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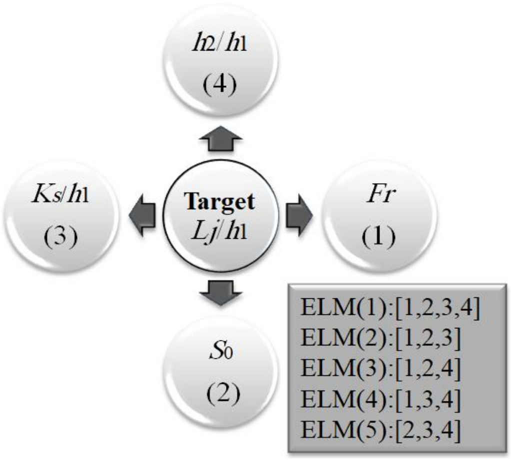
Simulation of hydraulic jump length on sloping coarse floors adopting extreme learning machine

Amir Hosein Azimi, Saeid Shabanlou*, Behrouz Yaghoubi

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

GRAPHICAL ABSTRACT



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ABSTRACT

In this paper, the hydraulic jump length on a slope rough floor is simulated through the extreme learning machine (ELM). Then, the parameters affecting the hydraulic jump on the slope rough bed are detected. After that, five different ELM model are developed so as to determine the influenced factor. Next, the results obtained from different ELM models are analyzed. The comparison of the results with the experimental data proves the acceptable accuracy of the mentioned numerical models. Regarding the results from the numerical method, the superior ELM model estimates the hydraulic jump length in terms of the flow Froude number, the ratio of bed roughness, the ratio of sequent depths and bed slope. The values of the root mean square error (RMSE), mean absolute percent error (MAPE), scatter index (SI) and correlation coefficient (R) for the superior model are respectively obtained 0.657, 3.507, 0.052 and 0.985. Based on the simulation, the flow Froude number at upstream is introduced as the most effective parameter in predicting the jump length on the sloping rough floor.

1. Introduction

The rapid change of supercritical flow into subcritical is always occurs with turbulence and considerable energy dissipation known as "hydraulic jump". Generally, a hydraulic jump occurs at the downstream of different hydraulic structures like ogee spillways, control valves and weirs. In addition, in order to protect structures and downstream facilities of ogee weirs, detention ponds are installed. To accurate design of a detention pond, the determination of the jump characteristics is essential. One of the most significant characteristics of hydraulic jump is length which numerous experimental, numerical and analytical investigations have been done on it. Hager and Wanoschek experimentally and analytically examined the characteristics of a jump in triangular flumes. They surveyed the ratio of conjugate depths, the roller depth and the jump length for various Froude numbers (F_1) (Hager & Wanoschek. 1987). Hager et al. (1990) through the analysis of the experimental results of the jump in an open flumes with different widths proposed a formula for calculating the roller length. In the work, the range of the F_1 varies from 2.5 to 8 and they also introduced the length of roller by using the F_1. Mohamed Ali (1991) conducted a series of experiments on rough beds using a cubic element to exhibit that the length of jump on rough floors compared to the classical case varies from 37.4 % to 67.4 %. Also, Ead and Rajaratnam (2002) experimentally Surveyed the phenomenon on labyrinth and smooth beds. The range of the F_1 of the jump in their experimental model was between 4 to 10 showing that the length of the jump on rough floors is almost half the corresponding length on smooth beds. They explained the jump reduction as a result of increasing the bed shear stress due to the interaction of supercritical flow with bed roughness. Subsequently, Ead (2007) conducted his experiments on three beds including sinusoidal wavy, trapezoidal and prismatic. He concluded that relative roughness and the shape of waves have no significant influence on the relative conjugate depth. Given that the crest level of all waves is at the same height of the channel in the

*Corresponding author Email: Saeid.Shabanlou@gmail.com

upstream, the distance between roughness sections has not a significant impact of the jump characteristics. Carollo et al. (2007) experimentally investigated the features of the phenomenon on rough and smooth floors. In order to analyze the results of their study, they suggested an equation in terms of relative roughness and the F_1 at the beginning of the hydraulic jump for calculating the roller length. Izadjoo and Shafai-Bejestan (2007) conducted their experiments on stripped trapezoidal beds. They indicated that the classical jump length is more than twice the jump length on the rough bed and this length depends on the crest distance of roughnesses.

