International Journal of Architectural, Civil and Construction Sciences
ISSN: 2415-1734
Vol:13, No:9, 2019

Modified Hybrid Genetic Algorithm-Based Artificial Neural Network Application on Wall Shear Stress Prediction

Zohreh Sheikh Khozani, Wan Hanna Melini Wan Mohtar, Mojtaba Porhemmat

Abstract**—**Prediction of wall shear stress in a rectangular channel, with non-homogeneous roughness distribution, was studied. Estimation of shear stress is an important subject in hydraulic engineering, since it affects the flow structure directly. In this study, the Genetic Algorithm Artificial (GAA) neural network is introduced as a hybrid methodology of the Artificial Neural Network (ANN) and modified Genetic Algorithm (GA) combination. This GAA method was employed to predict the wall shear stress. Various input combinations and transfer functions were considered to find the most appropriate GAA model. The results show that the proposed GAA method could predict the wall shear stress of open channels with high accuracy, by Root Mean Square Error (RMSE) of 0.064 in the test dataset. Thus, using GAA provides an accurate and practical simple-to-use equation.

Keywords**—**Artificial neural network, genetic algorithm, genetic programming, rectangular channel, shear stress.

I. Introduction

THE shear stress plays an important role in an open channel flow. In any channel, it is a principal factor in sedimentation, deposition, turbulence study, bed erosion and river morphological and geometric changes [1]-[3]. Therefore, it is considered as the main parameter in designing channels. Based on experimental data, the boundary shear stress depends on the cross-sectional shape, boundary roughness, hydraulics of flow and secondary flow [4]-[7]. Many studies have focused on measuring shear stress in the side wall and bed of smooth rectangular channels such as [6], [8]-[11], few of the studies were done on rectangular channel with non-homogeneous distribution roughness [12]. Besides experimental studies, some researchers have focused on establishing some analytical and numerical models in predicting of shear stress distribution along the wetted perimeter [13]-[17].

The applications by soft computing technique as a method for solving complex problems in the field of water resources are increasing [18]-[20]. Sheikh Khozani et al. [21] used Gene Expression Programming for predicting the shear stress distribution in circular channels with sediment. The authors indicated that the ANN model has better function in predicting shear force than the traditional shear force relations. Kisi et al. [22] used the soft computing techniques for estimating the daily suspended sediment load in two different stations. Khozani et al. [23] evaluated the percentage of shear force carried by walls in smooth rectangular channels by using GA model.

Determining the structural properties is one of the most important concerns in using ANN. In this study, the GAA method as a hybrid combination of ANN and GA is introduced and employed for predicting the wall shear stress in a rectangular channel. The aims of this study are to (1) employ the hybrid GAA method as one that could adjust the neuron numbers of the hidden layers, (2) examine various fitness functions and choose the best one for wall shear stress prediction, (3) consider different input combinations to find the most appropriate ones, (4) figure out an accurate equation that could predict the wall shear stress by using the most appropriate input parameters.

II. Material and Methods

A. Experimental Study

In order to examine the ability of ANN to predict the wall shear stress in rough rectangular channels, the data of Knight [12] were made use of. The experiments were done in a flume 15 m long, 0.46 m wide and set at a bed slope of 9.58×10^{-4}. Afterwards, the wall and bed shear stresses were measured by using the Preston pipe technique at different flow depths and roughness. According to the experimental results, Knight [12] could present an equation for predicting wall shear stress in a rectangular channel as:

$$\frac{\bar{\tau}_w}{\rho g h S_f} = \left(\frac{\%SF_w}{100}\right)\left(\frac{B}{2h}\right) \tag{1}$$

where $\bar{\tau}_w$ is the mean wall shear stress, B the channel width, h the water depth, ρ the fluid density and $\%SF_w$ the total shear force carried by the walls, calculated as:

$$\%SF_w = e^{\alpha}\left(\tanh(\pi\beta) - 0.5\left[\tanh(\pi\beta) - \beta\right]^2\right) \tag{2}$$

in which:

Z. Sheikh Khozani is with Universiti Kebangsaan Malaysia, Bangi, Malaysia, (corresponding author, e-mail: y.sheikh2131@gmail.com).

