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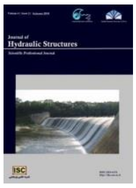

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Scour depth prediction around bridge abutment protected by spur dike using soft computing tools and regression methods

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Abstract

Scour depth around bridge abutment is a crucial parameter to design the protective spur dike. Costly and time-consuming experiments make it difficult to evaluate the scour depth in the problems involving scour phenomena. However, soft computing and regression methods may be applied based on the experimental results. In this paper, a set of experiments is performed and a database including 127 records is collected to evaluate the relation between scour depth and five independent variables including abutment length, flow discharge, flow depth, spur dike length and Spur dike distance from abutment to upstream. This paper presents a new application of the multi-layer perceptron neural network (MLP), group method of data handling (GMDH), non-linear regression (NLR) and multiple linear regression (MLR) to predict the scour depth. A sensitivity analysis is also performed to evaluate the influence of each variable on the scour depth. Results indicate that the first three methods are efficient and accurate enough to be applied in practical applications with determination coefficient (R2) above 90%, while, the MLR has shown a poor performance in this paper. It is observed that MLP and GMDH outperform other methods based on the test data. However, explicit equation derived by NLR has a major advantage to be applied in the field applications without skilled operators and computer packages.

Keywords: scour depth, protective spur dike, scour around abutment, GMDH, NLR.

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1. Introduction

Scouring around the bridge pier and abutment foundations is a common reason for bridge failures. The scour hole around bridge abutment is due to an alteration to the flow field caused by the placement of a structure in it. Construction of a spur dike, as an indirect method for preventing the scour in rivers and canals is a simple and economical method. Manufacturing of a protective spur dike in the upstream of the abutment makes changes in stream hydrodynamics around the abutment and can cause a reduction in maximum scour depth around the bridge

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abutment. Because of expensive procedure of the experimental studies, the numerical and soft computing methods such as artificial neural network (ANN) and group method of data handling (GMDH) have been examined, recently, for predicting the maximum scour depth.
Azmathullah et al. [1] developed a neural network model to predict the maximum depth, width, and location of the scour hole downstream of a sky-jump bucket. They compared the results obtained from the neural network with those obtained from the statistical methods. Results showed that despite needing a long time to train the feed forward network, the predictions are more satisfactory than those given by the regression equations. A feed forward neural network (FFNN) for predicting the scour depth formed below the ski-jumped spillways was developed by Azmathullah et al. [2]. They used field measurements published in the literatures for training the ANN model. They compared the ANN model with the traditional equations and found that the results obtained by ANN are more accurate. Choi and Cheong [3] used the ANN model to predict the local scour around bridge piers in the laboratories and the field. They found that the accuracy of the developed ANN model is more than some of the empirical relations. Using a sizable amount of the present laboratory data, an ANN model was developed by Muzzammil [4] for scour depth prediction at bridge abutments. The results showed that the developed ANN schemes are better than the regression models. Firat and Gungor [5] used the Generalized Regression Neural Network (GRNN) and FFNN methods to predict the scour depth around circular bridge piers. About 165 experimental data was used by them for developing the mentioned models. A comparison of the obtained results from GRNN and those obtained from FFNN, multiple linear regression (MLR), and empirical formula showed that GRNN may be applied to predict the scour depth, efficiently. Esfandmaz et al. [6] employed an ANN and Taguchi Method (TM) integrated approach to predict the local scour depth around the bridge pier during flood event. In their study, the TM reduced the number of experiments and was employed to analyze the results of ANN. TM was also used to find the optimal combination of the relevant parameters in the ANN. They found that the transfer function has the most significant effect on the results of the ANN. Khosravinia et al. [7] developed a multi-layer perceptron model to predict the maximum scour depth around abutments. The obtained results were compared with an empirical equation and experimental data. Results showed that the ANN model presented more precise results than the empirical equation. Application of artificial neural networks for predicting the scour depth around the bridge pier substrate with sticky sediments was evaluated by Rezazadeh et al. [8]. They developed an ANN model optimized by genetic algorithm. A comparison between the obtained results and the experimental data revealed that the recursive artificial neural network and genetic algorithm can improve the accuracy of the scour depth estimation.
In a study performed by Kaya [9], an ANN model was developed using 380 collected data from FHWA (Federal Highway Administration) for studying the observed pattern of local scour at bridge piers. Different choices of input variables were tested and effects of the inputs on the coefficient of determination were investigated. An evolutionary radial basis function neural network (ERBFNN) model was developed by Cheng et al. [10] to predict scour depth at bridge piers. The performance of the ERBFNN was compared with back-propagation neural network (BPNN), GP, M5 regression tree, and support vector machine (SVM). The comparisons revealed that the ERBFNN is more accurate than the other methods. Karkheiran et al. [11] developed a model for investigating scour around bridge piers in uniform and armored beds, under steady and unsteady flow conditions. They used a feed-forward back-propagation (FFBP) artificial neural network (ANN) combined with evolutionary algorithms including adaptive particle swarm optimization (APSO) and genetic algorithms (GA). The results showed that the FFBP-

ANN model combined with GA and APSO algorithms is more accurate than the FFBP model. Seifollahi et al. [12] used a Wavelet-neural network compilation method to predict the depth of local scouring from the cylindrical bridge pier. At first, five variables including pier diameter, the critical and average velocity, the average diameter of the sediments, and the flow depth, were passed through the wavelet filter and then passed to the ANN. The obtained results showed that the wavelet-neural network compilation method is more efficient than the usual neural network model.

