Prediction of pile group scour in waves using support vector machines and ANN

Samaneh Ghazanfari-Hashemi, Amir Etemad-Shahidi, Mohammad H. Kazeminezhad and Amir Reza Mansoori

ABSTRACT

Scour around pile groups is rather complicated and not yet fully understood due to the fact that it arises from the triple interaction of fluid–structure–seabed. In this study, two data mining approaches, i.e. Support Vector Machines (SVM) and Artificial Neural Networks (ANN), were applied to estimate the wave-induced scour depth around pile groups. To consider various arrangements of pile groups in the development of the models, datasets collected in the field and laboratory studies were used and arrangement parameters were considered in the models. Several non-dimensional controlling parameters, including the Keulegan–Carpenter number, pile Reynolds number, Shield's parameter, sediment number, gap to diameter ratio and number of piles were used as the inputs. Performances of the developed SVM and ANN models were compared with those of existing empirical methods. Results indicate that the data mining approaches used outperform empirical methods in terms of accuracy. They also indicate that SVM will provide a better estimation of scour depth than ANN (back-propagation/multi-layer perceptron). Sensitivity analysis was also carried out to investigate the relative importance of non-dimensional parameters. It was found that the Keulegan–Carpenter number and gap to diameter ratio have the greatest effect on the equilibrium scour depth around pile groups.

Key words | ANN, pile group, scour depth, soft computing approaches, SVM

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NOTATION

The following symbols are used in this paper:

b	additive noise
C	regularization parameter
D	pile diameter
d_{50}	mean grain diameter
f	friction factor
g	gravitational acceleration
G	spacing between piles
KC	Keulegan–Carpenter number
$K(x_i, y_i)$	kernel function
m	number of piles parallel to the flow
n	number of piles normal to the flow
N	number of data points
N_s	sediment number
O_i	network output
T_i	target output
Re	pile Reynolds number
S	equilibrium scour depth
SI	scatter index
S/D	non-dimensional scour depth
T	wave period
U_m	maximum undisturbed orbital velocity at the sea bed
U_{fm}	shear velocity at the undisturbed bed
w	weight vector
x_i	input vector
y_i	output vector
ϵ	error parameter

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μ	fluid dynamic viscosity
ξ_i, ξ_i^*	slack variables
ρ	fluid density
ρ_s	sediment density
θ	Shield's parameter
η_i, η_i^*, α_i, α_i^*	Lagrangian parameters

INTRODUCTION

The scour depth around pile groups as supports of marine structures is a major issue that needs to be considered in their design. Since most pile groups are constructed in erodible beds in the marine environment, prediction of scour depths around pile groups due to waves is of great importance. The arrangement of piles in addition to their geometry, sediment and wave characteristics should be considered to estimate the scour depth around a group of vertical piles.

Prediction of wave-induced scour depth around a single pile has been studied extensively (e.g. Palmer 1969; Wang & Hebrich 1983; Hebrich *et al.* 1984; Eadie & Hebrich 1986; Sumer *et al.* 1992a, 1993; Kobayashi & Oda 1994). However, limited models have been given for the scour depth around pile groups while most of them were concentrated on a unique arrangement or did not consider the parameters controlling the arrangements of piles in pile groups.

Chow & Hebrich (1986) studied pile groups made of three, four and six piles. They investigated the influence of gap to diameter ratio, G/D, where G is the space between piles and D is the pile diameter. Scour around different groups of vertical piles has also been investigated by Sumer & Fredsoe (1998). In their laboratory experiments, pile groups made of two, three and four piles in tandem, side by side and staggered arrangements were studied. They found that the equilibrium scour depth (S/D) was controlled by the Keulegan–Carpenter number (KC) number for small G/D ratios. They also noted that interactions between piles in a pile group increase with the decrease of G/D.

Experimental investigations made by Sumer & Fredsoe (1998) also showed the importance of the arrangement in a pile group scour. Chow & Hebrich (1986) and Sumer & Fredsoe (1998) studied various arrangements of piles in pile groups but no formula was given in their studies. Bayram & Larson (2000) studied the scour depth around pile groups in the field. Their study also showed that the equilibrium scour depth is governed by KC number. They presented an empirical relationship for estimating the equilibrium scour depth using the KC number in the 2×2 pile arrangement. Although it was shown by Sumer & Fredsoe (1998) that the equilibrium scour depth (S/D) is controlled by G/D, the quantitative influences of G/D and the number of piles were not explored in their studies since they studied only a 2×2 pile arrangement. Hence, development of a model for the prediction of scour depth in various arrangements of pile groups is required.

