Use of Radial Basis Function Neural Network for Bearing Pressure Prediction of Strip Footing on Reinforced Granular Bed Overlying Weak Soil

Srinath Shetty K., Shivashankar R., and Rashmi P. Shetty

Abstract—Earth reinforcing techniques have become useful and economical to solve problems related to difficult grounds and provide satisfactory foundation performance. In this context, this paper uses radial basis function neural network (RBFNN) for predicting the bearing pressure of strip footing on reinforced granular bed overlying weak soil. The inputs for the neural network models included plate width, thickness of granular bed and number of layers of reinforcements, settlement ratio, water content, dry density, cohesion and angle of friction. The results indicated that RBFNN model exhibited more than 84 % prediction accuracy, thereby demonstrating its application in a geotechnical problem.

Keywords—Bearing pressure, granular bed, radial basis function neural network, strip footing.

I. INTRODUCTION

AN increasing proportion of building development takes place on poor and difficult ground, which is a real challenge to any geotechnical engineer, in order to provide a satisfactory foundation performance. The foundation behavior can be modified by proper ground treatment, so that its properties can be improved [1]. Earth reinforcing techniques have become useful to solve many problems in geotechnical engineering practices [2]. This work is concerned with a locally available soil in the author's geographical location namely "shedi" soil. It is a lithomargic clay, which is a problematic weak soil, especially when fully saturated or submerged and without confinement [3]. Thus there is a need to improve its bearing capacity by 2 to 3 times, in order to support even light to moderately loaded structures. This work makes use of a compact reinforced granular bed laid over the soft soil to improve its bearing capacity and settlement response of footings placed over it.

A review of the literature reveals that there have been several research work related to load carrying capacity of footings. The earliest attempt to calculate bearing capacity of a strong layer overlying a weak layer was in 1948 [4]. Similarly, the first significant study on soil reinforcement in foundations was by Binquet and Lee in 1975 [5]-[6]. Shivashankar et al.[7]

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investigated the ultimate bearing capacity of a footing resting on granular bed overlying soft clay with or without an interfacial reinforcing layer.

They predicted the bearing capacity ratio values considering different effects and compared with some of the available experimental values in literature.

There is a lot of complexity involved in modeling the geotechnical problems. Artificial Neural Networks (ANN) is a form of artificial intelligence (AI), which try to simulate the biological structure of the human brain and nervous system [8]. ANNs can model the nonlinearity present in a problem and try to evolve a modeling system, which can help in prediction or classification. Some of the areas where ANN has been applied in geotechnical engineering include pile capacity prediction, prediction of settlement of structures, modeling soil properties and behavior, determination of liquefaction potential, site characterization, modeling earth retaining structures, evaluating the stability of slopes and the design of tunnels and underground openings [9]. The reason for increased interest in ANNs are due to their ability to solve direct mapping problems that are nonlinear, comprise several independent variables and are found to give more accurate solutions, when compared to traditional modeling techniques. They have superior prediction ability, can model complex behavior of materials , they can learn from experience and there is no need to make assumptions about the underlying distributions that govern the problem as required in conventional modeling techniques [10]-[11]. Most of the applications of ANN have been limited to use of multilayer perceptron (MLP) [12].

Radial basis function neural networks (RBFNN) are a relatively new class of neural networks, which have been used in classification or regression problems. They are robust classifiers, with the ability to generalize imprecise input data [13]. I. Yilmaz and O. Kaynar (2011) used MLP, RBFNN and ANFIS (adaptive neuro-fuzzy inference system) for prediction of swell potential of clayey soils and results were compared with multiple regressions (MR). It was found that the constructed RBFNN model exhibited a high performance than MLP, ANFIS and MR for predicting swell potential. The time taken by RBF for training was lesser, when compared to MLP and RBF was more sensitive to dimensionality [13]. Jaywardena & Fernando (1998) used two RBF type ANN models to simulate storm events in a small catchment. They

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found that RBF models can predict runoff with accuracy comparable with that of MLP approach [14]. Rajeev Jain et al (2010) used MLP and RBFNN to predict shear strength parameters of medium compressibility soil, which influenced the basic properties of soil in unconsolidated undrained condition. The prediction results of ANN models were compared and it was found that MLP with three hidden layers was better than RBFNN model [15]. In this paper an attempt was made to explore the applicability of RBFNN to model bearing pressure of strip footing on reinforced granular bed overlying weak soil, for prediction.

II. EXPERIMENTAL DETAILS

Laboratory experiments were conducted to extensively the bearing pressure and settlement of model strip footings of different widths on reinforced granular bed overlying weak soil. To find the basic properties of the soil and granular material, relevant laboratory experiment were carried out. The fill material used for the model tests was a weak soil, locally known as "shedi". The granular material used was quarry dust, consisting mainly of excess fines generated from crushing, washing and screening operations at granite quarries. The relative density of the granular bed was maintained at 75 %, which was found to be sufficient from application point of view. In the experimental study, mild steel hexagonal mesh was used as soil reinforcement material. Loading tests were performed using model strip footings of 60, 80, and 100 mm widths on reinforced granular bed overlying weak shedi soil. For soil five water contents were chosen such that two were on the dry side of the optimum and two on the wet side of the optimum, with one at the optimum. A manually operated jack of 100 kN capacity was used for loading. Table I shows the experimental conditions.

