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Prediction of Local Scour around Bridge Piers in the Cohesive Bed Using Support Vector Machines

Sung-Uk Choi[a] **and Seongwook Choi**[b]

[a]Member, Dept. of Civil and Environmental Engineering, Yonsei University, Seoul 03722, Korea
[b]Dept. of Civil and Environmental Engineering, Yonsei University, Seoul 03722, Korea

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ABSTRACT

Local scour around bridge piers is one of the most important factors threatening the life of bridges. The three-dimensional highly complicated horseshoe vortex and downflow are known to be the main agents responsible for pier scour. If the bed consists of cohesive sediment, it will add another level of complexity to the pier scour problem. Various approaches have attempted to predict scour depth, but no universal method is available to date. This study presents a prediction of local scour around bridge piers in the cohesive bed using support vector machines (SVMs), a machine learning technique. The maximum scour depth is predicted with seven dimensional variables, including velocity, flow depth, size of bed sediment, pier width, clay content, water content, and bed shear strength. The training and validation of the SVMs are conducted with 197 data from six datasets. Comparisons are made with the training and validation of the adaptive-network-based fuzzy inference system (ANFIS) method. The training of the ANFIS method appears successful, but the validation fails because of overfitting. The predictions with dimensionless variables are compared, and shown to be worse. In addition, the SVMs are found to predict the maximum scour depths better than three existing formulas, gene expression programming (GEP), and a non-linear regression model. The SVMs are applied to two datasets, revealing the importance of the coverage of the training data. Finally, to investigate the contributions of each variable, the mean absolute percent errors (MAPEs) and correlation coefficient are computed by predicting the maximum scour depths by excluding each variable.

1. Introduction

According to a survey of 823 bridge failures since 1950 in the United States, 60% of bridge failures are related to flow hydraulics, which includes bridge pier scour and channel instability (Shirole and Holt, 1991). Based on the same survey, 50-60 bridges fail each year in the United States. This situation is similar in Korea. It has been reported that 7,619 bridges failed in Korea due to flood flows for 48 years in the period of 1964 – 2012 (Ministry of the Interior and Safety, 2017). Moreover, about 100 bridges fail each year by pier scour in Korea. These failed bridges were located in mid- to small-sized streams, and in most cases, their foundations did not reach the bedrock layer.

The horseshoe vortex and downflow at piers are known to be the main agents responsible for pier scour. That is, when the approach flow is obstructed by the pier, the downflow occurs at the upstream front of the pier and the flow accelerates around the pier. This results in a horseshoe vortex, which scours bed sediment from around the base of the pier. Scour holes develop when the rate of sediment transport away from the base region is larger than the rate of the sediment supply into the base region. As scour proceeds, the strength of the horseshoe vortex decreases, reducing sediment transport away from the base region.

For the prediction of local scour around bridge piers in the non-cohesive bed, regression-based empirical methods, computational fluid dynamics, and artificial intelligence techniques are available (Choi et al., 2017). However, relevant studies on pier scour in the cohesive bed are rare, as little is known about the effect of the presence of cohesive sediment on local scour around bridge piers. The mechanics of cohesive sediment transport is poorly understood

CORRESPONDENCE Sung-Uk Choi schoi@yonsei.ac.kr Dept. of Civil and Environmental Engineering, Yonsei University, Seoul 03722, Korea

due to the complexity of the problem that comes from the interactions of various variables related to the cohesive bed.

To understand the erosion rate of cohesive soil, knowledge of clay particles is needed. Sediment particles with a size less than 0.004 mm is called clay. Clay particles are flat-shaped and carry a negative electric charge on their surface. Gravity and cohesive force determine the incipient motion of these particles. The cohesion of individual grains arises from molecular-scale physico-chemical attractive forces. These forces cause colliding grains to bond and form aggregates and play a key role in erosion, deposition, and sediment transport. For cohesive sediment, the cohesion resulting from physico-chemical forces is more important than the gravity force because of the large surface area per unit volume (Devi and Barbhuiya, 2017).

Previously, the predictions of pier scour in the cohesive bed relied on methods for the non-cohesive bed (Ting et al., 2001; Briaud et al., 2004). However, these methods yield too much conservative solutions for the cohesive bed. This is because the scour rate in the cohesive bed is about 1,000 times slower than that in the non-cohesive bed (Briaud et al., 2004). Moreover, existing formulas for the cohesive bed predict scour depths well under very limited conditions (Devi and Barbhuiya, 2017). Therefore, it is necessary to predict pier scour in the cohesive bed more or less correctly.

This study aims to predict local scour around bridge piers in the cohesive bed using the machine learning technique. Support vector machines (SVMs), which have the advantage of predicting correctly without overfitting, are used in this study. First, the variables affecting the maximum scour depth in the cohesive bed are determined. Then, the training and validation of the SVMs are carried out. Comparisons are made with the adaptive-network-based fuzzy inference system (ANFIS) method and the SVMs with dimensionless variables. Comparisons are also made with existing formulas including a formula for pier scour in the non-cohesive bed. Finally, the SVMs are applied to two datasets and the prediction results are presented and discussed.

