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Original paper

Modeling discharge capacity of labyrinth weirs through a learning machine approach

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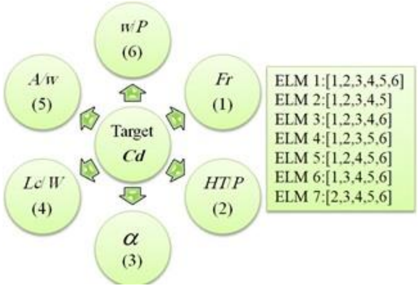
GRAPHICAL ABSTRACT



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ABSTRACT

In this paper, the discharge coefficient of weirs is simulated by the extreme learning machine (ELM). To this end, seven different ELM models are introduced by the input parameters. Also, the most optimal number of the neurons in the hidden layer is computed 7. Furthermore, different activation functions of the ELM model are assessed and the sigmoid activation function is taken into account as the most optimal one. Besides, the seven defined ELM models are analyzed and the superior model is introduced. This model approximates the discharge capacity with better performance in comparison with the other ELM models. It should also be noted that the superior ELM model is in terms of the dimensionless factors including Fr, H_T/P, L_c/W, A/w, w/P. For the superior ELM model, the R^2, VAF and NSC are respectively estimated 0.897, 89.626 and 0.892. Furthermore, the MAE and RMSE statistical indices for the ELM model are respectively estimated 0.024 and 0.031. Also, the most effective input parameters for modeling the discharge capacity of labyrinth weirs using the ELM are detected through the conduction of a sensitivity analysis, meaning that the H_T/P is identified as the most influenced input parameter. Lastly, an applicable equation for computing the discharge capacity of labyrinth weirs is suggested which can be used by hydraulic and environmental engineers.

1. Introduction

Weirs are broadly used in different shapes for adjusting and measuring the flow in open channels. Common sharp-edged weirs have various shapes such as rectangular, V-notch, trapezoidal, Sutro, circular, labyrinth and compound. One of the types of weirs installed along the flow is the labyrinth weir which is more effective than rectangular weirs. Numerous experimental, theoretical, and analytical works have been done on the hydraulic features of flow over the normal weirs. However, numerical models are very popular owing to their accuracy, functionalty, speed and so on (Azimi et al. 2018; Zeynoddin and Bonakdari 2019).

Moreover, artificial intelligence (AI) models have been recently utilized by researchers in various sciences for forecasting and pattern-cognition of nonlinear phenomena. For instance, different algorithms of the artificial neural network are utilized for solving different problems of hydraulics especially calculating the discharge coefficient. Khoshbin et al. (2016) managed to provide an optimized hybrid model for simulation of the discharge capacity of side weirs through the amalgamation of the genetic algorithm (GA), the Adaptive neuro-fuzzy inference system (ANFIS), and the singular value decomposition (SVD). Azimi et al. (2017a) performed a sensitivity analysis so as to examine the variabels affecting the discharge capacity of side weirs placed on trapezoidal canals. They ascertained the superior model along with the most important input parameter by means of the extreme learning machine (ELM). Then, Akhbari et al. (2017) simulated the discharge capacity of triangular labyrinth weirs by the M5' approach. Given the different hydraulic and geometric conditions, they put forward some formulae for computing the discharge capacity. Azimi et al. (2017b) employed the GEP method for simulating the discharge capacity of side weirs within trapezoidal flumes in subcritical flow regimes. They proposed a formula for estimating the target function. Besides, Roushangar et al. (2017)

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simulated the discharge capacity of labyrinth weirs using gene expression programming (GEP) model and ANFIS network. They analyzed the modeling results and demonstrated that the GEP model predicted target function with better performance. Also, Azimi and Shabanlou (2018) analyzed the discharge capacity of rectangular weirs installed on U-shaped channels by the theory of two-dimensional flow. They provided some relationships for computing the parameter in subcritical and supercritical conditions. Azimi et al. (2019) developed six different models using the support vector machine method for estimating the discharge coefficient of weirs in a trapezoidal channel and introduced the superior model through the conduction of a sensitivity analysis. A computational matrix was proposed for estimating the discharge coefficient of such hydraulic structures. Salazar and Crookston (2019) predicted the hydraulic features and the discharge coefficient of arch labyrinth weirs using learning machines such as random forests (RF) and neural networks (NN). Then, Bilhan et al. (2019) modeled the discharge capacity of labyrinth weirs by the support vector regression (SVR) and ELM. It was concluded that the ELM model approximates the target function with greater precision. Additionally, the effects of the upstream Froude number on flow field was simulated by Azimi and shabanlou (2019). The authors investicated the characteristics of flow in the vicinity of the side weir.

Firstly, the discharge capacity of a weir is perhaps the most important parameter for presenting an optimal design. The optimal discharge coefficient allows the maximum amount of flow to pass through under the current hydraulic and geometric conditions. Therefore, the identification of the most effective weir design parameters is of particular importance. On the other hand, the discharge coefficient of weirs has been simulated by various artificial intelligence algorithms and many researchers have studied this important parameter.

The ELM model is a new and robust artificial intelligence which has been applied to simulate discharge coefficient (Azimi et al. 2017a). The model is quite accurate and versetile to predicte vaarious problems. Also, the artificial intelligence (AI) technique is very quick compared with other soft computing approaches. According to the literature, there is no study about simulating the discharge coefficient of labyrnth weirs by using the ELM model. Thus, the discharge coefficient of the weirs is simulated through the new artificial intelligence method for the first time. To this end, the most influnced factors on the discharge capacity are initially identified and seven ELM models are introduced using them. The observation values are then divided into two categories: training and testing sub-groups. To optimize the ELM models, the best number of the neurons within the hidden layer is chosen. Afterthat, five membership functions of the ELM approach are evaluated and the best membership function is introduced. Subsequently, by performing a sensitivity analysis, the superior ELM model and the most important input variables are introduced. It should be noted that an applicable formula is proposed for estimating the discharge capacity of labyrinth weirs by the ELM method which can be used by engineers with the least knowledge of matrix computing.

2. Materials and methods

In the following, firstly, the extreme learning machine (ELM) is introduced and then the applied experimental model is presented. Next, all factors affecting the discharge coefficient are defined and seven ELM models are produced. Finally, the results of simulations are presented.

