



An ANFIS-based Approach for Predicting the Manning Roughness Coefficient in Alluvial Channels at the Bank-full Stage

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ABSTRACT

An intelligent method based on adaptive neuro-fuzzy inference system (ANFIS) for identifying Manning's roughness coefficient, n , in modeling of alluvial channels e.g. rivers is presented. The procedure for selecting values of the Manning n is subjective and requires engineering judgments and skills developed primarily through experience. During practical applications, researchers often find that a correct choice of the Manning n can be crucial to make a sound prediction of hydraulic problems. In this paper, an ANFIS model is set up to predict the Manning coefficient of river channels, with the mean bed particle size, mean flow depth and channel bed slope, as some three input parameters. The regression equations are also applied to the same data. Statistic measures are then used to evaluate the performance of the models. Based on the comparison of the results, it is well found that the ANFIS model presented here gives some better estimates than the other empirical relationships. Also, a sensitivity analysis showed that mean flow depth has a greater influence on the Manning coefficient than the other independent parameters in ANFIS model.

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1. INTRODUCTION

The Manning n is a coefficient which represents the roughness or friction applied to the flow by the channel. The procedure for selecting values of Manning's n is subjective and requires judgment and skill which are developed primarily through experience. Governmental agencies and private sectors in developed nations such as the USA are still doing research on predicting n values for rivers [1]. The Manning equation is an empirical equation that is applied to uniform flow in open channels to calculate mean water velocity and is a function of the channel velocity, hydraulic radius and channel slope. The Manning formula is also known as the Gauckler–Manning formula, or Gauckler–Manning–Strickler formula in Europe. It was first presented by a French engineer Philippe Gauckler in 1867, and later re-developed by the Irish engineer Robert Manning in 1890. The Gauckler–Manning formula states (in SI units):

$$V = \frac{1}{n} R^{2/3} S^{1/2} \quad (1)$$

where, V is the cross-sectional average velocity (m/s), n is the Gauckler–Manning coefficient, R is the hydraulic radius (m) and S is slope of the water surface or channel bed slope (m/m). Hydraulic radius, R , is defined as the ratio of the channel cross-sectional area, A , to its wetted perimeter, P . The discharge formula $Q=AV$, can be used to manipulate Gauckler–Manning's equation by substitution for V . Solving for Q then allows an estimate of the volumetric flow rate (discharge) without knowing the limiting or actual flow velocity. The Gauckler–Manning coefficient, often denoted as n , is an empirically derived coefficient, which is dependent on many factors, including surface roughness and sinuosity [2]. In natural streams, n values vary greatly along its reach, and will even vary in a given reach of channel with different stages of flow. By the year 1997, it was also considered by Mohammadi. Most researches show that n will decrease with stage, at least up to bank-full. Overbank n values for a given reach will vary greatly depending on the time of year and the velocity of flow. Summer vegetation will typically have a significantly

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higher n value due to leaves and seasonal vegetation. Research has shown, however, that n values are lower for individual shrubs with leaves than for the shrubs without leaves [3]. This is due to the ability of the plant's leaves to streamline and flex as the flow passes them thus lowering the resistance to flow. High velocity flows will cause some vegetation (such as grasses and forbs) to lay flat, where a lower velocity of flow through the same vegetation will not cause it [4].

Manning n is often assumed to be a constant that is independent of either flow discharge or depth [1]. However, Chow [5] indicates that the value of n is highly variable and depends on a number of factors: (1) surface roughness – fine sediment size such as sand will result in a relatively low value of n and coarse sediments such as gravels, in a high value of n ; (2) vegetation – may also be regarded as a kind of surface roughness depending on the height, density, distribution and type of vegetation; (3) channel irregularity – comprises irregularities in wetted perimeter and variations in cross section, size and shape along the channel length. A gradual and uniform change in cross section, size and shape will not appreciably affect the value of n ; (4) channel alignment – smooth curvature with large radius will give a relatively low value of n ; (5) silting and scouring – silting may change a very irregular channel into a comparatively uniform one and decrease n , whereas scouring may do the reverse and increase n ; (6) obstruction – the presence of log jams, bridge piers, and the like tends to increase n ; (7) size and shape of channel – an increase in hydraulic radius may either increase or decrease n depending on the condition of the channel; and (8) stage and discharge – n value in most streams decreases with increase in stage and discharge [1]. However, the n value may be large at high stages if the banks are rough and grassy.

