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GMDH to predict scour depth around a pier in cohesive soils

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ABSTRACT

This study presents new application of group method of data handling (GMDH) to predict scour depth around a vertical pier in cohesive soils. Quadratic polynomial was used to develop GMDH network. Back propagation algorithm has been utilized to adjust weighting coefficients of GMDH polynomial thorough trial and error method. Parameters such as initial water content, shear strength, compaction of cohesive bed materials, clay content of cohesive soils, and flow conditions are main factors affecting cohesive scour. Performances of the GMDH network were compared with those obtained using several traditional equations. The results indicated that the proposed GMDH-BP has produced quite better scour depth prediction than those obtained using traditional equations. To assign the most significant parameter on scour process in cohesive soils, sensitivity analysis was performed for the GMDH-BP network and the results showed that clay percentage was the most effective parameter on scour depth. The error parameter for three classes of *IWC* and C_p showed that the GMDH-BP model yielded better scour prediction in ranges of $IWC = 36.3$–42.28% and $C_p = 35$–100%. In particular application, the GMDH network was proved very successful compared to traditional equations. The GMDH network was presented as a new soft computing technique for the scour depth prediction around bridge pier in cohesive bed materials.

1. Introduction

Scouring phenomena is a significant problem for bridge engineering. There are several ocean and coastal structures located in rivers, sea and streams that may be prone to erosion due to combinations of scouring factors. It is believed that erosion in cohesive bed materials occurs when the fluid shear stress is sufficient to overcome the tensile strength of the bed material and submerged unit weight of the soil.

Investigations on scour depth in non-cohesive materials have been extensively carried out in the last few decades [1–5]. In contrast, few researchers have studied scouring in cohesive soils [6–15]. Most of the investigations resulted traditional equations based on regression models in limited experimental conditions [11,12,14,15]. Each of the traditional equations has focused on special parameters. Conditions of laboratory and field are limiting factors that can be caused to provide the prediction of scour depth with low accuracy.

Recently, various artificial intelligence approaches such as artificial neural network (ANN), adaptive neuro-fuzzy inference system (ANFIS), genetic programming (GP), linear genetic programming (LGP), data mining, and machine learning method were applied to develop the modeling of problems in scour prediction [16–23]. Among these methods, the GMDH network is known as a system identification method which is employed in various fields in order to model and forecast the behaviors of unknown or complex systems based on given input–output data pairs [24]. Recently, GMDH network has been utilized to predict scour depth around bridge piers, abutments, and pipelines in coarse bed sediment [25–28,29]. Results of performances indicated that combinations of iterative and evolutionary algorithms with GMDH network provided quite better prediction than those obtained using traditional equations and soft computing tools.

In addition, the GMDH approach has been used in different researches such as energy conservation, control engineering, system identification, marketing, economics and engineering geology [24,30–33].

The main objective of this study is to investigate the efficiency of the GMDH network and traditional equations in the prediction of scour depth in cohesive soils. Furthermore, influence of the effective parameters on the scour depth would be considered. In this way, GMDH network has been improved using back propagation (BP) technique, and a programming code was introduced.

2. Review on pier scour in cohesive soils

The scour of cohesive materials is fundamentally different from that of non-cohesive materials. It involves not only complex mechanical phenomena, including shear stress and shear strength of soils, but also the chemical and physical bonding of individual particles

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and properties of the eroding fluid [34]. Also, scouring process in cohesive soils is more complicated than that of non-cohesive soils. A few investigators have studied scour in cohesive soils. Molinas and Honsy [35] carried out experiments to study the effects of compaction, soil shear strength, initial water content, and the approaching flow conditions on pier scour in unsaturated and saturated cohesive soils. They presented two empirical equations for unsaturated and saturated cohesive soils. Briaud et al. [6,7] presented SRICOS–EFA (scour rate in cohesive soils–erosion function apparatus) method for the prediction of scour depth around a vertical pier in cohesive soils. Subsequently, Briaud et al. [8] developed SRICOS–EFA method for scour depth around cylindrical complex piers in fine-grained soils. Ting et al. [10] concluded that predicted equilibrium scour in tree type of clay soils correlated well with the pier Reynolds number. Also, the shape of scour hole depended directly on Reynolds number and an equation was derived based on function of the pier Reynolds number. Rambabu et al. [11] investigated current-induced scour around a vertical pile in cohesive soil. They presented an empirical equation based on Reynolds number, Froude number, and saturated shear strength of soil. Also, Ansari et al. [12] investigated influence of cohesion on scour around bridge pier. They presented a mathematical algorithm based on cohesive soils properties for scour depth prediction. Najafzadeh [14] has carried experiments, and developed a relationship between the ultimate scour depth and effective parameters, by using dimensional analysis. Finally, the experimental ultimate scour depths were compared with those calculated by traditional equations.

