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Predicting Velocity at Limit of Deposition in Storm Channels using two Data Mining Techniques

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ABSTRACT

In storm channel system design, the system should have the ability to transfer the entire input flow to the system as well as prevent sediment settling. Existing methods of determining the velocity at limit of deposition are minimum velocity or regression-based equations. Because minimum velocity methods fail to consider the effective flow and sediment transfer parameters and regression-based equations are not flexible in terms of various hydraulic conditions, they do not perform well. Thus, using such equations leads to a lack of designs with optimum, confident coefficients. In this study, Extreme Learning Machines (ELM) are employed to predict velocity at limit of deposition. ELM is a new algorithm for single-hidden layer feed-forward neural network (SLFN) training, which overcomes problems caused by gradient algorithms such as low velocity in network training. In this study, dimensional analysis is applied to identify the effective parameters on estimating the velocity at limit of deposition followed by ELM to predict the parameter values. ELM performance is compared with artificial neural networks (ANN) and regression-based equations. According to the results, using ELM increases the convergence speed to obtain optimum velocity results and is accordingly more accurate. The results represent the superior performance of ELM compared to existing regression-based equations.

Keywords: *Artificial Neural Network (ANN), Extreme Learning Machines (ELM), sediment transport, storm sewer, velocity at limit of deposition.*

1. INTRODUCTION

One of the most important concerns in storm water channel design is sediment transfer. Depending on flow velocity, solids in the flow path are washed and transferred by the flow and then enter the storm channel. If the flow entering the channel at a fixed slope does not have sufficient velocity to transfer the input sediment to the channel, sedimentation will occur on the bed. The presence of sediment on the channel bed causes an increase in bed roughness and a decrease in flow cross section, which is associated with flow capacity transfer reduction. Moreover, the velocity distribution and shear stress in the channel are altered. Therefore, a method is required to determine the minimum velocity required to prevent sediment deposition (i.e. minimum velocity at limit of deposition). One of the easiest methods entails using constant velocity in the range of 0.3-1 m/s according to different research works (Ebtehaj et al. 2014). As minimum velocity does not consider the effective parameters on sediment transport in channels, it often leads to velocity overestimation and underestimation with high relative errors (Nalluri and Ab Ghani 1996). Therefore, several researchers have employed different experimental data concerning the effective parameters on sediment transport, such as pipe diameter, flow resistance, hydraulic radius, particle diameter, etc., and presented different relationships using nonlinear regression. May et al. (1996) utilized 7 different datasets including a wide range of different variables and presented a semi-empirical relationship to calculate the limiting velocity as follows:

$$C_V = 3.03\times 10^{-2}\left(\frac{D^2}{A}\right)\left(\frac{d}{D}\right)^{0.6}\left(\frac{V^2}{g(s-1)D}\right)^{1.5}\left(1-\frac{V_t}{V}\right)^4 \tag{1}$$

$$V_t = 0.125\sqrt{g(s-1)d}\left(\frac{y}{d}\right)^{0.47} \tag{2}$$

where C_V is the volumetric sediment concentration, D is the pipe diameter, A is the cross-sectional flow area, s is the specific gravity of sediment ($=\rho_s/\rho$), y is the flow depth, d is the median diameter of particles, V is the flow velocity, g is the gravitational acceleration, and V_t is the velocity required for incipient sediment motion (Equation 2).

