

Scour Depth Prediction in Sand Beds using Artificial Neural Networks and ANFIS Methods

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Abstract

Background/Objectives: In this study, the maximum scour depth modeling of Multi-Layer Perceptron based artificial neural network (MLP), Radial Basis Function based neural network (RBF), Adaptive Neural-Fuzzy Inference System (ANFIS), multiple regression analysis and empirical relationships of Ingis, Shen & Schneider, Laursen & Toch, Breusers, Jain, Melville & Sutherland, and Melville & Chiew were used. **Methods/Statistical Analysis:** To compare the performance of each method, the standard tests such as standard Root Mean Square Error (NRMSE), standard Mean Absolute Error (NMAE), correlation coefficient (R) and Nash Sutcliffe index were implemented. **Findings:** The results demonstrate that the adaptive neural-fuzzy inference system with the lowest standard root mean square error (0.665) and the highest correlation coefficient (0.76), has the best performance compared to other methods Melville and Sutherland experimental method compared to other empirical methods yields more suitable performance (NRMSE = 1.058). The standard root mean square error of perceptron neural network, radial basis neural networks and multiple regression analysis were calculated as 0.665, 0.94 and 0.95 respectively. **Application/Improvements:** Percent improvement in the performance of fuzzy neural networks, perceptron neural networks, radial basis neural networks and multiple regression analysis compared to Melville and Sutherland 37.14, 27.60, 11.15 and 10.21 respectively.

Keywords: Artificial Neural Network, Fuzzy, Local Scour, Multiple Linear Regressions, Sand Bed

1. Introduction

Scour is a phenomenon that occurs when the bed is eroded by water flow and bed materials are transported by the force of water flow. The mechanism of this phenomenon is such that before destructive force of floods cause destruction structural, erosion around the pier of bridge (By the water flow) and causing damage (Ettema R., et al⁶).

The flow pattern of scour is caused by localized structures. Depending on the structure of the material forming the substrate, flow and sediment transport conditions, vortex, which caused additional erosion force is applied to the substrate flow (Breusers & Raudkivi²). The additional erosive force increases the rate of sediment movement around the structure and flow down to the local context (Melville & Coleman¹⁵). Clash of the basic

causes the horseshoe vortex and flow separation, vortex creates arose that two main factors are the cause scour (Melville & Chiwe¹⁴). Location of these zones is shown in Figure 1.

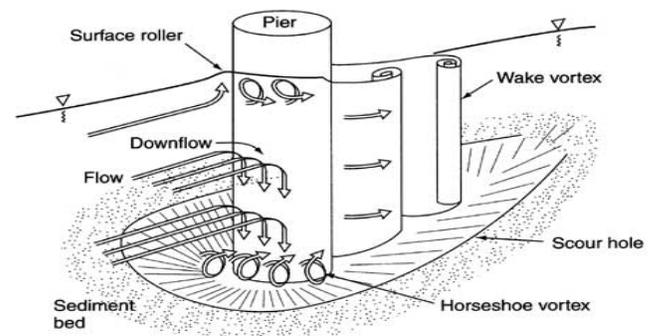


Figure 1. This figure shows how to create a bridge pier scour channel lab.

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Scour is one of the main reasons for the lack of stability of the bridge and ultimately defect them. Appropriate methods to control and reduce the scour in several issues are highly regarded. To reduce the scour around bridge piers, methods can be divided into two categories with retrofitting bed coating methods and techniques to transform the current division. Cover methods of retrofitting bed around the bridge to deal with shear stresses that occur during intense currents are used as a shield against the act. The change of the flow (hydraulic methods to protect the piers), by using the tools, the flow field around the base of the slip, results in erosion of the horseshoe vortex and flows downward and around the base of the bridge reduced. Of these methods, the bed of gravel and stone lace cited can be used to cover. Means changing the bridge at the base of the crown can be used to create a crack in the base, and the base-plates submerged victim respondents (turret) that are mentioned above the base of the bridge. Knowledge of the maximum depth scour for the design and maintenance of piers is imperative. The most accurate method for determining the maximum scour depth, hydraulic modeling and testing is done. Since the construction of hydraulic models is costly and time-consuming, researchers have been interested in experimental methods and computational software. The research that has been done in the field of empirical estimates of the maximum scour depth, we can study Ingus⁷, Shen and Schneider²³, Larsen and Touch¹¹, Breusers¹, Jane⁸, Colorado State University, Melville and Sutherland¹³ and Melville and Chiwe¹⁴, which has been described in the Materials and methods. The use of soft computing to predict complex phenomena in various fields of engineering, in particular, has greatly expanded. Chang and et al.³ method combines neural network with radial basis bee colony algorithm, genetic algorithm, and Support Vector Machines (SVM), M5 regression model and neural network to estimate the maximum scour depth and showed that the method used hybrid neural network and radial bee colony algorithm has better performance than other methods. Review of the literature demonstrates the high potential of soft computing methods to predict complex phenomena are, therefore, in this study, the methods of soft computing methods of the groups.