In recent decades, different artificial intelligence techniques and numerical models have been utilized in various engineering fields (Akhbari et al. 2017; Azimi et al. 2018a). Omid et al. modeled the hydraulic jump characteristics including the jump length and the ratio of conjugate depths in rectangular channel using the artificial neural network (Omid et al., 2005). Abbaspour et al. (2013) predicted the characteristics of jumps on rough sinusoidal beds for the Froude numbers between 3 and 10 using the genetic algorithm and the artificial intelligence network. Through the analysis of the results obtained by the numerical models showed that the artificial neural network model predicts the hydraulic jump characteristics with higher accuracy. Azimi et al. (2018b) applied generalized structural of group method of data haneling to simulate the roller length of hydraulic jump on the coase beds. The developed some models and then provided the best model. Also, Azimi et al. (2019) estimathed the roller length of a hydraulic jump upon a rough bed adopting gene expression programming (GEP) model. The authors introduced the most important parameter for simulation of roller length.

As discussed, different soft computation techniques have been used in predicting the hydraulic jump characteristics. One of the artificial intelligence-based models is the extreme learning machine (ELM). Compared to other learning algorithm as back-propagation, ELM acts very fast in the learning process and has a good performance in processing functions (He et al., 2015).The application of ELM in various engineering sciences have provided acceptable results in different fields such as the selection of features, classification and regression (Bhasin et al., 2016; Shen et al., 2016; Ebtehaj and Bonakdari, 2016). According to the authors' knowledge, no application of the ELM model in estimating the hydraulic jump length has been observed so far. Due to the considerable importance of the determination of the jump length, in the paper the hydraulic jump length on slope rough bed is estimated by the ELM technique. First, five different models are proposed based on the variables affecting the length of hydraulic jump. Then, the superior model is detected through the analysis of the mentioned models.

2. Materials and methods

2.1. Experimental apparatus

In order to verify the results from the ELM approach, the laboratory data measured by Kumar and Lodhi are employed (2016). In their experimental model they measured the flow rate (*Q*), bed slope (S_0), bed roughness height (*Ks*), the depth at the beginning of the jump (h_1), the flow depth at the upstream of the hydraulic jump (h_2) and the length of hydraulic jump (*Lj*) in a rectangular flume with a length of 8m, a width of 0.6m and the height of 0.6m. They a; so, considered the slope bed for three modes including 0.000463, 0.00986 and 0.01552. To create the bed roughness, Kumar and Lodehi (2016) used aggregates with the average diameters (d_{50}) equal to 0.00398m, 0.0056m, 0.007m and 0.011m. In Table1, the range of the data measured by Kumar and Lodhi are listed. In addition, the schematic layout of the jump on the sloping rough floor is shown in Fig. 1.

Table 1. Range of experimental measurements.

Q, m^3/s	S_0 (-)	Ks, m	h_1, m	h_2, m	Lj, m
0.0-34.072	0.0-5.016	0.0-2.011	0.0-3.087	0.0-26.344	0.0-3.9

2.2. Extreme learning machine (ELM)

The extreme learning machine (ELM) is considered as a neural network (Huang et al. 2004. 2006). The model computes weights of input randomly and then weights of output by using an analytical method. The only difference between ELM with the neural network is in not using the bias for the output neuron. Input layer neurons are linked with the neurons located in the middle layer. Middle or hidden layer neurons are created by a bias. Additionally, an activation (AF) function of hidden neurons is a piecewise continuous function, whilst is linear for output hidden neurons. The model utilizes different methods for calculating biases and weights leading to reduce the network training process notably. The computational form of the neural network model with n hidden nodes is written.

$$f_n(x)=\sum_{i=1}^{n}\beta_i G\left(a_i,b_i,x\right) \tag{1}$$

where, β_i is the weight between the output node and the i^{th} hidden node, a_i ($a_i \in R^n$) and b_i are training parameters located in hidden nodes and $G(a_i, b_i, x)$ is the i^{th} node in output layer for the input x. The AF g(x), which has various types, for the additive node $G(a_i, b_i, x)$ can be rewritten as the following form.

$$G\left(a_i,b_i,x\right)=g(a_i.x+b_i) \tag{2}$$

The AF is applied to estimate the output answer of neurons. The pattern of neurons is composed of two sections including the total weighted inputs and the function. Once a set of signals are applied, activation functions are used for obtaining the answer. Moreover, the same activation functions are used for neurons of a same layer which may be linear or non-linear. A straight linear graph is depicted in linear functions, whilst a curved line is drawn in non-linear functions. Given that in the non-linear functions the number of output and input parameters are not equal, classification issues are common in them (Pandey and Govind, 2016). The non-linear ELM activation functions discussed in the study include triangular bias (tribas), radial bias (radbas), sigmoid (sig), step function (hardlim) and sinusoidal (sin) are used in the following forms: In the ELM, the biases and weights between neurons of input and hidden layers are allocated randomly. Activation of neurons in hidden layer for each learning sample in an ELM network with j neurons within the hidden layer, i input neurons and k learning samples are computed as follows:

$$H_{jk}=g(\sum\left(W_{ji}X_{ik}\right)+B_j \tag{3}$$

here, g(.) is any non-linear activation function, B_j is the bias of the jth middle layer neuron, W_{ji} can be the i^{th} input neuron weight and the i^{th} neuron of the hidden layer, X_{ik} is the input neuron for the k^{th} training mode and H_{ik} is the AF of the jth neuron in the middle layer for the kth learning sample, so that the activation of all hidden layer neurons for samples used in the training is considered by this matrix. The j is the column and k is the row In the matrix. This matrix H is written as the output hidden layer matrix of the algorithm. Weights between neurons of the output and hidden layers are applied versus outputs of the neurons within the middle layer for each learning data and its computational form is expressed:

$$H\beta=T \tag{4}$$

$$\beta=\left(\beta_1,...,\beta_j\right)_{j\times 1} \tag{5}$$

here, β represents the weight between the neurons within middle layer and output layer neurons and the T is a vector indicating objective parameter to learn data presented as the following form:

$$T=\left(T_1,...,T_k\right)_{k\times 1} \tag{6}$$

Finally, the weights are computed as follows:

$$\beta=H'T \tag{7}$$

where,

$$H(\tilde{a},\tilde{b},\tilde{x})=\begin{bmatrix} G(a_1,b_1,x_1) & ... & G(a_L,b_L,x_L) \\ G(a_1,b_1,x_N) & ... & G(a_L,b_L,x_N) \end{bmatrix}_{N\times L} \tag{8}$$

$$\beta=\begin{bmatrix}\beta_1^T \\ : \\ \beta_L^T\end{bmatrix}_{L\times m} \quad \text{and} \quad T=\begin{bmatrix}T_1^T \\ : \\ T_L^T\end{bmatrix}_{L\times m} \tag{9}$$

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where, $\tilde{a} = a_1,...,a_L; \tilde{b} = b_1,...,b_L; \tilde{x} = x_1,...x_L$ is the vector of the weight between the neurons in middle layer and output layer neurons, H' is the Moore-Penrose quasi-inverse of the H. The T is the vector between weights of learning samples. According to the presented topics, the ELM training consists of two phases: the first one is the allocation of the weights randomly and biases to the neurons in middle layer and computing the middle layer neuron of the matrix H and the second stage is the estimation of the output weights through Moore-Penrose quasi-inverse of the H and objective parameters for various learning data. The training phase for finding the Moore-Penrose quasi-inverse of the matrix for the hidden layer (H) is fast so that is quicker than common iteration-based approach Levenberg–Marquardt containing no process of optimization. Therefore, the training process of the method reduces dramatically (Huang 2006). The ELM works a lot of non-linear input space simulations randomly and then every neuron is randomly connected with a single datum.

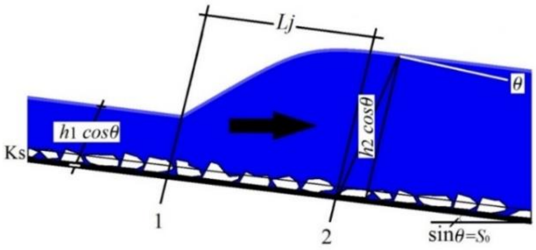

Fig. 1. A Schematic layout of hydraulic jump on sloping rough floor.

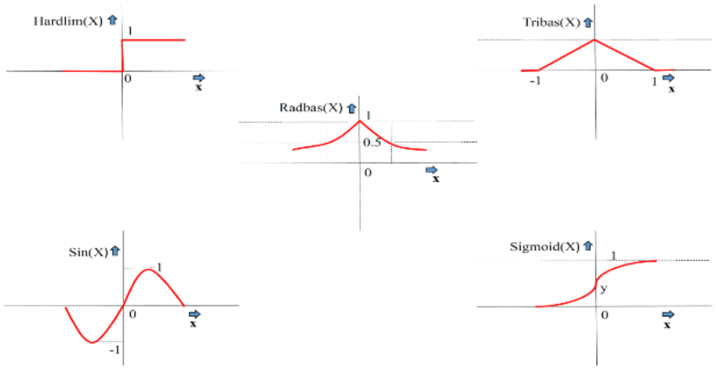

Fig. 2. Different activation functions in ELM model.

