Research Article – Vol. 01, Issue 02, No. 01

Advanced in Engineering and Intelligence Systems

Journal Web Page: https://aeis.bilijipub.com

Evaluate the Depth of Scouring of the Bridge Base Using Soft Calculation Techniques

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Highlights

- Assessment of bridge pier scoring under riverbed erosion Considering local margin price as a factor of power market factor besides customer payment factor
- Estimate the Estimated scavenger depth Considering operation and economic factors in the optimal model to achieve the best point
- Applying autonomous self-organizing map(SOM).
- Applying auto structured neural network.

Article Info

Received: 29 May 2022
Received in revised: 28 June 2022
Accepted: 28 June 2022
Available online: 03 July 2022

Keywords

Scouring,
Self-Organizing Map (SOM),
Neural Network,
Bridge Pier

Abstract

Scouring is caused by riverbed erosion by water flows and water-borne materials. In the present work, the depth of scouring is estimated using the autonomous neural network (SOM). The results have been compared to the results of other models. Regarding the obtained results, the auto structure of the neural network (SOM) was found to have a higher coefficient of correlation (0.98) than other processes. The mean squared error was also lower than other methods (RMSE = 0.112). Estimated scavenger depth using the SOM approach revealed that this method provides good results. So that the correlation coefficient in the program's execution is with subsequent data compared to the non-secondary data in the program. Moreover, the root mean square mistake (RSME = 0.09) was unclear in the subsequent data mode. In this study, sensitivity analysis has shown that the SOM program will be more sensitive to the average particle diameter when executed with subsequent data.

1. Introduction

The scouring of rivers and coastal engineering is one of the most significant subjects. The bridge docks, oil stationery, breakwaters, and buried tube are the most important structures threatening to scour. Bridges are extremely important as a very important structure in the arteries of communication in a country [1]. There will be several economic and social consequences of the destruction of these structures. Problems with rinsing water in bridge piers have traditionally been regarded as a difficulty, particularly during floods. Therefore, the protection of this structure against scouring is highly crucial. If the precautions required to avoid this phenomenon are not taken, the bridge scouring would adversely affect the structure, threatening the bridge's structure. Scouring is known as bed and water erosion since the stream or riverbed erosion passes downstream of hydraulic structures because of the high water volume and the vertical flow. [2]

This phenomenon has been paid a great deal of attention, and much research has been undertaken over recent decades. However, in certain areas, the quantity of such research appears to be insufficient. Because most laboratory research on this phenomenon has been done under simplified conditions, it has always been obvious that field investigations in actual samples are unavailable. Following a broad definition and numerous relationships established by different scientists, investigations on true

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samples will be provided, and the connected problems and aspects will be discussed. The local scouring of bridge piers involves numerous aspects. The three groups, comprising hydraulic, geometric, and geotechnical groups, are usually divided into components. Hydraulic variables include upstream flow parameters, downstream average speed, channel slope, unit width discharge, flow section, canal form, manpower ruggedness, fluid volume mass unit, and kinetic viscosity gravity acceleration. Geotechnical considerations often involve sediment parameters [3]. The parameters for the geometric shape of the pier, such as the perpendicular pier or the pier width to the water flow, the pier length in the direction of water flow, pier shape and the pier axis angle, flow direction, base spacing, smoothness, and ruggedness, contain geometric variables. The base level, pier support system, water flow floating items, And schematic and scouring mechanism around the base are shown in Fig 1.