Riprap of bridge piers is placed to eliminate local scour and to secure the pier from failure. However, riprap surfaces frequently rupture to protect bridges pier during deluges despite arrangement of riprap particles around its foundations. Improper design of proper extent for riprap cover greatly reduces the riprap efficiency in local scour

control. Therefore, in this research in order to determine the proper size of riprap cover at the angle of 60° of river bend, some experiments were carried out under clean water conditions in a flume of 180°. The effect of collar presence around the pier and also different size of collar on proper size of riprap were examined in different experiments. The results showed that the presence of collar around the cylindrical bridge pier decreased the proper size of riprap as 26% compared to the pier without collar. Moreover, as the collar diameter increased, the size of riprap cover decreased which is economically affordable (Nohani).

Pourbakhshian & Pouraminian²⁰ use the equation to estimate the situation of sediment transition and its changes through section during the time in future. As a result sediment transition equation is calculated based on analyzing of maximum stream flow and maximum sediment discharge in a month. In the third step, the maximum stream flow can be predicted in a future year (t) using ARIMA (Auto Regressive Integrated Moving Average). The results will be replaced in rating curve sediment and slope equations that are the results of second step. Finally they can calculate the independent parameters including river sediment discharge and river bed slope in year.

2. Materials and Methods

This study was designed to estimate the maximum depth scour around the bridge on sandy substrates, experimental methods, and multivariate linear regression, neural network (perceptron and radial) and adaptive neural fuzzy systems using any of the following methods the resolution will be presented.

2.1 Experimental Methods

The complexity of analytical methods for the determination of the maximum scour depth, researchers have been interested in experimental methods. Experimental methods for fitting a connection to data collected from experiments on hydraulic models or measurements are carried out on the sample results. Ingis⁷ conducted experiments on circular base with rectangular top with 1.7 lengths to width ratio between 0.3 and 1.3 mm particle diameter, the following equation is introduced in the metric system:

$$\frac{y_0 + d_s}{D} = 2.32 \left(q \frac{2}{3} \right)^{0.78} \quad (1)$$

In this regard, y_0 is depth of flow, q is discharge per unit width of the channel, and D is the width of the base and scour depth d_s . Upon the recommendation of Thomas should not be used beyond the scope of the formula (Landers and et al⁹). Shen and Schneider¹⁸ based on the Reynolds number, the maximum depth of scour at the bridge cylinder of diameter between 50 and 152 mm and the size of the bed material between 0.17 to 0.68 mm was variable, as a function of Reynolds number offered:

$$d_s = 0.00022R_e^{0.619} \rightarrow \left(R_e = \frac{VD}{\nu} \right) \quad (2)$$

The relationship between the diameter D , 'kinematic viscosity and V is the velocity of flow. Laursen and Touch¹¹ using the experimental data on the cylindrical pier in clear water and also without considering the impact of Part presented as follows:

$$\frac{d_s}{D} = 1.35 \left(\frac{y_0}{D} \right)^{0.3} \quad (3)$$

The relationship between the depth y_0 , D is the width of the base and scour depth d_s . Breusers¹ with regard to the influence of the diameter of the scour the following relationship:

$$\frac{d_s}{D} = fK_1K_2 \left(2tgh \left(\frac{y_0}{D} \right) \right) \quad (4)$$