Azamathulla et al. (2012) applied dimensional analysis and considered the sediment transport dimensionless parameters, viz. dimensionless particle number ($D_{gr}=(d(s\text{-}1)/\nu^2)^{1/3}$), volumetric sediment concentration (C_V), relative median diameter of particles to hydraulic radius (d/R), and overall sediment friction factor (λ_s). They presented the following relationships.

$$Fr=\frac{V}{\sqrt{g(s-1)d}}=0.22C_V^{\ 0.16}D_{gr}^{\ -0.14}\left(\frac{d}{R}\right)^{-0.29}\lambda_s^{\ -0.51} \tag{3}$$

$$\lambda_s=0.851\lambda_c^{\ 0.86}C_V^{\ 0.04}D_{gr}^{\ 0.03} \tag{4}$$

where λ_c is the clear water friction factor of the channel and Fr is the densimetric Froude number. Ebtehaj et al. (2014) used a wide range of data and modified Vongvisessomjai et al.'s (2010) equation as follows:

$$Fr=\frac{V}{\sqrt{g(s-1)d}}=4.49C_V^{\ 0.21}\left(\frac{d}{R}\right)^{-0.54} \tag{5}$$

The main problem with regression methods is the lack of accuracy in different hydraulic conditions. This relationship's results for different hydraulic conditions are different from the conditions used to determine the relationship, and it does not produce good results (Ebtehaj et al. 2014). Thus, some methods that have the ability to identify the complex relationship of nonlinear systems are still required.

In recent years, artificial intelligence (AI) has been used in hydraulic and water engineering (Ebtehaj and Bonakdari 2013; Khoshbin et al. 2015; Gholami et al. 2015; Karimi et al. 2015) and good estimations of different hydraulic parameters have been obtained. Thus, AI can be used as an alternative method to regression-based methods. Several AI methods, such as group method of data handling, gene expression programming, adaptive neuro fuzzy inference system, and a hybrid of ANN and an evolutionary algorithm (Azamathulla et al. 2012; Bonakdari and Ebtehaj 2015; Ebtehaj and Bonakdari 2014, 2015a) have been used to determine sediment transportation in stormwater sewer channels. One of the methods that is frequently used in sediment transport prediction is the Artificial Neural Network (ANN) (Ebtehaj and Bonakdari 2013, 2014). Extreme Learning Machines (ELM) is a new and simple method as a single-layer feed-forward neural network (SLFNN) whose velocity prediction is much higher than ANN. This method has demonstrated good performance in various applications, but based on the authors' knowledge, this method has not been used to predict sediment transport until now.

The main aim of this study is to predict the velocity at limit of deposition using Extreme Learning Machines (ELM). First, dimensional analysis is used to determine the effective parameters on limiting velocity estimation. Then ELM is used to predict the limiting velocity. Subsequently, the method results presented in this study are compared with ANN results and regression-based equations. Additionally, the effect of each input parameter on the proposed model is evaluated using sensitivity analysis.

2. MATERIALS AND METHODS

2.1. Artificial Neural Network (ANN)

The Artificial Neural Network (ANN), which is designed based on the human brain neuron system, is applied in diverse fields such as prediction, classification, and pattern recognition (Haykin 1999). ANN is a parallel data processing system that obtains the mapping between datasets in input-output form. A feed-forward MLP neural network generally consists of three different layers (an input layer, an output layer, and one or more hidden layers). Each layer of neurons is in contact with the next layer, and there is no connection between neurons in one layer. The neurons' output is calculated with the following equation:

$$y_m = F(r_m) \quad (6)$$

$$r_m = \sum_{i=1}^{n} (w_{mi} x_i + b_m) \quad (7)$$

where y_m is the output signal of a neuron, *F* is the activation function, r_m is the linear combiner output, x_i is the input signal, w_i is the synaptic weight, and b_m is the bias. Owing to the good performance of the sigmoid activation function in previous studies (Ebtehaj and Bonakdari 2013, 2015b), this activation function is used in the present study. It is defined as follows:

$$f(x) = \frac{1}{1 + exp(-x)} \quad (8)$$

To train the ANN, the Levenberg-Marquardt (LM) algorithm is applied, which is recognized as the best algorithm among gradient-based algorithms for predicting sediment transport (Ebtehaj and Bonakdari 2015b). The algorithm uses experimental observed inputs to estimate the weights and bias. The number of layers, number of neurons in hidden layers, number of iterations, and learning rate was 3, 19, 1000, and 0.5, respectively.

