

Original paper

Simulation of bridge pier scour depth base on geometric characteristics and field data using support vector machine algorithm

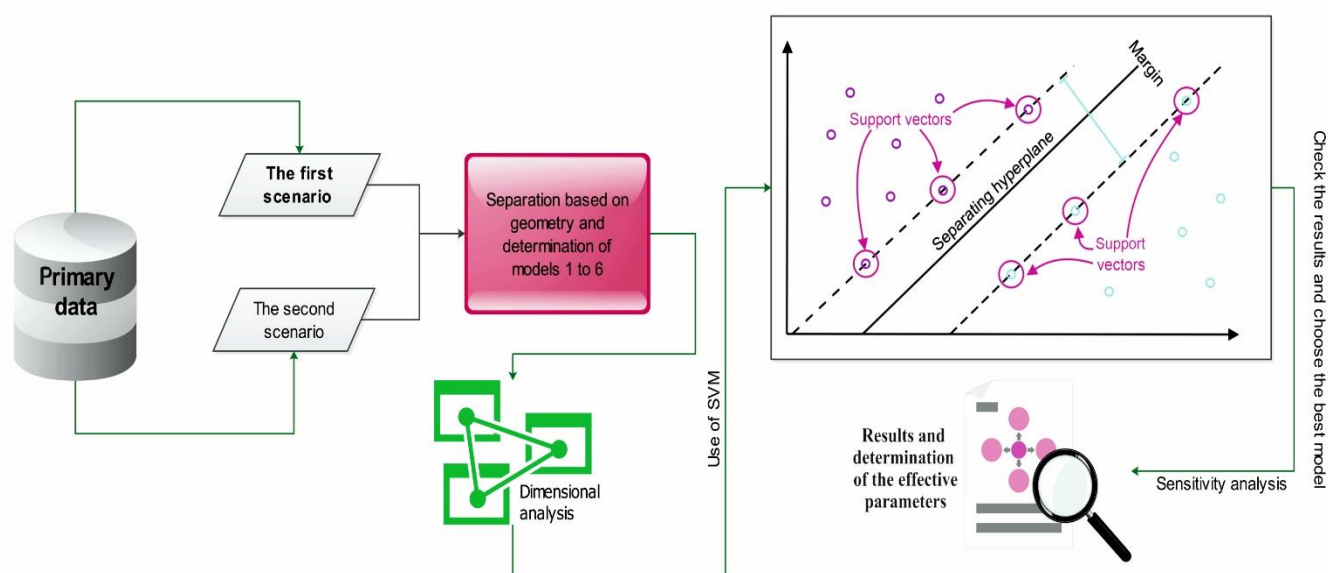
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GRAPHICAL ABSTRACT



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ABSTRACT

In this paper, two groups of datasets including Froehlich (1988) and USGS were implemented to simulate scour depth for bridge piers of three shapes (circular, sharp-nose and rectangular) using support vector machine (SVM) algorithm. The results of the SVM were compared with gene expression programming (GEP) and the non-linear regression model. Independent parameters extracted using dimensional analysis were Froude number (Fr), the ratio of pier length to pier width (L/b), the ratio of sediment particle diameters (d_{50}/d_{84}), the ratio of sediment mean size to pier width (d_{50}/b) and attack angle of water flow (α). Different combinations of independent variables were used to achieve optimum performance of the simulator. The results showed that among three simulators, the SVM algorithm had the best performance to predict local scour depth. The sensitivity analysis revealed that among independent parameters, the descending order of effectivity was Fr , sediment size, L/b , and α .

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1. Introduction

Scour as a challenging issue in river engineering, causes gradual erosion and destruction of a bridge structure. Many reports prove erosion as a destructive factor of bridges. Therefore, it's crucial to estimate bridge scour depth (Ghaderi et al. 2019). Despite diverse and numerous researches on scour depth of bridge pier due to its

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complexity, developing accurate simulators has a noteworthy position among researchers and engineers. The related scour researches can be classified into two main groups: laboratory tests and predictor models. As the former group, Laursen (1962) introduced the shape and the pier direction as the main factors of local scour depth. Shen (1969) performed tests on the scour depth and claimed that pier width has a more significant effect on the scour depth than on the spans. Jahnsen