The correlation coefficient k_1 shaped tip to the base of the circular base is equal to 1; the aerodynamic 0.75 and 1.3 is the rectangular base. k_2 is angle correction factor to the current approach, which is a function of the aspect ratio of the base and the angle of the collision. Threshold velocity v_c is the movement of particles. Jane⁸ with regard to the upstream calculated the Froude number scour around bridge piers in the creation, presented as follows:

$$\frac{d_s}{D} = 1.84 \left(\frac{y_0}{D} \right)^{0.3} \left(\frac{V^2}{gy} \right)^{0.25} \quad (5)$$

Relationship between Colorado State University by Richardson and Davis presented and the relationship CSU amended is as known:

$$\frac{d_s}{y} = 2K_I F_r^{0.43} \left(\frac{D}{y} \right)^{0.65} \quad (6)$$

The correlation coefficient k_1 shaped cylindrical base (in terms of clear water is equal to one) and Fr is the

Froude number (Ettma et al.⁵). Melville and Sutherland¹³ to estimate the maximum scour depth gave the following equation:

$$\frac{d_s}{D} = K_I K_y K_s K_D K_\phi K_\sigma \quad (7)$$

In the above equation, d_s final scour depth, D diameter cylindrical pier, K_I flow coefficient, K_y coefficient of flow depth, K_s basic form factor, K_D ratio, particle size, K_ϕ coefficient of particle size and K_σ angular coefficient of water hit the ground level is. Melville and Chiwe¹⁴ introduced a relationship as shown below:

$$d_s = K_I K_{yD} K_D \quad (8)$$

The relationship between the intensity factor K_p , K_{yB} coefficient of flow depth and diameter of the particle size is a factor K_D .

2.2 Neural Network (MLP)

Artificial neural system inspired by natural neural networks is built. Artificial neural networks are powerful in conformity with the complex phenomena that can be used to predict the behavior of these phenomena. In this research Forward propagation neural network with Levenberg-Markvad was used. The back-propagation algorithm, the performance index $F(W)$ according to the following equation with respect to the sum of squared error between the network output and the actual value is minimized (Landers and et al¹⁰).

$$F(w) = e^T e \quad (9)$$

In this regard, $w = [w_1, w_2, w_3, \dots, w_n]$ represents all network weights and e is the error vector. Generally, a three-layer perceptron neural network input, intermediate and output, is the number of neurons in each layer. In Figure 2., layers are shown as a Schematic of a neural network with an intermediate.

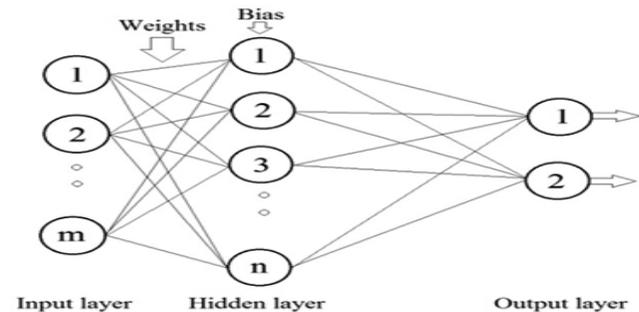


Figure 2. Schematic of a neural network with one hidden layer.

The input layer contains the input of the model is investigated. Inputs to neurons in the middle layers are a function of the weight matrix and the neurons of the input layer are calculated from the following equation.

$$z_j(x) = \frac{1}{1 + \exp(-\text{sig}_j(x))} \quad (10)$$

The relationship between the weight $W1ij$ input nodes and hidden nodes i and j hidden node j is $B1j$ bias. The output of the j hidden node using the sigmoid function is calculated according to the following equation:

$$O_k(x) = \sum W2_{kj} z_j + B2_k \quad (11)$$

Given an input vector x , k outputs have the following equations is obtained:

$$y_j = f\left(\frac{\|x_j - c_j\|}{2\sigma_j}\right) \quad (12)$$

The relationship between the weight ($W2kj$), hidden node j , output node k , and the output node $B2k$ may be biased. Training data are given as inputs to the network and its output is calculated. By calculating the error between the network output and the desired value, the network weights are adjusted so that the error is minimized. Follow these steps to decrease error, ideal for every vector in the training set is repeated. In this study, by taking an intermediate layer, the neural network was built. Neurons in the middle layer were considered. The optimal numbers of neurons in this layer were determined by trial and error.

