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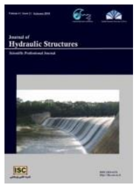

An Artificial Neural Network and Taguchi Method Integrated Approach to Predicting the Local Scour Depth around the Bridge Pier during Flood Event

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Abstract

Experiment design is believed to be an important part of investigating an engineering phenomenon for characterizing and optimizing the process. In this study, the Taguchi method (TM) reduced the number of experiments and was used to analyze the results of an artificial neural network (ANN) and find the optimal combination of the relevant parameters in the ANN. Accordingly, the phenomenon of the local scour depth around the bridge during flood events was considered as a case study. The study results indicated that TM could reduce the number of experiments compared to the previous original study and the full factorial method by 28% and 67%, respectively. According to TM, the flow intensity at the hydrograph peak was the most effective parameter providing the optimal state (minimum scour depth). Additionally, an ANN with three hidden layers and the main parameters, including several neurons in the first and second hidden layers, training function, and transfer function, was introduced. Adjusting the input parameters of the ANN, TM led to the emergence of networks with a reasonable correlation coefficient of R= 0.952. Finally, the results demonstrated that the transfer function had the most significant effect on the results of the ANN.

Keywords: Taguchi method, Artificial neural network, Scour depth, Bridge piers, Flood flow

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1. Introduction

Bridge pier scour is one of the main causes of bridge failure. For this reason, an accurate calculation of scour depth is crucial in the design of bridge piers and abutments. Several researchers have contributed to this field and numerous empirical equations have been proposed to estimate the depth of scour hole. In this regard, Melville and Chiew [1] calculated the

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equilibrium time of scour depth in front of a bridge pier. Using an equation, they introduced and determined the effective parameters in calculating the equilibrium time of scour depth. Zarrati et al. [2] conducted a study on riprap stability as a countermeasure method to control scouring around a bridge pier. They compared a regression model and an ANN to other experimental equations and showed the superiority of the developed regression model in terms of application and accuracy and the outperformance of the ANN in predicting the results. Najafzadeh et al. [3] used the Group Method of Data Handling, (GMDH) as a new soft computational method, to predict the scour depth around vertical piers in cohesive soils. The results indicated the advantage of the GMDH model over empirical equations in predicting the scour depth and in reducing scour depth around spur dikes with collars. Dang et al. [4] employed particle swarm optimization and firefly optimization algorithms to improve the prediction of scour depth around bridge piers under equilibrium conditions and to optimize ANN model. Their results revealed the high performance of this method compared to the single ANN model in calculating experimental data. Atarodi et al. [5] reported the advantage of TM in predicting results and determining optimal scour reduction around Spur Dikes by Collar. Samadi et al. [6] compared the three methods of MARS, CART, and ANN concerning the prediction of current-induced scour depth around pile groups under clear water conditions. According to their results, the highest accuracy belonged to the MARS method.

Since in the study of hydraulic phenomena like scour, we generally deal with empirical equations developed from experimental results, it is necessary to apply a method to design these experiments. TM has been widely used in industrial, mechanical, and petroleum engineering and more recently, in civil engineering. This method could reduce the number of experiments in experimental papers. In addition, different studies have indicated that TM can be used to adjust the input parameters of an ANN to achieve better results. However, the majority of these works are related to problems, not to hydraulic engineering.

In this context, Madic and Radovanovic [7] used TM to determine the parameters in an ANN and found the optimal ANN parameters.. Chen et al. [8] used ANN and TM for predicting or evaluating real estate. They utilized TM to find a combination of optimal parameters in ANN. By obtaining the optimal combination of neural network parameters, network accuracy significantly improved. The model proposed in this study had an optimistic prediction and significantly reduced the time consumption in simulation operations. Kant [9] used TM to minimize clustering in order to optimize an ANN and to model the drilling cutting parameters. Furthermore, he determined the optimal levels of effective parameters. Kavimani and Prakash [10] applied a combination of ANN and TM to predict the behavior of reinforced composite. Beeravelli et al. [11] used Taguchi to optimize the performance and emission of the Injection Diesel Engine with an ANN. Taguchi Signal/Noise (S/N) ratio analysis was also utilized to assess the effect of different parameters in the optimization process. Comparison of these results exhibited better performance of an ANN designed via TM. Alam et al. [12] found that the ANN outperformed TM in predicting the optimization results of aluminum matrix nanocomposites. In the prediction and optimization of control parameters in the milling of the aluminum hybrid metal matrix, Ajith Arul Daniel et al. [13] studied the effects of different control parameters on the response variables through the Taguchi S/N ratio. They concluded that ANN outperformed the regression model in predicting the response parameters. To reduce the local scour around bridge piers and to minimize the number of experiments, Ranjbar-Zahedi et al. [14] employed 27 proposed Taguchi experiments to determine the optimal size and location of the flow deflection structure.

