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Soil Shear Strength Prediction Model based on Artificial Neural Network and Osprey Optimization Algorithm

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Abstract: Soil shear strength is an essential parameter in geotechnical and civil engineering that is measured and used when building structures like retaining walls, pavements, and dams. The two factors that determine a soil sample's shear strength are internal friction and cohesiveness. When soil is subjected to a load, its shear strength determines how well it can tolerate internal movement and slippage. Thus, an infrastructure's capacity to endure damage is determined by its shear strength. Lab calculations may be used to determine a soil sample's shear strength, which is influenced by several variables including moisture content, plastic index, and liquid limit. However, estimating soil shear strength in labs is time-consuming and expensive due to instrument handling issues and lengthy measurement methods for consistent and precise data. Thus, soil shear strength may be precisely and quickly computed using artificial intelligence.In this research, a soil shear strength prediction model is designed with the help of artificial neural network (ANN) and osprey optimization algorithm (OOA). The ANN algorithm is utilized for reduce the error between the actual and predicted value in proposed model in order to enhance the accuracy of the model whereas osprey optimization algorithm is utilized for determine the best weight values of the ANN algorithm based on the objective function. In this work, root mean square error (RMSE) is taken as the objective function. Besides that, pre-processing of the dataset is done using the principal component analysis (PCA) in orders to reduce the dataset dimension. The simulation evaluation is done on the standard dataset which contains 12 attributes related to soil and one attribute is related to strength. The result shows that the proposed model achieves the minimum error between actual and predicted value. Besides that, convergence rate graph shows the osprey optimization algorithm is quickly find the optimal results. Finally, different parameters such as RMSE, MAPE, MAE, and determination of coefficient is measured for the proposed method and result shows that RMSE, MAPE, and MAE value is lower and determination of coefficient higher value over the existing models.

Keywords:ANN, Machine Learning, Metaheuristic, Neural Network, Osprey Optimization, PCA, Prediction,Soil Shear, Strength.

1. Introduction

Shear strength is an essential property of soils that has to be effectively assessed and understood to construct engineering structures. Soil shear strength is used in a variety of geotechnical applications, such as slope stability, retaining walls, pile foundations, excavations, erosion risk prediction, and other geotechnical applications associated with soil-structure interaction [1]. It is critical to evaluate the shear strength of unsaturated soils and quantify any changes in shear strength that may occur as a consequence of environmental circumstances. In addition, unsaturated soil shear strength is important in liquefaction research because desaturation may prevent it. On the other hand, measuring unsaturated strength of shear is difficult, costly, and alsotime-consuming. Thus, theoretical forecasts become an important strategy, especially for numerical modelling and at the initial design stage. However, the application of AI and approaches based on dependability analysis to the resolution of geotechnical and civil engineering issues have drawn significant interest in recent years. It is important to note that nonlinear parameter interaction makes the use of soft computing approaches interesting. However, there is a complicated and nonlinear connection between the soil's shear strength and these relevant characteristics. Shear strength is a function of many different parameters. Therefore, as many studies have proposed, using artificial intelligence approaches is useful [2].

This research aims to improve the accuracy of the soil shear strength prediction model. To accomplish this goal, an artificial neural network (ANN) is utilised in the prediction model by determining its weight values using the metaheuristic osprey optimisation algorithm (OOA). The osprey optimisation algorithm searches for the best weight values in the lower and upper limits of the weight values based on the objective function. This research adopts the root mean square error (RMSE) as the objective function. Besides that, pre-processing of the dataset is done using principal component analysis (PCA) to reduce the dimension of the dataset. The performance evaluation shows that the proposed method achieves minimum RMSE, MAPE, MAE, and a high value of determination of coefficient over the existing methods such as 'SVM,' 'MARS', 'RBFNN', 'GRNN', 'BPNN', 'MARS-RBFNN', 'AEFA-MARS', 'AEFA-RBFNN', and 'AEFA-MARSANN'.

This paper is subdivided into six sections. Section 2 shows the related work done in the soil shear strength prediction model. Section 3 explains the methodology by which databases, principal component analysis, artificial neural networks, and osprey optimisation are defined. Section 4 explains the proposed soil shear strength prediction model. Section 5 shows the simulation evaluation of the standard database using various performance metrics and comparative analysis. Finally, a conclusion and future scope are drawn in Section 6.

2. Related Work

This section explains the soil shear strength model is designed using the artificial intelligence technique. Hoque et al. [3], used the linear regression and random forest regression algorithms to measure the strength. Gnananandarao et al. [4], used the artificial neural network for determine the shear strength of the soil. However, the performance of ANN is highly dependent on the values of weight. Momeni et al. [5], deployed the XGBoost and salp swarm optimization algorithm for predicting the model's shear strength. The salp swarm optimization is utilized for hypertuning of the XGBoost algorithm. Cao et al. [6], used the metaheuristic artificial electric field algorithm with neural network such as multivariate adaptive regressionsplines and radial basis function neural network to optimize the performance of it using the hyper-tuning of parameters of it.From the literature survey, we found that the performance of the artificial intelligence technique is highly dependent on the parameter values of it. Therefore, in this research, the performance of the artificial intelligence technique is enhanced using the metaheuristic algorithm. The primary motive of the metaheuristic algorithm is to find the best parameter values of the artificial intelligence technique based on the objective function.