W.H.M. Wan Mohtar is with Department of Civil and Structural Engineering, Universiti Kebangsaan Malaysia, Bangi, Malaysia (e-mail: hanna@ukm.edu.my).

M. Porhemmat is with Universiti Kebangsaan Malaysia, Bangi, Malaysia, (e-mail: mph1363@gmail.com).

International Journal of Architectural, Civil and Construction Sciences
ISSN: 2415-1734
Vol:13, No:9, 2019

$$\alpha = -3.264\log\left(\frac{B}{h}+3\right)+6.211 \tag{3}$$

$$\beta = 1-\frac{\gamma}{5} \text{ and } \gamma = \log\left(\frac{k_{sb}}{k_{sw}}\right) \tag{4}$$

In this study, the results of ANN were compared with (1).

B. GAA Neural Network

The ANN is widely used in modeling the various complex engineering problems. Structurally, ANN consists of an input layer, an output layer, and one or more hidden layer. The neuron number of the input and output layers are equal to the number of input and output variables, respectively. But there is not a particular rule to identify the neuron number of the hidden layers, therefore, in numerous studies the trial and error method was used to find the appropriate hidden layer neuron number [24]-[27]. Because of the time the trial and error method consumes, it could not be used in practical situations. In this study, a modified GA was made use of to optimize the structure of ANN model and specify the neuron numbers of each hidden layer. The flowchart of the introduced GAA is shown in Fig. 1.

GA algorithm needs some modification to become appropriate to optimize the ANN structure, because of the random nature of the Levenberg-Marquardt Algorithm [28] in weights and bias determination, it is probable that an appropriate individual was put out from the GAA due to bad luck in this algorithm process. To overcome this defect, a modification was done in the elite population of the GA approach. Elites are the top 15% (in this study) of chromosomes that transfer directly from one generation to the next one. The GA method was used here to run the elite population several times in order to find the best cost of each chromosome and then transfer the chromosomes to the next generation (Fig. 1). By these modifications of the chromosomes of the elite population, they are not simply changed but are led to preventing the GAA method from trapping in the local minimums and also overcomes the random nature of the Levenberg-Marquardt algorithm.

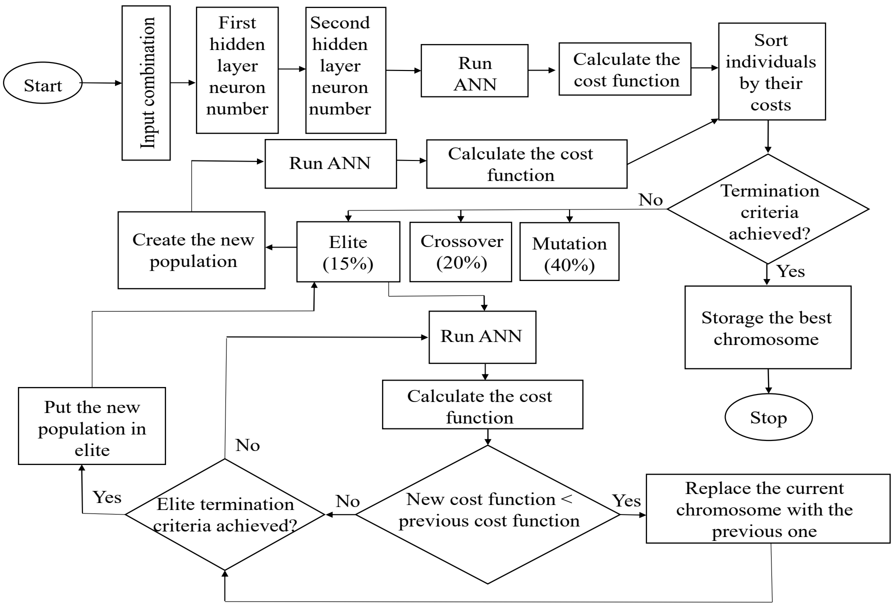

Fig. 1 GAA algorithm

III. Results

Based on the previous studies, the shear stress depends on some parameters such as bed and wall roughness (k_{sb}, k_{sw}), energy slope (S_f), flow velocity (V), channel width (B), flow depth (h), fluid density (ρ), gravitational acceleration (g) and hydraulic radius (R). Thus, the mean wall shear stress can be expressed as:

$$\bar{\tau}_w = F\left(\rho, g, B, h, k_{sb}, k_{sw}, S_f, V\right) \tag{5}$$

Using Buckingham's theorem, the dimensionless parameters affecting shear stress can be expressed as below:

$$\frac{\bar{\tau}_w}{\rho g h S} = f\left(\frac{B}{h}, \frac{k_{sb}}{k_{sw}}, Fr, \mathrm{Re}\right) \tag{6}$$

where B/h is aspect ratio, k_{sb}/k_{sw} relative roughness, Fr, Froude number and Re, Reynolds number.

Finding the most appropriate GAA for modeling, the mean wall shear stress of a rectangular channel was done in three steps (Fig. 2). RMSE and average absolute deviation ($\delta\%$) were used for the performance evaluation of each model. In the first step, by using the four non-dimensional parameters of B/h, k_{sb}/k_{sw}, Fr and Re, different fitness functions were investigated to find the more appropriate one. The assessment and the appropriate fitness functions are the most important processes in soft computing. A comparison was done between Sum of Squared Error (*SSE*), Mean Absolute Error (*MAE*), Mean Squared Error (*MSE*) and correlation coefficient (*R*) fitness functions. The results showed that the *SSE* fitness function performs better than the others.

In the second step, by using the *SSE* fitness function, various input combinations were examined. The comparison between five different input combinations showed that the GAA model that uses B/h, Fr and k_{sb}/k_{sw}, performs better than the others.

Up to now, the investigated models were used as a logarithmic transfer function, (7), in the hidden layers and as the purelin one, (8), in the output layer. In the third step, by using the hyperbolic tangent, (9), logarithmic and purelin transfer functions, four different situations were investigated. The result showed that the GAA model with the logarithmic and purelin transfer functions in hidden and output layers, respectively, exhibits better performance than the other models. It is to be noted that in each of the models that were investigated, the neuron number of hidden layers were determined by the GAA self-structured assigning process and is shown in the parentheses in Fig. 2.

