Estimation of local scour and energy loss at bridge piers using neural networks

Mohamed A. Nassar
Water and Water Structures Eng. Dept., Faculty of Eng., Zagazig University, Zagazig, Egypt

Information on the depth of the scour hole formed US of a bridge pier is necessary in determining the safety of bridge itself. Traditional formulae available to predict scour depth or flow energy loss through piers suffer from many limitations including one arising out of the technique of data analysis commonly employed, namely, statistical regression. This paper presents an alternative to regression in the form of neural networks. These types of ANN models need large amount of data which should be at hand before thinking to develop such models. The capability of ANN model to predict scour hole formed US of a bridge pier and flow energy loss is investigated. One of the most important tools of ANN applied in this paper is the multi-layer perceptrons (MLP) which is a neural network modeling tool that is optimized for prediction and forecasting applications. A tansh activation function is used at the hidden layer which consisted of 5-4-1. The conjugate gradient learning algorithm is adopted. Collected measurements from literature review are used to train the network. The validation of the developed network using observations that were not involved in the training indicated the usefulness of the neural network approach for the prediction problem under consideration. The results of proposed Networks are compared to developed statistical equations. Networks-yielded values are found to be more accurate than those given by the statistical equations.

لاشك أن حساب عمق النحر الموضعي أمام مقدمة بغال الكباري في القنوات القابلة للنحر تمثل تحديا كبيرا في مجال التصميم ، حيث يعتبر عمق النحر من أهم العوامل المؤثرة على سلامة بغال الكباري نفسها ويمكن القول بأن المعادلات الإحصائية المستخدمة في تقدير كل من عمق النحر الموضعي أو مقدار الفقد في الطاقة خلال بغال الكباري تعانى من محدودية قدرتها على التنبؤ في بعض الأحيان، ويرجع هذا إلى قصور فى الطرق الاحصائية المستخدمة في بناء هذه المعادلات ، ولهذا يقدم البحث الحالي وسيلة أكثر تطوراً ودقة للتنبؤ بكل من عمق النحر الموضعي و مقدار الفقد في الطاقة خلال بغال الكباري وتعتمد هذه الوسيلة على بناء شبكة عصبية ذات مواصفات خاصة تمكّنها من التنبؤ بالعناصر محل الدراسة بكفاءة أعلى ، وقد تم إستخدام المدركات الحسية ذات الطبقات (MLP) وهى عبارة عن لبنة من لبنات الشبكة العصبية والتى يتم ضبط خصائصها للوصول إلى الشبكة العصبية المثلي القادرة على التنبؤ بالحالة محل الدراسة، وقد تم الوصول لشبكة عصبية مثلى تتكون من ثلاث طبقات على الصورة 5-4-1 وتم استخدام دالة تعلم من النوع (tanch) ، وكما هو معرف فإن الشبكة العصبية تحتاج لقدر مناسب من البيانات للتعليم الذاتي ولهذا اعتمد البحث الحالي على القياسات المعملية المنشورة في أبحاث سابقة على نموذج لبغال الكباري على شكل نصف دائرة من الأمام ومسلوبة من الخلف مع وجود وسائل حماية على شكل مصدات للتيار زاوية الشكل " توضع أمام البغال" بغرض إبعاد خطوط السريان بعيدا عن مقدمة هذه البغال حتى يتم تفادى حدوث النحر حولها ، ولقد تم عرض شرح مبسط لفكرة الشبكات العصبية وسبب إستخدامها في المحاكاة وعمل النماذج ، حيث أنها تعطى نتائج أفضل كلما تم تغذيتها بكم أكبر من البيانات ، وقد بيّنت نتائج الشبكة العصبية المثلي إلى كفاءة هذا الأسلوب في التنبؤ بكل من عمق النحر الموضعي و مقدار الفقد في الطاقة خلال بغال الكباري ، و قد تم مقارنة نتائج هذه الشبكة العصبية بمثيلاتها الناتجة من المعادلات الإحصائية ، وقد تبيّن حدوث تفوق ملحوظ للشبكة العصبية بحوالى 35%، هذا وتعتبر نتائج هذه الدراسة هامة ومفيدة في مجال حماية مقدمة بغال الكبارى بطريقة سهلة وبسيطة.

Keywords: Local scour, Bridges piers, Neural networks, ANN, Open channels and rivers

1. Introduction

The scouring process in rivers can result from natural phenomena or from man-made alterations; either of these can produce effects over long reaches of the river or in some cases, locally. In addition to the extended effects of the natural river regime, local scouring can occur at bends and confluences. The local scour at bridge piers has to be added to general scour and constriction scour to obtain the maximum scour depth to be considered in the design procedure of bridge piers. A detailed study carried out by Melville [1] to gain a better understanding of the flow mechanisms leading to formation of the scour hole, Melville [1]. The flow pattern around a pier of cylindrical shape has been investigated by Hjorth [2], Melville [1], and Melville and Raudkivi [3].

Butch [4] computed scour-hole widths at 128 piers, and scour-hole lengths at 40 piers. These dimensions were a function of scour depth and the average slope of the streambed in a scour hole. Melville [1] introduced many of the results from an extensive program of bridge scour research undertaken at the University of Auckland, New Zealand and presented an integrated approach to the estimation of local scour depth at bridge piers and abutments. Yassin et al. [5] presented the effect of abutment shape and the alignment of the upstream abutment face on the formation of equilibrium local scour.

ANN were developed as a information storage models and their parameters are calculated in a manner that resembles natural processes McCulloch and Pitts [6]. Details of their properties and the computational process have been presented by Hopfield [7] and the learning process of ANN is described by Rumelhart and McClelland [8]. The use of ANN techniques in water resources and stream flow prediction is relatively new and has been reported by French et al. [9], Zurada [10], Hall and Minns [11], Zealand et al. [12], Minns [13] and Salazar et al. [14]. Although many applications in the field of Hydraulic Engineering are available such as Karunanith et al. [15], Grubert [16], Tawfik et al. [17], Thirumalaiah and Doe [18], Dibike et al. [19], Azmathullah et al. [20] and Dibike and Abbott [21]. A few applications in the field of sediment transport were published. Nagy [22], Jain [23] and Nagy et al. [24]. A little applications of ANN in the field of scour at bridge piers are available. Some of these publications described the method for predicting local scour around bridge piers using an artificial neural network ANN with out any protection tool, such as Sung-Uk C. et al. [25], S. M. Bateni et al. [26]. An important advantage of ANN compared to classical stochastic models is that they do not require variables to be stationary and normally distributed, Burke [27]. Non stationary effects present in global phenomena, in morphological changes in rivers and others can be captured by the inner structure of ANN, Dandy and Maier [28].

As mentioned before, several researchers have suggested different statistical methods to predict local scour at bridge piers. A recent study predicts local scour and flow characteristics US bridge piers at presence of protective deflector with reasonable accuracy using a relatively new computational tool. ANN, is used in the present paper to predict scour US bridge piers and energy loss in terms of the flow depth and deflector dimensions. Field measurements collected from Abdel-Aal et al. [29] are used for training and verification of the ANN model.