2. Local Scour around Bridge Piers

In general, the equilibrium scour depth (d_{se}) in the non-cohesive bed is given by

$$d_{se} = fn \text{ (flow, sediment, pier geometry)}, \tag{1}$$

in which the flow variables include water density, dynamic viscosity of water, velocity, flow depth, gravity, and the correction factor for bedform. The variables related to sediment are the median of the sediment particle size, the standard deviation of the particle size distribution, the density of the sediment particles, and the critical mean velocity associated with the initiation of particle motion on the bed. The pier geometry variables include the pier width, correction factors for pier shape, and flow angle of attack. Simplification leads to equilibrium scour depth such as

$$d_{se} = f\left(V, y, d, V_c, D\right), \tag{2}$$

where V = velocity, y = flow depth, d = particle size, V_c = critical mean velocity related to the initiation of particle motion on the bed, and D = pier diameter (or pier width). Such assumptions are made in Eq. (2) as no bedform effect, uniform sediment, and zero angle of attack (Choi et al., 2015).

For local scour in the cohesive bed, the functional relationship expressed in Eq. (2) should be modified. The equilibrium scour depth (d_{se}) should be replaced with the maximum scour depth ($d_{\max}$), as live-bed scour rarely occurs for the cohesive bed. That is, once the cohesive sediment is eroded, it is hardly deposited on the bed. For cohesive soil, the threshold velocity for which the particle initiates its motion on the bed is difficult to be determined. Instead, the bed shear strength (τ_s), which is more easily measurable, is used. In addition, clay content (C_p) and water content (W_c) should be added to the variables that affect local scour in the cohesive bed. Then, the maximum scour depth in the cohesive bed can be expressed by

$$d_{\max} = f\left(V, y, d, D, C_p, W_c, \tau_s\right). \tag{3}$$

Debnath and Chaudhuri (2010a) presented a non-dimensional form for the maximum scour depth such as

$$\frac{d_{\max}}{D} = f\left(\frac{V}{\sqrt{gD}}, \frac{y}{D}, \frac{d}{D}, C_p, W_c, \frac{\tau_s}{\rho V^2}\right), \tag{4}$$

where $V/\sqrt{gD}$ = pier Froude number (= F_p), y/D = dimensionless approach flow depth, D/d = dimensionless particle size, and $\tau_s/(\rho V^2)$ = dimensionless bed shear strength. Ettema et al. (2006) showed that the pier Froude number is related to the vorticity of wake vorticies behind bridge piers.

Further simplifications can be made in Eq. (4). For non-cohesive sediment, the particle size will not affect the maximum scour depth if $D/d > 50$ for clear-water scour (Ettema, 1980) and live-bed scour (Chiew, 1984). Debnath and Chaudhuri (2010a) made the same assumption for pier scour in the cohesive bed. In addition, it has been reported that the maximum scour depth is not affected by the approach flow depth for y/D > 2.6 for non-cohesive sediment (Melville and Sutherland, 1988) and for y/D > 2 for cohesive sediment (Briaud, 2004). If both particle size and approach flow depth can be ignored in bridge pier scour in the cohesive bed, then Eq. (4) can be simplified to

$$\frac{d_{\max}}{D} = f\left(\frac{V}{\sqrt{gD}}, C_p, W_c, \frac{\tau_s}{\rho V^2}\right), \tag{5}$$

which represents the dimensionless maximum scour depth in terms of four dimensionless parameters.

3. SVMs

SVMs are classification and regression methods developed by Vapnik (1995). The basic idea of SVMs is to map the original data into a feature space with high dimensionality using a non-linear kernel function. Support vector regression (SVR), which is used in the present study, is SVMs that deal with modeling and

Table 1. Ranges of Variables Used in Training and Validation

Type	V (m/s)	D (m)	y (m)	d (mm)	τ_s (kPa)	C_p (%)	W_c (%)	d_{max} (m)
Training	0.199 – 0.83	0.025 – 0.21	0.16 – 0.6	0.0006 – 0.55	1.1 – 44.13	2 – 65	19.2 – 39.28	0.0142 – 0.270
Validation	0.141 – 0.827	0.1 – 0.12	0.3 – 0.45	0.0055 – 0.182	5.7 – 35.6	8 – 52	10.7 – 45.92	0.0239 – 0.229

Table 2. Ranges of Variables Used in Applications

Exp.	V (m/s)	D (m)	y (m)	d (mm)	τ_s (kPa)	C_p (%)	W_c (%)	d_{max} (m)
Gudavalli (1997)	0.204 – 0.83	0.025 – 0.21	0.16 – 0.4	0.0006 – 0.006	12.51 – 39.56	75 – 100	26.2 – 39.3	0.011 – 0.25
Kothyari et al. (2014)	0.64 – 1.33	0.087 – 0.114	0.078 – 0.114	1.271 – 2.49	3.19 – 36.58	20 – 60	6.15 – 17.09	0.006 – 0.084

prediction. The purpose of SVR is to find a function whose prediction errors are less than ε for all training data. The non-linear model of the SVR is given by