3. Methodology

3.1 Database: Cao et al.'s [6] dataset is taken into consideration in this study. The dataset was gathered at the Le Trong Tan Geleximco Project's geotechnical study phase, which is situated west of Hanoi, Vietnam. The site study was carried out in April 2009. Approximately 135 hectares of land were used for this project, which included the development of entertainment venues, public infrastructure, and both high- and low-rise residences. Soil sampling based on boring is used to collect information on soil conditions. To prevent soil collapses, thin-walled metal tubes and slurry—a combination of bentonite and water—are used throughout the drilling process. Piston samplers are used to collect soil samples having a 91 mm diameter. The technique for collecting samples complies with the Vietnam's national standards.These standards are the TCN-259-2000 (soil sampling's protocol by boring methods) and TCXDVN-194-2006 (High Rise Building—Guide for Geotechnical Investigation). During the geotechnical study phase, 249 soil samples were taken from 65 boreholes. The soil samples that were taken vary in depth from 1.20 to 39.5 meters. The following variables are calculatedfrom samples of soil: (1) sample depth (m), (2)percentage of loam (%), (3) percentage of sand (%),(4)percentage of moisture content (%), (5) percentage of clay (%), (6)dry density (g/cm3), (7) wet density (g/cm3), (8)liquid limit (%), (9) void ratio, (10)plastic index (%), (11) plastic limit (%),and (12) liquidity index. These twelve variables are used as conditioning variables in order to determine the soil's shear strength.

3.2 Principal Component Analysis (PCA) Algorithm: In this research, PCA algorithm is utilized for reduce the dimension. To facilitate effective transfer learning, the Dimensionality Reduction (DR) technique aims to reduce the gap in a latent space between distributions of various data sets. The data indicate that the outcomes with Dimensionality Reduction (DR) are significantly better than those without lowered dimensionality for each device separately. The dimensionality curse is often mitigated by the low dimensional data representation of the original data, which is also readily examined, processed, and displayed. The advantage of using dimensionality reduction methods on a dataset are [7]:

- Reduce the number of dimensions and storage space for data.
- The computation time is reduced.
- You may remove duplicated, noisy, and irrelevant data.
- It's possible to optimize data quality.
- Enhances the accuracy and efficiency of an algorithm.
- Enable data visualization
- It improves performance and streamlines the categorization process.

Both feature extraction (FE) and feature selection (FS) are the two primary categories into which DR approaches are often divided. Given the exponential growth in data production, feature selection (FS) is regarded as an important approach for mitigating some of the major dimensionality issues. This technique can reduce redundancy, remove superfluous data, and improve the readability of the results. To increase the effectiveness of data processing and storage, Feature Extraction (FE) also addresses the problem of identifying the most unique, instructive, and concise collection of properties.

3.3 Artificial Neural Network (ANN) Algorithm: The popular artificial intelligence model that mimics biological neural networks is used in learning methodologies. An artificial neuron, or basic artificial neural network (ANN), is comprised of three simple rules: multiplication, addition, and activation. When two or more simple artificial neurons (nodes) are connected, a network is established. Artificial neural networks (ANNs) are useful for function estimation in general and can handle cases with complicated and nonlinear input-output relationships. There are many different kinds of artificial neural networks (ANNs), but the most common is the multilayer feed-forward ANN. Fig. 1 shows the structure of this particular AI model, which consists of three layers: input, output, and hidden. These layers are linked together via hidden nodes with varying connection weights [8-9]. The corresponding weight is multiplied by the inputs at each entry. To produce the intended outcome, ANNs need to be trained using specific learning algorithms. Among the many learning algorithms, one of the most often used techniques for training ANNs is back-propagation (BP). To determine the effectiveness of an interaction in solving a problem, a neural network uses weighted information. This widely used technique uses connection weights to transfer the input variables from the input layer to the hidden nodes. Next, all of the weighted inputs are added together by the computer unit. The transfer function, which is the last component of this AI model, assigns the summation to a sigmoid or tanh activation function. After applying the transfer function (sigmoid is preferable) to the hidden node's input, its net input is the its bias threshold + the weights of its incoming connections. Different functions are served by the nodes in each tier. All input nodes are just summed and weighted. Hidden nodes cannot access the final output or incoming data. An ANN's typical structure is shown in Figure 1.