Chow [5] suggested three values (minimum, normal, maximum) of n for each kind of channel. Table 1 gives values of n from Chow [5] relevant to the present study (at bankfull stage).

The term bankfull was originally used to describe the incipient elevation on the bank where flooding begins. In many stream systems, the bankfull stage is associated with the flow that just fills the channel to the top of its banks and at a point where the water begins to overflow onto a floodplain [6]. The most common definition of bankfull stage is the elevation of the active floodplain [7]. Another common definition of bank-full stage is the elevation where the width to depth ratio is a minimum [8]. In the field bankfull stage defines the boundary between the active channel which carries the systems sediment and floodplain features which dissipate energies of higher flows. A number of inventory, assessment, and design strategies have been developed utilizing the bankfull stage concept [9]. Figure 1 shows schematic view of bankfull level in a typical cross section.

TABLE 1. Suggested Manning's n for natural streams (after Chow [5])

Type of channel and description	Minimum	Normal	Maximum
Clean, straight, full stage, no rifts or deep pools	0.025	0.030	0.033
Same as above, but more stones and weeds	0.030	0.035	0.040
Clean, winding, some pools and shoals	0.033	0.040	0.045
Same as above, but some stones and weeds	0.035	0.045	0.050
Same as above, but more stones	0.045	0.050	0.060
Same as above, lower stages, more ineffective slopes and section	0.040	0.048	0.055
Sluggish reaches, weedy, deep pools	0.050	0.070	0.080

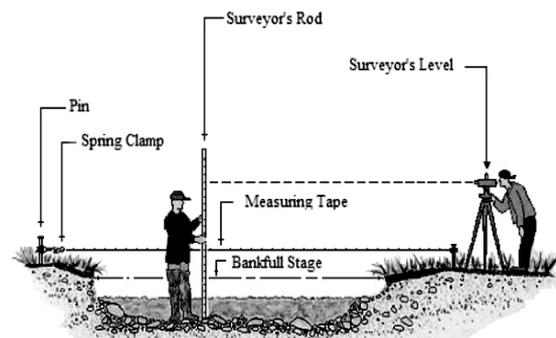


Figure 1. Schematic view of bankfull level in a typical cross section [10]

Due to complexities of physical processes, the exact value of Manning's n in Manning equation, is often uncertain. Many empirical formulations for estimating the n value in practical problems have been suggested in the past. Due to the difficulties in determining the values of empirical parameters, estimation of these parameters in modeling large scale problems are tedious, time-consuming, and with a high degree of uncertainties [11]. Currently, there are various Manning coefficient equations that have been developed based on different approaches to predict n . It is still difficult to obtain a general equation to provide accurate estimation of Manning coefficient due to a lack of knowledge of some physical processes associated with channel formation and maintenance.

In recent years, the new procedures of intelligent techniques such as fuzzy logic, artificial neural networks (ANN), neuro-fuzzy, genetic programming, decision support systems, support vector machines, and

fuzzy genetic programming used to describe different complex problems in various branches of science. One of the most practical methods of these new procedures is adaptive neuro-fuzzy inference system (ANFIS). In the previous years, the fuzzy logic has been used in the water resources and environmental engineering such as river pollution management [12], water demand forecasting [13], wastewater treatment [14], hydrological time-series modelling [15], stage-discharge-sediment concentration [16], modeling monthly mean flow in a poorly gauged basin [17], flood forecast model [18], suspended sediment estimation [19, 20], modelling of evaporation from the reservoir [21], fluvial hydraulics [22], forecasting of river flow [23], and scour depth prediction [24].

To the best knowledge of authors, no work has been reported in the literature that addresses the application of ANFIS approach for the estimation of Manning coefficient in alluvial channels at the bankfull stage. This provided an impetus for the present investigation. In this research, first, using a field database, schemes of ANFIS model were trained, and then an empirical equation was derived by regression analysis from the same data. Finally, this study regression equation, other proposed equations and ANFIS model were compared with other field database based on mean square error (MSE) and determination coefficient (R^2).