TABLE I
EXPERIMENTAL CONDITIONS

Variable	Values
B	60, 80, 100 mm
H	0.5B, 1.0B, 1.5B, 2.0B
n	1,2,3,4
S/B	0.10, 0.15, 0.20
w%	10, 15, 20, 25, 30
γ_d	13.7, 14.7, 14.75, 15.2, 15.78 kN/m^2
C	35, 45, 50, 55 kN/m^2
Ø	11.3, 21.3, 23.03, 24.25, 25.17°

In order to develop the predictive model for bearing pressure, the following input and output parameters were considered for study, input – plate width (B), thickness of granular bed (H), number of layers of reinforcement (n), settlement ratio (S/B), water content (w), dry density (γ_d), cohesion (C) and angle of internal friction (Φ) and output – bearing pressure (q).

A. Data Preprocessing

The available experimental data was divided into two data sets namely training data set to construct and train the neural network model and test data set to check the performance of the trained model, which included data not present in the training set. The total data set consisted of 324 patterns, out of which 85 % of data (274 patterns) were used in the training set and the remaining 15 % (50 patterns) were used in the test set.

The data was suitably preprocessed using a normalization scheme. This was done mainly to scale down the data of all the variables, so that all of them receive equal attention during training. A simple scheme was used, where each data pertaining to a variable was divided by the maximum value of that variable, so that values were between 0 and 1.0.

III. RADIAL BASIS FUNCTION NEURAL NETWORK (RBFNN)

RBFNN is supervised neural network architecture, whose design and working is different from that of a multilayer perceptron (MLP). The design of RBFNN can be viewed as a curve fitting problem in a high dimensional space. According to this, learning is equivalent to finding a surface in a multidimensional space that provides a best fit to the training data. Correspondingly generalization is equivalent to using this multi dimensional surface to interpolate the test data [16]. The main advantages claimed for the RBF model are its simplicity and the ease of implementation [17]. The structure of a RBF network is similar to that of an MLP, but has only one hidden layer. A typical RBFNN consists of an input layer, a hidden layer, which applies a nonlinear transformation from the input space to the hidden space and an output layer, which produces the network output. Each RBF unit in the hidden layer has two parameters; a center x_j and a width σ_j. The RBF units have a Gaussian transfer function, which is given by (1).

$$\phi_j(x) = e^{-\frac{\|x_j - \xi_i\|^2}{2\sigma_j^2}} \qquad (1)$$

where ξ_i is the input, j = 1, 2, 3, ………c is the number of centres. This center is used to compare with the network input vector to produce a radially symmetrical response. The width controls the smoothness properties of the interpolating function. The response of the hidden layer are scaled by the connection weights of the output layer and then combined to produce the network output, by passing though a nonlinear transfer function, namely a sigmoidal function, as given in (2).

$$O_k = \frac{1}{(1 + e^{-\sum w_{kj}\phi_j})} \qquad (2)$$

where w_{kj} are the weights between output layer k and hidden layer j.

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A. Training Strategies

The centers of the RBF units can be fixed using different learning strategies [16]. In this paper, centers of the RBF units have been selected randomly from the input data. The widths of the RBF units can be fixed using different methods – use of P-nearest neighbor heuristics [18] or can be evaluated using (3)

$$\sigma_j = \frac{d_{max}}{\sqrt{2m}} \qquad (3)$$

where d_{max} is the maximum Euclidean distance between chosen centres and m is the number of centres. It can also be fixed by trial and error method. In this paper, this method has been chosen, and the selection is based on the maximum prediction accuracy on test data. The weights of the output layer have been optimized using LMS algorithm or its variants [16].

IV. RBFNN MODELING

The RBFNN model used in the current work is shown in Fig. 1.
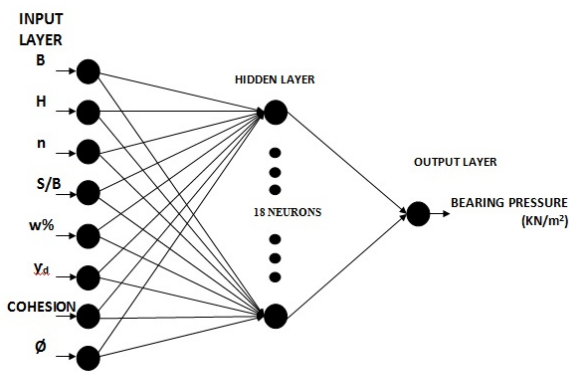

Fig. 1 RBFNN Model for Bearing Pressure

The centers of the RBF units have been selected randomly from the training data set, which consisted of 274 data. The simulation parameters required for training the RBF network were maintained constant at η =0.5 and α = 0.5. The network goal was fixed at 0.0001, which was the mean square error (MSE). MSE is defined as given in (4).

$$MSE = \frac{1}{2}\sum(O_k - \varsigma_k)^2 \qquad (4)$$

where O_k is the network output and ς_k is the actual output.