Recently, Debnath and Chaudhuri [15] reported experimental results of scour depth in cohesive soils. They also investigated the effect of clay-content and initial water content on maximum equilibrium scour depth, equilibrium scour hole geometry, scouring process, and time variation of scour.

3. Data collection

Based on the previous studies, the scour depth around a vertical pier in cohesive soils depends on initial water content of soil, compaction of cohesive soils, clay percentage, shear strength of bed soil [6–8,10–12,14,15]. Therefore, the following equation can be used for cohesive soils:

$$d_s = f(\rho, \mu, U, d_{50}, y, g, D, IWC, C_p, S) \tag{1}$$

where d_s, ρ, μ, U, d_{50}, y, g, D, IWC, C_p, and S are scour depth, mass density of water, fluid dynamic viscosity, flow velocity, medium diameter of bed material, flow depth, acceleration due to gravity, pier diameter, initial water content, clay percentage, and shear strength of cohesive soils, respectively.

The following equation was resulted using dimensional analysis:

$$\frac{d_s}{D} = f\left(R_{ep}, \frac{d_{50}}{D}, Fr_p, \frac{y}{D}, IWC, C_p, \frac{S}{\rho U^2}\right) \tag{2}$$

where d_s/D, R_{ep}, d_{50}/D, Fr_p, IWC, C_p, and $S/\rho U^2$ are non-dimensional scour depth, pier Reynolds number, non-dimensional particle size, pier Froude number, initial water content, clay fraction, and non-dimensional bed shear strength.

In this study, to reduce number of non-dimensional parameters and prevent the complexity of the GMDH networks, Fr_p and y/D have been combined with each other. This combination results in the flow Froude number:

$$Fr = \frac{U}{\sqrt{g.y}} \tag{3}$$

Also, pier Reynolds number is not an important parameter if the viscous effects are concerned but pier Reynolds number influences the frequency of vortex shedding. Pier Reynolds number is not a significant parameter if the flow around the pier is fully turbulent and is generally neglected in pier scour study [14,15,36,37]. Also, the present data sets were performed at $d_{50}/D < 50$ and based on the investigations of Ettema [3] and Chiew [38] the scour depth was independent of the sediment size:

$$\frac{d_s}{D} = f\left(Fr, IWC, C_p, \frac{S}{\rho U^2}\right) \tag{4}$$

Table 1.
Ranges of used data for development of the GMDH-BP network.

Parameters	Ranges
y	0.3–0.6 (m)
D	50–120 (mm)
d_{50}	0.00808–0.037 (mm)
S	1.88–35.6 (kPa)
IWC	10.7–45.92%
C_p	20–100%
ρ	1000 (kg/m^3)
d_s	7.3–224 (mm)
U	0.141–0.8187 (m/s)
g	10 (m^2/s)
μ	0.001 (Pa S)

The data sets used were collected from Najafzadeh [14] (12 data sets), Debnath and Chaudhuri [15] (71 data sets), and Rambabu et al. [11] (12 data sets). Table 1 presents the ranges of data sets parameters. Out of the total 95 data sets, about 75% (71 data sets) were selected randomly for training whereas the remaining 25% (24 data sets) were used for testing stage.

It was established that, use of grouped non-dimensional parameters produced better predictions of scour depth than that of dimensional parameters [16,18,21–23,25]. In this way, Eq. (4) was used to develop the GMDH network for the prediction of scour depth in cohesive soils. Furthermore, several traditional equations were presented in Table 2 for the evaluation of the scour depth in cohesive soils.