In the present study, TM was examined from two viewpoints: TM as an approach to reducing the number of studies and TM as optimization method. The results and outputs were analyzed and the results were compared to an ANN to be validated.

2. Materials and Methods

2.1. Taguchi method (TM)

The objective of TM is to determine the best possible combination of inputs to produce a product or respond to an experiment. Instead of using full factorial combinations, TM uses fractional factorial combinations in which specific tables, called orthogonal arrays, are used to design the combinations of levels (different states) of variables. An orthogonal array is a partial factorial matrix that rhythmically compares all variables or their interactions [15].
Taguchi presented 18 orthogonal arrays in a table, called the standard orthogonal array. The use of these tables facilitates the design of experiments. The degree of freedom of the parameters is used to select the appropriate orthogonal array. The amount of information that could be separately obtained from a set of data is called the degree of freedom. In cases where the number of levels of the parameters is highly inconsistent, the "column reduction operation" could be utilized. In other words, considering the highest number of levels of meta-parameters affecting a phenomenon, the levels of other meta-parameters with lower levels of change were assumed to equal the highest level [16]. The next step after optimizing the number of experiments is to analyze the test results using TM. Taguchi uses standard methods to analyze data with the analysis of mean (ANOM) and the signal-to-noise ratio (S/N).

Optimization analysis via mean or standard method is the result of only one experiment. Using Equation **(**1**)**, the mean values of each factor at each level are calculated and the optimal combination of parameters is then obtained with Taguchi response tables and graphs [15].

$$(M)_{Factor=m}^{Level=L} = \frac{1}{n_{Lm}} \sum_{j=1}^{n_{Lm}} \left[(f_x)_{Factor=m}^{Level=L} \right]_j . \tag{1}$$

where $n_{Lm}$is the number of parameter *m* occurrence at level *L* and $f_x$is the observational data based on the proposed Taguchi model.

Furthermore, the Taguchi (S/N) ratio could be also used to assess the effect of different input parameters in the optimization process. Therefore, the goal is to find the highest S/N ratio for each experiment [14]. Equation (2) is employed once the objective function is maximally better and Equation (3) is used when the objective function is minimally better.

$$S/N = -10\log\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right). \tag{2}$$

$$SN_s = -10\log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \tag{3}$$

where n is the number of experiments,y_i is the observed value *i*, and *M* is a definite value.
Moreover, one of the important capabilities of TM is determining the contribution of each parameter to the test results. This feature, which is obtained through the ANOVA table (statistical method of analysis of variance) for test data, helps the decision-maker to rank the factors according to their importance [17].

It should be noted that Taguchi, in its orthogonal arrays table, represents only a fraction of the total number of experiment states; in other words, it may not be the optimal state among the performed experiments. For this reason, the orthogonal array only contains a small fraction of all the possible states. The main feature of Taguchi is solving this problem. In fact, this method determines the optimal state among all the possible states only by performing limited experiments. To obtain the experiment result under optimal conditions, Equations (4) and (5) are used by obtaining the optimal combination in the previous steps [15].

$$\bar{Y} = \frac{\sum(Y_i)}{N}. \tag{4}$$

$$R_{opt} = \bar{Y} + \sum(Y_{opt\ x_i} - \bar{Y}). \tag{5}$$

where R_{opt} shows the optimal value, $\bar{Y}$ is the mean of the total responses, Y_i represents the response to each experiment, N is the number of experiments, and $Y_{opt\ x_i}$ is the response to the optimal combination obtained from the previous steps.

2.2. Artificial neural network

Artificial neural networks (ANNs), originated in 1950, are one of the prediction models based on artificial intelligence, which is a network structure of interconnected elements called neurons. Neurons have a simple function and each has an output and input. They are responsible for receiving information from the input layer and transferring it to the hidden layer for processing. The processed data are eventually transferred to the output layer. ANNs are divided into two types: monolayer and multilayer. Monolayer neural networks that cannot implement nonlinear functions include several neurons forming a single layer network. Multilayer perceptron networks, which are one of the most essential structures of ANNs, include input, hidden, and output layers, where the input signal is propagated as a layer through the network and in the forward path. In neural networks, the initial values of weights are of particular importance; therefore, prior to the start of training, all the weights' values should be small and randomly selected. Certain different training functions include Levenberg-Marquardt backpropagation (Trainlm), random order incremental training with learning functions (Trainr), and one-step secant backpropagation (Trainoss) [18].