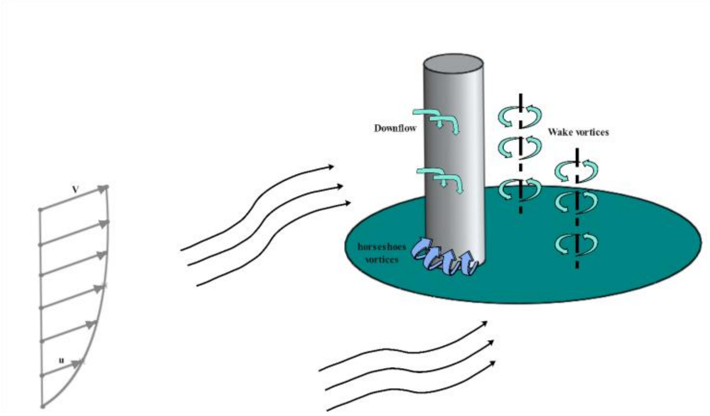

Fig. 1. Scrubbing and horseshoe vortices around a circular base

Due to the effects of different factors, the destruction of many of the world's bridges due to this phenomenon, and the imposition of significant economic expenses, a considerable deal of study has been undertaken in recent decades. Most of these studies were conducted in the preceding part to find a balance to forecast leaching depth due to the floods. There has been less attention to the problems associated with such occurrences involving the construction of the bridge structure. Several bridges were erected in the pier group, but little study has been done on the leaching process in this laboratory. Hannah has done some of these studies [4–7]. Less information is available about adhesive bridge piers. In this connection, the leaching depth of the bridge pier with GMDH was evaluated by Najafzaden et al.[8]. Until then, this was restricted to basic formulas calculating the scouring depth based on the width of the berth. Here, the formulation employed by Neil may be referred to, although there are numerous bridges on these materials around the globe [9]. The lack of knowledge and its application in design in this field, on the one hand, has led to the attention paid by contemporary local and international scientists to the scouring features surrounding the bridge piers. Coleman carried out scouring research at the bridge pier group where the pier group was based once he reached the bed surface at the base [10]. Also, in the case of binary and Ternary Peer Groups, Haidarpour conducted laboratory research on cleaning depth variations[11].

One of the key difficulties is the scouring phenomena, which should be further examined. The study of leaching by bridge piers is conducted under constant currents. However, researchers like Kothyari et al. and Chang et al. did a relatively limited number of laboratory experiments on this subject [12,13]. Azmatullah also carried out studies to calculate the number of clearances in-depth [14–16]. The current situation in this state is not permanent. This is crucial. In this respect, a number of studies have drawn attention to strategies to safeguard bridge piers that reduce the vortex stream mechanism by various geometric characteristics. The application of these solutions enhances the safety of bridge piers and minimizes bridge maintenance expenses. Models that replicate three-dimensional flow may be particularly beneficial since they are more compatible with the physical characteristics of the hydrological phenomena. Numerical simulation by three-dimensional numerical models of local scouring phenomena that may take the time parameter into account may be greatly used to improve understanding of the quantitative and qualitative phenomenon, notably in timing. Furthermore, given the circumstances and field information, the local phénomene of leaching at the bridge pier would be better investigated given circumstances and field information [17].

2. Methods

2.1.Self-Organizing Maps (SOM)

Auto-organizing maps are a unique artificial neural network widely employed to analyze complicated data areas. The functions of such a network are based on transforming the input area to a smaller dimensional area and generally a discreet two-Dimensional map with the necessary dimension. This is why such networks are viewed as reducing the size. The ultimate objective of employing self-organize maps is to obtain a simple raw data model to decrease data analysis calculations and complications. Self-organizing maps are frequently employed in various science domains, including data mining and complicated area analysis [18].

2.2. Organizing Maps Topology

In general, the two-layered structure of the self-organizing map is one layer and one output layer. Neurons of the input layer send data to the network. Generally speaking, its number is equal to the size of the input space vectors. These neurons provide network output because of their neighborhood linkages and interactions [19]. The number of nerve cells in the output layer relies on the user's problem investigation and definition. The input neurons attach grafting weights to every nerve cell in the output layer. Each of these output units, called vectors of reference, is measured by its output screen coordinates. The weight of the neurons, depending on the learning process, showing their coordinates on the outcome screen, is detailed in the following sections. The foundation for the change in the neural weight of the search with the most common similarities is the input pattern (earning neurons) and the movements of neurons. The outcome is modifications in weight, compact information, and space.