4. Principle of the GMDH network

GMDH is a learning machine based on the principle of heuristic self-organizing, proposed by Ivakhnenko in the 1960s. It is an evolutionary computation technique, which has a series of operations such as seeding, rearing, crossbreeding, and selection and rejection of seeds corresponding to the determination of the input variables, structure and parameters of model, and selection of model by principle of termination [24,39,40]. In fact, the GMDH network is a very flexible algorithm and it can be hybridized by using evolutionary and iterative algorithms such as genetic algorithm (GA) [24,32], genetic programming (GP) [25,41], particle swarm optimization (PSO) [42], and back propagations [25,30,43]. The previous researches established that hybridizations were successful in finding solutions of problems in different fields of engineering. By means of GMDH algorithm a model can be represented as set of neurons in which different pairs of them in each layer are connected through quadratic polynomial and thus produce new neurons in the next layer. Such representation can be used in modeling to map inputs to outputs. The formal definition of system identification problem is to find a function $\hat{f}$ that can be approximately used instead of actual function f, in order to predict the output $\hat{y}$ for a given input vector $X = (x_1, x_2, x_3, \ldots, x_n)$ as close as possible to its actual output y. Therefore, for a given n observation of multi-input–single-output data pairs:

$$y_i = f(x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in}) \quad (i = 1, 2, \ldots, M) \tag{13}$$

It is now possible to train a GMDH network to predict the output values $\hat{y}_i$ for any given input vector $X = (x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in})$, that is

$$\hat{y}_i = \hat{f}(x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in}) \quad (i = 1, 2, \ldots, M) \tag{14}$$

Table 2.
Traditional equations for prediction of pier scour depth in cohesive soils.

Equations	Authors	Eq. no.
$d_s/D = Fr^{0.641} R_{ep}^{0.64} (S/\rho_s gy)^{-0.976}$	Rambabu et al. [11]	(5)
$d_s/D = 0.0288 IWC^{1.14} (350/IWC^2 - Fr)^{0.6}$	Molinas and Honsy [35]	(6)
$d_s/y = 5565.05 (S/\rho_s gy)^{0.83} C_p Fr^{2.306}$	Najafzadeh [14]	(7)
$d_s/D = 2.05(U/\sqrt{g.D})^{1.72} C_p^{-1.29} (S/\rho U^2)^{-0.37}$, $C_p = 20-85\%$ and $IWC = 20-23.22\%$	Debnath and Chaudhuri [15]	(8)
$d_s/D = 3.64(U/\sqrt{g.D})^{0.22} C_p^{-1.01} (S/\rho U^2)^{-0.69}$ $C_p = 20-50\%$ and $IWC = 27.95-33.55\%$	Debnath and Chaudhuri [15]	(9)
$d_s/D = 20.52(U/\sqrt{g.D})^{1.28} C_p^{0.19} (S/\rho U^2)^{-0.89}$ $C_p = 50-100\%$ and $IWC = 27.95-33.55\%$	Debnath and Chaudhuri [15]	(10)
$d_s/D = 3.32(U/\sqrt{g.D})^{0.72} C_p^{-0.62} IWC^{0.36} (S/\rho U^2)^{-0.29}$, $C_p = 20-70\%$ and $IWC = 33.60-45.92\%$	Debnath and Chaudhuri [15]	(11)
$d_s/D = 8(U/\sqrt{g.D})^{0.61} C_p^{0.58} IWC^{1.24} (S/\rho U^2)^{-0.19}$, $C_p = 70-100\%$ and $IWC = 33.60-45.92\%$	Debnath and Chaudhuri [15]	(12)

In order to solve this problem, GMDH builds the general relationship between output and input variables in the form of mathematical description, which is also called reference. The problem is now to determine a GMDH network so that the square of difference between the actual output and the predicted one is minimized, that is:

$$\sum_{i=1}^{M} \left[\hat{f}\,(x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in}) - y_i \right]^2 \to \min. \tag{15}$$

General connection between inputs and output variables can be expressed by a complicated discrete form of the Volterra function a series in the form of:

$$y = a_0 + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n}\sum_{j=1}^{n} a_{ij} x_i x_j + \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n} a_{ijk} x_i x_j x_k + \ldots, \tag{16}$$

which is known as the Kolmogorov–Gabor polynomial [24,39,44,45].