2.1. Extreme learning machine (ELM)

Due to the difficulties of gradient algorithms that require the definition of different parameters such as the training speed, the iteration criterion and high number of iterations before start training, Huang et al. (2004) presented the ELM algorithm that is a single layer feed-forward neural network (SLFFNN) to overcome the mentioned problems. In this algorithm, the neuron in the hidden layer and input weight matrices are determined by random, while the output weight matrix is specified during the learning process using the Moore-Penrose generalized inverse (MPGI) method.

Given the N samples as training data in the form of $(x_i, y_i) \in R^n \times R^m (i = 1,2,...,n)$, L number of the neurons in the hidden layer and the transfer function f(x), the structure of the SLFFNN model is defined as follows (Huang et al., 2004).

$$\sum_{i=1}^{L} \beta_i f_i(x_j) = \sum_{i=1}^{L} \beta_i f(a_i \cdot b_i \cdot x), \ j = 1,2,...,N \tag{1}$$

In this relationship, $\beta_i = [\beta_{i1}, \beta_{i2}, ..., a_{im}]^T$ is the output weight matrix between the nodes in the hidden layer and the output layer, b_i is the bias of hidden layer neurons and $a_i = [a_{i1}, a_{i2}, ..., a_{in}]^T$ is the input weight matrix linking problem inputs in the input layer to hidden layer neurons. The following equation is established by rewriting the above relationship in a matrix form (Huang et al., 2004):

$$\sum_{i=1}^{L} \beta_i f_i(x_j) = H\beta \tag{2}$$

where, f(x) is the activation function and a matrix of the output weight (β), the output matrix of the hidden layer (H) and the matrix of estimated values (T) are defined as follows (Huang et al., 2004).

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_L^T \end{bmatrix}_{L \times m} \tag{3}$$

$$H = \begin{bmatrix} f(a_1 \cdot x_1 \cdot b_1) & \cdots & f(a_L \cdot x_1 \cdot b_L) \\ \vdots & \ddots & \vdots \\ f(a_1 \cdot x_N \cdot b_1) & \cdots & f(a_L \cdot x_N \cdot b_L) \end{bmatrix} \tag{4}$$

$$T = \begin{bmatrix} y_1^T \\ \vdots \\ y_L^T \end{bmatrix}_{N \times m} \tag{5}$$

In the ELM method, the matrix of input weights (*a*) and the bias of hidden layer neurons (*b*) are initialized. After the determination of these two values, the hidden layer output matrix is determined through the learning process of ELM. In fact, the learning process of SLFFNN using the ELM algorithm leads to solve a least square issue so that its objective function is obtained using the regularization theory as follows (Huang et al., 2004).

$$min\, L_{ELM} = \frac{1}{2}\|\beta\|^2 + \frac{c}{2}\|T - H\beta\|^2 \tag{6}$$

The solution of the above problem as a least square problem is as follows.

$$V - cH^T(T - H\beta) = 0 \tag{7}$$

If the number of training data is higher than the number of hidden layer nodes then the output weight matrix (*β*) is obtained as Eq. 8, otherwise Eq. 9 is used (Huang et al., 2004).

$$\beta = \left(\frac{1}{c} + H^T H\right)^{-1} H^T \tag{8}$$

$$\beta = H^T \left(\frac{1}{c} + HH^T\right)^{-1} T \tag{9}$$

2.2. Experimental apparatus

In this paper, the experimental model established by Seamons (2014) is utilized for verifying the results from the AI approache. In the mentioned laboratory study, the measurements were carried out within a rectangular flume with the length 14.6m, width 1.2m and height 0.9m. The flume slope in all tests is equal to zero and the channel is horizontal. Seamons (2014) measured the experimental values for two modes including normal orientation labyrinth weirs (NLWs) and inverted orientation labyrinth weirs (ILWs). Through the experimental investigation, he measured the flow rate (Q), the total head above the weir crest (H^T), height of the weir crest (P), cycle sidewall angles (α), length of the weir crest (L_c), the width of the labyrinth weir (W), length of apex geometry (A) and width of a single cycle (w). The layout of the experimental model provided by Seamons (2014) is illustrated in Fig. 1.

2.3. Discharge coefficient of labyrinth weir

The discharge coefficient of a weir is presented as follows (Seamons. 2014).

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$$C_d = \frac{3}{2}\frac{Q}{\sqrt{2g}L_c H_T^{3/2}} \tag{10}$$

Besides, the discharge capacity of labyrinth weirs is considered in terms of the following parameters (Seamons. 2014).

$$C_d = f\left(Fr, H_T/P, \alpha, L_c/W, A/w, w/P\right) \tag{11}$$

Thus, in the current study, the dimensionless factors of Equation11 are applied for calculating the discharge capacity by the artificial intelligence model. The amalgamation of the input factors for developing the ELM models are depicted in Fig. 2.

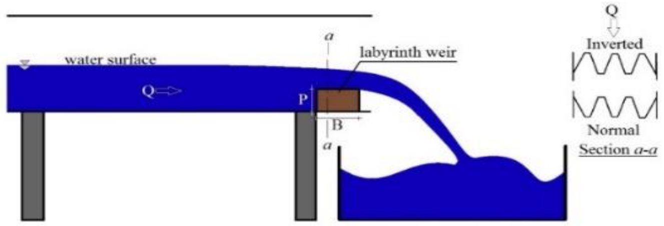


Fig. 1. Layout of Seamons' (2014) model.

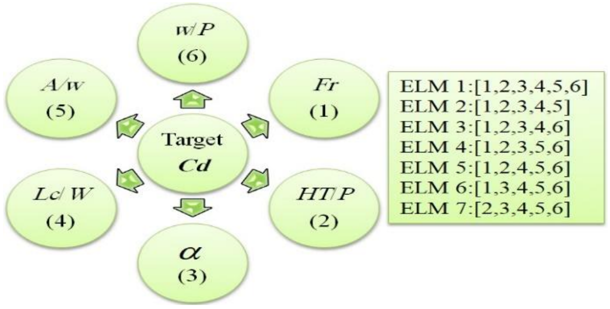


Fig. 2. Amalgamation of input factors for developing AI models.