This paper explores the use of neural networks to obtain the depth of a scour hole developed US a bridge elongated pier faced by protective deflector locating at different positions US the pier nose. Further, a new statistical regression equation is derived to predict the scour depth. Finally, the network predictions are compared with the new statistical equation.

2. Problem formulation

Application of ANN to scour and energy loss predictions requires a decision regarding two main aspects: selection of the variables that best explain phenomena, and design of the optimal network architecture.

It is important to develop a systematic procedure that can produce an ANN that captures most of the predictable information present in the data and that can be safely generalized to represent realizations different to the ones present in the training episodes. There is no unique and systematic methodology for the design and validation of an ANN model. This paper presents a procedure developed using current technical literature in artificial intelligence. The steps of the method are presented and detailed in main principal stages which are described as following:

2.1. Information analysis

No doubt, there is an interaction between a bridge pier and any protection tool located short distance upstream. When the flow takes place around the tool, the flow is separated and disturbance of large scale eddies grow up. If the pier nose was aligned downstream the tool in the wake zone, a reduction of the attacking velocity for the pier nose is occurred, and as a result, the generated scour depth is reduced. In the contrary, the energy loss through the pier is noticeably increased.

The majority of previous work on scour predictions US bridge piers are based on hydraulic model studies. These model studies have advantages like repeatability; they have helped more in exploring the scour mechanism and many other advantages. It was, thus, decided to calibrate the neural networks with the help of realistic collected measurements from literature review only. A survey of the literature reporting such observations indicated that the available types of information, namely, scour depth US the bridge pier, Froude number DS the pier, protection tool dimensions and energy loss are uniformly reported in many references. Information on other factors affecting scour was not commonly available across the various references.

The first part of problem formulation includes the preliminary data analysis, the selection of the most pertinent inputs and output. The experimental work developed by Abdel-Aal et al. [29] was used to generate training, validation and test data required for ANN. The experimental work was carried out in the Hydraulics and Water Engineering Laboratory of the Faculty of Engineering, Zagazig University, Egypt. The experimental study aimed to minimize local scour activities created US of bridge piers considering the different flow conditions. A tool was suggested to minimize the local scour; it was an angled-current deflector, which is solid and not perforated.

The deflector models have been changed and examined for different dimensions characteristics of the deflector including: deflection-angles, deflector relative heights h_d/h_3, positions of deflector, pier-deflector spacing L_d/b relative deflector-width b_d/b, fig. 1. The relative scour depth US bridge pier nose $h_s/h_3$and relative energy loss through bridge pier $\Delta E/E_3$ can be represented as following:

$$\frac{h_s}{h_3} \text{ or } \frac{\Delta E}{E_3} = f(F_3, \alpha, \frac{h_d}{h_3}, \frac{L_d}{b}, \frac{b_d}{b}), \tag{1}$$

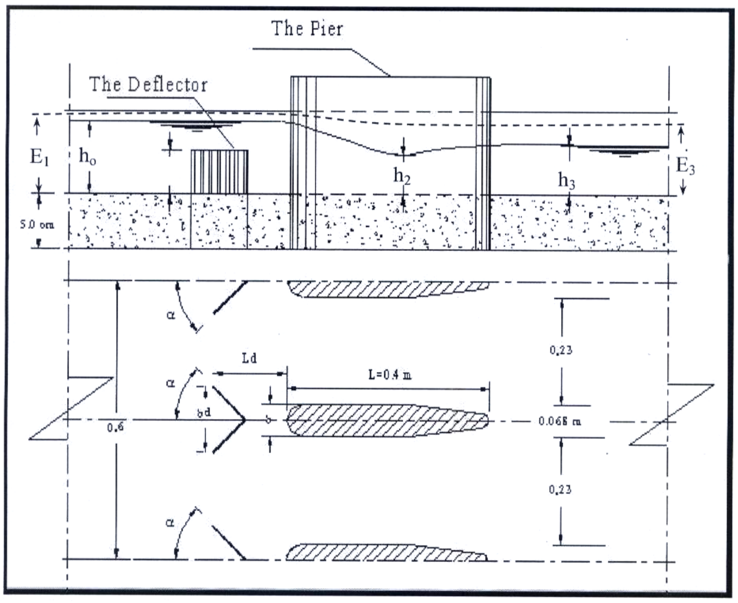


Fig. 1. Definition sketch for the bridge pier model and also the deflector [29].

where: F_3 is the Froude number DS the pier $F_3 = V_3 / \sqrt{g h_3}$; h_d / h_3 is the relative deflector height; L_d/b is the relative deflector-pier spacing, b_d/b is the relative deflector width, E_3 are the total energy US the deflector and DS the piers, respectively and ΔE is the energy loss due to the deflector and the bridge pier as well.

2.2. Development of the networks

Artificial Neural Network (ANN) prediction models are more efficient in predictions once they are trained from examples or patterns. A typical ANN consists of three layers (5-N-1) is shown in fig. 2. A neural network basically consists of interconnected neurons. Each neuron or node is an independent computational unit, which works as per the following equation.

$$y = f[\sum (x_1 w_1 + x_2 w_2 + x_3 w_3 + \ldots\ldots) + \theta], \qquad (2)$$

where: y is the output of the neuron; x_1, x_2, x_3,... are the input values; w_1,w_2,w_3, ... are the connection weights that determine the strengths of the connection; θ is the bias value, which increases the net input to the activation function, and, thus, accelerates the error convergence; and f is the transfer, activation or squashing function, which controls the output of a neuron or squashes it to a finite range like (0, 1) or (−1, 1).

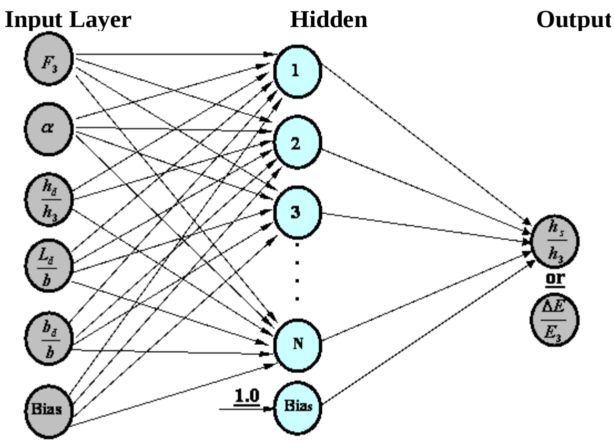


Fig. 2. Typical three layers feed-forward ANN.

The output layer is where the output are processed and are sent to an external source for further analysis or extra treatments or plotting, ..etc. The layers between the input and the output are hidden where the entire processing are not accessible. The number of neurons in the hidden layer (i.e. N) is determined by solving the application several times using networks of different sizes i.e. by a trial and error procedure until the error is minimized.

Training the network involves the determination of the weight vectors such that the sum of squares of the error between the actual value of the output and the desired value of the output is minimal. The network weights are randomly assumed within a particular range. Then they are updated through training of the network in the direction of minimizing the errors. The range within which weights are assumed should be selected carefully by trial and error.