Kazemzadeh and et al.²¹ was Suspended Sediment Concentration (SSC) in surface waters affects directly on the water quality, phytoplankton's fertility, pollution distribution and redistribution. In this study, temporal and spatial variations of SSC at Bahmshir Estuary (BE) in the southwest of Iran were investigated using five field campaigns and Moderate Resolution Imaging Spectroradiometer (MODIS) sensor images of a nine-year time series from 2003 to 2011. An Artificial Neural Network (ANN) model with one hidden layer that had good simulation performance was used against regression analysis. Results indicated ANN model has higher accuracy than regression analysis to model the SSC because it's higher capability in optimization of non-linear problems. R2 and RMSE were improved, 25 and 77% respectively when using ANN model.

2.3 Radial Basis Neural Network (RBF)

Radial Basis Neural Network (RBF) is layer types ahead

with an intermediate. In these networks, the number of neurons in the middle layer is obtained using trial and error. In addition to optimizing a radial basis neural network weights, the activity must be optimized functions. Weight and center of activity functions in accordance with the minimum sum of squared error gradient descent method to adjust menu. The networks of radial basis functions are used as the excitation of neurons of the intermediate layer (Cheng & et al³).

Norlaili and Daneshwar¹⁷ could Presence of dead-band in engineering process decreases the system performance. Modeling of systems with such nonlinear properties is a key factor in model-based control and in fact a challenging task by conventional mathematic methods. In this paper, application of radial basis neural networks in such systems is investigated. The nonlinear static part of the system can be decoupled first from linear dynamic part and then modeled using Radial Basis Function (RBF) network; the dynamic linear part of the system can be identified using linear models. Results show that RBF can capture well, the key model of the systems with dead band. In the RBF neural network, the output of the hidden node j and entry for XPare calculated from the following equation:

$$Z_k = \sum_{j=1}^L y_j w_{kj} \quad (13)$$

In this regard, $\| \cdot \|$ expresses soft vector and it is the Euclidean distance. It is considered that U_j is the radial basis function j (radial basis function f); σ is the gap radially from the center of RBF in which the function value is zero (Kumar & et al²²). RBF network output can be calculated from the following equation:

$$NRMSE = \frac{RMSE}{\bar{x}} = \frac{\sqrt{\frac{\sum_{i=1}^N (d_i^k - d_i^j)^2}{N}}}{\bar{x}} \quad (14)$$

In this regard, Z_k is the k th output of the network, W_{kj} is the weight between nodes and the output node is the middle layer. In this study, the MATLAB software was used to simulate the radial basis neural network.

2.4 Neuro-Fuzzy (ANFIS)

Fuzzy approach with regard to the elimination of ambiguity and uncertainty rather than ignoring it and promote multi-valued logic instead of the two-valued logic (Lee and Hoops¹²). Fuzzy inference system based on the rule "if, then" is based, so that the rules can be used to obtain the relationship between the number

of input and output variables. The process includes the steps of determining the membership functions and fuzzy inference to determine the inference system based on the data, the writing of inference rules and combine them to get a result and, if need be defuzzification. The problem is that sometimes the membership function of fuzzy logic system is difficult. The researchers propose to use a hybrid model of Adaptive Neuro-Fuzzy (ANFIS) in order to resolve this problem. Adaptive neuron-fuzzy hybrid model, a hybrid learning algorithm to identify parameters of Surgeon's fuzzy inference. Surgeon model was introduced in 1985 by Taking and surgeon. Surgeons model with the four main elements of membership functions, internal functions, rules and outputs consist (Kwong and et al.⁹). Adaptive fuzzy neural structure consists of five layers of input nodes. The nodes of the base are intermediate nodes, and node-by-node result is output. The first layer of each node belonging to each of the fuzzy sets with membership functions specified. By multiplying each input to each node, the second layer is calculated on the weight (W_i). The third layer is calculated in terms of the relative weight (\overline{W}_i). The fourth layer is a layer of code that perform operations on the input layer, one obtains ($\overline{W}_i f_i$). The final layer is the output layer, which aims to minimize the difference between the actual output and the output from the network. In this study, the trapezoidal membership functions for all inputs and fuzzy clustering method using subtractive, modeling was performed.