The polynomial order of PDs is the same in each layer of the network. In this scenario the order of the polynomial of each neuron (PN) is maintained the same across the entire network. For example, assume that the polynomials of the PNs located at the first layer are those of the 2nd order (quadratic):

$$\hat{y} = G\,(x_i, x_j) = a_0 + a_1 x_i + a_2 x_j + a_3 x_i x_j + a_4 x_i^2 + a_5 x_j^2 \tag{17}$$

Here, all polynomials of the neurons of each layer of the network are the same and the design of the network is based on the same procedure. The second order polynomial is fundamental structure of the GMDH network that has been proposed by Ivakhnenko [39]. Generally, different types of polynomial such as bilinear, quadratic, tri-quadratic, and 3rd order were used to design self-organized systems [42,46,47]. Use of tri-quadratic and 3rd order polynomial generated more complicated network in comparison with quadratic polynomial. Bilinear polynomial produced lower complicated structure in comparison with quadratic polynomial. Quadratic polynomial has six weighting coefficients that generated good results in engineering problems [24,25,30–33]. Based on previous investigations, selection of polynomials could depend on minimum error of objective function and complexity of polynomial type. In this study, quadratic polynomial was utilized for modeling of scour depth around bridge pier. The weighting coefficients in Eq. (17) were calculated using regression techniques [24,44] so that the difference between actual output, y, and the calculated one, $\hat{y}$, for each pair of x_i, x_j as input variables was minimized. In this way, the weighting coefficients of quadratic function G_i were obtained to optimally fit the output in the whole set of input–output data pair, that is:

$$E = \frac{\sum_{i=1}^{M} (y_i - G_i\,())^2}{M} \to \min. \tag{18}$$

4.1. Application of BP Algorithm in the topology design of GMDH network

In this section, the GMDH network was improved using back propagation algorithm. This method included two main steps. The first, the weighting coefficients of quadratic polynomial were determined using least square method from input layer to output layer in form of forward path. The second, weighting coefficients were updated using back propagation algorithm in a backward path. Again, this mechanism could be continued until the error of training network (E) was minimized. The other details of training stages were presented in literatures [25,43]. In present study, number of neurons used in GMDH structure is 10 and 6 of them are the selective neurons that have been selected based on trial and error process. The structure of GMDH network has been adjusted by training error and learning rate values of 0.034 and 0.01, respectively. Also, Fig. 1 indicates training error values of each neuron thorough three layers. From the GMDH performances, the corresponding selective polynomials are presented as follows:

$$\begin{aligned}\left(\frac{d_s}{D}\right)_3^1 &= 0.3278 + 0.0022 IWC \\ &-0.585 Fr + 0.1309 IWC.Fr \\ &-0.00048 IWC^2 - 1.35 Fr^2\end{aligned} \tag{19}$$

$$\begin{aligned}\left(\frac{d_s}{D}\right)_5^1 &= -0.2806 + 0.00288\frac{S}{\rho U^2} \\ &+5.347 Fr - 0.0232\frac{S}{\rho U^2.Fr} - \\ &-7.62\times 10^{-7}\left(\frac{S}{\rho U^2}\right)^2 - 2.42133 Fr^2\end{aligned} \tag{20}$$

$$\begin{aligned}\left(\frac{d_s}{D}\right)_6^1 &= 1.657 - 0.0573 C_p + 2.304 Fr - 0.0675 C_p.Fr + \\ &0.000586 C_p^2 + 7.834 Fr^2\end{aligned} \tag{21}$$

$$\begin{aligned}\left(\frac{d_s}{D}\right)_2^2 &= 0.1303 - 0.128\left(\frac{d_s}{D}\right)_3^1 \\ &+0.507\left(\frac{d_s}{D}\right)_6^1 - 0.5687\left(\frac{d_s}{D}\right)_3^1\left(\frac{d_s}{D}\right)_6^1 \\ &+0.5865\left(\left(\frac{d_s}{D}\right)_3^1\right)^2 + 0.4168\left(\left(\frac{d_s}{D}\right)_6^1\right)^2\end{aligned} \tag{22}$$

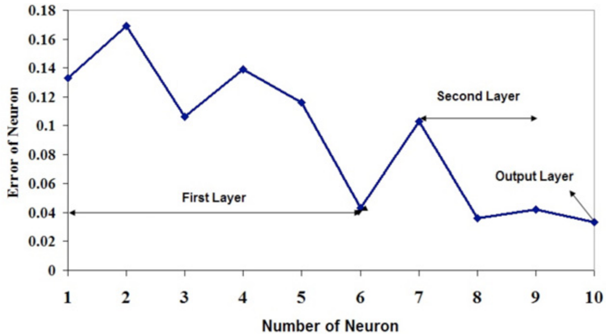

Fig. 1. Training error and number of neurons in the structure of GMDH network.