2.3. Length of jump on sloping rough bed

Hager et al. (1990), Rajaratnam (2002) and Carollo et al. (2007) stated that the length of jump was as a function of the ratio of channel floor roughness to the flow depth at upstream (Ks/h_1) and the Froude number at the beginning of the jump (F_1). Moreover, Azimi et al. (2016) simulated the hydraulic jump length on the rough floor using the F_1, Ks/h_1 and the ratio of conjugate depths (h_2/h_1). However, Kumar and Lodhi in their experimental study also considered the influence of the channel slope (S_0). Thus, in the present study, the influence of the F_1, the ratio of bed roughness (Ks/h_1), the ratio of conjugate depths (h_2/h_1) and the flume floor slope (S_0) on the hydraulic jump length is also taken into account (Azimi et al. 2018; Azimi. 2019).

$$\frac{Lj}{h_1} = f\left(F_1, \frac{h_2}{h_1}, \frac{Ks}{h_1}, S_0\right) \tag{10}$$

Thus, for predicting the hydraulic jump length using the ELM model, the influence of the F_1, the ratio of bed roughness (Ks/h_1), the ratio of conjugate depths ($h_2/h1$) and the bed slope (S_0) are taken into account. In the paper, the Monte Carlo simulations (MCs) are applied to increase the performance of the ELM algorithm. The principle of this approach is based on resolving issues that may be real in the world through a making decision randomly. The MCs are commonly used to estimate general problems in math and physics that cannot be solved using other approach. Also, in this paper, the k-fold cross validation approach is employed for verifying the ELM models. In the method, all data are randomly classified to k groups. Amongst the groups, a group is applied as the validation values and the rest as the testing values for each ELM models and then the procedure iterates k times. After that, the outcomes computed from the k folds are averaged and then calculated as an estimate. The benefit of the approach is the random iteration of the groups in training and testing modes for all data. This means that each datum is exactly applied once for testing the artificial intelligence model. In the paper, in order to simulate the hydraulic jump on sloping rough bed, five different ELM models are defined. The combinations of the input parameters for five ELM models are shown in Fig. 3.

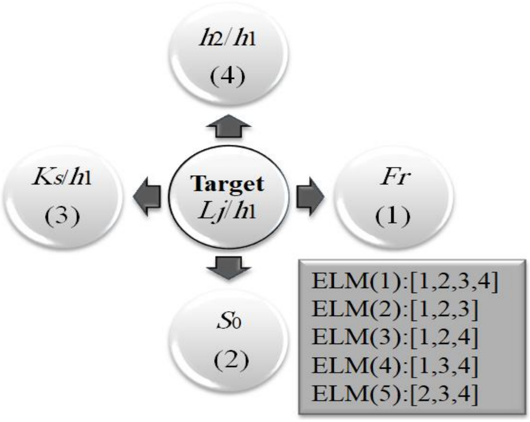

Fig. 3. Combination trend of input variables for various models of extreme learning machine.

3. Results and discussion

In the paper, to evaluate the performance of the numerical models the scatter index (SI), the root mean square error (RMSE), the correlation coefficient (R), the mean absolute percent error (MAPE) and the BIAS and the are utilized as follows (Azimi et al. 2018; Azimi. 2019).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{\left|(Lj/h_1)_{(Predicted)_i} - (Lj/h_1)_{(Observed)_i}\right|}{(Lj/h_1)_{(Observed)_i}}\right) \times 100 \tag{11}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left((Lj/h_1)_{(Predicted)_i} - (Lj/h_1)_{(Observed)_i}\right)^2} \tag{12}$$

$$SI = \frac{RMSE}{(Lj/h_1)_{(Observed)}} \tag{13}$$

$$BIAS = \frac{1}{n}\sum_{i=1}^{n}\left((Lj/h_1)_{(Predicted)_i} - (Lj/h_1)_{(Observed)_i}\right) \tag{14}$$

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$$R=\frac{\sum_{i=1}^{n}\left(\left(Lj/h_1\right)_{(Observed)i}-\overline{\left(Lj/h_1\right)}_{(Observed)}\right)\left(\left(Lj/h_1\right)_{(Predicted)i}-\overline{\left(Lj/h_1\right)}_{(Predicted)}\right)}{\sqrt{\sum_{i=1}^{n}\left(\left(Lj/h_1\right)_{(Observed)i}-\overline{\left(Lj/h_1\right)}_{(Observed)}\right)^2\sum_{i=1}^{n}\left(\left(Lj/h_1\right)_{(Predicted)i}-\overline{\left(Lj/h_1\right)}_{(Predicted)}\right)^2}} \tag{15}$$

where, $(Lj/h_1)_{(Observed)i}$ is the experimental values, $(Lj/h_1)_{(Predicted)i}$ is the predicted values and *n* is the number of experimental measurements. In order to evaluate the ELM models precisely, different statistical indices including absolute, relative error and correlation criteria were applied.