(1995) performed a comparative study of mathematical predictors. He showed that predictors usually over-estimate values (in some cases up to fivefold). Melville and Suthurland (1988) presented a computational method to estimate the maximum depth of the pier scour. The considered parameters were pier shape, the pier alignment, the pier size, non-uniformity of materials, and flow depth and velocity. Last few decades scour risks across the world have engaged comprehensive notice (Kumcu et al. 2007; Heidarpour et al. 2010; Lanca et al. 2013; Pandey et al. 2018; Ghaderi and Abbasi 2019 and Moradinejad et al. 2019). Daneshfraz et al. (2019) completed experimental measurements on the transformation and development of the scour hole due to the bed material mining on the constructed bridge pier in the flow direction. They found that the mining on local scour around the upstream bridge pier is greater than the downstream influence. Majedi Asl et al. (2019) conducted experimental research on the effect of material mining on the local scour around an armored bridge pier group. They asserted that material mining from the downstream and upstream of the pier group has increasing and decreasing impact on the scour depth, respectively. They also found that an increase in Froude number contributes significantly to the scour depth. The application of the data-mining method (e.g. ANN, GA, GEP, ANFIS, GRNN, and SVM) as predictor models have become very popular recently to provide more accurate predictions. These methods are an alternative to experimental relationships to simulate complex physical phenomenon and can be more used for scour depth prediction (Ghaemi, 2013). Bateni et al. (2007a, b) used two separate studies to illustrate that artificial intelligence and fuzzy neural inference systems can predict the bridge pier scour depth more accurately than other methods. Zoonemat Kermani et al. (2009) used ANN, ANFIS, and RBF to simulate local scour around bi-ridge pier groups. Their results demonstrated the most accurate performance of the ANN (FFBP) model than other methods. Eghbali et al. (2013) simulated temporal development trends of local scour dimensions around wing-wall abutments using genetic programming. They proved the capability of the genetic approach for modeling temporal development of the scour hole depth. Akib et al. (2014) utilized linear regression and fuzzy inference system methods to simulate the local scour depth of the bridge pier. They illustrated the better performance of the fuzzy method than to regression one. Geol (2015) used the SVM algorithm to predict bridge pier scour depth using the RBF Kernel function. The results illustrated the successful employment of SVM as an alternative option to simulate local scour depth for bridge pier. Sharafi et al. (2016) used the SVM algorithm with different Kernel functions to design and predict scour depth of the bridge pier. Their results demonstrated that SVM-polynomial predicted scour depth with higher accuracy and lower error than when using ANN, ANFIS, and nonlinear regression-based equations. Chou and Pham (2017) applied an original hybrid smart artificial firefly colony algorithm (SAFCA)-based support vector regression (SAFCAS) model for the determination of the local scour around the bridge piers. Sreedhara et al. (2019) evaluated the implementation of the SVM and the ANFIS to predict the scour depth around the bridge pier. They stated that the SVM model can be adopted as an accurate and efficient alternative approach in predicting scour depth of the pier. Vaghefi et al. (2019) used the box plot, histograms, linear regression, k-nearest neighbors, local outlier factor, k-medoid clustering, multilayer perceptron, and self-organizing map for the determination of outliers in flow pattern experiments. For comparison of the results of these data mining methods, they considered a spur dike in a 90° bend. They declared that the box plot and local outlier factor methods as superior methods are can be applied for this objective. Thendiyath and Prakash (2020) employed data-mining models (FFNN and MARS) to survey bridge pier scour. They compared the result of the intelligent models' accuracy with empirical ones. The results showed the superiority of data-mining models over others.

As discussed, using intelligent and data-based methods to predict scour depth for bridge piers has been developed in recent decades. In this paper, three types of simulators have been compared: classic regression models, data-mining models including SVM and GEP, and empirical equations. The comparison has been performed using gathered field data. Application of different predictor types and using filed data with eliminating experimental limitations are the novelty of this research work.

2. Materials and methods

2.1. Dimensional analysis

Maximum equilibrium scour depth around bridge pier can be expressed in a functional form as:

$$F(\rho_s, d, C_u, SF, U, \rho, \mu, \vartheta, L, b, \alpha, g, \varphi) = 0 \quad (1)$$

where, ρ_s is the mass density of sediment, d is sediment particle size, C_u is uniformity coefficient of sediment, SF is shape factor of sediment, φ is the angle of repose, b is pier width, L is pier length, α is the angle between bridge pier and flow direction, U is flow velocity, ρ is fluid mass density, μ is fluid viscosity, ϑ is fluid kinematic viscosity, g is the gravitational acceleration. Due to the constant values of ρ_s , C_u , SF and φ the numbers of independent variables of Eq. (7) decreases as follows:

$$F(d, U, \rho, \mu, \vartheta, L, b, \alpha, g) = 0 \quad (2)$$

By applying the Buckingham π -theorem with repeating variables as b , U and ρ , the following dependence is obtained for the non-dimensional scour depth (d_s/b):

$$\frac{d_s}{b} = F\left(Fr, \frac{L}{b}, \frac{d_{50}}{b}, \frac{d_{50}}{d_{84}} \alpha\right) \quad (3)$$

where, Fr is the Froude number.