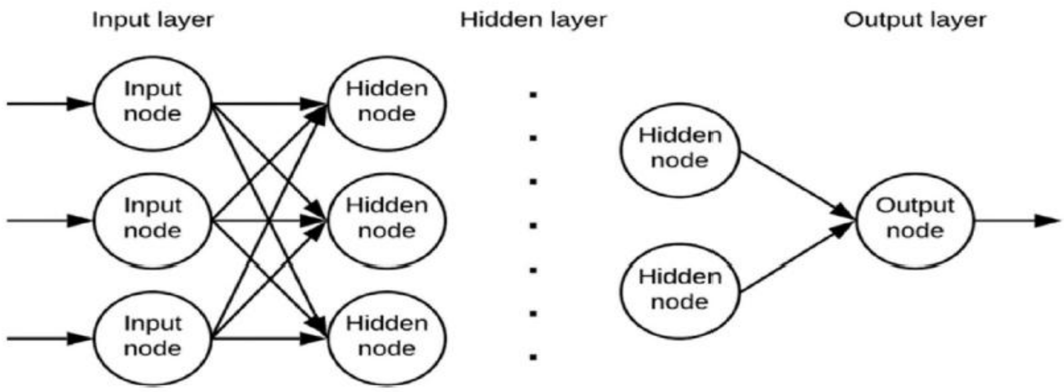

Figure 1: ANN Architecture [8]

In this research, the performance of the ANN network is enhanced by determining the optimal weight values of it using the metaheuristic osprey optimization algorithm. The detailed description of the osprey optimization algorithm is given below.

3.4 Osprey Optimization Algorithm: The OOA is a novel metaheuristic algorithm inspired by osprey behavior in the wild, is used in this study to find the ideal weight values for the ANN algorithm. Inspiration for OOA mostly comes from the tactic used by ospreys to catch fish in the ocean. Using this hunting tactic, the osprey locates its prey, hunts it, and then takes it to a good eating location. Based on a simulation of osprey behavior during hunting, OOA's suggested two-phase method of exploration and exploitation is mathematically described [10]. The flowchart of the osprey optimization is shown in Figure 2.

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{N\times m} = \begin{bmatrix} x_{1,1} & \cdots & x_{1,j} & \cdots & x_{1,m} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ x_{i,1} & \cdots & x_{i,j} & \cdots & x_{i,m} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ x_{N,1} & \cdots & x_{N,j} & \cdots & x_{N,m} \end{bmatrix}_{N\times m}, \quad (1)$$

$$x_{i,j} = lb_j + r_{i,j} \cdot (ub_j - lb_j), \; i = 1, 2, \ldots, N, \; j = 1, 2, \ldots, m, \quad (2)$$

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix}_{N\times 1} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(X_i) \\ \vdots \\ F(X_N) \end{bmatrix}_{N\times 1}, \quad (3)$$

$$FP_i = \{X_k | \, k \in \{1, 2, \ldots, N\} \wedge F_k < F_i\} \cup \{X_{best}\}, \quad (4)$$

$$x_{i,j}^{P1} = x_{i,j} + r_{i,j} \cdot (SF_{i,j} - I_{i,j} \cdot x_{i,j}), \quad (5-a)$$

$$x_{i,j}^{P1} = \begin{cases} x_{i,j}^{P1}, & lb_j \le x_{i,j}^{P1} \le ub_j; \\ lb_j, & x_{i,j}^{P1} < lb_j; \\ ub_j, & x_{i,j}^{P1} > ub_j. \end{cases} \quad (5-b)$$

$$X_i = \begin{cases} X_i^{P1}, & F_i^{P1} < F_i; \\ X_i, & else, \end{cases} \quad (6)$$

$$x_{i,j}^{P2} = x_{i,j} + \frac{lb_j + r \cdot (ub_j - lb_j)}{t}, \; i = 1, 2, \ldots, N, \; j = 1, 2, \ldots, m, \; t = 1, 2, \ldots, T, \quad (7-a)$$

$$x_{i,j}^{P2} = \begin{cases} x_{i,j}^{P2}, & lb_j \le x_{i,j}^{P2} \le ub_j; \\ lb_j, & x_{i,j}^{P2} < lb_j; \\ ub_j, & x_{i,j}^{P2} > ub_j, \end{cases} \quad (7-b)$$

$$X_i = \begin{cases} X_i^{P2}, & F_i^{P2} < F_i; \\ X_i, & else, \end{cases} \quad (8)$$

