

Settlement Prediction of Shallow Foundations on Cohesionless Soil Using Hybrid PSO-ANN Approach



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Abstract Settlement estimation of shallow foundations on cohesionless soil possesses a higher level of complexity, sole reason for which can be pointed towards the uncertainties involved in factors that affect the magnitude of settlement. For a safe and perfect shallow foundation design an unerring estimation of foundation settlement is rather essential. Unlike the conventional settlement prediction techniques AI techniques have shown greater accuracy, the potential which can be exploited for the settlement prediction of shallow foundations. This study approaches the settlement prediction problem using hybrid PSO—ANN technique (Particle swarm optimization—Artificial neural network). Dataset consisting of footing dimensions, net applied pressure, depth of embedment of footing, SPT N value and depth of water table are used as input data for developing the PSO—ANN model, whereas settlement is chosen as the output data. From about more than 300 runs an optimum network of 6-13-1 was developed. The developed model obtained coefficient of correlation, $R = 0.953$ and mean square error, $MSE = 0.119$ m. For assessing effectiveness of the model developed, different performance indices such as RMSE, VAF, MAE, PI, RSR, NS etc. were chosen. All these parameters gave values corresponding to a model with good predictive capacity.

Keywords Settlement · Cohesionless soil · PSO—ANN · SPT N · Performance indices

1 Introduction

Types of settlement that are generally encountered by shallow foundations include immediate settlement, consolidation settlement and compression settlement, which solely depends on the soil type and conditions in which they are laid. Considering cohesion less soil, the major concern is the former said—immediate settlement.

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The latter two are mostly related to cohesive soil. Higher degree of permeability exhibited by cohesion less soils lay path for instant occurrence of settlement with applied load [1], which could affect the stability of structure in short notice leaving no time to execute remedial measures. Two major criteria that control the design of shallow foundations on cohesionless soils are bearing capacity and settlement of foundation. In terms of serviceability, excessive settlement is unacceptable. Consequently settlement is considered as the controlling criterion for the foundation design rather than bearing capacity, condition being critical when least width of footing is greater than 1 m [2]. Hence settlement prediction is a major concern and is an essential criterion in the shallow foundation design. Thus accurate estimate of shallow foundation settlement is indispensable.

For the prediction of shallow foundation settlement on cohesionless soils, researchers have introduced a fair number of theoretical, empirical, semi empirical and numerical methods. Most of these available methods incorporate several assumptions related to the factors that influence settlement of shallow foundations and hence simplifies the problem. Consequently, fails to achieve consistent success during settlement prediction. Recently soft computing techniques have emerged as tool for solving such highly complex, multivariate problems. One such technique is Artificial Neural Network (ANN). Although ANN rectifies many of the shortcomings of traditional methods it still poses some drawbacks such as overfitting, getting trapped in local minima etc. If a hybrid model of ANN—PSO is used these drawbacks could be sorted out and a better predictive model could be developed [3].

In this study PSO is used as the training technique for ANN instead of the usual backpropagation method. A total of 6 input parameters and one output parameter is used, the database for which is acquired from the literature. The prediction model is developed and its performance is analyzed using various fitness parameters.

2 Model Development

The methodology considered for developing the model includes model input and output determination, division of data followed by pre-processing, determination of appropriate network architecture, model training, and performance analysis.

2.1 Database

The initial step includes determination of parameters that influences settlement estimation. For this study SPT N value, footing dimensions, depth of water table below the footing and net applied pressure are considered as the input values whereas settlement is the single output value [4]. These data were collected from literature [5]. A total of 236 data were collected, reference to which is listed in Table 1.

Table 1 Reference for database

References	No: of cases
Bazaraa (1967)	5
Briaud and Gibbens (1999)	4
Burbidge (1982)	22
Burland and Burbidge (1985)	147
Wahls (1997)	31
Maugeri et al. (1998)	2
Picornell and Del monte (1988)	1
Robert E. Kimmerling (2002)	5
Sargand et al. (1999)	19
Total	236

2.2 Data Division and Preprocessing

These dataset values are normalized using the equation given below [6].

$$X_n = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (1)$$

where

- X_n Normalized value.
- X Actual value.
- X_{\max} Maximum value.
- X_{\min} Minimum value.