2.4. Goodness of fit

To examine the performance of the AI models, the correlation coefficient (R), variance accounted for (VAF), Scatter Index (SI), Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Nash-Sutcliff efficiency Coefficient (NSC) are utilized as follows (Azimi et al. 2017b).

$$R = \frac{\sum_{i=1}^{n}\left(F_i - \overline{F}\right)\left(O_i - \overline{O}\right)}{\sqrt{\sum_{i=1}^{n}\left(F_i - \overline{F}\right)^2 \sum_{i=1}^{n}\left(O_i - \overline{O}\right)^2}} \tag{12}$$

$$\mathrm{VAF} = \left(1 - \frac{\operatorname{var}\left(F_i - O_i\right)}{\operatorname{var}\left(F_i\right)}\right) \times 100 \tag{13}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(F_i - O_i\right)^2} \tag{14}$$

$$SI = \frac{RMSE}{\overline{O}} \tag{15}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|F_i - O_i\right| \tag{16}$$

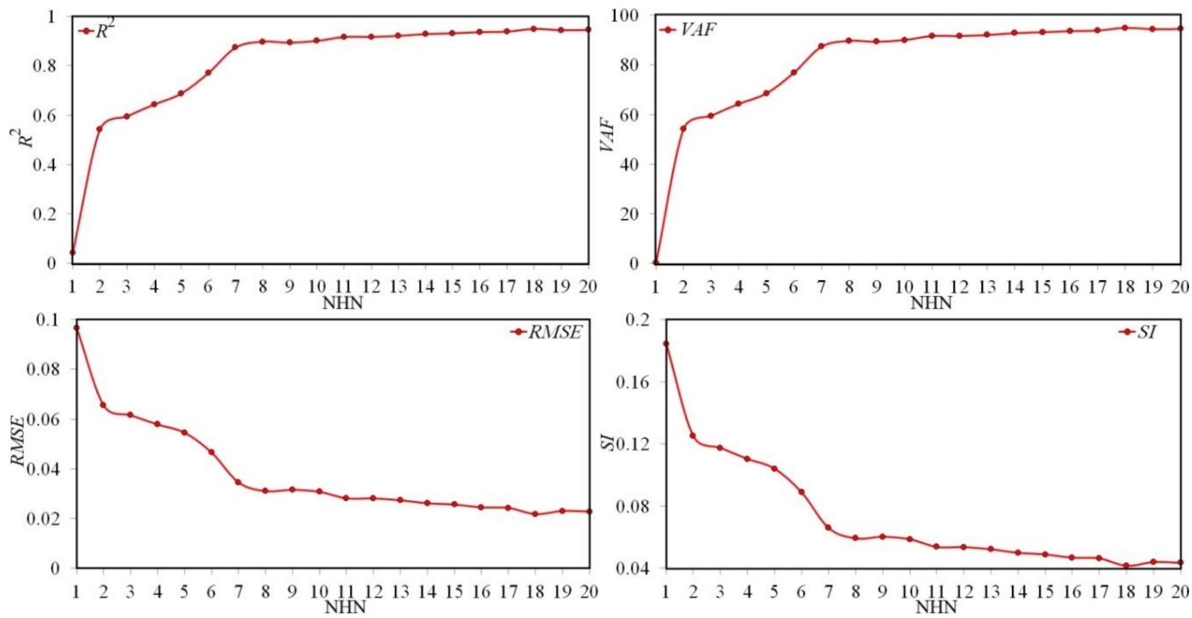
$$NSC = 1 - \frac{\sum_{i=1}^{n}\left(O_i - F_i\right)^2}{\sum_{i=1}^{n}\left(O_i - \overline{O}\right)^2} \tag{17}$$

where, the F_i and O_i are simulated and observed values. Also, the $\overline{F}$, $\overline{O}$ are the averaged of simulated and observed values and the n is the number of experiment. The closeness of the RMSE, MAE and SI to zero indicates the high accuracy of the ELM models. The closeness of the R and NSC indices to one show high correlation of the numerical model with experimental measurements. In general, the superior model has a larger VAF than other numerical models.

3. Results and discussion

3.1. Neurons in hidden layer

In this section, the number of the neurons in hidden layer of the ELM method is investigated. In Fig. 3, the variations of various statistical indices versus the number of neurons within the hidden layer are plotted. As seen, by increasing the values, the accuracy of the numerical model increases significantly. The initial number of the neurons starts from 1 and continues to 20. The most optimal number of the hidden layer neuron is considered equal to 7. For example, when the number of neurons is one, the NSC, VAF and RMSE are obtained 36374.600, 0.156 and 0.097, respectively. In contrast, R^2, RMSE and SI for this number of neurons are yielded 0.873, 0.034 and 0.066, respectively. Additionally, in the case that the number neurons are 7, the NSC, MAE and VAF values are calculated 0.856, 0.026 and 87.382, respectively. Thus, the optimized number of the neurons is considered 7. In Fig. 4, the comparison of the simulated target function by the artificial intelligence model with 7 hidden layer neurons along with the scatter plot is shown. As shown, the accuracy of the numerical model in this case is acceptable. It should be noted that by increasing the hidden layer neurons the computational time increases and finding hidden layer neurons is very important in terms of modeling accuracy and computational time.



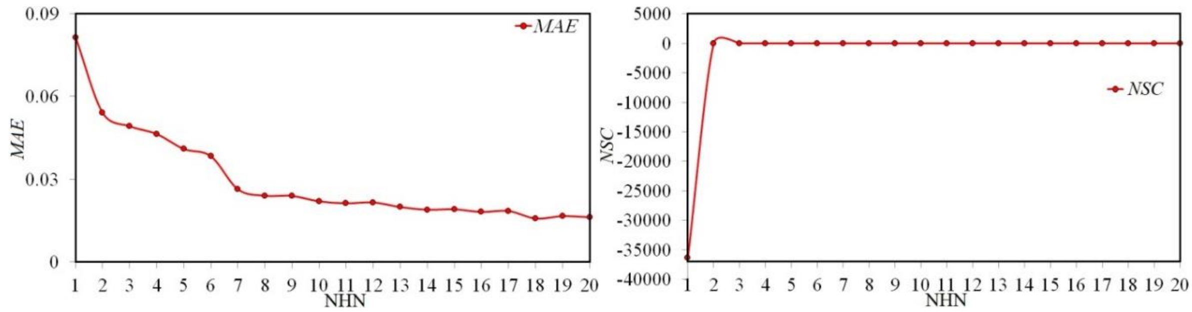


Fig. 3. Changes of different statistical indices versus number of neurons in hidden layer.

