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Optimizing the prediction accuracy of load-settlement behavior of single pile using a self-learning data mining approach

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Abstract. Pile foundations usually are used when the upper soil layers are soft clay, hence, unable to support the structures' loads. Piles are needed to carry these loads deep into the hard soil layer. Therefore, the safety and stability of pile-supported structures depends on the behavior of the piles. Additionally, an accurate prediction of the behavior of the piles is very important to ensure a satisfactory performance of the structures. Although there are many methods in the literature to estimate the settlement of the piles, both theoretically and experimentally, methods for predicting load-settlement of piles comprehensively are very limited. This study develops a new data mining approach called self-learning support vector machine (SL-SVM) to predict the load-settlement behavior of single piles. The SL-SVM performance is investigated using 446 training data points, and 53 test data points of cone penetration test (CPT) data that were obtained from previous literature. The actual prediction accuracy is then compared to other prediction methods using three statistical measurement including mean absolute error (MAE), coefficient of correlation (R), and root mean square error (RMSE). The obtained results show that the SL-SVM achieve better accuracy than LS-SVM and BPNN. This confirms the capability of the proposed data mining method for modeling the accurate load-settlement behavior of single piles through CPT data. The paper proposes beneficial insights to the geotechnical engineers which are involved in estimating pile behavior.

1 Introduction

Pile foundation are usually used to transmit the axial load from the upper structures to the hard soil layer. At times, pile foundation can be more advantageous than shallow foundation due to the its cost-effectiveness in the construction [1]. One important aspect in the designing of the pile foundation is the evaluation of its load-settlement. Poulos and Davis [2] showed that the elastic settlement of the pile has major contribution to the total settlement. Especially in pile on sand, the elastic settlement is almost as big as the total settlement. Usually, the elastic settlement is analyzed by semi-empirical method.

Although there are many methods in geotechnical engineering to predict the settlement of the pile, theoretical and experimental, methods to predict the load-settlement of the pile thoroughly are very limited. In civil engineering world, data mining technique has become an important research area. Several studies have shown the advantages of data mining technique to produce better prediction models than the traditional methods [3,4]. Shahin [5] developed an artificial neural network (ANN) model to predict the load-settlement of a steel pile using recurrent neural network (RNN). This RNN model had been calibrated using 23 in situ, full scale load tests, as well as with cone penetration test (CPT) data. Even though RNN model from Shahin [5] showed good results, this model was derived from a limited data, i.e. 23 full scale load tests. In addition to that, Shahin model is focused to steel driven piles and only has one input parameter to calculate the variation of the soil strength along the pile shaft, i.e. the mean value of cone resistance of CPT.

Lately, least squares support vector machine (LS-SVM) has become one of the most prominent data mining technique used to solve a complex problem in the world [6,7]. Although LS-SVM has produced a higher accuracy of prediction results, an incorrect tuning parameter can reduce the accuracy of LS-SVM. The objective of this study is to improve the accuracy of the prediction model using parameter optimization. Identifying the most optimal parameters is optimization problem. Therefore, the latest studies integrate a machine learning technique with a metaheuristic-based optimization tool, instead of using only machine learning technique [8-11]. This study introduces a new hybrid data mining model called self-learning support vector machine (SL-SVM) to accurately predict the individual pile behavior in test records. Tests were done directly in the field and took into account various types of soil, several types of pile, and also various geotechnical problems commonly encountered in the field. The hybrid approach used by SL-SVM combines techniques from

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SOS and LS-SVM. SOS is used to optimize the γ and σ parameters of LS-SVM, then LS-SVM creates an improved input-output relationship from a dataset by performing a supervised-learning based predictor.

In this study, 499 test records were obtained from the previous literature. The proposed SL-SVM model can fully predict the load-settlement behavior of concrete, steel, and composite piles; bored or driven piles. To accurately model the non-uniformity of the soil along the pile shaft, the length of the embedded pile is divided into 5 segments of equal length. In each segment, the mean value of q_c and shaft friction of CPT (f_s) are calculated.

2 Methodology

2.1 Regression model: LS-SVM

LS-SVM was first developed by [6] an improved version of support vector machine (SVM). As a data mining technique, LS-SVM has been successfully applied in many civil engineering related problems [12-15]. LS-SVM utilizes a cost function based on least squares principle as supposed to the quadratic loss function that have been used in the original SVM [16]. The objective function and the constraints for minimizing the cost function of LS-SVM are shown as follows:

$$\text{Minimize } J_p(w,e) = \frac{1}{2}w^T w + \gamma\frac{1}{2}\sum_{k=1}^{N} e_k^2 \quad (1)$$

$$\text{Subjected to } y_k = w^T\phi(x_k) + b + e_k,\ k = 1,\ldots,N \quad (2)$$

where γ is a regularization constant, e_k denotes error variable, x_k and y_k are the input and output data points of the given training dataset of N data points.