2.2. Extreme Learning Machines (ELM)

To overcome the problems of ANN, such as local minima, over-fitting, and long computational time, Huang et al. (2006) proposed a single-layer feedforward neural network (SLFNN) known as Extreme Learning Machines (ELM). The main difference between ELM and traditional ANN in terms of parameter determination lies in the feedforward network's input weights and bias. Unlike ANN, in the ELM method, it is not necessary to determine these as they are obtained randomly. However, the output weight values are calculated using the Moore-Penrose generalized inverse. Thus, according to the random selection of weights and biases, SLFNN can be considered a linear system. This characteristic leads to considerably faster calculations by ELM than ANN. Considering a data series with *N* different samples as (x_i, t_i), the ELM algorithm with $\tilde{N}$ hidden neurons is expressed as follows:

$$\sum_{i=1}^{\tilde{N}} \beta_i G(x_j; w_i, b_i) = o_j \qquad j = 1,2,3,..., N \quad (9)$$

where $\beta_i = [\beta_{i1}, \beta_{i2}, \beta_{i3}, ..\beta_{im}]^T$ is the connecting weight vector between the i^{th} hidden neuron and the output neurons, $G(x_j; w_i, b_i)$ is the i^{th} hidden node related to x_j as the input and b_i, and $w_i = [w_1, w_2, w_3,..., w_{\tilde{N}}]$ are the hidden node learning parameters. Regarding the $x = [x_1, x_2, x_3,..., x_N]$, $w = [w_1, w_2, w_3,...w_N]$, $b = [b_1, b_2, b_3,..., b_N]$ parameters, an ELM algorithm with $\tilde{N}$ hidden neurons can approximate the $g(x)$ function with N samples as follows:

$$\sum_{j=1}^{N} \left\| o_j - t_j \right\| = 0 \quad (10$$

In fact, a combination of β_i, w_i and b_i exists as

$$H(x; w, b)\beta = T \quad (11)$$

in which

$$H(x_1,...x_{\tilde{N}}, w_1,..., w_{\tilde{N}}, b_1,...b_{\tilde{N}}) = \begin{bmatrix} G(x_1, w_1, b_1) & ... & G(x_1, w_{\tilde{N}}, b_{\tilde{N}}) \\ . & ... & . \\ . & ... & . \\ . & ... & . \\ G(x_N, w_1, b_1) & ... & G(x_N, w_{\tilde{N}}, b_{\tilde{N}}) \end{bmatrix}_{N \times \tilde{N}}, \quad \beta = \begin{bmatrix} \beta_1^T \\ . \\ . \\ . \\ \beta_{\tilde{N}}^T \end{bmatrix}_{\tilde{N} \times m}, \quad T = \begin{bmatrix} t_1^T \\ . \\ . \\ . \\ t_N^T \end{bmatrix}_{N \times m}$$

Fixed weights w_i and hidden layer bias b_i in ELM training are comparable to the least squares solution (*β)* of the linear system ($H = \beta T$) as follows:

$$\left\| H\left(w_1,\ldots,w_{\tilde{N}},b_1,..b_{\tilde{N}}\right)\beta - T\right\| = \min_{\beta}\left\| H\left(w_1,\ldots,w_{\tilde{N}},b_1,..b_{\tilde{N}}\right)\beta - T\right\| \quad \backslash \tag{12}$$

The above linear equation can be rewritten as

$$\hat{\beta} = H^{+}T \tag{13}$$

For RBF hidden nodes with Gaussian function $g(.)$, the following equation is used:

$$G\left(x_j; w_i, b_i\right) = g\left(b_i \left\| x_j - w_i \right\|\right) \tag{14}$$

where b_i and w_i are the impact factor and centre of the i^{th} RBF node, respectively. In this study, to develop ELM for predicting velocity at limit of deposition, the neuron number in the hidden layer and the number of iterations was equal to 17 and 3000, respectively.