Okolobah & Ismail¹⁹ ANFIS models are developed for these IMFs. The target model proposed in this paper, EMD-ANFIS, is achieved by combining the predictions from these IMF-ANFIS models together and this is used for forecasting purposes. A real life data obtained from Power Holding Company of Nigeria (PHCN), Bida, was used to evaluate the forecast accuracy of the proposed model. The results revealed that the proposed EMD-ANFIS model yields better results when compared to ANN and EMD-ANN models. The proposed EMD-ANFIS model recorded 2.76% and 50.05% improvements over EMD-ANN and traditional ANN models, respectively as judged by the overall MAPE of the models.

3. Experimental Data Presentation

In this study, in order to model the maximum scour depth of 219 data relating to the tests carried out by Mubeen¹⁶,

Eattma⁵, Farooq Mia and Hiroshi, Melville and Chiwe¹⁴, Dey and Raju⁴ have been used. This data includes the parameters of the maximum scour depth ($d_s(mm)$) flow rate ($Q(m^3/s)$), the average diameter of sediment particles ($D_{50}(mm)$) depth of flow ($Y(mm)$) the critical velocity of sediment particles ($V_c(m/s)$) the diameter of the base of the bridge ($d(m)$) and the width of the cross-flow ($b(m)$) are listed in Table 1. of each.

Table 1. The data used were

Parameter used	Measuring range for each parameter
The maximum depth of scour (d_s)	(mm) 4-940
Flow rate (Q)	(m ³ /s) 7.248 – 0.007542
The average diameter of the particles sediment (D_{50})	(mm) 31.75 – 0.00184
Flow depth (Y)	(m) 6 – 0.0201
Critical velocity of sediment particles (V_c)	(m/s) 1.208 – 0.099075
Diameter of bridge (D)	(m) 0.766 – 0.00463
Width of cross-section of flow (b)	(m) 2.121 – 0.2286

4. Standards Measurement of the Error

In order to compare the performance of different methods of modeling, statistical analysis, standard root mean square error (NRMSE), standard mean absolute error (NMAE), the correlation coefficient (R) and the coefficient of Nash Sutcliffe was used later to calculate each the parameters are described.

$$NMAE = \frac{MAE}{\overline{ds}} = \frac{\sum_{i=1}^N |ds^o - ds^s|}{N \times \overline{ds}} \quad (15)$$

$$NMAE = \frac{MAE}{\overline{ds}} = \frac{\sum_{i=1}^N |ds^o - ds^s|}{N \times \overline{ds}} \quad (16)$$

$$NSE = 1 - \frac{\sum_{i=1}^N (ds_i^o - ds_i^s)^2}{\sum_{i=1}^N (ds_i^o - \overline{ds})^2} \quad (17)$$

In these equations, ds^o is the measured air flow, ds^s is

air flow forecasts, N is the number of data and ds is average air flow rate is measured. The NRMSE and NMAE closer to zero than the model show good performance. NSE is a number between 1 and $-\infty$. NSE and the correlation coefficient are closer to 1, the better the performance.

5. Results and Discussion

After training models, the maximum scour depths in sandy substrates were estimated for test data and the comparison was considered. Also of Angus, sand and Schneider, Laursen and touch, Breusers, Jane, Colorado State University, and Chiwe Melville and Sutherland empirical relations are evaluated their performance. Table 2 presents the results of different experimental methods for the test data.

Table 2. Results of experimental methods (test data)

Method	Standards of measurement the error			
	NRMSE	NMAE	R	NSE
Melville & Sutherland	0.665	0.455	0.76	0.535
Breusers	0.766	0.517	0.68	0.384
Melville & Chiew	0.940	0.611	0.62	0.073
Jain	0.950	0.716	0.60	0.215
Colorado State University	1.058	0.669	0.486	-0.174
Laursen & Toch				
Shen & Schneider				
Ignis				

The results show that the correlation provided by Melville and Sutherland with the lowest root mean square error of the standard (1.058) and minimum mean absolute error standard (0.669) is better than other methods of operation. Angus root mean square error of the proposed method with the highest standard (21.665) and the maximum mean absolute error standard (11.929) and the lowest correlation coefficient (-0.254) and the index of NSE (-491.327) quantitative accuracy in estimating the maximum depth of scour. Training and Radial Basis Neural substrates of different Narvon between the results of the two methods are shown in Figure 3.