$$logsig(x) = \frac{1}{1+e^{-x}} \tag{7}$$

$$purelin(x) = x \tag{8}$$

$$tansig\,(x) = \frac{2}{1+e^{-2x}} - 1 \tag{9}$$

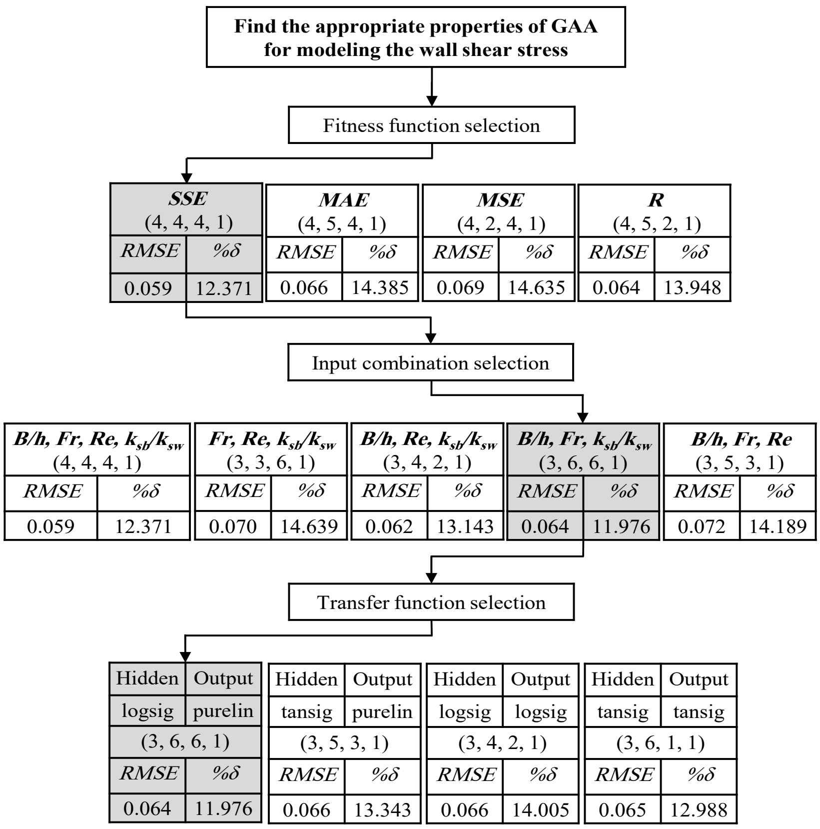

Fig. 2 Finding the appropriate characteristics of GAA

The equation, obtained from the selected GAA with *SSE* fitness function, B/h, Fr and k_{sb}/k_{sw} input combination, logarithmic transfer functions in hidden layers and linear transfer functions in output layer, is shown in (10). The goal of this equation is to calculate the mean wall shear stress of a rectangular channel.

$$\frac{\bar{\tau}_w}{\rho g h S} = purelin((logsig((logsig(input \times iw + b_1)) \times lw + b_2)) \times ow + b_3 \tag{10}$$

$$input = \begin{bmatrix} \frac{B}{h} & Fr & \frac{k_{sb}}{k_{sw}} \end{bmatrix} \tag{11}$$

$$iw = \begin{bmatrix} 0.089 & -0.522 & 0.218 & 0.383 & -0.580 & -0.365 \\ 24.320 & -12.102 & -23.601 & 5.373 & -19.963 & -19.545 \\ -0.001 & 0.000 & -0.001 & 0.000 & 0.000 & -0.008 \end{bmatrix} \tag{12}$$

$$lw = \begin{bmatrix} 0.648 & 0.949 & -0.680 & -1.417 & -5.040 & 4.107 \\ 4.355 & 5.242 & 3.208 & -2.355 & -1.875 & -0.342 \\ 0.586 & 1.199 & -3.648 & 0.834 & -1.412 & -2.529 \\ 4.562 & 1.786 & -1.862 & -4.171 & -2.136 & -5.265 \\ -1.218 & 2.876 & 4.016 & -4.372 & 4.521 & 2.115 \\ -3.706 & 3.409 & 3.504 & 3.483 & 1.084 & 0.776 \end{bmatrix} \quad (13)$$

$$ow = [0.507 \quad 0.674 \quad -0.556 \quad -0.662 \quad 0.474 \quad 0.218]^T \quad (14)$$

$$b_1 = [-12.473 \quad 14.602 \quad 4.974 \quad -1.417 \quad 7.597 \quad 5.817] \quad (15)$$

$$b_2 = [-6.582 \quad -10.532 \quad -2.254 \quad 3.257 \quad 0.069 \quad 4.296] \quad (16)$$

$$b_3 = [0.090] \quad (17)$$

The scatter plot of the selected GAA in the test and train datasets is shown in Fig. 3. In the trend line equation, the $y=C_1x+C_2$, the closer C_1 to 1 and closer C_2 to 0 indicate that the errors of the scatter plot are spread more homogeneously around the exact line, and the model has higher performance. Also, the coefficient of determination (R^2) closer to 1 shows how well the data fit the statistical model. According to Fig. 3 (a), the GAA model in both training and testing processes shows high performance and there is almost no over- or underestimation. Also, the closing performance of GAA in the training and testing processes indicate that no over-fitting has occurred.

The comparison between the Knight [12] proposed equation (1) and the GAA equation (10) for the entire dataset is shown in Fig. 3 (b). From this figure, the trend line equation of the GAA, by C_1 and C_2 of 0.956 and 0.008, respectively, performs much better than that of Knight [12], by C_1 and C_2 of 0.777 and 0.097. In addition, a comparison between the GAA and Knight shows that the Knight shear stress prediction gets trapped in over-estimation in $\frac{\bar{\tau}_w}{\rho ghS} < 0.45$ and under-estimation in $\frac{\bar{\tau}_w}{\rho ghS} > 0.45$, but GAA does not get trapped in any over- or under-estimation.