2.3. Goodness of Fit

To evaluate the accuracy of models GEP (1) to GIP (4), the statistical indices mean average percentage error (*MARE*), root mean square error (*RMSE*), correlation coefficient (*R*), scatter index (*SI*), and *BIAS* are used as follows:

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left(\frac{\left|(Fr)_{(\mathrm{Predicted})_i} - (Fr)_{(Observed)_i}\right|}{(Fr)_{(Observed)_i}}\right) \tag{15}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left((Fr)_{(\mathrm{Predicted})_i} - (Fr)_{(Observed)_i}\right)^2} \tag{16}$$

$$R = \frac{\sum_{i=1}^{n}\left((Fr)_{(Observed)i} - \overline{(Fr)}_{(Observed)}\right)\left((Fr)_{(\mathrm{Predicted})i} - \overline{(Fr)}_{(\mathrm{Predicted})}\right)}{\sqrt{\sum_{i=1}^{n}\left((Fr)_{(Observed)i} - \overline{(Fr)}_{(Observed)}\right)^2 \sum_{i=1}^{n}\left((Fr)_{(\mathrm{Predicted})i} - \overline{(Fr)}_{(\mathrm{Predicted})}\right)^2}} \tag{17}$$

$$SI = \frac{RMSE}{\overline{(Fr)}_{(Observed)}} \tag{18}$$

$$BIAS = \frac{1}{n}\sum_{i=1}^{n}\left((Fr)_{(\mathrm{Predicted})_i} - (Fr)_{(Observed)_i}\right) \tag{19}$$

3. METHODOLOGY

Laboratory and analytical studies conducted on sediment transport in stormwater channels show that the minimum velocity required to prevent sediment deposition on the channel bed (limiting velocity) depends on the hydraulic conditions, channel geometry, and input sediment characteristics (Ab Ghani 1993; May et al. 1996; Vongvisessomjai et al. 2010; Azamathulla et al. 2012; Ebtehaj et al. 2013; 2014; 2015a). Thus, the functional equation between the limiting velocity and the effective parameters can be expressed as follows:

$$V = f(R, d, C_V, g, s, D_{gr}) \tag{20}$$

where V is the limiting velocity, R is the hydraulic radius, d is the median diameter of particles, C_V is the volumetric sediment, g is the gravitational acceleration, s is the specific gravity of sediment, and D_{gr} is the dimensionless particle number. As the dimensionless parameters can lead to more accurate prediction of sediment transport in stormwater channels compared with using dimensional parameters, dimensional analysis and a dimensionless functional equation are used to estimate the limiting velocity using ELM presented as follows:

$$Fr = \frac{V}{\sqrt{g(s-1)d}} = f(C_V, D_{gr}, d/R, \lambda_s) \tag{21}$$

The relationship above is used to develop the ELM method to predict the limiting velocity. In this study, 218 data were collected from three different datasets (Ab Ghani 1993; Ota and Nalluri 1999; Vongvisessomjai et al. 2010) to model the *Fr* using ELM. Via random selection, 30% of data (65 data) were chosen for model testing and the remaining 70% (153 data points) were used for model training. Additional explanations about the experimental data are provided in previous studies (Ebtehaj and Bonakdari 2013; Ebtehaj et al. 2014). The data ranges employed are as follows: $1<C_V$ (ppm)<1280; $0.006<d/R<0.246$; $0.84<y/D<0.133$; $5.06<D_{gr}<142$; $0.013<\lambda_s<0.053$.