Considering the complexity of modeling the scour process and scour hole properties around pile groups due to waves, the existing approaches are not capable of accurate estimation of the scour depth around pile groups with different arrangements. Hence, a robust model is very useful for the estimation of scour depth. One of the most common approaches as an alternative to empirical approaches is the soft computing method. Artificial neural networks (ANN) as a famous data-mining method have been widely applied in scour estimation (e.g. Liriano & Day 2001; Kambekar & Deo 2003; Bateni & Jeng 2007; Zounemat-Kermani *et al.* 2009; Kazeminezhad *et al.* 2010). Kambekar & Deo (2003) developed various artificial neural networks with different input variables to predict scour hole properties around pile groups due to waves. In their study, the field data of Bayram & Larson (2000) with a unique arrangement was considered and the effects of different arrangements were not investigated. Results of their study showed that ANN provides a better alternative to the statistical curve fitting. Bateni & Jeng (2007) applied an Adaptive Neuro-fuzzy Inference System (ANFIS) to estimate scour depth around pile groups and compared the results with those of empirical approaches. Their results showed that ANN outperforms the existing empirical equations. Also in their study, only a specific arrangement of pile groups was tested and the effects of geometrical parameters such as the distance between the piles and their number were not investigated. The main aims of this study are to consider all important parameters including the pile group parameters and also application of a new soft computing method which has not been considered in this field. In this way, soft computing models can be developed for the first time to estimate wave-induced scour depth around pile groups with various arrangements.

Recently, a new soft computing approach named Support Vector Machines (SVM) has been successfully applied in problems such as the prediction of wind speed (Mohandes *et al.* 2004), runoff modeling (Bray & Han 2004), prediction of storm surge (Rjasekaran *et al.* 2008), hourly reservoir inflow forcasting (Lin *et al.* 2009a), effective forecasting of hourly typhoon rainfall (Lin *et al.* 2009b) and prediction of significant wave height (Mahjoobi & Mosabbeb 2009). However, the performance of the SVM approach in the prediction of scour hole properties in a pile group has not been investigated yet. In this study, two soft computing models, SVM and ANN, were developed and applied to estimate the scour depth around pile groups with various arrangements. Performances of both methods were compared with those of empirical approaches.

SCOUR AROUND PILES

Wave-induced scour around a single pile depends on several groups of variables such as the characteristics of the wave and the sediment properties and geometry of the pile. Thus, the following functional relationship can be used to describe the equilibrium scour depth for a single pile (Sumer *et al.* 1992b):

$$S = f(T, d_{50}, U_m, U_{fm}, D, s, v) \tag{1}$$

where S is the equilibrium scour depth, T is the wave period, d_{50} is the medium sediment diameter, U_m is the maximum undisturbed orbital velocity at the sea bottom just above the wave boundary, U_{fm} is the shear velocity at the undisturbed bed given by $U_{fm} = (0.5f)^{0.5}U_m$ in which f is the wave friction factor, D is the pile diameter, s is the specific gravity of sediments and v is the kinematics viscosity. Using the dimensional analysis, the above relationship can be presented in non-dimensional form as follows (Sumer *et al.* 1992b):

$$\frac{S}{D} = f(\mathrm{Re}, N_s, \theta, KC) \tag{2}$$

where Re is the pile Reynolds number, N_s is the sediment number, θ is the Shield's parameter and KC is the Keulegan–Carpenter number defined as follows:

$$Re = \frac{U_m D}{v} \tag{3}$$

$$N_s = \frac{U_m}{\sqrt{g(s-1)d_{50}}} \tag{4}$$

$$\theta = \frac{U_{fm}^2 D}{(s-1)gd_{50}} \tag{5}$$

$$KC = \frac{U_m T}{D}. \tag{6}$$

The non-dimensional parameters should include the effect of various physical processes occurring during the scour, i.e. flow–seabed interaction, flow–structure interaction and sediment transport. In Equation (2) the Reynolds number and Keulegan–Carpenter number describe the flow pattern around piles, whereas the Shield's parameter and sediment number represent the mutual effects of flow on the seabed. For a group of vertical piles, in addition to the above parameters, spacing between the piles (G), number of piles normal to the flow (n) and number of piles parallel to the flow (m) are also important in the estimation of scour depth around pile groups. Considering these new parameters, the maximum scour depth S normalized by pile diameter D can be best expressed as follows (see also Zounemat-Kermani *et al.* (2009)):

$$\frac{S}{D} = f\left(R_e, N_s, \theta, KC, \frac{G}{D}, \frac{m}{n}\right). \tag{7}$$

The existing empirical methods for estimating scour depth at pile groups are briefly given in Table 1. The equations given in this table were originally for single piles and are modified to be used for pile groups using the concept of effective diameter, D_e (Bayram & Larson 2000). D_e is the diameter of a hypothetical circle, having an area equal to that of a parallelogram circumscribing the pile group . In the following subsection, models developed based on these non-dimensional numbers are given in detail.

METHODS

In this subsection, two data-mining approaches, including artificial neural networks and support vector machines, are introduced briefly.

Table 1 | Summary of the empirical approaches used for comparison in this study

Formula	Author
$\frac{S}{D_e} = 1.3\{1 - \exp[-0.03(KC - 6)]\} \quad for \quad KC \geq 6$	Sumer *et al.* (1992b)
$\frac{S}{D_e} = 0.023KC$	Bayram & Larson (2000)
$\frac{S}{D_e} = 1.3\{1 - \exp[-0.043(KC - 4.2)]\} \quad for \quad KC \geq 4.2(a)$	Myrhaug & Rue (2005)
$\frac{S}{D_e} = 1.3\{1 - \exp[-0.054(KC - 3.3)]\} \quad for \quad KC \geq 3.3(b)$	

Artificial neural networks

ANN is the most famous data-mining approach that imitates some functions of the human brain (Singh *et al.* 2008). Neural networks are the general-purpose computing tools that can solve complex nonlinear problems (Fischer 1998). The network comprises of a large number of simple processing elements linked to each other by weighted connections according to a specified architecture. These networks learn from the training data by adjusting the connection weights (Bishop 1995). The connection of neurons to each other can be carried out in various configurations. Hence, the simplest way of modeling a neural network consists of three layers: input layer, hidden layer and output layer. The optimum topology of ANN is usually determined by a trial-and-error procedure. More details can be found in Jain & Deo (2006).