Table 3.
Performances of the proposed GMDH-BP in training and testing stages.

Method	R	RMSE	MAPE	BIAS	SI
Training	0.92	0.183	0.26	0.00	0.218
Testing	0.91	0.184	0.74	−0.045	0.22

$$\left(\frac{d_s}{D}\right)_3^2 = 0.0489 - 0.369\left(\frac{d_s}{D}\right)_5^1 + 1.138\left(\frac{d_s}{D}\right)_6^1 - 0.6505\left(\frac{d_s}{D}\right)_5^1\left(\frac{d_s}{D}\right)_6^1 + 0.5937\left(\left(\frac{d_s}{D}\right)_5^1\right)^2 + 0.2156\left(\left(\frac{d_s}{D}\right)_6^1\right)^2 \quad (23)$$

$$\left(\frac{d_s}{D}\right)_1^3 = 0.0208 + 2.9068\left(\frac{d_s}{D}\right)_2^2 - 1.957\left(\frac{d_s}{D}\right)_3^2 - 0.9366\left(\frac{d_s}{D}\right)_2^2\left(\frac{d_s}{D}\right)_3^2 - 0.445\left(\left(\frac{d_s}{D}\right)_2^2\right)^2 + 1.4092\left(\left(\frac{d_s}{D}\right)_3^2\right)^2 \quad (24)$$

in which superscript and subscript of each parameter present the number of pertaining layer and neuron, respectively.

5. Results and discussion

The results of GMDH network and traditional equations are presented in this section. In addition, influences of the non-dimensional parameters on the scour depth have been considered. In this way, correlation coefficient (R), root mean square error (RMSE), scatter index (SI), BIAS, and mean absolute percentage of error (MAPE) are the commonly used prediction error indicators in the training and testing stage [16,22,25].

5.1. Performances of the GMDH network and traditional equations

Validation of the GMDH network for the training and testing stages provided relatively low error in the prediction of scour depth. The main advantage of proposed GMDH is that only six weighting coefficients are available in each neuron. In this way, structure of GMDH network has been developed by 10 quadratic polynomials to reduce volume of calculations.

The R and RMSE for both training and testing stages were approximately same values whereas MAPE values were obtained 0.26 and 0.74, respectively (Table 3).

Furthermore, several traditional equations were used to compare their performances with those obtained using GMDH network. The validation results of traditional equations were presented in Table 4.

From performances of these equations, it was found that Eq. (5) predicted the scour depth with high error of parameters ($R = 0.86$, RMSE = 67.3, MAPE = 298.4, BIAS = −59.03, and SI = 81.64). Eq. (5) included only two effective parameters of shear strength and Froude number on the scour depth in cohesive soils. On other hand, the

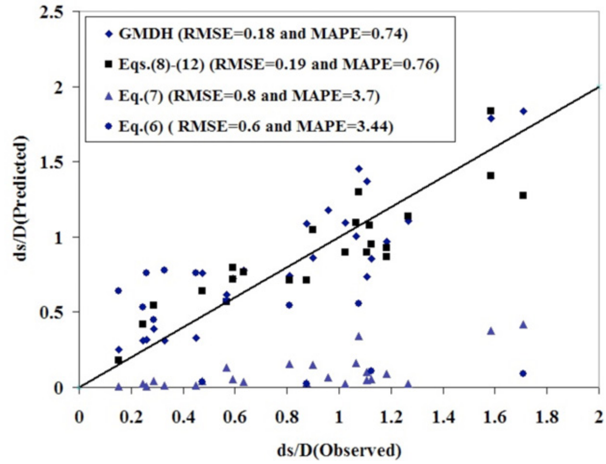

Fig. 2. Comparison between the observed and predicted non-dimensional scour depths using the GMDH network and traditional equations.

Reynolds number has an insignificant role in fully turbulent condition. Also, Eqs. (6) and (7) provided remarkably lower error in comparison with Eq. (5) due to the existence of the crucial parameters such as initial water content, clay percentage, and shear strength of bed soils. Validation of Debnath and Chaudhuri equation has been carried out in five ranges of *IWC* and C_p. Furthermore, validations of Eqs. (8)–(12) provided quite better scour depth prediction ($R = 0.88$, RMSE = 0.19, MAPE = 0.6, BIAS = 0.012, and SI = 0.2) than other traditional equations. Traditional equations were controlled by range of parameters in limited conditions of laboratory and field. In fact, the GMDH network covered well restrictions of traditional equations and it produced good agreements with observed data sets.