After normalization the whole dataset is divided to obtain two subsets: training set and testing set. Random division is carried out for two subsets of 80 and 20% data. Data division is done in python using `train_test_split` function from scikit-learn library. Subset with 80% data comprises the training set whereas the second one with 20% data constitutes test set. It is essential that both of these subsets represent the same population and all the patterns present in the training set are available in testing set also [7]. Thus randomly different combinations are selected and then checked for its statistical consistency. This is continued until both the subsets are statistically consistent. The statistical parameters chosen include mean, standard deviation, maximum and minimum.

2.3 Development of Network

Network architecture can be determined by following a series of steps, starting with selection of number of hidden layers followed by fixing the number of nodes in each of these hidden layers. Studies have shown that one hidden layer is enough in a

neural network to approximate any continuous function [8], thus for the present study, one hidden layer is used. Therefore a three layer architecture for neural network is finalised: input layer, one hidden layer and output layer. The number of input nodes is chosen as six which is equal to the number of input parameters and number of output neuron as one which is equal to the number of output parameters i.e. settlement. Caudell (1988) suggested that the maximum number of nodes possible in a single hidden layer model is given by $(2I + 1)$, where I is the number of inputs [9]. Thus the upper limit for number of nodes in hidden layer is taken as 13. For the study 10 different values for number of nodes in hidden layer are considered.

In this study, optimum training of the network is performed using PSO. Here, the objective is to minimize the objective function, i.e., mean square error (MSE) of the network. The parameters associated with PSO are number of particles in the swarm (Swarm size), acceleration factor (c_1 and c_2) and inertia weight (w). The inertia weight (w) is generally assigned random value between 0 and 1. From various studies carried out, researchers have reported that usually when c_1 takes a value within the range 1–2.5 and c_2 value between 2 and 3, the network exhibits optimum performance [10]. In this study varying values of these parameters are selected, shown in Table 2, and a considerable number of runs are carried out to determine the optimum combination of network parameters with a higher R value and a lower MSE value. MATLAB R2020b is used for the network development. All the possible combinations of acceleration factors for each swarm size and number of neurons chosen are considered. Rather than adopting sensitivity analysis for determining optimum values of parameters, trial and error method is adopted. The former method has been reported ineffective.

2.4 Stopping Criteria

Stopping criteria considered [11]:

Maximum iteration: 20,000

If improvement in objective function for 100 successive iterations is below is 10^{-8} .

Table 2 Values of different parameters considered for network development

Acceleration factor		Swarm size	Number of neurons
c1	c2		
1	2	10	4
1.5	2.25	20	6
1.3	2.5	30	8
		50	10
		100	11
			12
			13

3 Model Validation

After successfully training the model using PSO it is required to validate the performance of trained model. The major intention behind validating the model is to ensure that the model is not simply memorizing the relationship between input and output available in the training data but has the ability to generalize within the limits of training data. Model validation is carried out using test data.

4 Fitting Examination

The result of fitting examination of PSO-ANN model is given in Table 3. The best performing acceleration factor (c_1 and c_2) corresponding to a given number of neurons in the hidden layer and swarm size is depicted in Table 3. Results for $n = 6, 8, 10, 11, 12$ & 13 and swarm size = $10, 20, 30, 50$ & 100 are reported. Corresponding prediction evaluating indices MSE and R value for training and the testing data-set has been also presented. More the R value closer to 1 and MSE value closer to 0, better will be the performance of model. Figure 1a, b shows actual and predicted settlement values of training and testing set respectively (Fig.1).

The variation of MSE with number of iterations is shown in Fig. 2. Upto 100 iterations MSE value showed significant change. Later on the value remained constant towards 10,000. Thus maximum iteration is chosen as 20,000. All the runs performed got completed before 20,000 iterations. Iteration number for the final model and the related details are given in Table 4. The highest and lowest value of R and MSE respectively are obtained for 13 number of hidden neurons, $c_1 = 1.3$ and $c_2 = 2.25$. Thus the predictive model is developed as a 6–13-1 network. Architecture of the neural network is shown in Fig. 3.

5 Performance Analysis

Root mean square error, RMSE and coefficient of determination, R^2 are the commonly used parameters to evaluate the performance of model. In order to ensure the efficiency of prediction model, a number of fitness parameters has been considered for this study. Fitness parameters used to assess the model and their corresponding values obtained are given in Table 5.