2.2. Support vector machine (SVM)

Introduced by Vapnik (1995), SVM operates based on data mining algorithms like other artificial intelligent methods (Norouzi et al. 2019). This method is a common machine learning approach in which a set of input-output data is presented to a system; the system tries to learn a function between the input and the output. Supervised learning needs a set of input data to train the system. The SVM is a new model based on the theory of statistical training which is applied to predict different parameters. The SVM contrary to other artificial intelligence approaches that decrease computational errors targets operational risk as a function to achieve optimal value. The cardinal problem of SVMs with nonlinear data, which is presented using slack variables ξ_i and the error penalty constant C can be expressed as (Schölkopf and Smola, 2002).

$$\min \frac{1}{2} w^2 + C \sum_{i=1}^M \xi_i \quad (4)$$

$$\text{s.t.} \begin{cases} y_i [W^T \phi(x_i) + b] \geq 1 - \xi_i \forall i \\ \xi_i \geq 0 \end{cases} \quad (5)$$

Introducing Lagrange multipliers along with removing the primal variables respective to the Lagrangian formulation by partial derivation can be resolved the dual problem. The dual quadratic optimization problem can be stated as follows (Vapnik. 1999):

$$\min L(\alpha) = \frac{1}{2} \sum_{i,j=1}^M \alpha_i \alpha_j y_i y_j x_i \cdot x_j - \sum_{i=1}^M \alpha_i \quad (6)$$

$$\text{s.t.} \begin{cases} \alpha_i \geq 0 \\ \sum_{i=1}^M \alpha_i y_i = 0 \end{cases} \quad (7)$$

The decision function $f(x)$ is gained as follows:

$$f(x) = \text{sgn} \left[\sum_{i,j=1}^M \alpha_i y_i (x_i \cdot x_j) + b \right] \quad (8)$$

a kernel function is implemented instead of the dot product between input data to reach nonlinear classification. The nonlinear decision function is given as (Vapnik. 1999):

$$f(x) = \text{sgn} \left[\sum_{i,j=1}^M \alpha_i y_i K(x_i, x_j) + b \right] \quad (9)$$

The kernel functions used in the SVM are presented in Table 1. These four functions have adjacent parameters that should be set using a trial and error process to achieve optimal fitness between measured and predicted data during train and test phases.

2.3. The GEP algorithm

The newly developed technique, Gene expression programming (GEP) as an extension of the GP approach includes mathematical functions, decision tree, and logical expression has been employed in this research work to predict the scour depth for the bridge pier. The GEP method is coded in the form of linear chromosomes expressed in expression trees (Najafzadeh et al. 2016). Five steps are included for

GEP development: (1) select the fitness function; (2) opting the appropriate functions to generate the chromosomes; (3) configuring the chromosome architecture; (4) opting the linking function; (5) setting genetic operators casing variation and their rates. The GEP flowchart has been shown in Fig. 1. More expressions about GEP have been presented in the literature (Azamathulla and Haque, 2012).

Table 1. Types of Kernel functions.

Number	Kernel name	Definition
1	Linear	$K(x_i, x_j) = (x_i, x_j)$
2	Polynomial	$K(x_i, x_j) = [(x_i, x_j) + 1]^d$
3	Radial basis function or RBF	$K(x_i, x_j) = \exp[-\frac{\ x_i - x_j\ ^2}{2\sigma^2}]$
4	Exponential radial basis Function or ERBF	$K(x_i, x_j) = \tanh[-\alpha(x_i, x_j) + c]$

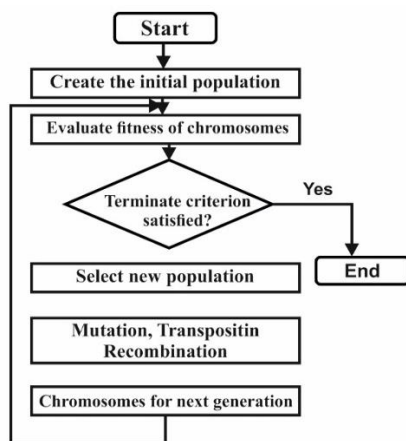


Fig. 1. The GEP flowchart.

