Journal of Applied Research in Water and Wastewater 11(2019) 8-15

Journal of
Applied Research in Water and Wastewater

Journal homepage: www.arww.razi.ac.ir

Original paper

Prediction of the hydraulic jump length on sloping rough beds using meta-heuristic neuro-fuzzy model and differential evolution algorithm

Rahim Gerami Moghadam, Behrouz Yaghoubi*, Mohammad Ali Izadbakhsh, Saeid Shabanlou

Department of Water Engineering, Kermanshah Branch, Islamic Azad University, Kermanshah, Iran.

ARTICLE INFO

Article history:
Received 7 December 2018
Received in revised form 13 February 2019
Accepted 25 February 2019

Keywords:
ANFIS
Rough Bed
Sloping Channel
Hydraulic jump
Differential Evolution Algorithm

ABSTRACT

Generally, Hydraulic jumps usually happen at the downstream of hydraulic structures like ogee spillways. In addition, one of the parameters affecting the proper design of stilling basin is calculation of the hydraulic jump length. In this study, a hybrid method (ANFIS-DE) was proposed for modeling hydraulic jumps on sloping rough beds for first time. This approach forecasts values of the jump length by combining the Adaptive Neuro-Fuzzy Inference System (ANFIS) and the Differential Evolution (DE) algorithm. First, the variables affecting the hydraulic jump length including the ratio of bed roughness, the Froude number, the ratio of sequent depths and the bed slope were identified. Then, by combining the input parameters, five different numerical models were introduced. Furthermore, the k-fold cross validation (k=4) was utilized so as to verifying the numerical models. The results of the analysis of different numerical models indicated that the model with four input parameters (superior model) simulated the length of the hydraulic jump with higher accuracy. For the best model, the mean absolute percent error (MAPE), the correlation coefficient (R) and the root mean square error (RMSE) were predicted 4.875, 0.978 and 0.807, respectively. Finally, two parameters including the ratio of sequent depths and the Froude number were identified as the most important parameters in modeling the hydraulic jump length on sloping rough beds.

1. Introduction

Hydraulic jumps occur after structures like ogee spillways in order to dissipate the flow energy. To prevent an ogee spillway downstream from flooding and erosion, stilling basin are usually installed. Prediction of hydraulic jump characteristics is very important for determining dimensions of stilling basin. There are various studies carried out on the hydraulic jump due to its importance. For example, Hager (1985) experimentally examined the behavior of the hydraulic jump inside a horizontal and non-prismatic rectangular channel. In addition, Hager et al. (1990) suggested a relationship predicting the roller length as the Froude number was range between 2.5 to 8. The relationship predicted the roller length as a function of the Froude number at the hydraulic jump upstream. Ead and Rajaratnam (2002) conducted an experimental investigation on hydraulic jumps on labyrinth beds. In their experimental model, the range of the Froude number at the hydraulic jump upstream was between 4 and 10. They studied the features of the hydraulic jump in three relative roughness conditions including 0.25, 0.43 and 0.5 and showed that the shear stress on rough beds are three times greater than smooth beds. Additionally, Carollo et al. (2007) by conducting an experimental work, examined the features of the hydraulic jump on rough and smooth beds. They proposed an equation in terms of the Froude number and relative roughness for calculating the roller length. Also, Pagliara et al. (2008) experimentally examined the hydraulic jumps in rectangular channels located on non-homogeneous and homogeneous rough beds and provided a number of relationships for calculating the roller length. Their relationships predicted the roller length as a function of the Froude number and bed roughness. Furthermore, Carollo et al. (2009) developed an analytical approach for computing hydraulic jumps. They proposed some relationships for calculating sequent depths of the jump on rough and smooth beds. Moreover, Carollo et al. (2013) surveyed the sequent depths of B-jump hydraulic jumps for both rough and smooth beds in sloping flumes. Also, Ahmed et al. (2014) examined the effect of rough beds on the characteristics of jumps. They proposed a relationship in terms of the Froude number to predict the roller length of hydraulic jumps. Velioglu et al. (2015) examined the hydraulic jumps on rough beds. They showed that bed roughness causes to reduce the tailwater of the hydraulic jump. In recent years, soft computing has been significantly employed in predicting various engineering phenomena (Naderpour et al. (2018), Naderpour and Alavi (2017)). Furthermore, soft computing techniques have been used for modeling the characteristics of hydraulic jumps. For example, Omid et al. (2005) modeled the jumps in rectangular flumes by implementing the artificial neural network (ANN). They proved that the mentioned algorithm predicts the sequent depths and the hydraulic jump length with reasonable accuracy. Naseri and Othman (2012) simulated the hydraulic jump length in rectangular channels using ANN for Froude numbers between 1.7 and 19.5. It was indicated that the numerical model had a suitable accuracy so that the determination coefficient for the model was 0.9962. Using the Gene Expression Programming (GEP), ANN and the Support Vector Regression (SVR) models, Karbasi and Azamathulla (2016) approximated the roller length and the sequent depths of hydraulic jumps on rough beds. They proved that the GEP model predicts the hydraulic jump with higher accuracy. Additionally, Azimi et al. (2018a) simulated the roller length of jumps on rough beds by employing the group method of data handling model.

As seen, numerous studies have been carried out on the hydraulic jump on rough floors because calculation of hydraulic jump length is quite important for designing stilling basins. However, modeling of the jump length on sloping rough beds using soft computing methods requires further investigations. Moreover, novel artificial intelligence

*Corresponding author E-mail: behrouz.yaghoubi.h@gmail.com

Please cite this article as: R. Gerami Moghadam, B. Yaghoubi, M.A. Izadbakhsh, S. Shabanlou, Prediction of the hydraulic jump length on sloping rough beds using meta- heuristic neuro-fuzzy model and differential evolution algorithm, Journal of Applied Research in Water and Wastewater, 6 (1), 2019, 8-15.

techniques such as hybrid or meta-heuristic approaches should be applied to simulate this phenomenon. In this study, the length of hydraulic jumps on rough sloping beds is modeled by combining the Adaptive Neuro-Fuzzy Inference System (ANFIS) and Differential Evolution (DE) algorithm using MATLAB software for the first time. In other words, the ANFIS network is optimized by employing DE algorithm. Firstly, the influence of various parameters on the length of jumps on sloping rough beds flumes is evaluated. Finally, the best model and the parameters affecting the length of the hydraulic jump are introduced.