Figure 3. shows that both neural network methods used in this study, the increase in the number of neurons in the middle layer, the model during the training phase, the increase. The neural network performance for data analysis related to the case where the intermediate layer has 9 neurons and radial basis neural network with the best performance of 22 neurons in the middle layer, has

the best performance. For observing the performance of different methods, Results of soft computing techniques and Melville - Sutherland are showing in Table 3.

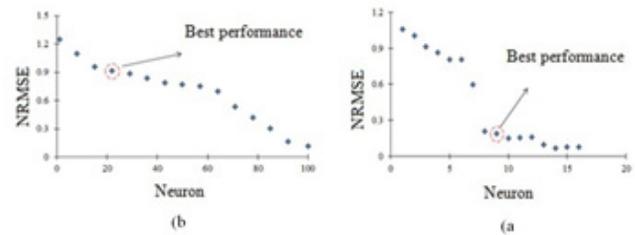


Figure 3. Evaluation of neural network models: (a) Neural Network, (b) Radial Basis Neural Network.

Table 3. Results of soft computing and Melville-Sutherland experimental methods (training data)

Method	Standards of measurement the error			
	NRMSE	NMAE	R	NSE
Fuzzy neural	0.562	0.364	0.9	0.804
Neural Network Prosperous	0.19	0.11	0.99	0.978
Radial Basis Neural Network	0.918	0.388	0.69	0.479
Multiple regression analysis		0.622	0.48	0.235
Melville & Sutherland	0.198	0.611	0.48	0.112

The results in Table 3., show that the neural network training phase, the performance is better than other methods (NRMSE = 0.190). After the neural network, fuzzy neural adaptive method with root mean square error of the model is the standard 0.562 scour depth. The method of neural network (perceptron and radial basis) by changing the number of neurons in the middle layer can be estimated error rate is lower in the training phase, but this change will reduce the accuracy of the predicted scour depth in the test phase. The best performance of the predictive ability of the model to test data is high in the estimation of scour depth; scour depth estimation results in Table 4. are compared to experimental data.

According to Table 4., the combination of fuzzy neural standard with a maximum root mean square error (0.665) and R (0.76) and minimum mean absolute error standard (0.455) compared to other methods used, is better. NSE factor for neuron-fuzzy method compared to other methods used in this research is closer to 1 which confirms the better performance of this method (NSE = 0.535). The experimental techniques, best practices, the approach is provided by Melville and Sutherland (Table

2). The result in Table 4. also shows that soft computing techniques perform better than empirical methods. The root mean square error for the standard method is 1.058. Melville and Sutherland were calculated and compared to other methods; it is higher than all other statistical parameters which are also confirmed this statement. The artificial neural network techniques using neural network with 9 neurons in the middle layer of the radial basis neural network with 22 neurons in the middle layer, the performance is better. To compare and evaluate the performance of each of the methods used in this study, the charts of each method are plotted in Figure 4.

Table 4. Results of soft computing and Melville-Sutherland experimental methods (test data)

Method	Standards of measurement the error			
	NRMSE	NMAE	R	NSE
Fuzzy neural	0.665	0.455	0.76	0.535
Neural Network	0.766	0.517	0.68	0.384
Prosperous				
Radial Basis Neural Network	0.940	0.611	0.62	0.073
Multiple regression analysis	0.950	0.716	0.60	0.215
Melville & Sutherland	1.058	0.669	0.486	-0.174

In Figure 4. plots the performance of any of the methods used in this study are drawn together with experimental results. The two lines are more consistent with each other, indicating better performance model is used. Draw a line for the fuzzy neural model (ANFIS) than our other models show that this method is more Tituba, scour depth more accurately than other methods estimates. Line drawing of the experimental method of calculating Melville - Sutherland compared to less compliance with our program show that soft computing techniques, more accurately estimate the maximum scour depth. Another method that can be used to evaluate the performance of various methods, scatter diagrams are plotted the graphs for soft computing techniques and experimental methods Melville and Sutherland in Figure 5. are plotted.

