Prediction of Load-Settlement Response of Rock-Socketed Piles in Mumbai Region using Artificial Neural Networks with Genetic Algorithm

Kulkarni R. U.
Research Scholar
Department of Civil Engineering
IIT Bombay
Mumbai, India

Dewaikar D. M.
Adjunct Professor
Department of Civil Engineering
IIT Bombay
Mumbai, India

Abstract—**The load-settlement response of rock-socketed piles is fairly complex. It primarily depends on the pile geometry and geologic conditions. The pile load test is the most reliable way to measure the non-linear load-settlement response of rock-socketed piles. However, these tests are time-consuming and expensive. Hence, need arises to derive alternative techniques to simulate the load-settlement response. Artificial Neural Network is capable of simulating complex input-output behavior as it has the capability of dealing with non-linear characteristics. In the present study, a hybrid model is proposed using Artificial Neural Network in combination with Genetic Algorithm to simulate pile behavior using geotechnical investigation data. A multi-layer perceptron architecture is used to develop the proposed model. The proposed model is trained using Genetic Algorithm. Rock-socketed pile load test dataset of 148 cases collected from the various sites of Mumbai region is employed in the present study to analyze the load-settlement response of piles. The results indicate a close agreement with the load-settlement response obtained from the pile load tests.**

Keywords— Artificial Neural Network; Genetic Algorithm; Pile Load Test; Load-Settlement Response; Rock-Socketed Pile

I. INTRODUCTION

The pile load test is the most accepted way of determining the load-settlement characteristics of a rock-socketed pile. However, the test is time-consuming and expensive. The pile analysis is naive in the case of homogeneous strata. Nevertheless, in the cases of spatially variable strata, the problem becomes fairly complex and is difficult to simulate the site-specific load-settlement response using numerous empirical, semi-empirical, theoretical or experimental methods available in the literature.

Artificial Neural Network (ANN) method is one such alternative which can surpass the conventional computational methods (Flood, 2008). The linear relationship between the input and output parameters in a two-dimensional (z-x) space can be modeled as, for instance, $z=mx+c$, where m is the slope and c is the intercept. The error, in this case, is minimized by changing the slope and the intercept.

ANN is well-known to handle complex problems where, the relationship between the input and output parameters is non-linear (Garrett 1994, Chan et al.1995, Goh 1995 and Shahin et al., 2001). In the present study, the slope is analogous to the synaptic weights and intercept is analogous to the biases/threshold (Zurada, 1996). The slope and intercept in the present study are changed using the optimization tool of Genetic Algorithm (GA).

The load-settlement response of an axially loaded pile using ANN is analyzed through numerous studies (Patil, 2000; Basarkar, 2004; Alkroosh et al., 2010; Momeni et al., 2014 and Shahin, 2014). The details of some these methods are reported by Shahin (2016).

As of now, the load-settlement prediction of rock-socketed pile using hybrid GA-based ANN is attempted employing intact rock properties. An attempt is made here to examine the feasibility of GA-based ANN using rock-mass properties.

II. PILE LOAD TEST

The Pile Load Test (PLT) is conducted in Mumbai region in accordance with IS:2911, Part IV, (1985, Reaff. 2010). The rock-socketed piles are loaded in axial compression at the top by hydraulic jack by means of suitable loading frame. The top head settlement is recorded by dial gauges. Each loading is applied at an increment of 20% of the safe load.

The first load increment is maintained for 30 minutes. If the settlement recorded is less than 0.1 mm, the next load increment is applied else next loading is applied at 0.2 mm in first one hour or till two hours whichever occurs the first. The PLT is continued till the settlement is within the permissible limit of 12 mm. The test load is maintained for 24 hours. PLT is conducted on maximum 2% of the total number of piles for a routine test (one and half times the design load); whereas, on maximum two piles in the case of an initial test (two times the design load). The load test performed on rock-socketed piles is interpreted as per IS 14593 (1998).

III. GEOLOGY OF MUMBAI

The geology of the Mumbai region comprises considerable amounts of evolved rock types such as Basalts, Breccias, Rhyolites, Trachytes and Felsic and basic Tuffs. The lava

flows in the major part of the Deccan Trap occur as nearly horizontal sheets, each flow is ranging in the thickness from about 10 m to 30 m. They are formed as sub-aerial eruption and are all Basaltic in composition. The different types of formation process have led to different types of rocks. Some rocks are formed from magmatic gases that produce gas cavities. This sometimes chemically alters the basalts and the rendered, Hydrothermal Alterations (HTA) are poor in quality.

Tachylitic basalts are formed as very fine-grained variety since their degree of crystallization is very low and they consist mostly of basalt glass. Tuff is formed by the process of ejection of consolidated volcanic ash ejected from vents during a volcanic eruption.

