables to the model (Equation 10). Therefore, the input and output to the model are expressed as:

$$y_s = f_1(V, h, d_{50}, D) \quad (11)$$

2.3.3 Particle Swarm Optimization

The PSO method is an excellent method for exploring the iterative search space. When searching membership function parameters, the PSO method can be used to search the surrounding areas in order to find the highest solutions.

Moreover, the fitness function guarantees that the searched parameters produce the best answer. We assume the mean parameters and variance of each membership function during the k -th iteration are known (i.e., we have $c_1, c_2, \dots, c_k$) and $(\sigma_1, \sigma_2, \dots, \sigma_k)$. We seek to find the mean and variance at the $(k+1)$ -th iteration. The PSO fitness function at the $(k+1)$ -th iteration is calculated from Equation 12. Thus, the problem takes the form of a multi-objective optimization problem.

$$E = \text{Target-Model} \quad (12)$$

Where Target and Model are the actual values and predicted values of scour depth. First, the values of neighborhood radius R_a , weight W , learning rates $C1$ and $C2$, population size popSize , and number of iterations maxIter are set. In the next step, the zero iteration is set and the revenues obtained from teaching particle swarm optimization are used for finding membership function parameters.

The model optimizes and updates different particle parameters, and presents the best values upon evaluating the results. Each particle moves to its next position according to Equations 8 and 9.

2.3.4 The PSO-ANFIS Model

This model involves the following steps:

- Step 1: Receive the initial values for R_a , W , C_1 and C_2 , popSize , and maxIter from the PSO
- Step 2: Calculate parameter values in each cluster from equation 3 at iteration zero
- Step 3: Use PSO to improve the parameters and obtain new parameters through the following subroutine.
 - Step 3.1: Run the initial particle swarm in a search space with mean parameters and variance as calculated from Equation 12 (set for iteration zero).
 - Step 3.2: Update the P_{id} for each particle and P_{GD} for international swarm. Calculate update Velocity each particle by the equation (8).
 - Step 3.3: Update the new position of each particle using Equation 9

Table 1. The sites selected by USGS for scour data

Site	Drainage area (km ²)	Slope (m/m)
Knik River at S.R. 1 near Eklutna, AK	–	0.001
Arkansas River at C.R. 613 near Nepesta, CO	24,346	0.0005
Eel River at S.R. 59 near Clay City, IN	2,279	0.00035
White River at S.R. 157 at Worthington, IN	11,375	0.0002
Red River at S.R. 3032 near Shreveport, LA, W.B.	157,212	0.0001
Big Pipe Creek at S.R. 194 at Bruceville, MD	264	0.00157
Homochitto River at U.S. 84 at Eddiceton, MS	469	0.00093
Chemung River at S.R. 427 at Chemung, NY	6,491	0.00075
Delaware River at Route 6 at Port Jervis, NY	7,951	0.00114
Schoharie Creek at S.R. 30 at Middleburg, NY	1,383	0.002
Susquehanna River at C.R. 314 at Conklin, NY	5,781	0.00057
Clear Creek at U.S. 33 near Rockbridge, OH	238	0.0019
Grand River at S.R. 84 near Painesville, OH	1,774	0.00109
Great Miami River at S.R. 128 at Hamilton, OH	9,402	0.00049
Hocking River at S.R. 278 at Nelsonville, OH	1,492	0.00038
Honey Creek at S.R. 67 at Melmore, OH	386	0.0014
Killbuck Creek at C.R. 621 at Killbuck, OH	1,197	0.00023
Little Miami River at S.R.350 at Fort Ancient, OH	1,748	0.00084
Mad River at U.S. 36 near Urbana, OH	420	0.00136
Ottawa River at Township Road 122 at Lima, OH	337	0.00144
Scioto River at S.R. 159 at Chillicothe, OH	9,969	0.00035
Sugar Creek at U.S. 250 at Strasburg, OH	805	0.00087
Todd Fork at S.R. 22 at Morrow, OH	679	0.00179
Tuscarawas River at C.R. 14 near Port Washington, OH	6,216	0.00047
Walnut Creek at C.R. 17 near Ashville, OH	559	0.00068
Bush River at U.S. 460 near Rice, VA	166	0.0011
Dan River at U.S. 501 at South Boston, VA	7,071	0.00025
Little Nottoway River S.R. 603 nr Blackstone, VA	–	0.002
North Fork Holston River at S.R. 633 near North Holston, VA	–	0.001
Nottoway River at S.R. 653 near Sebrell, VA	3,680	0.00016
Pamunkey River at S.R. 614 near Hanover, VA	2,800	0.00012
Reed Creek at S.R. 649 near Wytheville, VA		0.0001
Tye River at S.R. 56 near Lovingson, VA	240	0.0029

