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Prediction of Spread Foundations' Settlement in Cohesionless Soils Using a Hybrid Particle Swarm Optimization-Based ANN Approach

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***Abstract*—Proper estimation of foundation settlement is a crucial factor in designing shallow foundations. Recent literature shows the applicability of Artificial Neural Networks (ANNs) in predicting the settlement of shallow foundations. However, conventional ANNs have some drawbacks: getting trapped in local minima and a slow rate of learning. Utilization of an optimization algorithm such as Particle Swarm Optimization (PSO) can greatly improve ANN efficiency. In this study, a PSO-based ANN predictive model of settlement is established. A database comprising 80 footing load tests on cohesionless soils compiled from the literature was used for training the predictive model. For training purposes, footing geometrical properties (length, width, and depth of embedment) as well as soil properties (friction angle, stiffness, and effective stress below footing) were used as inputs to the model while the settlement was set to be the output of the model. Close agreement between the settlements predicted using the developed model and the measured settlements suggests the accuracy and efficiency of the hybrid PSO-based ANN model in predicting the settlement of spread foundations in cohesionless soils.**

Keywords—Spread foundation, Settlement, Artificial Neural Network, Particle Swarm Optimization, cohesionless soils

I. Introduction

The bearing capacity of the soil beneath the foundation and the soil settlement are two important criteria which control the design of spread foundations in granular soils. Nevertheless, as suggested by Schmertmann [1], in terms of serviceability, excessive settlements could be problematic; hence the design of spread foundations on cohesionless soils is often controlled by settlement rather than bearing capacity. There are numerous methods for estimating the settlement, only Douglas [2] reported the existence of 40 different methods for predicting the settlement in sandy soils.

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Polous [3] highlighted the common procedures used for foundation settlement analysis from empirical to nonlinear finite element analyses. In fact, the complexity of settlement estimation, which is due to the uncertainty associated with soil behaviour, the stress–strain history of the soil, and difficulty in collecting undisturbed samples, is the most important reason behind many attempts conducted to estimate settlement [4]. Apart from the conventional method of settlement estimation, recently, soft computation techniques have been applied successfully for predicting the settlement of foundations [4,5]. One of the most widely used soft computation techniques is the Artificial Neural Network (ANN). The application of an ANN in predicting the settlement of shallow foundations is discussed in more detail in the following sections. However, conventional ANN techniques have some drawbacks: getting trapped in local minima and a slow rate of learning [6]. Utilization of an optimization algorithm such as the Particle Swarm Optimization (PSO) algorithm can greatly improve the ANN's performance and accuracy [7, 8]. In this paper, the authors have developed a hybrid PSO-based ANN model to predict the settlement of spread foundations in cohesionless soils.

II. Review of Recent Literature

The use of ANNs in predicting the settlement of spread foundations is highlighted in several studies. This is due to the ability of ANNs to find nonlinear and complex interactions between variables [5]. Among different researchers who established ANN predictive models of settlement, Li and Bu [9] reported the applicability of the Back-propagation Artificial Neural Network (BP-ANN) in predicting the settlement of soft clay foundations in highways. They used a dataset comprising the results of 200 field tests. Their ANN-based predictive model of settlement was trained with multiple input variables such as time, fill height, treatment thickness, and composite modulus. PooyaNejad et al. [10] developed an ANN model for predicting the settlement of deep foundations. In their study, almost 1000 data, collected from different works in the literature, were used for network construction. Their data contained recorded cases of field measurements of pile settlement. According to their results, ANN outperforms the conventional method of settlement estimation. In another study, Soleimanbeigi and Hataf [11] investigated the potential of ANN implementation in predicting the settlement of spread foundations in reinforced cohesionless soils. They used BP-ANN for developing their predictive model. In their study, the footing size, soil properties, and reinforcement characteristics

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of 123 recorded cases from both laboratory and field measurement were used for training the ANN model.

They suggested that the BP network could reasonably predict the settlement of shallow foundations. Another study by Yu et al. [12] confirms that ANNs can be used as a practical tool for predicting the surface settlement. Nevertheless, in their study, the authors implemented an ANN for predicting the settlement induced by a foundation pit excavation rather than the settlement of the foundation itself due to the applied load.