The scatter plot by taking one of the axes of the coordinate system as the other and axes measured as the estimated data plotted. Line graphs are plotted in Figure 5. is half of the machine axes with each axis, makes an angle of 45 degrees. The distribution points are closer to the 45 degree line model shows better performance. The scatter plot for the fuzzy neural approach Comparison to other methods is closer to the 45 degree line, indicating that the method has better performance. Distribution of Melville and Sutherland relation to other methods of dispersion

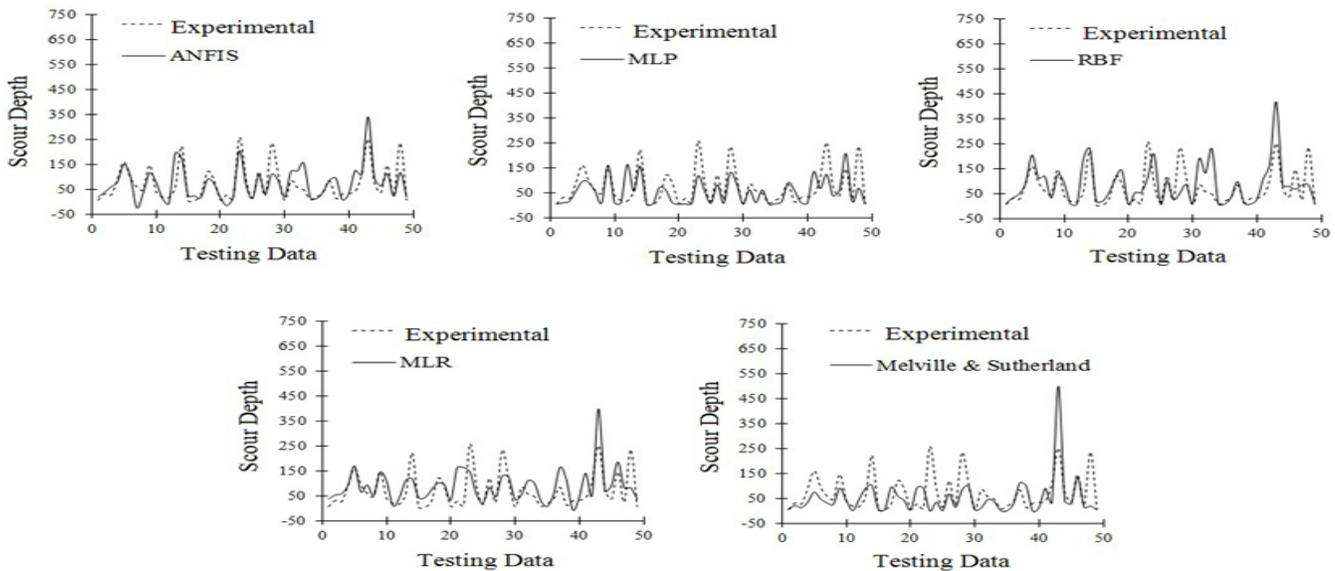


Figure 4. Diagram of soft computing techniques and experimental methods Melville and Sutherland.

