Journal of Rock Mechanics and Geotechnical Engineering 7 (2015) 584–592

Contents lists available at ScienceDirect

Journal of Rock Mechanics and Geotechnical Engineering

journal homepage: www.rockgeotech.org

Full length article

Regressive approach for predicting bearing capacity of bored piles from cone penetration test data

Iyad S. Alkroosh [a], Mohammad Bahadori [b], Hamid Nikraz [c], Alireza Bahadori [d,*]

[a] Department of Civil Engineering, College of Engineering, Al-Qadissiya University, Al Diwaniyah, Iraq
[b] School of Soil Science and Engineering, University of Tehran, Tehran, Iran
[c] Department of Civil Engineering, Curtin University, Perth, Australia
[d] School of Environment, Science and Engineering, Southern Cross University, Lismore, New South Wales, Australia

ARTICLE INFO

Article history:
Received 27 April 2015
Received in revised form
12 June 2015
Accepted 30 June 2015
Available online 5 August 2015

Keywords:
Bored piles
Cone penetration test (CPT)
Bearing capacity
Least square support vector machine (LSSVM)
Training
Validation

ABSTRACT

In this study, the least square support vector machine (LSSVM) algorithm was applied to predicting the bearing capacity of bored piles embedded in sand and mixed soils. Pile geometry and cone penetration test (CPT) results were used as input variables for prediction of pile bearing capacity. The data used were collected from the existing literature and consisted of 50 case records. The application of LSSVM was carried out by dividing the data into three sets: a training set for learning the problem and obtaining a relationship between input variables and pile bearing capacity, and testing and validation sets for evaluation of the predictive and generalization ability of the obtained relationship. The predictions of pile bearing capacity by LSSVM were evaluated by comparing with experimental data and with those by traditional CPT-based methods and the gene expression programming (GEP) model. It was found that the LSSVM performs well with coefficient of determination, mean, and standard deviation equivalent to 0.99, 1.03, and 0.08, respectively, for the testing set, and 1, 1.04, and 0.11, respectively, for the validation set. The low values of the calculated mean squared error and mean absolute error indicated that the LSSVM was accurate in predicting the pile bearing capacity. The results of comparison also showed that the proposed algorithm predicted the pile bearing capacity more accurately than the traditional methods including the GEP model.

© 2015 Institute of Rock and Soil Mechanics, Chinese Academy of Sciences. Production and hosting by Elsevier B.V. All rights reserved.

1. Introduction

Bearing capacity is one of the most important factors that govern the design of pile foundations. Therefore, it has been the subject of interest for many researchers throughout the history of the geotechnical engineering profession. As a result, numerous theoretical and experimental procedures have been proposed to predict the pile behavior and bearing capacity. However, accurate evaluation of pile bearing capacity and certain interpretation of pile load transfer mechanism are still far from being accomplished due to the complexity of the problem.

The theoretical solutions, which employ the theory of bearing capacity to calculate the pile shaft and tip resistance, involve shortcomings resulting from considerable uncertainty over the factors that influence the bearing capacity. Among those factors are the effect of installation method, stress history and soil compressibility. For bored piles embedded in layered soil, the problem is more complex due to sensitivity of the factors that affect the behavior of the pile and the difficulty in quantifying those factors. For instance, the friction angle between pile and the surrounding soil cannot be exactly determined because of the effect of installation procedure and the difficulty in finding the real soil properties.

The experimental solutions that correlate the results of in-situ tests such as standard penetration test (SPT) or cone penetration test (CPT) with pile bearing capacity also involve setbacks. That may be attributed to that the SPT has substantially inherent variability and does not reflect soil compressibility (Abu-Kiefa, 1998). Moreover, the SPT results are affected by many factors, such as operator, drilling, hammer efficiency, and rate of blows. Hence, the accuracy of the proposed correlations between SPT data and pile bearing capacity is not assured. Although the correlation between pile capacity and CPT data can be a better alternative to the SPT correlation, comparative studies of the available CPT-based methods carried out by a number of researchers (e.g. Briaud, 1988; Roberston et al., 1988; Eslami, 1997; Abu-Farsakh and Titi, 2004; Cai et al., 2008) have shown that the capacity predictions can be very

* Corresponding author. Tel.: +61 2 6626 9347.
E-mail address: Alireza.bahadori@scu.edu.au (A. Bahadori).