Besides the studies performed based on the neural networks, some of researchers have been predicted the scour hole characteristics using the genetic programming (GP). Azamathulla et al. [13] employed GP, ANN and regression methods to predict the local scour depth below river pipelines. About 398 field data sets collected from the published literatures were used to develop the network. Results showed that the accuracy and efficiency of the GP model is more than the regression equations and the ANN model. In another study, Azamathulla and Ghani [14] studied the local scour depth below river pipelines using GP, ANN and regression methods. To train the developed models, they used some published laboratory measurements. They found that efficiency of the GP is more than two other methods. Melihyanmazand and Kose [15] developed a semi-empirical model for evaluating the time-dependent variations of sediment transport in the scour hole at bridge abutments. Comparing the results with the empirical ones showed that those obtained from the developed model agreed well with the test results. Based on some experimental data collected from 7 study, Şarlak and Tiğrek [16] developed an ANN model for predicting local scour depth around bridge abutments. Their investigations showed that the heterogeneity of the data set and the physical context of the subject is effective in the accuracy of the soft computing methods such as ANN. Najafzadeh and Barani [17] used the GMDH method for predicting the scour around a vertical bridge pier. Two models of the GMDH network were developed based on the GP and backpropagation (BP) algorithm. Comparing the results obtained from the GMDH-GP with those obtained from GMDH-BP and some traditional equations indicated that although the developed GMDH-GP scheme is very time-consuming, it is more reliable and accurate in predicting the scour depth. A gene-expression programming (GEP) was used by Azamathulla [18] in order to predict scour depth at bridge abutment. It was concluded that the obtained results are more reasonable than those obtained by the older predictors and the ANN model in studying the abutment scour depth. A sensitivity analysis was performed by Farzin et al. [19] to evaluate the effect of various parameters of a protective spur dike on the scour depth reduction. The parameters were protective spur dike angle, protective spur dike length, main spur dike length, distance from the main spur dike, flow intensity and Froude number. They used the GMDH and GEP models, where the results showed that the GMDH is more accurate than the GEP.

Najafzadeh et al. [20] applied the GMDH method with a backpropagation algorithm to predict the scour depth around a vertical pier in cohesive soils. The results indicated that the GMDH-BP model yielded better predictions in comparison to some traditional equations. Mohammadpour et al. [21] experimentally investigated the local scour dimensions and its variations with time at a vertical wall abutment. Predicting the time variations of the scour depth was done by MLR, GEP and ANN models. Results showed that although the ANN technique produced better results in comparison with the GEP and MLR techniques, both GEP and MLR are more practical methods. Azamathulla and Yusoff [22] presented the GEP method for predicting the scour below underwater pipelines across river. Results showed that the developed GEP model is a favorable approach to predict the scour depth. Basser et al. [23] proposed an approach for determining the optimum parameters of a protective spur dike to control the scour around the main spur dikes. They showed that the accuracy and capability of the generalization based Support Vector Regression (SVR) is more reliable than the adaptive neuro-fuzzy inference system (ANFIS) and ANN. Based on the some published experimental data, a GEP model was developed by Muzzammil et al. [24] to predict the scour depth at bridge piers in a bed with cohesive sediments. They compared the results obtained from the developed GEP with those from nonlinear regression model. It indicated the better performance of the GEP model. Scour depth around the inclined bridge piers were predicted by Esmaeili Varaki et al. [25] using optimized ANFIS parameters with GA, ANFIS and ANN models. The comparisons showed that optimization of ANFIS parameters improved the accuracy of the predictions.