2.4. Classic regression model

In this paper, a non-linear regression model was developed to predict scour depth for bridge pier. The general form of this Eq. is as following:

$$\frac{d_s}{b} = a(Fr^b) \left(\frac{L}{b}\right)^c \left(\frac{d_{50}}{b}\right)^d \left(\frac{d_{50}}{d_{84}}\right)^e (\alpha)^f \quad (10)$$

where, a, b, c, d, e, and f are the constants and are determined using statistical methods.

2.5. Statistical evaluation criteria

It is necessary to evaluate SVM model performance using precision measurement criteria. The following indices have been used to achieve this goal:

$$R = \frac{\sum_{i=1}^N (x_{oi} - \bar{x}_o)(x_{pi} - \bar{x}_p)}{\sqrt{\sum_{i=1}^N (x_{oi} - \bar{x}_o)^2 \sum_{i=1}^N (x_{pi} - \bar{x}_p)^2}} \quad (11)$$

$$MNE = \frac{\left| \sum_{i=1}^N \frac{x_{oi} - x_{pi}}{x_{oi}} \right|}{N} \quad (12)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (x_{oi} - x_{pi})^2}{N}} \quad (13)$$

$$NRMSE = \frac{RMSE}{\bar{x}_o} \times 100 \quad (14)$$

where, x_o and x_p are observed and predicted variables, $\bar{x}_o$ and $\bar{x}_p$ are the mean of observed and predicted variables, and N is the total number of data. The correlation coefficient (R) describes the quality of the connection between the predicted and observed data. Mean normalized absolute error (MNE) and root mean square error (RMSE) is used to quantify the difference between the predicted and observed

data. Normalized Root Mean Square Error (NRMSE) is used for comparing the models with various measures. Model performance concerning NRMSE is categorized as below (Mihoub et al. 2016):

Excellent if: $NRMSE < 10\%$.

Good if: $10\% < NRMSE < 20\%$.

Fair if: $20\% < NRMSE < 30\%$.

Poor if: $NRMSE > 30\%$.

2.6. Data characteristics

Two groups of field data have been used to predict local scour depth for bridge piers: (a) Froehlich's field data including 83 datasets gathered from 44 bridges; (b) the U.S. Geological Survey (USGS) data from different locations including a set of 312 data. The range of field data is presented in Table 2. The shapes of the bridge piers along with their geometric symbols are shown in Fig. 2.

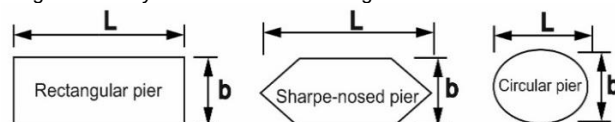


Fig. 2. Types of Bridge piers shapes.

3. Results and discussion

3.1. The first scenario

In the first scenario, only USGS data have been used to simulate the maximum local scour depths. Three bridge pier shapes, presented in Fig. 2, were implemented to predict scour depth based on different combinations of dimensionless parameters introduced in Eq. 3. The final superior predictor model for each pier shape with the values of performance assessment criteria are illustrated in Table 3. According to the table, the SVM model is a superior simulator for scour depth for all three pier shapes. The best values of assessment indices for the SVM algorithm belongs to the sharp-nose pier. The amount of correlation coefficient for train and test phases are 0.9454 and 0.9748, respectively. The values of NRMSE during train and test processes are 0.1114 and 0.1087 respectively, were indicating good performance based on the NRMSE domain. This point is noteworthy that the values of setting parameters of the SVM algorithm for the sharp-nose pier are $C=95$ and $\gamma=50$.

The final form of the regression equation for the sharp-nose pier is as following:

$$\frac{d_s}{b} = 0.0711(Fr^{-0.2477}) \left(\frac{L}{b}\right)^{0.4603} \left(\frac{d_{50}}{b}\right)^{0.2713} (\alpha)^{0.01003} \quad (15)$$

Also, the run of the GEP algorithm for the sharp-nose pier shape based on a combination of all genetic operators (mutation, transposition, and crossover) mentioned in Table 4 has been presented in Fig. 3. The constants and parameters in Fig. 3 are as follows $G1C0=-8.572266$; $G1C1=-9.480194$; $G2C0=-6.643463$; $G2C1=8.936036$; $G3C0=-1.441193$; $G3C1=7.690613$; $d0=\alpha$; $d1=L/b$; $d2=d_{50}/b$ and $d3=Fr$. A Scatter plot of observed versus predicted values of scour depth for sharp-nose pier during train and test phase has been shown in Fig. 4. The distribution of points around line 1:1 indicates the conformity of two data series (i.e. observed and predicted). As it is clear the SVM model has the acceptable performance to predict scour depth of the bridge pier. The next accurate conformity between measured and calculated data has been presented in Fig. 5. In this Fig., all data series, train, and test phases have been plotted against each other. The greater the correspondence between the red and black lines, the greater the accuracy of the simulation. The accuracy of the SVM algorithm at the test phase is more than the train phase that's an expected result.