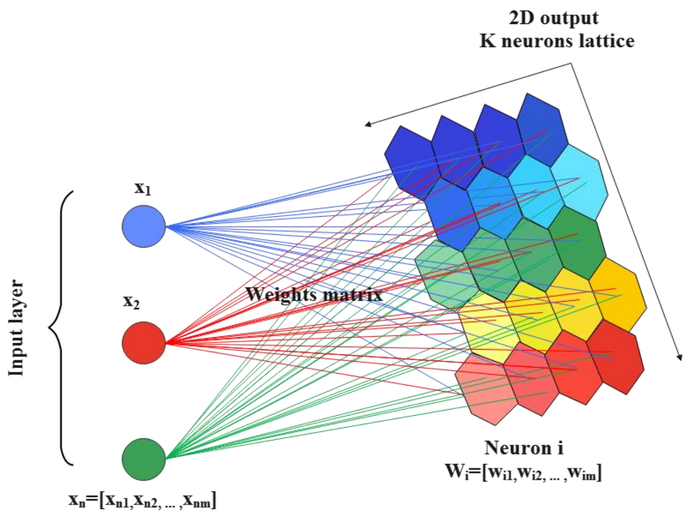

Fig. 2. The structure of a self-organizing map (5 × 4)

2.3. Self-organizing learning algorithm Maps

An autonomous algorithm is a sort of disobedient algorithm. In first-order equations, the observational learning procedure may be calculated. These equations describe how the network's weight adapts to the discreet state's time or repeat. In order to match the weights, the scale or pattern division is utilized to lead the learning process and guide us in some kinds of correlation, clustering, or competing for networking. The self-organized map study algorithm is mainly based on selecting winning neurons and the movement of the neurons mentioned above.

Self-organization is a sort of algorithm not seen. In first-order equations, it may be determined the observational learning algorithm. These equations describe how the weight of the network adapts to the time or repeated conditions. In order to match the weights, the similarity scale or pattern division is utilized to guide and steer us to certain sorts of correlation, grouping, and competitive networking behavior. The self-organizing map-learning method is generally based on the choice of victorious neurons and the movement of the above-noted neurons.

$$\|X - W\| = \left(\sum_{i=1}^{d} (X_i - w_i)^2\right)^{\frac{1}{2}} \tag{1}$$

The input X will then be concurrently compared to all the network elements. The neurons winning are neurons with the minimum distance from all reference input data patterns.

$$\|X - m_c\| = \min_i\{\|X - m_r\|\} \tag{2}$$

where the winning vectors are $m_c$and m_r and reference vectors m_r. Identification of neighboring neurons: a collection of neighbors whose values have to be altered should be established after the identification of the winning neurons. Changing neuronal values usually takes place in two different ways [20]. In the first scenario, the radius around the winning cell is picked for the given neighborhood. This way, the input with a constant factor moves all neurons in the network to a given distance from the winning neurons. The input is moved to all nerve cells in the network with uniform coefficients in a second way. This uneven coefficient has the highest value in the neuron and drops when it leaves the neuron that wins. Fixed weight: Finally, it must be modified depending on the network input of the neuron's weights and neighbors. The following Equation refers to these changes:

$$m_r(t+1) = m_r(t) + \alpha(t).\, h_{cr}(t)[x(t) - m_r(t)] \tag{3}$$

Where: x (t) is the timeline input vector (t), m_r (t) is a timeline reference rhythm, t) is the timeline reference, t, $h_{\ cr}$(t) does the nucleus function define the function of the neighborhood:

$$h_{cr}(t) = exp\left(-\frac{\|k_c - k_r\|^2}{2\sigma(t)^2}\right) \tag{4}$$

The following: (5) Where: Weight adjustment and migration of the above-stated neurons towards the study sample outcome. Where: T (t) is an algorithm convergence-controlled parameter and iteration-dependent. For stability of the network, 0 < bis (t) should be achieved, figure 2. and t should be decreased consistently. Unmonitored learning is often more difficult than supervisory learning, which requires a long time to learn pathways.