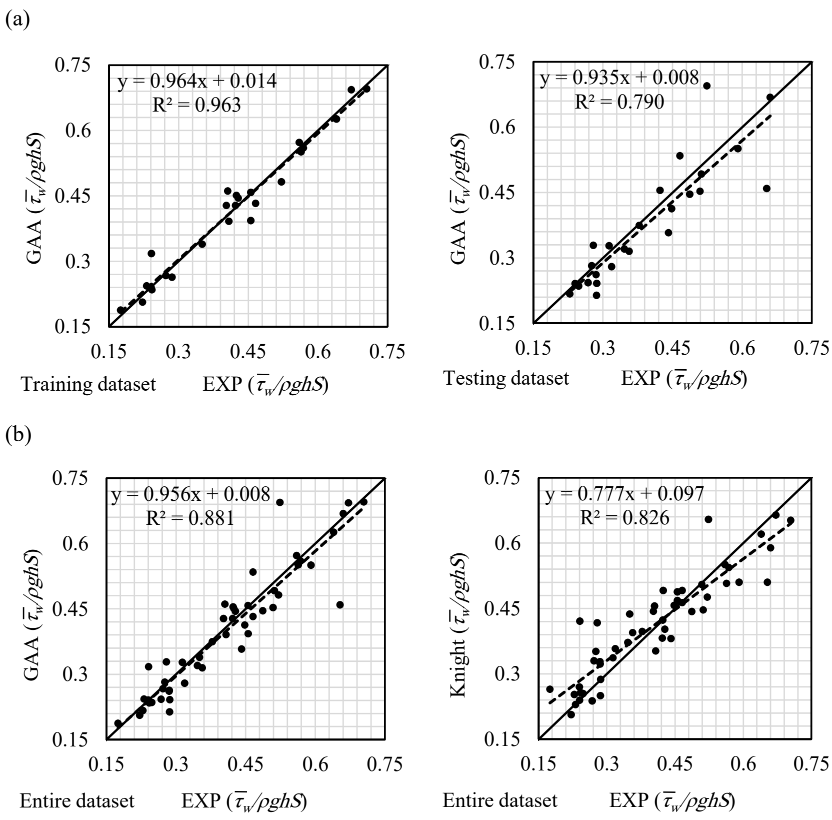

Fig. 3 Scatter plots of (a) GAA model in test and training dataset (b) GAA model and equation by [12] for entire dataset

IV. Conclusion

In this study, a new hybrid combination of ANN and GA is introduced. The GAA method represents a self-structured adjustable process that is determined by the hidden layers neuron number by applying a modified GA. The GAA method is employed to predict the mean wall shear stress of a rectangular channel. There are no comprehensive soft computing studies available about shear stress prediction. The GAA fitness function, input combination and transfer functions were adjusted, and the equation that was obtained from the selected GAA is presented. The results of comparison between the GAA results and the traditional equation of Knight [12] show that the GAA method could predict the mean wall shear stress of the rectangular channel with higher accuracy and represents more acceptable results. Because of the non-dimensional input parameters of the GAA equation, it could be used in practical situations and other studies around the mean wall shear stress prediction without concern of scale variation.

References

[1] N. Chien N, Z. H. Wan Mechanics of sediment transport, ASCE press, New York, USA (1999).

[2] P. Y. Julien Erosion and sedimentation, Cambridge University Press, Cambridge, U.K. (1995).

[3] S. R. Khodashenas, A. Paquier, River bed deformation calculated from boundary shear stress, J. Hydraul. Res. 40(5) (2002) 603-609.

[4] D. W. Knight, K. W. H. Yuen, A. A. I. Al Hamid, Boundary shear stress distributions in open channel flow, In: Physical Mechanisms of Mixing and Transport in the Environment, (K Beven, P Chatwin, J Millbank (eds)) Wiley New York, pp.51-87 (1994).

[5] T. P. Flintham, P. A. Carling, The prediction of mean bed and wall boundary shear in uniform and compositely rough channels, Proc. Int. Conf. River Regime, Wiley, Chichester, 1988.

[6] S. N. Ghosh, N. Roy, Boundary Shear Distribution in Open Channel Flow, J. Hydraul. Div. 96 (4) (1970) 967-994.

[7] I. Nezu, H. Nakagawa, Turbulence in open channel flows, IAHR Series, A. A. Balkema, Rotterdam, The Netherlands (1993).