$$f(x) = \langle w, \phi(x) \rangle + b \,, \tag{6}$$

where $f(x)$ = output of the model, w = weight vector, $\phi(x)$ = non-linear function in the feature space, b = bias term, and $\langle\,\rangle$ denotes the inner product. Here, a smaller value of w means the flatness of Eq. (6), which is made possible by minimizing by the Euclidean norm $\|w\|$ (Smola, 1996). Now, the problem is to find the best weight vector w and the non-linear function $\phi(x)$, which is an optimization problem such as

$$\begin{aligned} &\text{minimize } \frac{1}{2}\|w\|^2 \\ &\text{subject to } y_i - \langle w, \phi(x_i) \rangle - b \le \varepsilon \\ &\qquad\qquad \langle w, \phi(x_i) \rangle + b - y_i \le \varepsilon \end{aligned} \tag{7}$$

If such slack variables as (ξ_u, ξ_i^*) are introduced into Eq. (7) to make the constraints feasible, then the problem is to estimate w and b that minimize the following function:

$$\begin{aligned} &\text{minimize } \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}(\xi_i + \xi_i^*) \\ &\text{subject to } y_i - \langle w, \phi(x_i) \rangle - b \le \varepsilon + \xi_i \\ &\qquad\qquad \langle w, \phi(x_i) \rangle + b - y_i \le \varepsilon + \xi_i^* \\ &\qquad\qquad \xi_i \xi_i^* \ge 0 \end{aligned} \tag{8}$$

where C is a parameter that balances between the flatness of the vector and penalizing for errors greater than ε.

4. Results

4.1 Training and Validation

Eight datasets in the literature are collected and used for model training, validation, and applications. The eight datasets include 257 data, providing maximum scour depths with seven independent variables, as in Eq. (3). A total of 114 data from four different sources (Ting et al., 2001; Molinas et al., 1999; Rambabu et al., 2003; Debnath and Chaudhuri, 2010a) are used to train the model. A total of 83 data from Debnath and Chaudhuri (2010b) and Najafzadeh and Barani (2014) are used for model validations. Debnath and Chaudhuri (2010b) used clay-sand mixtures in their experiments, but Najafzadeh and Barani (2014) used only clay. Table 1 lists the ranges of the variables of the data used for training and validation. The ranges of variables of the training

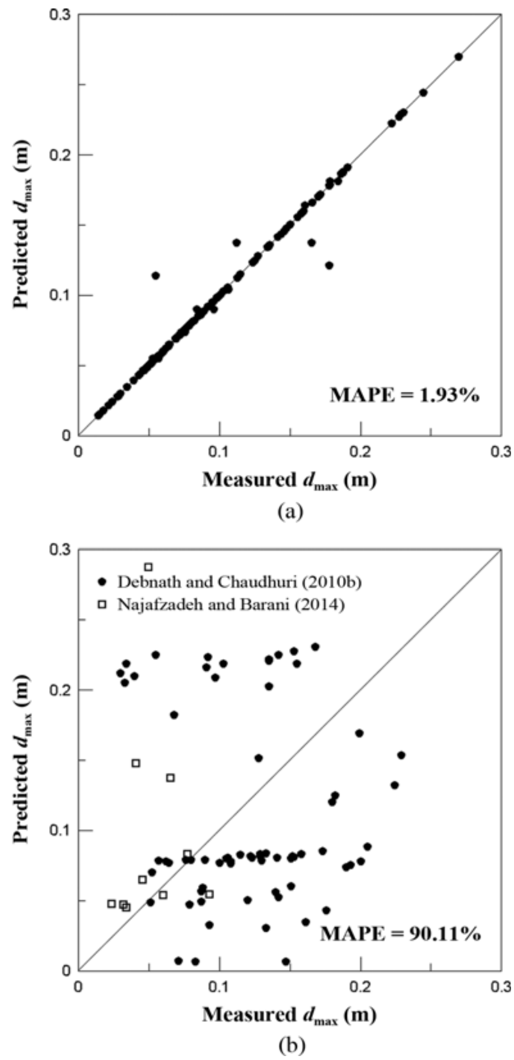


Fig. 1. Training and Validation of ANFIS Model: (a) Training, (b) Validation

data nearly cover those of the validation data.

Two datasets from Gudavalli (1997) and Kothyari et al. (2014), with 35 and 25 data, respectively, are used for the model application. Table 2 presents the ranges of the variables of the data for application. For Gudavalli (1997) data, the pier diameter and flow depth are beyond the ranges of the training data. For Kothyari et al. (2014) data, the velocity, particle size, and water content exceed the ranges of the training data.

To test the model performance in training, validation, and application, the following mean absolute percent error (MAPE) is calculated:

$$MAPE = \frac{1}{n}\sum \frac{\left|d_{\max}^{m} - d_{\max}^{p}\right|}{d_{\max}^{m}} \times 100 \ (\%) \ , \tag{9}$$

where $d_{\max}^{p}$ and $d_{\max}^{m}$ are the predicted and measured maximum scour depths, respectively.