For function estimation, the following equation expressed the LS-SVM model:

$$y(x) = \sum_{k=1}^{N} \alpha_k K(x_k, x_l) + b \quad (3)$$

where α_k and b represent the solutions to the linear system.

This study employed the radial basis function (RBF) kernel with the following formula shown below:

$$K(x_k, x_l) = \exp\left(-\frac{\|x_k - x_l\|^2}{2\sigma^2}\right) \quad (4)$$

where σ denotes the kernel function parameter.

2.2 Optimization algorithm: SOS

Initially developed Cheng and Prayogo [17], the SOS algorithm took an inspiration from symbiotic interactions among a group of organisms. Its initial application was to solve continuous optimization problems [17] and has been used to solve various problems from multiple disciplines [18-26]. SOS utilized nature-inspired operators which are mutualism phase, commensalism phase, and parasitism phase to guide the organisms (solutions) to the global optima region (best solution).

In "mutualism phase" each organism is modified as follows:

$$new\_O_i = O_i + U(0,1) \times [O_{best} - (1 + round(rand(0,1)) \times (O_i + O_j)/2] \quad (5)$$

$$new\_O_j = O_j + U(0,1) \times [O_{best} - (1 + round(rand(0,1)) \times (O_i + O_j)/2] \quad (6)$$

where O_i and O_j denotes the i-th and j-th organism vectors, respectively, such that i ≠ j; $U(0,1)$ denotes the uniform random numbers between 0 to 1; O_{best} represent the best organism; new_O_i and new_O_j are the generated candidate solutions after O_i and O_j performing the interaction.

In "commensalism phase", each organism is modified as follows:

$$new\_O_i = O_i + U(-1,1) \times (O_{best} - O_j) \quad (7)$$

where $U(-1,1)$ denotes the uniform random numbers between –1 to 1.

In "parasitism phase", each organism is modified as follow:

$$O_{par} = F \times O_i + (1 - F) \times (U(0,1) \times (ub - lb) + lb) \quad (8)$$

where O_{par} denotes the parasite that attempts to eliminate the host O_j, ub and lb represent the lower and upper bounds of the given problem, respectively; and F and $(1 - F)$ are the binary random matrix and its inverse, respectively.

2.3 SL-SVM system integration

In this study, two different artificial intelligence (AI) are combined, which are SOS and LS-SVM, to form a new hybrid data mining technique called SL-SVM. The relationship between the input and output variables of a given set of data is accurately mapped out through the LS-SVM that has a key role as a predictor. To find the most suitable LS-SVM parameters γ and σ, the SOS is utilized. The architecture of SL-SVM is shown in Fig. 1.

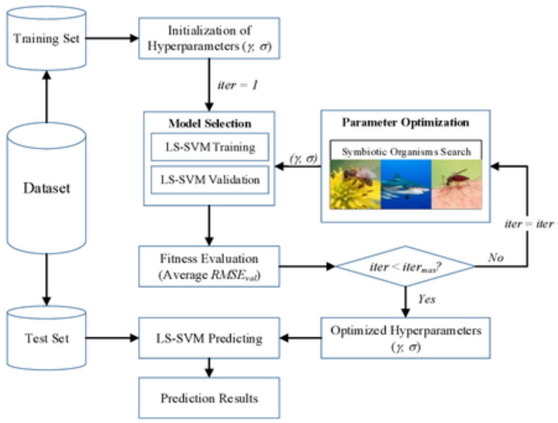

Fig. 1. Flow-chart of SL-SVM.

Throughout these test phases and training, the six main steps of the SL-SVM are conducted and are delineated below:

(1) Dataset: the dataset is usually grouped into a test set and a training set. Furthermore, the datasets were scaled into a (0,1) range [27], to curb the circumstances when one or some of the input variables are dominant over others.

(2) Hyperparameters' initialization: using the formula written below in the first iteration, the parameters are randomly initialized within the boundary range.

$$x = U(0,1) \times (ub - lb) + lb \qquad (9)$$

where x represents candidate solution (hyperparameters of LS-SVM).

(3) Model selection: in order to build the accurate learning model, this step is a very important and critical step. Utilizing the initial hyperparameters and the training set, LS-SVM model is trained with a key focus to finding the accurate relationship between input and output variables. The process of the training is conducted in an iterative manner and the tuning parameters from LS-SVM are optimized gradually by utilizing the SOS algorithm. A fitness function that correlates with the accuracy of the prediction model is now developed in the bid to evaluating the accuracy of the learning system. k-fold cross validation, a well-known sampling technique, is incorporated in the fitness function. The dataset is now grouped into k-folds in which the $(k - 1)/k$ part of the given dataset is assigned for training and the remaining part is assigned for the validating the trained model.