The geology of the Mumbai region made of the Deccan Trap formation primarily comprises basalts. Sethna (1999) classified the Deccan basaltic flow and associated pyroclastic and plutonic rocks as Sahyadri Group. The rock type Basalt exists in two variations; compact and amygdaloidal basalt. The compact Basalts are always jointed and are never massive. On the other hand amygdaloidal basalts are always unjointed.

IV. OVERVIEW OF ADOPTED METHODS

The methods adopted in the present analysis for the development of the proposed model are detailed below.

A. Load transfer method for analysis of load-settlement response

The load-settlement (P-δ) response is computed using the proposed model. In order to derive the input parameters to train the network using the engineering properties derived using geotechnical investigation, Kulkarni and Dewaikar (2017) method is referred. This method, based on the load transfer technique, is derived using the step-by-step procedure of Kiousis and Elansary (1987). The springs in this method are based on O'Neill and Hassan (1994) criteria to develop the non-linear hyperbolic load-settlement response.

The factors affecting the load-settlement behavior are detailed below (Kulkarni and Dewaikar, 2016 and Kulkarni and Dewaikar, 2017).

The non-linear hyperbolic q-z relationship as per O'Neill and Hassan's (1994) criterion is represented in the following expression.

$$q_p = \frac{w_n}{\dfrac{2.5D}{E_m} + \dfrac{w_n}{q_{max}}} \tag{1}$$

where,
w_n = vertical displacement at the tip of the nth element
q_p = unit point resistance at the pile base and
D = diameter of pile
E_m = modulus of elasticity of rock mass
q_{max} = limit point resistance
The value of E_m is derived based on compressive strength, σ_c, of intact rock using the following expression (Kulkarni and Dewaikar, 2017).

$$E_m = 267\, \sigma_c^{0.5} \tag{2}$$

The value of q_{max}, based on compressive strength, σ_{cm}, of rock mass is expressed by the following relationship (Kulkarni and Dewaikar, 2016).

$$q_{max} = 3\sigma_{cm}^{0.5} \tag{3}$$

Eq. (4) represents the expression for σ_{cm} derived from compressive strength, σ_c of intact rock (Zhang, 2010).

$$\frac{\sigma_{cm}}{\sigma_c} = 10^{0.013RQD-1.34} \tag{4}$$

The non-linear hyperbolic t-z relationship for shearing stress distribution along an element for the socket material extending up to the socket length, L_s as per O'Neill and Hassan (1994) criterion is adopted as per the following expression.

$$f_s = \frac{w(Z)}{\dfrac{2.5D}{E_m} + \dfrac{w(Z)}{f_{max}}} \tag{5}$$

where,
f_s = unit skin friction in the pile socket and
$w(Z)$ = vertical displacement at depth Z
f_{max} = limit skin friction in socket = $0.2\sigma_{cm}^{0.5}$ (Kulkarni and Dewaikar, 2016)

The non-linear hyperbolic t-z relationship for shearing stress distribution along an element for the weathered stratum as per O'Neill and Hassan (1994) criterion is represented using the following expression.

$$f_w = \frac{w(Z)}{\dfrac{2.5D}{E_m} + \dfrac{w(Z)}{f_{wmax}}} \tag{6}$$

where,
f_w = unit skin friction in the weathered stratum and
f_{wmax} = limit skin friction in the weathered stratum
Cole and Stroud (1977) recommend f_{wmax} to be 0.3 times the shear strength.

Eq. (7) represents the axial load, P at the mid-height of each element.

$$P = \int_{Z=0}^{L} 0.5\Pi(Z)t(Z)dZ + Q \tag{7}$$

where,
L = length of pile
$\Pi(Z)$ = perimeter of the pile at depth Z
$t(Z)$ = shear stress distribution in the pile for the respective stratum
Q = tip load acting on pile cross-sectional area, $A_b = A_b\, q_p$
The pile elastic compression, Δ_i is computed as per Eq. (8) for the ith element along depth Z.

$$\Delta_i = \int_{Z_i}^{L} \frac{P}{2A_b E_p}dZ \tag{8}$$

Where,
E_p = modulus of elasticity of pile
The vertical displacement, $w(Z)$ at the mid-height of each element is estimated as per the following expression.