Figures 1(a) and 1(b) show the predicted versus measured maximum scour depths for the training and validation of the ANFIS method, respectively. The ANFIS method has shown excellent performance in predicting pier scour in the non-cohesive bed (Choi et al., 2017). In the figures, the 45° line indicates perfect agreement. As shown in Fig. 1(a), the training of the ANFIS method results in a MAPE value of 1.93%, indicating the successful training of the ANFIS method. However, the model fails to predict, as shown in Fig. 1(b). Two possible reasons can account for the poor prediction of the ANFIS method, namely overfitting and poor quality of validation data (Al-Hmouz et al., 2011). In the present study, the failure of prediction by the ANFIS method is considered due to overfitting, as the prediction is improved with the use of SVMs, which will be shown later.

Figure 2(a) shows the results of the training of SVMs with seven dimensional variables in Eq. (3). In the SVMs, various kernel functions are used and the optimal values of parameters such as C, ε, and k (a parameter in the kernel function) in the respective ranges of 0.1 – 10, 10^{-3} – 10^{-5}, and 0.1 – 10 are sought in training and validation. In the present study, a polynomial function with k = 5, C = 0.1, and $\varepsilon = 10^{-5}$ is used. The MAPE obtained in the training of SVMs is 18.63%, which is larger than that obtained using the ANFIS method. The results of the model

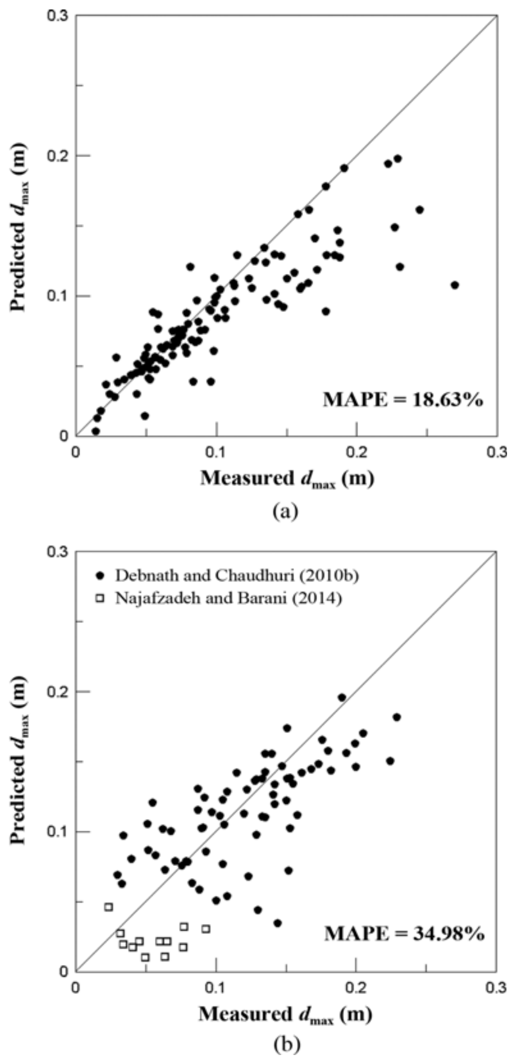


Fig. 2. Training and Validation of SVMs: (a) Training, (b) Validation

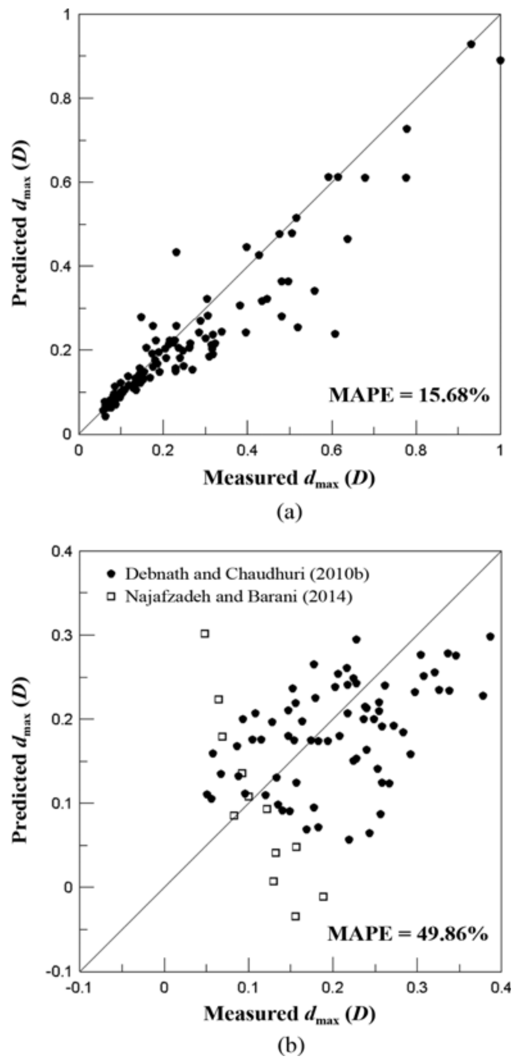


Fig. 3. Training and Validation of SVMs Using Dimensionless Variables: (a) Training, (b) Validation

validation for the SVMs are given in Fig. 2(b). The MAPE value is 34.98%, indicating a significant improvement in the validation, compared with the ANFIS method.