2.3. Selection of the optimal model

The results obtained with the validation set for each of the selected model architectures are analyzed in order to choose the best model for the required scour depth and energy loss prediction. To judge which model has the best performance, graphical and analytical comparisons can be used. One can compare graphs of observed and predicted and dispersion diagrams of observed and calculated values. Errors or residues should be analyzed to test them for normality, independence, autocorrelation and cross correlation. Both numerical and graphical results should be considered with respect to predetermined criteria to select the best model. The statistics used for the objective function are the ones presented in table 1. It measures the goodness of fit of the model and the ability of the network to generalize or extrapolate the results outside of the range of the learning set. In addition, it measures the presence of over fitting problems and the sensibility of the network to initial conditions. Also, it checks the errors due to the use of a specific combination of learning and validation sets. In general, RMSE evaluates the variance of errors independently of the sample size. A high value of RMSE will usually indicate a deficiency in generalization of the network due to a bad selection of the number of hidden neurons or a weak learning process.

3. Proposed methodology for network building

As mentioned before, there is no unique and systematic methodology for the design and validation of ANN network. Actually, there are many factors affect the accuracy of the network. The main steps of the method are included in the block diagram presented in fig. 3 and the principal stages which are information analysis and model identification, are described below.

Table 1
Statistics for model comparison

Concept	Name	Formula
Root Mean Square Error	RMSE	$\sqrt{\sum_i^j (Mes - \Pr e)^2 / N}$
Coeff. of Determination	R^2	$\sum_i^j (\Pr e - avg.Mes)^2 \Big/ \sum_i^j (Mes - avg.Mes)^2$

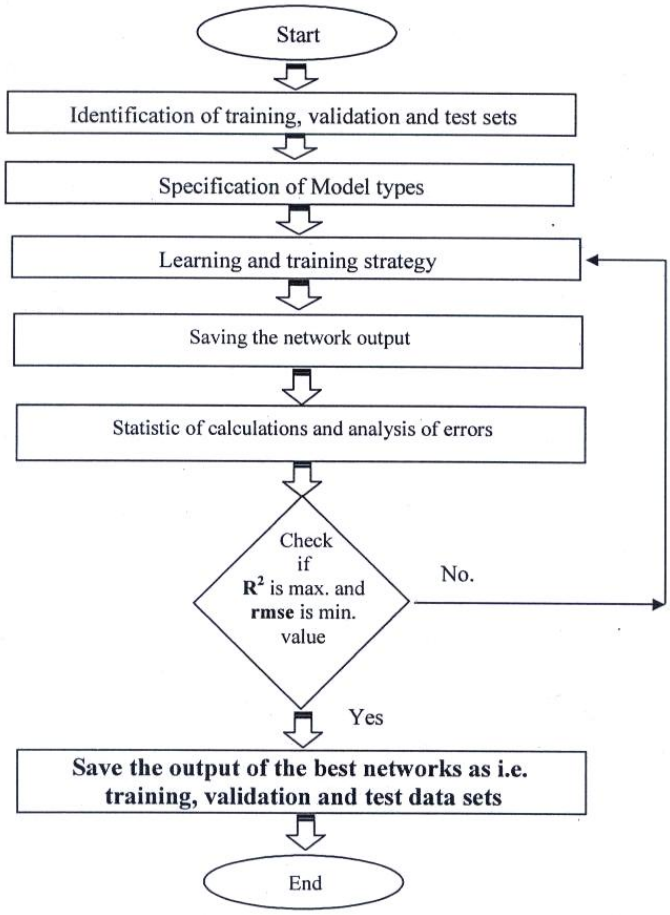


Fig. 3. Stages in ANN model formulation.

All the development networks in this paper have single output either h_s/h_3 or $\Delta E/E_3$. A network for all data models was tried and the result was not satisfied. Also a network with multi output was tried, and it was found that the networks with single output are better. The following steps were followed to develop each ANN network:

1. The data set for each case are prepared in a separate file with the suitable format for the Neural Connection Software.
2. The input tool is used to specify and allocate the input data. The data is randomized and is divided into three sets, training, validation, and test set. The three sets are selected randomly.
3. The MLP tool is used to specify the following parameters
   - Selection of Training, validation and testing sets,
   - Selection of activation function,
   - Determine of the initial weights range, and
   - Determine of the best number of iterations.
4. The output files are transferred to another software to enable the computations of,
   - The determination coefficient (R^2) between the target and the output of the developed ANN model, and
   - Root Mean Square Error (RMSE).
5. The best network is allowed to train several times with different starting point to obtain the global solution.
6. The final network is compared with the measured data in three figures for training, validation, and test data. The residuals for all the whole data set in each case are plotted against the network to check nature of results.

3.1. Selection of training, validation and testing sets

Once the input and output variables are defined, fig. 2. It is convenient and suitable to classify the complete data set in three categories: training, validation and test. This classification was obtained by using an ANN model with the same input and output variables. The selection of the input-output pairs which form the validation, training and testing sets is not random, in order to have a model with adequate predictive capability for the whole range of the data. The training data is used to train the proposed ANN and is taken as T% of the total records. Validation data is used to monitor neural network performance during training phase and it represents ((100-T)/2) % of total input data. Test data is used to test the performance of a trained ANN in generating the required prediction. The test data set is unseen data to the ANN model and represents ((100-T)/2) % of the total utilized records by the present application. The procedure is achieved by conducting many computer experiments. In the present application, the best value of "T" is 70. The results of the conducted experiments are presented in figs. 4 and 5 in terms of R^2 and RMSE for the relative scour depth US bridge pier nose h_s/h_3 and relative energy loss through bridge pier $\Delta E/E_3$, respectively.

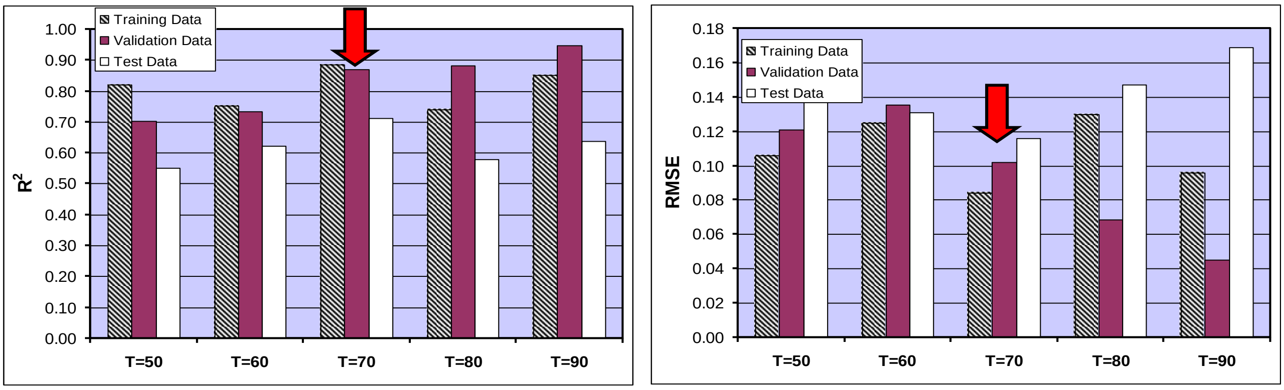
3.2. The initial values of the connections weights

The choice of the connections weights has a large effect on the performance of the network. The best initial values of the connections weight are found by trial and errors by conducting many computer experiments. The values of the weights that generate output with maximum R^2 and minimum RMSE are chosen, figs. 6 and 7 in terms of R^2 and RMSE for the relative scour depth h_s/h_3 and relative energy loss $\Delta E/E_3$, respectively. In the present application, the best initial weights were assumed to be in the range $\pm$ 1.0.