Thus, a k sets of training and validation subset are formed and carried out for model selection. For measuring the model accuracy, the root mean square error (RMSE) are selected as the fitness function as shown in the following equation:

$$fit\_val = \frac{\sum_{k=1}^{S} RMSE_{val}}{S} \qquad (10)$$

where fit_val is a fitness value calculated from RMSE between the predicted output and actual output from the validation subset and S is the total number of folds.

(4) SOS for parameter search: in order to identify the best set of these hyperparameters, the hybrid AI system utilizes SOS in exploring various simulations of γ and σ. Through the generation of the initial population, the search process commences. The initial population, however, serves as the initial candidate for the hyperparameters searched. SOS uses parasitism, commensalism and mutualism phases for each iteration to gradually bring about improvement in the fitness value of every candidate solution present in the population.

(5) Optimal hyperparameters: when the stopping criterion is met, the loop stops. This implies that the input–output mapping relationship has been identified by the prediction model with optimal γ and σ parameters.

(6) LS-SVM predicting: To predict the test set, it is pertinent that the prediction model is established. Thus, the training phase gave brought about the optimal LS-SVM γ and σ parameters that was utilized in establishing the prediction model.

3 Data preprocessing

There are 4 fundamental parameters are used in many established methods to predict the load-settlement behavior of single pile. These main parameters namely are: geometry of the pile, material properties of the pile, soil properties, and load applied to the pile. In addition to the main parameters, there are several extra parameters, such as: pile installation method, load test type, and whether the pile tip is open or closed. Geometry of the pile, material properties of the pile, and load applied to the pile are easy to quantify and identify. Instead, soil properties are tricky to quantify and identify.

In this study, the dataset is derived from load tests which comprised of 499 data points, obtained from Pooya Nejad and Jaksa [28]. In the literature, CPT is used for quantifying and identifying soil properties. The 499 data points are divided into 446 training data points and 53 test data points. To accurately model the non-uniformity of the soil along the pile shaft, the length of the embedded pile is divided into 5 segments of equal length. In each segment, the mean value of q_c and f_s are calculated. Finally, the attributes of the dataset are shown in Table 1 alongside the statistical description of the dataset.

Table 1. Statistical description of the dataset.

Attributes	Unit	Min	Max	Avg	Std
X_1: Type of the load test	1: Maintained load, 2: Constant rate of penetration				
X_2: Material properties of the pile	1: Concrete, 2: Steel, 3: Composite				
X_3: Pile installation method	1: Bored, 2: Driven				

X_4: End of pile	1: Closed, 2: Open				
X_5: Axial rigidity of the pile	MN	796.74	33106.3	11459.8	11680.0
X_6: Cross-sectional area of the pile	cm^2	100.00	7854.00	3411.78	2638.14
X_7: Perimeter of the pile	cm^2	58.50	957.56	320.31	280.47
X_8: Pile length	m	5.50	56.39	21.84	13.63
X_9: Embedded length of the pile	m	5.50	45.00	18.03	10.39
X_{10}: q_{c1}	MPa	0.00	10.38	3.57	2.64
X_{11}: f_{s1}	KPa	0.00	273.91	59.11	52.29
X_{12}: q_{c2}	MPa	0.05	17.16	4.73	3.51
X_{13}: f_{s2}	KPa	1.83	275.50	75.59	63.24
X_{14}: q_{c3}	MPa	0.30	31.54	6.18	6.55
X_{15}: f_{s3}	KPa	1.62	618.67	90.95	97.18
X_{16}: q_{c4}	MPa	0.25	33.37	8.52	7.72
X_{17}: f_{s4}	KPa	4.42	1292.67	200.31	215.31
X_{18}: q_{c5}	MPa	0.25	53.82	10.54	10.30
X_{19}: f_{s5}	KPa	7.99	559.00	139.86	144.50
X_{20}: q_c at the end of the pile	MPa	0.25	70.29	13.40	13.02
X_{21}: load applied to the pile	KN	0.00	30000.0	2585.01	3652.62
Y: Pile settlement	mm	0.00	137.88	10.57	16.14

4 SL-SVM application

4.1 Model selection and training results

This study implements the parameter setting of SOS as follows: ecosystem size = 50 and total iterations = 30. The searching range for the tuning parameters, γ and σ^2, was between 10^{-5} and 10^5. In order to have a balance training and validation data points, cross-validation was used. In order to have a splitting ratio of 2:1 between training and validation, 3-fold cross validation is used. SOS is then performed the model selection using the 3 sets of training and validation data subsets. The fitness value was determined as the average validation errors in the model selection. The model performance in training process is shown in Fig. 2. The optimal hyperparameters found by SOS were as follows: final $\gamma = 28.9507$ and final $\sigma^2 = 0.0547$ with the fitness value of 10.5514 mm.