4.2 Prediction with Dimensionless Variables

Figure 3 shows the same plots as the previous ones but with the use of SVMs with dimensionless variables. The dimensionless maximum scour depth is expressed by the six dimensionless variables in Eq. (4). As shown in Figs. 3(a) and 3(b), the use of dimensionless variables results in about 30% and 40% increases in MAPE in training and validation, respectively. This means that SVMs with dimensional variables predict better than SVMs with dimensionless variables. This is consistent with the prediction of equilibrium scour depths in the sand bed using the ANFIS method in Choi et al. (2017).

4.3 Prediction Using Various Formulas

Unlike the case of pier scour in the non-cohesive bed, previous studies that compared the performance of formulas for pier scour in the cohesive bed are rare. Devi and Barbhuiya (2017) compared eight formulas for predicting maximum scour depths around piers in the cohesive bed. They computed scour depths around piers on both laboratory and field scales. In this section, three formulas that yielded moderate estimates of scour depths in Devi and Barbhuiya (2017) test are selected and used for predicting scour depths using the validation data in Table 2. The three formulas include Ting et al. (2001) formula, Briaud et al. (2004) formula, and Debnath and Chaudhuri (2010a) formula. They are, respectively, given by

$$d_{\max} = 0.12 R_p^{0.682}, \tag{10}$$

$$d_{\max} = 0.18 R_p^{0.635}, \tag{11}$$

$$\frac{d_{\max}}{D} = 8.2 F_p^{0.79} C_p^{-0.28} W_c^{0.15} \left(\frac{\tau_s}{\rho V^2}\right)^{-0.38}, \tag{12}$$

where R_p = pier Reynolds number. Fig. 4 shows the prediction results of the three formulas. Interestingly, all three formulas

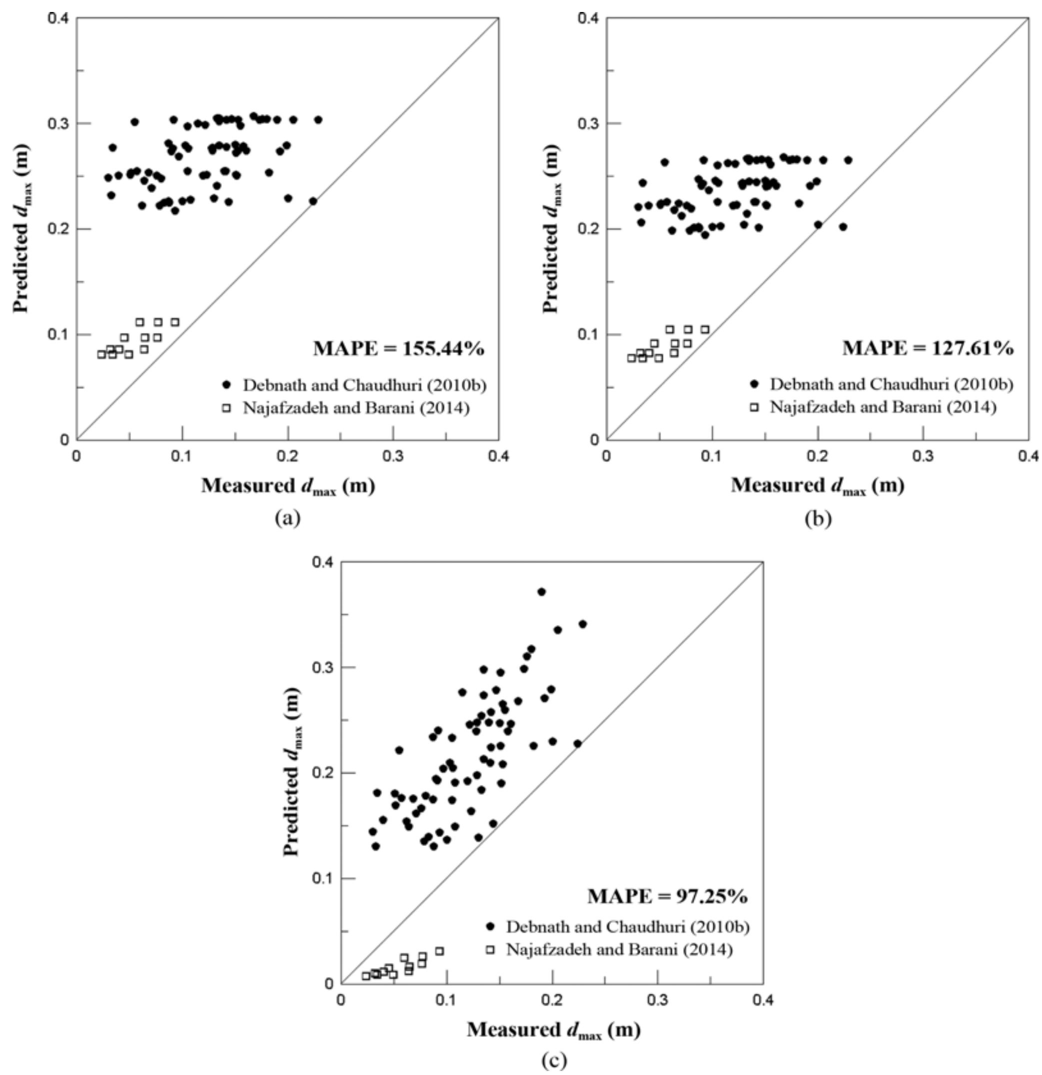


Fig. 4. Prediction with Various Formulas: (a) Ting et al. (2001), (b) Briaud et al. (2004), (c) Debnath and Chaudhuri (2010b)