3.3. Number of hidden layer's neurons.

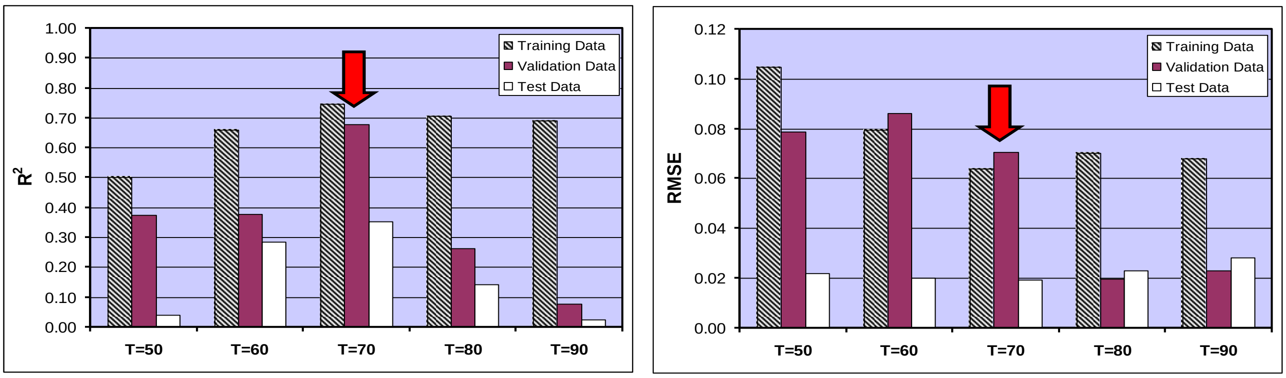
According to the previously mentioned steps, the best number of hidden layer's neurons was investigated. Generally, the number of neurons depends on the complexity of the data and on both the number of input and output variables. The procedure is achieved by conducting many computer experiments. In the present application, the best number of neurons in the hidden layer is 4.0. The results of the conducted experiments are presented in figs. 8 and 9 in terms of R^2 and RMSE for the relative scour depth h_s/h_3

and relative energy loss $\Delta E/E_3$, respectively. The best value of R and the minimum value of RMSE are when the network has a size of 5-4-1.



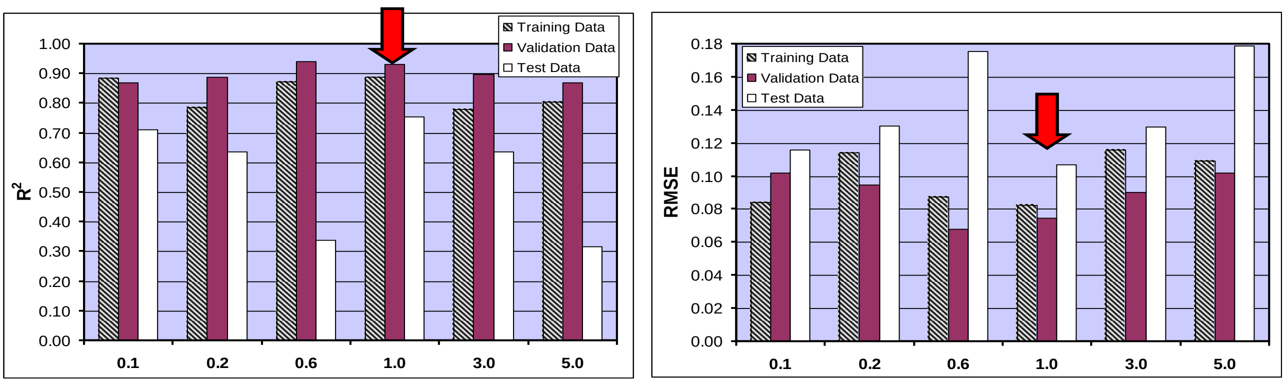
(a) (b)

Fig. 4. Typical performance of the proposed network while determining "T" for relative scour depth US bridge pier nose h_s/h_3 in terms of [A] R^2 and [B] RMSE.



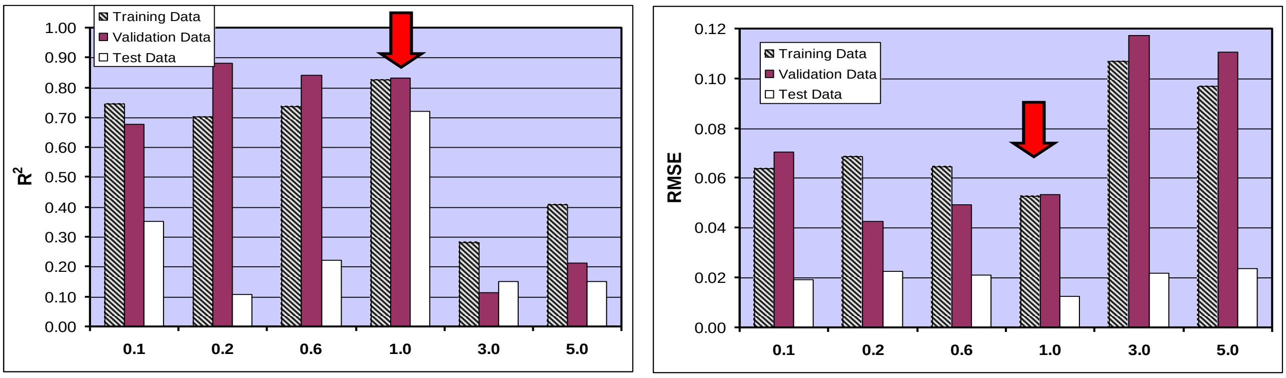
(a) (b)

Fig. 5. Typical performance of the proposed network while determining "T" for relative energy loss through bridge pier $\Delta E/E_3$ in terms of [A] R^2 and [B] RMSE.



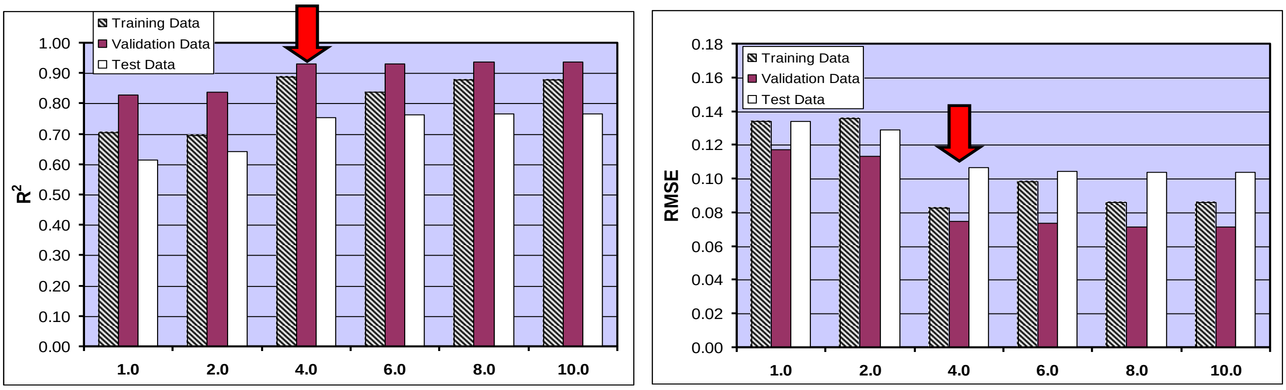
(a) (b)

Fig. 6. Typical performance of the proposed network while determining the connections weights for relative scour depth US bridge pier nose h_s/h_3 in terms of [A] R^2 and [B] RMSE.



