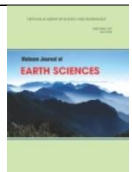
Vietnam Journal of Earth Sciences, 45(2), 219-237, https://doi.org/10.15625/2615-9783/18338

Vietnam Journal of Earth Sciences
https://vjs.ac.vn/index.php/jse



A novel swarm intelligence optimized extreme learning machine for predicting soil shear strength: A case study at Hoa Vuong new urban project (Vietnam)

Viet-Ha Nhu[1,*], Binh Thai Pham[2], Dieu Tien Bui[3]

[1]*Department of Geological-Geotechnical Engineering, Hanoi University of Mining and Geology, Hanoi, Vietnam*
[2]*University of Transport Technology, Hanoi 1000, Vietnam*
[3]*GIS group, Department of Business and IT, University of South-Eastern Norway, Gullbringvegen 36, 3800 Bø I Telemark, Norway*

Received 20 September 2022; Received in revised form 26 December 2022; Accepted 15 May 2023

ABSTRACT

In geotechnical engineering, soil shear strength is one of the most important parameters used in the design and construction of construction projects. However, determining this parameter in the laboratory is costly and time-consuming. Therefore, the main objective of this work is to develop a new alternative machine learning approach based on extreme learning machine (ELM) and Particle Swarm Optimization (PSO), namely PSO-ELM, for the shear strength prediction of soil for the Hoa Vuong new urban project in Nam Dinh province, North Vietnam. For this purpose, twelve soil parameters were collected on data from a survey of 155 soil samples to construct and validate the proposed model. We assessed the model's performance using the root-mean-square error (RMSE), the mean absolute error (MAE), and the coefficient of determination (R^2). We compared the model's capability with five benchmark models, support vector regression (SVR), Gaussian process (GP), multi-layer perceptron neural network (MLP-NN), radial basis function neural network (RBF-NN), and the fast-decision tree (Fast-DT). The results revealed that the proposed PSO-ELM model yielded the highest prediction performance and outperformed the five benchmark models. It suggests that PSO-ELM can be an alternative method in estimating the shear strength of soil that would help geotechnical engineers reduce the cost of construction.

Keywords: extreme learning machine, particle swarm optimization, soil, shear strength.

1. Introduction

Due to urbanization, industrialization, and rapid population growth, many projects have been implemented in developing countries, resulting in high pressure and significant changes in soil conditions and their characteristics. In this context, a determination of the shear strength of soil plays a crucial role in geotechnical investigations. The literature review shows that soil shear strength is largely influenced by several factors involved, such as the plasticity index (*PI*), the liquid limit (*LL*), the water content (*W*), and the content of clay (Kaya, 2009; Das et al., 2011; Das and

*Corresponding author, Email: nhuvietha@humg.edu.vn

Sobhan, 2013). It can be generally determined by geotechnical experiments, such as the direct shear and the triaxial compression tests. However, these tests are often time-consuming and costly. Thus, previous studies attempted to predict soil shear strength using different approaches. Hatanaka and Uchida (Hatanaka and Uchida, 1996) pointed out the correlation between the parameters of shear strength and the Standard Penetration Test (SPT). For unsaturated soil, the soil property was predicted by employing the relation between the moisture content and the soil suction using the characteristic of the soil-water curve (Fredlund et al., 1994; Öberg and Sällfors, 1997; Khalili and Khabbaz, 1998; Toll and Ong, 2003; Sheng et al., 2008). In addition, the shear strength could also be estimated by multiple regression analysis (Lebert and Horn, 1991).

In recent years, machine learning and artificial intelligence (AI) approaches have been popularly used in various fields, including civil engineering, particularly in geotechnical engineering (Yoo and Kim, 2007; Yagiz et al., 2009; Wu and Chau, 2013; Taormina and Chau, 2015; Bui et al., 2018; Faizollahzadeh Ardabili et al., 2018; Yaseen et al., 2019; Banan et al., 2020; Fan et al., 2020). Besides, recently, some new meta-heuristics such as Slime Mould Algorithm (SMA), Heap-Based Optimizer, and Harris Hawks Optimization (HHO) have been employed to solve many problems in civil engineering (Bui et al., 2019; Askari et al., 2020; Li et al., 2020; Moayedi et al., 2021; Tiachacht et al., 2021). For example, SMA algorithm was employed to accurately predict the location and damage level of the frame structure (Tiachacht et al., 2021). Besides, HHO algorithm has been applied in estimating landslide problems as well as the bearing capacity of the foundation (Bui et al., 2019; Moayedi et al., 2021). Regarding estimating the compressive strength of soil, Das et al. (2011) used the AI method to estimate the compressive strength of cement-treated soil, whereas Gunaydin et al. (2010). applied the artificial neural network (ANN) technique for computing the compressive strength of artificial soil. Gunaydin et al. (2010) also revealed that the model using ANN produced a better performance prediction than traditional statistical models for estimating the compressive strength of the soil. Das and Basudhar (2008) used ANN to estimate soil's residual friction angle (i.e, clay). In addition, the ANN method was also employed to predict the compressive strength of clayed soil stabilized by geopolymer (Mozumder and Laskar, 2015). Recently, the shear strength parameters of weak soil were estimated using different methods of machine learning such as the ANN and Classification And Regression Trees (CART) models (Kanungo et al., 2014), the models using Particle Swarm Optimization based Adaptive Neuro-Fuzzy Inference System (PANFIS), Genetic Algorithm based Adaptive Neuro-Fuzzy Inference System (GANFIS), the ANN, and the SVR (Pham et al., 2018).

More recently, ELM (extreme learning machine) is a speedy-performing method, which was first introduced by Huang et al. (2006) and has been extensively employed in predicting and evaluating slope stability (Liu et al., 2014). It has also been used to estimate the resilient modulus of subgrade soils (Pal and Deswal, 2014). Numerous studies have used the ELM technique for various domains, such as landslide susceptibility modeling (Vasu and Lee, 2016), flash flood susceptibility mapping (Bui et al., 2019), the prediction of horizontal load-bearing capacity for piles (Muduli et al., 2013), and the estimation of the compressive strength for carbonated rocks (Liu et al., 2015). Based on the above literature, it can be accepted that ELM could apply and solve many problems. This is because, as reported, ELM could overcome some disadvantages of ANN, Support Vector Machine, or Random Forest, such as backpropagation and its variant, the Levenberg-Margquardt (Huang et al., 2006). Besides, it was reported that ELM can be thousands of times faster than traditional algorithms and achieve SLFN (single-hidden layer feedforward neural network) with better generalization performance (Huang et al., 2006; Pacifico and Ludermir, 2012). Furthermore, ELM also could avoid many difficulties, such as stopping criteria, learning rate, learning epochs, and local minima (Huang et al., 2006; Cao et al., 2011). However, it was indicated that ELM tends to require more hidden neurons than traditional algorithms in many cases (Huang et al., 2006), which may cause ELM to respond slowly to unknown data (Pacifico and Ludermir, 2012).

PSO (Particle swarm optimization) is a heuristic global optimization technique for solving nonlinear problems (Eberhart and Kennedy, 1995; Cheng et al., 2007). The PSO algorithm is commonly used in numerous fields of civil engineering because of its advantages compared to other optimized algorithms (Bui et al., 2018; Hajihassani et al., 2018). Prior studies have shown that the PSO method has been usually employed in a wide range of geotechnical engineering applications, for example, the analysis of slope stability, soil, and rock mechanics as well as pile foundation engineering (Armaghani et al., 2014; Hasanipanah et al., 2016; Sharma et al., 2017; Hajihassani et al., 2018). For slope stability, PSO has been successfully applied to computing the safety factor of potential slip surfaces and finding the critical slide surface of 2D problems, which could be a potential candidate for solving 3D problems (Kalatehjari et al., 2014). For the applications of the PSO algorithm in pile and foundation design and shallow foundation, it can be accurately used in predicting the capacity of rock-socketed piles, the behavior of load-deformation of axially loaded piles, and the single pile (Zhao and Yin, 2010; Ismail et al., 2013; Armaghani et al., 2014). In the case of rock mechanics, the properties of rock were estimated using the PSO method. For example, Babanouri et al. (2013) employed the PSO technique and the multi-layer perceptron neuron networks to predict the crack length of unevenness profiles (D) and the standard dimension of rocks. In addition, the unconfined compressive strength of rock was also estimated using the PSO approach (Mohamad et al., 2015; Momeni et al., 2015; Mohamad et al., 2018). For the case of soil mechanics, the characteristics of soil erosion, properties of unsaturated soils, and the interaction of soil-structure, as well as soil parameters were predicted using PSO algorithm (Yunkai et al., 2010). From the above discussion, it is known that PSO has been popularly employed in many problems mentioned above because PSO has some advantages concerning evolutionary algorithms (Eberhart and Kennedy, 1995; Han et al., 2013); for instance, PSO has no complicated operators as evolutionary algorithms as it has fewer parameters that need to be adjusted (Ludermir and De Oliveira, 2013).