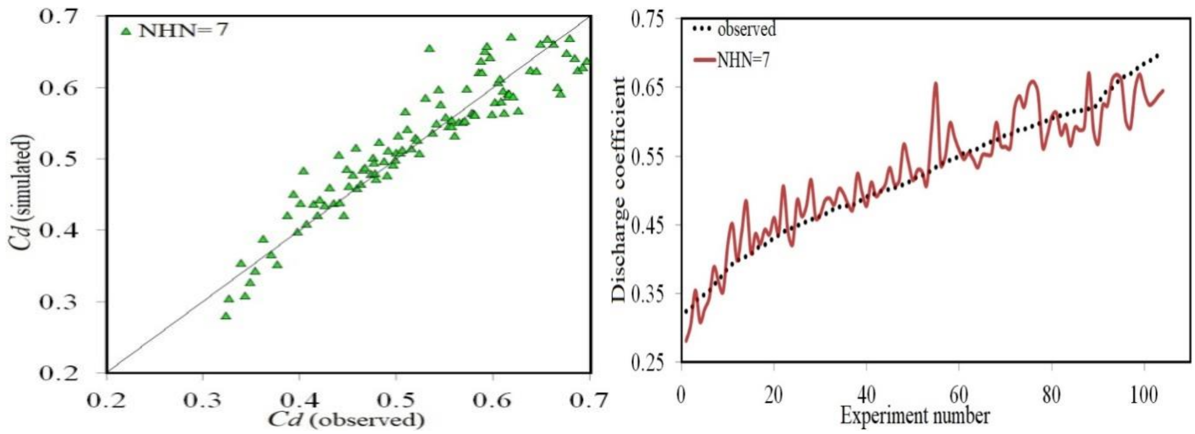
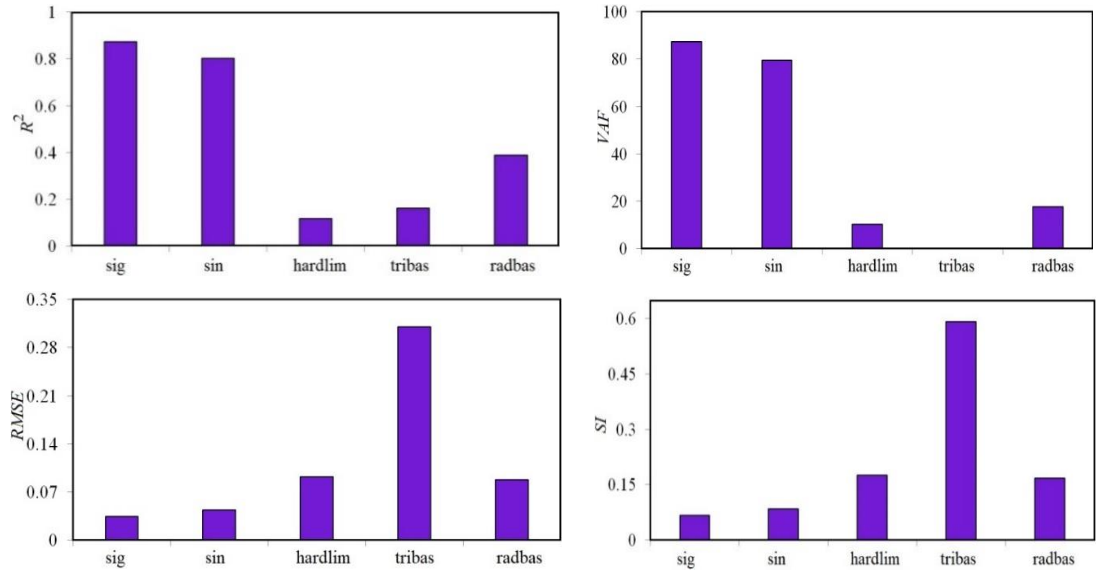


Fig. 4. Comparison of observational and simulated discharge coefficients along with scatter plot for NHL=7.

3.2. Activation function

In the part, the optimal activation function in simulating the discharge capacity of labyrinth weirs is evaluated. As discussed above, ELM owns five activation functions consist of sigmoid, sin, hardlimit, Tribas and Radbas. Furthermore, the results of various statistical indices for all activation functions of ELM are listed in Fig. 5. In Figure 6, the comparison of the simulated and observed discharge coefficients along with the corresponding scatter plots for different activation functions are plotted. For sigmoid, the values of the determination coefficient and the scatter index are obtained 0.874 and 0.066, respectively. Furthermore, VAF, RMSE and MARE for this activation function are calculated 87.382, 0.034 and 0.026, respectively. In contrast, R^2 and RMSE for the sin activation function are estimated to be 0.802 and 0.044, respectively. However, MAE for sin is approximated equal to 0.031. Moreover, for the hardlimit activation function, the SI, MAE and R^2 statistical indices are calculated 0.175, 0.077 and 0.117, respectively. In addition, NSC and VAF for this activation function are respectively estimated -17.612 and 10.243. Among all activation functions, hardlimit owns the lowest correlation with the laboratory values. Also, the determination coefficient and the scatter index for the Radbas activation function are 0.161 and 0.592, respectively. Based on the simulation results, the MAE, VAF and RMSE for the Radbas activation function are 0.241, -598.120 and 0.310, respectively. Among all activation functions of the ELM mode, the Radbas function has the maximum error. Also, the RMSE, MAE and R^2 statistical indices for the Tribas activation function are obtained 0.088, 0.068 and 0.398, respectively. It is worth mentioning that SI, NSC and VAF for Tribas are computed 0.168, 0.299 and 17.737, respectively. According to the examination of the ELM activation functions, sig owns the highest correlation with the observed values. In the following, this activation function is applied for simulation of the discharge capacity of labyrinth weirs.