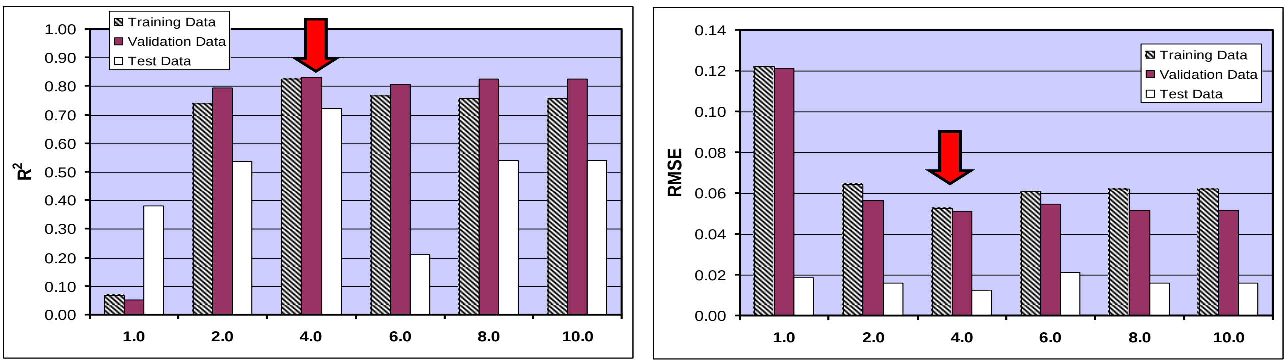
(a) (b)

Fig. 7. Typical performance of the proposed network while determining the connections weights for relative energy loss through bridge pier $\Delta E/E_3$ in terms of [A] R^2 and [B] RMSE.



(a) (b)

Fig. 8. Typical performance of the proposed network while determining of neurons in the hidden layer for relative scour depth US bridge pier nose h_s/h_3 in terms of [A] R^2 and [B] RMSE.



(a) (b)

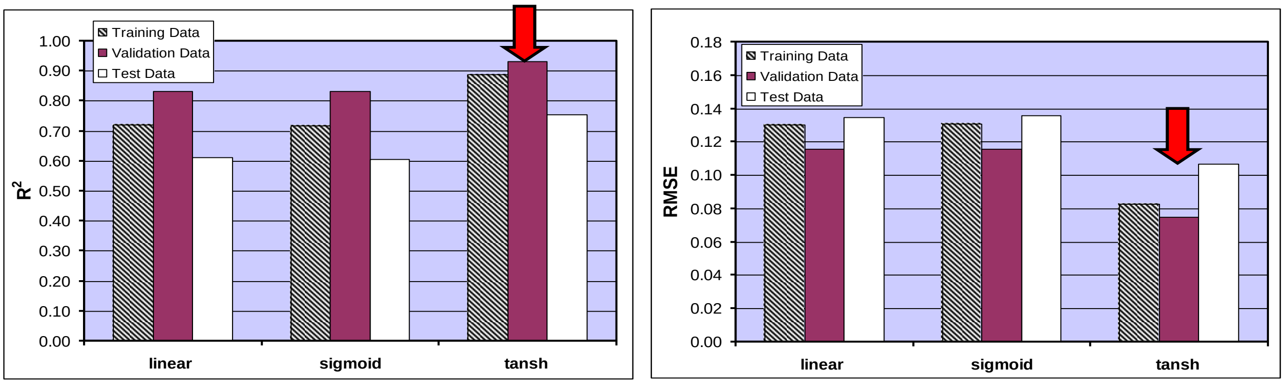
Fig. 9. Typical performance of the proposed network while determining of neurons in the hidden layer for relative energy loss through bridge pier $\Delta E/E_3$ in terms of [A] R^2 and [B] RMSE

3.4. Activation function

The type of activation functions used in the hidden layer is chosen by trials. In this application the tansh activation function is found to be the best one compared to the linear or the sigmoid. The results of the conducted experiments are presented in figs. 10 and 11 in terms of R^2 and RMSE for the relative scour depth h_s/h_3 and relative energy loss $\Delta E/E_3$, respectively.

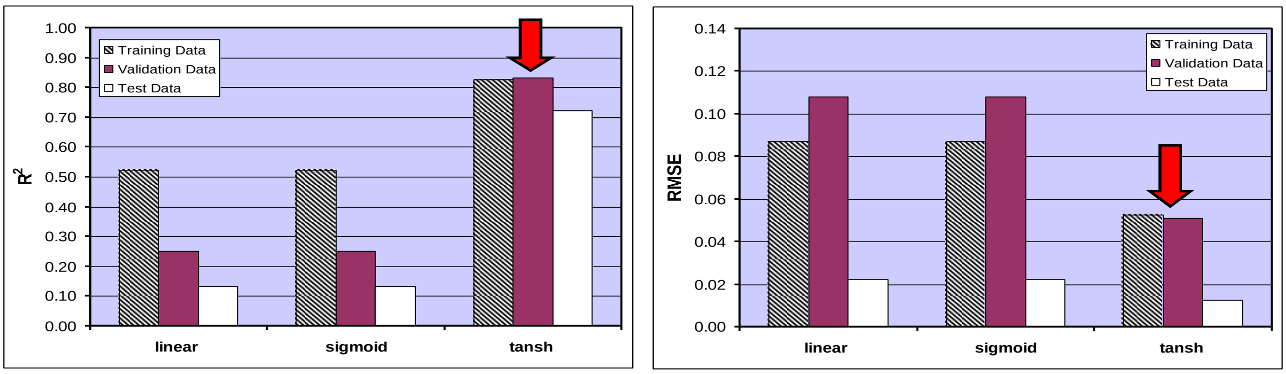
3.5. Training cycles

No doubt, increasing the number of training cycles improves the performance of network on the training data, but not necessarily on the validation data. If so many training cycles are used in a network, the network will have enough weights to exactly represent all the training patterns. Such network will be poor network because it will be able to generalize the solution. It means that the network is over trained. Either over trained or under trained networks is not desirable. The correct number of training cycles is assessed by looking at the performance of the network on the validation data. The procedure is achieved by conducting many computer experiments. In the present application, the best number of training cycles is 400. The results of the conducted experiments are presented in figs. 12 and 13 in terms of R^2 and RMSE for the relative scour depth h_s/h_3 and relative energy loss $\Delta E/E_3$, respectively.