Peer review under responsibility of Institute of Rock and Soil Mechanics, Chinese Academy of Sciences.
1674-7755 © 2015 Institute of Rock and Soil Mechanics, Chinese Academy of Sciences. Production and hosting by Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.jrmge.2015.06.011

different for the same case depending on the method employed. It is also found that these methods cannot provide consistent and accurate prediction of pile bearing capacity.

Considering the limitations of the proposed procedures for predicting pile bearing capacity and the limited success that they have achieved in terms of providing accurate prediction of pile bearing capacity, further research is required to overcome the complications associated with the problem. Artificial intelligence techniques may be better alternatives, due to the capability of being able to deal with complex and highly nonlinear functions, and employing the considerable capacity of computers to perform enormously iterated work. The modeling advantage of these techniques is their ability to capture the nonlinear and complex relationships between the targeted output and the factors affecting it, without having to assume a priori formula describing this relationship. A number of researchers (e.g. Teh et al., 1997; Abu-Kiefa, 1998; Das and Basudhar, 2006; Ardalan et al., 2009; Shahin, 2010; Ornek et al., 2012; Tarawneh, 2013) have successfully applied artificial neural network (ANN), which is a form of artificial intelligence, to solving engineering problems. Genetic programming (GP), which is another form of artificial intelligence, has been used successfully in solving engineering problems (Rezania and Javadi, 2007; Alavi et al., 2011; Alkroosh and Nikraz, 2011a, b; Gandomi, 2011; Gandomi and Alavi, 2012). Recently, an emerging algorithm, i.e. the least square support vector machine (LSSVM), which is a developed version of support vector machine (SVM), has been found successful in solving engineering problems (Das et al., 2011a, b; Samui and Kothari, 2011). This study investigates the feasibility of using the LSSVM to predict the bearing capacity of bored piles embedded in sand and mixed soils more accurately than the available methods.

2. Support vector machine (SVM)

The SVM is a method developed using the statistical learning concept (Suykens and Vandewalle, 1999). It has been widely used across the world (Cortes and Vapnik, 1995; Bazzani et al., 2001; Suykens et al., 2002; Amendolia et al., 2003; Baylar et al., 2009; Übeyli, 2010; Chen et al., 2011; Chamkalani et al., 2013; Rafiee-Taghanaki et al., 2013; Shokrollahi et al., 2013).

If we have training samples with given data $x_i \in \mathbb{R}^n$ and result data $y_i \in \mathbb{R}$ with labels -1 and 1, respectively, the SVM estimates the function shown below (Suykens and Vandewalle, 1999; Suykens et al., 2002):

$$y = \boldsymbol{w}^{\mathrm{T}}\Phi(x) + b \tag{1}$$

where $\Phi(x)$ is the function that maps x, and $\boldsymbol{w}$ and b are the weight vector and bias variable. When the data are separable, we will have (Suykens and Vandewalle, 1999; Suykens et al., 2002):

$$\left.\begin{array}{ll} \boldsymbol{w}^{\mathrm{T}}\Phi(x_k) + b \geq 1 & (y_k = 1) \\ \boldsymbol{w}^{\mathrm{T}}\Phi(x_k) + b \leq 1 & (y_k = -1) \end{array}\right\} \tag{2}$$

Eq. (2) is nearly equal to (Das et al., 2011a, b; Chamkalani et al., 2013):

$$y_k\left[\boldsymbol{w}^{\mathrm{T}}\Phi(x_k) + b\right] \geq 1 \quad (k = 1,\ 2,\ \ldots,\ N) \tag{3}$$

The further development of linear SVM to non-independent case was also created by Cortes and Vapnik (1995). Simply, it is done by presenting extra variables into Eq. (3) (Suykens and Vandewalle, 1999; Suykens et al., 2002):

$$y_k\left[\boldsymbol{w}^{\mathrm{T}}\Phi(x_k) + b\right] \geq 1 - \zeta_k,\ \ \zeta_k \geq 0 \quad (k = 1,\ 2,\ \ldots,\ N) \tag{4}$$

where ζ_k is the deviation factor.

The optimal separating hyperplane is predicted using the vector $\boldsymbol{w}$ that minimizes the functional conditions using the constraints (Eq. (4)) (Suykens and Vandewalle, 1999; Suykens et al., 2002; Übeyli, 2010):

$$\Phi(\boldsymbol{w},\ \zeta_i) = \frac{1}{2}\boldsymbol{w}^{\mathrm{T}}\boldsymbol{w} + \frac{C}{2}\sum_{i=1}^{N}\zeta_i^p \tag{5}$$

where p is the upper limit, and C is a coefficient.