Step 3.4: Compute E. If E is minimized, then return to Step 3.1

Step 3.5: Set “Counter = Counter + 1”. If Counter < max-Iter, then go to Step 2.3, otherwise, end PSO and go to Step 4.

Step 4: If the end criterion is satisfied, then go to Step 6, otherwise go to Step 5.

Step 5: Set “K = K + 1” and return to Step 3. Select the data points with the highest potential as mean and variance. Then, obtain a new mean and variance using the PSO.

Step 6: Select the last values for mean and variance as the optimum values.

3. Analysis of the Empirical Results

During the initial test, the values of the parameters used in the proposed PSO-ANFIS were set as follows. C_1 (training factor) and C_2 (social learning) were given the values 1.6 and 1.1, respectively. To select these values, the sensitivity analysis was conducted during execution. The number of particles and the maximum number of iterations were set at 200 and 1000, respectively. The inertial weight was selected as 0.9, the maximum velocity as 2, and the dynamic range for one particle as (-10 80). The initial value for the local radius was $R_a = 0.5$ and the search range between 1 and 100.

3.1 PSO-ANFIS Results using Field Data

In this method, first the model was run for three different iterations, namely, 100, 500, and 1000. The membership functions values for each parameter at iteration are given in Table 2, Figure 2 compares the test data for the model with the objective data during the 1000th iteration. Most of the model data have values greater than those obtained for the actual data. Figure 3 shows another comparison. In this case, the predicted scour depth values are also greater than the actual values. As shown in the figure, the model can well describe the above scour depths.

Table 2. Summary of membership function results used for each model

Iteration	Variable	Range of membership	σ	c
100	pier width	2–14	1.014859	4.135136
	upstream depth	0.62–14.7	1.250636	3.772834
	upstream flow velocity	1.5–36.7	4.253301	7.320521
	mean particle size	0.15–72	6.025211	2.434901
500	pier width	2–14	0.889802	2.836716
	upstream depth	0.62–14.7	1.023943	4.943696
	upstream flow velocity	1.5–36.7	3.186146	7.842915
	mean particle size	0.15–72	18.491645	54.648383
1000	pier width	2–14	0.867431	4.577799
	upstream depth	0.62–14.7	1.325233	5.926551
	upstream flow velocity	1.5–36.7	3.443459	11.455236
	mean particle size	0.15–72	9.667821	26.243248

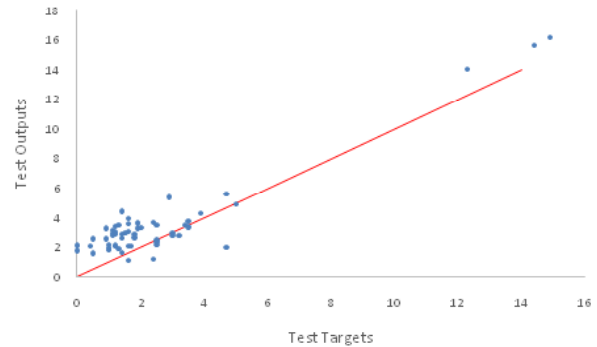


Figure 2. Predicted vs. actual scour depths.