2. Materials and methods

2.1. Adaptive Neuro-fuzzy inference systems (ANFIS)

The ANFIS is a hybrid approach based on soft computing techniques combining the advantages of the ANN method the fuzzy logic characteristics as parallel processing. The processing of this method has high convergence speed and high accuracy. In the current study, the approach introduced by Jang et al. (1997) is employed for modeling the hydraulic jump length taking place on sloping rough floor using ANFIS. This model has a similar approach with the first order Sugeno fuzzy model. A sample from this process is considered for a fuzzy inference system (FIS) and an output (f). To define this problem, according to the interested problem of this study, for one model of models provide for modeling the hydraulic jump length on rough floor the parameters *x* and *y* can be considered as the Froude number (*Fr*) and the sequent depths (h_2/h_1). Also, the output *f* in this study represents the function L_j/h_1. This example is evaluated for two input parameters of this study. A sample set rules can be expressed by two if-then rules for a first order Takagi-Sugeno fuzzy model as follows:

$$Rule1: IF\ x = A_1,\ y = B_1\ Then \qquad f_1 = p_1x + q_1y + r_1 \tag{1}$$

$$Rule1: IF\ x = A_2,\ y = B_2\ Then \qquad f_1 = p_2x + q_2y + r_2 \tag{2}$$

The antecedent section has the fuzzy nature and the consequent section (if and then, respectively) is a fragile function from the antecedent part as a linear relationship or a rule. If the modeling input parameters L_j/h_1 are considered only as two parameters including *Fr* and h_2/h_1, relationships 1 and 2 are rewritten as follows:

$$\begin{aligned}&\text{Rule 1: IF } Fr \text{ is LOW and } (h_2/h_1) \text{ is LOW,}\\ &\text{THEN } L_j/h_1 = p_1 Fr + q_1(h_2/h_1) + r_1\end{aligned} \tag{3}$$

$$\begin{aligned}&\text{Rule1: IF} Fr \text{ is HIGH and } (h_2/h_1) \text{ is MEDIUM,}\\ &\text{THEN} L_j/h_1 = p_2 Fr + q_2(h_2/h_1) + r_2\end{aligned} \tag{4}$$

where, the parameters p_i, q_i and r_i (i=1, 2, 3… n) are parameter set related to different rules (Rule 1… Rule n). The schematic layout of ANFIS with two inputs and the structure of the ANFIS used in this study with four input parameters are illustrated in Figure 1. The performance of different layers in this picture is as follows:

First Layer: each node in this layer creates membership degrees related to an input variable.

$$O_i^1 = \mu_{A_i}(Fr) \qquad i = 1,2 \tag{5}$$

where, *Fr* is the ith input and A_i is the linguistic label for this node. Also, for h_2/h_1 (second input parameter) another function is considered as follows:

$$O_i^1 = \mu_{B_{i\ 2}}(h_2/h_1) \qquad i = 3,4 \tag{6}$$

In Equation 5, O_i^1 is considered as the membership function of A_i and specifies the degree that given input (*Fr*) meets for the quantity A_i. The membership function used in this study is a bell-shaped function which has had a good performance in recent studies and is defined as follows:

$$A_i(C_V) = \frac{1}{1 + \left(\frac{F_1 \quad c_i\,)}{a_i}\right)^{2b_i}} \tag{7}$$

Here, {a_i, b_i, c_i} is the parameters set and μ is the membership function related to A_i. Change in each parameter leads to providing different membership functions. The parameters of this layer are introduced as the prismatic parameters. For each model input in this study, three membership functions are considered.

Second layer: This layer includes specific circular nodes denote by Π multiplying input signals by each other as the following equation and sends for the production output.

$$O_i^2 = w_i = A_i(Fr)B_i(h_2/h_1), \qquad i = 1,2 \tag{8}$$

Each output node represents the firing strength of the defined rule.

Third layer: In this layer, N circular nodes compute the ratio of the firing strength of the i_{th} rule to the sum of all firing strengths of rules as follows:

$$O_i^3 = \overline{w}_i = \frac{w_1}{w_1 + w_2}, \qquad i = 1,2 \tag{9}$$

The output of this layer is provided as the normalized firing strength.

Fourth layer: in this layer, values of p, q and r are optimized. In fact, all nodes in this layer are adapted by a node function as follows:

$$O_i^4 = \overline{w}_i(\,p_i F_1 + q_i(h_2/h_1) + r_i\,) \tag{10}$$

Where, {p_i, q_i, r_i} are the parameters set and $\overline{W}$ is the output of this layer. Parameters of this layer are known as the antecedent parameters.

Fifth layer: The single circular node in this layer (∑) calculates all outputs as the sum of ll input signals as follows (Jang et al., [15]):

$$O_i^5 = \sum \overline{w}_i f_i = \frac{\sum w_i f_i}{\sum w_i} \tag{11}$$

Learning of ANFIS is done using two algorithms including back propagation and the hybrid algorithm (combination of back propagation and least square). In the first algorithm, the back propagation is utilized for all data, but in the hybrid algorithm, the back propagation is used for input data (prismatic data) and the least square is used for outputs (antecedent parameters). Considering that the hybrid algorithm is more accurate than the back propagation, in this study the hybrid algorithm is implemented for simulating the hydraulic jump length on sloping rough floor. In addition, in order to use these two algorithms, in recent years, the application of differential evolution algorithms for optimizing values of membership functions have led to enhance prediction results by ANFIS (Shoorehdeli (2009), Chang (2011) and Chen (2013)). Hence, in this study, the differential evolution (DE) algorithm is used for learning ANFIS and the results are compared with the ANFIS-DE.

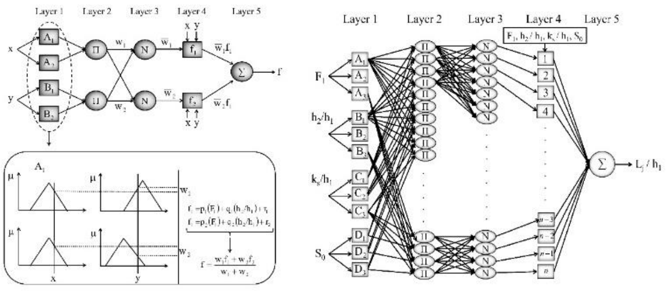


Fig. 1. ANFIS structure used in this study as quaternary and general.