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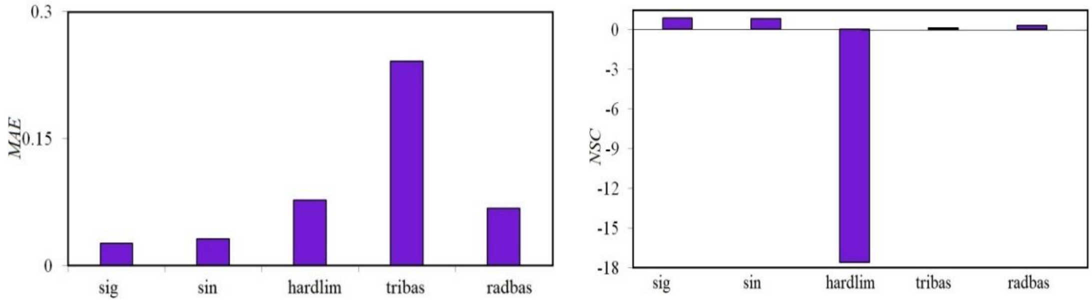
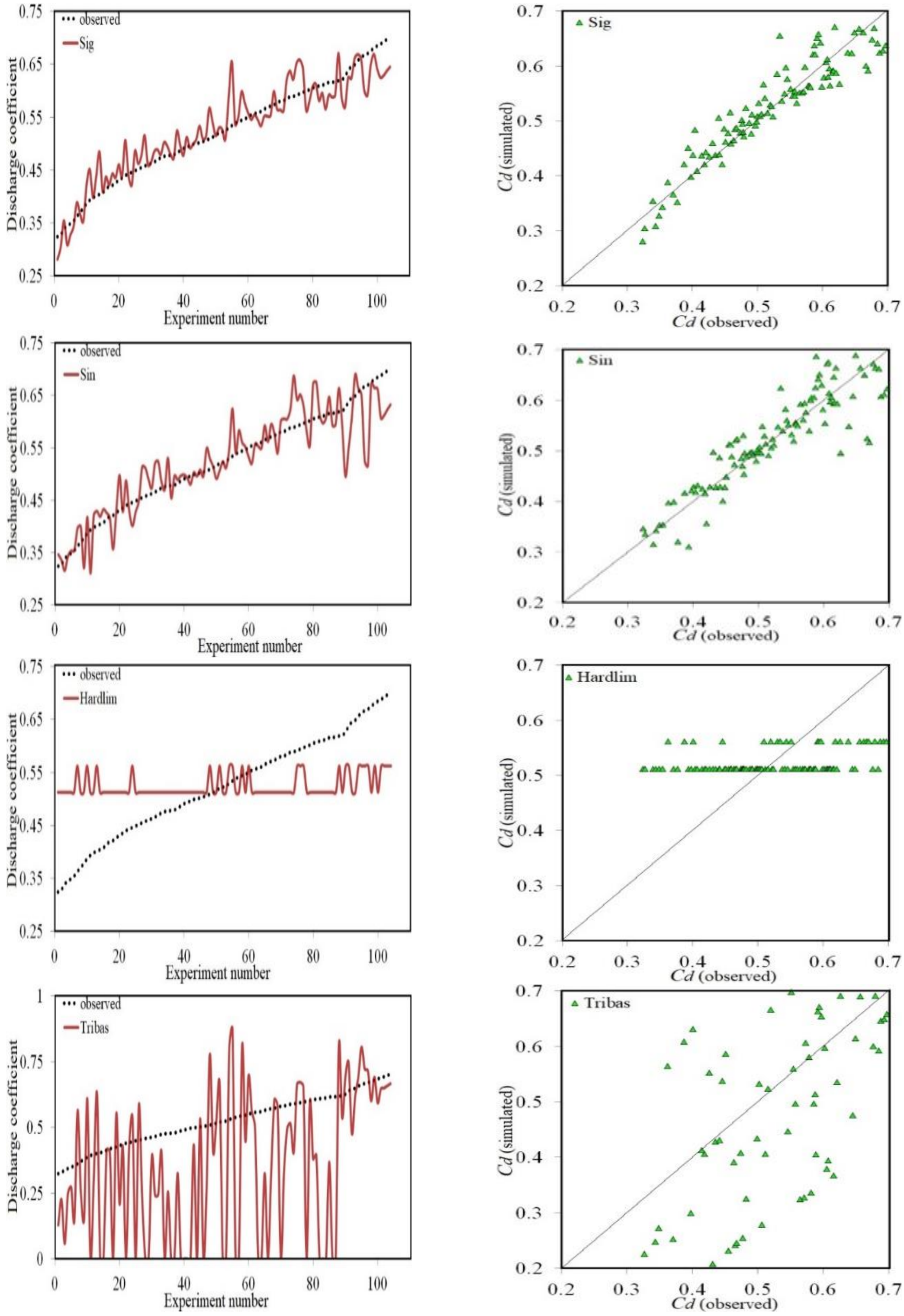


Fig. 5. Results of statistical indices for different activation functions.