Support vector machines (SVM)

Support vector machines, like artificial neural networks, are a kind of data-mining approach. SVM have been successfully applied to a number of applications ranging from particle identification, facial identification and text categorization to engine knock detection, bioinformatics and database marketing. The classification problem is used to investigate the basic concepts behind SVM and to examine their strengths and weaknesses from a data-mining perspective (Campbell 2000). Regression algorithms of support vector machines are achieved by some modification to the classification algorithms of SVM.

In support vector regression the objective is to find a function $f(x)$ which has at most ϵ deviation from the actually obtained targets y_i for all the training data $\{(x_1 y_1), \ldots, (x_i y_i)\}$ and at the same time is as flat as possible. In other words, errors are negligible as long as they are less than ϵ and any deviation larger than this is not accepted. $f(x)$ can be expressed as (Smola & Scholkopf 2004)

$$f(x) = (w, x) + b, w \in X, b \in R \tag{8}$$

where w is a weight vector ($w \in R^n$); b is additive noise ($b \in R$) and (w, x) denote dot points in X. Flatness of the regression function $f(x)$ can be achieved by smaller values of w. One way to ensure this is to minimize the Euclidean norm as defined by $\|w\|^2 = (w,w)$. The minimization problem can be written as a convex optimization problem (Singh *et al.* 2008):

$$\begin{cases} minimize & \frac{1}{2}\|w\|^2 \\ subject\ to & \begin{cases} y_i - (w, x_i) - b \leq \epsilon \\ (w, x_i) + b - y_i \leq \epsilon \end{cases} \end{cases} \tag{9}$$

The optimization problem can be feasible if the error on any training data is less than ϵ. Sometimes, it is allowed to have some more errors. Hence slack variables ξ_i and ξ_i^* can be introduced and the minimization formula (9) will be written as follows (Vapnik 1995):

$$\begin{array}{ll} minimize & \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{m}(\xi_i + \xi_i^*) \\ subject\ to & \begin{cases} y_i - (w_i, x_i) - b \leq \epsilon + \xi_i \\ (w_i, x_i) + b - y_i \leq \epsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0 \end{cases} \end{array} \tag{10}$$

The constant $C > 0$ determines the trade-off between the flatness of $f(x)$ and the tolerable amount larger than ϵ which is defined by the user.

By introducing the Lagrangian parameters η_i, η_i^*, α_i and α_i^* and multiplying the constraints to these parameters the

Lagrangian form of (10) can be written as

$$L = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{m}(\xi_i + \xi_i^*) - \sum_{i=1}^{m}(\eta_i\xi_i + \eta_i^*\xi_i^*)$$
$$- \sum_{i=1}^{m}\alpha_i(\epsilon_i + \xi_i - y_i + (w, x_i) + b)$$
$$- \sum_{i=1}^{m}\alpha_i^*(\epsilon_i + \xi_i^* - y_i + (w, x_i) + b);$$
$$\begin{cases} \alpha_i, \eta_i \geq 0 \\ \alpha_i^*, \eta_i^* \geq 0 \end{cases}. \tag{11}$$

The saddle points of Equation (11) can be calculated as below:

$$\frac{\partial L}{\partial b} = 0 \Rightarrow \sum_{i=1}^{m}(\alpha_i^* - \alpha_i) = 0 \tag{12}$$

$$\frac{\partial L}{\partial w} = 0 \Rightarrow w - \sum_{i=1}^{m}(\alpha_i^* - \alpha_i)x_i = 0 \tag{13}$$

$$\frac{\partial L}{\partial \xi_i^*} = 0 \Rightarrow C - \alpha_i^* - \eta_i^* = 0. \tag{14}$$

Substituting Equations (12)–(14) into Equation (11) yields the dual maximization problem (Smola & Scholkopf 2004):

$$maximize \begin{cases} -\frac{1}{2}\sum_{i=1}^{m}(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)(x_i, x_j) \\ -\epsilon\sum_{i=1}^{m}(\alpha_i + \alpha_i^*) + \sum_{i=1}^{m}y_i(\alpha_i - \alpha_i^*) \end{cases}$$
$$subject\ to\ \sum_{i=1}^{m}(\alpha_i - \alpha_i^*) = 0 \text{ and } \alpha_i, \alpha_i^* \in [0, C]. \tag{15}$$

Finally, the prediction function can be written as

$$f(x) = \sum_{i=1}^{m}(\alpha_i - \alpha_i^*)(x_i, x) + b. \tag{16}$$

Nonlinear support vector regressions can be used in complex and nonlinear problems by introducing kernel functions (Vapnik 1995). Solving nonlinear problems can be achieved by mapping the data into a higher-dimensional feature space with the help of kernel functions.