2.2. Differential evolution algorithm (DE)

The DE algorithm is a powerful evolutionary approach in global optimization provided for the first time by Storn and Price (1997). Due to the good convergence of this algorithm and its easy understanding, it has many applications in different practical cases (Liu and Lampinen (2002)). If the desired objective function that must be optimized is called *f*, so:

$$f(V): R^D \rightarrow R \tag{12}$$

Here, R indicates real datum and D represents the number of the target function f(V). The purpose of the use of the DE algorithm is minimizing the objective function value through optimization of parameters values:

$$V = (v_1, \ldots, v_D), \quad V \in R^D \tag{13}$$

Please cite this article as: R. Gerami Moghadam, B. Yaghoubi, M.A. Izadbakhsh, S. Shabanlou, Prediction of the hydraulic jump length on sloping rough beds using meta- heuristic neuro-fuzzy model and differential evolution algorithm, Journal of Applied Research in Water and Wastewater, 6 (1), 2019, 8-15.

Here, *V* is a vector containing the target function parameters. In this paper, the target function is as the mean square error between estimated and real values. Parameters of the objective function are defined on the following domain:

$$v_i^{(L)} \le v_i \le v_i^{(U)} \tag{14}$$

where, $v_i^{(L)}$ and $v_i^{(U)}$ are the lower and upper bounds, respectively.

As other evolutionary algorithms, DE also acts on populations of the response candidate, P_G, to achieve an optimal response. If we consider G as a generation of the population, the population examined by DE can be expressed as follows:

$$P_G = (v_{1,G}, v_{2,G}, ..., V_{NP,G}) \; G = 0, ..., G_{max} \tag{15}$$

Each vector contains *D* real parameter considered as unique chromosomes.

$$v_{i,G} = (v_{1,i,G}, v_{2,i,G}, ..., V_{D,i,G}) \quad i = 1,2,...,NP \quad G = 0,...,G_{max} \tag{16}$$

In order to create a start point for optimal search, the initial population must be created. Generally, there is no information about the situation of the optimal response but the problem parameters. Thus, one of the ways for determining the initial population, P_G=0, is the random selection among existing limitations as follows:

$$v_{j,i,0} = rand_j[0,1](v_j^{(U)} \quad v_j^{(L)}) + v_j^{(L)} \; i = 1,2,...,Np, \; j = 1,2,...,D \tag{17}$$

Here, $rand_j$ [0, 1] is the random value of the uniform distribution on the domain [0,1] selected for each new j. The re-production procedure of DE is different from other evolutionary algorithms. From the initial production towards common population vectors, P_G is randomly sampled and combined to generate candidate vectors for the next generation (P_{G+1}). The candidate population or obtained vectors are calculated through several trials as follows:

$$u_{j,i,G+1} = \begin{cases} \begin{cases} v_{j,r3,G} + F(v_{j,r1,G} - v_{j,r2,G}) & \text{if } v_j^{(L)} < y_{j,i,G+1} < v_j^{(U)} \\ \text{otherwise} & \text{and}_j[0,1](v_j^{(U)} - v_j^{(L)}) + v_j^{(L)} \end{cases} \\ \text{otherwise} \quad v_{j,i,G} \end{cases} \tag{18}$$

r_1, r_2 and r_3 are different variables which their values vary from one run to another. In addition, *i* is a parameter that its value must be determined. Thus, correct values of the parameters r_1, r_2 and r_3 are randomly chosen for each *i* value. Selection in DE algorithm is different from other evolutionary algorithms, so that the population for the next generation (P_{G+1}) is selected from the existing population (P_G) and the offspring population follows the following formula:

$$V_{i,G+1} = \begin{cases} U_{i,G+1} & \text{if } f(U_{i,G+1}) \le (V_{i,G}) \\ V_{i,G} & \text{otherwise} \end{cases} \tag{19}$$

So, each unique member of the temporary population is compared with its counterparts in the existing population. Assuming that the objective function is maximized, the vector with the least value of the objective function obtains a new location in the next generated population. Therefore, all unique people of the next population are good or better than their counterparts in the existing population.

2.3. Hybrid method

In this sub-section, the proposed hybrid method of ANFIS with differential evolution (DE) as a global optimization algorithm is presented (ANFIS-DE). The DE algorithm is employed to optimize the adjustable network parameters which are has the significant effect on to gain an optimize results. The introduced ANFIS-DE is encoded in MATLAB software. Firstly, a primary ANFIS model is generated for the hydraulic jump length data using the training dataset. The tuned values for antecedents and consequents parameters of the ANFIS model produced by training data are not optimized. Then, the DE algorithm is applied to optimize the antecedent and consequent parameters of the model. Before start the training stage, some features should be defied to solve the desired problems. One of the most important of these features is the method of the fuzzy inference system (FIS) generation. Due to the good performance of grid partitioning (GP) in literature studies, the GP technique is employed in this study. Another parameter that has a high effect to attain an optimum model is membership function (MF) type. In this study, Gaussian, triangular and bell shape MFs are used and fins the bell shape as the optimum one. After defining the MF type, the number of MF is defined to find an accurate and simple model simultaneously. Through a trial and error process, the number of three is obtained as the best value for number of the MFs. Moreover, the number of the population used in this study is 50, the mutation constant is 0.2, the crossover constant is 0.85 and the data domain is [-10 10]. The learning process of the network continues until reaching to the convergence criterion determined as the number of iterations or reaching to the objective function value. The selection process done by the DE algorithm is as follows:

First, in order to avoid evolutionary iteration, constraints values and the objective function for the parameter $V_{i,G}$ are stored in variables. Then, the value of $U_{i,G+1}$ which violates more constraints values than the value of $V_{i,G}$ is rejected without re-evaluation. If the value of $V_{i,G}$ satisfies all constraints, the trial $U_{i,G+1}$ is also conducted, because values of constraints are still less than the value of $V_{i,G}$. In the situation where values of $U_{i,G+1}$ and $V_{i,G}$ are searched, the value of the objective function must be evaluated for the new trial (U_{G+1}). It continues until the value of $U_{i,G+1}$ will be more than $V_{i,G}$. In this situation, the value of the membership function is not re-evaluated.

The minimum defined error and the maximum number of iterations is considered as stopping criteria so if one of these criteria is satisfied, the training process of the ANFIS-DE model is finished. In this paper, the root mean square error (RMSE) is defined as the objective function such that the lower value of it results to better performance of the trained model. The values of the antecedent and consequent parameters at termination time are considered as the optimum ones. After finding the optimum values of the parameters of the ANFIS-DE model (i.e. antecedent and consequent parameter), this model could be employed to model the hydraulic jump length which are not existed in the training phase. In Figure 2, the flowchart of the proposed hybrid method for simulating the hydraulic jump length on the sloping rough bed is illustrated.