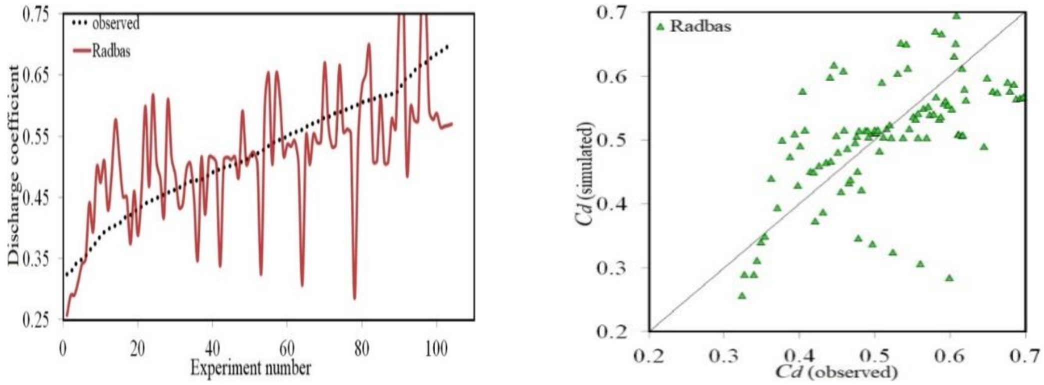
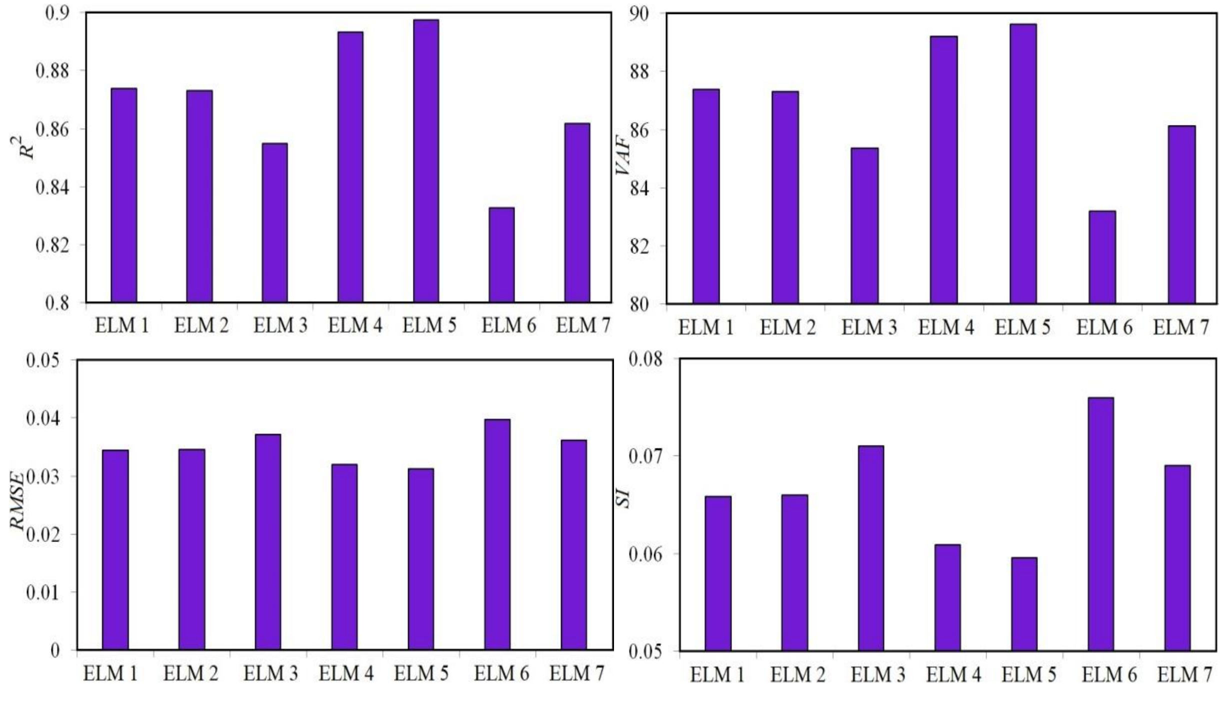


Fig. 6. Comparison of simulated and observed discharge coefficients along with scatter plots for different activation functions.

3.3. Sensitivity analysis

The results of the ELM1 to ELM7 models are evaluated through the conduction of a sensitivity analysis. The comparison of all statistical indices is illustrated in Figure 7. In addition, the comparison of the observed and simulated discharge coefficients along with the corresponding scatter plots is illustrated in Figure 8. The ELM 1 model estimates the discharge capacity using a combination of all input parameters $(Fr, H_T/P, \alpha, L_c/W, A/w, w/P)$. As one of the ELM models, ELM 1 owns the best performance and the lowermost error value. For instance, the values of SI, RMSE and NSC for the ELM1 model are estimated 0.066, 0.034 and 0.856, respectively. Also, the MAE and VAF for the model are respectively calculated 0.026 and 87.382. In the following, the models by means of five input factors are studied. In other words, the ELM2 to ELM7 models approximate the objective function in terms of five input factor. For example, ELM 2 estimates the discharge capacity using $Fr, H_T/P, \alpha, L_c/W, A/w$ and the effects of the dimensionless factors w/P are eliminated for the model. Moreover, the RMSE, MAE and NSC for this model are respectively obtained 0.035, 0.027 and 0.858. Besides, VAF and SI for this model are estimated 87.299 and 0.066, respectively. Then, the ELM 3 model is evaluated. This model forecasts the discharge capacity by means of $Fr, H_T/P, \alpha, L_c/W, w/P$. In other words, the impact of the factor A/w is removed for the model. For the model, the NSC, SI and MAE are respectively computed 0.840, 0.071 and 0.027. Furthermore, the values of RMSE and VAF for ELM3 are computed 0.037 and 85.358, respectively. Subsequently, the results of the ELM4 model are examined. This model is as a function of the dimensionless factors $Fr, H_T/P, \alpha, A/w, w/P$. For estimating the discharge coefficient by this model, the effects of L_c/W are removed. For the model, the MAE and SI are yielded 0.022 and 0.061, in turn. Furthermore, MAE and RMSE for ELM 4 are respectively calculated 0.022 and 0.032. Among all artificial intelligence models with five input parameters, the ELM5 model simulates the discharge capacity with better performance compared with the other AI models. This model is a function of $Fr, H_T/P, L_c/W, A/w, w/P$. The impact of the factor α is eliminated for this model. Additionally, NSC and SI for ELM 5 are calculated 0.892 and 0.060, respectively. It is worth mentioning that MAE, VAF and RMSE for this model are obtained 0.024, 86.626 and 0.031, in turn. Regarding to the simulation results, ELM 6 owns the lowest correlation with the observed values among all artificial intelligence models. To estimate the discharge capacity of labyrinth weirs by this model, the influences of the parameters $Fr, \alpha, L_c/W, A/w, w/P$ are taken into account. It should be mentioned that the impact of the parameter H_T/P is removed. For ELM6, the SI and RMSE are surmised 0.076 and 0.040, in turn. Besides, VAF, MAE and NSC for this model are computed 83.195, 0.029 and 0.808, respectively. It should be noted that the ELM 6 model owns the bottommost error amongst the ELM models. ELM 7 model approximated the objective function data in terms of the dimensionless parameters $H_T/P, \alpha, L_c/W, A/w, w/P$. For the model, the impact of the Froude number (Fr) is removed. For the model, the RMSE and MAE are computed 0.036 and 0.029, in turn. Furthermore, the VAF, SI and NSC statistical indices are calculated 86.113, 0.069 and 0.846, respectively.