The training algorithm plays a role in the error rate and its accuracy in prediction. One of the most common training algorithms of an ANN is the backpropagation algorithm. This algorithm is commonly used in ANNs related to hydraulic phenomena. In this algorithm, in order to reduce the difference between the target output data and the actual output data (training error), the internal communication weight of the neural network is adjusted during the training process. To adjust the weight of an ANN with the backpropagation algorithm, the data are returned from the output layer to the hidden layer and then reprocessed. In an ANN, neurons process the network input data using a transmission function. In the backpropagation algorithm, hyperbolic tangent sigmoid (tansig), log-sigmoid (logsig), and linear function (purelin) transfer functions are used [19].

2.3. Taguchi and artificial neural network

To improve the performance of an ANN, proper design of the network structure by optimizing the parameters of ANN is essential. One of the most frequently applied methods of determining this structure is trial and error. However, its time-consuming nature and lack of guarantee of a proper structure necessitates using an alternative to this method. The design method of Taguchi experiments can be introduced for finding the best neural network structure and thus the best answer with the least error. According to the previous explanations, this method is a significant parameter for each factor and the percentage of factors provides the answer [20].

2.4. Local scour phenomenon around a bridge pier during flood event

Studying the local scour phenomenon around a bridge pier, the main objective is to calculate the scour depth. Furthermore, due to complex and very turbulent flow fields, along with the vortex around piers, the numerical solution of this phenomenon is highly complicated. Therefore, physical modeling is needed for a detailed study of this phenomenon. Accordingly, it is necessary to primarily perform a dimensional analysis on the effective parameters. Karimaee and Zarrati [21] investigated the local scour around bridge piers and added a new correction factor to the empirical Equation (6), known as HEC-18, to determine the final scour depth during flood event.

$$\frac{d_{sf}}{y_p} = 2.0 \times K_s K_\theta K_b K_a K_h \times \left(\frac{y_p}{B}\right)^{0.35} \times Fr_p^{0.43} \tag{6}$$

where d_{sf} denotes the final scour depth, B is the bridge pier width, y_p is the upstream depth, Fr_p is the Froude number for the peak hydrograph flow, and K_s, K_θ, K_b, K_a, and K_h represent the correction factors for bridge pier form, collision angle of flow, bed shape, sediment particle size distribution, and flow unsteadiness, respectively.

Flow unsteadiness has a considerable effect on the structure of the flow field and the motion of sediment particles, thereby affecting the dispersion of pollutants and river ecology [22]. Karimaee and Zarrati [21] conducted several experiments to calculate the correction parameter K_h, which is the correction parameter related to the effect of flow unsteadiness on the equilibrium scour depth. Using the dimensional analysis, the parameters affecting K_h, which are shown in Equation (7), were identified. These parameters include the ratio of the time for hydrograph rising limb to the time for the equilibrium for scour depth considering the hydrograph peak flow condition (T_r/T_{eqp}), the difference of flow intensity at the hydrograph peak flow to the base flow condition (ΔI), and the ratio of time for hydrograph falling limb to time for the hydrograph rising limb (T_f/T_r).

$$K_h = f\left(\frac{T_r}{T_{eqp}}, \frac{T_f}{T_r}, \Delta I\right). \tag{7}$$

Based on the experimental data and the non-linear regression analysis, Karimaee and Zarrati [21] presented the following equation between effective parameters:

$$K_h = 3.2 \times \left(\frac{T_r}{T_{eqp}}\right)^{0.18} \times \left(\frac{T_f}{T_r}\right)^{0.01} \times \Delta I^{0.96} \tag{8}$$

In the present study, both experimental and theoretical parts of Karimaee and Zarrati's original work were reconsidered based on TM and ANN [21].

2.5. Evaluation index of models

To evaluate the performance of ANN models in this research, the correlation coefficient R (Eq. 9) was used. This coefficient determines the relationship between the two variables and the closer it is to +1, the better it is; this indicates a stronger correlation between the studying variables.

$$R = \frac{\sum_{i=1}^{n}(x_i^0 - \overline{x^0})(x_i^p - \overline{x^p})}{\sqrt{\sum_{i=1}^{n}(x_i^0 - \overline{x^0})^2 \sum_{i=1}^{n}(x_i^p - \overline{x^p})^2}}. \tag{9}$$

where x_i^0 is the observed parameter, x_i^p is the predicted parameter, and n is the number of dataset. Furthermore, to evaluate the accuracy of the predicted values with experimental ones, the square power of R, denoted as R^2, was used.