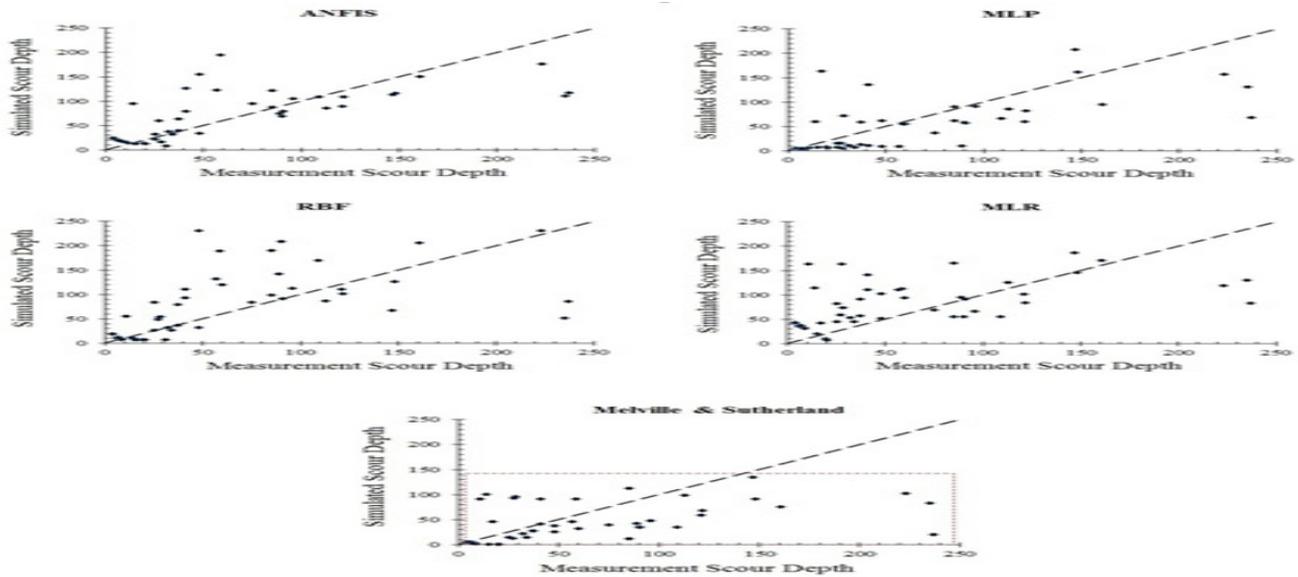


Figure 5. Distribution of soft computing techniques and experimental methods Melville – Sutherland.

around the 45 degrees that do not show the method is less accurate in estimating scour depth. The distribution of these points, the dash line is shown. Placing most of the dispersion relation Melville and Sutherland, below 45 degrees, the simulation shows that this method is low and scour depth is estimated to be underestimated. The distribution of neural fuzzy, almost equally above and below 45° is showing that this method is more or less a simulator than being indifferent. Draw a diagram to show the performance of neural network simulator that this method is low. Radial basis neural network and multiple regression analysis, and estimation of scour depth greater than the actual value estimates. If the error sum of different ways to be positive, indicating low simulator and if it is negative, indicating that the model is more simulator. Total error of the methods used in this study is listed in Table 5.

According to Table 5., the total error of the method used in this study is negative, indicating that this method is more simulators. Total error of neural network, the relationship between Melville and Angus Sutherland and positive relationship indicates that these methods are low simulator. The mean absolute error of the fuzzy neural sum is less than other methods that represent more or less indifferent to the simulation of this method being. To determine the level of performance, using soft computing methods in Table 6., the recovery rate of each method compared to Melville and Sutherland presented.

Table 5. The collect error for methods were use in this study

Method	Total error
Fuzzy neural	-90
Neural Network Prosperous	933
Radial Basis Neural Network	-706
Multiple regression analysis	-815
Melville & Sutherland	981
Breusers	-475
Melville & Chiew	-2902
Jain	-2243
Colorado State University	-3973
Laursen & Toch	-6499
Shen & Schneider	-3184
Ignis	34005

Table 6. Percentage recovery of soft computing methods (compared to Melville and Sutherland)

Estimation method	ANFIS	MLP	RMF	MLR
Percent recovery	37.14	27.60	11.15	10.21

The results in Table 6. show that the adaptive neural fuzzy method with 37.14 percent performance improvement (compared to experimental Melville and Sutherland) better performance than other methods Calculation soft. Multivariate linear regression with a 10.21 percent performance improvement over other methods of soft computing, performance is poorer.

6. Conclusion

In this study, the estimated maximum scour depth in sandy beds of soft computing and experimental methods were used. Soft computing techniques include using artificial neural network perceptron (MLP), radial basis neural network (RBF), adaptive neural fuzzy (ANFIS) and multiple linear regressions is (MLR). Experimental methods, including equations Angus, sand and Schneider, Larsen and touch, Breusers, Jane, Colorado State University, Melville and Chiew, Melville and Sutherland and professionalism. The results showed that soft computing techniques to experimental methods are more accurate in estimating the maximum scour depth. of soft computing techniques, adaptive neural fuzzy method (ANFIS) is more accurate (NRMSE = 0.665). The experimental techniques, equation given by Melville and Sutherland Mtlvb Try performance is compared to other experimental methods (NRMSE = 1.58). Angus relationship among all the methods used in this study is the weakest performance (NRMSE = 21.665). The results also showed that the fuzzy neural simulator is more or less indifferent to the method of multiple linear regression and radial basis neural networks are more simulator. The experimental method and Neural Network Simulator Melville and Sutherland are low.

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