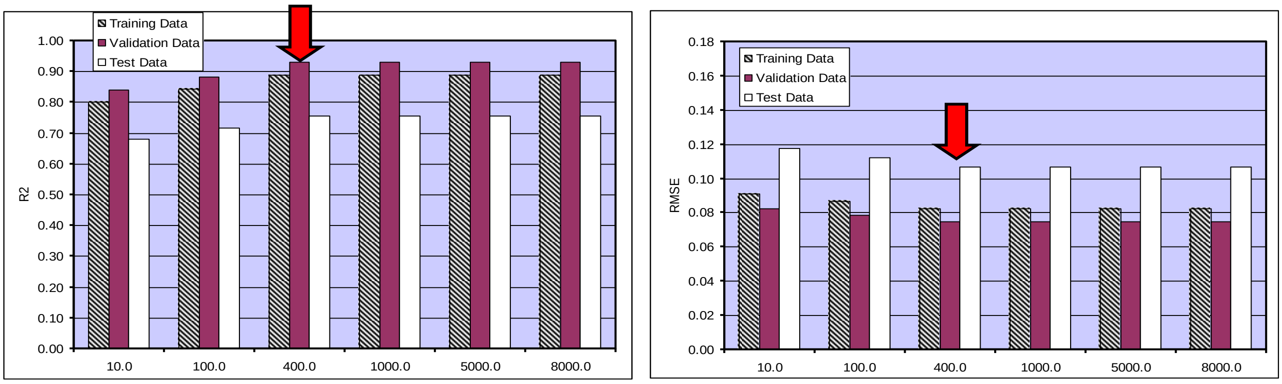
(a) (b)

Fig. 10. Typical performance of the proposed network while determining of activation functions for relative scour depth US bridge pier nose h_s/h_3 in terms of [A] R^2 and [B] RMSE.



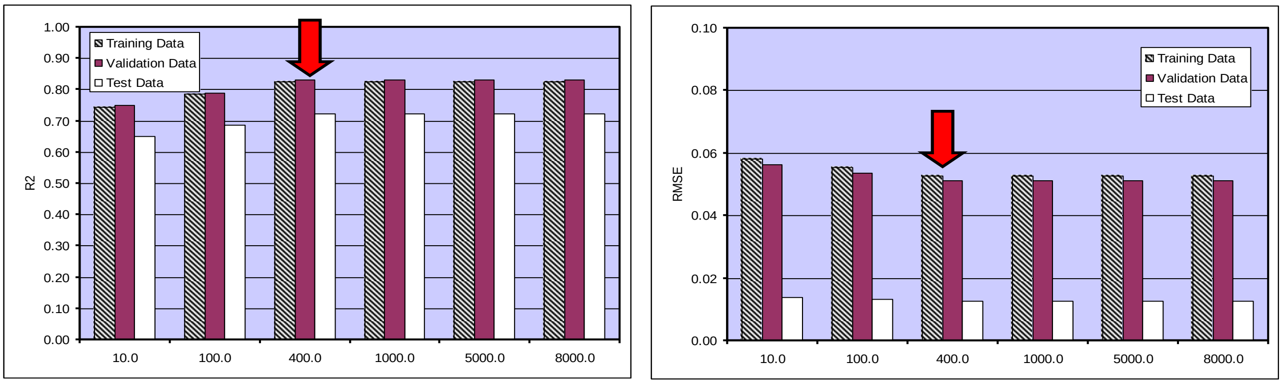
(a) (b)

Fig. 11. Typical performance of the proposed network while determining of activation functions for relative energy loss through bridge pier $\Delta E/E_3$ in terms of [A] R^2 and [B] RMSE.



(a) (b)

Fig. 12. Typical performance of the proposed network while determining of training cycles for relative scour depth US bridge pier nose h_s/h_3 in terms of [A] R^2 and [B] RMSE.



(a) (b)

Fig. 13. Typical performance of the proposed network while determining of training cycles for relative energy loss through bridge pier $\Delta E/E_3$ in terms of [A] R^2 and [B] RMSE.

4. Results of the developed networks

The developed ANN model 5-4-1 with a tansh activation function and 400 iterations (Training cycles) is used to predict the relative scour depth US bridge pier nose h_s/h_3 and relative energy loss through bridge pier $\Delta E/E_3$. The results of the network are presented in three figures. Fig. 14 presents the comparison between the ANN estimation and the collected values training data set. The determination coefficient, R^2, for this set of data is 0.888 and 0.826 for the relative scour depth h_s/h_3 and relative energy loss $\Delta E/E_3$, respectively. Clearly, perfect agreement is obtained for this set. Figs. 15 and 16 present the results of ANN model for validation and test data sets versus those of the collected values. The minimum determination coefficient is (R^2 =0.722). Table 2 presents the coefficient of determination R^2, and RMSE for different target with the experimental data for different data sets and all data used in developing the model. Fig. 17 represents the variation of the residuals for all the three data sets versus the network predictions. The residuals seem to be distributed around the line of zero error, uncorrelated with the ANN outputs and of very small values. The determination coefficient of the residuals with the network prediction is very small and equals -0.0172.

5. Comparison with other developed models

It is important to compare the multiple linear regression models (MLR) with the results of the developed ANN models. Based on the experimental data and using the statistical methods at presence of the different flow conditions, several models were proposed and their coefficients were estimated. Out of all trials, the best equation predicting the relative scour depth US bridge pier nose h_s/h_3 and relative energy loss through bridge pier $\Delta E/E_3$ can be put in form Eqs. (3 and 4), respectively.

$$\frac{h_s}{h_3} = 0.1340 - 2.5890F_3 + 0.0346\alpha + 0.0285\frac{h_d}{h_3} + 0.0327\frac{L_d}{b} + 0.0014\frac{b_d}{b} \quad . \tag{3}$$

$$\frac{\Delta E}{E_3} = -0.1724 + 0.7161F_3 - 0.0253\alpha + 0.5164\frac{h_d}{h_3} - 0.0318\frac{L_d}{b} + 0.000078\frac{b_d}{b} \quad . \tag{4}$$