3. Discussion And Results

Data from the paper 'In two training modes with genetic algorithm and recursive algorithm GMDH comparison methods were employed to estimate scouring depth [15]. 184 Mulias and Abdo, 14 Shapard groups, 24 Shapard and Miller groupings, 18 Dee groupings, and 5 Mia and Nago were detected in the data collection. The variables in Formula 5 are used to wash the bridge pier [15]:

$$ds = f(u, y, d50, \sigma, D, \mu, \rho, g) \tag{5}$$

It has been discovered in Eq (5) that the depth of slag relies on such elements as flow speed and flow depth. Average particle diameter, standard particle size variation, the diameter of the pier, viscosity, density, and acceleration in gravity. The Buckingham approach is then used to non-dimensionalize the parameters. Eq (6) [15]:

$$ds/y = f(Fr, D/y, d50/y, Re, \sigma) \tag{6}$$

Is the basis of the non-dimensional scouring Eq (6) The following: (5) Re is a number of the Reynolds with the following Equation:

$$Re = u.D/v \tag{7}$$

Bridge scouring depth estimate analysis utilizing SOM was based on the fact that a large number of neural networks were not utilized to forecast the depth of the bridge and neural SOM network leaking. This article is based on an evaporation dissertation from the University of Ferdowsi with five non-dimensional inputs and one output. The following conclusions from the next SOM data analysis are: Table 1 shows that the estimate of the SOM depth using the following data has the appropriate coefficient of correlation, but the RSME error (mean error square) is of a smaller value. SOM Sensitivity program examination of the bridge pier cleaning prediction for future data.

Table 1. Evaluating the depth of the bridge pier by SOM

Program	RMSE	R^2
SOM	0.091293	0.99163

The following information in Table 2 shows that the SOM program is sensitive to the medium particle diameter parameter in predicting the depth of bridge pier wash as the correlation coefficient has fallen to 0.987. By eliminating this parameter from the principal function and restarting the program, the RMSE (Square Mid Error) error is up to 0.109. Moreover, if the mean particle diameter is deleted from the program and executed, the mean square mistake (MSE) value increases. Non-dimensional data SOM application analysis. The results of the non-dimensional data analysis of the SOM software are as follows: Table 2.

Table 2. The result from the SOM program sensitivity study in evaluating the pier cleaning depth of the bridge for dimensional data

Studied parameter	**RMSE**	R^2
D_{50}	0.109	0.987
σ_g	0.092	0.991
D	0.080	0.993
Y	30.088	0.992
V	0.096	0.990
Fr	0.078	0.993

Table 3 shows that using the SOM program, a clean depth estimate has a strong correlation coefficient with non-dimensional data. The mean MSE error is a good number in this scenario. SOM sensitivity analysis tool for forecasting the depth of the bridge pier using non-dimensional data. This fact is also clear in Figs 3 and 4. In Fig 3, the value of the correlation coefficient is equal to 0.98, and in Fig 4, the horizontal axis of the predicted value and the vertical axis shows the value of the scouring depth parameter, which Its fitting line is suitable.

Table 3. Results of estimating bridge pier scouring depth using SOM in non-dimensional data