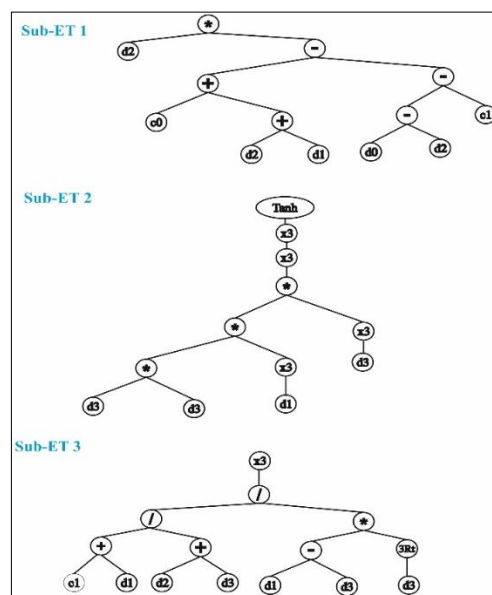


Fig. 3. Tree expression of GEP model for the sharp-nose pier.

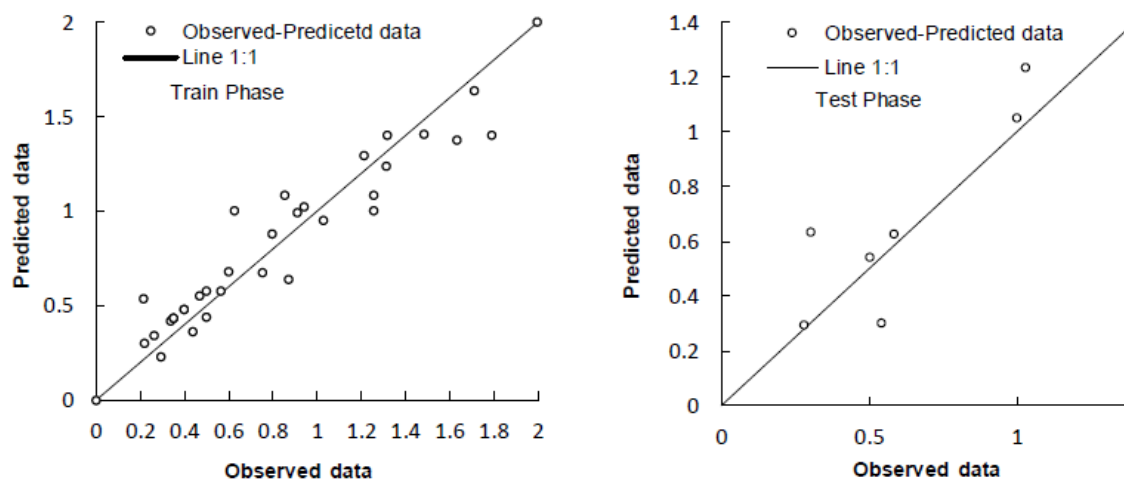


Fig. 4. A comparison between observed vs predicted local scour depths of the SVM for the sharp-nose pier at the first scenario.

Table 2. Changes in range of parameters used in this study.

Data source	Characteristics	Parameter						
		b, m	L, m	α , deg	y, m	U, m/s	D ₅₀ , mm	D ₈₄ , mm
Froehlich	Maximum	5.5	27.4	85	20.02	4.08	32.9	N.A*
	Minimum	0.29	2.46	0	0.12	0.089	0.046	N.A
	Mean	1.54	10.08	5.46	4.63	1.37	2.49	N.A
	S.D.	4.07	12.28	9.80	11.90	2.62	18.89	N.A
USGS	Maximum	19.5	38.00	35.00	19.50	3.67	90.00	38.9
	Minimum	0.29	0.98	0.00	0.43	0.15	0.01	0.056
	Mean	3.28	10.27	5.99	4.07	1.57	16.59	5.87
	S.D.	3.75	7.75	10.30	4.40	0.82	25.96	23.65

* Not available

Table 3. Summary of GEP parameters.