In the SVM, optimal separating hyperplane is calculated using the quadratic method (Cortes and Vapnik, 1995):

$$\begin{aligned}\Phi(\boldsymbol{w},\ b,\ \alpha_i,\ \zeta_i,\ \beta_i) = {} & \frac{1}{2}\boldsymbol{w}^{\mathrm{T}}\boldsymbol{w} + \frac{C}{2}\sum_{i=1}^{N}\zeta_i \\ & - \sum_{i=1}^{N}\alpha_i\left[y_i\left(\boldsymbol{w}^{\mathrm{T}}x_i + b\right) - 1 + \zeta_i\right] - \sum_{j=1}^{N}\beta_i\zeta_i a\end{aligned} \tag{6}$$

where a is the adjustable parameter, α_i and β_i are the Lagrange multipliers (Suykens and Vandewalle, 1999; Suykens et al., 2002).

In contrast to the SVM, the LSSVM is developed using minimization of cost equation (Suykens and Vandewalle, 1999; Suykens et al., 2002):

$$\Phi(\boldsymbol{w},\ \zeta_i) = \frac{1}{2}\boldsymbol{w}^{\mathrm{T}}\boldsymbol{w} + \frac{C}{2}\sum_{i=1}^{N}\zeta_i^2 \tag{7}$$

$$y_i\left[\boldsymbol{w}^{\mathrm{T}}\Phi(x_i) + b\right] = 1 - \zeta_i \quad (i = 1,\ 2,\ \ldots,\ N) \tag{8}$$

To derive the dual problem for the nonlinear classification problem of LSSVM, the Lagrange function is defined as (Suykens and Vandewalle, 1999; Suykens et al., 2002):

$$\begin{aligned}L(w,\ b,\ \zeta,\ \alpha) = {} & \frac{1}{2}\boldsymbol{w}^{\mathrm{T}}\boldsymbol{w} + \frac{C}{2}\sum_{i=1}^{N}\zeta_i^2 \\ & - \sum_{i=1}^{N}\alpha_i\left\{y_i\left[\boldsymbol{w}^{\mathrm{T}}\Phi(x_i) + b\right] - 1 + \zeta_i\right\}\end{aligned} \tag{9}$$

The conditions for optimality can be obtained as

$$\left.\begin{array}{l} \dfrac{\partial L}{\partial \boldsymbol{w}} = 0 \Rightarrow \boldsymbol{w} = \displaystyle\sum_{i=1}^{N}\alpha_i y_i \Phi(x_i) \\ \dfrac{\partial L}{\partial b} = 0 \Rightarrow \displaystyle\sum_{i=1}^{N}\alpha_i y_i = 0 \\ \dfrac{\partial L}{\partial \zeta_i} = 0 \Rightarrow \alpha_i = \gamma\zeta_i \quad (i = 1,\ 2,\ \ldots,\ N) \\ \dfrac{\partial L}{\partial \alpha_k} = 0 \Rightarrow y_i\left[\boldsymbol{w}^{\mathrm{T}}\Phi(x_i) + b\right] = 1 - \zeta_i \quad (i = 1,\ 2,\ \ldots,\ N) \end{array}\right\} \tag{10}$$

By defining $\boldsymbol{Z}^{\mathrm{T}} = [\Phi^{\mathrm{T}}(x_1)y_1,\ \Phi^{\mathrm{T}}(x_2)y_2,\ \ldots,\ \Phi^{\mathrm{T}}(x_N)y_N]$, $\boldsymbol{Y} = [y_1,\ y_2,\ \ldots,\ y_N]$, $\overrightarrow{1} = [1,\ 1,\ \ldots,\ 1]$, $\boldsymbol{\zeta} = [\zeta_1,\ \zeta_2,\ \ldots,\ \zeta_N]$, $\boldsymbol{\alpha} = [\alpha_1,\ \alpha_2,\ \ldots,\ \alpha_N]$, Eq. (10) is finally converted into the below form (Minoux, 1986; Suykens and Vandewalle, 1999):

Download English Version:

https://daneshyari.com/en/article/286545

Download Persian Version:

https://daneshyari.com/article/286545

Daneshyari.com