Due to the advantages of PSO, some previous studies have tried to combine PSO and ELM (Figueiredo and Ludermir, 2014; Du et al., 2020; Zhu et al., 2020). It was found that the combination of PSO and ELM could enhance the generalization capacity of the SLFNs (Eberhart and Kennedy, 1995). Besides, PSO-ELM has been employed in predicting landslide displacement and daily evapotranspiration. They concluded that PSO-ELM outperformed compared to single machine learning, such as ELM alone and a hybrid model of PSO-SVM (Du et al., 2020; Zhu et al., 2020). Although the hybrid model of PSO-ELM has some advantages and successful application in the geotechnical engineering field, until now, no study of ELM-PSO for estimating the parameters of soil's shear strength has been conducted carried out. Thus, this work aims to fulfill this gap in the present literature by inspecting and verifying the potential use of a combination of the ELM and the PSO methods for the prediction of the shear strength of soil for a case study of a real-life project of the Hoa Vuong new urban area at the Nam Dinh province, north of Vietnam.

The structure of this study is arranged as follows: the second section reviews the background of algorithms used in this study, including ELM and PSO. The third section describes the study site and dataset collection, followed by the presentation of the proposed PSO-ELM model for estimating the soil's shear strength. The next section shows the results and discussion, followed by several concluding remarks in the final section.

2. Mathematical background of the algorithms used

2.1. Extreme Learning Machine

The soil shear strength can be expressed by the function Su = f (γ, W, PI, PL, e, etc.). This section depicts the extreme learning machine (ELM) method to determine the shear strength of the collected soils. The ELM was first introduced by Huang et al. (2006) and has been appealed to much more attention from various applications. It is carried out as single-layer feedforward networks (SLFNs) that can be employed as an assessor for the regression problem.

There are three layers in the ELM, namely the input layer, output layer, and hidden layer. In the ELM, for the hidden layer, the weight of this layer (*i.e.*, ζ_{ij} shown in Fig. 1) can be assigned arbitrarily; therefore, we only need to consider the weights (δ_j shown in Fig. 1) of the output layer and optimizing these weights (Huang et al., 2011). This optimization technique is implemented by employing the generalized inverse proposed by Moore-Penrose (Martínez-Martínez et al., 2011). Thus, we can infer that the ELM can be considered a simple theory and rapid technique for estimating the shear strength parameters for soil.

For a specified training dataset (x_i, t_i), x_i = $[x_{i1}, x_{i2}, \ldots, x_{in}]^T \in R^n$ and $t_i = [t_{i1}, t_{i2}, \ldots, t_{im}]^T \in R^m$, the output of a typical SLFNs containing L hidden nodes to predict the soil shear strength as follows:

$$o_i = \sum_{j=1}^{L} \delta_j . q\left(\zeta_j . x_i + c_j\right), i = 1, 2, \ldots, N \qquad (1)$$

Where $q(\ldots)$ is the activation function, $\zeta_j = [\zeta_{j1}, \zeta_{j2}, \ldots, \zeta_{jn}]^T$ is the weight vector, c_j represents the threshold of the hidden node j^{th}, $\delta_j = [\delta_{j1}, \delta_{j2}, \ldots, \delta_{jm}]^T$ means the weight vector that connects the j^{th} hidden node to the output node, x_i is the regularized variable at the i^{th} node, o_i is the estimated output. The aforementioned N formula can be expressed simply as O = Hδ.

$$H = \begin{bmatrix} \left[p\left(\zeta_1 . x_1 + c_1\right)\right] & \cdots & \left[p\left(\zeta_L . x_1 + c_L\right)\right] \\ \vdots & \cdots & \vdots \\ \left[p\left(\zeta_1 . x_N + c_1\right)\right] & \cdots & \left[p\left(\zeta_L . x_N + c_L\right)\right] \end{bmatrix}_{N \times L} \qquad (2)$$

$$\delta = \left[\delta_1^T, \ldots, \delta_L^T\right]_{L \times m}^T \text{ and } O = \left[o_1^T, \ldots, o_L^T\right]_{N \times m}^T$$

where H is considered as the matrix of hidden output. If the sum of neutrons of the hidden layer L = N (sum of training dataset), with ∀ ζ and c, the error of ELM can be approximately equal to zero error (Huang et al., 2006), in other words $\sum_{i-1}^{n} \left\| o_i - t_i \right\| = 0$, the standard SLFNs will be written as below.

$$o_i = \sum_{j=1}^{L} \delta_j . q\left(\zeta_j . x_i + c_j\right) = t_i \ \ , i = 1, 2, \ldots, N \quad (3)$$

As aforementioned, the input weight and threshold are randomly allocated in ELM, then the output matrix of the hidden layer and output weights are calculated. This algorithm solves the obstacle related to adjusting all parameters, which cannot be tackled in other conventional learning techniques (Vasu and Lee, 2016).

Because the hidden layer (node) parameters are arbitrarily allocated, the training process in SLFNs problem can be converted to a problem to search the output weights of the network that can be resolved using a least-square technique as the following:

$$\hat{\delta} = H^{+}T \quad (4)$$

Where H^+ is called as the Moore-Penrose inverse matrix of H, and T denotes the goal value matrix.

The structure of ELM for predicting shear strength is expressed in Fig. 1.

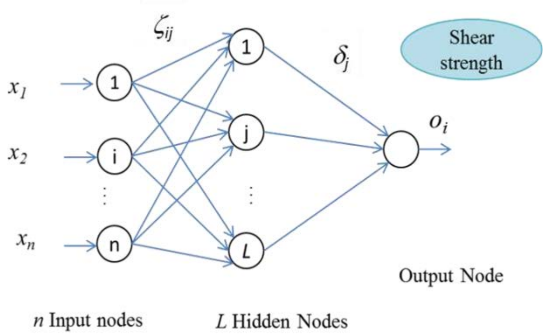


Figure 1. Structure of the ELM for the shear strength prediction

2.2. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a powerful optimization technique used popularly for optimization problems in soil mechanics (Cheng et al., 2007; Bui et al., 2018; Pham et al., 2018). This method is constructed to imitate simplified social models and swarm theory for finding an optimal solution in a given space (Eberhart and Kennedy, 1995; Poli et al., 2007).

PSO starts with a random group of particles, and each particle plays a specific approach to solving the problem. It comprises a cluster of particles, in which each particle position is governed by the most surrounding optimal position when each individual moves (Awad et al., 2012). The fitness of the particles' position was validated using the RMSE (root-mean-square error) and *MAE* (mean absolute error) on the training set. In detail, the lower *RMSE* or *MAE* shows the more accurate model. The individual position of a particle is updated concerning its present position and its velocity in each iteration (Qi et al., 2018). The following swarm was created based on the updated position of particles that took into account the best position of the swarm (called Gbest) and each best position of the particle (Pbest) in former times (Qi et al., 2018). The position and velocity of particles are determined by the following equation:

$$V_i^{t+1} = wV_i^t + c_1 r_1 (p_{best,i}^t - Y_i^t) + c_2 r_2 (g_{best,i}^t - Y_i^t) \quad (5)$$

$$Y_i^{t+1} = Y_i^t + V_i^{t+1} \quad (6)$$

Where V_i^t and V_i^{t+1} are velocities at repetition t and $t+1$ of particle i, respectively; Y_i^t and Y_i^{t+1} denote positions at iteration t and $t+1$ of particle i; c_1, c_2, and w represent the social effect parameter, inertia parameter, and cognitive parameter, respectively; r_1 and r_2 symbolize random numbers ranging [0, 1]; $p_{best,i}^t$ and $g_{best,i}^t$ are the best location of particle i and the best location formed by particles, respectively.

The particle and swarm best positions at the next iteration are determined as following equations to minimize problems (Qi et al., 2018).

$$p_{best,i}^{t+1} = \begin{cases} Y_i^{t+1}, f\left(Y_i^{t+1}\right) < f\left(p_{best,i}^{t}\right) \\ p_{best,i}^{t}, f\left(Y_i^{t+1}\right) \geq f\left(p_{best,i}^{t}\right) \end{cases} \quad (7)$$

$$g_{best}^{t+1} = \arg\min\left\{ f\left(p_{best,0}^{t+1}\right), \ldots, f\left(p_{best,ns}^{t+1}\right), f\left(g_{best}^{t}\right) \right\} \quad (8)$$

Where *ns* represents the sum of particles that belong to the swarm, the PSO algorithm is described using a flowchart shown in Fig. 2.