GEP parameters	Description
Population Size	50
Genes per chromosome	4
Gene head length	10
Gene tail length	11
Mutation rate	0.044
Inversion rate	0.1
Gene transposition rate	0.1
One point recombination rate	0.3
Two-point recombination rate	0.3
Gene recombination rate	0.1
Fitness function	Root mean square error

Table 4. The comparison of bridge pier simulator for the first scenario.

Pier shape	Simulator	Involved parameters	Simulators' accuracy performance level							
			Train phase				Test phase			
			R	RMSE	NRMSE	MNE	R	RMSE	NRMSE	MNE
Circle	SVM	$Fr, \frac{L}{b}, \frac{d_{50}}{b}, \alpha$	0.8551	0.3324	0.1400	0.7329	0.8964	0.2315	0.1924	0.6527
	GEP	$Fr, \frac{L}{b}, \frac{d_{50}}{b}, \alpha$	0.8215	0.3625	0.3406	0.7825	0.8468	0.3058	0.3211	0.7204
	Regression	$Fr, \frac{L}{b}, \frac{d_{50}}{b}, \alpha$	0.6237	0.6897	0.6574	0.9568	0.6354	0.7024	0.5587	0.9487
Sharp-nose	SVM	$Fr, \frac{L}{b}, \frac{d_{50}}{b}, \alpha$	0.9454	0.1757	0.1114	0.2131	0.9748	0.0658	0.1087	0.1096
	GEP	$Fr, \frac{L}{b}, \frac{d_{50}}{b}, \alpha$	0.822498	0.219625	0.2465	0.3365	0.848076	0.2897	0.2987	0.095352
	Regression	$Fr, \frac{L}{b}, \frac{d_{50}}{b}, \alpha$	0.565056	0.30061	0.4521	0.43587	0.582628	0.3465	0.3854	0.40587
Rectangular	SVM	$Fr, \frac{L}{b}, \frac{d_{50}}{b}, \alpha$	0.8706	0.4225	0.1584	0.3950	0.8702	0.4236	0.5098	0.4566
	GEP	$Fr, \frac{L}{b}, \frac{d_{50}}{b}, \alpha$	0.7458	0.5548	0.2658	0.4321	0.7745	0.5024	0.3458	0.5427
	Regression	$Fr, \frac{L}{b}, \frac{d_{50}}{b}, \alpha$	0.6208	0.7896	0.3567	0.5598	0.6459	0.5428	0.4427	0.6087

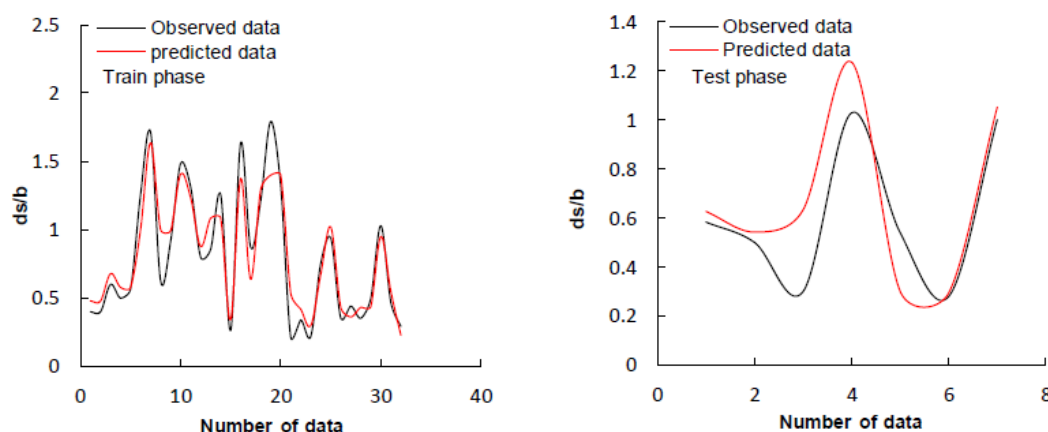
3.2. The second scenario

For this scenario, 395 datasets have been used to predict local scour depth. The result of the simulation is presented in Table 5. Three simulators were implemented to calculate scour depth based on dimensionless parameters. The results show that the SVM is a superior model to other models. Among the three shapes, the best results have occurred for the rectangular shape pier. The amount of setting parameters of the SVM is $\gamma=41$ and $C=105$. Two GEP and regression

predictors were used to compare the predictive capability among different models. As it clear, the results of the SVM are closer to observed data than to others. The predicted vs observed scour depth data as scatter plot have been presented in Fig. 6 during train and testing phases. The distribution of data around line 1:1 during the test phase is obvious in this Fig. All measured and simulated data have been plotted in Fig. 7. The alignment between the two red and black lines on each other indicates an accurate performance of the SVM model.