Also, Fig. 2 illustrates the comparison between the observed and predicted scour depths by proposed GMDH network and traditional equations. From Fig. 2, it can be found that performance of the GMDH network is superior to the traditional equations.

5.2. Influences of the non-dimensional parameters on the scour depth

In this section, influences of the shear strength of cohesive soils, initial water content, clay percentage, and Froude number on the scour depth would be considered.

5.2.1. Influences of the shear strength of cohesive bed material on the scour depth

Rambabu et al. [11] and Najafzadeh [14] proposed following equations to investigate influence of the shear strength on the scour depth [11,14]:

$$\frac{d_s}{D} = 1.349S^{-1.134} \quad (25)$$

$$\frac{d_s}{y} = 5.29S^{-1.27} \quad (26)$$

Eqs. (25) and (26) were validated for saturated and unsaturated cohesive soils, respectively. 24 data sets are available for testing stage that 18 of them are related to the unsaturated data sets and the reminding of data sets is in saturated mode. Statistical error parameters for Eqs. (25) and (26) were calculated to compare validation of the empirical equations with those obtained using GMDH network. Result of performances indicated that Eqs. (25) and (26) predicted the scour depth with lower accuracy in comparison with GMDH network ($R = 0.76$, RMSE = 0.29, MAPE = 1.22, BIAS = 0.017, and SI = 0.015). From Table 5, it is apparent that the proposed GMDH network can be used in both saturated and unsaturated conditions of cohesive

Table 4.
Performances result of the GMDH network and traditional equations.

Method	Eq. no.	R	RMSE	MAPE	BIAS	SI
GMDH network	(19)–(24)	0.91	0.18	0.74	−0.045	0.22
Rambabu et al. [11]	(5)	0.8637	67.3	298.4	−59.035	81.64
Molinas and Honsy [35]	(6)	0.6	0.67	3.44	0.193	1.042
Najafzadeh [14]	(7)	0.68	0.8	3.7	0.725	0.97
Debnath and Chaudhuri [15]	(8)–(12)	0.88	0.19	0.76	0.016	0.2

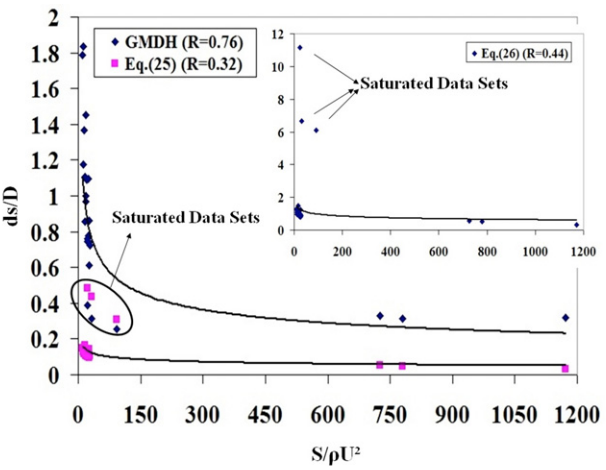

Fig. 3. Modeling of influence of the saturated and unsaturated shear strength on scour depth using GMDH network.

soils whereas Eqs. (25) and (26) were presented in saturated and unsaturated of experimental data sets, respectively. Fig. 3 illustrates variations of shear strength and the scour depth obtained using Eq. (25) and GMDH network.

From this figure, predicted scour depth by Eq. (25) concentrated in the scour depth between 0 and 0.2. It can be seemed that this equation has not remarkable capability to illustrate variations of shear strength and scour depth because Eq. (25) was proposed to validate the scour depth in saturated cohesive soils (R = 0.32, RMSE = 0.82, MAPE = 3.6, BIAS = 0.68, and SI = 0.041). These results coincided promisingly with Molinas and Honsy's [35] experimental outcomes. They concluded that the scour depth does not depend on shear strength in saturated condition of cohesive soils. Also, Eq. (26) has predicted the scour depth with highly abrupt in saturated conditions for three pairs of the $S/\rho U^2$ and d_s/D: 22.99, 11.6; 32.35, 6.64; 92.35, 6.11. In fact, this equation was proposed for validation of the scour depth in unsaturated conditions. From the indicators error parameters, Eq. (26) cannot provide the scour depth with high accuracy in saturated conditions of cohesive soils.