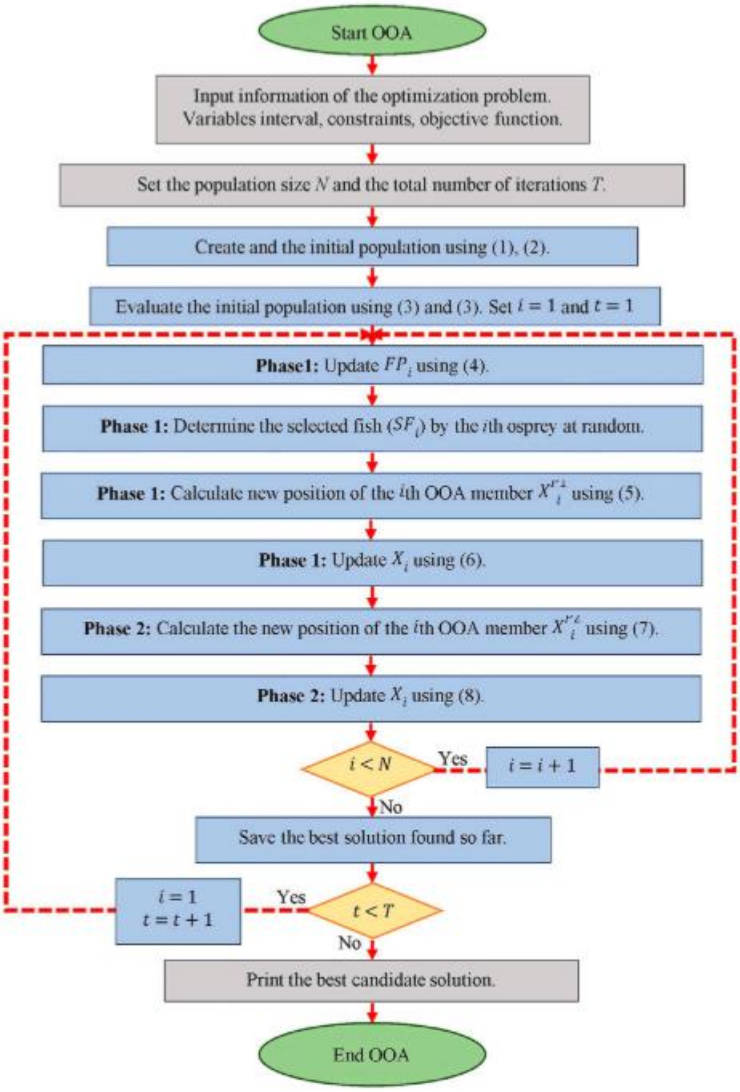

Figure 2: Flowchart of the Osprey Optimization Algorithm [10]

3.5 Performance Metrics: In this research, four parameters (Root Mean Square Error, Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), Determination of Coefficient (R^2)) are determined to evaluate the proposed method over the existing methods [11-13]. These parameters are basically evaluating the proposed model by comparing the actual strength and predicted strength by model. These parameters are determined using Eq. (9-12).

$$R^2 = \frac{\sum_{i=1}^{N}(E_i - \overline{A_i})(A_i - \overline{A_i})}{\sqrt{\sum_{i=1}^{N}(E_i - \overline{A_i})^2 \sum_{i=1}^{N}(A_i - \overline{A_i})^2}} \quad (9)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(E_i - A_i)^2 \quad (10)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|E_i - A_i| \quad (11)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(E_i - A_i)^2} \quad (12)$$

In the Eq. (1-4), E_i is the predicted value, A_i is the actual value, and N denotes the total number of samples in the dataset.

4. Proposed Soil Shear Strength Prediction Model

This section explains the proposed soil shear strength prediction model which is designed using artificial neural network and osprey optimization algorithm. The main motive of the proposed model is to enhance the prediction over the existing models. Figure 3 shows the flowchart of the proposed soil shear strength prediction model.