significantly over-predict the maximum scour depths. The MAPE values range from 97.25% to 155.44%, which is larger than 34.98% by SVMs. This indicates that SVMs are a better predictor of pier scour in the cohesive bed than existing formulas.

4.4 Prediction Using Formula for Pier Scour in the Sand Bed

Sheppard et al. (2014) performed an extensive comparative study on 22 existing formulas for predicting pier scour depths in the sand bed. They collected a large amount of data on both laboratory and field scales. Sheppard et al. ranked each formula and proposed a new one called Sheppard and Melville's formula.

In the present section, Sheppard and Melville's formula is used to predict the maximum scour depths using the validation data in Table 1. Fig. 5 shows the prediction results of Sheppard and Melville's formula. The formula moderately predicts the maximum scour depths when applied to Najafzadeh and Barani (2014) data, but fails the predictions for Debnath and Chaudhuri (2010b) data. As stated earlier, Najafzadeh and Barani (2014) and Debnath and Chaudhuri (2010b) used only clay and clay-sand mixtures in their experiments, respectively. The successful prediction by Sheppard and Melville's formula when applied to the data of Najafzadeh and Barani (2014) is consistent with the previous findings of Ting et al. (2001). Ting et al. (2001) investigated pier scour in the only clay bed through laboratory experiments and reported that the HEC-18 equation for pier scour in the sand bed successfully predicted the maximum scour depths. However, for clay-sand mixtures, the addition of clay to sand significantly increases erosion resistance (Mitchener and Torfs, 1996). This makes the maximum scour depth very sensitive to the clay content and water content (Ansari et al., 2002), which cannot be considered in scour prediction formulas in the sand bed.

4.5 Comparisons with Other Models

Based on Debnath and Chaudhuri (2010a) data, Muzzammil et al. (2015) presented two dimensionless relationships for the maximum scour depth around bridge piers in the cohesive bed. The relationships are given by

$$\frac{d_{\max}}{D} = 4.77 C_p^{-0.23} W_c^{0.28} F_p^{0.53} \left(\frac{\tau_s}{\rho V^2}\right)^{-0.25}, \tag{13}$$

$$\frac{d_{\max}}{D} = 0.656 + 2F_p - 3C_p + W_c + \frac{\rho V^2}{\tau_s}, \tag{14}$$

which were obtained by the non-linear regression and gene expression programming (GEP), respectively. In the present study, the two models are applied to the validation data in Table 1. Fig. 6 shows the prediction results of the two models. It can be seen in Fig. 6(a) that the non-linear regression model under- and over-predicts the scour depths for Najafzadeh and Barani (2014) data and Debnath and Chaudhuri (2010b) data, respectively. However, GEP generally over-predicts scour depth, as shown in Fig. 6(b). The respective MAPE values are 95.13% and 83.49%, indicating that SVMs predict much better than these two models.

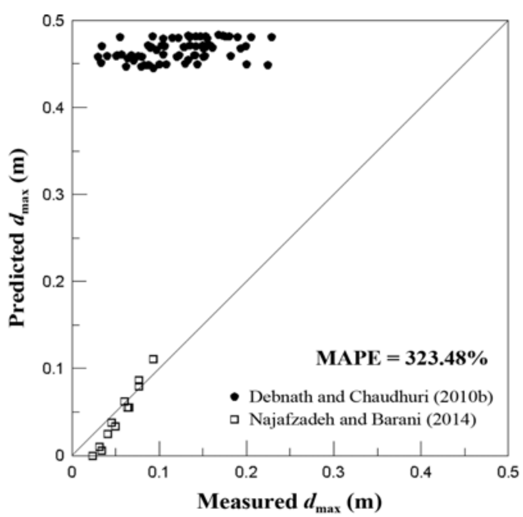
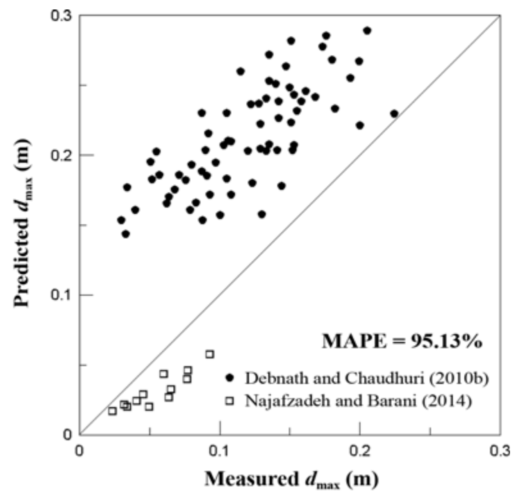
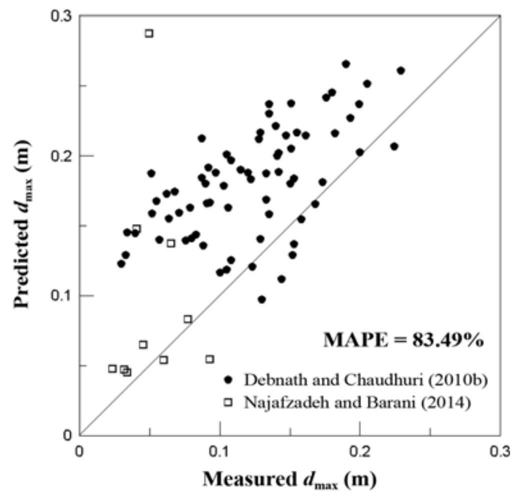