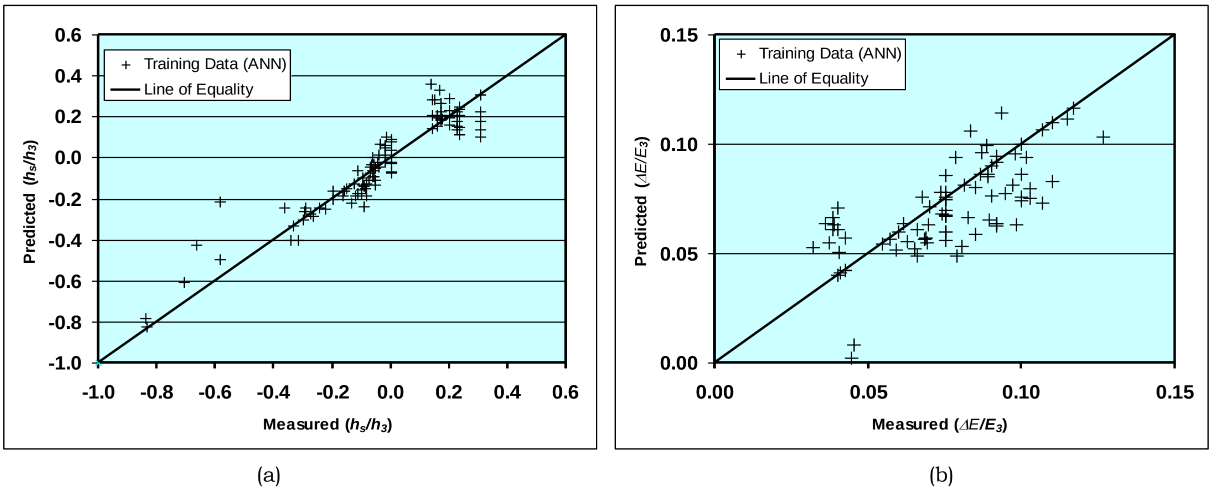


Fig. 14. Comparison between experimental Training data sets and predicted ones [A] relative scour depth US bridge pier nose h_s/h_3 [B] relative energy loss through bridge pier $\Delta E/E_3$.

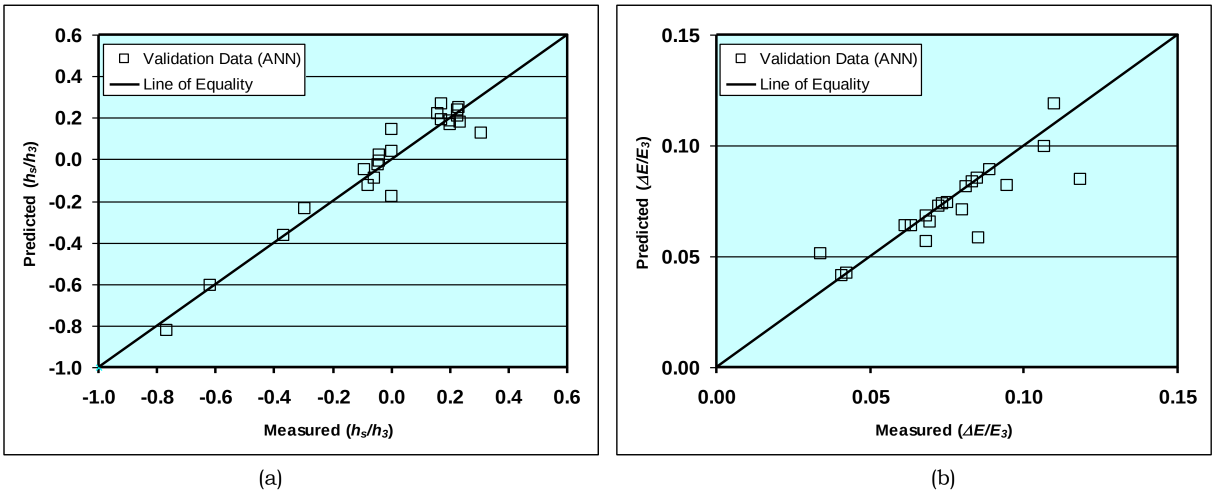
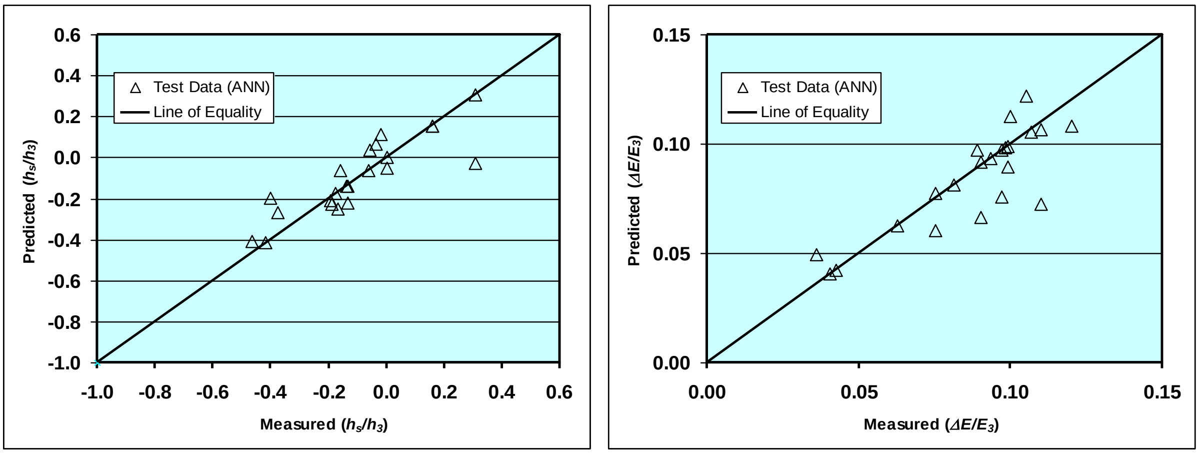
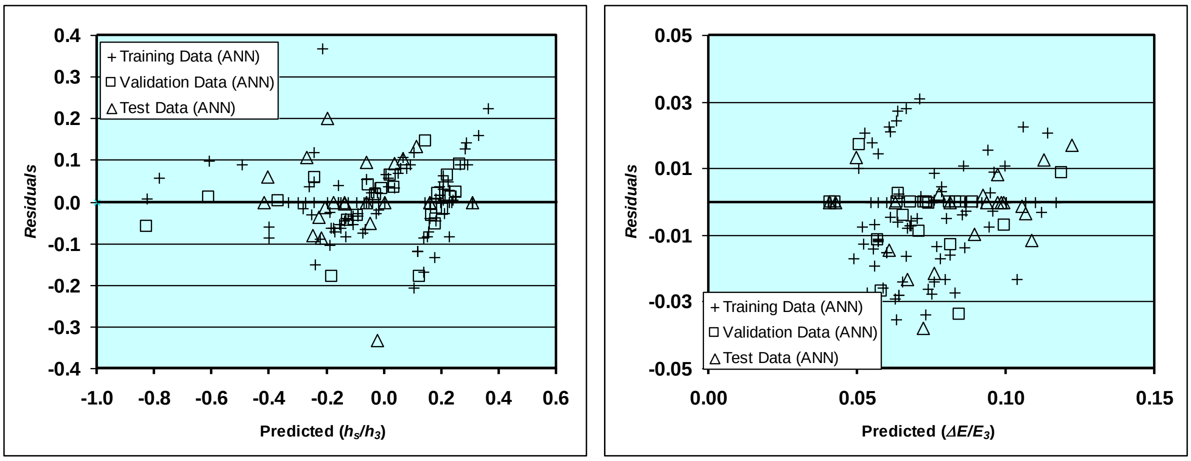


Fig. 15. Comparison between experimental Validation data sets and predicted ones [A] relative scour depth US bridge pier nose h_s/h_3 [B] relative energy loss through bridge pier $\Delta E/E_3$.