3.1. Activation functions (AFs)

ELM owns five activation functions (AFs) called "sigmoid, sin, hardlimit, tribas and radbas". Given that ELM 1 has the influence of all variables affecting in modeling length of jump on sloping rough floor, thus the results of the activation functions are examined for this model (see Table2). As shown, the correlation coefficient (*R*) for the sig activation function is 0.985. Furthermore, the SI and RMSE for the function are respectively calculated 0.052 and 0.657. Among all activation functions, hardlimit has the maximum error. For instance, the value of BIAS for this function is predicted to be -2.444E-14.

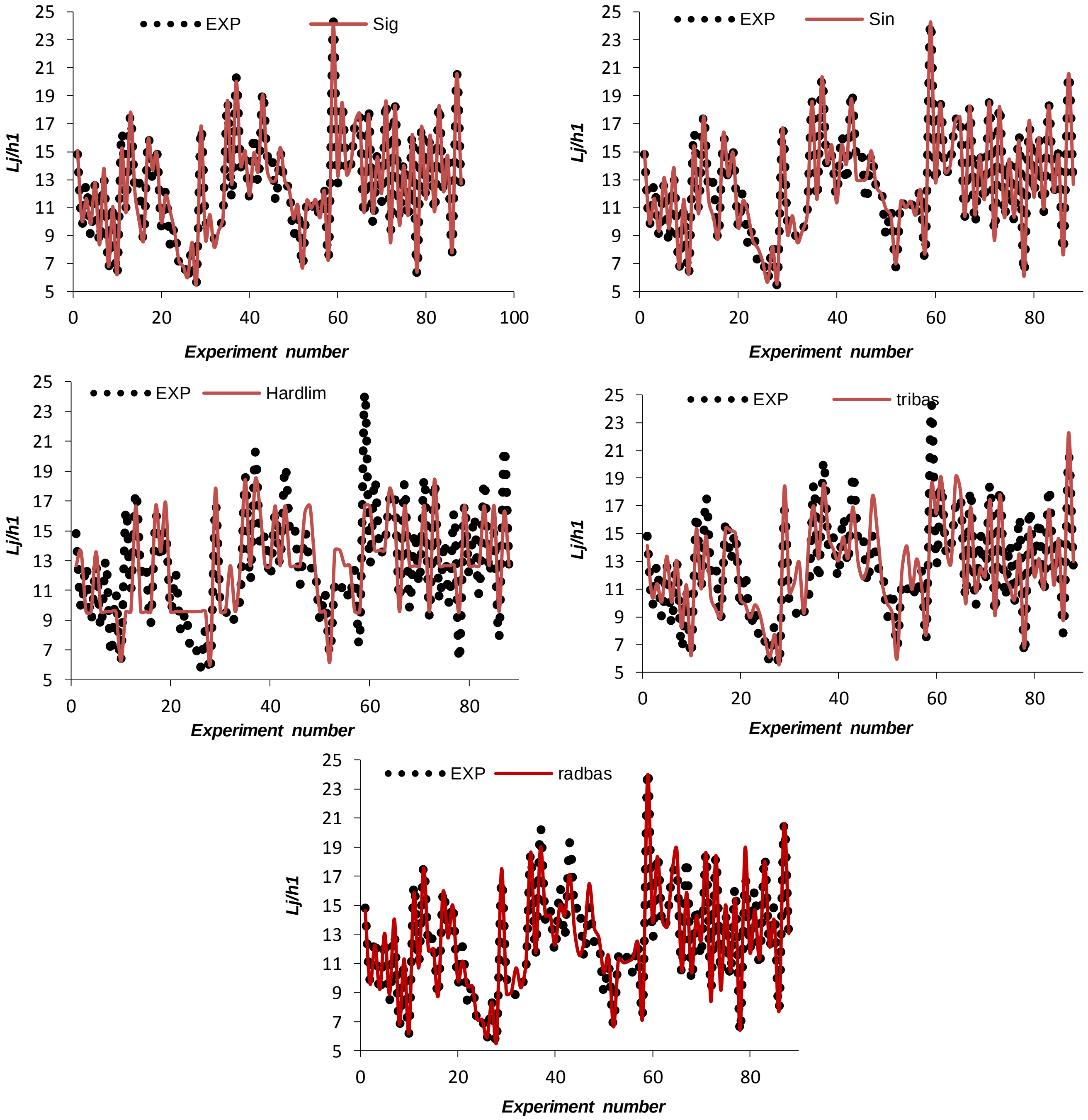

Fig. 4. Results of hydraulic jump length simulated by different activation functions.