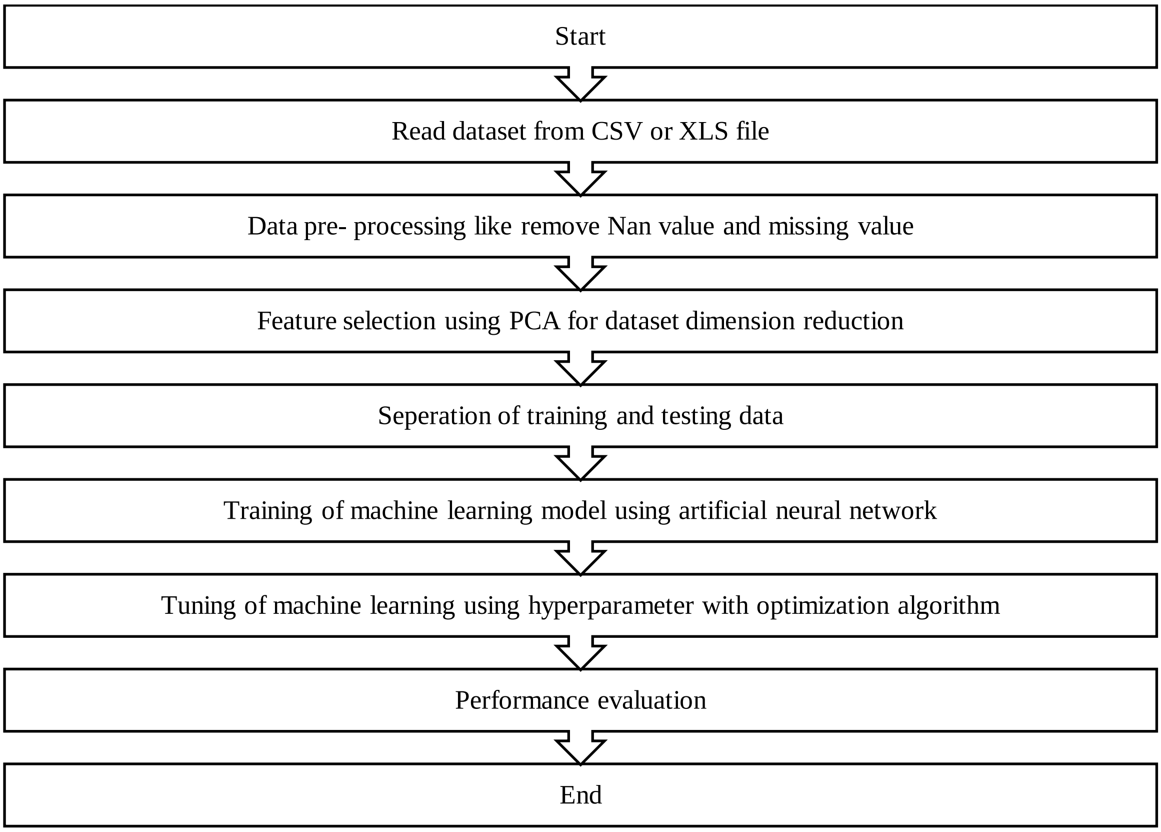

Figure 3: Flowchart of the Proposed Soil Shear Strength Prediction Model

Initially, standard dataset of soil shear strength is read from the CSV or XLS file. After that, pre-processing of the dataset is done to check the missing value and NaN value in the dataset and fill it using the appropriate values. After that, feature selection from the dataset is done using the principal component analysis (PCA) for dataset dimension reduction. After that, dataset input and output attributed are determined and dataset is split into training and testing dataset. Further, in the proposed model, the machine learning model is trained using the training dataset. In this work, artificial neural network is used as the machine learning algorithm. Besides that, the hyper-parameter tuning of the ANN algorithm is done with the optimization algorithm. In this work, osprey optimization algorithm is utilized for determine the weight values of the ANN algorithm. Finally, the performance evaluation of the proposed model is done using the various performance metrics.

5. Simulation Evaluation

This section represents the simulation results of the proposed method and comparative analysis with the existing method. The proposed model is evaluated in MATLAB 2018a software for the standard dataset. In the dataset, several factors of soil sample are taken as input such as depth of the sample, sand, loan, clay, moisture content percentage, etc and soil shear strength is taken as output variable in the model. Table 1 shows the parameter values is initialised for the simulation purposes for the PCA, osprey optimization, and neural network.

Table 1: Simulation Parameter Values of the Proposed Soil Shear Strength Model

Parameter	**Value**
PCA Number of Components	10
Training and Testing Ratio	70:30
Neural Network	Feed ford
Number of iterations	100
Number of Osprey Population	100
Alpha	0.1
Beta	0.1
Gamma	0.1
Delta	0.1

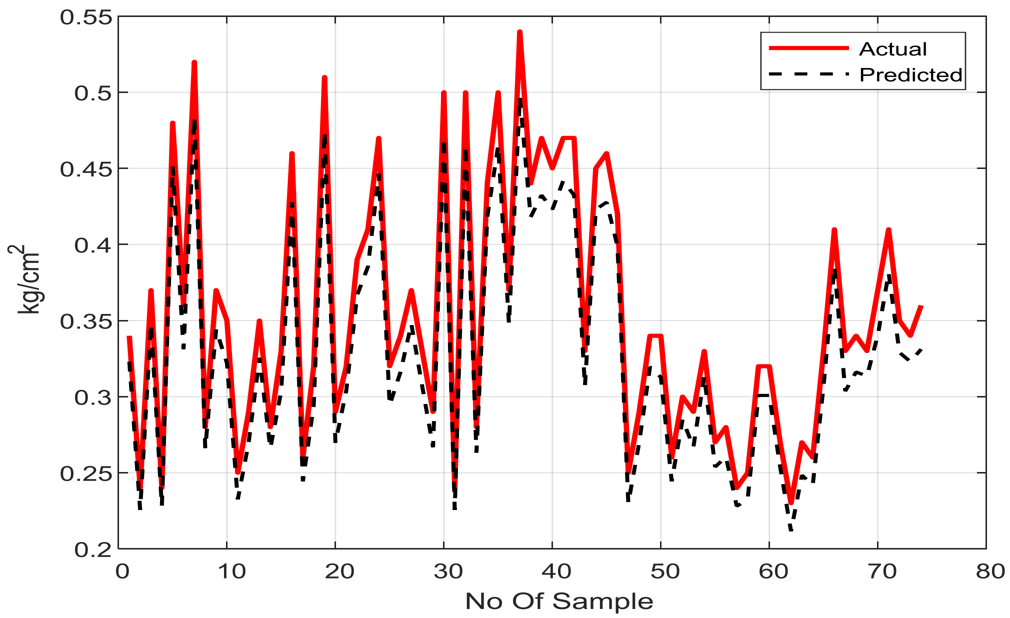

Figure 4 Comparative Analysis between Actual and Predicted Strength by Proposed Model

Figure 4 shows the comparative analysis of actual and predicted soil shear strength prediction done by proposed model for soil samples are taken into consideration. The result shows that the predicted value approximate overlap the actual values because root mean square error is taken as the objective function to optimal tune the weight values of the artificial neural network.