The problem of support vector regression in the feature space can be written by substituting x_i, x_j in (16) by $K(x_i, x_j)$. Finally $f(x)$ can be written as (17) in the feature space as

$$f(x) = \sum_{i=1}^{m}(\alpha_i - \alpha_i^*)K(x_i, x) + b. \tag{17}$$

In addition to the choice of a kernel, SVM requires the setting up of kernel-specific parameters. Furthermore, optimum values of the regularization parameter C and the size of error in the sensitive zone need to be determined. The choice of these parameters controls the complexity of the prediction. One major advantage of SVM is its optimization algorithm, which entails solving a linearly constrained quadratic programming function leading to a unique, optimal and global solution (Singh *et al.* 2008; Lin *et al.* 2009a, b). The other advantages of SVM in comparison to ANN are producing a model with less generalization error and the immunity to overfitting because of independence from the variations of the training data. In addition, SVM needs less computational time and fewer parameters than ANN which leads it to be trained more rapidly (Mahjoobi & Mosabbeb 2009; Lin *et al.* 2009a, b).

Dataset used

In this study, both prototype and small-scale data, i.e. datasets collected by Bayram & Larson (2000) in the field and by Sumer & Fredsoe (1998) in the laboratory were used. The details of these experiments are as follows.

Laboratory data of Sumer & Fredsoe (1998)

Small-scale experiments of Sumer & Fredsoe (1998) were conducted in a wave flume of 4 m in width, 1 m in depth and 28 m in length. The medium sediment diameter d_{50} was 0.2 mm and the water depth was maintained at 40 cm. The development of scour was monitored using an underwater mini-video camera and undisturbed-flow velocity measurements were made at a distance of 5 cm away from the bed. From this study 44 datasets of side-by-side, tandem and 4×4 arrangements were selected. These arrangements of pile groups are shown in Figure 1. The ranges of different parameters are given in Table 2. As shown in Table 2, the configurations selected from this study covers a wide range of G/D from 0 to 2, KC numbers ranging from 3 to 37, and arrangement parameters m/n which varies from 0.33 to 3.0.

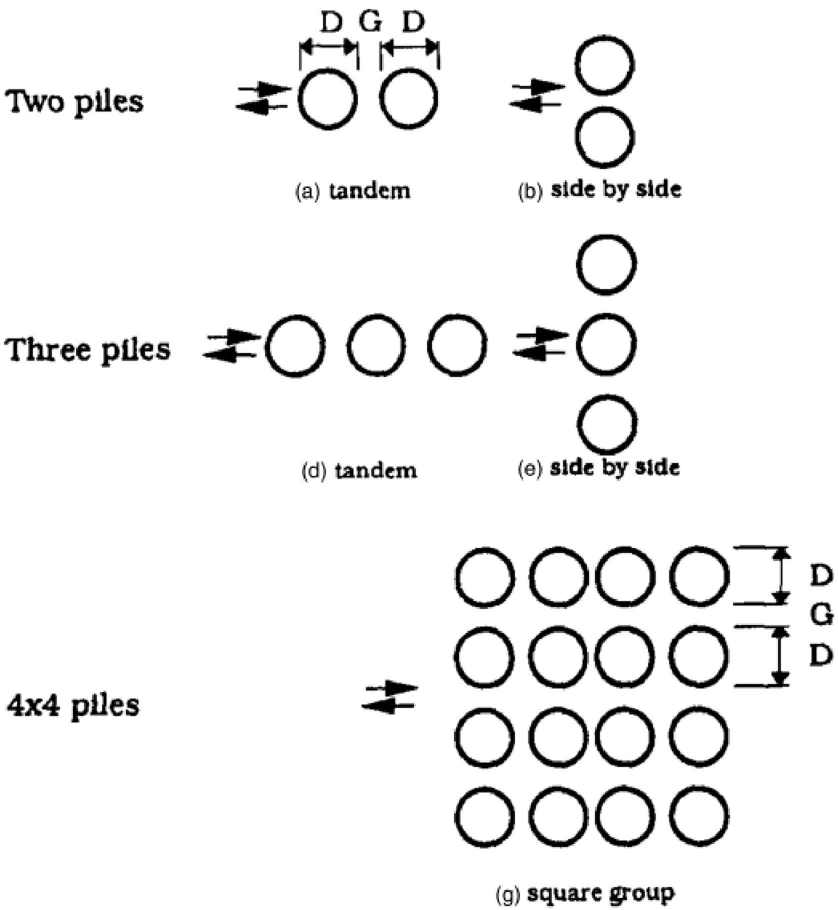

Figure 1 | Configurations of the pile groups used in the laboratory (after Sumer & Fredsoe 1998).