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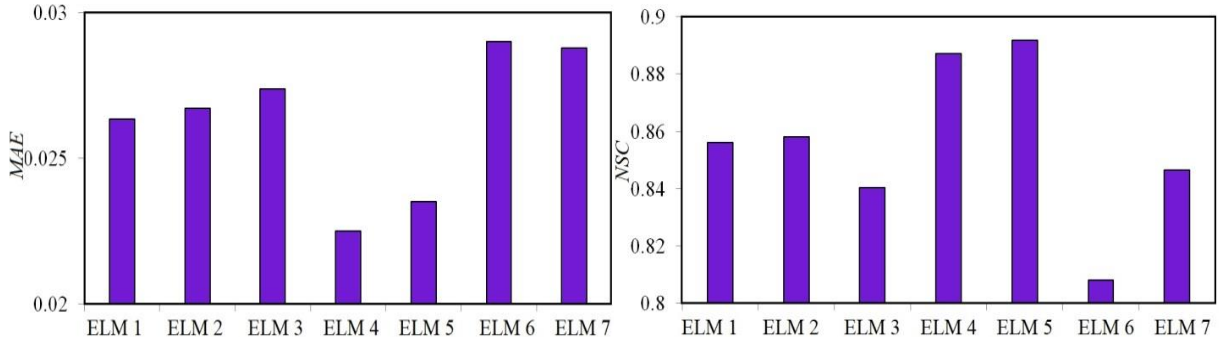
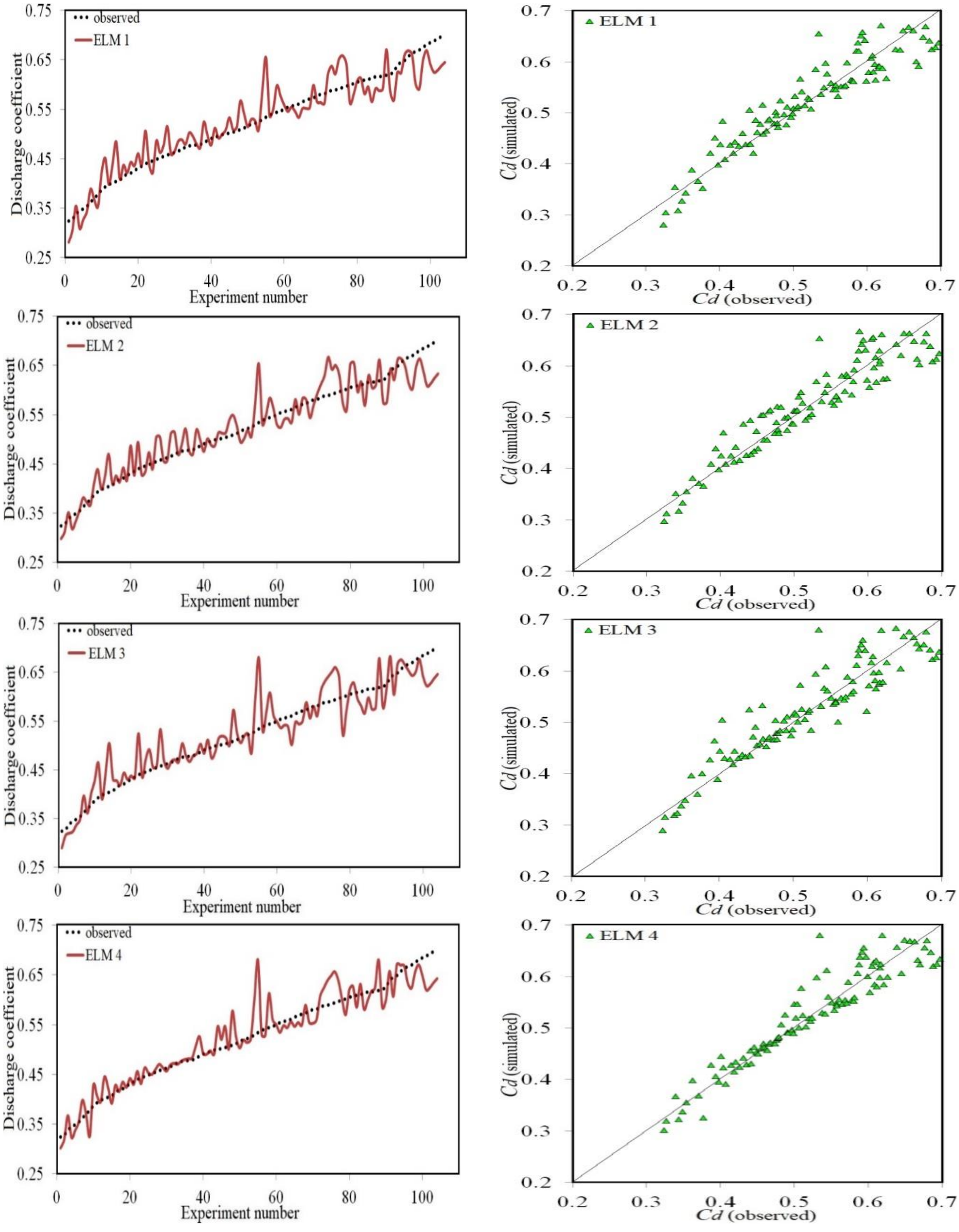


Fig. 7. Results of statistical indices for different ELM models.