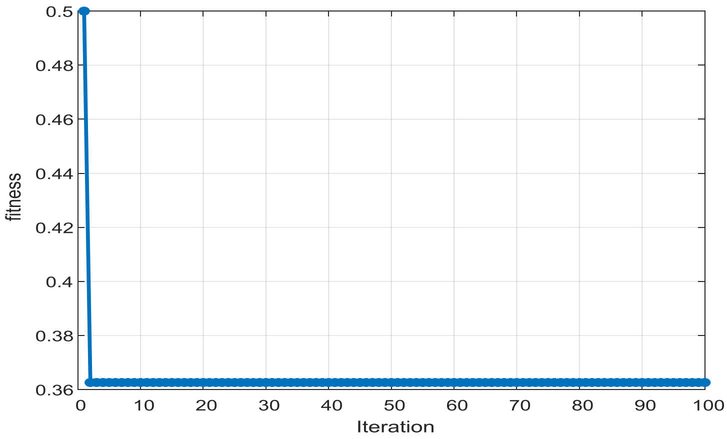

Figure 5: Convergence Rate Graph of Osprey Optimization Algorithm to determine the Optimal Weight of ANN

Figure 5 shows the convergence rate graph of the osprey optimization algorithm. The osprey optimization algorithm is utilized for determine the weight values of the ANN algorithm. The result shows that in the initial iterations, the proposed model achieves the desired fitness function. Further, Table 2 shows the parameters are determined for the proposed model to evaluate the performance of it. The RMSE and MAE is near to zero value of the proposed model. Thus, the minimum error is generated between the actual and predicted value by the proposed model. Further, MAPE value achieves the desired value as required in the prediction model. Finally, determination of coefficient (R^2) achieves the high value near to 1 for the proposed model.

Table 2: Performance Analysis of the Proposed Soil Shear Strength Model

Parameter	Value
RMSE	0.024112
MAPE	6.5541
MAE	0.023177
R^2	0.99884

Table 3 shows the comparative analysis of the proposed model over the existing models based on RMSE parameter [6]. The result shows that the proposed model achieves the lowest RMSE value (0.024) over the existing models as shown in Figure 6.

Table 3: Comparative Analysis based on RMSE Parameter

Algorithms	RMSE
SVM	0.045
MARS	0.045
RBFNN	0.042
GRNN	0.044
BPNN	0.047
MARS-RBFNN	0.040

AEFA-MARS	0.041
AEFA-RBFNN	0.039
AEFA-MARSANN	0.035
Proposed Method	**0.024**

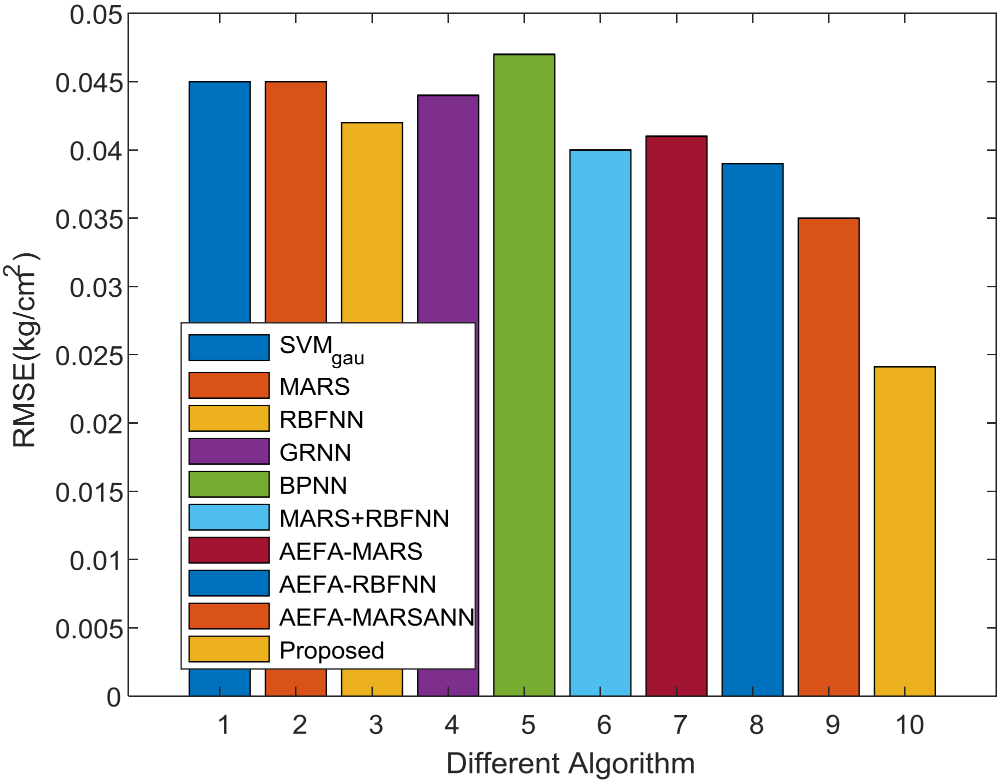

Figure 6 Comparative Analysis of Different Algorithms based on RMSE

In Table 4, MAPE parameter value is compared with the existing models [6]. The result shows that the proposed model achieves the lowest MAPE value (6.55) over the existing models as shown in Figure 7.