5.2.2. *Influences of the initial water content and clay percentage on the scour depth*

Influence of the initial water content and clay percentage on the scour depth has been investigated for three ranges of *IWC* and C_p. Fig. 4 illustrates variations of *IWC* with d_s/D. From Fig. 4, the scour depth increased with increase in initial water content (15%–20%) and decrease in clay percentage (34–41%). For $20 \leq IWC \leq 21$, with increase in clay percentage (35–50%), at first decreased thereafter increased. In the second range of *IWC* and C_p (IWC = 27.96–35.08% and C_p = 35–100%), scour depth decreased with increase in initial water content from 29.96% to 32.17% and increase in clay percentage from 35% to 85%. In contrast, scour depth increased with increase in *IWC* from 32.2% to 35.08% and decrease in clay percentage from 100% to 44%.

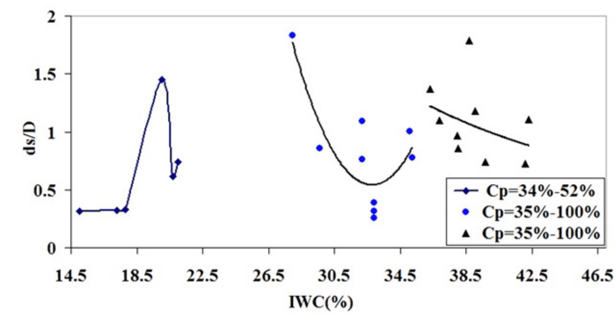

Fig. 4. Influence of the initial water content on the scour depth using the GMDH network.

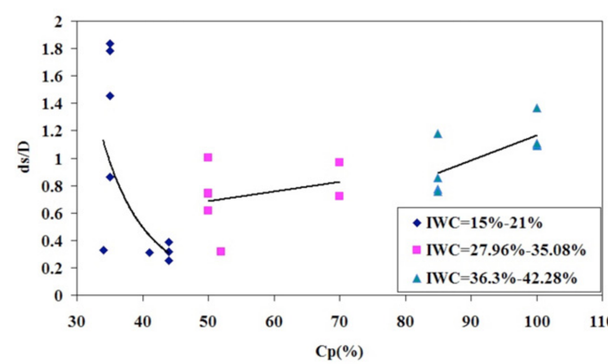

Fig. 5. Influence of the clay percentage on the scour depth using the GMDH network.

From the third range of *IWC* and C_p, it can concluded that scour depth decreased generally with increase in *IWC* (36.3–42.28%) and increase in clay percentage from 35% to 100%. Furthermore, the GMDH predicted the scour depth in ranges of the IWC = 36.3–42.28% and C_p = 35–100% with higher accuracy (MAPE = 1.9) than other ranges. The MAPE values were obtained 3.28 and 2.31 for the first and second ranges, respectively.

Also, Fig. 5 indicates the scour depth as a function of C_p for clay soils. For cohesive soils with lower initial water content (15–21%), the scour depth decreased meaningfully with increase in C_p from 34% to 44%. For cohesive beds with higher initial water content (27.96–35.08% and 36.3–42.28%), the scour depth increased steadily with increase in C_p from 50% to 70% and 85% to 100%.

Outcomes of the GMDH network for the three ranges of *IWC* and C_p can be coincided promisingly with Molinas and Honsy [35], Najafzadeh [14], and Debnath and Chaudhuri [15] experimental studies.

5.2.3. *Influence of the Froude number on the scour depth*

Another effective parameter on the scour depth is the Froude number. In this way, comparison of the scour depth as function of the Froude number was carried out based on three ranges of clay percentage (Fig. 6). From Fig. 6, the scour depth increased with increase

Table 5.
Error parameters for influence of the shear strength on the scour depth using GMDH network and traditional equations.

Method	Eq. no.	*R*	RMSE	MAPE	BIAS	SI
GMDH	(19)–(24)	0.76	0.298	1.22	0.017	0.015
Rambabu et al. [11]	(25)	0.33	0.824	3.65	0.68	0.0416
Najafzadeh [14]	(26)	0.44	2.86	5.91	−1	0.144

Table 6.
Sensitivity analysis for independent parameters in the testing set of the GMDH network.