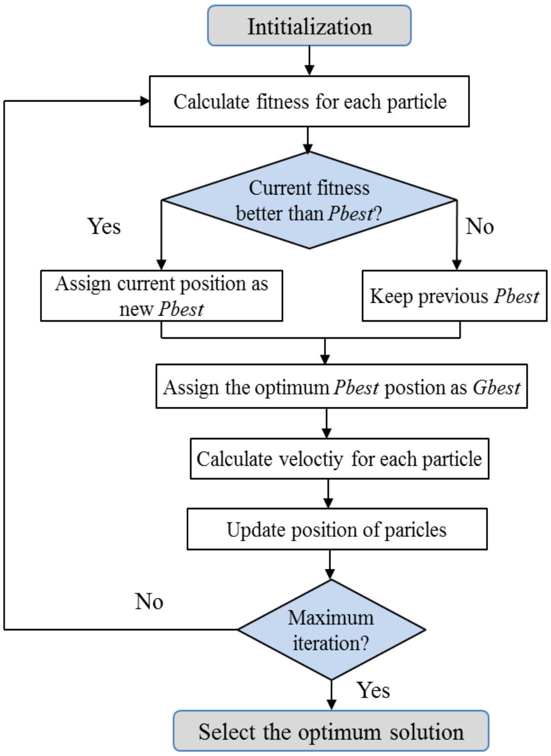


Figure 2. Framework of the PSO algorithm (Qi et al., 2018)

3. Study site and data used

The study site covering an area of 55.4 ha is called the Hoa Vuong new urban housing project located in Nam Dinh City, around 90 km to the southeast of Hanoi capital (Fig. 3). This urban housing project was selected as a case study because this project is located in the Red River delta (Hong river delta), which is known as one of the most extensive delta plains in Vietnam. The geological of this region is covered mainly by the alluvial clay layer (containing soft clay). The geological profile of this area can represent the typical geological condition of the Red-river Delta in the North of Vietnam. In this urban housing project, about 48.12% and 16.99% of the total area are used for road systems and public utilities, respectively, whereas approximately 34.89% is used for housing. Total investment is estimated at around 65.2 million US$. The urban housing connects to Hanoi capital and Hai Phong city via national road 21 and national road 10, respectively.

The geotechnical engineering survey was conducted for the project area of 55.4 ha to derive the soil characteristics under the surface. Accordingly, soil samples for the study site were collected using the boring method (Tien Bui et al., 2019). Slurry and metal tubes were adopted to prevent boreholes from collapsing (Bui et al., 2018). For this project, 6 boreholes were drilled for the project. The total drilling length was 294.5 m, whereas the highest and lowest drilling depths were 55.5 m and 45 m, respectively. As a result, 155 samples at depths varying from 1.6 m to 55.5 m below the surface were obtained.

In the next step, three laboratory tests, including the SPT (Standard penetration test), the CPT (Cone penetration test) (Schmertmann, 1978), and the VST (Vane shear test) (ASTM, 2016) were conducted to derive the physical properties of these soil samples, which were used for the assessment of the geological conditions of the construction site for the project area. As a result, the soil shear strength (SS) was obtained for each sample and used as the output variable of the machine learning model in this research. A total of twelve parameters consisting of Depth of sample (IP1), sand (IP2), Loam (IP3), Clay (IP4), moisture content (IP5), wet density (IP6), dry density (IP7), void ratio (IP8), liquid limit (IP9), plastic limit (IP10), plastic index (IP11), and liquid index (IP12) were used as inputs of the model. These twelve soil parameters are known as the most important factors that directly affect the soil's shear strength. In addition, previous studies also used these soil parameters for modeling to estimate the shear strength of soil (Bui et al., 2018; Tien Bui et al., 2019).

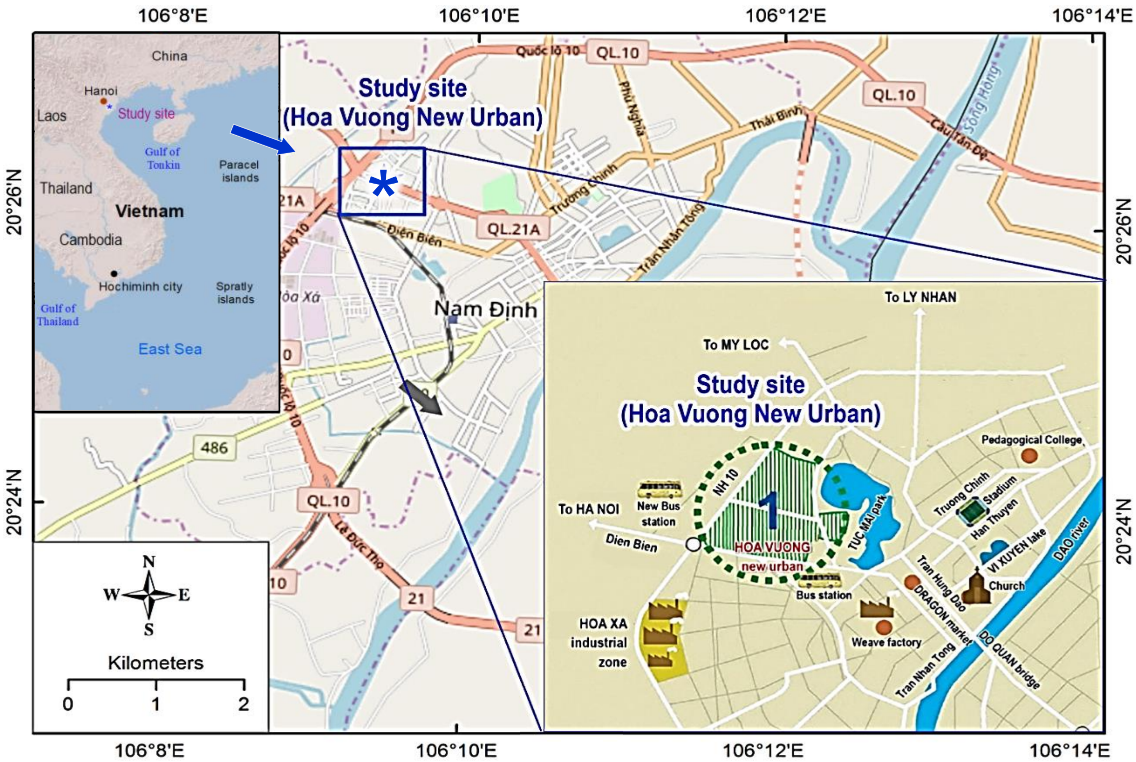


Figure 3. Location of the Hoa Vuong Township Project (North Vietnam)

An example of the data used in this analysis is shown in Table 1. Statistics of the soil data used for the current project are shown in Table 2, and the frequency distribution of the soil variables is depicted in Fig. 4.

Table 1. Example of the soil data of the Hoa Vuong new urban project used

Sample	IP1	IP2	IP3	IP4	IP5	IP6	IP7	IP8	IP9	IP10	IP11	IP12	y
1	1.8	28.0	41.0	31.0	59.9	1.55	0.97	1.775	56.7	36.5	20.2	1.16	0.100
2	3.8	55.0	31.0	14.0	54.7	1.58	1.02	1.634	48.5	34.9	13.6	1.46	0.093
3	2.0	26.0	40.0	34.0	62.9	1.58	0.97	1.794	55.5	33.5	22.0	1.34	0.105
…	…	…	…	…	…	…	…	…	…	…	…	…	…
153	52.3	72.0	19.0	9.0	21.4	2.01	1.66	0.619	25.7	20.0	5.7	0.25	0.434
154	43.8	72.5	20.0	7.5	23.0	1.93	1.57	0.708	27.7	22.0	5.7	0.18	0.457
155	55.3	74.0	18.0	8.0	22.6	1.89	1.54	0.738	28.7	22.0	6.7	0.09	0.450

Table 2. Descriptive statistics of the soil data of the Hoa Vuong new urban project

Soil parameter	Coding	Lowest	Highest	Mean	Median
Depth of sample (m)	IP1	1.6	55.3	25.3	25.8
Sand (%)	IP2	12.5	75.5	41.5	37.8
Loam (%)	IP3	17.5	49.0	33.8	35.5
Clay (%)	IP4	5.0	40.0	24.7	26.5
Moisture content (%)	IP5	21.4	62.9	38.8	37.7
Wet density (g/cm^3)	IP6	1.55	2.01	1.74	1.74
Dry density (g/cm^3)	IP7	0.97	1.66	1.26	1.27
Void Ratio	IP8	0.619	1.794	1.163	1.123
Liquid limit (%)	IP8	25.7	64.6	43.0	42.8
Plastic limit (%)	IP10	20.0	39.7	26.4	25.2
Plastic Index (%)	IP11	5.5	29.4	16.7	16.6
Liquidity index	IP12	0.1	1.46	0.71	0.74
Shear strength (kG/cm^2)	y	0.09	0.50	0.28	0.29