Najafzadeh et al. [26] studied the local scour depth at bridge abutments in thinly armored beds and coarse sediments. They developed alternative GMDH networks using gravitational search algorithm (GSA), PSO and BP. Their investigations revealed that GMDH network can be used successfully in prediction of scour phenomena. In another work, Najafzadeh and Mahmoudi Rad [27] used a neuro-fuzzy model based on GMDH (NF-GMDH) for predicting the scour depth at bridge pier under effect of debris accumulations. The NF-GMDH network was developed using evolutional algorithms including GA, PSO and gravitational search algorithm (GSA). Comparing the obtained results showed that the NF-GMDH-PSO and NF-GMDH-GA had relatively similar performance. In a study performed by Karbasi and Azamathulla [28], the maximum depth of the scour hole downstream of a sluice gate caused by 2D horizontal jets was predicted using five soft computing techniques including ANN, SVR, GEP, GMDH and ANFIS. They showed that the accuracy of the developed ANN model is more than the other soft computing techniques as well as regression-based equations. Bonakdari and Ebtehaj [29] predicted the scour depth around a bridge pier using ANN, ANFIS and NLR methods. The obtained results showed that both ANN and ANFIS can predict scour depth better than the NLR. They also performed a sensitivity analysis on the values of the scour depth. Majedi asl et al. [30] used support vector machine method to improve the accuracy of the scour depth prediction around the inclined single and group piers. The results revealed that using the compounds of the sedimentary and hydraulic parameters in the support vector data model provide better results in comparison to using them, separately. Also, some non-linear equations were presented for predicting the scour depth. Zarbazoo Siahkali et al. [31] estimated the scour depth around circular bridge piers in non-cohesive soils using ANN, GMDH, multivariate adaptive regression splines (MARS), and Gaussian process models (Kriging). A comparison between the mentioned models and the empirical formulations showed that Kriging is more accurate than the other models.

To our knowledge, there are presently limited numbers of studies proposing ANN and GMDH models in order to predict the scour depth at the bridge abutments in compound channels. In the current study, the ANN, GMDH and NLR methods are employed to predict the scour depth around the bridge abutment nose in floodplain of a compound channel in the presence of a protective spur dike at the upstream. In fact, it is tried to determine which method is more accurate, using 127 experimental datasets. Ultimately, by applying sensitivity analysis, the effectiveness of the selected parameters on the performance of the models is determined.

2. Experimental procedure

All experimental data for this research were conducted in the Institute for Soil Conservation and Watershed Management of Jahad Keshavarzi of Iran. The arrangement of the abutment and the spur dike in the experiments are presented in Fig. 1. The flume has a compound section with 14m in length, 1m in width and a 0.2 m main channel with a depth of 0.10m in the center line.

Total depth of the channel was 0.80m. Plexiglass was used to build the sides of the flume with a supporting metal frame and the bed was made with the masonry. An abutment with cylindrical nose was placed in one side of the flume in the flood plain with lengths of 0.20m and 0.30m, and 6m distance from the upstream, as shown in Fig. 2.

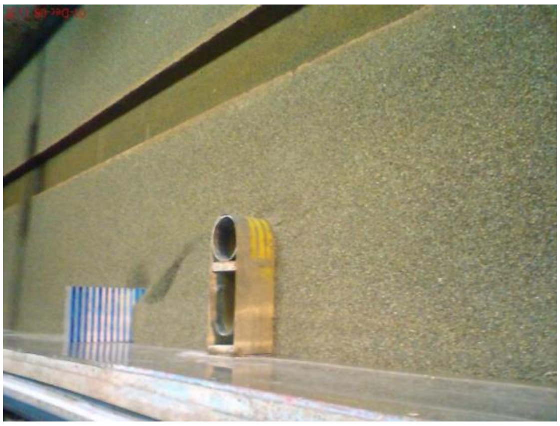

Figure 1. Experimental flume section and location of the abutment

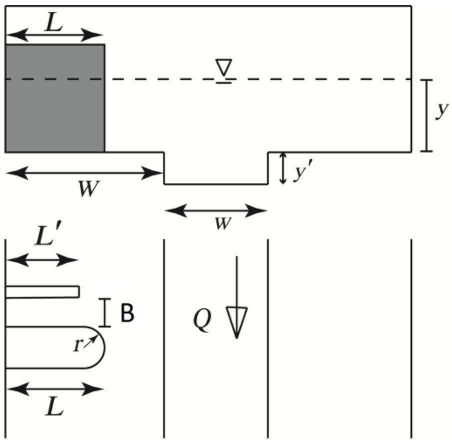

Figure 2. Schematic of flume section and abutment location

Across the channel, two layers of materials including a coarse sediment layer with a height of 0.3m and a layer with fine materials located on the coarse layer with a height of 0.2m had been located in the channel bed with an average diameter equal to d_{50}=0.001m.
In addition, a protective spur dike with different length and distance was placed at the upstream of the abutment.

In the present study, five different values of the flow discharge were used for investigating the scour depth. In order to measure the flow discharge, a triangular sharp-crested weir was set up at the end of the flume. For each value of discharge, the experiments were conducted based on four spur dike length, five spur dike distance from the abutment, and two abutment lengths. The different values of the parameters used have been shown in Table (1). More details about experimental setup and collecting datasets are explained in [32].

Table 1. Value of parameters in the experimental study

parameter	value				
discharge Q(m^3s^{-1})	0.014	0.016	0.018	0.020	0.022
spur dike length L'(m)	0.04	0.08	0.12	0.16	
spur dike distance B(m)	0.10	0.20	0.30	0.40	0.50
abutment length L(m)			0.20 and 0.30		

In Table (2), the input parameters used for developing the models have been presented. The statistical properties are also specified in Table (3).