2. MATERIALS AND METHODS

2.1. ANFIS Model The concept of Fuzzy Logic (FL) was conceived by Zadeh [25] and presented not as a control methodology, but as a way of processing data by allowing partial set membership rather than crisp set membership or non-membership.

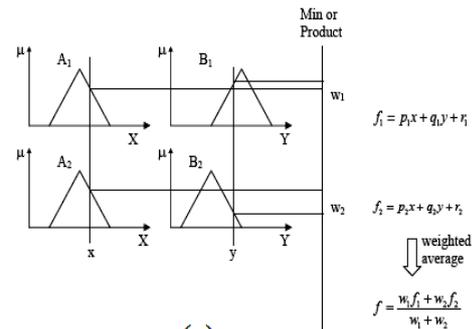
The ANFIS is the abbreviated of adaptive neuro-fuzzy inference system. ANFIS, first introduced by Jang [26], is a universal approximator and, as such, is capable of approximating any real continuous function on a compact set to any degree of accuracy [27]. Actually, this method is like a fuzzy inference system with this different that here a backpropagation is used which tries to minimize the error. The performance of this method is like both ANN and FL. In both ANN and FL case, the input pass through the input layer (by input membership function) and the output could be seen in output layer (by output membership functions). Since, in this type of advanced fuzzy logic, neural network has been used, therefore, by using a learning algorithm the parameters are changed until the optimal solution is reached. Actually, in this type the FL tries by using the neural network advantages to adjust its parameters. As we know, the difference between real and network output in ANN is one of the common methods to evaluate its performance [28]. Therefore, ANFIS uses either

backpropagation or a combination of least squares estimation and backpropagation for membership function parameter estimation [27]. Some of the definitions are necessary to know which are described in the following paragraphs:

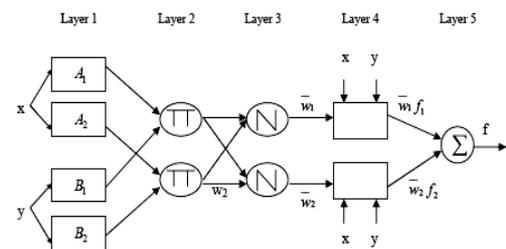
Membership Function: is a function through which it would be possible to present the input. The aim of using this function is by using the weights which is with the inputs, the functional overlap between the inputs would be defined and lead to output determination.

Rules: is some instruction which through them it would be possible for input that by using the membership values and their definitions, give the final output.

It is a network statement of Sugeno-type fuzzy models and is introduced by Jang [26]. The structure of an ANFIS is shown in Figure 2. Figure 2 (a) shows the fuzzy reasoning mechanism for the Sugeno model to derive an output function f from a given input vector $[x,y]$. The corresponding equivalent ANFIS construction is shown in Figure 2 (b).



(a)



(b)

Figure 2. Structure of ANFIS system:
 (a) Fuzzy inference system;
 (b) Equivalent ANFIS architecture [29]

Let x and y be the two typical input values fed at the two input nodes, which will then transform those values to the membership functions (say bell-shaped) and give the output as follows. (Note in general, w is the output from a node, m is the membership function, and M_i and N_i are fuzzy sets associated with nodes x, y).

$$\mu_{M_i}(x) = \frac{1}{1 + |(x - c_i) / a_i|^{2N_i}} \quad (2)$$

where; a_1 , b_1 , and c_1 are changeable premise parameters. Similar computations are carried out for the input of y to obtain $\mu_{N_i}(y)$. The membership functions are then multiplied in the second layer, e.g:

$$w_i = \mu_{M_i}(x) \cdot \mu_{N_i}(y) \quad (i=1,2) \quad (3)$$

where, x (or y) is the input to the node; M_i (or N_i) is a linguistic label (such as ‘low’ or ‘high’) associated with this node, characterized by the form of the membership functions in this node and can be any suitable function that is continuous and piecewise differentiable such as Gaussian, trapezoidal shaped, generalized bell shaped and triangular shaped functions. Figure 3 shows membership functions in this study.