Table 5. The comparison of bridge pier simulator for the second scenario.

Pier shape	Simulator	Involved parameters	SVM accuracy performance level							
			Train phase				Test phase			
			R	RMSE	NRMSE	MNE	R	RMSE	NRMSE	MNE
Circle	SVM	$Fr, \frac{L}{b}, \frac{d_{50}}{d_{84}}, \alpha$	0.8556	0.2641	0.3267	0.3850	0.7601	0.2721	0.3366	0.4001
	GEP	$Fr, \frac{L}{b}, \frac{d_{50}}{d_{84}}, \alpha$	0.8193	0.3108	0.3940	0.4467	0.7499	0.3316	0.4108	0.4328
	Regression	$Fr, \frac{L}{b}, \frac{d_{50}}{d_{84}}, \alpha$	0.5998	0.6469	0.6893	0.5982	0.5729	0.6878	0.7254	0.6287
Sharp-nose	SVM	$Fr, \frac{L}{b}, \frac{d_{50}}{d_{84}}, \alpha$	0.8573	0.2149	0.2659	0.2992	0.8341	0.2618	0.3239	0.3419
	GEP	$Fr, \frac{L}{b}, \frac{d_{50}}{d_{84}}, \alpha$	0.8301	0.4287	0.40379	0.3797	0.7688	0.3309	0.4084	0.3967
	Regression	$Fr, \frac{L}{b}, \frac{d_{50}}{d_{84}}, \alpha$	0.6213	0.6693	0.6908	0.5744	0.5957	0.6692	0.6893	0.5908
Rectangular	SVM	$Fr, \frac{L}{b}, \frac{d_{50}}{d_{84}}, \alpha$	0.9672	0.1737	0.2149	0.2172	0.9898	0.0774	0.100	0.0819
	GEP	$Fr, \frac{L}{b}, \frac{d_{50}}{d_{84}}, \alpha$	0.9370	0.2588	0.2709	0.2983	0.8986	0.1558	0.2314	0.3037
	Regression	$Fr, \frac{L}{b}, \frac{d_{50}}{d_{84}}, \alpha$	0.7599	0.5194	0.5348	0.4878	0.7106	0.4582	0.5548	0.5185

**Fig. 5.** Observed-Predicted scour depth data for the sharp-nose pier during train and test phases at the second scenario.

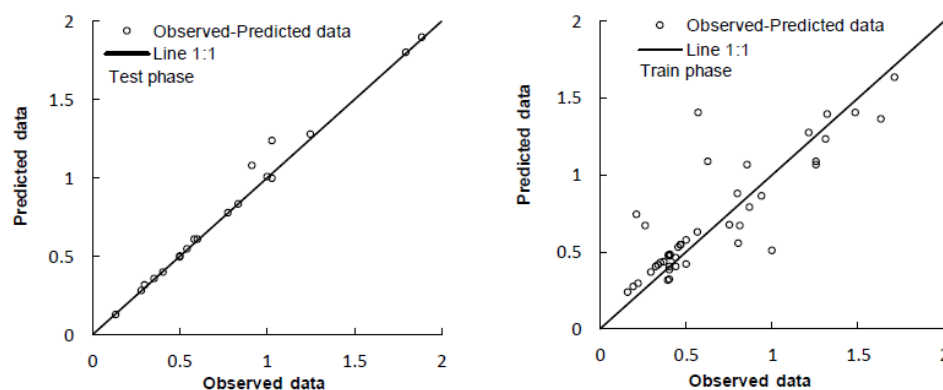


Fig. 6. Comparison between observed and predicted local scour depths for the sharp-nose pier at the second scenario.