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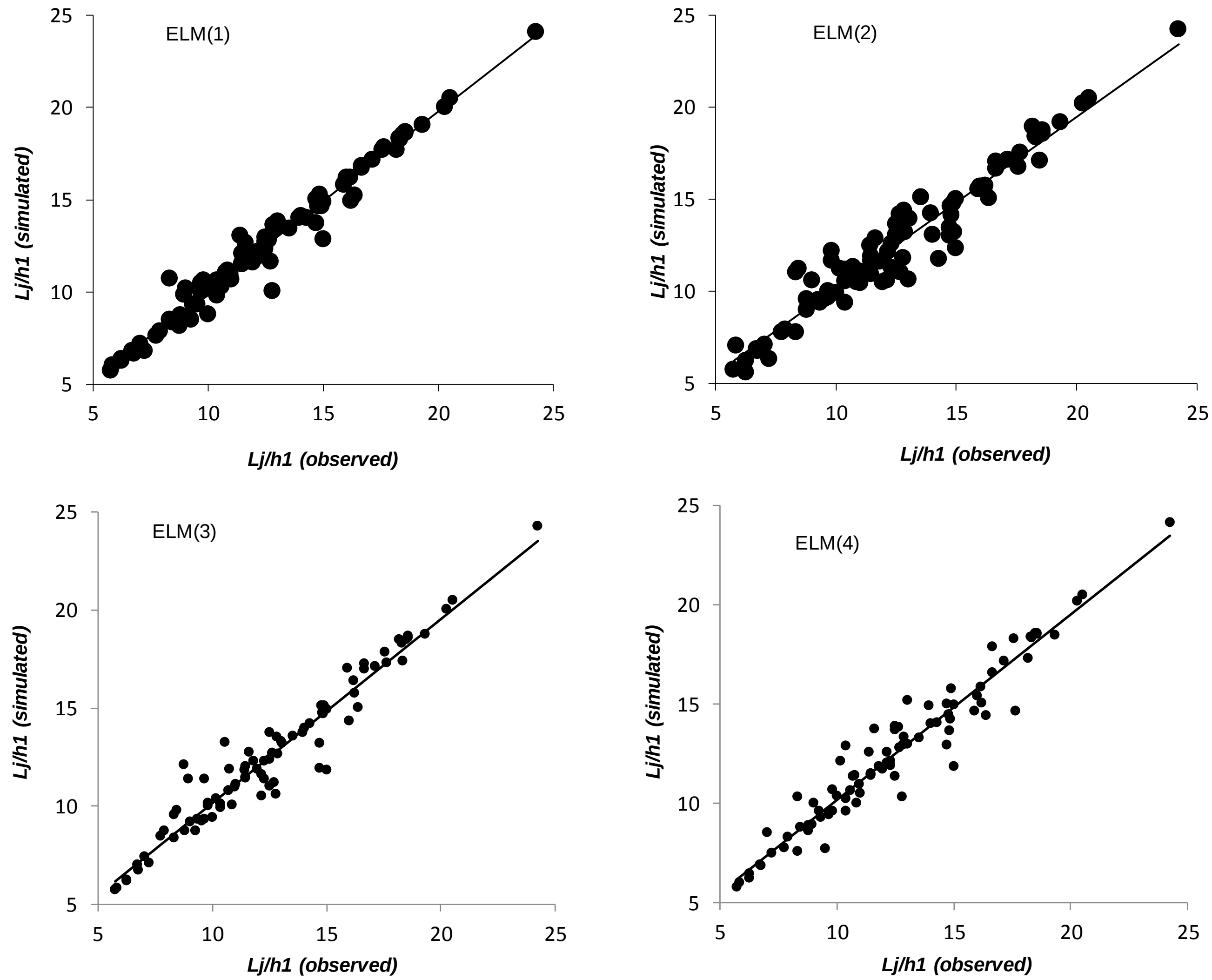
3.2. ELM models