Such products or firing strengths are then averaged:

$$\bar{w}_i = w_i / \sum w_i \quad (i=1,2) \quad (4)$$

Nodes of the fourth layer use the above ratio as a weighting factor. Furthermore, using fuzzy if-then rules produces the following output: (an example of an if-then rule is: if x is M_1 and y is N_1 , then $f_1 = p_1x + q_1y + r_1$)

$$\bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i) \quad (i=1,2) \quad (5)$$

where; p , q and r are changeable consequent parameters. The final network output f was produced by the node of the fifth layer as a summation of all incoming signals, which is exemplified in Eq. (5). A two-step process is used for faster training and to adjust the network parameters to the above network. In the first step, the premise parameters are kept fixed, and the information is propagated forward in the network to layer 4. In layer 4, a least-squares estimator identifies the important parameters.

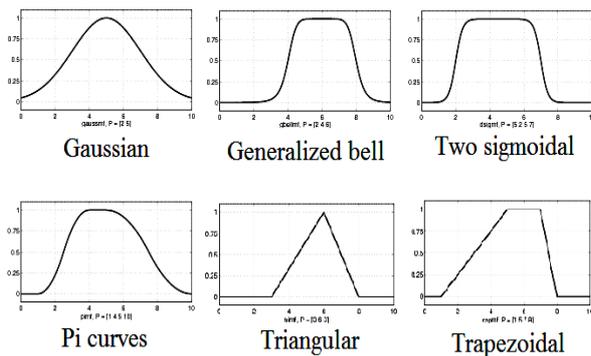


Figure 3. Membership functions in this study

In the second step, the backward pass, the chosen parameters are held fixed while the error is propagated. The premise parameters are then modified using gradient descent. Apart from the training patterns, the

only user-specified information required is the number of membership functions for each input. The description of the learning algorithm is given in Kisi [29], Azmatullah et al. [30] and Tahmasebi and Hezarkhani [28].

2. 2. Database The total data set of 661 measurements covers a wide range of flow conditions of sand, gravel and cobble bed channels. All 661 available data points were split randomly into two separate individual groups: training and testing. Therefore, 561 data points which describe alluvial channels were used for models training and validation and the remaining 100 data points were used for testing or comparison of models. Also, in total data set, 124 and 537 data points were sandy and gravel bed channels, respectively. The data includes Simons [31], Kellerhals et al. [32], Charlton et al. [33], Church and Rood [34], Andrews [35], Bathurst [36], Van den berg [37], Soar and Thorne [38], Pitlick and Cress [39], Parker et al. [40], Mccandless [41], Rinaldi [42], Wohl et al. [43], Wohl and Wilcox [44], Parola et al. [45], Sherwood et al. [46], Christiane et al. [47], Arbeláez et al. [48] and Kallio [49]. Table 2 shows the ranges of the used dataset for all applying groups (Training and Testing).

2. 3. Application of ANFIS for Estimating n The following scenarios are considered in building the ANFIS model (see Figure 4) with the inputs and output shown in the network. From the group of training data sets used in this study, around 80% were used for training (chosen randomly until the best training performance was obtained), while the remaining patterns (20%) were used for validating the ANFIS model. The method involves the training of ANFIS with bankfull discharge (Q), median size of bed particles (d_{50}), and channel slope (S) as input and the Manning coefficient (n) as output.

TABLE 2. Data range in this study (Total 661 measurements)

Notations	Training data	Testing data
Number of data	561	100
W (m)	1.25-832	1.25-104
Q (m ³ /s)	0.137-16950	1.2-510
S (-)	0.00004-0.2	0.00005-0.031
D50 (m)	0.00003-0.4	0.00019-0.176
n	0.003-0.2	0.014-0.1
h (m)	0.1-14	0.2-3.2
V (m)	0.1-8.6	0.58-3.27
τ^* (-)	0.0004-1.6	0.0005-0.52