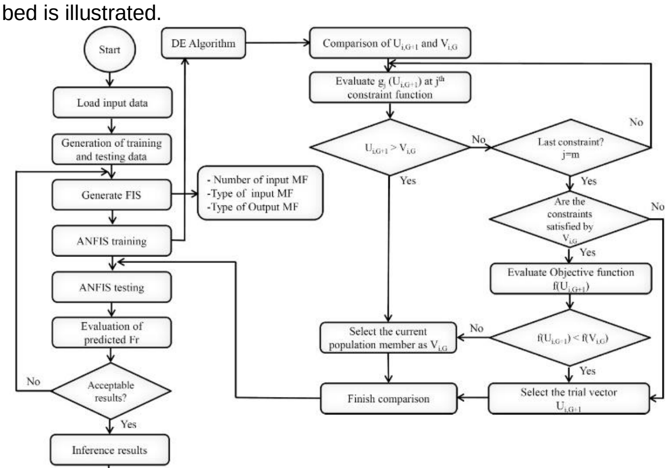


Fig. 2. Flowchart of ANFIS-DE algorithm.

2.4. Experimental model

In the current study, in order to validate the numerical models, the Kumar and Lodhi's (2016) experimental model is utilized. Their experimental model contains a sloping rectangular channel with the length of 8m, the width and the height of 0.6m. The experimental values for three slopes were measured 0.000463, 0.00986 and 0.01552. In the mentioned experimental model, stone materials with the average diameter (d_{50}) of 0.00398m, 0.0056 m, 0.007m and 0.011m were used for creating a rough bed. In Kumar and Lodhi (2016) experimental model, the parameters *Q*, S_0, *Ks*, h_1, h_2 and L_j are discharge, bed slope, height of bed roughness, flow depth at upstream of the hydraulic jump, flow depth at downstream of the hydraulic jump and the hydraulic jump, respectively. In Table 1, the range of experimental values is listed. In addition, the layout of Kumar and Lodhi (2016) experimental model is illustrated in Figure 3.

Table 1. Range of experimental values.

Parameter	Maximum	Minimum	Mean
Q (m^3s^{-1})	0.072	0.034	0.057
F_1	5.258	1.398	2.572
S_0 (-)	0.016	0.0005	0.009
Ks (m)	0.011	0.002	0.006
h_1 (m)	0.087	0.03	0.054
h_2 (m)	0.344	0.026	0.262
Lj (m)	0.9	0.3	0.638

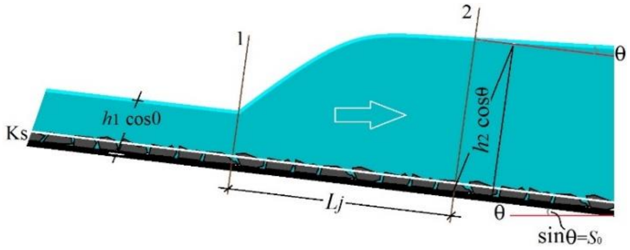


Fig. 3. Layout of experimental model of hydraulic jump on steep rough surface.

2.5. Hydraulic jump Length on sloping rough bed

Hager et al. (1990), Ead and Rajaratnam (2002) and Carollo et al. (2007) showed that the length of the hydraulic jump is a function of the Froude number (Fr) and the ratio of the bed roughness to the flow depth at the upstream of the jump (Ks/h_1):

$$\frac{Lj}{h_1}=f\left(F_1,\frac{Ks}{h_1}\right) \tag{20}$$

In addition, Azimi et al. (2018a) and Azimi e al. (2018b) assumed the hydraulic jump length on rough beds as a function of the Froude number (*Fr*), the ratio of bed roughness to the flow depth at the jump upstream (Ks/h_1) and the sequent depths (h_2/h_1):

$$\frac{Lj}{h_1}=f\left(F_1,\frac{h_2}{h_1},\frac{Ks}{h_1}\right) \tag{21}$$

Furthermore, Kumar and Lodhi (2016) considered the influence of the channel slope (S_0) in their experimental study. Thus, in this study, the effects of *Fr*, Ks/h_1, h_2/h_1 and the channel bed slope (S_0) on the hydraulic jump length are considered. Therefore, equation (21) is written as follows:

$$\frac{Lj}{h_1}=f\left(F_1,\frac{h_2}{h_1},\frac{Ks}{h_1},S_0\right) \tag{22}$$

Thus, for simulating the hydraulic jump length using the ANFIS-DE model, the effects of *Fr*, Ks/h_1, h_2/h_1 and S_0 are considered. In this study, for examining the effectiveness of each of the input parameters, five different numerical models are defined as figure 4. It should be noted that for calibrating the performance of the ANFIS-DE models, the Monte Carlo simulations (MCs) are applied. In addition, the k-fold cross validation approach (k=4) is utilized for validating the simulation results. The number of data is 88. Regarding with k=4, 25% of the data are used for testing and 75% for training in each validation. The schematic of the k-fold cross validation method is illustrated in figure 5.

3. Results and discussion

3.1. Criteria for examining accuracy of numerical model

In the current study, the statistical indices including mean absolute percent error (*MAPE*), root mean square error (*RMSE*), Scatter Index (*SI*), BIAS and the correlation coefficient (*R*) are utilized for examining the accuracy of the numerical models as follows:

$$MAPE=\frac{1}{n}\sum_{i=1}^{n}\left(\frac{\left|(Lj/h_1)_{(\text{Predicted})_i}-(Lj/h_1)_{(Observed)_i}\right|}{(Lj/h_1)_{(Observed)_i}}\right)\times 100 \tag{23}$$

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left((Lj/h_1)_{(\text{Predicted})_i}-(Lj/h_1)_{(Observed)_i}\right)^2} \tag{24}$$

$$SI=\frac{RMSE}{(Lj/h_1)_{(Observed)}} \tag{25}$$

$$BIAS=\frac{1}{n}\sum_{i=1}^{n}\left((Lj/h_1)_{(\text{Predicted})_i}-(Lj/h_1)_{(Observed)_i}\right) \tag{26}$$

$$R=\frac{\sum_{i=1}^{n}\left((Lj/h_1)_{(Observed)i}-\overline{(Lj/h_1)}_{(Observed)}\right)\left((Lj/h_1)_{(\text{Predicted})i}-\overline{(Lj/h_1)}_{(\text{Predicted})}\right)}{\sqrt{\sum_{i=1}^{n}\left((Lj/h_1)_{(Observed)i}-\overline{(Lj/h_1)}_{(Observed)}\right)^2\sum_{i=1}^{n}\left((Lj/h_1)_{(\text{Predicted})i}-\overline{(Lj/h_1)}_{(\text{Predicted})}\right)^2}} \tag{27}$$

In equations (23) to (27), $(Lj/h_1)_{(Observed)i}$, $(Lj/h_1)_{(Predicted)i}$, $\overline{(Lj/h_1)}_{(Observed)i}$ and n the measured hydraulic jump length, the predicted hydraulic jump length, the average of experimental jump lengths and the number of experimental measurements.