3. Results and Discussion

In the current study, 35 experimental datasets (Karimaee and Zarrati, [21]) were utilized and considered in the TM and ANN integrated method. Table 1 depicts the values of different effective parameters at each level.

Table 1. Main parameters and levels estimating the local scour depth

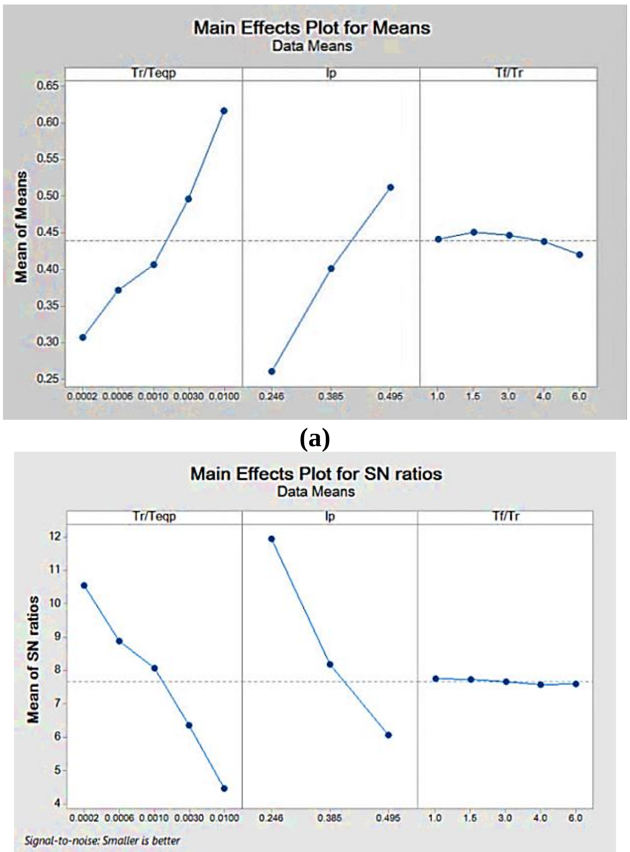
Parameter	Number of Levels	Level 1	Level 2	Level 3	Level 4	Level 5
Tr/Teqp	5	0.0002	0.0006	0.001	0.003	0.01
ΔI	3	0.246	0.385	0.495	-	-
Tf/Tr	5	1	1.5	3	4	6

3.1. Reducing the number of experiments

According to the number of levels selected for each parameter (Table 1), 75 experiments (5×3×5 =75) will be required using the full factorial method. However, TM could reduce this amount. According to the principles of this method, the total average of one degree of freedom and each of the five-level parameters (T_r/T_{eqp} and T_f/T_r) have four (4 = 5-1) degrees of freedom. The three-level ΔI parameter also has two (3-1=2) degrees of freedom. As Table 1 depicts, two parameters (T_r / T_{eqp} and T_f / T_r) have five levels and parameter ΔI has three levels, which could be recognized. To obtain higher accuracy in results, a similar number of level (five levels) for each parameter was considered. Hence, the method of column reduction was applied. According to these reducing columns, arrays L18 (18 different cases of the combination of the levels should be considered) and L25 are suitable by changing the degree of freedom to 13 (1+3× (5-1) =13) and according to the Taguchi standard table, array L25 is selected for better results. Therefore, instead of 75 experiments, 25 different experiments or 25 states of the parameter combination are examined. Using TM guidelines, the number of experiments was reduced by 28% and 67%, compared to Karimaee and Zarati's study [21] and the complete factorial method, respectively. This demonstrates its efficiency in saving time and money.

3.2. Evaluation of TM in determining the scour depth

We performed the evaluation of the results of 25 Taguchi proposed combinations to reduce the scour depth via the graphs of ANOM and S/N. The results in the ANOM diagram in Fig. 1(a) indicate that the first parameter (T_r/T_{eqp}) at the first level, the second parameter (ΔI) at the first level, and the third parameter (T_f/T_r) at the fifth level lead to the lowest value for the scour depth. This diagram also reveals that as the ratio of the time for the hydrograph rising limb to the time for the scour equilibrium (T_r/T_{eqp}) is lower, the value of the correction parameter will be lower. This is also true for the parameter of the difference between the peak and the unit hydrograph flow intensity (ΔI). In other words, the smaller the difference between the peak and the unit hydrograph flow intensity is (ΔI) or the closer the two parameters are to each other, the smaller the correction parameter K_h is and consequently, the lower the scour depth will be. The output of the S/N ratio diagram in Fig. 1(b) also shows better status of all the three parameters (optimal combination) at its first level. The analysis of this diagram is also consistent with the ANOM graph. Table 2 presents the results of the optimal output combination of each analysis.