Field data of Bayram & Larson (2000)

Bayram & Larson (2000) investigated the scour around a group of vertical piles in an arrangement of 2×2 (Figure 2). They collected the field data of a pile group located in Ajigaura Beach in Japan. The measurements of that survey started from 1975 and ended in 1996. Each single pile had 0.6 m diameter and was installed 2.67 m apart from the other ones in a 2×2 arrangement. Weekly surveys were made of nine groups of vertical piles located 30 m apart from each other from 80 stations with a spacing of 30 m. The reported data was limited to two outermost seaward groups to ensure non-breaking-wave condition. The ranges of governing parameters of the 58 data points used are given in Table 3. The ranges of G/D and S/D are much wider than those of the laboratory data of Sumer & Fredsoe (1998).

Development of models

The ANN and SVM models were developed using the previously mentioned six non-dimensional numbers as input parameters and the measured non-dimensional scour depths

Table 2 | Ranges of the experimental data presented by Sumer & Fredsoe (1998)

Std. dev.	Mean	Range	Parameters
0.024	0.086	0.02–0.18	θ
0.749	4.16	1.94–6.54	N_s
9.695	17.12	3–37	KC
6339	16659	3000–30 000	Re
0.568	0.492	0–2	G/D
0.963	1.428	0.33–3	m/n
0.406	0.559	0.1–1.95	S/D

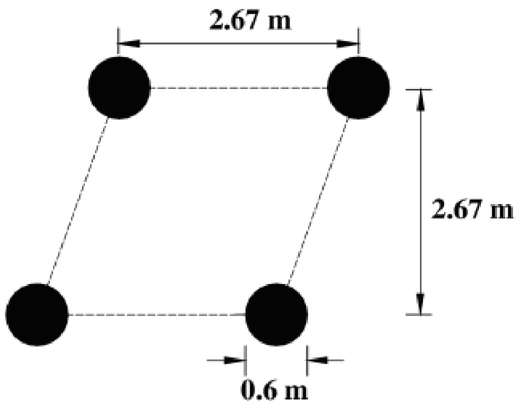

Figure 2 | Configuration of the pile group in the field (after Bayram & Larson 2000).

were used as outputs. The whole dataset consisting of 102 data points was divided into two parts randomly for training and testing purposes. About 38% of the test data were collected in the laboratory and the remaining were collected in the field. KC numbers varied from 3 to 37 and 8.3 to 37 in training and testing datasets, G/D ranges were from 0 to 3.45 and 0.01 to 3.45 in training and testing sets, respectively. The arrangement parameter m/n varied from 0.33 to 3.0 in both training and testing sets. The number of 4×4 arrangements in training and testing were 90 and 2, 2×2 were 45 and 13, 2×1 were 10 and 1, 1×2 were 6 and 2, 3×1 were 7 and 1 and the number of 1×3 arrangements in training and testing were 4 and 3, respectively.

ANN model

In this study, the multi-layer perceptron neural network (MLP with a 6-1-1 architecture) with one hidden layer and back-propagation training algorithm was used. The learning rate was assumed 0.2 and the training of the ANN models was stopped either when the acceptable level of error of about 0.03 per epoch was achieved or when the number of iterations exceeded a prescribed maximum of 8000. The performances of models were assessed quantitatively using the following statistical parameters: coefficient of correlation (CC), root mean square error ($RMSE$) and scatter index (SI) which are defined as the following relationships:

$$CC = \frac{\sum(T_i - \overline{T_i})(O_i - \overline{O_i})}{\sqrt{\sum(T_i - \overline{T_i})^2 \sum(O_i - \overline{O_i})^2}} \tag{18}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(O_i - T_i)^2}{N}} \tag{19}$$

$$SI = \frac{RMSE}{\overline{T_i}}. \tag{20}$$

In the above formulae, O_i and T_i represent target and network outputs for the ith output, respectively; $\overline{O_i}$ and $\overline{T_i}$ are the average of target and network outputs and N is the total number of data points. A higher value of CC and smaller values of $RMSE$ and SI mean a better model performance. Networks with different numbers of neurons were developed and their skills were compared based on the $RMSE$ values. Over-training was checked by using 10-fold cross-validation. In addition the training phase of the ANN model was stopped when the results of the validation phase seemed to decrease. Finally, a 6-6-1 architecture with error statistics shown in Table 4 was selected.

Table 3 | Ranges of the field data presented by Bayram & Larson (2000)

Std. dev.	Mean	Range	Parameters
0.113	0.259	0.08–0.64	θ
1.562	5.949	3.22–10.69	N_s
3.754	13.136	7.6–22.5	KC
162 116	64 9137	340 000–1100 000	Re
0	3.45	3.45	G/D
0	1	1	m/n
0.511	1.801	0.7–3.5	S/D

SVM model

The use of SVM requires setting of a few user-defined parameters, such as the regularization parameter (C) and the type of kernel (polynominal or RBF). Previous investigators such as Singh *et al.* (2008) have shown that the polynominal kernel can be used successfully and we used the same type. The regularization parameter C and the size of error in sensitive zone parameters control the complexity of prediction. A value of $C = 3.44$ and $\epsilon = 0.000\,010$ were selected based on the process of error minimizing shown in Table 5. For choosing the optimal C and ϵ, first ϵ was kept constant and

Table 4 | Error statistics of the number of hidden nodes in ANN

Error statistics of testing phase		Error statistics of training phase		
RMSE	*CC*	*RMSE*	*CC*	Number of hidden neurons
0.3956	0.8528	0.2943	0.9279	6

C was varied. This was also tested vice versa and the final results did not change significantly.