III. Hybrid PSO-based ANN model

Many attempts have been made to increase the accuracy and performance of ANNs using optimization algorithms as a consequence of the fact that the optimum search process of conventional ANNs might fail, returning an unsatisfactory solution [13]. Several scholars studied the ability of PSOs to train ANNs and demonstrated that the PSO is an effective tool to train ANNs instead of BP [7, 8,14].

In a PSO-based ANN model, in each iteration, PSO searches for a set of weights and biases to minimize an objective function such as the Mean Square Error (MSE) or Root Mean Square Error (RMSE). This process is continued to find the best weights and biases for an ANN to minimize the error function. The following sections describe the procedures of ANNs as well as PSO.

A. *Artificial Neural Network*

An ANN is a computer-based modelling technique based on our understanding of human-brain information processing [15]. Although the ANN structure depends on the type of problem, a typical ANN model comprises three key components: the transfer function, network architecture, and learning rule [16]. In general, ANNs are divided into two major types: recurrent and feedforward. However, if there is no time-dependent parameter, a feedforward ANN can be utilized for computation purposes [4].

Among feedforward ANNs, the use of a Multi-Layer Perceptron (MLP) neural network is common and well respected; this type of ANN consists of a number of neurons in different layers, for example input, hidden, and output layers connected to each other through random adjustable weights. In MLP networks, input data are presented to the networks and the networks start to feed forward until output generation.

The reason why the implementation of an MLP ANN has advantageous attributes is its high efficiency in approximating different functions in high dimensional spaces [17,18].

It is worth mentioning that in ANNs, prior to information interpretation, the ANN model needs to be trained using a prepared database of the desired output(s) and some relevant input parameters.

One of of the most widely used algorithms for training ANNs is the backpropagation (BP) algorithm [19]. The purpose of BP training is to iteratively modify the weights which connect neurons together in a way that minimizes the Mean Square Error (MSE) of the model, where MSE is defined as the squared difference between the predicted and actual outputs [20]. Detail of the BP algorithm is out of the scope of this study and can be found in many works in the literature, for example [21, 22]

B. *Particle Swarm Optimization*

PSO is an evolutionary population-based optimization technique originated from the social behaviour of particles in swarm-like bird flocks which can be used to solve global optimization problems within a nonlinear procedure [23]. In PSO, particles represent candidate solutions to the optimization problem. The particles are flown in the multidimensional search space and move throughout this space. The particles' positions are changed based on their experience and that of neighboring particles, and therefore take advantage of their own and their neighbors 'experience [24].

The process of solving an optimization problem using PSO is operated with an initialization of random particles (each particle is a solution) which are assigned with random positions and velocities. Subsequently, PSO searches for the best solution through iterative procedures [25]. In the optimization process, each particle keeps a record of its best position, known as the personal best (p_{best}) and also the overall best value obtained by other particles, known as the global best (g_{best}). In each iteration, both p_{best} and g_{best} positions are updated by computing a new velocity. In comparison to the other optimization algorithms, PSO has a simple procedure [26]. The PSO procedure is conducted on the basis of two simple equations as follows:

$$\overrightarrow{v_{new}} = \vec{v} + r_1 c_1 \times \left(\overrightarrow{p_{best}} - \vec{p}\right) + r_2 c_2 \times \left(\overrightarrow{g_{best}} - \vec{p}\right) \tag{1}$$

$$\overrightarrow{p_{new}} = \vec{p} + \overrightarrow{v_{new}} \tag{2}$$

where, v_{new}, v, p_{new}, and p denote the new velocity, current velocity, new position, and current position of particles, respectively,c_1 andc_2 are acceleration constants, p_{best} is the personal best position of the particle, g_{best} is the global best position among all particles, and r_1 and r_2 are random values in the range (0,1) sampled from a uniform distribution.