Statistical parameter	**RMSE**	R^2
SOM	80.11	0.9859

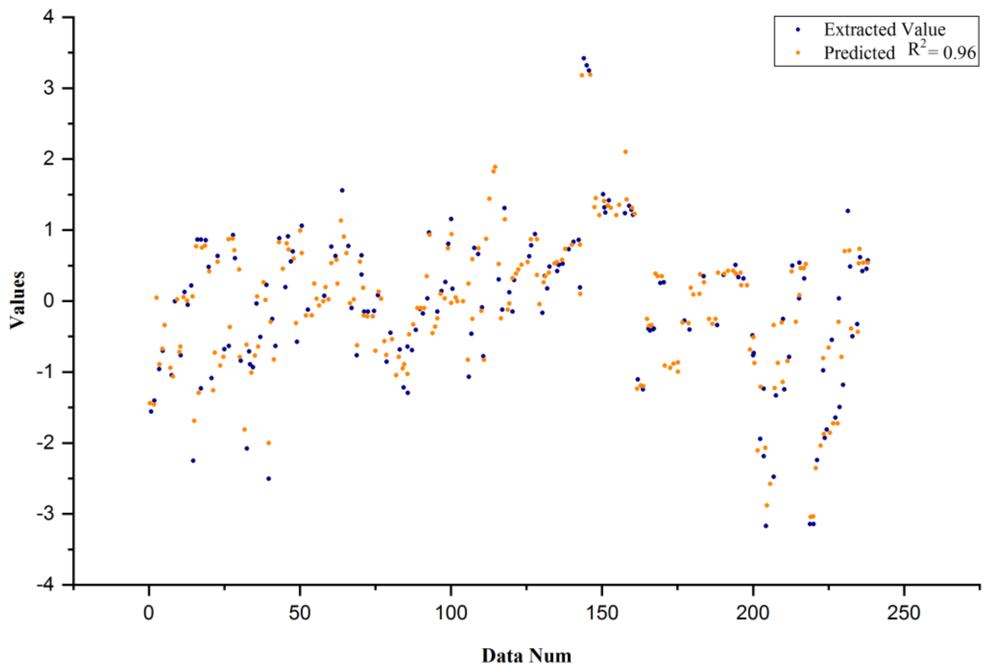

Fig. 3. Dispersion of predicted and actual values with self-organizing topology

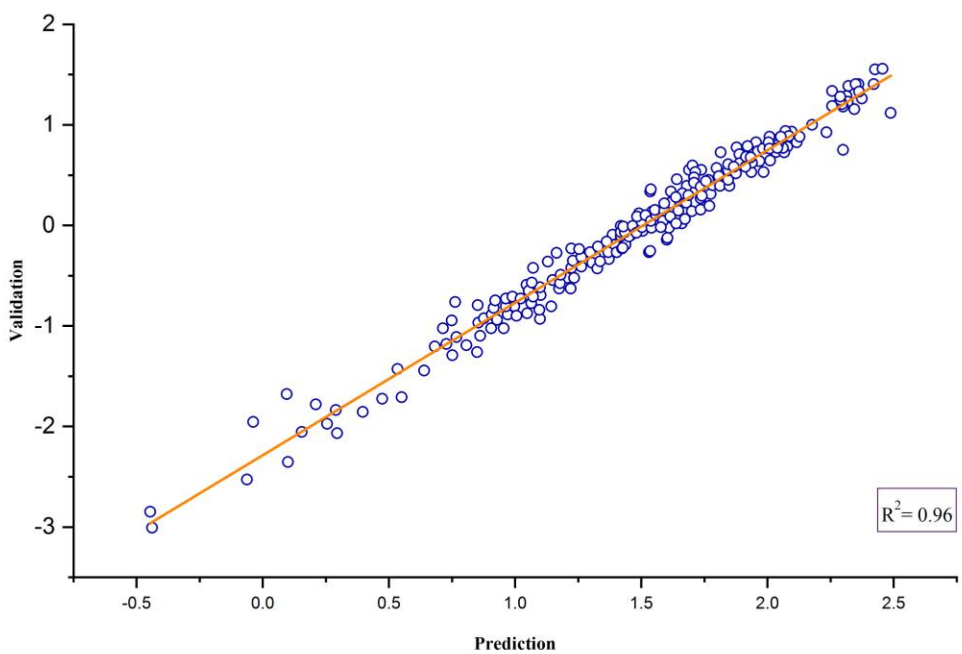

Fig. 4. The line of fit of the predicted value and the actual value of the self-organized program

Analysis of SOM water depth rinsing sensitivity Table 4 SOM software Estimate of non-dimensional Data Bridge.

Table 4. Results of the sensitivity SOM program study for bridge washing water depth estimation

Studied parameter	RMSE	R^2
FR	0.11096	0.987
D/Y	0.11566	0.986
d_{50}/Y	0.11107	0.987
Re	0.11332	0.987
σ_g	0.10451	0.989

Using non-dimensional information, Table 4 suggests that the SOM program's estimation of bridge pier leaching depth was sensible since it was increased in value to 0.986 and the RMSE error to 0.115 by eliminating this parameter from the original performance and re-run of the program. When the average particle diameter is deleted and executed from the program, an average square error (MSE) is also raised. Comparison of models to estimate the depth of bridge pier washing with the SOM program. The results of several approaches are compared with the results of the SOM approach in this section.

4. CONCLUSION

Based on Table 5, the coefficient of correlation (R^2) of the SOM approach was shown to be greater than any other approach. It may therefore be stated that the dehydrating depth of the bridge pier has greater accuracy. Moreover, there were fewer errors than in other approaches using the mean square error (RSME).