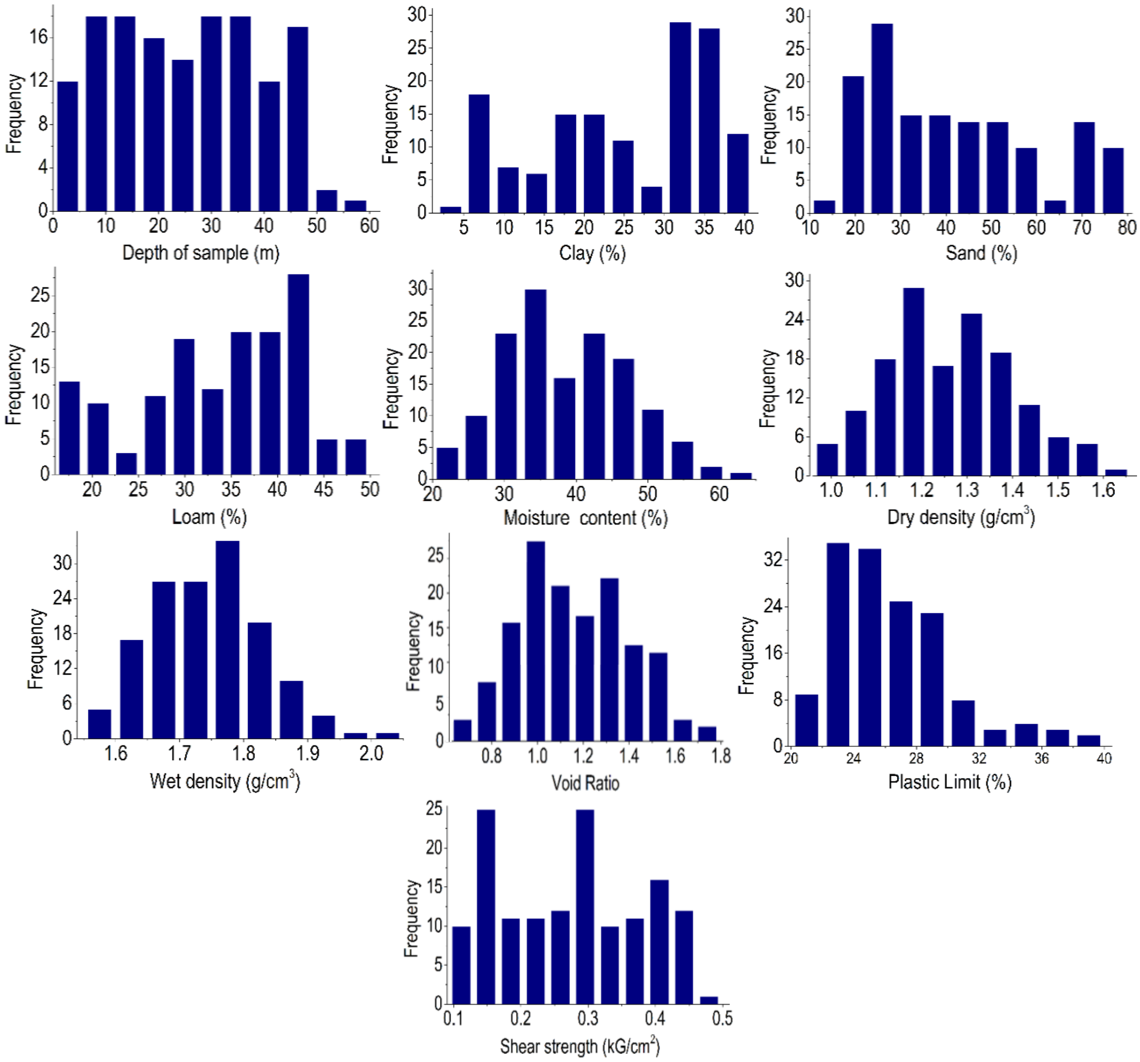


Figure 4. Frequency distribution of the soil variables in this project

4. Proposed PSO-ELM for the prediction of Soil Shear Strength

This section describes the implementation of the PSO-ELM method employed for predicting the soil shear strength in this project. The concept of the proposed PSO-ELM model is shown in Fig. 5.

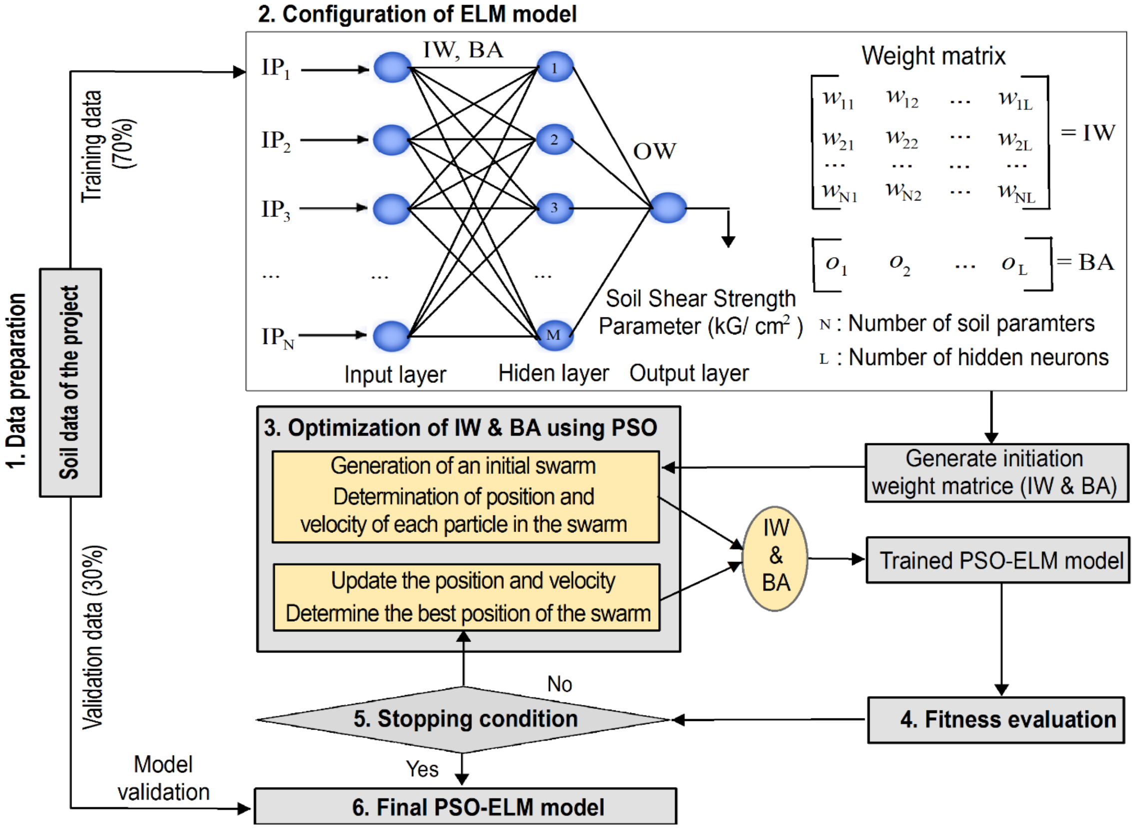


Figure 5. Diagram of the proposed PSO-ELM in this project

4.1. Data preparation

The soil dataset was rescaled, ranging from 0.01 to 1.00, using Eq. 9 (Rafiq et al., 2001) to preclude the model from being biased due to significant differences in the magnitudes of the soil variables.

$$IP_{norm} = \frac{IP - IPmin}{IPmax - IPmin} \quad (9)$$

Where IP_{norm} is the rescaled value; IP is the original value of the soil variable; IP_{max} and IP_{min} are the maximum and minimum values of the original soil dataset.

In the current work, a total of 155 soil samples were divided into two parts, of which 70% was used for the training phase to construct the model, whereas the remaining data (30%) was employed for the validation phase to test the model. We chose this ratio of 70:30 for the training and testing of the models based on the authors' experience and similar studies carried out by other researchers to obtain the best performance of the models (Nguyen et al., 2021).

4.2. Designing the ELM structure

As the structure and weights of the ELM model control the model performance, therefore, they must be properly determined beforehand based on the study area data. A total of 12 soil variables were considered as the inputs, whereas the soil shear strength (SS) was the output. It is noted that the size of input weight (IW) and bias (BA) matrices is dependent on the number of hidden neurons (L) used. Thus, we used a trial-and-error test with L = 10 showed the highest performance in terms of the mean absolute error (MAE) (Eq.11).

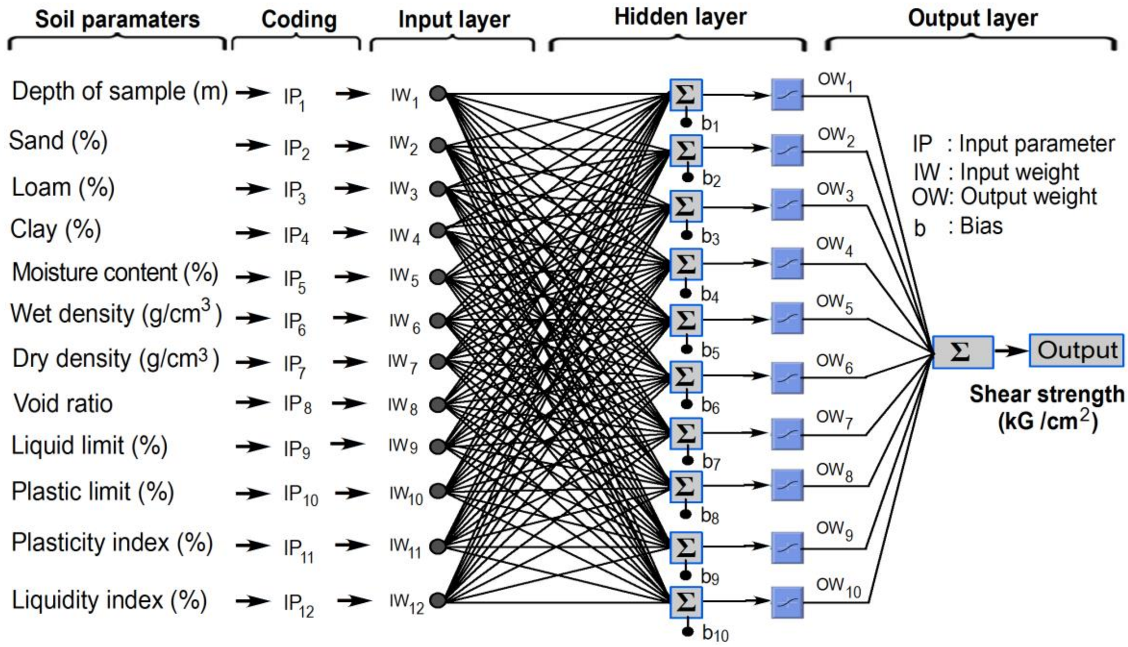


Figure 6. The PSO-ELM model in this research

Consequently, the structure of the ELM model consisted of 12 input neurons, 10 hidden neurons, and 01 output; therefore, the size of 12×10 was used for IW while its corresponding number was 10×1 used for the OW. These weights were also determined and optimized using the PSO algorithm described in the next step. Figủe 6 shows the structure of the PSO-ELM model used in this study.