Table 4: Comparative Analysis based on MAPE Parameter

Algorithms	MAPE
SVM	11.15
MARS	11.02
RBFNN	10.55
GRNN	10.80
BPNN	12.03
MARS-RBFNN	9.95
AEFA-MARS	9.47
AEFA-RBFNN	9.05

AEFA-MARSANN	7.94
Proposed Method	**6.55**

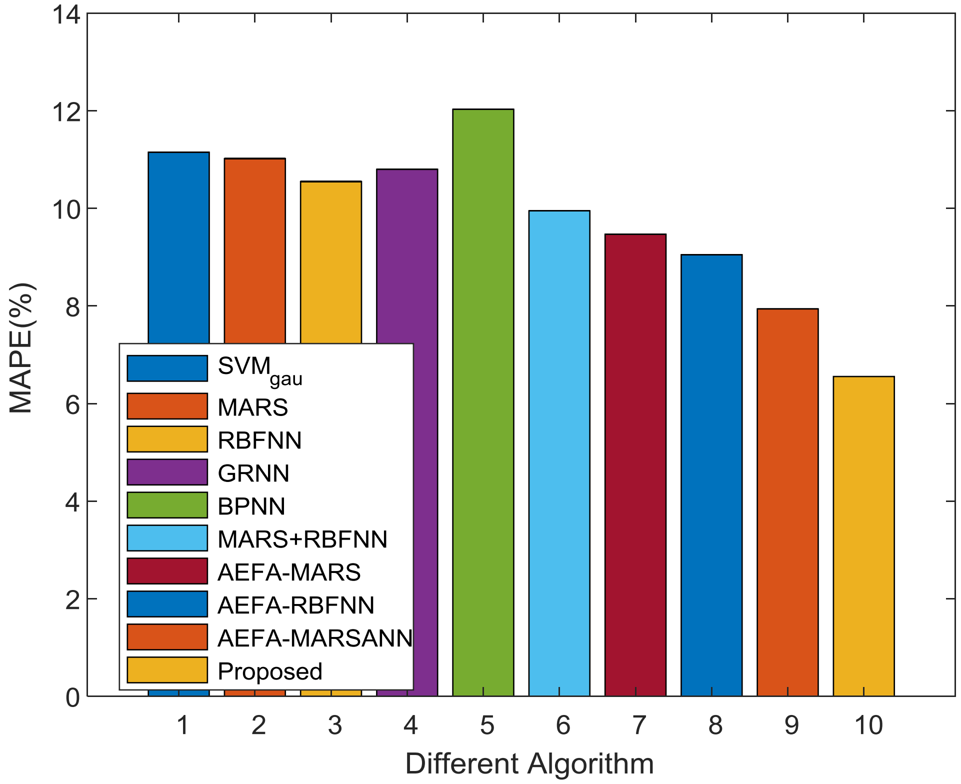

Figure 7 Comparative Analysis of Different Algorithms based on MAPE

Table 5 shows the comparative analysis of the proposed model over the existing models based on MAE parameter [6]. The result shows that the proposed model achieves the lowest MAE value (0.023) over the existing models as shown in Figure 8.

Table 5: Comparative Analysis based on MAE Parameter

Algorithms	**MAE**
SVM	0.036
MARS	0.036
RBFNN	0.034
GRNN	0.035
BPNN	0.038
MARS-RBFNN	0.032
AEFA-MARS	0.031
AEFA-RBFNN	0.029
AEFA-MARSANN	0.026