4. RESULTS AND DISCUSSION

Figure 1 compares the performance of two feedforward neural networks (FNN), including ELM and ANN. This figure shows that ELM has good precision in *Fr* estimation. All values determined by this method were estimated with less than 10% relative error, with the highest relative error in *Fr* estimation by ELM being around 9%. The average relative error presented by the model was about 2.5%, which indicates the high accuracy of this model in limiting velocity estimation. ANN also performed well and estimated about 60% of the total determined data with less than 10% relative error. The statistical index values indicate that between the values of both indices shown in Figure 1, they were higher for ANN (*RMSE* = 0.15 & *MAPE* = 2.54) than for ELM (*RMSE* = 0.15 & *MAPE* = 2.54). In addition, the error distribution of *Fr* estimation indicates ELM's superiority over ANN in estimating this parameter. Therefore, besides the fact that ELM modelling is much more rapid than ANN, model accuracy is significantly higher than ANN as well.

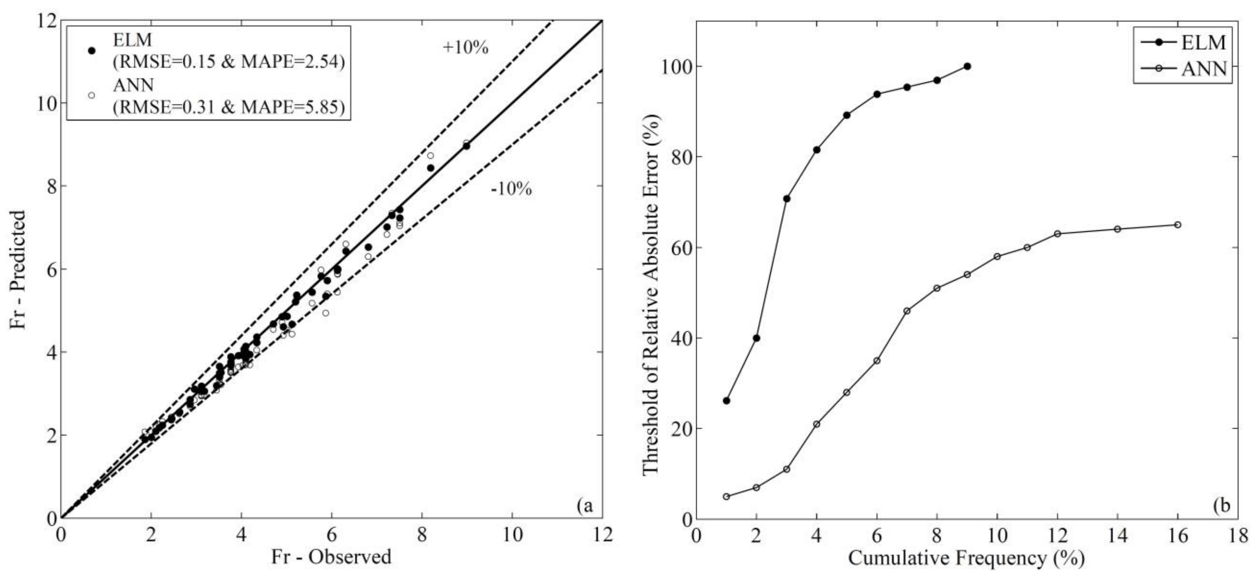

Figure 1 (a) Scatter plot for ELM and ANN, and (b) error distribution for ELM and ANN

ELM with relative error below 3% (*MAPE* = 2.54) estimated the *Fr* parameter with high accuracy. All estimations made by this method have less than 10% relative error. Also, according to the presented error distribution, about 90% of estimations have less than 5% relative error. The BIAS of -0.07 indicates that the values estimated by ELM are on average 0.07 lower than the observed laboratory values. In fact, the model performs with underestimation due to the lack of statistical indices, but this ELM underestimation performance does not lead to significant problems with sediment deposition. Ebtehaj et al.'s (2014) relation uses only two parameters, C_V and *d/R,* in *Fr* estimation and other parameters considered by ELM (D_{gr} and λ_S) are not as effective. This equation shows relatively good performance, but with increasing the *Fr* value, the model performs with underestimation. Because the relative error values of Ebtehaj et al.'s (2014) equation are over 10%, using this relationship may lead to sediment deposition on the channel bed although the statistical index values in Table 1 show that this model generally performs well (R^2 = 0.99; *MAPE* = 7.51, *RMSE* = 0.54, *SI* = 0.13, *BIAS* = -0.38).