RESULTS AND DISCUSSIONS

As mentioned before, a BP neural network and a polynominal SVM model were developed to predict the equilibrium scour depth. In the following section, the results are compared and discussed for both data-mining approaches and they are compared with previous approaches.

Comparison of data-mining approaches

To assess the performance of the models, observed normalized equilibrium scour depth values were plotted against the predicted ones for the training and testing datasets. Figures 3 and 4 display the observed and predicted values for the testing data using the developed ANN and SVM models. These figures illustrate that the SVM model provides better results compared to the ANN model. The *RMSE* value has decreased about 23% and the *CC* value has increased about 6% when using SVM instead of ANN. In addition, according to Tables 4 and 5, the results of the training and testing of SVM are closer compared to those of ANN and there is about a 20% reduction in *SI* values when using the SVM instead of ANN approach. In data-mining approaches a closer result in training and testing phases can be considered as the stability of a model and one can expect to get results with the accuracy of the training phase in testing. In the current study, SVM can be considered as a more stable model since it has closer results in training and testing processes.

Table 6 summarizes the computation time using a PC with a Pentium 4 processor of 2.4 GHz and 512 MB RAM for training the SVM and ANN models. As shown, SVM is a less time-consuming model in comparison with ANN. In addition, less required setting parameters is another advantage of SVM in comparison with ANN (see also Lin *et al*. (2009a, b)).

Comparison with previous models

To evaluate the accuracy and capability of the developed models in predicting the scour depth around pile groups due to waves, their results were also compared with those of three existing semi-empirical methods. Figure 5 shows scour depth values using two data-mining models and the existing formulae for the same dataset. As illustrated, the methods proposed by Myrhaug & Rue (2005), Bayram & Larson (2000) and the ANN model overestimate the scour depth, while other approaches underestimate it. Table 7 illustrates the error statistics of all models. Note that the same dataset was used for all of them. As seen, both data-mining models provide better results compared to the previous empirical methods. In addition, for the best existing method (Bayram & Larson 2000), *RMSE* is 1.2526 and *SI* is 0.9728 compared to, respectively, 0.3214 and 0.2496 for the SVM model. This shows a fourfold decrease in error measures when using the developed SVM model. To sum up, comparison between the results of two soft computing methods, i.e. SVM and ANN, with those of empirical methods shows that complex problems like scour around pile groups can be modeled more accurately using soft computing methods.

Sensitivity analysis

To extend the outcomes of the study, sensitivity tests were also conducted to determine the relative significance of each input variable on the normalized scour depth (output) for the SVM model. Table 8 demonstrates each model performance in the absence of each input parameter. The results in Table 8 show that G/D and KC have the most significant effect on equilibrium scour depth since, by ignoring each of them, the *SI* and *RMSE* values increase by about 50%. According to Sumer & Fredsoe (1998), the G/D value determines the interaction between piles in pile groups. They showed that piles will act as a unique pile in a pile group if $G/D < 0.1$ or they will act separately for large values of G/D (>1–3). This is because the interaction of piles and vortices decreases as the gap between piles increases. In this case, the number of piles is less important in the scour process since they act

Table 5 | (a) Error variation as a function of C

Error statistics of testing phase		Error statistics of training phase		
RMSE	*CC*	*RMSE*	*CC*	*C*
0.3123	0.9113	0.337	0.9036	3
0.3145	0.91	0.3363	0.904	3.1
0.3162	0.9086	0.3359	0.9044	3.2
0.3177	0.9075	0.3355	0.9047	3.3
0.3211	0.9053	0.3347	0.9052	3.4
0.3208	0.9054	0.3347	0.9052	3.41
0.3211	0.9053	0.3347	0.9052	3.42
0.3206	0.9053	0.3347	0.9053	3.43
0.3214	**0.905**	**0.3345**	**0.9053**	**3.44**
0.3214	0.9049	0.3345	0.9053	3.45
0.3222	0.9045	0.3342	0.9054	3.46
0.3208	0.9052	0.3343	0.9054	3.47
0.3222	0.9045	0.3343	0.9055	3.48
0.3216	0.9047	0.3342	0.9054	3.49
0.3213	0.9049	0.3342	0.9055	3.5
0.3232	0.9038	0.3342	0.9056	3.55
0.3333	0.8963	0.3316	0.9071	4
0.3582	0.8795	0.3275	0.9098	5

(b) Error variation as a function of ϵ

Error statistics of test phase		Error statistics of train phase		
RMSE	*CC*	*RMSE*	*CC*	ϵ
0.3468	0.8911	0.3478	0.8959	0.1
0.3204	0.9046	0.3322	0.9065	0.01
0.321	0.9052	0.3343	0.9054	0.001
0.3209	0.9053	0.3345	0.9053	0.000 1
0.3214	**0.905**	**0.3345**	**0.9053**	**0.000 01**
0.3216	0.9049	0.3344	0.9054	0.000 001
0.3207	0.9055	0.3346	0.9053	0.000 000 1
0.3217	0.9049	0.3345	0.9052	0.000 000 01

more or less separately. In the current study, the majority of data points had large gaps and less importance of m/n in comparison with G/D is physically sound. It can be concluded that in various arrangements of pile groups, G/D and KC play the main roles. These findings are in line with those of Sumer & Fredsoe (1998) and Bayram & Larson (2000) about the relative importance of the input parameters on equilibrium scour depth around pile groups due to waves. Bateni & Jeng (2007) also noted the strong dependence of S/D on KC. In their work, only a 2×2 pile arrangement was studied; hence, geometric parameters were not considered in their investigations. The error measures in Table 8 also show that the arrangement parameters, i.e. G/D and m/n are more important than other parameters (except KC). In fact, as seen by excluding N_s, Re and θ do not change the accuracy of the model significantly. Table 8 shows that sensitivity analysis of