Proposed Method	**0.023**

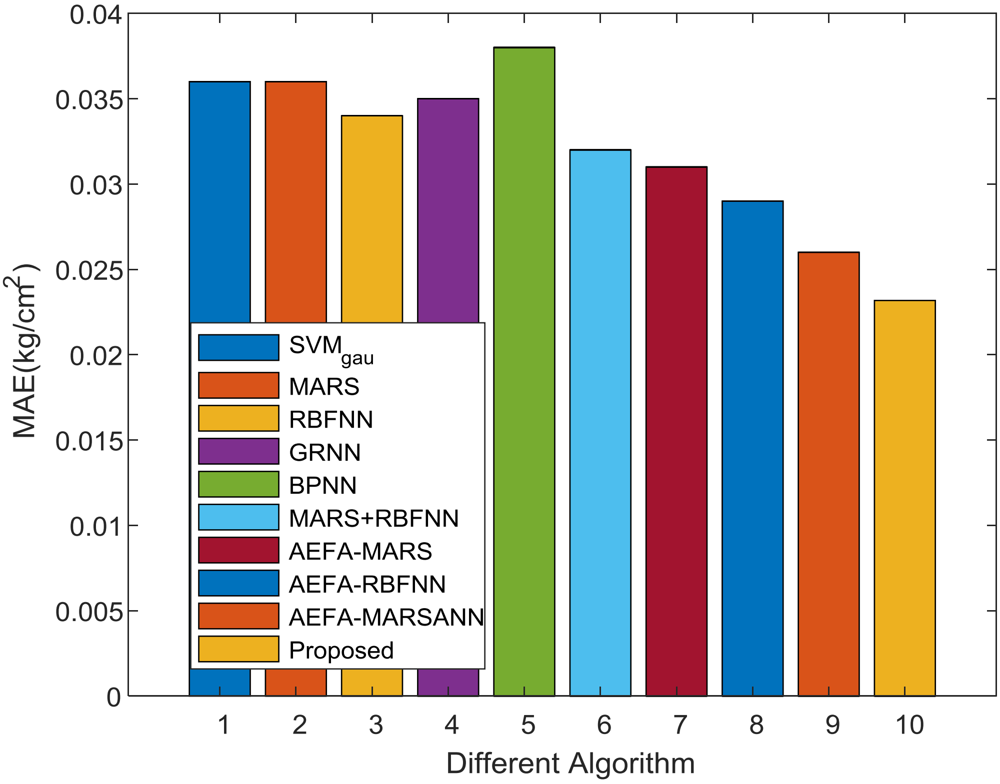

Figure 8 Comparative Analysis of Different Algorithms based on MAE

Finally, Table 6 shows the comparative analysis of the proposed model over the existing models based on determination of coefficient parameter [6]. The result shows that the proposed model achieves the highest R^2 value (0.999) over the existing models as shown in Figure 9.

Table 6 Comparative Analysis based on R^2 Parameter

Algorithms	R^2
SVM	0.708
MARS	0.696
RBFNN	0.736
GRNN	0.711
BPNN	0.659
MARS-RBFNN	0.768
AEFA-MARS	0.758
AEFA-RBFNN	0.777
AEFA-MARSANN	0.826

Proposed Method	**0.999**

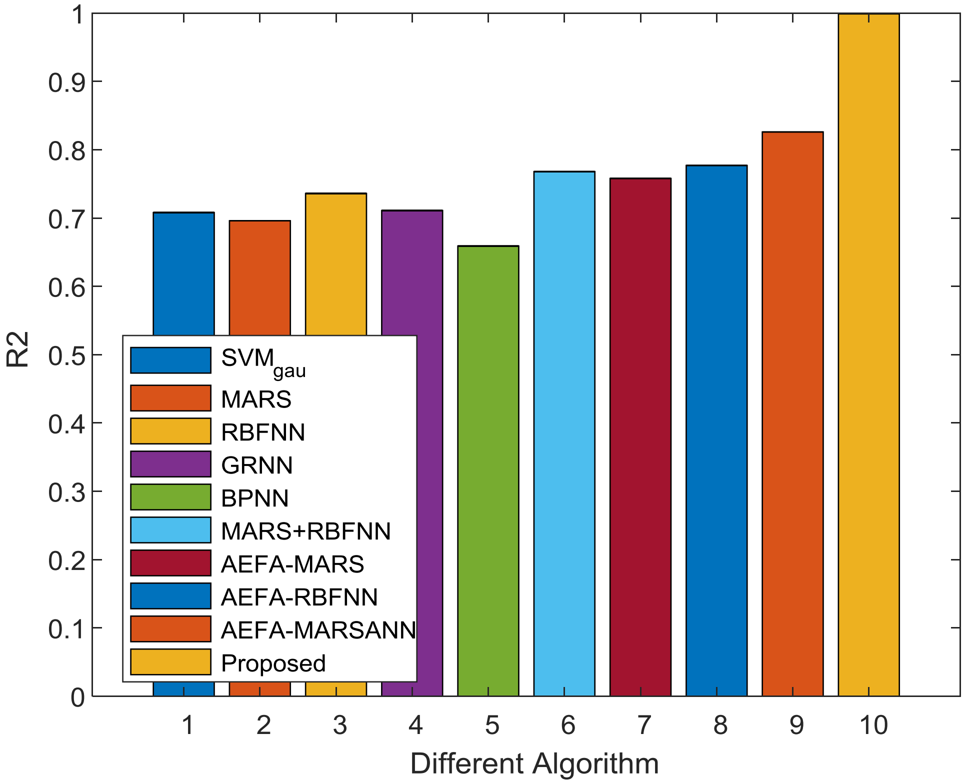

Figure 9 Comparative Analysis of Different Algorithms based on Determination of Coefficient

6. Conclusion and Future Scope

In this research, a soil shear strength prediction model is designed to reduce the error factor between the actual and predicted value. In order to accomplish this goal, pre-processing of the dataset is done using the PCA algorithm to reduce the dimension. After that, artificial neural network is utilized along with osprey optimization algorithm to predict the soil shear strength. The main motive of the osprey optimization algorithm in the ANN algorithm is to determine the optimal weight of it based on the objective function. RMSE is taken as the objective function. The result shows that the proposed model achieves the minimum error between actual and predicted value. Besides that, convergence rate graph shows the osprey optimization algorithm is quickly find the optimal results. Finally, different parameters such as RMSE, MAPE, MAE, and determination of coefficient is measured for the proposed method and result shows that RMSE, MAPE, and MAE value is lower and determination of coefficient higher value over the existing models. In the future, multiple parameters are taken into consideration to design the multi-objective function. Further, multiple machine learning algorithms are utilized to design ensemble learning based classifier in order to enhance the accuracy of the model.

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