IV. Dataset for developing Settlement prediction model

The reliability of an ANN-based predictive model of settlement depends on a thorough understanding of the factors affecting settlement. A review of the recent literature [27,4] (see Section 3) suggests that six major parameters have the most significant effect on the settlement of shallow foundations in granular soils: footing geometrical properties (width, *w*; length, *L*; depth of embedment, D_f), effective stress at *w/2* below the footing (σ′), soil stiffness within the influenced zone of the footing, E, and the friction angle of the soil (ϕ). Knowing the importance of these factors, a database consisting of 80 footing load tests in cohesionless soils was

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collected from different works in the literature [28, 29]. Table 1 shows the range of data used in this study. As shown in this table, the database comprises the aforementioned effective factors in settlement analysis (model inputs) as well as the settlement of the footing under the failure loads (model output). Nevertheless, it is worth mentioning that for the soil stiffness parameter, the secant modulus at 1% of the footing widths was used.

TABLE I. RANGE OF DATABASE

Parameters		Range of Data		
		Minimum	*Maximum*	*Unit*
Inputs	W	0.25	3.02	m
	L	0.25	3.02	m
	D_f	0	1.04	m
	E	2328	203000	kPa
	ϕ	28	53	-
	σ'	2.3	124.1	kPa
Output	S	11.5	194	mm

V. Modelling Procedure

A MATLAB code was developed to simulate the footing settlement using a PSO-based ANN model. A series of sensitivity analyses was conducted to determine the PSO parameters, which comprise the number of particles and acceleration constants for g_{best} (C_1) and p_{best} (C_2). A model with one hidden layer was selected and the number of nodes in the hidden layer was determined using the trial-and-error method. In order to evaluate the model performance, the data were divided into two parts: 80% to train the model and 20% for testing purposes. The model performance was evaluated using the coefficient of determination (R^2) and Root Mean Square Error (RMSE) for the testing datasets.

To obtain the optimum number of particles in the swarm, a series of sensitivity analyses was conducted. While a small swarm may fail to converge to a global solution, choosing a large swarm may lead to delay in the convergence and decrease efficiency. The analyses were performed by setting a fixed iteration number of 1000 repetitions for each model with various numbers of particles.

Figure 1 shows the values of R^2 and RMSE for various models with different swarm sizes. According to this figure, the values of R^2 increased and values of RMSE decreased when the number of particles was increased to between 5 and 125. Afterwards, no significant increase in the values of R^2 or decrease in the values of RMSE can be seen. Therefore, a swarm size of 125 was selected for use in the modelling.

The optimum acceleration constants, C_1 and C_2, were determined in the next step. In the sensitivity analyses, based on literature studies, a series of acceleration constants was used. Table 2 shows the results of the sensitivity analyses. According to this table, in terms of R^2 and RMSE for testing datasets, models 3 and 4 perform best.

However, model 3 was selected because it yields better results in terms of training datasets, as compared to model 4. Therefore values of 1.714 and 2.286 were selected for C_1 and C_2 to be used in the prediction model.

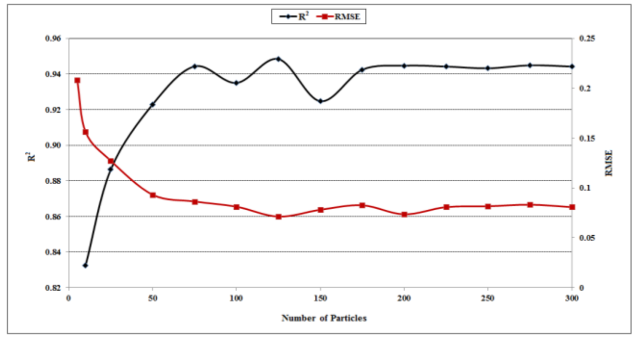

Figure 1. R^2 and RMSE for models with different swarm sizes

TABLE II. SENSITIVITY ANALYSES RESULTS FOR DETERMINATION OF ACCELERATION CONSTANTS

Model	C_1	C_2	Training		Testing	
			R^2	*RMSE*	R^2	*RMSE*
1	0.8	3.2	0.958	0.077	0.897	0.084
2	1.333	2.667	0.965	0.070	0.602	0.162
3	1.714	2.286	0.945	0.078	0.930	0.110
4	2	2	0.939	0.094	0.918	0.066
5	3.2	0.8	0.857	0.114	0.925	0.136
6	2.667	1.333	0.890	0.108	0.887	0.151
7	2.286	1.714	0.885	0.096	0.906	0.158

As previously mentioned, the number of nodes in the hidden layer was determined using the trial-and-error method. After determining the PSO parameters, the trial-and-error method was conducted. Therefore, eight models with different numbers of nodes (3, 6, 9, 12, 15, 18, 21, and 24) were considered. All models were trained with optimized PSO parameters obtained in previous sensitivity analyses. The results of the analyses are shown in Table 3.