Functions	*R*	RMSE	MAPE	BIAS	SI
$d_s/D = f(S/\rho U^2, C_p, IWC)$	0.71	0.37	1.73	−0.163	0.4
$d_s/D = f(S/\rho U^2, C_p, Fr)$	0.86	0.24	1.11	−0.04	0.324
$d_s/D = f(IWC, C_p, Fr)$	0.89	0.22	0.93	0.004	0.251
$d_s/D = f(S/\rho U^2, Fr, IWC)$	0.7	0.528	1.36	0.267	0.77

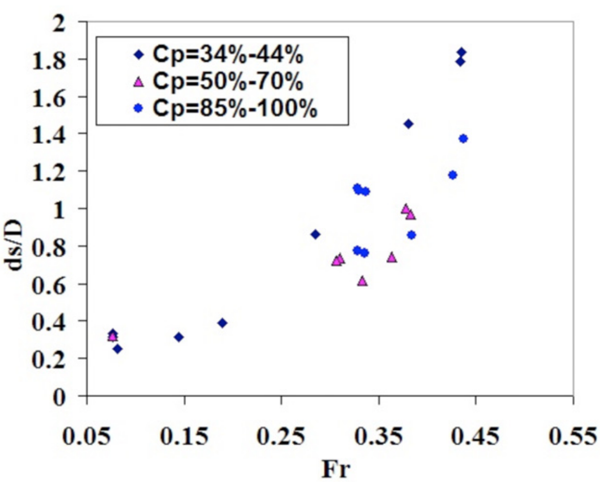

Fig. 6. Influence of the Froude number on scour depth using the GMDH network.

in Fr values. The GMDH network provided relatively better prediction of scour depth in range of $C_p = 34$–44% (MAPE = 1.9) than other ranges in Fig. 6. Result of performances indicated that MAPE values for two ranges of $C_p = 50$–70% and $C_p = 85$–100% were obtained 2.4 and 2.71, respectively. Also, Debnath and Chaudhuri [15] presented variations of d_s/D with the *Fr* based on Ting et al. [10] and Briaud et al. [8] data sets. From their experiments, it was found that d_s/D values were in general agreement with that observed by Ting et al. [10] and Briaud et al. [8] for $C_p = 100\%$ and $Fr = 0.2$–1.

6. Sensitivity analysis

To determine the importance of each input variable on scour depth, sensitivity analysis was performed on the GMDH-BP. In the analysis, one parameter of Eq. (4) was eliminated each time to evaluate its effect on the output. In this way, the RMSE values are characterized as common statistical errors. Accordingly, the clay percentage (C_p) was found to be the most effective parameter ($R = 0.7$, RMSE = 0.528, MAPE = 1.38, BIAS = 0.267, and SI = 0.77) on the scour depth and whereas the non-dimensional shear strength ($R = 0.89$, RMSE = 0.22, MAPE = 0.93, BIAS = 0.004, and SI = 0.251) has the least influence on scour depth, respectively. The other effective parameters on d_s/D in GMDH-BP include the Froude number and initial water content (*IWC*) which were ranked from higher to lower values, respectively (Table 6).

7. Conclusion

The GMDH-BP network was proposed as a new soft computing tool for the scour depth prediction around a vertical pier in cohesive soils. The GMDH network was developed using quadratic polynomial neurons. Also, back propagation algorithm was utilized to yield correction of weighting coefficients in the training stage. The crucial parameters on the scour depth were considered using dimensional analysis. Clay percentage, initial water content, non-dimensional shear strength of bed soil, and the Froude number were identified as main effective parameters that could play key role in the development of the GMDH network. The proposed GMDH-BP network was proved to be significantly accurate compared to the traditional equations. Also, the efficiency of the GMDH-BP network was investigated by three classification ranges of *IWC* and C_p, and it was shown that the GMDH-BP network had remarkably higher performance in $IWC = 36.3$–42.8% and $C_p = 35$–100% thorough Eqs. (19)–(24). Furthermore, the GMDH-BP predicted variation of d_s/D with C_p in different ranges of the *IWC* as well as those of previous investigations. Another contribution of this study is the dependency of the scour depth on shear strength of bed soil. Result of performances indicated that the GMDH network produced better scour depth prediction than those of Eqs. (25) and (26). Also, clay percentage was defined as the most significant parameter thorough sensitivity analysis. Thus the GMDH-BP network has demonstrated its high capability as a powerful technique for the scour depth prediction.

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