Table 2. Input parameters employed for developing the models

parameter	symbol
Abutment length	L
Flow discharge	Q
Flow depth	y
Spur dike length	L′
Spur dike distance from abutment to upstream	B

Table 3. The range of values of input and output parameters within dataset

Parameter	L	Q	y	L'	B	$\widehat{H}$
min	20	14	2.95	4	10	0
max	30	22	4.2	16	60	9.5

3. Methodology

In this paper, four well-known soft computing models, i.e., GMDH, MLP, MLR and NLR are employed to predict the scour depth around the bridge abutment nose. In this section, the fundamentals of these methods have been described.

3.1 The GMDH model

GMDH was developed by Ivakhnenko in 1968. This method is a family of learning algorithms that has capabilities like regression, time series forecasting and classification. GMDH structure like some other learning algorithms consists of small units called neurons laid in several layers. The first layer receives input (independent) variables where the output (dependent) variable is concluded from the last layer. Middle layers are called "hidden layers" that perform the simulation process. Each neuron in GMDH has relatively simple structure solely; however complex combination of neurons makes GMDH capable to simulate nonlinear behavior of a system. In other words, gradual complexity due to combination of neurons in successive layers is achieved by limited number of neurons. Generally, the structure of a neuron in hidden or the last layer is according to Eq. (1). This relation is identified as Kolmogorov-Gabor polynomials in mathematics.

$$Y(x_1, x_2 \ldots, x_n) = a_0 + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n} \sum_{j=1}^{n} a_{ij} x_i x_j + \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{n} a_{ijk} x_i x_j x_k + \ldots \quad (1)$$

where "n" stands for the number of input variables and $x_1, x_2, \ldots, x_n$ are the input variables to the neuron. "Y" is the neuron output and a_0, a_i, a_{ij}, a_{ijk} are regression parameters determined during training process. Independent variables enter the first hidden layer while in next layers, inputs are in fact the outputs from the previous layer. In most practical applications of GMDH, a quadratic polynomial (n=2) is applied consisting of three right hand side terms in Eq. (1). Thus each neuron normally has two inputs and one output. Output structure of a neuron is indicated in Eq. (2).

$$\widehat{H} = a_0 + a_1 x_i + a_2 x_j + a_3 x_i x_j + a_4 x_i^2 + a_5 x_j^2 \tag{2}$$

Where "$\widehat{H}$"is the predicted value for the maximum scour depth and parameters a_0 to a_5 are determined using neuron inputs after minimization of a common error function like Root Mean Square Error calculated by Eq. (3).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{M}(H_i - \widehat{H}_i)^2}{M}} \tag{3}$$

Where "M" is the number of available data for training and $\widehat{H}_i$ and H_i are the predicted and real value for "i"th training data, respectively.

3.2 The MLP model

MLP is an efficient tool for predicting different engineering phenomena because it can approximate a desired behavior without the need to specify a particular function. A neural network is characterized by its architecture (the pattern of connections between the neurons), its learning algorithm (the method of determining the weights on connections), and its activation function. Among the applied neural networks, the FFNNs are the most common models in predicting various phenomena. Learning these ANNs is performed by first or second order learning algorithms. In the first order schemes, like backpropagation and the steepest decent methods, the first derivative of error is used and they follow the gradient descent approach. The second-order algorithms, like Gauss-Newton and Levenberg-Marquardt methods, rely on both first and second derivatives of errors in the search for the optimal weights [33]. The optimal weights on the connections are found by minimizing an error function like "RMSE".

3.3 The MLR and NLR models

Each mathematical model has two major specifications: the model structure and the incorporated parameters. It is required to specify them for constructing the model. In this paper, a multiplicative structure according to Eq. (4) is employed for NLR model based on the experience while Eq. (5) indicates the MLR structure.

$$\widehat{H} = \alpha \times (L)^{\beta} \times (Q)^{\gamma} \times (y)^{\lambda} \times (L')^{\kappa} \times (B)^{\theta} + \eta \tag{4}$$

$$\widehat{H} = \alpha \times (L) + \beta \times (Q) + \gamma \times (y) + \lambda \times (L') + \kappa \times (B) + \theta \tag{5}$$

where $\alpha, \beta, \gamma, \lambda, \kappa, \theta$ and η are the model parameters and other variables are defined as before. Parameter η is employed in NLR in order to eliminate the bias effects in multiplicative form. Determining the incorporated parameters is known as model calibration and is performed through solving an optimization problem. The objective function is assumed to minimize the "RMSE" indicating the discrepancy between the observed and predicted values of the scour depth according to the training data. The decision variables are in fact the model parameters determined in such a way that minimum difference (RMSE) between the observed and predicted values are obtained. The developed optimization problem is generally non-convex and, as a result, efficient algorithms are required to find optimum answer. GA is one of the most famous algorithms suitable for solving non-convex problems. GA is available and easy to use through "Solver" add-in in Excel package and is employed in this research. After calibration, the parameter values in regression models are obtained according to Table (4).