(a)

(b)

Figure 1. Evaluation of TM results (a): ANOM, (b): S/N ratios.

Table 2. The optimal combination of effective parameters proposed by TM

Method	Levels			Response
	T_r/T_{eqp}	ΔI	T_f/T_r	d_s/B
ANOM	0.0002	0.246	4	0.186
S/N ratios	0.0002	0.246	1	0.179

According to Table 2, the optimal combinations purposed by TM based on ANOM and S/N analysis are similar in the two effective parameters ΔI and T_r/T_{eqp} and they are different for the parameter T_f/T_r. In other words, the smallest scour depth will occur once T_r/T_{eqp} is equal to 0.0002, ΔI is equal to 0.246 and T_f/T_r is 1 or 6. Table 2 illustrates the scour depth relative to the pier width (d_s/B) for each of these optimal combinations. Table 3 also presents the sensitivity analysis of the effective parameters using the ANOVA method. According to this table, parameter ΔI with the participation percentage of P= 54.49% is the most effective parameter and parameter T_f/T_r with P=0.04% is the least effective parameter on scour depth during a hydrograph event.

Table 3. The results of the ANOVA table and the participation of each factor

Parameter	**Degree freedom (DF)**	**Squares sum (SS)**	**Mean Squares sum (MS)**	**Variance (V)**	**Percentage of participation (P)**
T_r/T_{eqp}	4	109.184	27.296	7631.12	45.43%
ΔI	2	130.963	65.481	18306.48	54.49%
T_f/T_r	4	0.115	0.0287	8.03	0.04%
Residual Error	14	0.05	0.0036		
Total sum	24	240.312			99.96%

Figure 2 illustrates the effect of each parameter on scour depth. According to this figure, parameter ΔI at the first level (0.246) has the most significant effect on the reduction of scour depth. This diagram also shows that parameter T_f/T_r has the least effect on the scour depth.

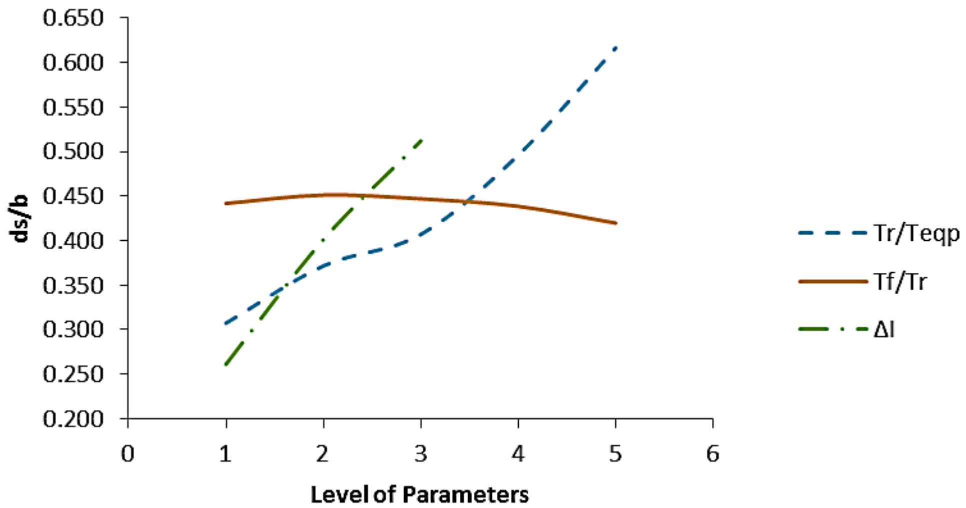


Figure 2. Diagram of the effect of the parameter level on the response.

The results obtained from the previous diagrams (Figs. 1- a, b) also apply to the diagrams in

Fig. 2. According to these diagrams, the ΔI and T_f/T_r parameters have the highest and lowest effect on reducing d_s/B, respectively. Moreover, the variations in T_f/T_r at the corresponding levels are only 0.031, confirming the minor effect of this parameter on d_s/B.

3.3. Application of TM in the optimal design of ANN

In this study, multilayer perceptron neural network and feed-forward backpropagation (FFBP-NN) type were employed. The training algorithm in this network is Levenberg-Marquardt (trainlm). A total of 55 experimental data sets were presented as an input to the network, 80% of which was used for training and 20% for the experiment. In the present study, to increase the amount of the data set, Equation (9) was applied for generating new experimental values. The input parameters in the ANN are the parameters affecting the unsteadiness flow condition, including T_r/T_{eqp}, ΔI, and T_f/T_r, and the output parameter is considered d_s/B.