Fig. 5. Prediction with Sheppard and Melville's Formula



(a)



(b)

Fig. 6. Prediction with Non-linear Regression Model and GEP: (a) Non-linear Regression Model, (b) GEP

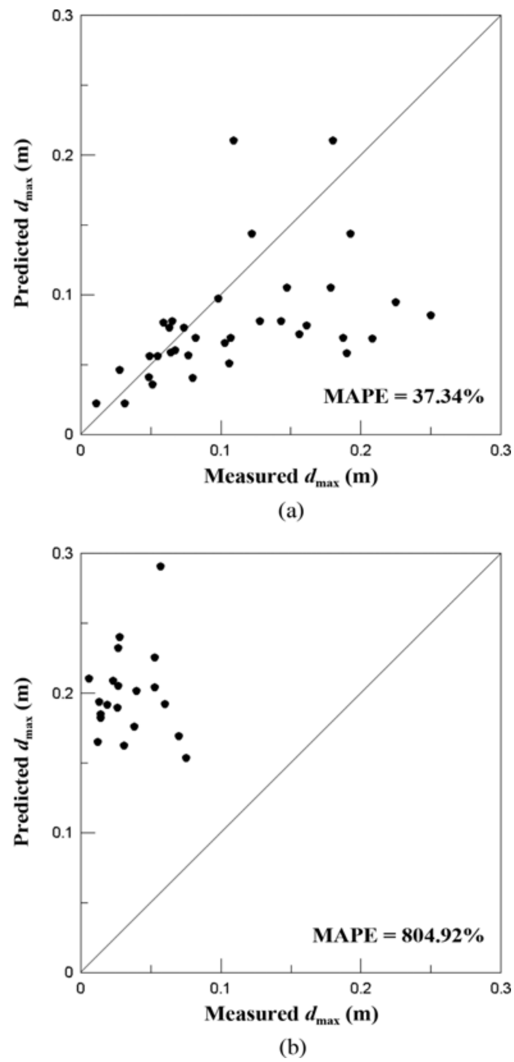


Fig. 7. Applications of SVMs: (a) Gudavalli (1997), (b) Kothyari et al. (2014)

4.6 Applications

Figure 7(a) shows the predicted versus measured maximum scour depths when SVMs are applied to Gudavalli (1997) data. It can be noted that the model predicts moderately if the maximum scour depths are small, i.e., $d_{max} \leq 0.15$ m. However, the model performs serious under-predictions if the maximum scour depths are large, i.e., $d_{max} \geq 0.15$ m. This is due to the pier diameter D of Gudavalli (1997) data being out of the range of the training data for large maximum scour depths. The computed MAPE value is 37.34%, indicating a moderate level of prediction accuracy except for some serious under-predictions.

The prediction results of the SVMs when applied to Kothyari et al. (2014) data are presented in Fig. 7(b). It can be seen that the model performs serious over-predictions, resulting in a MAPE value of 804.92%. The failure of the prediction can be attributed to that the bed particles of the Kothyari et al.'s data include gravel the size of which is far beyond the range of particle size of the training data.

4.7 Contribution of Each Variable

Table 3 presents the Pearson correlations between the seven variables in Eq. (3) and the maximum scour depth. The datasets for training are used to compute the correlations. The table shows that the particle size d and flow depth y are poorly correlated with the maximum scour depth, which is consistent with the assumptions for Eq. (5). It also turns out in the table that the water content W_c has a low correlation with the maximum scour depth.