Table 4. Values of incorporated parameters in MLR and NLR regression models after calibration

	α	β	γ	λ	κ	θ	η
MLR	0.288	-0.326	4.06	-0.603	-0.149	0.239	---
NLR	0.012	1.657	0.067	2.185	-0.568	-0.229	-2.009

3.4 GMDH and MLP Construction

Regression ability of GMDH is employed in this paper to predict the maximum scour depth using input variables introduced in Table (2).

Assuming five input variables for GMDH in the first hidden layer, 10 states (C(5,2)) of selection is possible for selecting two variables from five ones and thus 10 neurons are needed. In the second hidden layer, 45 selection states (C(10,2)) are possible, however various running of GMDH model in this research indicate very less number of neurons (about 10 or even less) is adequate. Thus, maximum 10 neurons are assumed in all layers of GMDH. These neurons are of course the superior ones among 45 possible neurons. Superior neurons are the ones with the least value of RMSE compared with other neurons. Consideration of GMDH performance for number of layers indicates four layers have enough accuracy in this research.

Regarding points mentioned above, the GMDH structure is proposed according to Fig. 3. It is impossible to indicate the exact relationship between neurons in hidden layers, because the superior neurons are not specified before simulation. However, the relationship is obvious in the first layer as indicated in Fig. 3. The last layer needs only one neuron because the final output ($\hat{H}$) is a scalar variable. In Fig. 3, "$N_{i,j}$" is the "j"th neuron in "i"th layer of the network.

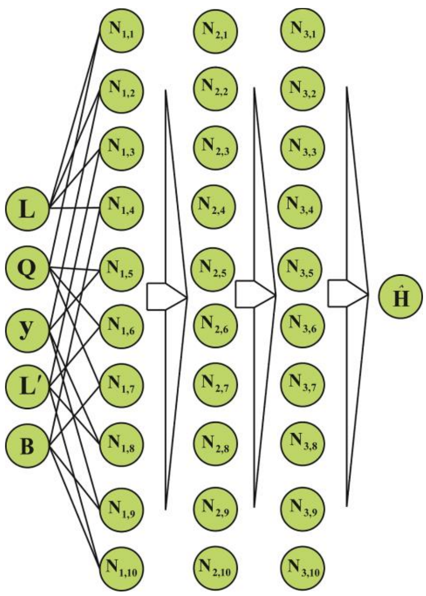

Figure 3. GMDH structure with input and output variables

Modeling with the MLP, at first, we determined the architecture of the neural network. To reach this, the Kolmogorov's theorem was used. Based on this theorem, any function of n variables can be represented by the superposition of a set of "$2n+1$" univariate functions. This implies that the maximum number of the hidden neurons (h) can be given according to Eq. (6) [34].

$$h \leq 2n + 1 \tag{6}$$

where "n" is the number of input neurons. As a result, the developed neural network has 5 input neurons (as presented in Table (2)), 11 hidden neurons, and one neuron as the output one. Schematic sketch of the developed neural network is shown in Fig. 4.

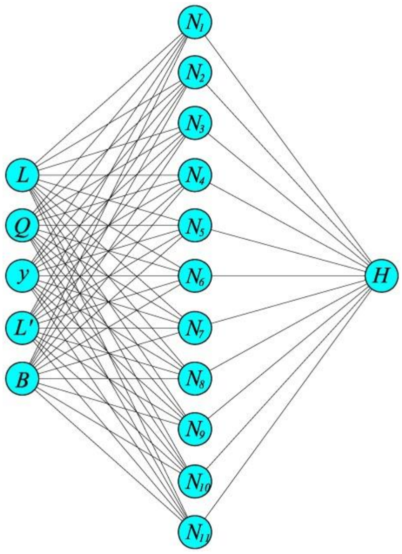

Figure 4. Schematic sketch of the developed neural network

To train the MLP, the Levenberg-Marquardt algorithm has been employed. This algorithm uses Eq. (7) to calculate the weights (**W**) in subsequent iterations.

$$W_{new} = W_{old} - [J^T J + \gamma I]^{-1} J^T E(W_{old}) \tag{7}$$

in which "**J**" is the Jacobian of the error function (E), $\gamma$is the parameter used to define the iteration step value and "**I**" is the identity matrix. Finally, a hyperbolic tangent function is used in this paper as an activation function. To use this function, it is required to normalize the training data set in the range of -1 to +1. The hyperbolic tangent function is given in Eq. (8).

$$f(x) = \frac{exp(x) - exp(-x)}{exp(x) + exp(-x)} \tag{8}$$

GMDH and MLP like other learning algorithms should be trained initially and then tested for their performance evaluation. Most of the available data (about 80%) are required for training and remaining (about 20%) are employed for test. Table (5) indicates the number of employed data for training and testing of GMDH. For eliminating any time trend or bias, all data are mixed, randomly, before assigning them for training. 20% of training data are employed to test the neurons performance and select superior neurons in each layer. Selecting superior neurons by some data other than those employed for determining parameters a_0 to a_5 has two advantages. This approach enhances the "Generalization" ability and prevents the GMDH from "Overtraining". Thus, selection of superior neurons in each layer is assumed as a stage of training process. Similar to GMDH, to train the MLP, the data set is divided into training, checking, and testing parts. Here, preventing the overtraining of the developed neural network by the training data is the reason for using checking data set. About 80% of the available data is used as training and checking data and the remaining ones are employed as testing data for test of network. As a result, 102 data is used as the training and checking data set and 25 data are used as the testing data set.