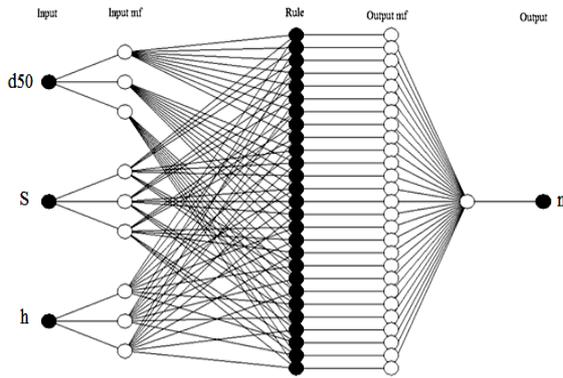


Figure 4. Adaptive neuro-fuzzy structure in this study

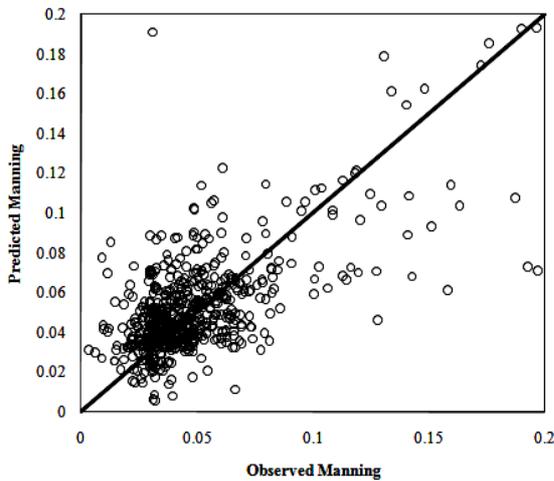


Figure 5. Agreement between observed and predicted values in training process

TABLE 3 . Data range in this study (Total 661 measurements)

Membership function	Performance in training process	
	R ²	MSE (×10 ⁻³)
Gaussian	0.70	1.83
Bell	0.68	1.94
Two sigmoid	0.68	2.23
Pi curves	0.66	2.91
Triangular	0.65	3.85
Trapezoidal	0.67	2.92

The performance of models configurations was evaluated based on coefficient (R²) and mean-square error (MSE) of the linear regression line between the predicted values from the neural network model and the desired outputs, as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^P (O_i - t_i)^2}{\sum_{i=1}^P (O_i - \bar{O}_i)^2} \tag{6}$$

$$MSE = \frac{\sum_{i=1}^P (O_i - t_i)^2}{P} \tag{7}$$

where O_i and t_i are target and network output for the i^{th} output, \bar{O}_i is the average of target outputs, and P is the total number of considered events.

Training of neuro-fuzzy has several steps. At the first step of training, the initial fuzzy sets should be determined. During training, all of the training dataset would be present to network and it tries by learning the spatial relationship between the data minimize the error. Sometime lower error could not guaranty the better performance of network and it may be because of network overtraining [28]. By error monitoring of training dataset, it would be possible to supervise on network training. The objective function which has been used here is MSE. Definitely, the aim of using this network or the entire models is to reach the smallest error and also it is true here.

According to the strategy based on the rank of MSE, several networks were investigated to obtain the desired structure that was done according to our base. As mentioned earlier, three type fuzzy membership functions were selected to describe the input and output variables. This is translated in 33 = 27 rules (regarding the three inputs with three fuzzy sets) as shown in Figure 3.

One of the most important steps in neuro-fuzzy modeling is the fuzzy membership values definition. As mentioned earlier, some membership functions specified by three parameters were used in the present model. There are six membership functions, Gaussian, Bell, two sigmoid, pi curves, triangular and trapezoidal membership functions. MSE is used to determine how much the network has reached the desired output values. Results show that network with Gaussian membership function can estimate Manning coefficient of alluvial channels at the bankfull stage better than other functions. Table 3 shows performance of proposed ANFIS model. Also, Figure 5 shows results of ANFIS model versus observed data in training process.

2. 4. Sensitivity Analysis The sensitivity tests are commonly carried out to ascertain the relative significance of each independent parameter. The results of sensitivity analysis for the Manning coefficient parameters are shown in Table 4. This table provides a comparison between the ANFIS model (with Gaussian membership function) of all independent parameters and ANFIS model having one of the independent variables removed in each case.