In order to investigate the importance of an individual variable in predicting the maximum scour depth, various predictions are made without each variable in Eq. (3). Tables 4 lists the MAPE values and the Pearson correlation coefficient obtained under such conditions. Herein the datasets for validation are used. It can be seen that predictions without particle size, velocity, and clay content result in increased MAPEs or reduced correlation coefficients. Therefore, particle size, velocity, and clay content play important roles in predicting the maximum scour depths using Eq. (3). Moreover, both MAPE and the correlation coefficient reveal that the predictions without water content or flow depth are close to the prediction with all the seven variables. This indicates that the water content and flow depth are less important in the prediction, which is consistent with the results in Table 3. However, unlike the results in Table 3, the prediction without particle size is worse. This is thought to come from the fact that the data used for Table 3 are different from those for Table 4. The table also lists the results of the prediction without both flow depth and particle size. It is seen that MAPE increases and the correlation coefficient decreases, compared with the case of using all seven variables, suggesting that the prediction has not

Table 3. Pearson Correlation between the Variables and Maximum Scour Depth

Type	V (m/s)	D (m)	y (m)	d (mm)	τ_s (kPa)	C_p (%)	W_c (%)	d_{max} (m)
V (m/s)	1							
D (m)	0.163	1						
y (m)	0.129	0.418	1					
d (mm)	0.033	0.583	-0.605	1				
τ_s (kPa)	-0.088	0.023	-0.115	0.194	1			
C_p (%)	0.051	-0.126	0.323	-0.188	0.481	1		
W_c (%)	0.503	-0.095	0.316	-0.341	-0.221	0.265	1	
d_{max} (m)	0.415	0.278	-0.123	0.050	-0.235	-0.374	0.196	1

Table 4. MAPE and Correlation Coefficient under Various Computational Conditions

	all variables	w/o V	w/o D	w/o y	w/o d	w/o τ_s	w/o C_p	w/o W_c	w/o y and d
MAPE	34.98	47.44	42.91	37.75	50.58	44.65	48.72	34.77	51.02
CC	0.740	0.155	0.446	0.700	-0.205	0.567	0.437	0.763	0.430

improved.

It should be emphasized that the results of the present analysis strongly reflect the limitation of the data used. Thus, to obtain a more consolidated result, collections of high-quality data on pier scour in the cohesive bed are required.

5. Conclusions

This study presented predictions of maximum scour depths around bridge piers in the cohesive bed using the SVMs, a machine learning technique. Using the data collected in the literature, model training, validation, and application were carried out. For the model training and validation, 114 data from four datasets and 83 data from two datasets were used, respectively. For the model applications, 60 data from two datasets were used.

First, the model training and validation with SVMs were compared with those with the ANFIS method. The predictions were made with seven dimensional variables related to the maximum scour depth. It was found that the model training using the ANFIS method was successfully carried out with an extremely small MAPE. However, the model validation showed that the ANFIS method was not capable of properly predicting the maximum scour depth in the cohesive bed because of overfitting. By contrast, the training and validation of SVMs were conducted with a moderate level of accuracy.

The predictions with six dimensionless variables were compared with the previous predictions with seven dimensional variables. It was found that the predictions with dimensional variables resulted in smaller MAPEs than the predictions with dimensionless variables. This is consistent with the case of predicting pier scour in the non-cohesive bed using the ANFIS method (Choi et al., 2017).

Predictions using various formulas were conducted and the results were compared with predictions using SVMs. The formulas included Ting et al. (2001) formula, Briaud et al. (2004) formula, and Debnath and Chudhuri (2010a) formula. The comparisons revealed that the MAPEs by the three formulas ranged 280% – 440% of those obtained by SVMs, indicating that the SVMs performed much better predictions than these formulas. Poor predictions by existing formulas can be attributed to that they were proposed from laboratory experiments under limited conditions.

Sheppard and Melville's formula for pier scour in the non-cohesive bed was used to predict the maximum scour depths in the cohesive bed. It was found that Sheppard and Melville's formula predicted well for the clay only bed but incorrectly for the clay-sand mixture bed. This conforms to Ting et al. (2001) findings that the formula for the non-cohesive bed predicted successfully when applied to pier scour in the only clay bed, but not in the clay-sand mixture bed.

The non-linear regression model and GEP for pier scour in the cohesive bed, recently proposed in the literature, were used to predict maximum scour depths. In general, the two models were found to over-predict the maximum scour depths with larger MAPEs, compared with the SVMs.

The SVMs were then applied to two different datasets to predict the maximum scour depths in the cohesive bed. The application results indicated that the SVMs would predict the maximum scour depths well if the application data were within the range of the training data but would fail the predictions otherwise. This provides a particular lesson for the prediction of pier scour in the cohesive bed. That is, the sediment particle is more likely to range widely for the cohesive bed, than for the non-cohesive bed. This adds another level of difficulty to predicting pier scour in the cohesive bed with the machine learning technique.

Finally, predictions were made using the developed SVMs by excluding each variable to investigate the contribution of each variable in predicting the maximum scour depth. The water content and flow depth were found to affect the maximum scour depth the least. These results are not entirely consistent with the previous findings of Ettema (1980), Chiew (1984), Melville and Sutherland (1988), Briaud (2004), and Debnath and Chaudhuri (2010a) in that particle size and flow depth are less important to the maximum scour depth compared with the other five variables. This is because the results of the present study reflect the limitation of the data used in the analysis, suggesting the importance of acquiring high-quality data in the prediction of pier scour in the cohesive bed.

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ORCID

Sung-Uk Choi https://orcid.org/0000-0002-0802-7705

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