A comparison of Ebtehaj et al.'s (2014) relationship with the ELM results indicates that the average relative error is about 3 times higher than the index for ELM. Azamathulla et al.'s (2012) relationship, which has similar inputs to the ELM inputs (C_V, d/R, D_{gr} and λ_S) does not exhibit high accuracy but rather underestimation performance (*BIAS* = -1.1) and the estimated values compared to the observed values are greatly different. By increasing the *Fr* value, the estimation error increases with this relationship. Using this relationship leads to significant sediment deposition on the channel bed and reduced transmission capacity. Among the models presented in Table 2, this relationship has the weakest performance. The relative error is about 21% (*MAPE* = 21.52), which is almost 10 times higher than this index value for ELM. May et al.'s (1996) relationship is a semi-empirical equation and performs with underestimation (*BIAS* = -0.04). The index value for May et al.'s (1996) model compared to other models has the lowest absolute value because this relationship approximates the estimated values as both less and more than the experimental values with large errors, and the sum of the negative and positive values results in decreased *BIAS*. The *MAPE* index shows that the average *Fr* estimation accuracy of this model is about 9% (*MAPE* = 9.21) compared with the two ELM models, and Ebtehaj et al.'s (2014) equation shows weaker performance. The error distribution diagram shows that May et al.'s (1996) relationship estimates 20% of data with more than 20% relative error and a maximum of 35% relative error. Therefore, using May et al.'s (1996) relationship in stormwater channel design with large error in both underestimation and overestimation leads to significant sediment deposition on the channel bed and uneconomic plans, respectively.

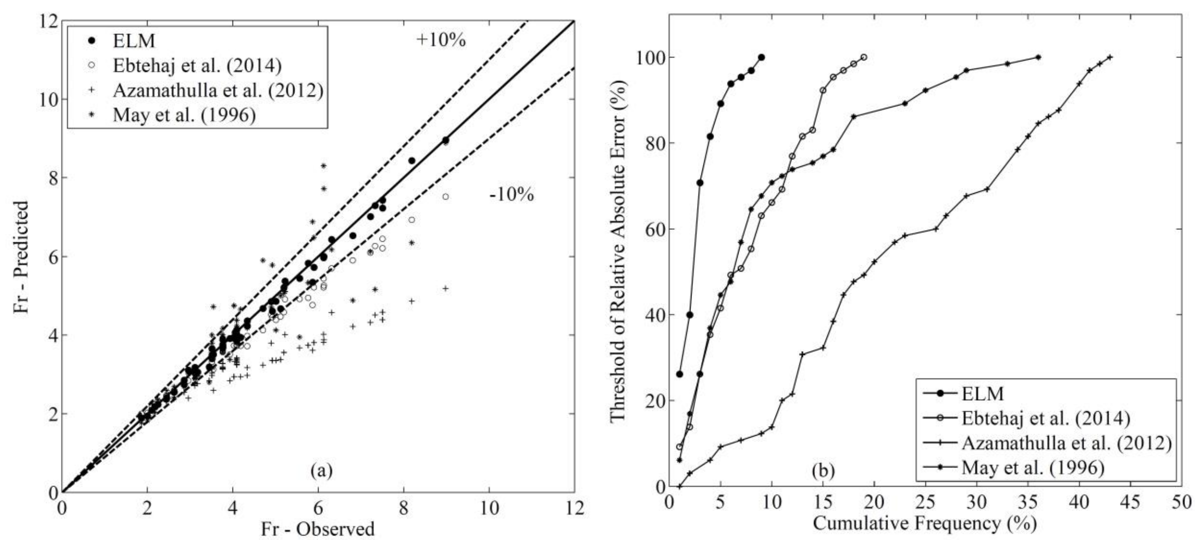

Figure 2. (a) Comparison of ELM and regression-based equations and (b) Scatter plot error distribution