4.3. Optimizing the ELM model using PSO

Once the ELM structure has been determined, PSO is adopted to train the ELM model. The training process aims to find the optimized values in the two weight matrices that minimize MAE (Eq.11). In the current study, we converted and combined the IW and the bias matrices into a new matrix with a size of 130×1 and assigned this dimension to the coordinate of the particles in the swarm. Each particle can be a solution for the PSO-ELM model. Thus, all swarm particles fly in searching space to find their best locations where the most petite MAE is attained. It is noted that the original ELM algorithm computes the OW. Once the best location of the swarm has been found, the coordination values of this location are converted to values of the IW and the bias matrices, and the final PSO-ELM model is trained.

4.4. Performance evaluation

The performance of the final PSO-ELM model in this study was evaluated using the root-mean-square error (RMSE), the mean absolute error (MAE), and the correlation coefficient (R^2) (Mohammadzadeh et al., 2014; Pham et al., 2017; Hoa et al., 2019).

These evaluation criteria are known as good indicators and are usually used in many previous studies to assess the model's performance.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(SSo_i - SSm_i)^2} \quad (10)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}(SSo_i - SSm_i) \quad (11)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(SSo_i - SSm_i)^2}{\sum_{i=1}^{n}(SSo_i - \overline{SSo})^2} \quad (12)$$

Where SSo and SSm are the output of the actual and predicted value, respectively; $\overline{SSo}$ is the measured mean values of the project; n is the total soil samples in the project.

5. Results and discussion

5.1. Training and validation results

The prediction results of the PSO-ELM model used for estimating soil shear strength are shown in Figs. 7 and 8. As can be seen, the model performance was tested and evaluated on both the training and the validation datasets using standard metrics. Based on the experimental outcomes measured by the RMSE and the MSE values, it was observed that the RMSE values of the proposed model in the training and the testing phases were 0.0145 and 0.0242, respectively. These numbers were lower than the standard deviation values of the training dataset (0.0146) and the validation dataset (0.0244), showing that the PSO-ELM model had a good prediction performance.

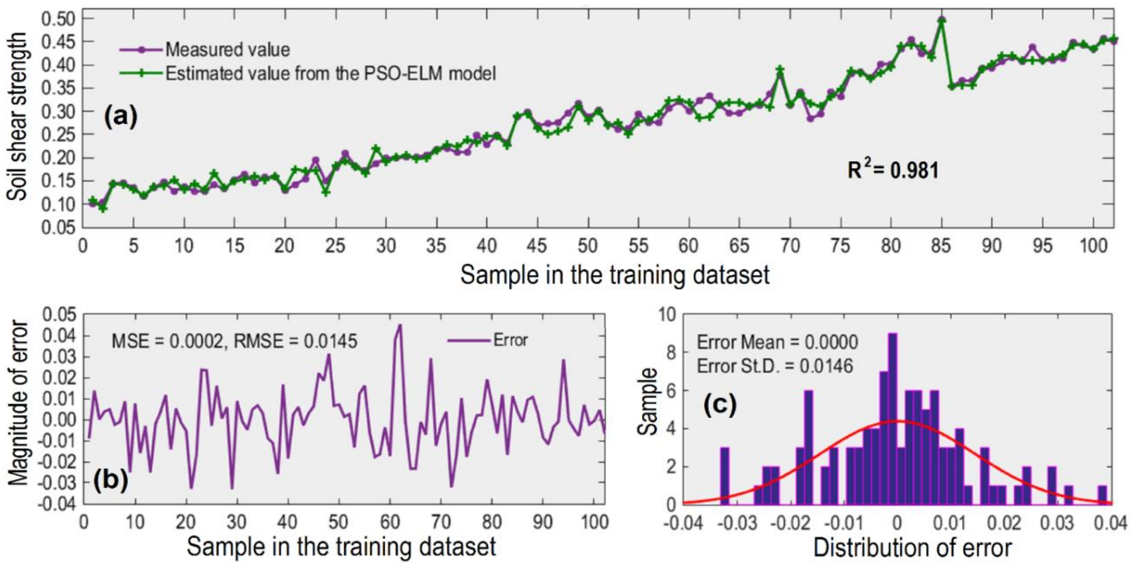


Figure 7. Performance metrics of the proposed model on the training dataset: (a) Measured and computed value; (b) Error magnitude; and (c) Error distribution

Additionally, R^2 and MAE values of the proposed PSO-ELM model were 0.981 and 0.0108 for the training phase, whereas these corresponding numbers were 0.952 and 0.0197 for the testing phase, indicating that the novel model proposed in the current work had a high precision and performed well.

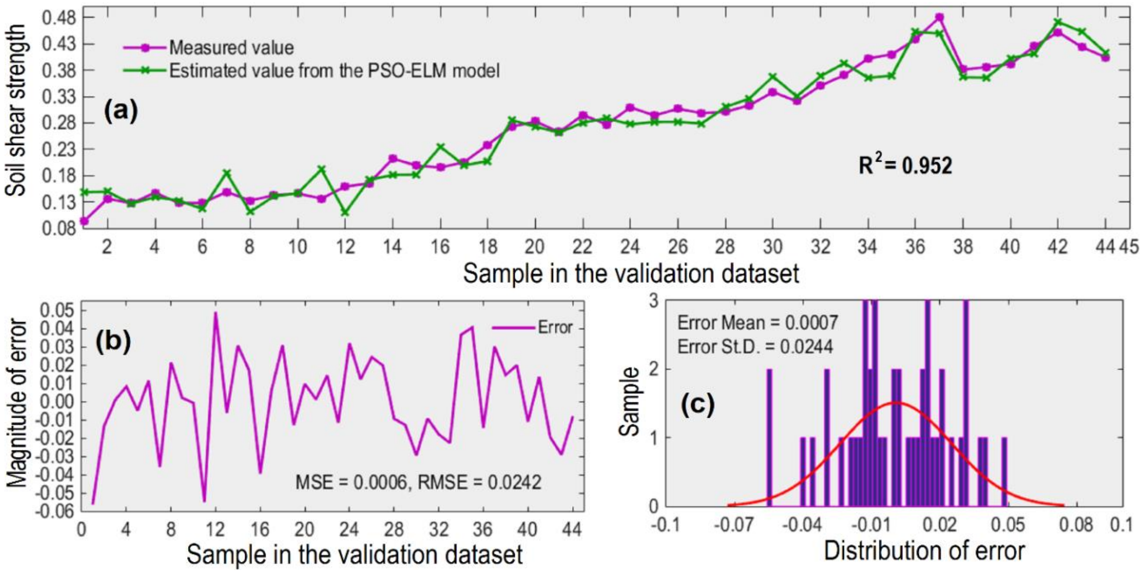


Figure 8. Performance metrics of the proposed model on the validation dataset: (a) Measured and computed value; (b) Error magnitude; and (c) Error distribution