TABLE 4. Sensitivity analyses of the ANFIS model

Parameter	Performance in training process	
	R ²	MSE (×10 ⁻³)
All	0.70	1.83
No h	0.13	4.23
No S	0.14	4.60
No d50	0.62	2.34

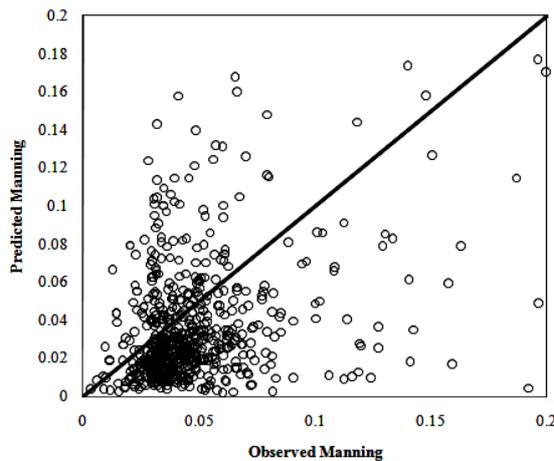


Figure 6. Agreement between observed and predicted values for regression equation

Table 4 indicates that h and d50 have respectively the most and the least effects on the Manning coefficient (n). These results are consistent with the current understanding of the relative importance of the various parameters on the Manning coefficient of alluvial channels.

2. 5. Regression Analysis for Estimating Manning’s Coefficient

A nonlinear regression method was used to get the regression between parameters and Manning coefficient equation using 80% data after removing the outliers in the data set. It leads to the following equation for estimation of n in alluvial channel at the bankfull stage.

$$n = 1.24h^{1.251} S^{1.012} d_{50}^{-0.474} \tag{8}$$

Figure 6 shows results of regression equation versus observed data for regression equation.

The range of applicability of the proposed Manning coefficient equation is a channel width 0.1<W<850 m, bankfull discharge 0.1<Q<17000 m³/s, mean flow depth 0.05<h<14 m, mean flow velocity 0.01<V<9 m/s, mean bed particle size 0.00003<d50<0.4 m, channel slope 0.00004<S<0.2 and 0.02<τ*<1.6, respectively.

3. RESULTS AND DISCUSSION

Several available equations to predict values of n for rivers can be found in the work done by Ghani et al. [1]. These equations can be categorized as: (1) equations that are based on bed sediment size; (2) equations that are based on the ratio of flow depth or hydraulic radius over sediment size; and (3) equations that includes water-surface slope besides bed sediment size and hydraulic radius or flow depth [1]. In these equations the mean flow depth of channel (h), instead of the hydraulic radius (R) is used. As it can be seen from the above reasoning, R is physically more significant than h for narrow channels. Nevertheless, almost all practical cases are referred to wide channels, in which it is possible to accept the approximation: R=h [50].

TABLE 5. Comparison of equations

Input Parameter	Reference	Equation	R ² Training	R ² Testing	MSE Testing (×10 ⁻³)
D50	Strickler [51]	$n = \frac{1}{21.1} d_{50}^{1/6}$	-	0.18	2.25
d50, R or h	Limerinos [52]	$n = \frac{0.113R^{1/6}}{0.35 + 2 \text{Log}_{10}(R/d_{50})}$	-	0.04	4.40
	Bray [53]	$n = \frac{0.113h^{1/6}}{1.09 + 2.2 \text{Log}_{10}(h/d_{50})}$	-	0.18	1.96
d50, S and R	Brownlie [54]	$n = \left[1.893(R/d_{50})^{0.1374} S^{0.1112} \right] \times 0.034 \times d_{50}^{0.167}$	-	0.31	1.98
	Bruschin [54]	$n = (d_{50}^{1/6} / 12.38) \times (S \times R / d_{50})^{1/7.3}$	-	0.32	1.79
d50, S and h	This study	$n = 1.24h^{1.251} S^{1.012} d_{50}^{-0.474}$	0.50	0.62	1.13
	This study	ANFIS model	0.70	0.74	0.53

A comparison of ANFIS model with empirical equations has been carried out to assess the accuracy of the intelligent models over the regression methods in the prediction of the Manning's coefficient at the alluvial channels using the testing data. As mentioned earlier, Table 2 shows range of effective hydraulic parameters in testing data set.

In the present study, five empirical equations accompanied by this study regression equation and ANFIS model were evaluated based on the MSE and R2. These equations are shown in Table 5. Also, Figures 7-13 show Manning coefficient prediction in each method, respectively. It can be seen that the ANFIS model predicted the Manning coefficient better than other methods.