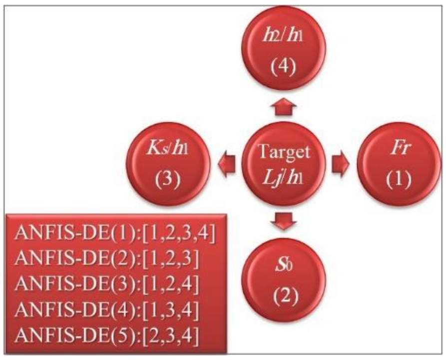


Fig. 4. Combinations of Froude number (F1), ratio of bed roughness (Ks/h1), sequent depths (h_2/h_1) and bed slope (S0) parameters in different models of ANFIS-DE.

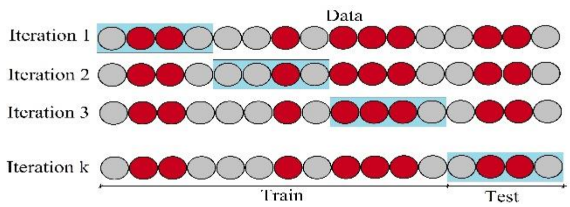


Fig. 5. Dealing of k-fold validation method with experimental values.

3.2. Sensitivity analysis

To study the parameters affecting jumps on sloping rough floors, five various models are developed in this study. The ANFIS-DE (1) model predicts values of the hydraulic jumps using a combination of all input parameters. Furthermore, four models including ANFIS-DE (2) to ANFIS-DE (5) simulate the length of the hydraulic jump by combining three input parameters. In other words, in order to identify the effective parameter, the influence of each of the input parameters on these four models has been eliminated. In figure 5, the scatter plots are shown for different models. Based on the results of the numerical modeling, the values of mean absolute percent error and root mean square error for the ANFIS-DE (1) model are calculated 4.875 and 0.807, respectively. In addition, the *R* for this model is 0.978. This model predicts values of the length of the hydraulic jump in terms of the Fr, the Ks/h_1, the sequent

Please cite this article as: R. Gerami Moghadam, B. Yaghoubi, M.A. Izadbakhsh, S. Shabanlou, Prediction of the hydraulic jump length on sloping rough beds using meta- heuristic neuro-fuzzy model and differential evolution algorithm, Journal of Applied Research in Water and Wastewater, 6 (1), 2019, 8-15.

depths (h_2/h_1) and bed slope (S_0). Whereas, the value of SI for ANFIS-DE (1) is 0.064 and the value of BIAS for this model is also estimated $2.1*10^{-06}$. According to the analysis of the modeling results, among all models, ANFIS-DE (1) has highest accuracy in modeling the hydraulic jump length. For simulating the hydraulic jump length using ANFIS-DE (2), the influence of the sequent depths is neglected. In other words, the model simulates the hydraulic jump length in terms of three input parameters including the Fr, Ks/h_1 and S_0. For the model, the values of RMSE, MAPE and BIAS are obtained 1.388, 8,741 and $-5.4*10^{-06}$. In addition, the correlation coefficient for the ANFIS-DE (2) is calculated 0.932. Among the models with three input parameters, the ANFIS-DE (2) model has the lowest accuracy. The SI for the ANFIS-DE (3) is calculated 0.089. The ANFIS-DE (3) model simulates the target function by employing the Froude number, the sequent depths and bed slope. For this model, the influence of the ratio of bed roughness is removed. However, the R and RMSE for the model are calculated 0.957 and 1.119, respectively. Among the models with three input parameters, the ANFIS-DE (3) has the highest accuracy in modeling the Lj/h_1. It should be noted that the value of BIAS is obtained equal to $9.3*10^{-07}$. The ANFIS-DE (4) model simulates the Lj/h_1 as a function of the Froude number, the ratio of bed roughness and the sequent depths. For this model, the influence of the bed slope is neglected. The values of the correlation coefficient, MAPE and RMSE for the ANFIS-DE (4) models are calculated 0.951, 6.858 and 1.187, respectively. In addition, for the model, the values of SI and BIAS are computed 0.095 and $-2.3*10^{-05}$, respectively. After ANFIS-DE (3), the ANFIS-DE (4) has the highest accuracy among the models with three input parameters. For the ANFIS-DE (5) model, the values of RMSE, MAPE and R are calculated 1.367, 8.929 and 0.034, respectively. Also, the SI and BIAS for this model are 0.109 and $9.2*10^{-07}$, respectively. For the model, the influence of the Fr is eliminated and the mentioned model simulates the Lj/h_1 in terms of the ratio of bed roughness (Ks/h_1), the sequent depths (h_2/h_1) and bed slope (S_0). According to the modeling results, after the ANFIS-DE (2) model, the ANFIS-DE (5) model has the maximum error. Based on the analysis of the numerical modeling results, the ANFIS-DE (1) is introduced as the superior model. Furthermore, the sequent depths (h_2/h_1) and the Froude number (Fr) are the most important input in modeling the Lj/h_1on sloping rough beds.