(a) (b)

Fig. 16. Comparison between experimental Test data sets and predicted ones [A] relative scour depth US bridge pier nose h_s/h_3 [B] relative energy loss through bridge pier $\Delta E/E_3$



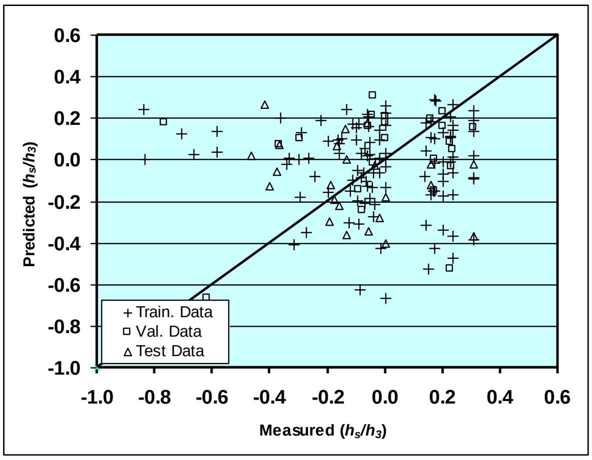
(a) (b)

Fig. 17. Variations of residuals for different data sets with predicted data [A] relative scour depth US bridge pier nose h_s/h_3 [B] relative energy loss through bridge pier $\Delta E/E_3$.

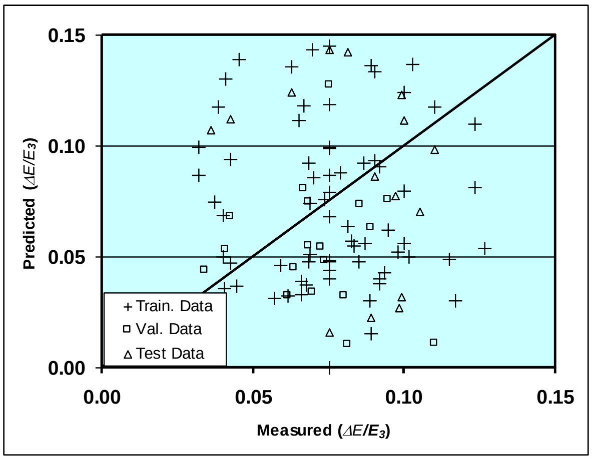
Table 2
Basic features of the developed models using ANN

Out put	Training .set		Validation set		Test set		Average	
	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE
h_s/h_3	0.755	0.107	0.930	0.075	0.888	0.082	0.857	0.087
$\Delta E/E_3$	0.722	0.013	0.832	0.051	0.826	0.053	0.794	0.038

Fig. 18 shows a comparison between the measured relative scour depth US bridge pier nose h_s/h_3 and relative energy loss through bridge pier $\Delta E/E_3$ and the predicted ones using Eqs. (3 and 4). The results of different models are presented in fig. 19. Based on R^2, and RMSE, it is clear that ANN models show the best results in all cases.

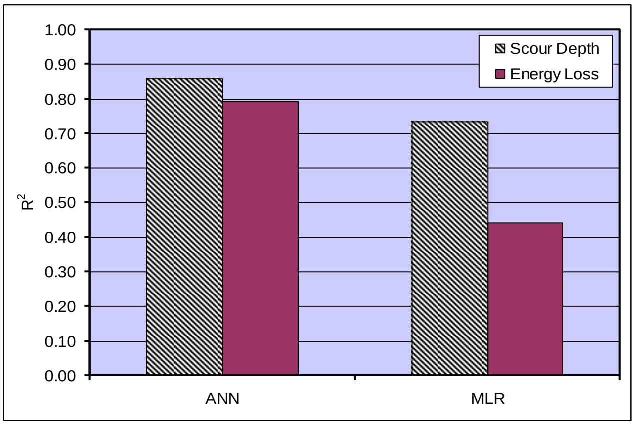


(a)

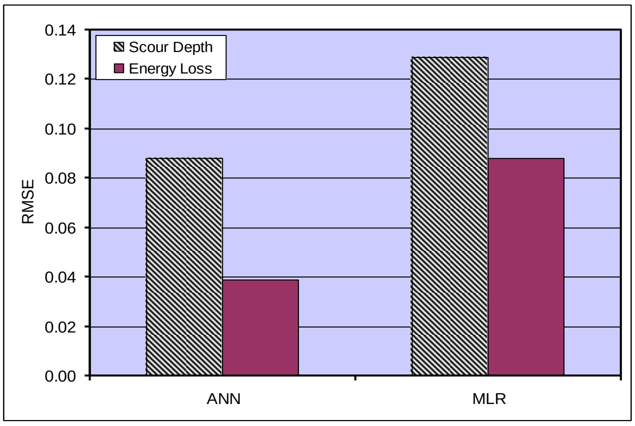


(b)

Fig. 18. Comparison between different experimental data sets and predicted ones [A] relative scour depth US bridge pier nose h_s/h_3 [B] relative energy loss through bridge pier $\Delta E/E_3$.



(a)



(b)

Fig. 19. Comparison between results of ANN and MLR models using all data of each ANN model [A] R^2 and [B] RMSE.

6. Conclusions

Traditional equations based on statistical techniques used to predict scour depths US of a bridge pier and flow energy loss suffer from limitations arising out of their experimental basis. A systematic methodology has been proposed to develop neural networks for scour hole formed US of a bridge pier and flow energy loss prediction. Published hydraulic data are collected from laboratory experiments on relative scour depth and relative energy loss through bridge pier. It has been established that the scour and energy loss predictions could be substantially improved if neural networks are used in place of the Statistical methods. A multilayer artificial neural network (5-4-1) is used as a prediction toll based on the flow and protection tool characteristics. Such a network was also found to be more satisfactory than a new regression equation worked out from the compiled field data. The present paper proved that the ANNs are a powerful computational tool for predicting the values of relative scour depth US bridge pier nose h_s/h_3 and relative energy loss through bridge pier $\Delta E/E_3$. The proposed method has significant benefits for optimal use of bridge protection. The conjugate gradient learning algorithm is adopted. The results of proposed Networks are compared to developed statistical equations.

Networks-yielded values are found to be more accurate than those given by the statistical equations.

List of symbols

The following symbols were used in this study:

b is the width of pier [L],
b_d is the deflector width [L],
d_{sd} is the deposition depth US the deflector [L],
D_{50} is the mean diameter of bed layer [L],
E_1 is the total energy US the pier,
E_3 is the total energy DS the pier,
ΔE is the energy loss thought the bridge [E_1-E_3],
F_3 is the froude number DS the bridge pier,
g is the acceleration due to gravity [LT^{-2}],
h_1 is the water depth US the bridge [L],
h_2 is the water depth between the bridge piers [L],
h_3 is the tail water depth DS the bridge [L],
h_d is the deflector height [L],
h_o is the water depth for local clear-water scour [L],
h_s is the scour depth US the bridge pier [L],
h_{sd} is the scour depth US the deflector [L],
L_p is the length of the bridge pier [L],
L_d is the spacing between the deflector and the pier nose [L],
V_3 is the mean tail flow velocity DS the bridge [LT^{-1}],
α is the deflection angle of the deflector [degrees],
γ is the specific weight of bed layer,
ρ is the mass density of water [ML^{-3}], and
ρs is the mass density of bed layer [ML^{-3}].

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