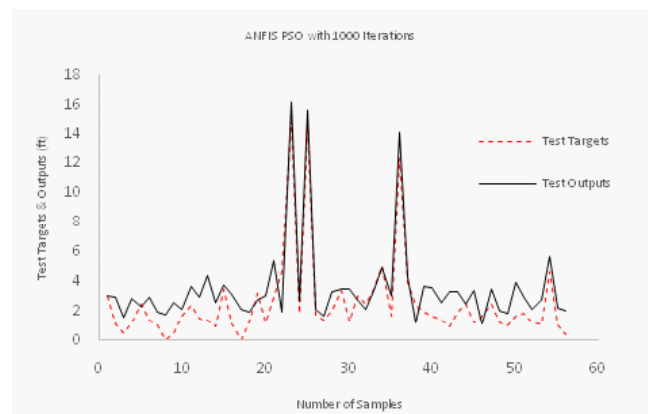


Figure 3. Actual vs. predicted scour depth results (based on the specimen).

The simulation results improved at higher iterations. Table 3 shows the errors resulting from the simulation at different iterations. As can be seen, the error is reduced as the number of iterations grows.

Figure 4 compares the predicted results obtained from the model with the actual results obtained from the FDOT and HEC-18 equations. As can be seen, The ANFIS-PSO results are closer to the actual scour depth results than the FDOT and HEC-18 results. The RMSE values obtained for the ANFIS-PSO, the FDOT, and the HEC-18 models were 1.43, 5.61, and 5.00, respectively.

Table 3. Simulation errors produced by the model at various iterations

Iteration	RMSE	MSE
100	1.4807	2.1925
500	1.4584	2.1268
1000	1.4355	2.0607

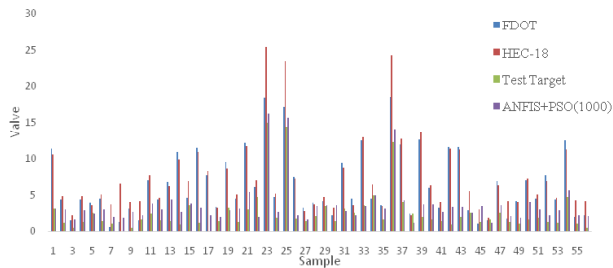


Figure 4. Comparison of results obtained from the proposed model and those obtained from the FDOT and HEC-18 equations with actual results.

4. Conclusion

The scour depth was predicted using four inputs, namely, mean particle size, upstream water head, pier width, and upstream flow velocity. A set of 188 scour depth data supplied by USGS were used for training and testing. The PSO-ANFIS model can avoid being trapped by the local optimized value by implementing the PSO algorithm, thus increasing the accuracy and search capability for teaching ANFIS. The proposed model generates lower MSE and RMSE and has a higher value than other models and equations. The proposed momentum method is a suitable method for online learning due to its quick learning and convergence within a large data set. Further research is required on other ANFIS-oriented soft computation methods for comparison purposes. It is recommended that a larger data set be used for more exact evaluation of parameters.

5. References

1. Ahmad M. Experiments on design and behavior of spur dikes. ASCE: Proceedings of Minnesota International Hydraulic Convention; 1953.
2. Arbib MA. The handbook of brain theory and neural networks. MIT press; 2003.
3. Arneson L, et al. Evaluating scour at bridges; 2012.
4. Bateni SM, et al. Neural network and neuro-fuzzy assessments for scour depth around bridge piers. Engineering Applications of Artificial Intelligence. 2007; 20(3):401–14.
5. Blench T. Mobile-bed fluviology; 1969.
6. Chitale S. Discussion of scour at bridge crossings. In: EM Laursen editor. ASCE, Transactions. 1962; 217(1):191–6.
7. Firat M, Gungor M. Generalized regression neural networks and feed forward neural networks for prediction of scour depth around bridge piers. Adv Eng Software. 2009; 40(8):731–7.
8. Freeman JA, Saad D. Online learning in radial basis function networks. Neural Comput. 1997; 9(7):1601–22.
9. Murrillo JA. The scourage of scour. ASCE, Civ Eng. 1987; 57(7):66–9.
10. Toth E, Brandimarte L. Prediction of local scour depth at bridge piers under clear-water and live-bed conditions: Comparison of literature formulae and artificial neural networks. Journal of Hydroinformatics. 2011; 13(4):812–24.