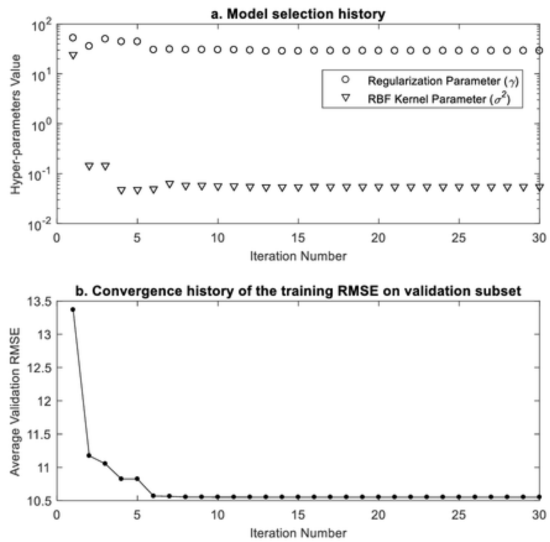

Fig. 2. Model selection process and convergence history of the training RMSE.

4.2 Prediction results

The accuracy of the training and test results between predicted output (y') and actual output (y) of n data points can be compared through three metrics which are correlation coefficient (R), root mean square error (RMSE), and mean absolute error (MAE). Each metric can be expressed as shown in Table 2.

Table 2. Performance metrics for measuring prediction results.

Performance Metrics	Formula
R	$\dfrac{n\sum y \times y' - (\sum y)(\sum y')}{\sqrt{n(\sum y^2) - (\sum y)^2}\sqrt{n(\sum y'^2) - (\sum y')^2}}$
RMSE	$\sqrt{\dfrac{1}{n}\sum_{j=1}^{n}(y_j - y'_j)^2}$
MAE	$\dfrac{1}{n}\sum_{j=1}^{n}\lvert y_j - y'_j\rvert$

The developed SL-SVM was validated and compared with other predictive models, including the original LS-SVM and back-propagation neural network (BPNN). The comparison between SL-SVM and other predictive algorithms may imply the advantages of using the optimization method to tune the optimal parameters. BPNN settings included: learning rate = 1, maximum hidden layers = 1, number of neurons in the hidden layer = 21 (following the total input variables). Finally, the LS-SVM parameters for γ and σ^2 were set to 1 as suggested in [6].

The experimental results between the proposed method and other prediction method are shown in Table 3. It is shown that the SL-SVM model outperformed LS-SVM and BPNN in all performance metrics. The SL-SVM produces the best value in R, RMSE, and MAE. Meanwhile, Fig. 3 further illustrates the actual and predicted settlement of the developed model in both training and test dataset.

Table 3. Training and test performance of SL-SVM and other methods.

AI methods	Training		
	R	RMSE (mm)	MAE (mm)
BPNN	0.7264	10.4378	6.602
LS-SVM	0.7354	12.0865	6.9043
SL-SVM	0.9513	5.2468	2.5634
AI methods	Test		
	R	RMSE (mm)	MAE (mm)
BPNN	0.7876	8.5783	6.0188
LS-SVM	0.5501	7.4134	5.2907
SL-SVM	0.7523	7.0517	4.7118

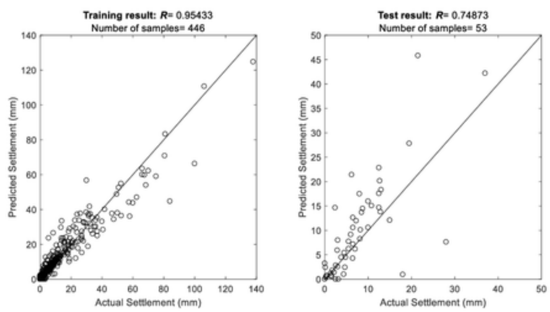

Fig. 3. Actual and predicted settlement of SL-SVM in training and test dataset.

5 Conclusions

In this study, we propose an automatic-tuning data mining technique called the self-learning least squares support vector machine (SL-SVM) to predict the settlement of a single pile. The experimental dataset was acquired from a past literature that contains a 499 samples of load tests. Three performance metrics were utilized to assess the proposed data mining technique and a comparison with various predictive techniques is conducted. The result indicates that the most accurate prediction model is the proposed SL-SVM. The SL-SVM is able to outperform the original LS-SVM due to the success of the SOS in searching the most suitable LS-SVM parameters. This established data mining technique, SL-SVM, can potentially help the geotechnical engineers to model the pile behavior for pile design. The trained model can model the pile settlement with a higher accuracy in comparison with other predictive technique.

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