Table 5. Comparison with findings from various approaches of the SOM program

Method	R^2	RMSE
SOM	0.9859	0.118
GMDH-GP [15]	0.8649	0.23
GMDH-BP [15]	0.7921	0.25
Laursen and Toch (1956)	0.6889	0.56
Shen *et al.* (1969)	0.7744	0.63
Melville and Sutherland (1988)	0.7056	1.46
Johnson (1992)	0.8464	0.42
HEC-18 (2001)	0.7921	0.45

An organized neural network model was discovered to be sensitive to the average particle diameter parameter and subsequent data. Furthermore, the non-dimensional SOM model was sensitive to the flow depth-diameter parameter.

REFERENCES

[1] Rafat A, Javan H, Saeedi F. A study of accuracy and application of genetic programming for estimation of scour depth around bridge piers, below pipelines and downstream of bucket overflow. Bulletin of Environment, Pharmacology and Life Sciences 2014;4:90–6.

[2] Najafzadeh M, Barani G-A, Kermani MRH. Abutment scour in clear-water and live-bed conditions by GMDH network. Water Science and Technology 2013; 67:1121–8.

[3] Zomorodian SMA, Ghaffari H, Ghasemi Z. Comparison of Linear and Triangular Arrangements of Submerged Sacrificial Piles on Local Scour Depth around Cylindrical Bridge Piers. Irrigation Sciences and Engineering 2019; 42:167–80.

[4] Hannah CR. Scour at pile groups. University of Canterbury, NZ. Civil Engineering, Research Report 1978:92.

[5] Raudkivi AJ. Functional trends of scour at bridge piers. Journal of Hydraulic Engineering 1986; 112:1–13.

[6] Breusers HNC, Raudkivi AJ. IAHR hydraulic structures design manual: Scouring, Vol. 2. Balkema, Rotterdam, The Netherlands 1991.

[7] Nazariha M. Design relationships for maximum local scour depth for bridge pier groups. University of Ottawa (Canada); 1996.

[8] Najafzadeh M, Barani G-A, Azamathulla HM. GMDH to predict scour depth around a pier in cohesive soils. Applied Ocean Research 2013; 40:35–41.

[9] Risk RCB. The Nineteenth-Century Foundations of the Business Corporation in Ontario. The University of Toronto Law Journal 1973; 23:270–306.

[10] Coleman SE. Clearwater local scour at complex piers. Journal of Hydraulic Engineering 2005; 131:330–4.

[11] Heidarpour M, Afzalimehr H, Izadinia E. Reduction of local scour around bridge pier groups using collars. International Journal of Sediment Research 2010; 25:411–22.

[12] Kothyari UC, Hager WH, Oliveto G. Generalized approach for clear-water scour at bridge foundation elements. Journal of Hydraulic Engineering 2007; 133:1229–40.

[13] Chang W-Y, Lai J-S, Yen C-L. Evolution of scour depth at circular bridge piers. Journal of Hydraulic Engineering 2004; 130:905–13.

[14] Tafarojnoruz A. Discussion of "Genetic Programming to Predict Bridge Pier Scour" by H.

Md. Azamathulla, Aminuddin Ab Ghani, Nor Azazi Zakaria, and Aytac Guven. Journal of Hydraulic Engineering 2012; 138:669–71.

[15] Najafzadeh M, Azamathulla HM. Group method of data handling to predict scour depth around bridge piers. Neural Computing and Applications 2013; 23:2107–12.

[16] Najafzadeh M, Azamathulla HM. Group method of data handling to predict scour depth around bridge piers. Neural Computing and Applications 2013; 23:2107–12.

[17] Kiraga M, Popek Z. On local scouring downstream small water structures. PeerJ 2020;8: e10282.

[18] Seo S, Obermayer K. Self-organizing maps and clustering methods for matrix data. Neural Networks 2004; 17:1211–29.

[19] Chang P-C, Liao TW. Combining SOM and fuzzy rule base for flow time prediction in semiconductor manufacturing factory. Appl Soft Comput 2006; 6:198–206.

[20] Beale MH, Hagan MT, Demuth HB. Neural network toolbox. User's Guide, MathWorks 2010;2:77–81.