The number of RBF units or centres in the hidden layer was varied in steps of 10 from 120 to 200. Sample results for a few centres are given in Table II.

TABLE II
PERFORMANCE OF RBFNN MODEL WITH VARIATION OF CENTRES
(FOR 0.14 WIDTHS)

CENTRE	150	160	170	180	190
Training data accuracy	79.56	90.51	88.68	71.16	59.85
Test data accuracy	68	70	84	56	54
Average MRE	19.69	13.04	9.79	18.37	19.05

Similarly the width of the RBF units was selected by trial and error and the criterion was maximum prediction accuracy on the test data. In this work, it was varied from 0.1 to 0.18 in steps of 0.02. The corresponding results are given in Table III.

TABLE III
PERFORMANCE OF RBFNN MODEL WITH VARIATION OF WIDTHS
(FOR 170 CENTRES)

CENTRE	0.10	0.12	0.14	0.16	0.18
Training data accuracy	83.57	87.22	88.68	20.0	13.1
Test data accuracy	66	80	84	32	16
Average MRE	14.50	10.77	9.79	33.96	46.69

The focus of this work was to select the optimum number of centres and width value, such that the prediction accuracy on test data was maximum. It is clear from Table II & III that for 170 centers and 0.14 width values, the prediction accuracy on the training and test data was maximum.

The network performance was evaluated based on mean relative error (MRE). It is defined as given in (5):

$$MRE = \frac{1}{N}\sum_{i=1}^{N} 100\frac{(\varsigma_k - O_k)}{\varsigma_k} \qquad (5)$$

where N is the number of data in the data set, ς_k is the actual or experimental value, O_k is the predicted value by the ANN model. Table IV gives the prediction accuracy based on MRE, average MRE and R^2 value for training and test data. For determining the prediction accuracy, a maximum MRE of 15 % was considered which is acceptable for these applications [19].

TABLE IV
PERFORMANCE INDICES OF RBFNN MODEL

Performance Index	Training data	Test data
R^2	0.96	0.91
Prediction accuracy	88.7	84.0
Average MRE	7.98	9.79

The prediction accuracy on test data is 84 % and the corresponding value of R^2 is 0.91, with an average MRE of 9.79.

Fig. 2 (a) and (b) shows the plot of experimental vs RBFNN model predicted bearing pressure for training and test data. There is less scatter in the data, with respect to the ideal behavior and it is acceptable, thereby establishing the effectiveness of RBFNN based prediction model for bearing pressure.
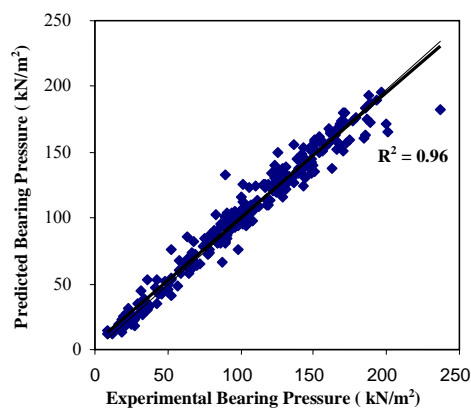

$R^2 = 0.96$

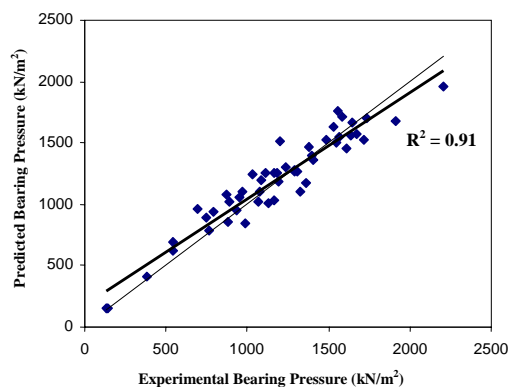Fig. 2 (a) Experimental vs RBFNN Model predicted Bearing Pressure (Training data)

$R^2 = 0.91$

Fig. 2 (b) Experimental vs RBFNN Model predicted Bearing Pressure (Test data)

V. CONCLUSION

RBFNN, a supervised ANN architecture is similar to MLP, with a different procedure to design the network architecture. Both are nonlinear, layered feed forward networks and are universal approximators. RBFNN has several advantages, which includes use of a single layer and use of a non-monotonic Gaussian function, which has better local approximation capability. These generalize well, when there is sufficient data available for training. In this work, RBFNN was used to predict bearing pressure of strip footing on reinforced granular bed overlying weak soil. Eight parameters have been used to train the network. The centers of the RBF units and widths have been fixed by trial and error. This learning though is the simplest, requires several trials to fix the optimum number of RBF units and the width value, which is

time consuming. The evolved RBFNN model has been able to predict bearing pressure with an accuracy of more than 84 %, thereby demonstrating the effectiveness of this model in this application, where MLP is very widely used.

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