5.2. Model comparison

As the purpose of this work was to predict the shear strength of soil, the usability of the proposed PSO-ELM model should be assessed and confirmed in its effectiveness. Therefore, we compared five machine learning models, i.e., the SVR, the GP, the MLP-Neural-Nets, the RBF-Neural-Nets, and the Fast-DTree. The results in Table 3 revealed that all six machine learning models performed satisfactorily using the training and validation datasets. Analysis of the R^2, the RMSE, and the MAE values for the soil shear strength prediction in the training dataset showed that the PSO-ELM model had the highest performances (R^2 = 0.981, RMSE = 0.0145, MAE = 0.0108), followed by the Fast-DTree model (R^2 = 0.938, RMSE = 0.0262, MAE = 0.0169), the MLP-Neural-Nets model (R^2 = 0.932, RMSE = 0.0296, MAE = 0.0224), the GP model (R^2 = 0.926, RMSE = 0.0312, MAE = 0.0250), and the SVR model (R^2 = 0.870, RMSE = 0.0586, MAE = 0.0507), whereas the RBG-Neural-Nets model had the minor performance (R^2 = 0.771, RMSE = 0.0503, MAE = 0.0411). Remarkably, a similar trend was observed using the validation dataset, showing that the PSO-ELM model yielded the best prediction accuracy (R^2 = 0.952, RMSE = 0.0242, MAE = 0.0197). It is noticeable that the Fast-DTree model achieved the second-best method in terms of the R^2, the RMSE, and the MAE values (R^2 = 0.946, RMSE = 0.0260, MAE = 0.0171) while the RBF-Neural-Nets model had the lowest performance (R^2 = 0.765, RMSE = 0.0538, MAE = 0.0409. The results also showed that a combination of ELM and PSO metaheuristic produced significantly better accuracy than the MLP Neural Nets and the RBF-Neural-Nets in the validating phase, thus, reflecting that the proposed PSO-ELM method helps construct the machine learning model for the prediction of the shear strength of soil at the study area. This study's results are consistent with previous studies using the hybrid model of PSO-ELM in estimating landslide displacement and daily evapotranspiration (Du et al., 2020; Zhu et al., 2020). They indicated that the performance of PSO-ELM model was better than other single models, such as ELM alone. Overall, the experimental results suggested that six machine learning models performed well and can be used to estimate soil shear strength in this project.

Table 3. RMSE, MAE, and R^2 of the proposed PSO-ELM model and the five benchmark models

Regression model	Training dataset			Validation dataset		
	RMSE	MAE	R^2	RMSE	MAE	R^2
PSO-ELM	0.0145	0.0108	0.981	0.0242	0.0197	0.952
SVR	0.0586	0.0507	0.870	0.0653	0.0568	0.883
GP	0.0312	0.0250	0.926	0.0385	0.0318	0.899
MLP-Neural-Nets	0.0286	0.0224	0.932	0.0248	0.0199	0.850
RBF-Neural-Nets	0.0503	0.0411	0.771	0.0538	0.0409	0.765
Fast-DTree	0.0262	0.0169	0.938	0.0260	0.0171	0.946

5.3. Accuracy assessment of the shear strength prediction

Figures. 9 and 10 show the scatterplots of predicted versus observed soil shear strength, indicating the accuracy of the predicted soil shear strength by six machine learning methods at the study site. As can be seen, the proposed PSO-ELM yielded the highest prediction performances for the shear strength of soil in the study area using the training and validation dataset with R^2 = 0.981 and R^2 = 0.952, respectively, followed by the Fast-DTree model with R^2 = 0.938 for the training dataset and R^2 = 0.952 for the validation dataset. This result agreed well with the results of previous studies in estimating landslide displacement and daily evapotranspiration using the hybrid model of PSO-ELM (Du et al., 2020; Zhu et al., 2020). This is because the combination of PSO and ELM could enhance the generalization capacity of SLFNs (Figueiredo and Ludermir, 2014). Four remaining machine learning algorithms achieved acceptable prediction performances regarding the correlation coefficient, ranging from 0.771 to 0.932 for the training phase, whereas these corresponding values were between 0.765 and 0.899 for the testing phase.

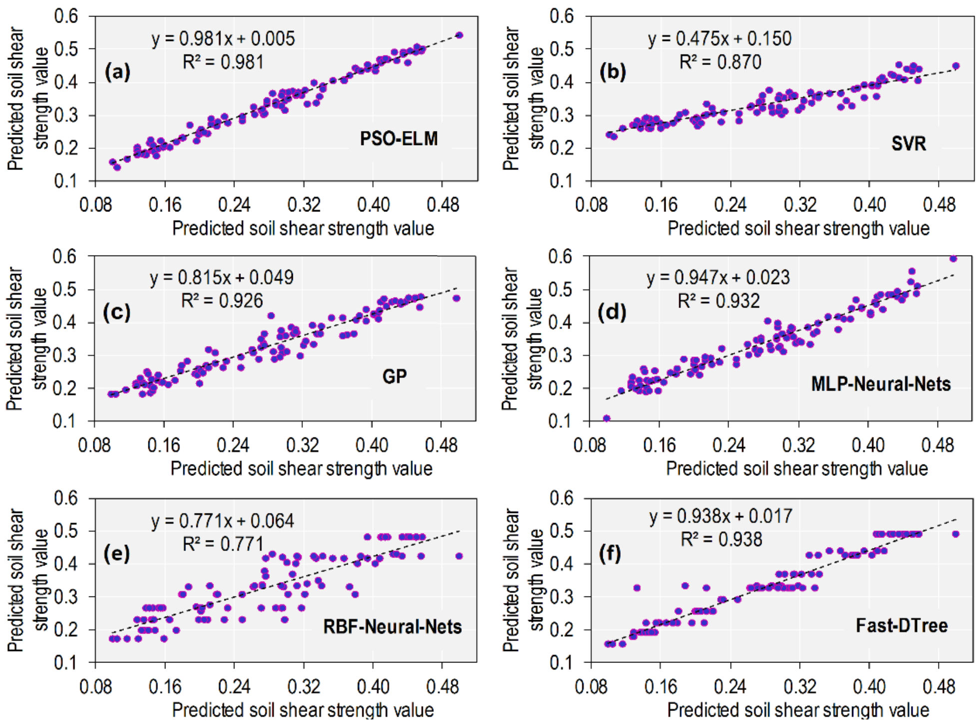


Figure 9. R^2 of the models on the training dataset: a) the proposed PSO- ELM model; b) the SVR model; c) the GP model; d) the MLP-Neural-Nets model; e) the RBF-Neural-Nets model; f) the Fast-DTree model

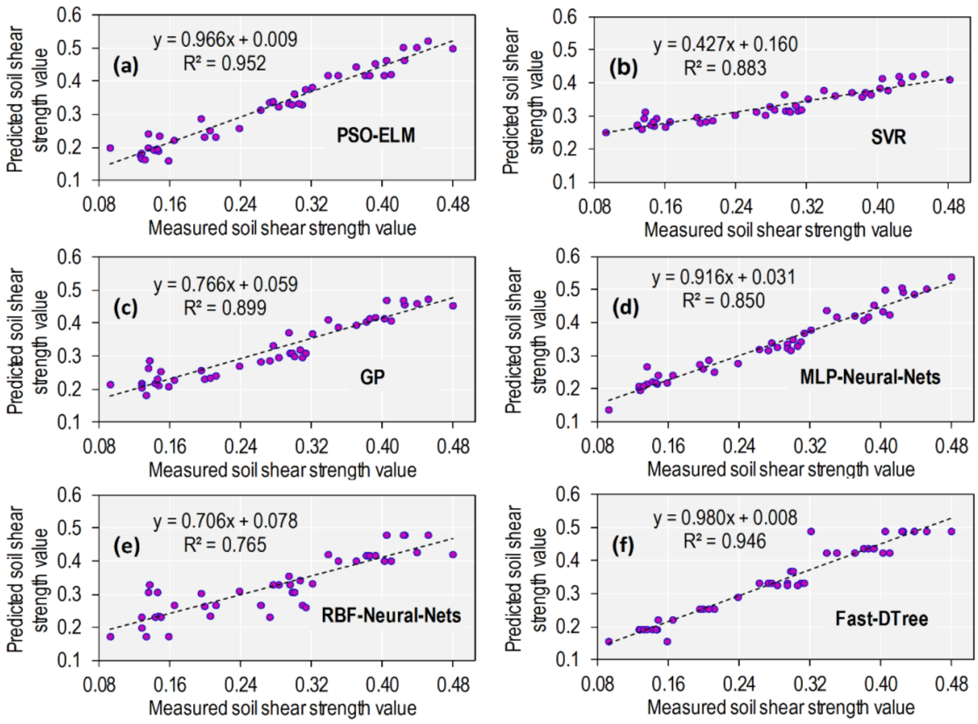


Figure 10. R^2 of the models using the validation dataset: a) the proposed PSO- ELM model; b) the SVR model; c) the GP model; d) the MLP-Neural-Nets model; e) the RBF-Neural-Nets model; f) the Fast-DTree model

Remarkably, all machine learning models show reasonable ability in predicting the shear strength of soil exceeding 0.46 (kG cm^{-2}) (Fig. 10). In this range, the proposed PSO-ELM had a higher performance than other machine learning models, followed by the Fast-DTree model. It is noted that this number is slightly lower than that of a case study in South Vietnam reported by (Tien Bui et al., 2019). It is likely due to the significant differences in soil properties from North to South Vietnam. Because in general, soil's shear strength depends on many factors, such as soil type (including particles and minerals of soil), water content, and other conditions. However, this number is similar to the predicted soil compression coefficient reported by (Bui et al., 2018), as this study was also conducted in an urban area.