TABLE III. TRIAL-AND-ERROR METHOD TO FIND THE OPTIMUM NUMBER OF NODES IN THE HIDDEN LAYER

Model	Number of Nodes	Training		Testing	
		R^2	*RMSE*	R^2	*RMSE*
1	3	0.965	0.071	0.556	0.167
2	6	0.945	0.078	0.930	0.110
3	9	0.951	0.077	0.930	0.099
4	12	0.950	0.076	0.967	0.072
5	15	0.960	0.077	0.887	0.071
6	18	0.959	0.077	0.717	0.126
7	21	0.950	0.076	0.954	0.084
8	24	0.946	0.079	0.933	0.104

Figures 2 and 3 show the R^2 and RMSE values for different trained models. According to these figures, for testing datasets, model4, with 12 nodes in the hidden layer, presents the best performance; therefore, this model was selected as the final model for settlement prediction.

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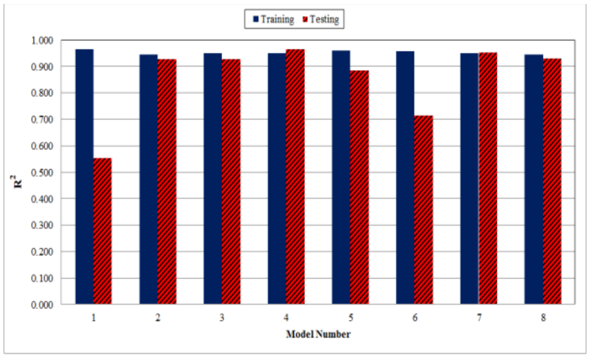

Figure 2. Performance of different PSO-based ANN models based on R^2

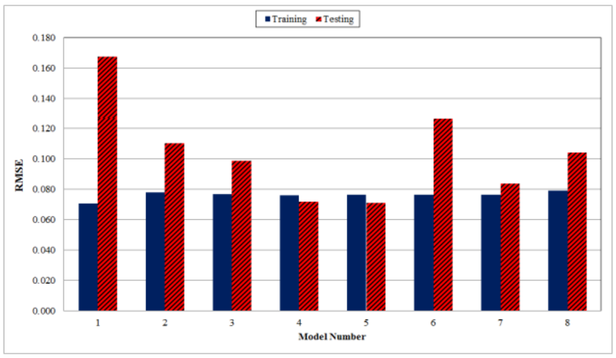

Figure 3. Performance of different PSO-based ANN models based on RMSE

VI. Results and Discussion

The performance of the PSO-based ANN model in predicting the settlement of spread foundations in cohesionless soils is discussed in this section. As mentioned before, the coefficient of determination values were used for evaluating the performance of the developed model. As shown in Figures 4 and 5, the R^2 values equal to 0.95 and 0.97 for the training and testing datasets respectively are a good indicator showing that the developed PSO-based ANN model performs best.

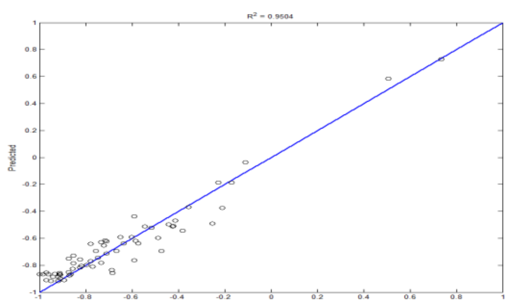

Figure 4. Perforamnce of the selected PSO-based ANN model (training dataset)