Nash–Sutcliffe efficiency (NS) indicates the predictive power of the models. The predictive capacity increases as the NS value gets closer to 1. Here 0.909 is obtained for training set indicating good prediction. Root Mean Square Error (RMSE) closer or equal to 0 indicates marginal error in prediction. The obtained value is 0.345 which indicates marginal error. Variance Account Factor

Table 3 Best R and MSE for varying number of hidden neurons

Number of neurons	Swarm size	Acceleration factors		Train		Test	
		c1	c2	R	MSE	R	MSE
6	10	1.5	2.5	0.91	0.21	0.84	0.47
	20	1.5	2.5	0.92	0.19	0.86	0.45
	30	1.3	2.25	0.89	0.25	0.86	0.44
	50	1.3	2.5	0.92	0.19	0.92	0.267
	100	1.3	2.25	0.916	0.198	0.888	0.346
8	10	1.3	2.5	0.91	0.213	0.845	0.479
	20	1.5	2.5	0.915	0.202	0.891	0.338
	30	1.5	2.25	0.921	0.187	0.897	0.322
	50	1.3	2.25	0.921	0.187	0.869	0.404
	100	1.5	2.25	0.926	0.175	0.894	0.354
10	10	1.3	2.5	0.926	0.176	0.895	0.331
	20	2	2	0.915	0.202	0.896	0.324
	30	1	2.5	0.945	0.132	0.888	0.355
	50	2	2	0.931	0.164	0.923	0.244
	100	2	2	0.927	0.174	0.909	0.285
11	10	1.3	2.5	0.923	0.184	0.882	0.362
	20	2	2	0.919	0.192	0.904	0.3
	30	1.5	2.5	0.932	0.162	0.889	0.351
	50	1.5	2.25	0.937	0.15	0.912	0.287
	100	1.3	2.25	0.942	0.138	0.902	0.324
12	10	2	2	0.914	0.204	0.868	0.408
	20	2	2	0.912	0.207	0.882	0.362
	30	1.5	2.25	0.94	0.144	0.916	0.269
	50	1.5	2.25	0.928	0.172	0.89	0.317
	100	1.3	2.25	0.932	0.161	0.907	0.299
13	10	1.3	2.5	0.94	0.144	0.849	0.485
	20	1.5	2.25	0.929	0.168	0.88	0.357
	30	1.5	2.5	0.937	0.151	0.87	0.452
	50	1.3	2.5	0.931	0.166	0.901	0.31
	100	1.3	2.25	0.953	0.119	0.932	0.217

(VAF) equal to 100% indicates that model performance gives a reasonable result. Obtained value is 99.98% for training set which is much closer to 100%. R^2 (Coefficient of determination) and $Adj.R^2$ (adjusted determination coefficient) values should be closer to 1. Both closer to each other show that the model reflected most of the variability in soil parameters. Here values of R^2 and $Adj.R^2$ are closer to 1 and also closer to each other, 0.908 and 0.906 respectively are obtained.

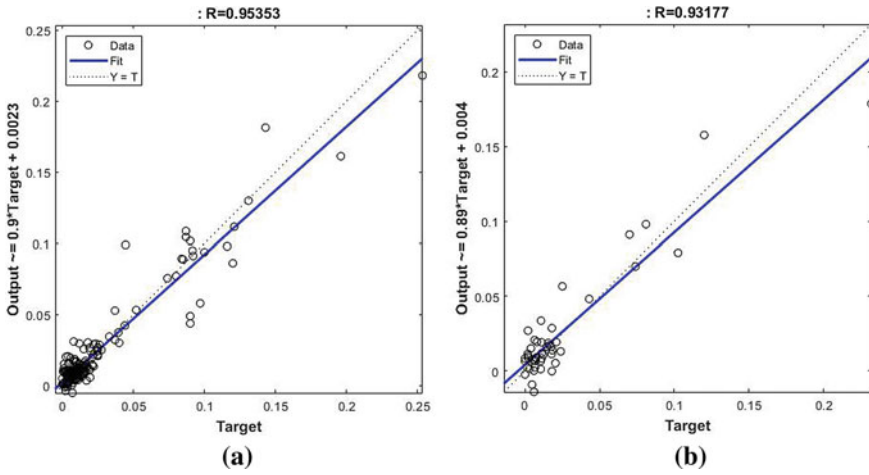


Fig. 1 Actual and predicted settlement of a training and b testing set (actual value on x-axis and predicted value on y-axis)