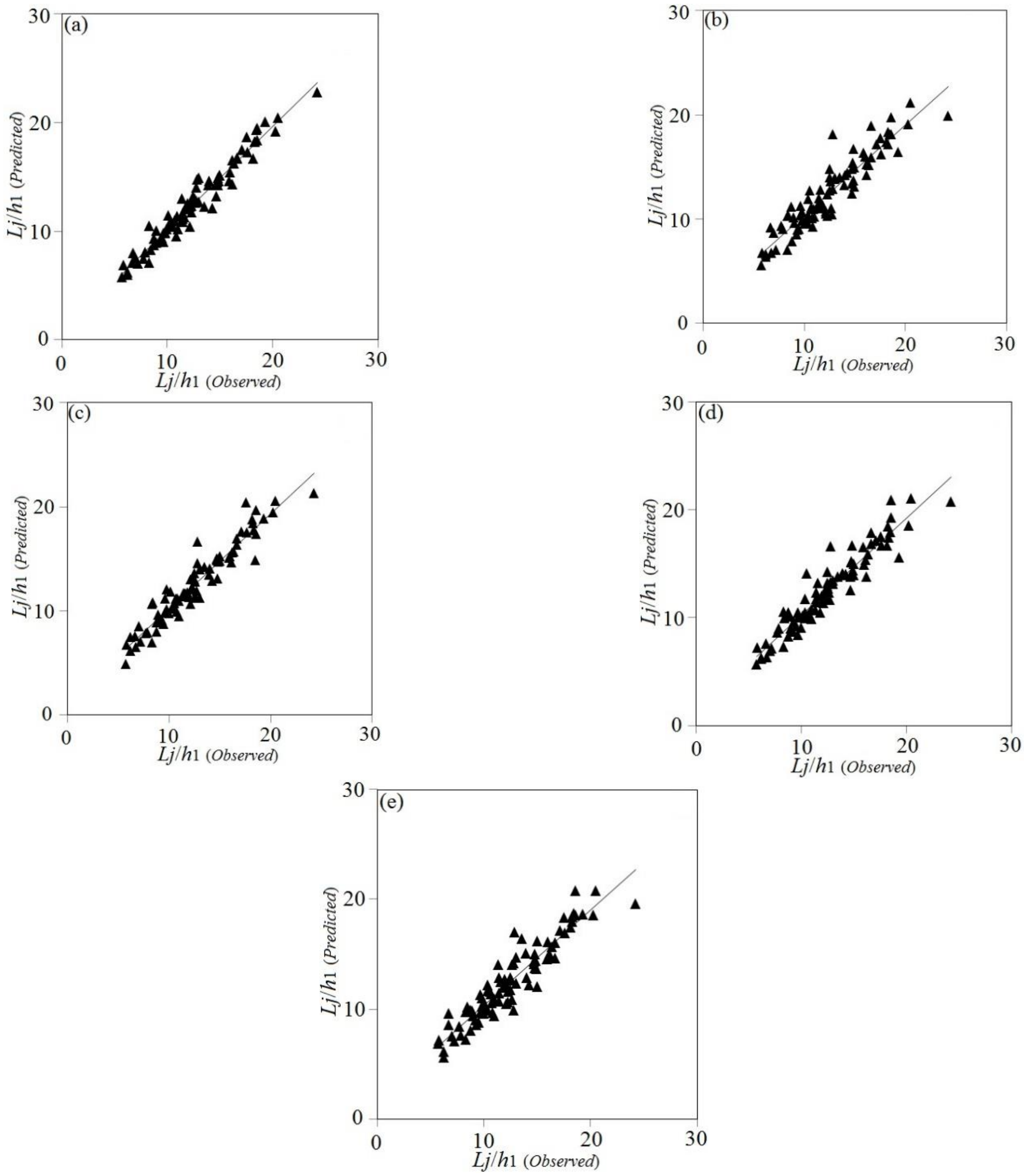


Fig. 6. Scatter plots for models: (a) ANFIS-DE; (b) ANFIS-DE; (c) ANFIS-DE; (d) ANFIS-DE; (e) ANFIS-DE.

Please cite this article as: R. Gerami Moghadam, B. Yaghoubi, M.A. Izadbakhsh, S. Shabanlou, Prediction of the hydraulic jump length on sloping rough beds using meta- heuristic neuro-fuzzy model and differential evolution algorithm, Journal of Applied Research in Water and Wastewater, 6 (1), 2019, 8-15.

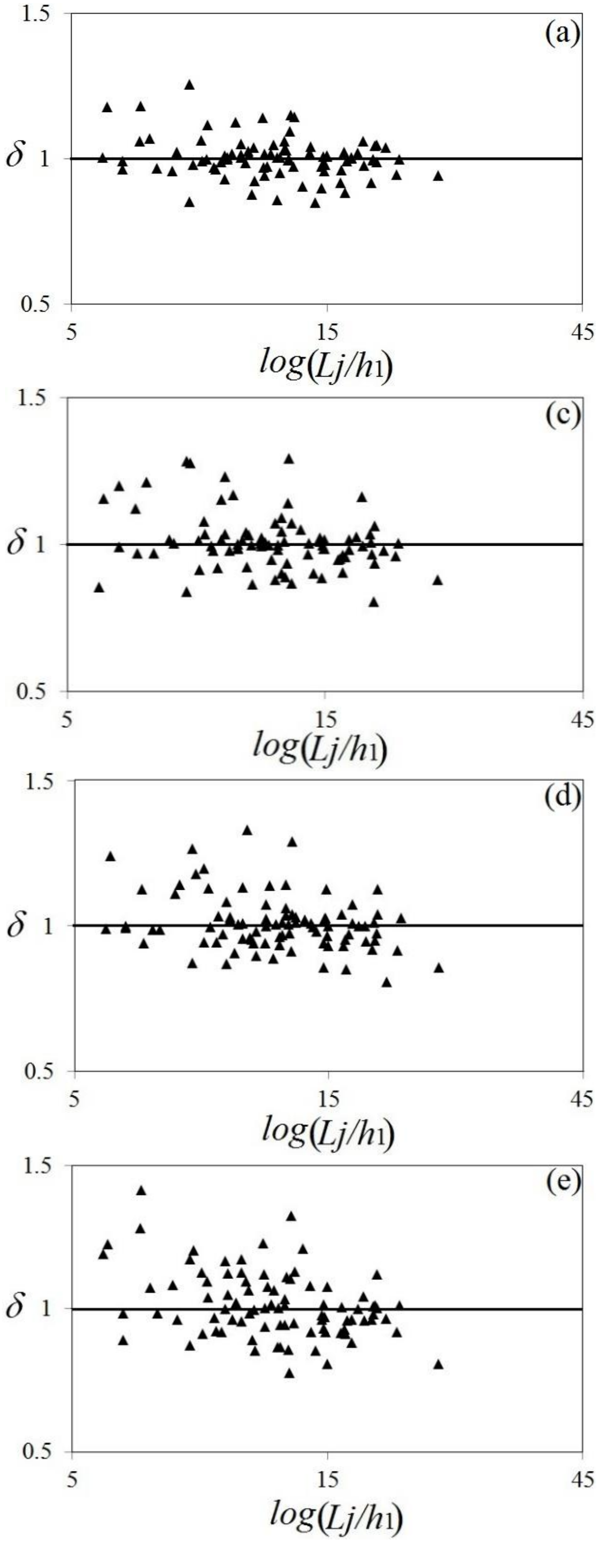
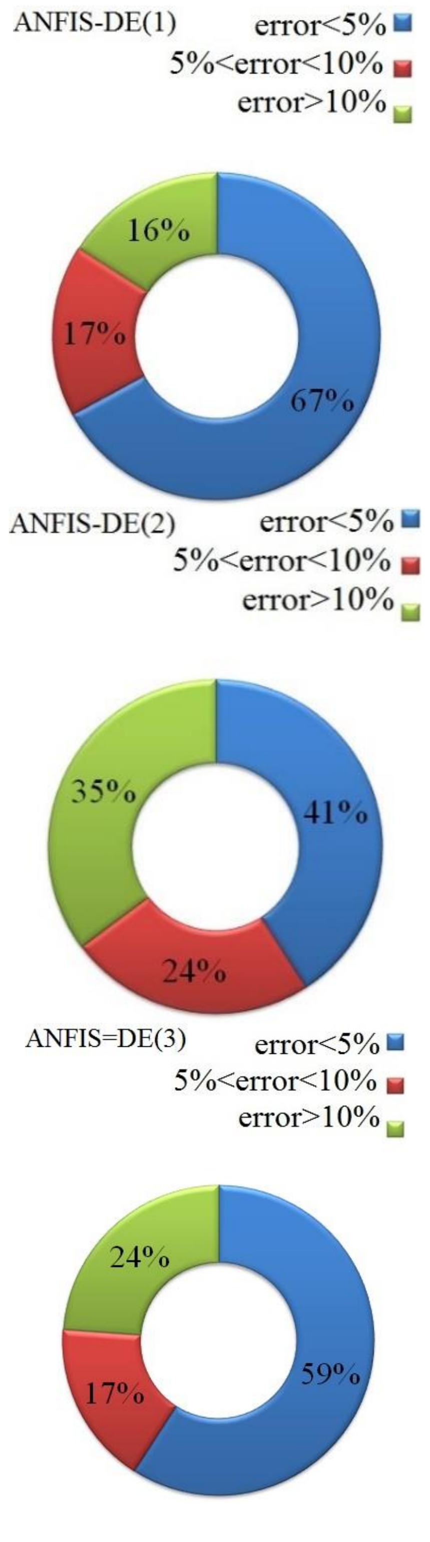