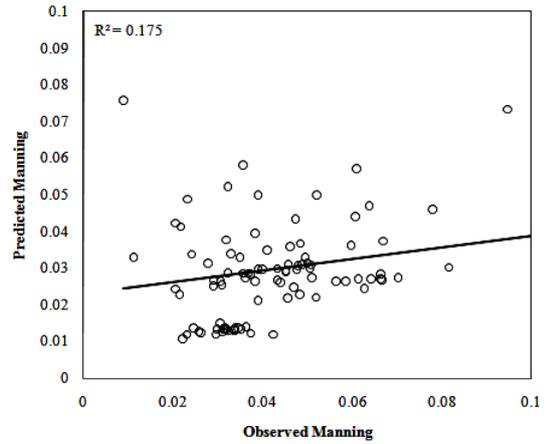


Figure 9. Plot of observed and predicted n for equation of Bray [52]

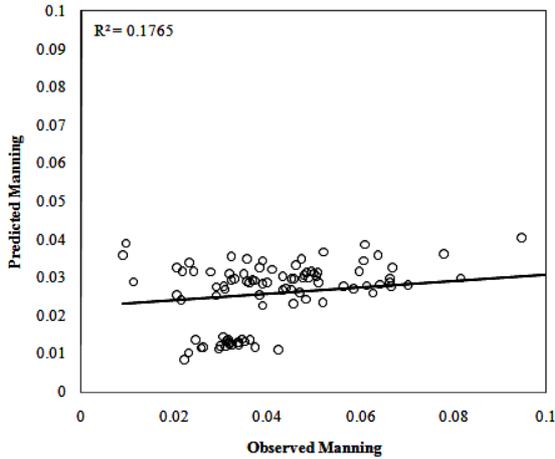


Figure 7. Observed values of n versus predicted values by equation of Strickler [51]

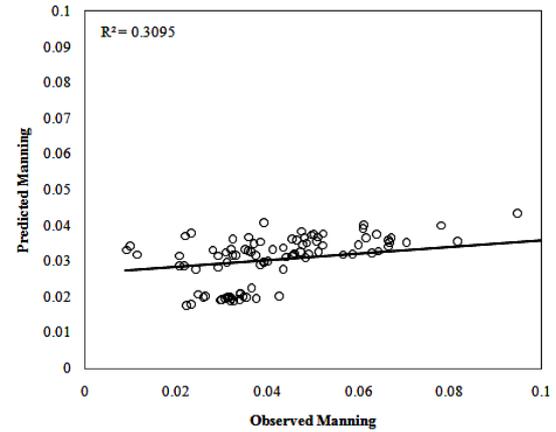


Figure 10. Plot of observed and predicted n for equation of Brownlie [54]

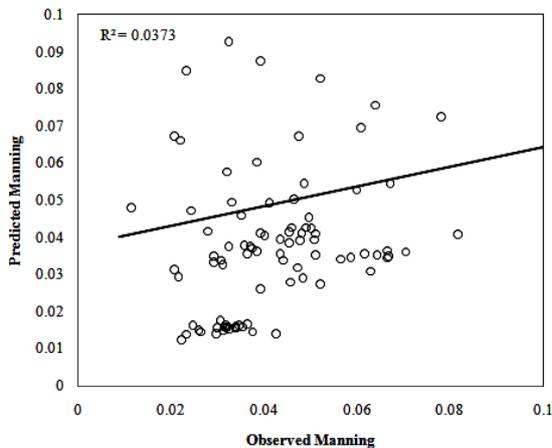


Figure 8. Plot of observed and predicted n for equation of Limerins [52]

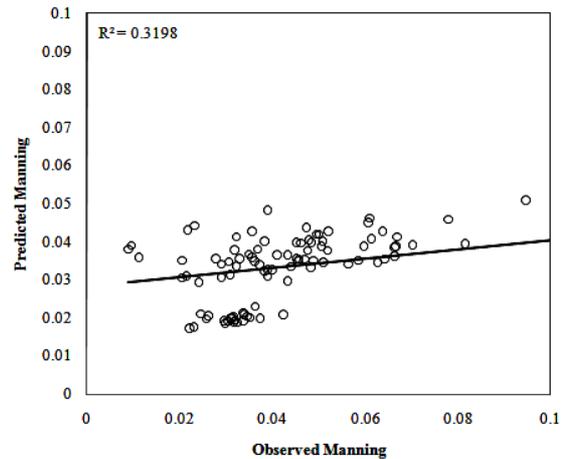


Figure 11. Plot of observed and predicted n for equation of Bruschin [54]