In the following, the results of five ELM models are examined. As shown in Fig. 3, a model with four input parameters (ELM1) and four models with three input parameters (ELM2-ELM5) predict the values of the jump length. In other words, to identify the influenced variables in modeling the hydraulic jump length using ELM, the effect of each of the input variable is removed and then the modeling results are analyzed. In Table 3, the results from ELM (1) to ELM (5) are shown. Also, the scatter diagrams for the ELM methods are depicted in Fig. 5. Then, the ELM1 model simulates the values of the hydraulic jump length using all input parameters $\left(F_1, h_2/h_1, Ks/h_1, S_0\right)$. ELM1 owns the highest precision amongst all ELM approaches. As an example, the R, BIAS and SI for ELM1 are computed 0.985, 0.052 and 9.831E-8, respectively. Also, MAPE and RMSE for ELM1 are respectively predicted 3.507 and 0.657. For ELM 2, the influence of the ratio of conjugate depths (h_2/h_1) is neglected. In other words, the model estimates the hydraulic jump length using the Froude number, the ratio of bed roughness and the channel slope. For the model, the MAPE and RMSE are respectively obtained 6.236 and 1.016. Furthermore, for the model, R is calculated 0.964. In contrast, the BIAS and SI for ELM (2) are respectively predicted -6.810E-5 and 0.081. Amongst the AI models with three input variables, ELM3 model has the highest accuracy. In other words, R, SI and BIAS are computed 0.968, 0.076 and -2.625E-6, respectively. This model approximates the hydraulic jump length using the F_1, the h_2/h_1 and the flume bed slope. For this model, the influence of the ratio of bed roughness is removed. In addition, RMSE for Elm (3) is obtained 0.955. In addition, the value of MAPE for ELM (4) is 5.364. For the model, the impact of the channel bed slope is removed, meaning that the model is considered in terms of $F_1, h_2/h_1, Ks/h_1$. For ELM (4), BIAS is computed equal to 1.002E-6 and for this model the scatter index is obtained 0.078. Furthermore, the R, MAPE and RMSE for the model are approximated 0.966, 5.364 and 0.983, respectively. For ELM (5), the value of the correlation coefficient is 0.949. Also, the mean absolute percentage error and RMSE for the model are respectively calculated 0.949 and 8.459. Amongst all ELM models with three input variables, the ELM (5) model has the lowest correlation and the highest error. For the model, the influence of the F_1 is ignored. The model simulates the jump length using the ratio of conjugate depths, the ratio of bed roughness and channel bed slope. Therefore, as shown, ELM (1) model is considered as the best ELM model in estimating the length of hydraulic jump. Additionally, the Froude number at the jump upstream (F_1) is identified as the most influenced factor. Furthermore, Regarding the modeling results, after the Froude number the ratio of conjugate depths (h_2/h_1), bed slope (S_0) and the ratio of bed roughness (Ks/h_1), respectively have the highest impact on the estimation of the hydraulic jump length on sloping rough beds using ELM.



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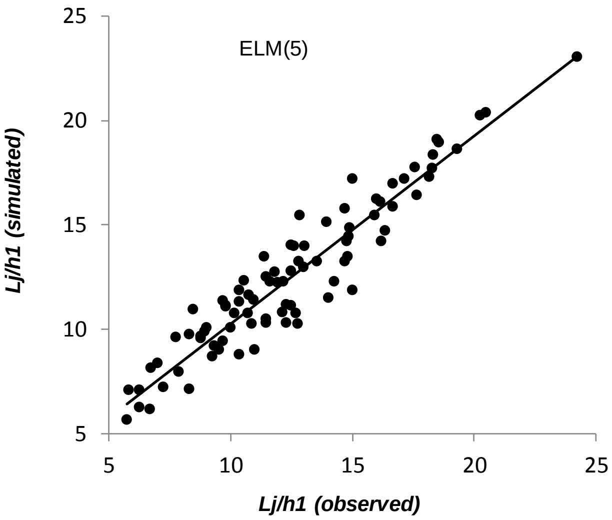

Fig. 5. Scatter plots for ELM (1) to ELM (5) models.

Table 2. Results of activation functions for ELM (1) model.

Activation function	R	MAPE	RMSE	SI	BIAS
Sig	0.985	3.507	0.657	0.052	9.831E-8
Sin	0.984	3.631	0.673	0.054	1.871E-8
Hardlim	0.801	15.182	2.298	0.183	-2.444E-14
Tribas	0.894	10.521	1.720	0.137	0.001
Radbas	0.974	4.769	0.875	0.070	-3.906E-6