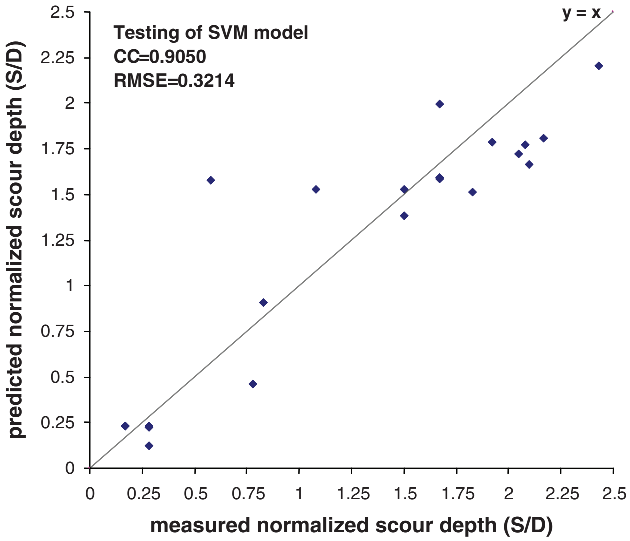

Figure 3 | Comparison between the observed and predicted normalized scour depths by the SVM model.

the SVM model is in line with previous studies and the nature of scouring.

To extend the outcomes of the study, a parametric analysis was conducted using the trained SVM and ANN models. This was done by varying an important parameter while keeping other parameters constant. The variations of the output (S/D) against KC, and G/D against m/n are shown in Figure 6. As seen, the SVM model is more consistent with the underlying physical processes while it seems that the ANN model is sometimes too sensitive to the variations of the governing parameters.

Table 6 | Required training times for ANN and SVM approaches

Approach	Time (s)
ANN	17.88
SVM	1.05

SUMMARY AND CONCLUSIONS

In this paper, the development and application of a multilayer perceptron neural network with a 6-1-1 architecture, learning rate = 0.2, error per epoch = 0.03 and number of iterations = 8000 and the support vector machine with a polynomial kernel, a value of $C = 3.44$ and $\epsilon = 0.000\ 010$ were outlined for estimation of the wave-induced scour depth around pile groups. Two sets of laboratory and field data, including various arrangements of piles in a group, were used to train and test both data-driven models. Then, the results were compared with those of previous empirical approaches. It was shown that ANN and support vector machines can predict scour depth more accurately than the existing empirical methods. The data-mining results were generally more satisfactory than those of empirical methods

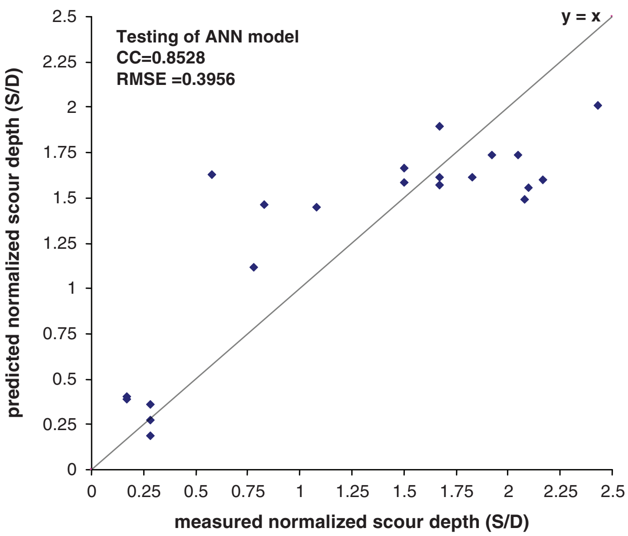

Figure 4 | Comparison between the observed and predicted normalized scour depths by the ANN model.

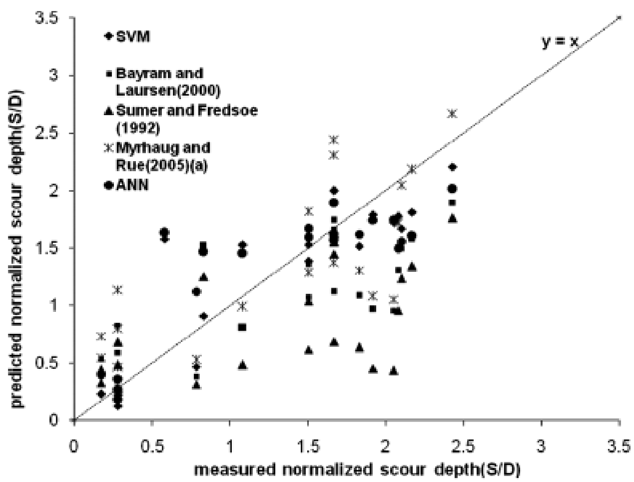

Figure 5 | Comparison of measured and predicted normalized scour depth using different approaches.