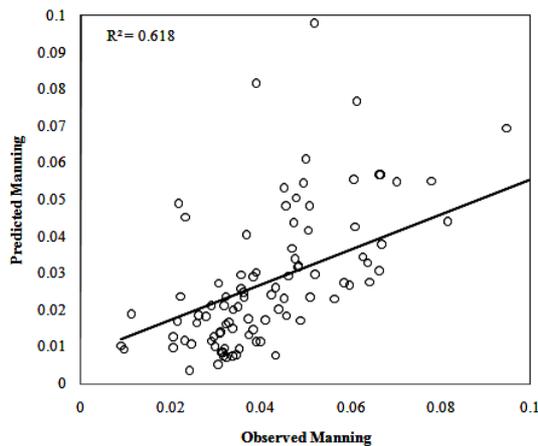


Figure 12. Plot of observed and predicted n for equation of this study

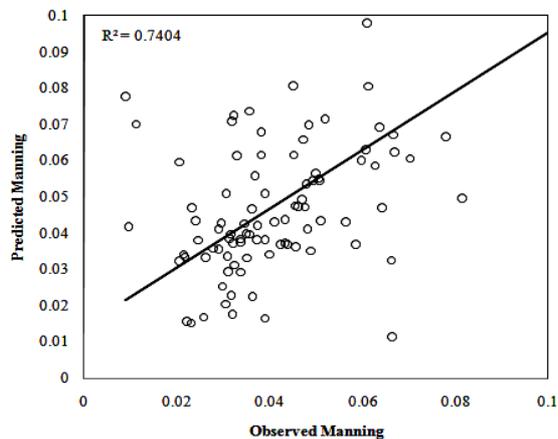


Figure 13. Plot of observed and predicted n for ANFIS model

4. CONCLUSIONS

This study indicates the ability of adaptive neuro-fuzzy inference system (ANFIS) model to predict the Manning coefficient of alluvial channels. The ANFIS model performs better than the regression equations (Empirical formulas) in estimation of Manning's coefficient in open channels. The ANFIS with Gaussian membership function was selected as optimum model to predict Manning coefficient. Also, sensitivity analysis of ANFIS model demonstrated that h and d_{50} have respectively the most and the least effect on the Manning coefficient (n). The results of the study are highly encouraging and suggest that an adaptive neuro-fuzzy approach is viable for modeling Manning's coefficient of alluvial channels. The study only used a few field data points of alluvial channels from available literature and further works using more data from various channels may be required to strengthen these conclusions.

5. ACKNOWLEDGEMENTS

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An ANFIS-based Approach for Predicting the Manning Roughness Coefficient in Alluvial Channels at the Bank-full Stage

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در این مقاله یک روش هوشمند مبتنی بر سیستم استنتاج فازی عصبی تطبیقی (ANFIS) برای تشخیص ضریب مقاومت مانینگ در مدل سازی کانال های آبرفتی مثل رودخانه ها ارائه شده است. روش انتخاب مقادیر n مانینگ ذهنی بوده و نیاز به قضاوت ها و مهارت های مهندسی دارد که عمدتاً از طریق تجربه میسر است. در کاربردهای عملی، محققان اغلب میدانند که انتخاب صحیح n مانینگ در بررسی مسائل هیدرولیکی می تواند بسیار مهم و اساسی باشد. در این مقاله، یک مدل ANFIS برای پیش بینی ضریب مانینگ در کانال های آبرفتی، با استفاده از اندازه متوسط ذرات بستر، میانگین عمق جریان و شیب کف کانال به عنوان پارامترهای ورودی تشکیل گردید. معادلات رگرسیون نیز به همان داده ها اعمال شد. آنگاه مقایسه های آماری برای ارزیابی عملکرد مدل ها مورد استفاده قرار گرفت. براساس مقایسه نتایج، نشان داده می شود که مدل ANFIS برآورد بهتری نسبت به سایر روابط تجربی دارد. همچنین، تجزیه و تحلیل حساسیت نشان داد که میانگین عمق جریان تاثیر بیشتری بر ضریب زبری مانینگ نسبت به دیگر پارامترهای مستقل در مدل ANFIS دارد.

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