Table 5. The number of employed data for training and testing within GMDH

Total experimental data	GMDH Training (80% of total data)		GMDH Testing (20% of total data)
	Required data for selecting superior neurons in each layer based on minimum RMSE (20% of training data)	Required data for determining the parameters of Eq. (2) by minimizing the RMSE (80% of training data)	
127	20	82	25

4. Results and Discussion

The experimental and predicted values of the 25 testing data set have been shown in Fig. 5. Also, in Fig. 6, the error values of the testing data set modeled by the NLR, GMDH and MLP have been presented. It can be seen that the fluctuations of errors in the GMDH model are greater than those for the MLP and NLR models. A comparison between the experimental and predicted data sets is indicated in Fig. 7. As can be seen, the correlations obtained from the MLP model are better than those obtained by the GMDH model for the testing data.

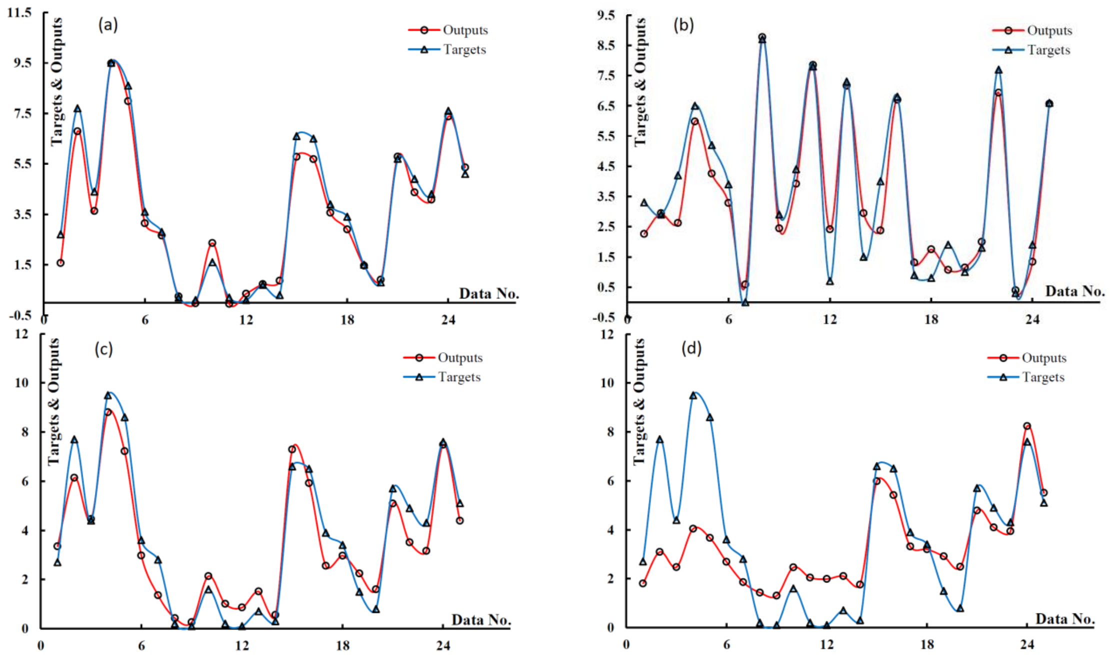

Figure 5. Predicted (Outputs) and experimental (Targets) values in terms of 25 test data obtained from (a) MLP, (b) GMDH, (c) NLR and (d) MLR models

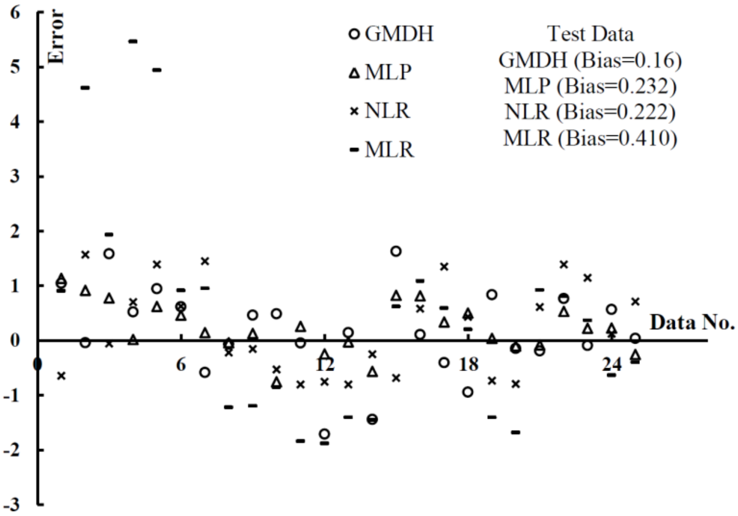

Figure 6. Error and bias values employing 25 test data obtained from the GMDH, MLP, NLR and MLR models