3.3. Best ELM model

ELM 1 was identified as the best ELM model because it has the best performance amongst the ELM models. This means that ELM 1 has the lowest error and the highest correlation with experimental measurements. Here, the following relationship is suggested for the superior ELM model:

$$Lj/h_1 = \left[\frac{1}{\left(1+exp\left(InW \times InV + BHN\right)\right)}\right]^T \times OutW \tag{16}$$

where, the InV, InW, OutW and *BHN* are matrix of input parameters, output weights and BIAS of hidden nodes. The proposed matrix can be applied to estimate the roller length of the hydraulic jump with a reasonable accuracy. Values of the matrices for the mentioned model are as follows:

$$\text{BHN} = \begin{bmatrix} 0.684 \\ 0.634 \\ 0.141 \\ 0.079 \\ 0.876 \\ 0.420 \\ 0.487 \\ 0.460 \\ 0.515 \\ 0.271 \\ 0.231 \\ 0.899 \\ 0.908 \\ 0.603 \\ 0.365 \\ 0.598 \\ 0.668 \\ 0.894 \\ 0.087 \\ 0.539 \end{bmatrix} \quad InW = \begin{bmatrix} 0.625 & 0.234 & 0.472 & 0.398 \\ 0.807 & -0.288 & 0.144 & -0.915 \\ 0.080 & -0.274 & -0.982 & 0.055 \\ 0.635 & -0.863 & 0.436 & -0.487 \\ 0.416 & 0.734 & -0.101 & -0.182 \\ -0.913 & -0.084 & 0.319 & 0.895 \\ -0.708 & 0.844 & 0.506 & 0.838 \\ -0.533 & 0.809 & 0.609 & -0.757 \\ 0.506 & -0.436 & -0.941 & 0.183 \\ -0.659 & 0.227 & 0.559 & -0.280 \\ -0.529 & 0.323 & 0.134 & 0.438 \\ -0.449 & -0.599 & -0.847 & 0.047 \\ 0.903 & 0.919 & -0.496 & -0.478 \\ -0.306 & 0.330 & -0.733 & -0.013 \\ -0.405 & 0.082 & 0.128 & 0.711 \\ -0.191 & 0.737 & 0.081 & 0.448 \\ -0.395 & 0.114 & -0.862 & -0.601 \\ 0.514 & -0.957 & 0.976 & -0.685 \\ -0.280 & -0.034 & -0.497 & -0.259 \\ -0.750 & 0.615 & -0.369 & 0.724 \end{bmatrix} \quad \text{Outw} = \begin{bmatrix} 2926.571 \\ -36.847 \\ 2025.539 \\ 2859.905 \\ -11581.333 \\ -1831.217 \\ -567.041 \\ 1338.222 \\ 4398.126 \\ -761.373 \\ 4666.871 \\ -8564.739 \\ 2261.990 \\ 4980.318 \\ -178.041 \\ 671.198 \\ -1739.815 \\ 163.096 \\ 1858.0714 \\ 1003.231 \end{bmatrix} \tag{17}$$

Table 3. Statistical indices for various ELM models.

Model	R	MAPE	RMSE	SI	BIAS
ELM(1)	0.985	3.507	0.657	0.052	9.831E-8
ELM(2)	0.964	6.236	1.016	0.081	-6.810E-5
ELM(3)	0.968	5.099	0.955	0.076	-2.625E-6
ELM(4)	0.966	5.364	0.983	0.078	1.002E-6
ELM(5)	0.949	8.459	1.210	0.096	-2.29E-7

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4. Conclusions

In order to proper and optimize design of detention ponds, the determination of the hydraulic jump length is crucially important. In the paper, the jump length on sloping coarse beds was estimated through a new approach entitled "Extreme Learning Machine". First, the parameters affecting the hydraulic jump length were identified. Then, to determine the most effective parameter in modeling the hydraulic jump length, five different ELM models were introduced. Additionally, the K-fold cross validation technique was applied so as to verify the simulation results. Based on the analysis of the results obtained from the activation functions, sig predicted the experimental values with higher performance. After that, the results of five extreme learning machine (ELM) techniques were analyzed and the premiere combination and the most important input parameter were detected. The best model simulated the jump length by using the Froude number, the ratio of conjugate depths, the ratio of bed roughness and bed slope. For the model, the R, MAPE and RMSE are respectively estimated 0.985, 3.507 and 0.657. Furthermore, the flow Froude number was introduced as the most effective parameter in modeling the hydraulic jump length. Regarding the simulation results, after the Froude number, the ratio of conjugate depths, bed slope and the ratio of bed roughness, respectively, had the highest effects. Finally, the superior model matrix was presented for calculating the hydraulic jump length. It is suggested that other artificial intelligence tools can be applied to simulated features of a hydraulic jump. For example, other characteristics of a hydraulic jump can be estimated by using the devices very well because a stilling basin is designed by the optimized length of hydraulic jump.

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