Fig. 7. Changes graphs of δ parameter versus logarithm of ratio of hydraulic jump length for models: (a) ANFIS-DE; (b)- ANFIS-DE; (c) ANFIS-DE; (d) ANFIS-DE; (e) ANFIS-DE.

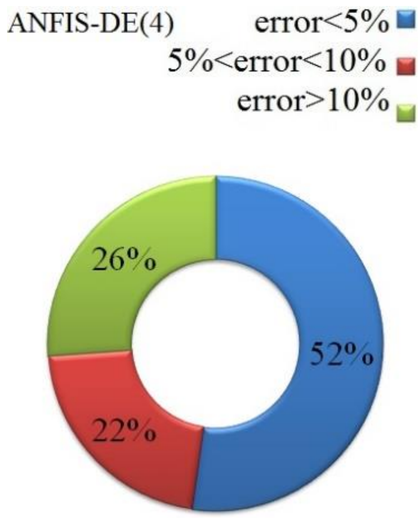
Table 2. Values of $\delta_{(max)}$, $\delta_{(\min)}$ and $\delta_{(ave)}$ for different models of ANFIS-DE.

	$\delta_{(\max)}$	$\delta_{(\min)}$	$\delta_{(ave)}$
ANFIS-DE (1)	1.255	0.848	1.005
ANFIS-DE (2)	1.409	0.814	1.013
ANFIS-DE (3)	1.292	0.804	1.008
ANFIS-DE (4)	1.331	0.807	1.009
ANFIS-DE (5)	1.415	0.776	1.013

Additionally, error distribution for ANFIS-DE (1) to ANFIS-DE (5) is illustrated in figure 7. For instance, almost 67% of discharge coefficient simulated using ANFIS-DE (1) has an error less than 5%, whilst roughly one fifth of ANFIS-DE (1) results have error between 5% to 10%. However, about 16% of ANFIS-DE (1) results have an error more than 10 percent. Also, approximately 40 per cent of results obtained using ANFIS-DE (2) has error less than 5%. For this model, approximately one-third of results has an error more than 10%. According to the error distribution, nearly a quarter of ANFIS-DE (3) results has error more than 10%. Furthermore, about half of discharge coefficient modeled using ANFIS-DE (4) has error less than 5%. Moreover, just 35% of results predicted using ANFIS-DE (5) has error more than 10%. Also, for error less than 5%, this figure is roughly 39%.



Please cite this article as: R. Gerami Moghadam, B. Yaghoubi, M.A. Izadbakhsh, S. Shabanlou, Prediction of the hydraulic jump length on sloping rough beds using meta- heuristic neuro-fuzzy model and differential evolution algorithm, Journal of Applied Research in Water and Wastewater, 6 (1), 2019, 8-15.



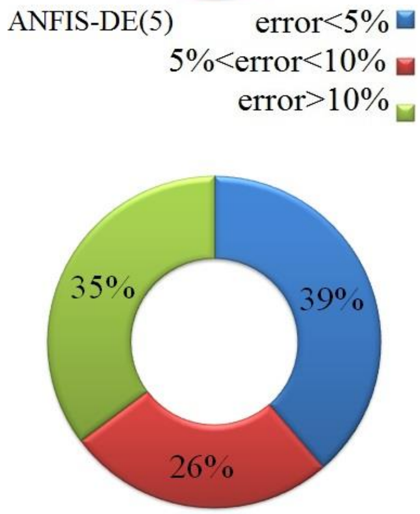


Fig. 8. Error distribution for ANFIS-DE (1) to ANFIS-DE (5).

Next, results of the superior model (ANFIS-DE 1) are compared with ANFIS and ANFIS-Genetic Algorithms (ANFIS-GA) models (Fig. 9). According the numerical models, the correlation coefficient and scatter index for the ANFIS model are 0.936 and 0.108, respectively. Additionally, the MAPE and RMSE for ANFIS-GA models are estimated 7.306 and 1.196, respectively. Thus, as it can be obviously seen, the ANFIS-DE has better performance so as to simulate the roller length of the hydraulic jump on sloping rough beds.