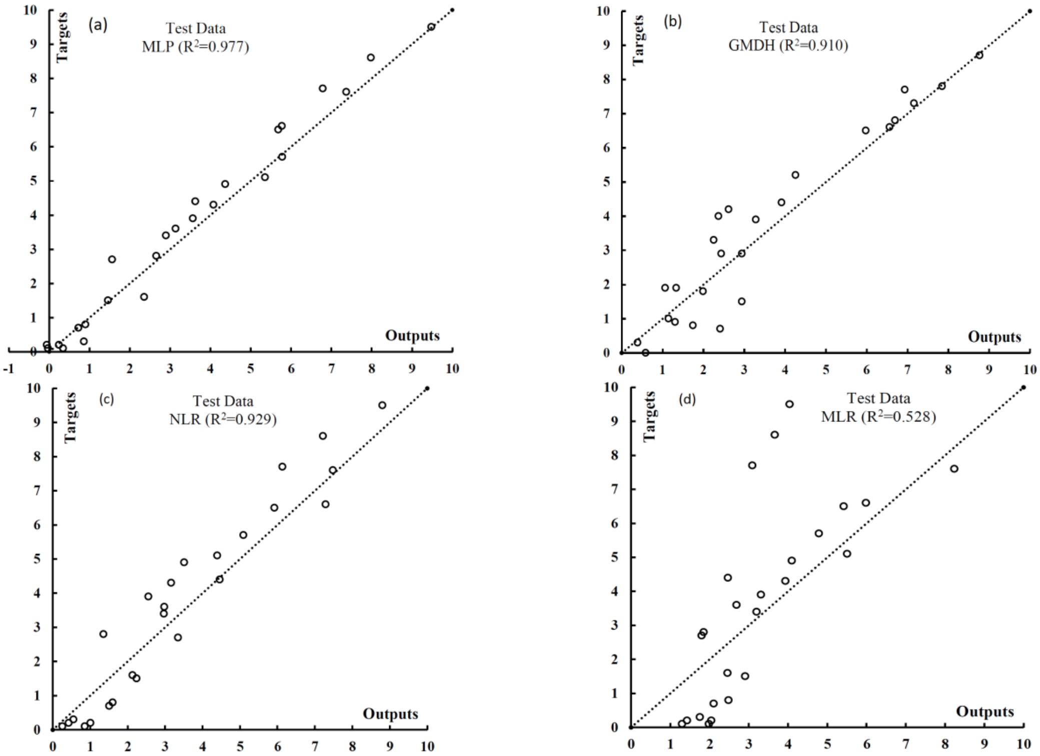

Figure 7. Determination coefficient between predicted (Outputs) and experimental (Targets) data applying 25 test data based on the (a) MLP, (b) GMDH, (c) NLR and (d) MLR methods

To apply a comprehensive study on the developed GMDH and MLP models, a statistical comparison was carried out between the experimental and predicted parameters using bias, mean absolute error (MAE), RMSE, scatter index (SI), and correlation coefficient (R) defined in Eq. (9) to Eq. (12).

$$Bias = \frac{\sum_{i=1}^{M}(H_i - \hat{H}_i)}{M} \tag{9}$$

$$MAE = \frac{\sum_{i=1}^{M}\left|H_i - \hat{H}_i\right|}{M} \tag{10}$$

$$SI = \frac{RMSE}{\bar{H}_m} \times 100 \tag{11}$$

$$R = \frac{\sum_{i=1}^{M}(H_i - \bar{H}_m)\left(\hat{H}_i - \bar{\hat{H}}_m\right)}{\sqrt{\left(\sum_{i=1}^{M}(H_i - \bar{H}_m)^2\right)\left(\sum_{i=1}^{M}\left(\hat{H}_i - \bar{\hat{H}}_m\right)^2\right)}} \tag{12}$$

where $\bar{H}_m$ is the observed mean value, and $\bar{\hat{H}}_m$ is the predicted mean value. The results of the comparison have been shown in Table (6). As can be seen, the developed GMDH model overestimates the scour depth while the MLP model underestimates it. The bias value is 0.16 cm for the GMDH model and its value is -0.23 cm for the MLP model. Although the RMSE of the MLP model is greater than two other ones, the values of mean absolute error and determination coefficient show a better fitting of the output results with the experimental data obtained from the developed MLP model in comparison to the developed GMDH, MLR and NLR methods. The determination coefficient for MLP is 0.977 that is greater than the GMDH, MLR and NLR models with values equal to 0.91, 0.528 and 0.929, respectively. As a result, it is clear that the developed MLP model is a little more accurate than the developed GMDH model in predicting the scour depth.