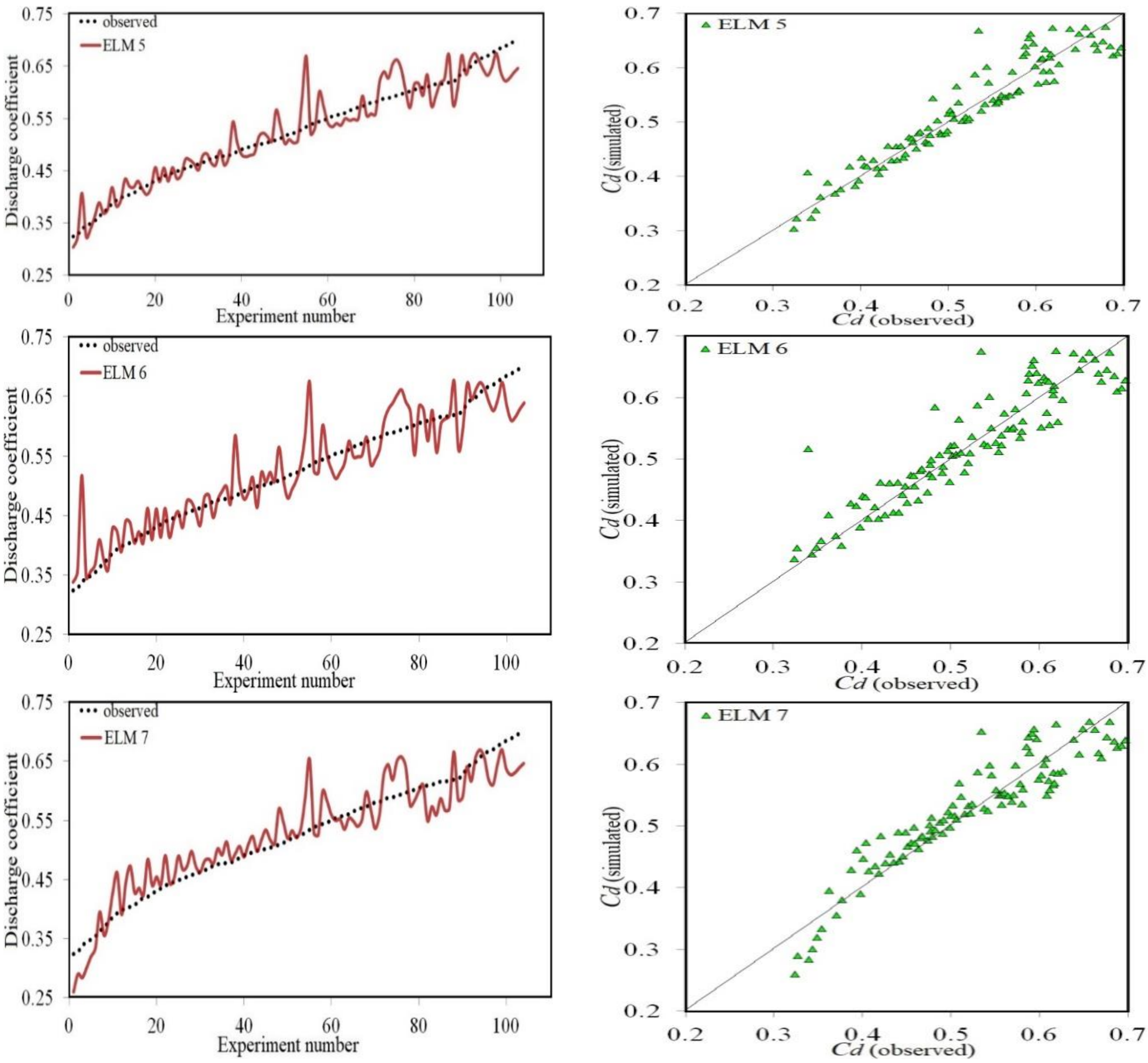


Fig. 8. Comparison of simulated and observed discharge coefficients with corresponding scatter plots for different ELM models.

Additionally, the comparison of the simulated and observed discharge coefficients along with the corresponding scatter plots for the ELM models are shown in Figure8. Regarding to the sensitivity analysis results, the ELM 5 model is presented as the best AI model in estimating the discharge capacity of labyrinth weirs. This model simulated the target function by using the dimensionless parameters $Fr, H_T/P, L_c/W, A/w, w/P$. Furthermore, the ELM6 and ELM3 model the lowest accuracy and correlation, respectively. It should also be noted that regarding to the sensitivity analysis results, the dimensionless factors H^T/P and A/W are identified as the most important input parameters in simulating the discharge coefficient.

Superior model: In this section, for the ELM 5 model which is a function of the dimensionless parameters $Fr, H_T/P, L_c/W, A/w, w/P$, a formula is presented for estimating the discharge capacity of the weirs. The general expression of the proposed equation is as follows.

$$\frac{h_s}{h_t} = \left[\frac{1}{\left(1+exp\left(InW \times InV + BHN\right)\right)}\right]^T \times OutW \tag{18}$$

where, InW, InV, BHN and OutW are the matrix of input weight, input weights, input variables, the bias of hidden layer neurons and output weights, respectively. Values of each matrix is presented as the following relationships.

$$InV = \begin{bmatrix} Fr \\ H_T/P \\ L_c/W \\ A/w \\ w/P \end{bmatrix} \tag{19}$$

$$InW = \begin{bmatrix} 0.303 & 0.743 & -0.689 & -0.343 & 0.360 \\ 0.409 & -0.440 & 0.683 & 0.991 & -0.257 \\ 0.562 & -0.533 & -0.520 & -0.010 & 0.575 \\ 0.618 & -0.477 & 0.598 & -0.075 & -0.895 \\ -0.430 & 0.146 & 0.017 & 0.0855 & -0.778 \\ 0.290 & 0.874 & 0.951 & 0.968 & 0.493 \\ 0.227 & 0.877 & 0.811 & -0.321 & -0.354 \end{bmatrix} \tag{20}$$

$$BHN = \begin{bmatrix} 0.488 \\ 0.083 \\ 0.400 \\ 0.172 \\ 0.323 \\ 0.387 \\ 0.770 \end{bmatrix} \tag{21}$$

$$OutW = \begin{bmatrix} -1.916 \\ -1.173 \\ 1.841 \\ -1.121 \\ 1.785 \\ 0.539 \\ 0.590 \end{bmatrix} \tag{22}$$

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4. Conclusions

In this paper, the discharge capacity of labyrinth side weirs placed in rectangular channels was simulated using a new artificial intelligence (AI) method called "Extreme Learning Machine (ELM)". Initially, the parameters influencing the discharge coefficient of labyrinth weirs were detected. Then seven distinctive ELM models were developed using the effective parameters. It is worth mentioning that 70% of the experimental data were used for training the models, while the remaining 30% were employed to test them. All parts of the ELM model including the number neurons in the hidden layer and the activation function were optimized. In other words, the most optimal number neurons in the hidden layer of the ELM model was considered equal to 7. The RMSE, MAE and SI for the neurons were equal to 0.034, 0.026 and 0.066, respectively. Moreover, five activation functions of the ELM model were examined and the sig function was finally chosen as the best one. The values of R^2, RMSE and VAF for this activation function were approximated 0.873, 0.034 and 87.382, respectively. After that, the results of all ELM models were investigated and the best model was presented through the conduction of a sensitivity analysis. This model simulated the discharge capacity with reasonable performance. For instance, the NSC, VAF and R^2 for the superior ELM model were computed 0.892, 89.626 and 0.897, respectively. Besides, the sensitivity analysis results demonstrated that the dimensionless parameters H_T/P and A/w are the most important input factors in predicting the discharge coefficient through the ELM method. Finally, an applicable matrix was presented for estimating the discharge capacity of labyrinth weirs using the superior ELM model. This formula can be easily used by engineers and researchers with the least knowledge of matrix computations. This matrix can be used in applicable problems without prior knowledge of artificial intelligence.

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