Table 1. Comparison of ELM and regression-based equations using statistical indices

Method	R^2	*MAPE*	*RMSE*	*SI*	*BIAS*
ELM	0.997	2.54	0.15	0.04	-0.07
Ebtehaj et al. (2014)	0.995	7.51	0.54	0.13	-0.38
Azamathulla et al. (2012)	0.968	21.52	1.44	0.33	-1.10
May et al. (1996)	0.904	9.21	0.70	0.16	-0.04

Table 2 evaluates the effect of each parameter considered in this study as an effective parameter in $Fr = f(C_V, D_{gr}, d/R, \lambda_s)$ estimation. Models ELM (2) to ELM (5) that do not include one of the parameters in Fr estimation are less accurate than ELM (1). In fact, it is necessary to use the parameters provided in relationship 21 to predict Fr. Among the $C_V, D_{gr}, d/R, \lambda_s$ parameters; not using the volumetric sediment concentration (C_V) parameter caused the greatest reduction in modelling accuracy. The relative error was about 10 times higher than ELM (1) (MAPE = 21.89). This status is also evident for the RMSE, SI, and R^2 indices. In all models, the *Fr* prediction process was constant and ELM performed with underestimation. Not using the overall sediment friction factor (λ_S) and relative median diameter of particles to hydraulic radius (*d*/*R*) parameters demonstrated approximately the same results and led to the lowest decrease in modelling accuracy. However, the lack of these two parameters increased the relative error value in *Fr* estimation by about 10% in using ELM.

Table 2. ELM model sensitivity analysis results

Model	Input combination	R^2	*MAPE*	*RMSE*	*SI*	*BIAS*
ELM (1)	$Fr = f(C_V, D_{gr}, d/R, \lambda_s)$	0.997	2.54	0.15	0.04	-0.07
ELM (2)	$Fr = f(C_V, D_{gr}, d/R)$	0.914	12.49	0.74	0.17	-0.34
ELM (3)	$Fr = f(C_V, D_{gr}, \lambda_s)$	0.931	12.86	0.68	0.16	-0.27
ELM (4)	$Fr = f(C_V, d/R, \lambda_s)$	0.859	15.89	0.90	0.21	-0.27
ELM (5)	$Fr = f(D_{gr}, d/R, \lambda_s)$	0.563	21.89	1.34	0.31	-0.17

5. CONCLUSIONS

Regarding the importance of determining the limiting velocity to prevent sediment deposits entering stormwater channels, Extreme Learning Machines (ELM) were employed in this study to predict the limiting velocity. First, dimensional analysis of the important parameters in limiting velocity estimation was done. The parameters are dimensionless particle number (D_{gr}), volumetric sediment concentration (C_V), relative median diameter of particles to hydraulic radius (*d*/*R*), and overall sediment friction factor (λ_S). ELM was used to predict the *Fr* parameter. According to the modeling results, ELM showed good accuracy in *Fr* estimation (R^2 = 0.997, *MAPE* = 2.54, *RMSE* = 0.15, *SI* = 0.04, *BIAS* = -0.07) as all estimated values had less than 10% relative error. To examine the proposed method's accuracy, the ELM results were compared with the ANN artificial intelligence method and regression methods. The results signified that ELM produced better results than ANN and the regression methods. Although ANN demonstrated good results, this method sometimes had relatively high error estimates that are associated with uncertainty. Among the regression methods, Ebtehaj et al. (2014) and Azamathulla et al.'s (2012) showed the strongest and weakest performance, respectively. Also, through sensitivity analysis on ELM, it was observed that not using each of the four input parameters significantly impacts ELM modeling results; the greatest error increase was related to ELM (5), in which the C_V parameter was not considered as an input parameter, and, consequently, the relative error increased up to about 24%.

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