Investigating on the previous works performed on the scour depth prediction, it is obvious that there is not any works that studied the performance of the soft computing tools and regression methods, together, on forecasting the scour depth around the bridge abutment protected by a spur dike at the upstream. Najafzadeh et al. [26] evaluated the performance of the three GMDH based models including GMDH-BP, GMDH-PSO, and GMDH-GSA in predicting of the scour depth at bridge abutments. Their investigations showed that the GMDH-BP model has better accuracy among the developed models with R equal to 0.93. According to Table (6), in the present study, the developed GMDH model is more accurate than the GMDH-BP model with R equal to 0.954.

In another work, Şarlak and Tiğrek [16] developed an ANN model in order to predict the scour depth around the bridge abutments. Based on the results reported by them, in the best conditions, with 5 input parameters, the R value is about 0.98 that is a little smaller than the R value of the developed MLP model in the present study that is about 0.99. Also, the R value for 7 input parameters reported by Şarlak and Tiğrek [16] is equal to 0.79.

Table 6. Statistics of the predicted scour depth by methods of GMDH, MLP, MLR and NLR employing testing data

Methods	Average observed value (cm)	Average predicted value (cm)	Bias (cm)	MAE (cm)	RMSE (cm)	SI (%)	R^2
GMDH	3.72	3.56	0.160	0.61	0.81	21.7	0.910
MLP	3.71	3.47	-0.232	0.40	1.30	35.1	0.977
MLR	3.71	3.30	0.410	1.53	2.05	55.3	0.528
NLR	3.712	3.48	0.222	0.74	0.85	22.9	0.929

5. Sensitivity Analysis

Sensitivity analysis (SA) may be defined as considering the model output due to variations in input variables. There are various methods to perform SA, while mathematical approach is employed in this paper. Based on this approach, the differential of output variable within model is calculated in terms of input variables using partial differentials according to Eq. (13). For larger variations of variables, Eq. (14) is estimated employing Eq. (13). Afterwards, two side of Eq. (14) are divided by "*H*" and some mathematical manipulation is carried out to obtain Eq. (15). The coefficients in Eq. (15) are calculated using model parameters available in Eq. (4).

$$dH = \frac{\partial H}{\partial L} dL + \frac{\partial H}{\partial Q} dQ + \frac{\partial H}{\partial y} dy + \frac{\partial H}{\partial L'} dL' + \frac{\partial H}{\partial B} dB \tag{13}$$

$$\Delta H \approx \frac{\partial H}{\partial L} \Delta L + \frac{\partial H}{\partial Q} \Delta Q + \frac{\partial H}{\partial y} \Delta y + \frac{\partial H}{\partial L'} \Delta L' + \frac{\partial H}{\partial B} \Delta B \tag{14}$$

$$\frac{\Delta H}{H} \approx 2.43 \times \frac{\Delta L}{L} + 1 \times \frac{\Delta Q}{Q} + 1.88 \times \frac{\Delta y}{y} - 0.82 \times \frac{\Delta L'}{L'} - 0.3 \times \frac{\Delta B}{B} \tag{15}$$

Following conclusions may be drawn from Eq. (15).

a. "*L*", "*Q*" and "*y*" have positive effect on the "*H*", where $\frac{\Delta H}{H}$ increases with increasing $\frac{\Delta L}{L}$, $\frac{\Delta Q}{Q}$ and $\frac{\Delta y}{y}$ with sensitivity coefficients of 2.43, 1 and 1.88, respectively. "*L*" has the most and "*Q*" has the least positive effect on the "*H*".

b. "*L'*" and "*B*" have negative effect on the "*H*", where $\frac{\Delta H}{H}$ decreases with increasing $\frac{\Delta L'}{L'}$ and $\frac{\Delta B}{B}$ with sensitivity coefficients of 0.82 and 0.3, respectively. Variation of "*L'*" is more effective than variation of "*B*" on the "*H*" value.

c. The best approach to decrease "*H*" is increasing "*L'*" and decreasing "*L*" to the extent that is possible.

6. Conclusion

Two soft computing methods including the MLP and GMDH as well as MLR and NLR were employed to predict the scour depth around bridge abutment. To reach this, the models were developed using some experimental data and then the performance of the developed models were investigated by 25 testing data. The inputs of the models were Abutment length (*L*), Flow discharge (*Q*), Flow depth (*y*), Spur dike length (*L'*) and Spur dike distance from abutment to upstream (*B*) to predict the scour depth around bridge abutment (*H*). The developed MLP model has three layers consist of an input layer with five neurons, one hidden layer with 11 neurons, and an output layer with one neuron. In the case of developed GMDH, investigations showed that for reaching an appropriate accuracy, four layers are enough. Then, in addition to five input neurons, the developed model has 30 neurons within three layers and one neuron in the last layer as the output neuron. A comparison between the developed models shows that the soft computing methods developed here are more accurate than the MLR and NLR models. Based on the results, the developed MLP model has a better determination coefficient in comparison with three other methods. Neglecting the lower accuracy, the NLR model is more applicable than the soft computing models as a result of presented explicit equation. The presented equation by NLR may be employed more easily in practical applications without need to skilled operators or computer packages.

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