Determining soil shear strength is essential in designing geotechnical structures and constructions. However, conducting lab experiments for computing soil shear strength is fairly time-consuming and requires a considerable cost apparatus (Vanapalli et al., 1996). Therefore, the development of a new machine-learning solution for the prediction of the shear strength of soil is an essential task in this context. Nonetheless, few attempts have been carried out to predict soil shear strength using state-of-the-art machine learning techniques (Samui, 2008; Samui and Sitharam, 2008; Chou et al., 2016). More importantly, no universal method is available to predict soil shear strength. Therefore, we performed and compared the six advanced machine learning approaches, i.e., the PSO-ELM, the SVR, the GP, the MLP-Neural-Nets, the RBF-Neural-Nets, and the Fast-DTree models for the estimation of the shear strength of soil.

The machine learning techniques used in the current work, such as the PSO-ELM and the Fast-DTree models, are likely more advanced approaches than the remaining models in predicting the shear strength of the soil. However, the accuracies of these models mainly depend on the data quality (Mair et al., 2000). In geotechnical problems, parameters used in a model are controlled by different trials based on the number of samples taken, resulting in the bias of the models used. In this paper, six machine learning models perform well, showing satisfactory performance. The overall accuracies might be improved by using more sample data because these models are likely to be more regressive (He and Garcia, 2009) in dealing with imbalanced dataset (Krawczyk, 2016). Additionally, the performance of the selected combination of inputs can vary on the models' results, which should be considered for future studies.

It should be noted that soil shear strength prediction remains a challenging problem because of the inherent variability of the soil itself. Soils are composed of various complicated materials and parameters, resulting in predictive difficulty to their properties (Minasny and Hartemink, 2011). Some properties can be obtained from laboratory experiments. However, several factors could affect the results, such as equipment, experimental conditions, experience of testers, etc. In this project, we developed and verified a novel hybrid machine learning model, PSO-ELM, for the prediction of the shear strength of soil with satisfactory performances. Thus, the proposed machine learning technique should be used and tested in other study areas in future studies to support geotechnical engineers for construction projects in urban regions.

6. Concluding remarks

The current work proposed a novel PSO-ELM machine learning model and compared its prediction performance with the five machine learning models, namely, the Fast-Dtree, the MLP-Neural-Nets, the GP, the SVR and the RBF-Neural-Nets for predicting the shear strength of soil in a case study at Hoa Vuong new urban project, Vietnam. The experimental results reveal that all machine learning models produce satisfactory performance, and the soil shear strength prediction results are greatly influenced by the model used. Compared with the benchmark models, the proposed PSO-ELM model achieves the best prediction performance, showing that the PSO-ELM model is a valuable tool for predicting soil shear strength.

This study demonstrated that a novel machine learning (ML) model based on a combination of the PSO and the ELM algorithms might provide an effective alternative tool for predicting soil shear strength. Although the PSO-ELM model demonstrated high prediction performance, this method investigated to the specific soil parameters as the inputs in the compiled database used in this study. Further studies, therefore, should consider more soil parameters using novel machine learning algorithms. Besides, the major demerit of the proposed model is the determination of the search space of the parameters in PSO, which restricts the position of particles. Due to no thumb regime existing; thus trial-and-error tests must be conducted to find the most appropriate search space. Another disadvantage is that PSO only incorporated with ELM was discovered; therefore, the model's performance could be improved in a newer alteration of PSO or other metaheuristic optimization algorithms examined. Finally, the size of the dataset of this study is still relatively small; as a result, more case studies of shear strength tests of soil need to be collected to improve the generalization of the machine learning-based model. Despite the limitations, the results of the current work highlighted the potential use of the hybrid swarm intelligence optimized extreme learning machine for predicting soil shear strength that would help geotechnical engineers reduce the construction cost in urban areas.

Author contributions

V.-H.N. did fieldwork, collected soil samples, and processed data. D.T.B. designed modeling concepts and implemented the modeling process. D.T.B., V.-H.N B.T.P. wrote and checked the manuscript.

Acknowledgments

This research was supported by GIS group, Department of Business and IT, University of South-Eastern Norway.

References

Armaghani D.J., et al., 2014. Indirect measure of shale shear strength parameters by means of rock index tests through an optimized artificial neural network. Measurement, 55, 487-498.

Askari Q., M. Saeed, I. Younas, 2020. Heap-based optimizer inspired by corporate rank hierarchy for global optimization. Expert Systems with Applications, 161, 113702.

ASTM, 2016. Standard test method for laboratory miniature vane shear test for saturated fine-grained clayey soil.

Awad Z. K., et al., 2012. A review of optimization techniques used in the design of fibre composite structures for civil engineering applications. Materials & Design, 33, 534-544.

Babanouri N., S.K. Nasab, S. Sarafrazi, 2013. A hybrid particle swarm optimization and multi-layer perceptron algorithm for bivariate fractal analysis of rock fractures roughness. International Journal of Rock Mechanics and Mining Sciences, 60, 66-74.

Banan A., A. Nasiri, A. Taheri-Garavand, 2020. Deep learning-based appearance features extraction for automated carp species identification. Aquacultural Engineering, 89, 102053.

Bui D.T., Moayedi H., Kalantar B., Osouli A., Pradhan B., Nguyen H, Rashid A.S.A., 2019. A Novel Swarm Intelligence-Harris Hawks Optimization for Spatial Assessment of Landslide Susceptibility. Sensors, 19(16), 3590. https://doi.org/10.3390/s19163590.

Bui D.T., Ngo P.T.T. , Pham T.D., Jaafari A., Nguyen Q.M., Pham V.H., Samui P., 2019. A novel hybrid approach based on a swarm intelligence optimized extreme learning machine for flash flood susceptibility mapping. Catena, 179, 184-196. https://doi.org/10.1016/j.catena.2019.04.009.

Bui D.T., V.-H. Nhu, N.-D. Hoang, 2018. Prediction of soil compression coefficient for urban housing project using novel integration machine learning approach of swarm intelligence and multi-layer perceptron neural network. Advanced Engineering Informatics, 38, 593-604.

Cao J., Z. Lin, G.-B. Huang, 2011. Composite function wavelet neural networks with differential evolution and extreme learning machine. Neural Processing Letters, 33, 251-265.

Cheng Y.M., et al., 2007. Particle swarm optimization algorithm for the location of the critical non-circular failure surface in two-dimensional slope stability analysis. Computers and Geotechnics, 34, 92-103.

Chou J.-S., K.-H. Yang, J.-Y. Lin, 2016. Peak shear strength of discrete fiber-reinforced soils computed by machine learning and metaensemble methods. Journal of Computing in Civil Engineering, 30, 04016036.

Das B., K. Sobhan, 2013. Principles of Geotechnical Engineering. CENGAGE Learning, Stamford, USA.

Das S., et al., 2011. Machine learning techniques applied to prediction of residual strength of clay. Open Geosciences, 3, 449-461.

Das S.K., P.K. Basudhar, 2008. Prediction of residual friction angle of clays using artificial neural network. Engineering Geology, 100, 142-145.

Das S.K., P. Samui, A. K. Sabat, 2011. Application of artificial intelligence to maximum dry density and unconfined compressive strength of cement stabilized soil. Geotechnical and Geological Engineering, 29, 329-342.

Du H., et al., 2020. Prediction model oriented for landslide displacement with step-like curve by applying ensemble empirical mode decomposition and the PSO-ELM method. Journal of Cleaner Production, 270, 122248.

Eberhart R., J. Kennedy, 1995. Particle swarm optimization. Proceedings of the IEEE international conference on neural networks, Citeseer.

Faizollahzadeh Ardabili S., et al., 2018. Computational intelligence approach for modeling hydrogen production: A review. Engineering Applications of Computational Fluid Mechanics, 12, 438-458.

Fan Y., et al., 2020. Spatiotemporal modeling for nonlinear distributed thermal processes based on KL decomposition, MLP and LSTM network. IEEE Access., 8, 25111-25121.

Figueiredo E.M., T.B. Ludermir, 2014. Investigating the use of alternative topologies on performance of the PSO-ELM. Neurocomputing, 127, 4-12.

Fredlund D., A. Xing, S. Huang, 1994. Predicting the permeability function for unsaturated soils using the soil-water characteristic curve. Canadian Geotechnical Journal, 31, 533-546.

Gunaydin O., A. Gokoglu, M. Fener, 2010. Prediction of artificial soil's unconfined compression strength test using statistical analyses and artificial neural networks. Advances in Engineering Software, 41, 1115-1123.

Hajihassani M., D. Jahed Armaghani, R. Kalatehjari, 2018. Applications of particle swarm optimization in geotechnical engineering: a comprehensive review. Geotechnical and Geological Engineering, 36, 705-722.

Han F., H.-F. Yao, Q.-H. Ling, 2013. An improved evolutionary extreme learning machine based on particle swarm optimization. Neurocomputing, 116, 87-93.

Hasanipanah M., et al., 2016. Feasibility of PSO-ANN model for predicting surface settlement caused by tunneling. Engineering with Computers, 32, 705-715.

Hatanaka M., A. Uchida, 1996. Empirical correlation between penetration resistance and internal friction angle of sandy soils. Soils and foundations, 36, 1-9.

He H., E.A. Garcia, 2009. Learning from imbalanced data. IEEE Transactions on knowledge and data engineering, 21, 1263-1284.