$$w(Z) = w_n + \int_0^L w_i(Z)dZ + \int_0^L \Delta_i(Z)dZ \tag{9}$$

B. Artificial Neural Network

In the present study, Feed Forward Network (FFN) comprising Multi-layer Perceptrons (MLPs) architecture is

used. The proposed MLP comprises an input layer, one or more hidden layers and an output layer. Each layer comprises neurons which form the processing element. Fig. 1 depicts a typical neuron (processing unit). McCulloch and Pitts (1943) were the first to design an elementary computing neuron.
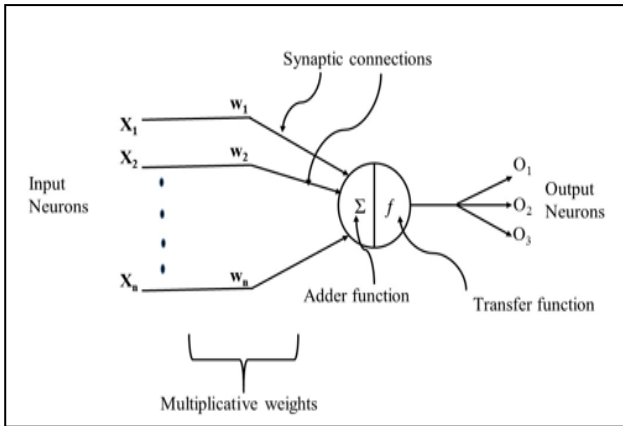

Fig. 1.   A typical neuron

Initially, random values of synaptic weights and biases are generated. The matrix multiplication is performed between input and the synaptic weights and their corresponding biases are summed to this product (Maizir and Kassim, 2013). This adder function is expressed as:

$$I_{j} = \sum_{i=1}^{n} w_{ji} x_{i} + \theta_{j} \qquad (10)$$

Where,

w_{ji} = synaptic weights at node j and input i

x_{i} = normalized input

θ_{j} = biases for node j

Nonlinearity is introduced in terms of transfer function $f(I_j)$. The transfer function is operated on this product-sum to estimate output of the neurons in the hidden layer. The types of transfer functions used in the present study are represented by Eqs. (11) and (12).

- Log-sigmoid

$$f(I_j) = \frac{1}{1 + \exp(-I_j)} \qquad (11)$$

- Hyperbolic tangent

$$f(I_j) = \tanh(I_j) \qquad (12)$$

Figs. 2 and 3 show typical variation of log-sigmoidal and hyperbolic tangent curves.
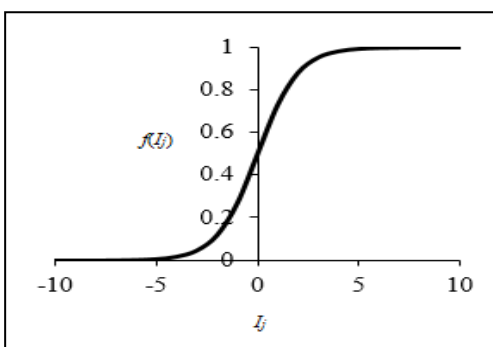

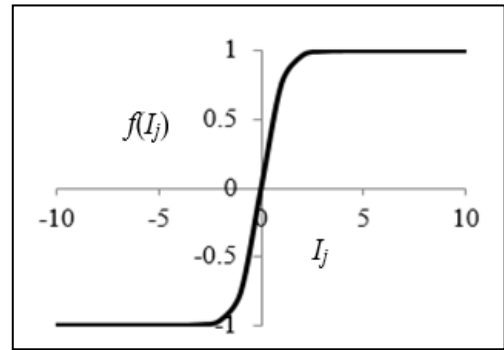Fig. 2.   A typical variation of log-sigmoidal curve in the range of 0 to 1

Fig. 3.   A typical variation of hyperbolic tangent curve in the range of -1 to 1

The non-linear matrix operator, Γ, maps the input space (x) to the output space of hidden layer (y). The matrices of these operations are indicated next (Zurada, 1996). The operator from input to hidden layer is represented by the following expression.

$$y = \Gamma\,[wx] \qquad (13)$$

Eq. (14) represents the input space.

$$x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_j \end{bmatrix} \qquad (14)$$

Eq. (15) represents the output of hidden layer.

$$y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_k \end{bmatrix} \qquad (15)$$

The connection weights at the input to hidden layer are represented by the following matrix.

$$w = \begin{bmatrix} w_{11} & w_{12} & . & . & . & w_{1j} \\ w_{21} & w_{22} & . & . & . & w_{2j} \\ . & . & . & . & . & . \\ wk_1 & wk_2 & . & . & . & w_{kj} \end{bmatrix} \qquad (16)$$

The nonlinear diagonal operator $\Gamma\,[.]$ is represented by the following expression.

$$\Gamma\,[.] = \begin{bmatrix} f(.) & o & . & . & . & . & o \\ o & f(.) & . & . & . & . & o \\ . & . & . & . & . & . & o \\ o & o & . & . & . & . & f(.) \end{bmatrix} \qquad (17)$$