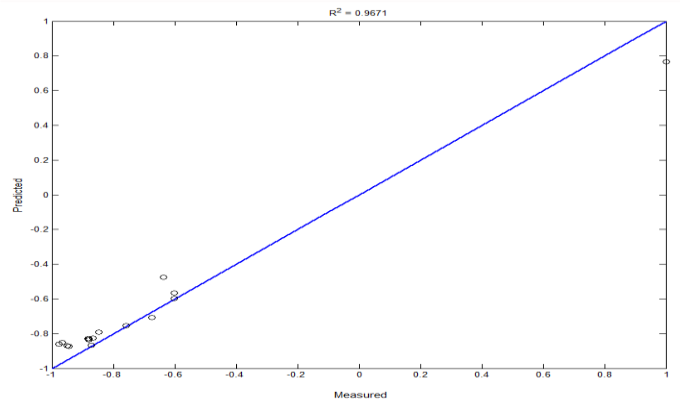

Figure 5. Perforamnce of the selected PSO-based ANN model (testing dataset)

Figures 6 and 7 show a graphical comparison between measured and predicted values of settlement for both training and testing datasets. As displayed in the figure, the predicted values of settlement obtained by employing the proposed PSO-based ANN model are in close agreement with the measured values.

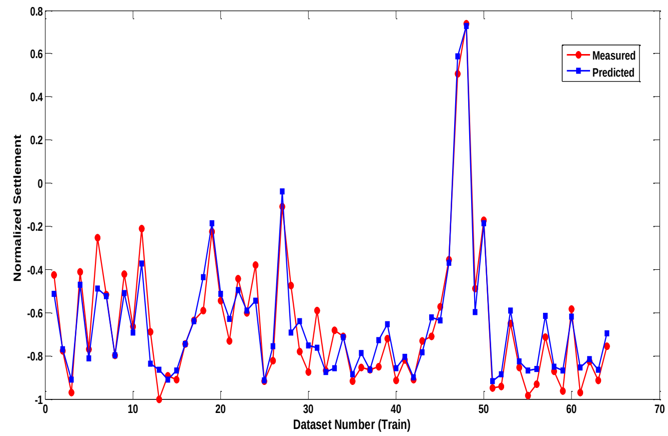

Figure 6. Comparison between measured and predicted settlements (training dataset)

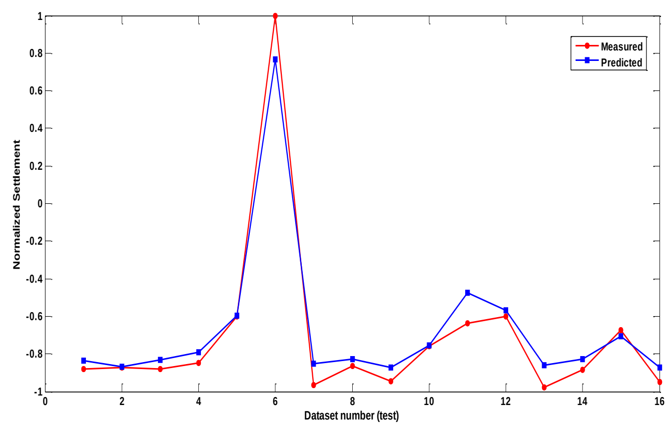

Figure 7. Comparison between measured and predicted settlements (testing dataset)

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VII. Summary and Conclusion

To apply the PSO-based ANN for predicting the settlement of spread foundations, 80 datasets were collected, each involving six inputs, including the footing geometry (length, width, and embedded depth) and soil properties (friction angle of soil, soil stiffness, and effective stress) as well as one singular output (settlement) .In order to evaluate the performance of the models, 20% of the datasets were selected for testing; these datasets play no role in the learning procedure. A series of sensitivity analyses was performed to determine the optimum PSO parameters. Eventually, an optimized PSO-based ANN model was selected to be used in settlement prediction. Close agreement, that is, R^2= 0.97, between the measured and predicted settlements for the testing datasets suggests that the PSO-based ANN predictive model is a feasible and practical tool that can be utilized for predicting the settlement of spread foundations in cohesionless soils.

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The applicability of Artificial Neural Networks (ANNs) in predicting the settlement of shallow foundations shows a promising way of engineering prediction. Getting trapped in local minima and a slow rate of learning is a normal drawback. However by utilization of an optimization algorithm such as Particle Swarm Optimization (PSO) can greatly improve ANN efficiency. This paper proved the method apply.