Three hidden layers were selected to create this neural network. The adjustable components of the neural network included the number of neurons in the first and second hidden layers, training function, and transfer function in each layer, which are represented in Table 4. The method proposed by Chen et al. [8] in Table 4 was used to find the number of neurons. Table 5 demonstrates the main parameters and the levels assumed for each parameter. Fig. 3 displays the ANN made with the above specifications.

Table 4. Number of neurons in the hidden layer

Levels	**Number of neurons**	
	First layer	Second layer
Level 1	$\sqrt{N+P}$	$\frac{N+P}{2}$
Level 1	2N+1	$2N+1+\frac{2N+1}{3}$
Level 1	$P\times(N+1)$	$P\times(N+1)+\frac{P\times(N+1)}{3}$

Table 5. Levels of important factors for ANN

Parameter	**Number of Levels**	**Level 1**	**Level 2**	**Level 3**
Number of neurons in first layer	3	6	7	4
Number of neurons in second layer	3	2	10	6
training function	3	trainlm	trainoss	trainr
transfer function	3	lagesig	purelin	tansig

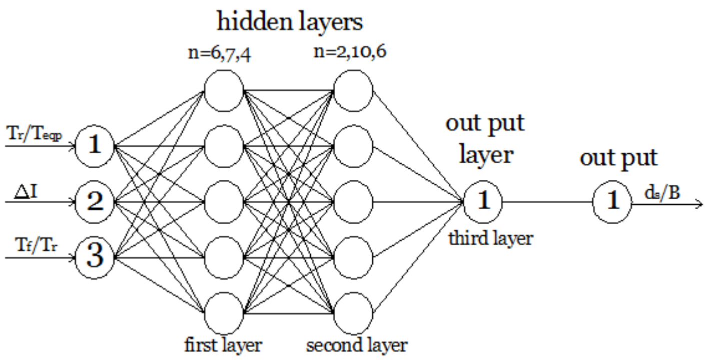


Figure 3. The structure of ANN in estimating the scour depth.

Based on Taguchi's proposed orthogonal array table, nine neural networks with the proposed Taguchi structure were created in the Matlab software. Each created network was run and evaluated for five times and the related correlation coefficient (R) values were determined. Instead of correlation coefficient (R) for analyzing the results, the Taguchi S/N analysis was utilized in the Minitab software.

Since higher values of S/N are better in most situations, the objective function created in this ANN model maximized the value of S/N in Equation (2). Based on TM, nine different neural networks were suggested. Each proposed network was run five times in the MATLAB software. Table 6 presents the characteristics of each network and their correlation coefficient (R).

Table 6. Analysis results for five replications in ANN

Number of study	**Number of neurons**		**Training function**	**Transfer function**	**R for different runs**					**S/N ratio**
	Layer1	**Layer2**			**First**	**Second**	**Third**	**Forth**	**Fifth**	
1	6	2	trainlm	Logesig	0.812	0.812	0.812	0.808	0.808	**-1.82609**
2	6	10	Trainoss	Purelin	0.950	0.950	0.951	0.951	0.951	**-0.44005**
3	6	6	Trainr	Tansig	0.936	0.937	0.939	0.941	0.943	**-0.54494**
4	7	2	Trainoss	Tansig	0.785	0.868	0.869	0.891	0.908	**-1.30129**
5	7	10	Trainr	Logesig	0.282	0.283	0.283	0.284	0.292	**-10.9113**
6	7	6	Trainlm	Purelin	0.952	0.952	0.952	0.952	0.952	**-0.42726**
7	4	2	trainr	Purelin	0.951	0.951	0.951	0.952	0.951	**-0.43457**
8	4	10	Trainlm	Tansig	0.932	0.943	0.996	0.996	0.996	**-0.25301**
9	4	6	trainoss	logesig	0.000	0.000	0.000	0.000	0.000	**-119.15**

Accordingly, the S/N values obtained in row 8 were the highest values among the nine experiments. However, as mentioned earlier, the optimal state may not be among the proposed Taguchi combinations since these nine proposed orthogonal arrays are only a fraction of the total number of experiment states. Therefore, the results of the TM S/N analysis were used. Figure 4 shows the output results.