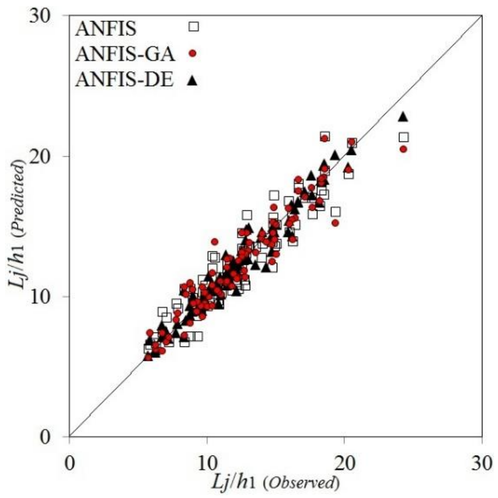


Fig. 9. Comparison of ANFIS-DE with ANFIS and ANFIS-GA models.

4. Conclusions

At the downstream of different structures such as gates, spillways and ogee spillways, hydraulic jumps are happened. In this study, a hybrid method was developed for simulating the hydraulic jumps length on sloping rough floors by combining the ANFIS and the Differential Evolution (DE) algorithm. First, using the input parameters, five different models were introduced for identifying the effective parameter in modeling the hydraulic jumps length. The hybrid models predicted the hydraulic jumps length with reasonable accuracy. Then, the results of the modeling were analyzed and a model with four input parameter including the Froude number, the ratio of bed roughness, the sequent depths and bed slope was introduced as the superior model. For this model, the *SI* and *BIAS* were calculated 0.064 and $2.1*10^{-06}$, respectively. In addition, the sequent depths and the Froude number were introduced as the effective parameters in modeling the length of the hydraulic jump.

References

Ahmed H.M.A., El Gendy M., Mirdan A.M.H., Ali, AAM., Abdel Haleem F.S.S., Effect of corrugated beds on characteristics of submerged hydraulic jump, Ain Shams Engineering Journal 5 (2014) 1033-1042.

Azimi H., Bonakdari H., Ebtehaj I., Gharabaghi B., Khoshbin F., Evolutionary design of generalized group method of data handling-type neural network for estimating the hydraulic jump roller length, Acta Mechanica 229 (2018a) 1197-1214.

Azimi H., Bonakdari H., Ebtehaj I., Michelson D.G., A combined adaptive Neuro-fuzzy inference system–firefly algorithm model for predicting the roller length of a hydraulic jump on a rough channel bed, Neural Computing and Applications 29 (2018b) 249-258.

Carollo F., Ferro V., Pampalone V., Hydraulic Jumps on Rough Beds, Journal of Hydraulic Engineering 133 (2007) 989-999.

Carollo F., Ferro V., Pampalone V., New Solution of Classical Hydraulic Jump, Journal of Hydraulic Engineering 135 (2009) 527–531.

Carollo F., Ferro V., Pampalone V., Sequent depth ratio of B-jumps on smooth and rough beds, Journal of Agricultural Engineering 44 (2013) 82-86.

Chang J.R., Wei L.Y., Cheng C.H., A hybrid ANFIS model based on AR and volatility for TAIEX forecasting, Applied Soft Computing 11 (2013) 1388-1395.

Chen M.Y., A hybrid ANFIS model for business failure prediction utilizing particle swarm optimization and subtractive clustering, Information Sciences 220 (2013) 180-195.

Ead S., Rajaratnam N., Hydraulic Jumps on Corrugated Beds, Journal of Hydraulic Engineering 128 (2002) 656-663.

Hager W.H., Hydraulic jump in non-prismatic rectangular channels, Journal of Hydraulic Research 23 (1985) 21-35.

Hager W.H., Bremen R., Kawagoshi N., Classical hydraulic jump: length of roller, Journal of Hydraulic Research, 28 (1990) 591-608.

Jang J.S.R., Sun C.T., Mizutani E., Neurofuzzy and soft computing: a computational approach to learning and machine intelligence, New Jersey: Prentice-Hall (1997).

Karbasi M., Azamathulla H.M., GEP to predict characteristics of a hydraulic jump over a rough bed, KSCE Journal of Civil Engineering 20 (2016) 3006-3011.

Kumar M., Lodhi A.S., Hydraulic jump over sloping rough floors, ISH Journal of Hydraulic Engineering 22 (2016) 127-134.

Liu J., Lampinen J., On setting the control parameter of the differential evolution method, In Proceedings of the 8th international conference on soft computing (2002) 11–18.

Naderpour H., Rafiean A.H. Fakharian P., Compressive strength prediction of environmentally friendly concrete using artificial neural networks, Journal of Building Engineering 16 (2018) 213-219.

Naderpour H., Alavi S.A., A proposed model to estimate shear contribution of FRP in strengthened RC beams in terms of Adaptive Neuro-Fuzzy Inference System, Composite Structures 170 (2017) 215-227.

Naseri M., Othman F., Determination of the length of hydraulic jumps using artificial neural networks, Advances in Engineering Software 48 (2012) 27–31.

Omid M.H., Omid M., Esmaeeli V.M., Modelling hydraulic jumps with artificial neural networks, In Proceedings of the Institution of Civil Engineers-Water Management 158 (2005) 65–70.

Pagliara S., Lotti I., Palermo M., Hydraulic jump on rough bed of stream rehabilitation structures, Journal of Hydro-environment Research 2 (2008) 29-38.

Shoorehdeli M.A., Teshnehlab M., Sedigh A.K., Khanesar M.A., Identification using ANFIS with intelligent hybrid stable learning algorithm approaches and stability analysis of training methods, Applied Soft Computing 9 (2009) 833-850.

Storn R., Price K., Differential evolution-A simple and efficient heuristic for global optimization over continuous spaces, Journal of Global Optimization 11 (1997) 341–359.

Velioglu D., Tokyay N.D., Dincer, A.I., A numerical and experimental study on the characteristics of hydraulic jumps on rough beds, In E-proceedings of the 36th IAHR World Congress 28 (2015) 1-9.

Please cite this article as: R. Gerami Moghadam, B. Yaghoubi, M.A. Izadbakhsh, S. Shabanlou, Prediction of the hydraulic jump length on sloping rough beds using meta- heuristic neuro-fuzzy model and differential evolution algorithm, Journal of Applied Research in Water and Wastewater, 6 (1), 2019, 8-15.