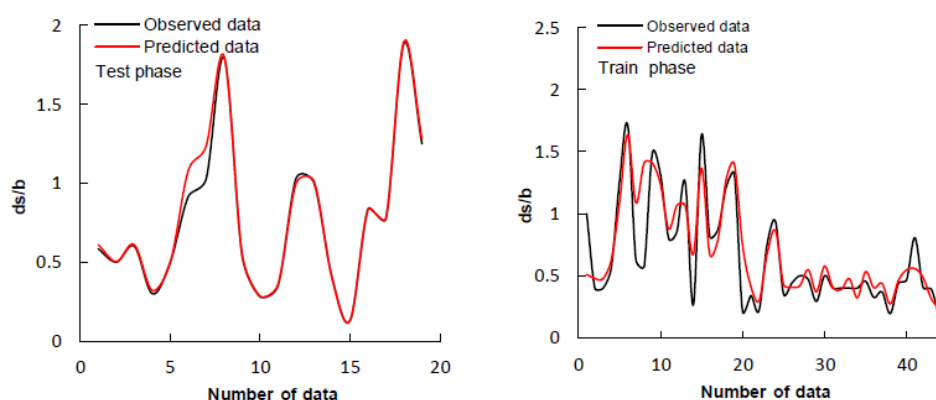


Fig. 7. Comparison between observed and predicted local scour depths for the sharp-nose pier at the second scenario.

3.3. Sensitivity analysis

The sensitivity analysis was performed to determine the share of each parameter on scour depths for bridge piers (Table 6). This preprocessing was done for two scenarios. As it is clear, for the first scenario, the rank of sensitive parameters (descending) is Fr , d_{50}/b , and L/b , respectively. The corresponding parameters for the second

scenario are as Fr , d_{50}/d_{84} , L/b and α . It can be concluded that the most significant parameter in the scour process is the Froude number.

Also, the sediment size plays the second important parameter to predict local scour depth. The bridge pier shape is the third significant variable that can play a role in the SVM model to predict scour depth accurately. Water attack angle has the lowest role in the SVM prediction process.

Table 6. Sensitivity analysis for the first and the second scenarios.

Scenario number	Involved parameters	Omitted parameters	Train				Test			
			R	RMSE	NRMSE	MNE	R	RMSE	NRMSE	MNE
First	$Fr, \frac{L}{b}, \frac{d_{50}}{b}$	-	0.9454	0.1757	0.1114	0.2131	0.9748	0.0658	0.1087	0.1096
	$Fr, \frac{L}{b}, \frac{d_{50}}{b}$	Fr	0.3429	1.012	0.6897	0.5879	0.3606	0.9687	0.6287	0.6247
	$Fr, \frac{L}{b}, \frac{d_{50}}{b}$	$\frac{L}{b}$	0.6347	0.8247	0.5248	0.6542	0.6503	0.7598	0.5341	0.6452
	$Fr, \frac{L}{b}, \frac{d_{50}}{b}$	$\frac{d_{50}}{b}$	0.4839	0.9938	0.4821	0.7234	0.4908	0.9654	0.4728	0.6954
Second	$Fr, \frac{L}{b}, \frac{d_{50}}{d_{84}}, \alpha$	-	0.9672	0.1737	0.2149	0.2172	0.9898	0.0774	0.100	0.0819
	$Fr, \frac{L}{b}, \frac{d_{50}}{d_{84}}, \alpha$	α	0.9587	0.1802	0.2312	0.2287	0.9601	0.1014	0.1501	0.1120
	$Fr, \frac{L}{b}, \frac{d_{50}}{d_{84}}, \alpha$	Fr	0.4238	0.6542	0.5238	0.8791	0.4408	0.6897	0.5649	0.8829
	$Fr, \frac{L}{b}, \frac{d_{50}}{d_{84}}, \alpha$	$\frac{d_{50}}{d_{84}}$	0.5368	0.6014	0.4287	0.7598	0.5529	0.6125	0.4658	0.8024
	$Fr, \frac{L}{b}, \frac{d_{50}}{d_{84}}, \alpha$	$\frac{L}{b}$	0.5809	0.4982	0.3987	0.6327	0.5927	0.4868	0.3754	0.6237

* The best performance

4. Conclusions

The ability of the SVM algorithm to predict bridge pier scour depth has been investigated based on the pier shape. The GEP and non-linear regression model were implemented to compare the capability of simulators. Two field data series were used with two scenarios for rectangular, cylindrical, and sharp-nosed pier shapes. Each scenario consisted of models with six different combinations of parameters (a

total of 36 models). The models were analyzed and run during train and test phases. The results showed that the best model for the first scenario belongs to a sharp-nosed pier. For the second scenario, the sharp-nosed pier shape with parameters Fr , L/b , and d_{50}/d_{84} had superior performance compared to the others. The least and the most effective parameters to improve SVM predictions were water attack angle and Froude number, respectively.

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