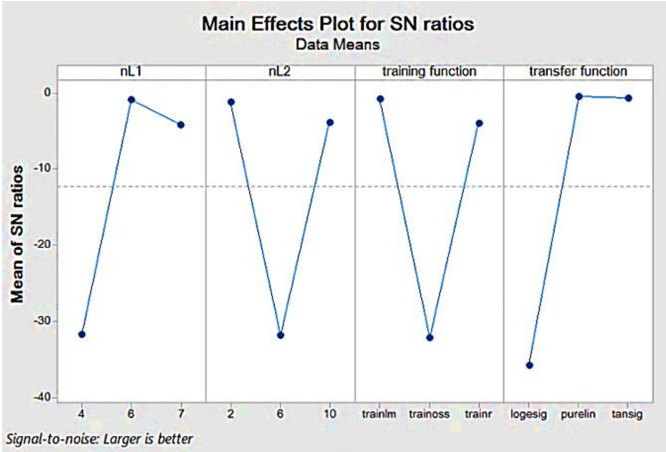


Figure 4. Taguchi's output in Minitab for the mean S/N in ANN.

According to the diagram in Fig. 4, the best ANN for the minimum scour depth will be obtained once the first and fourth parameters are at the second level, and the second and third parameters are at the first level. The diagram also implies that trainlm and trainloss training functions are the best and worst training functions, respectively. The results related to purelin and tansig transfer functions are much more suitable than those related to the logesig transfer function. However, no specific patterns were observed concerning the number of neurons in the first and second hidden layers. In other words, the diagram shows that the best neural network is obtained when the number of neurons in the first hidden layer is 6, the number of neurons in the second hidden layer is 2, the training function is trainlm, and the transfer function of each layer is purelin. Thus, the best proposed Taguchi neural network was created and trained to analyze its results. The diagrams in Fig. 5 also exhibit the regression diagrams of the best ANN created by the proposed TM combination by specifying the (R) correlation coefficient for experimental, validation, and training data and the overall result. The correlation coefficient R= 0.952 also confirms the suitability of the created neural network. Table 7 displays the optimal combination of ANN and its output for five replications.

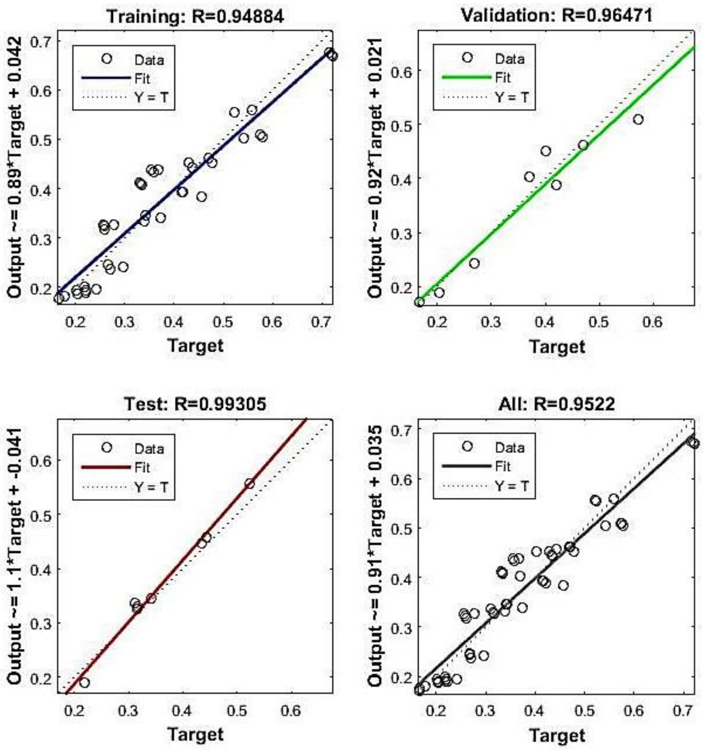


Figure 5. Regression diagram of the best ANN data by Taguchi.

Table 7. Taguchi's optimal combination for the best ANN by the Taguchi S/N analysis

Number of neurons		**Training function**	**Transfer function**	**R in different runs**					**S/N ratio**
Layer1	**Layer1**			**First**	**Second**	**Third**	**Forth**	**Fifth**	
6	2	tranlm	Purelin	0.95	0.95	0.95	0.95	0.95	**41.7**

According to Table 7, the S/N ratio is optimally higher than all the nine proposed combinations in Table 6, confirming the results of TM. Table 8 also represents the percentage of participation of each parameter in the TM analysis. According to the participation percentage column in Table 8, the transfer function parameter has the most significant effect (32.15%) on the ANN performance. Moreover, other parameters with the level of effects close to each other are in the next ranks. Owing to the fair distribution of the percentage of participation of the parameters, the decision-maker must be more meticulous in selecting all the four parameters, particularly the transfer function.