Table 7 | Performance indices of various approaches to predict the scour depth

Error statistics			
SI	***RMSE***	***CC***	**Approach**
1.3029	1.6776	0.2333	Myrhaug & Rue (2005)
0.9728	1.2526	0.1176	Bayram & Larson (2000)
1.0029	1.2914	0.04516	Sumer *et al.* (1992b)
0.2496	0.3214	0.9050	SVM (present study)
0.3072	0.3956	0.8528	ANN (present study)

because of low errors and higher correlation coefficients. It is concluded that SVM outperforms ANN (MLP/BP) while the assessment of other algorithms of ANN and comparing their results with those of SVM with various kernels and training algorithms can be another research topic that is beyond the scope of our work.

Comparison of ANN (MLP/BP) with SVM illustrates that, although the former trains better than the latter, the SVM results are more accurate. This indicates that SVM is a more reliable model with better generalization error, independent from the variations of the training data in addition to its robustness and less required time to be trained which are the main advantages of SVM over ANN(MLP/BP) (see also Lin *et al.* (2009a)). A sensitivity analysis was also conducted to investigate the effect of different input parameters on the equilibrium scour depth. The sensitivity analysis showed that the scour depth was mainly governed by the Keulegan–Carpenter (*KC*) number and the gap to diameter ratio.

Table 8 | Sensitivity analysis of the governing parameters for the SVM model

Error statistics			
SI	***RMSE***	***CC***	**SVM model in the absence of:**
0.3750	0.4828	0.8502	KC
0.3781	0.4869	0.8506	G/D
0.2748	0.3538	0.8818	m/n
0.2696	0.3472	0.8856	N_s
0.2575	0.3315	0.8969	Re
0.2550	0.3284	0.9028	θ
0.2496	0.3214	0.9050	

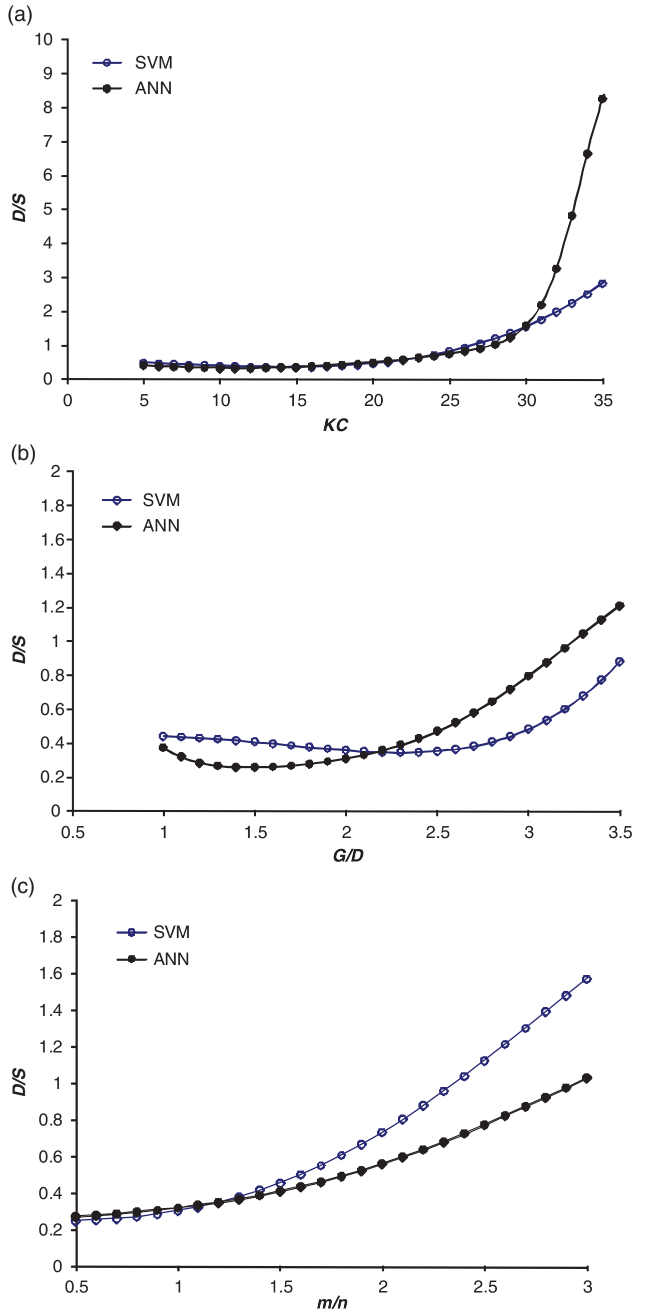

Figure 6 | Parametric analysis of developed models. (a) Variation of *S/D* against *KC*, (b) variation of *S/D* against *G/D* and (c) variation of *S/D* against *m/n*.

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