Hoa P.V., et al., 2019. Soil salinity mapping using SAR Sentinel-1 data and advanced machine learning algorithms: a case study at Ben Tre Province of the Mekong River Delta (Vietnam). Remote Sensing, 11, 128.

Huang G.-B., et al., 2011. Extreme learning machine for regression and multiclass classification. IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), 42, 513-529.

Huang G.-B., Q.-Y. Zhu, C.-K. Siew, 2006. Extreme learning machine: theory and applications. Neurocomputing, 70, 489-501.

Ismail A., D.-S. Jeng, L. Zhang, 2013. An optimised product-unit neural network with a novel PSO-BP hybrid training algorithm: Applications to load-deformation analysis of axially loaded piles. Engineering Applications of Artificial Intelligence, 26, 2305-2314.

Kalatehjari R., et al., 2014. The effects of method of generating circular slip surfaces on determining the critical slip surface by particle swarm optimization. Arabian Journal of Geosciences, 7, 1529-1539.

Kanungo D., S. Sharma, A. Pain, 2014. Artificial Neural Network (ANN) and Regression Tree (CART) applications for the indirect estimation of unsaturated soil shear strength parameters. Frontiers of Earth Science, 8, 439-456.

Kaya A., 2009. Residual and fully softened strength evaluation of soils using artificial neural networks. Geotechnical and Geological Engineering, 27, 281-288.

Khalili N., M. Khabbaz, 1998. A unique relationship for χ for the determination of the shear strength of unsaturated soils. Geotechnique, 48, 681-687.

Krawczyk B., 2016. Learning from imbalanced data: open challenges and future directions. Progress in Artificial Intelligence, 5, 221-232.

Lebert M., R. Horn, 1991. A method to predict the mechanical strength of agricultural soils. Soil and Tillage Research, 19, 275-286.

Li S., et al., 2020. Slime mould algorithm: A new method for stochastic optimization. Future Generation Computer Systems, 111, 300-323.

Liu Z., et al., 2014. An extreme learning machine approach for slope stability evaluation and prediction. Natural Hazards, 73, 787-804.

Liu Z., et al., 2015. Indirect estimation of unconfined compressive strength of carbonate rocks using extreme learning machine. Acta Geotechnica, 10, 651-663.

Ludermir T.B., W.R. De Oliveira, 2013. Particle swarm optimization of MLP for the identification of factors related to common mental disorders. Expert Systems with Applications, 40, 4648-4652.

Mair C., et al., 2000. An investigation of machine learning based prediction systems. Journal of Systems and Software, 53, 23-29.

Martínez-Martínez J.M., et al., 2011. Regularized extreme learning machine for regression problems. Neurocomputing, 74, 3716-3721.

Minasny B., A.E. Hartemink, 2011. Predicting soil properties in the tropics. Earth-Science Reviews, 106, 52-62.

Moayedi H., et al., 2021. Comparison of dragonfly algorithm and Harris hawks optimization evolutionary data mining techniques for the assessment of bearing capacity of footings over two-layer foundation soils. Engineering with Computers, 37, 437-447.

Mohamad E.T., et al., 2018. Rock strength estimation: a PSO-based BP approach. Neural Computing and Applications, 30, 1635-1646.

Mohamad E.T., et al., 2015. Prediction of the unconfined compressive strength of soft rocks: a PSO-based ANN approach. Bulletin of Engineering Geology and the Environment, 74, 745-757.

Mohammadzadeh D., J.B. Bazaz, A.H. Alavi, 2014. An evolutionary computational approach for formulation of compression index of fine-grained soils. Engineering Applications of Artificial Intelligence, 33, 58-68.

Momeni E., et al., 2015. Prediction of uniaxial compressive strength of rock samples using hybrid particle swarm optimization-based artificial neural networks. Measurement, 60, 50-63.

Mozumder R.A., A.I. Laskar, 2015. Prediction of unconfined compressive strength of geopolymer stabilized clayey soil using artificial neural network. Computers and Geotechnics, 69, 291-300.

Muduli P.K., S.K. Das, M.R. Das, 2013. Prediction of lateral load capacity of piles using extreme learning machine. International Journal of Geotechnical Engineering, 7, 388-394.

Nguyen Q.H., et al., 2021. Influence of data splitting on performance of machine learning models in prediction of shear strength of soil. Mathematical Problems in Engineering, 1-15.

Öberg A., G. Sällfors, 1997. Determination of shear strength parameters of unsaturated silts and sands based on the water retention curve. Geotechnical Testing Journal, 20, 40-48.

Pacifico L.D., T.B. Ludermir, 2012. Improved evolutionary extreme learning machines based on particle swarm optimization and clustering approaches. International Journal of Natural Computing Research (IJNCR), 3, 1-20.

Pal M., S. Deswal, 2014. Extreme learning machine based modeling of resilient modulus of subgrade soils. Geotechnical and Geological Engineering, 32, 287-296.

Pham B.T., et al., 2018. Prediction of shear strength of soft soil using machine learning methods. Catena, 166, 181-191.

Pham T.D., K. Yoshino, D.T. Bui, 2017. Biomass estimation of Sonneratia caseolaris (l.) Engler at a coastal area of Hai Phong city (Vietnam) using ALOS-2 PALSAR imagery and GIS-based multi-layer perceptron neural networks. GIScience & Remote Sensing, 54, 329-353.

Poli, R., J. Kennedy and T. Blackwell, 2007. Particle swarm optimization: An overview. Swarm Intelligence, 1, 33-57.

Qi C., A. Fourie, Q. Chen, 2018. Neural network and particle swarm optimization for predicting the unconfined compressive strength of cemented paste backfill. Construction and Building Materials, 159, 473-478.

Qi C., et al., 2018. A strength prediction model using artificial intelligence for recycling waste tailings as cemented paste backfill. Journal of Cleaner Production, 183, 566-578.

Rafiq M., G. Bugmann, D. Easterbrook, 2001. Neural network design for engineering applications. Computers & Structures, 79, 1541-1552.

Samui P., 2008. Prediction of friction capacity of driven piles in clay using the support vector machine. Canadian Geotechnical Journal, 45, 288-295.

Samui P., T. Sitharam, 2008. Least-square support vector machine applied to settlement of shallow foundations on cohesionless soils. International Journal for Numerical and Analytical Methods in Geomechanics, 32, 2033-2043.

Schmertmann J.H., 1978. Guidelines for cone penetration test: performance and design. U.S. Department of Transportation, 1-158.

Sharma L., et al., 2017. Evaluating the modulus of elasticity of soil using soft computing system. Engineering with Computers, 33, 497-507.

Sheng D., D.G. Fredlund, A. Gens, 2008. A new modelling approach for unsaturated soils using independent stress variables. Canadian Geotechnical Journal, 45, 511-534.

Taormina R., K.-W. Chau, 2015. ANN-based interval forecasting of streamflow discharges using the LUBE method and MOFIPS. Engineering Applications of Artificial Intelligence, 45, 429-440.

Tiachacht S., et al., 2021. Inverse problem for dynamic structural health monitoring based on slime mould algorithm. Engineering with Computers, 1-24.

Tien Bui D., N.-D. Hoang, V.-H. Nhu, 2019. A swarm intelligence-based machine learning approach for predicting soil shear strength for road construction: a case study at Trung Luong National Expressway Project (Vietnam). Engineering with Computers, 35, 955-965.

Toll D., B. Ong, 2003. Critical-state parameters for an unsaturated residual sandy clay. Géotechnique, 53, 93-103.

Vanapalli S., et al., 1996. Model for the prediction of shear strength with respect to soil suction. Canadian Geotechnical Journal, 33, 379-392.

Vasu N.N., S.-R. Lee, 2016. A hybrid feature selection algorithm integrating an extreme learning machine for landslide susceptibility modeling of Mt. Woomyeon, South Korea. Geomorphology, 263, 50-70.

Wu C., K.-W. Chau, 2013. Prediction of rainfall time series using modular soft computingmethods. Engineering Applications of Artificial Intelligence, 26, 997-1007.

Yagiz S., et al., 2009. Application of two nonlinear prediction tools to the estimation of tunnel boring machine performance. Engineering Applications of Artificial Intelligence, 22, 808-814.

Yaseen Z.M., et al., 2019. An enhanced extreme learning machine model for river flow forecasting: State-of-the-art, practical applications in water resource engineering area and future research direction. Journal of Hydrology, 569, 387-408.

Yoo C., J.-M. Kim, 2007. Tunneling performance prediction using an integrated GIS and neural network. Computers and Geotechnics, 34, 19-30.

Yunkai L., et al., 2010. Analysis of soil erosion characteristics in small watersheds with particle swarm optimization, support vector machine, and artificial neuronal networks. Environmental Earth Sciences, 60, 1559-1568.

Zhao H.-B., S. Yin, 2010. A CPSO-SVM model for ultimate bearing capacity determination. Marine Georesources and Geotechnology, 28, 64-75.

Zhu B., et al., 2020. Hybrid particle swarm optimization with extreme learning machine for daily reference evapotranspiration prediction from limited climatic data. Computers and Electronics in Agriculture, 173, 105430.