Table 8. Participation of each factor in the best ANN

Percentage of participation (P)	Degree freedom (DF)	Squares sum (SS)	Mean Squares sum (MS)	Variance (V)	Percentage of participation (P)
Number of neurons in layer1	2	1722.42	861.21	861.21	22.30%
Number of neurons in layer2	2	1733.77	866.88	866.88	22.45%
Training function	2	1783.11	891.56	891.55	23.09%
Transfer function	2	2482.95	1241.47	1241.47	32.15%
Total sum		7722.25			100%

3.4. Validation of the results

To evaluate the results of the TM and ANN integrated method, 20 different combinations of effective parameters were selected. The output values for each combination (d_s/B) were compared to the experimental results. Fig. 6 shows the accuracy of TM and ANN in predicting experimental results. As this figure depicts, TM has a better performance in predicting the results with R^2 = 0.99 than ANN with R^2 = 0.91. Table 9 compares the optimal combination to the response of TM and ANN methods. Accordingly, both TM and ANN methods offer a similar optimal combination.

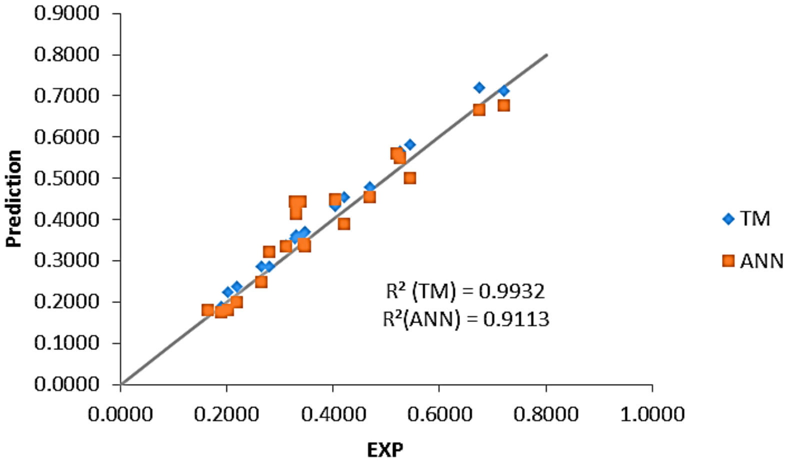


Figure 6. Evaluation diagram of the validation results using TM and ANN.

Table 9 Comparison of the optimal combination and response of TM and ANN

Optimization Algorithm	Type of analysis	Levels of parameters			d_s/B
		T_r/T_{eqp}	ΔI	T_f/T_r	
TM	ANOM	0.0002	0.246	6	0.186
ANN	S/N	0.0002	0.246	6	0.171

4. Conclusions

The TM method was investigated as one of the experimental design methods based on reducing the number of experiments and proposing different but limited combinations for study. In addition, the analysis of the results was conducted using the diagram of the ANOM and S/N and the best combination of parameters was introduced. Using the ANOVA analysis, the effect of the levels of each parameter and finally the effective parameters were determined. Through the use of the ANOVA analysis, the effect of each parameter's level and finally, the useful parameters were determined. The results were evaluated through an ANN. It should be noted that TM was utilized to adjust the adjustable parameters of the ANN, such as the number of neurons in hidden layers, training function, and transfer function. This is to find the best ANN for the phenomenon of the local scour depth around bridge piers under flood conditions. The output results of the MATLAB software were analyzed via TM S/N while the effect of levels of each parameter was evaluated with ANOVA. Based on the results, the most influential parameters were introduced. Concerning the local scour depth around bridge piers under flood conditions, TM outperformed the number of experiments performed by the previous researchers and the full factorial method by a 28% and 67% reduction in the number of experiments and in saving time and money, respectively. In the analysis of the results using TM, it was found that the lowest scour depth would occur once $T_r/T_{eq} = 0.0002$, $\Delta I = 0.246$, and $T_f/T_r = 1$, and in this regard, parameter ΔI was introduced as the most influential factor. Moreover, the best ANN is provided based on the optimal combination introduced by TM as well as the analysis of outputs using S/N diagrams when the first hidden layer consists of six neurons, the second hidden layer consists of two neurons, the training function is made of tranlm, and the transfer function is purelin. Furthermore, according to ANOVA, the most influential parameter with a participation rate of 32.15% is the transfer function. Ultimately, the TM with a detection coefficient of 0.99 outperformed an ANN with a detection coefficient of 0.91 in predicting the results related to the reduction of the local scouring depth around the ladder base.

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