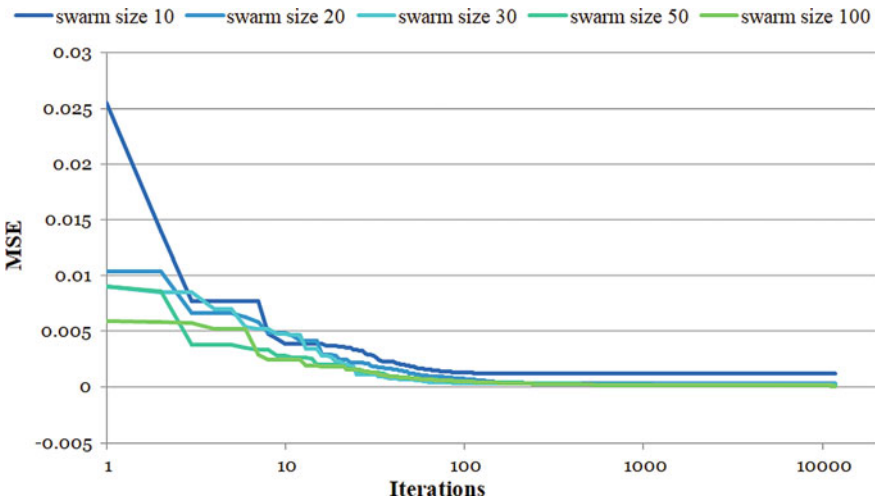


Fig. 2 MSE Variation with number of iterations

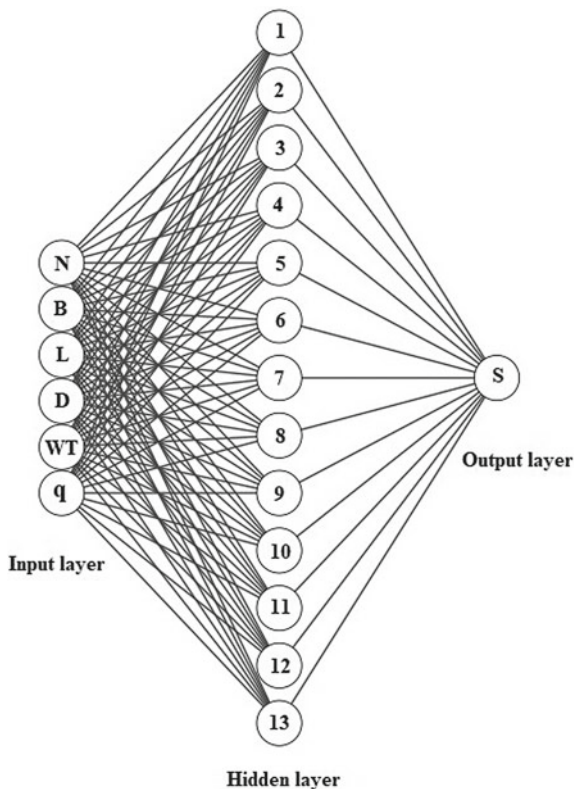


Fig. 3 Architecture of neural network developed (N = SPT N value, B = Breadth of footing, L = Length of footing, D = Depth of footing, WT = Depth of water table below footing, q = Net applied pressure, S = Settlement)

Table 4 Description of the hybrid ANN PSO model developed

Number of hidden neurons	13
Swarm size	100
c1	1.3
c2	2.25
Iterations	20,000 ^a (13,841)
w	0.4926
Stopping criteria	Max. iteration = 20,000 or Tolerance = 10^{-8}
Space search	(-1.5, 1.5)

^aSecond criteria got satisfied and iterations got completed at 13,841

Table 5 Performance parameters

Performance parameter	Training set	Testing set
NS	0.909	0.892
RMSE	0.345	0.466
MSE	0.119	0.217
R	0.953	0.932
R ²	0.908	0.869
VAF	99.989	99.98
Adj. R ²	0.906	0.85
PI	1.561	1.384
MAPE	0.006	0.068
MAE	0.00621	0.0088

6 Conclusion

From about more than 300 runs the optimum predictive model was developed as a 6–13–1 network ie, with 6 input parameters and 13 hidden neurons. c_1 and c_2 values for the model developed are 1.3 and 2.25 respectively. An R value of 0.953 for training set and 0.932 for testing set was obtained. MSE value of 0.119 m for training and 0.217 m for testing was obtained. All the other performance parameters also gave values proving the model to be good in prediction. Thus PSO –ANN hybrid model can be used to accurately predict the settlement of shallow foundations on cohesionless soil.

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