[8] W. R. C. Myers, Momentum transfer in a compound channel, J. Hydraul. Res. 16 (2) (1978) 139-150.

[9] D. W. Knight, J. A. Macdonald, Open channel flow with varying bed roughness, J. Hydraul. Div. 105 (9) (1979) 1167-1183.

[10] D. W. Knight, J. D. Demetriou, M. E. Hamed, Boundary shear stress in smooth rectangular channel, J. Hydraul. Eng. 10 (4) (1984) 405-422.

[11] G. Seckin, N. Seckin, R. Yurtal, Boundary shear stress analysis in smooth rectangular channels, Can. J. Civ. Eng. 33 (2006) 336-342.

[12] D. W. Knight, Boundary shear in smooth and rough channels, J. Hydraul. Div. 107 (7) (1981) 839-851.

[13] Cokljat D, B.A. Younis, Second-order closure study of open-channel flows, J. Hydraul. Eng. 121(2) (1995) 94-107.

[14] Y. Zheng, Y. C. Jin, Boundary shear in rectangular ducts and channels, J. Hydraul. Eng. 124(1) (1998) 86-89.

[15] A. R. Zarrati, Y. C. Jin, S. Karimpour, Semianalytical model for shear stress distribution in simple and compound open channels, J. Hydraul. Eng. 134 (2) (2008) 205-215.

[16] K. Yang, R. Nie, X. Liu, S. Cao, Modeling Depth-Averaged Velocity and Boundary Shear Stress in Rectangular Compound Channels with Secondary Flows, J. Hydraul. Eng. 139 (1) (2013) 76-83.

[17] H. Bonakdari, Z. Sheikh, M. Tooshmalani, Comparison between Shannon and Tsallis entropies for prediction of shear stress distribution in circular open channels, Stoch. Environ. Res. Risk Assess. 29 (1) (2015) 1-11.

[18] M. I. Komurcu, N. Tutkun, I. H. Ozolcer, A. Akpinar, Estimation of the beach bar parameters using the genetic algorithms, Appl. Math. Comput. 195 (2008) 49-60.

[19] O. Kisi, J. Shiri, Sh. Shamshirband, Sh. Motamedi, D. Petkovic, R. Hashemi, A survey of water level fluctuation predicting in Urmia Lake using support vector machine with firefly algorithm, Appl. Math. Comput. 270 (2015) 731-743.

[20] Z. Sheikh Khozani, H. Bonakdari, A. H. Zaji, Application of soft computing technique in prediction percentage of shear force carried by walls in rectangular channel with Non-homogenous roughness, Water Sci. Technol. DOI: 10.2166/wst.2015.470.

[21] Z. Sheikh Khozani, H. Bonakdari, I. Ebtehaj, An analysis of shear stress distribution in circular channels with sediment deposition based on Gene Expression Programming, Int. J. Sediment Res. 32 (2017) 575-584.

[22] O. Kisi, A. Hosseinzadeh Dailr, M. Cimen, J. Shiri, Suspended sediment modeling using genetic programming and soft computing techniques, J. Hydrol. 450-451 (2012) 48-58.

[23] Z. Sheikh Khozani, H. Bonakdari, A. H. Zaji, Application of a genetic algorithm in predicting the percentage of shear force carried by walls in smooth rectangular channels, Measurement. 87 (2016) 87-98.

[24] A. H. Zaji, H. Bonakdari, Application of artificial neural network and genetic programming models for estimating the longitudinal velocity field in open channel junctions, Flow. Meas. Instrum. 41 (2015) 81-89.

[25] O. Kisi, The potential of different ANN techniques in evapotranspiration modelling, Hydrol. Process, 22 (2008) 2449-2460.

[26] O. Bilhan, M. Emin Emiroglu, O. Kisi, Application of two different neural network techniques to lateral outflow over rectangular side weirs located on a straight channel, Adv. Eng. Softw. 41(83) (2010) 1-7.

[27] O. Kisi, H. Kerem Cigizoglu, Comparison of different ANN techniques in river flow prediction, Civ. Eng. Environ. Syst. 24 (2007) 211-231.

[28] K. Levenberg, A method for the solution of certain non-linear problems in Least-Squares, Qu. Appl. Math. 2 (1944) 164-168.