Further, the matrix operator maps the output space (o) from y using the connection weights (v).

$$o = \Gamma\,[vy] \qquad (18)$$

The output space is represented as,

$$o = \begin{bmatrix} o_1 \\ o_2 \\ . \\ . \\ . \\ o_r \end{bmatrix} \qquad (19)$$

The connection weights at the hidden layer to output layer are represented by the following matrix.

$$[v] = \begin{bmatrix} v_{11} & v_{12} & . & . & . & . & v_{1k} \\ v_{21} & v_{22} & . & . & . & . & v_{2k} \\ . & . & . & . & . & . & . \\ . & . & . & . & . & . & . \\ v_{l1} & v_{l2} & . & . & . & . & v_{kj} \end{bmatrix} \qquad (20)$$

FFN is employed in the present study. The structure (topology) of the network consists of three main components: input neurons, neurons in the hidden layer and output neuron (Beltratti et al., 1996). The parameters and their numbers to be chosen as input depend on the problem definition.

The final output is compared with target output for n patterns and the difference between the two values represents error, E estimated as:

$$E = y_m - y_p \qquad (21)$$

Where,

y_m = normalized predicted output and

y_p = normalized target output

Neural networks with various neurons are studied. The output predicted by this FFN is compared with the desired target and the error is computed. This error is minimized by optimizing the synaptic weights and biases. This is attempted using GA.

C. Genetic Algorithm

GA is a probabilistic algorithm developed by Holland (1975) based on biological genetics and natural selection which is primarily Darwin's theory of 'survival of the fittest'. GA are a subset of Evolutionary Algorithms which are a subset of Guided random search techniques. GA has the capability of converging to the global optima and at a much faster rate compared to ANN. It basically has five stages namely, generation of the initial population, evaluation of fitness function, selection, cross-over and mutation. Large population is chosen so that it is not trapped into a local minimum. The fitness (objective) function sets the criterion for processing combinations of the individuals to generate fitter solutions. The selection criterion sets the acceptance of qualified individuals and their off-springs. The crossover stage marks the combination of genes of the parents to form off-springs. At the mutation stage, the values of these genes are altered. The termination criterion for this algorithm is reached either when the objective function is satisfied or at the end of a pre-defined number of generations. In this study, the synaptic weights are optimized using commercially available GA software, SolveXL Version: 1.0.5.2. The SolveXL is a tool which works as "Add-in" to Excel Worksheet. The analyses of the hybrid model is performed by altering the GA operators.

V. DEVELOPMENT OF SIMULATION MODEL

The input parameters are chosen based on the analyses of data for Mumbai region (Kulkarni and Dewaikar, 2016 and Kulkarni and Dewaikar, 2017). In the present study, the topology comprises one input layer, one hidden layer and one output layer. Each layer has neurons or nodes. The error estimated using FFN is minimized using GA.

A. Selection of input and output parameters

The input and output parameters are selected based on the discussion on load transfer mechanism given earlier.

As per Eqs. (1), (2), (3), (5), and (7)

$$P/\delta \propto D, E_m \text{ and } \sigma_{cm} \qquad (22)$$

Further, from Eqs. (6) and (7)

$$P/\delta \propto f_w \qquad (23)$$

Eqs. (7) and (9) show,

$$P/\delta \propto L, L_s, L_w \qquad (24)$$

The following relationship is derived from Eqs. (8) and (9)

$$P/\delta \propto E_p \qquad (25)$$

Thus, the design variables are, D, E_m, σ_{cm}, L_s/D, L_w/D, f_w, L/D and E_p. In addition to these, the parameter X, from Paikowsky and Tolosko (1999) method is included in the present study to give due weightage to geometry of the pile. The load increments applied during the pile load test are also considered as input parameters and corresponding settlement forms the output parameter.

B. Data Normalization

The transfer functions require the data to be in the range of 0 to 1. Also, for faster learning rate the data range is scaled to the interval of 0 to 1.

The input parameters are normalized using the following expression:

$$N = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \qquad (26)$$

Where,

N = normalized value

X = actual value of an input parameter

X_{min} = minimum value from the range of an input parameter

X_{max} = maximum value from the range of an input parameter

C. Data Division

Based on statistical significance, data is divided and 67% of the cases are considered for training of the network and 33% for testing for each pile diameter.

D. Topology

In the present study, Feed Forward Network is employed comprising one input layer with fourteen neurons, one hidden layer with three to nine hidden neurons and one output layer with five neurons. The biases are added to the neurons in the hidden layer and the output layer. Fig. 4 shows a typical topology of 14-7-5 adopted in the present study.
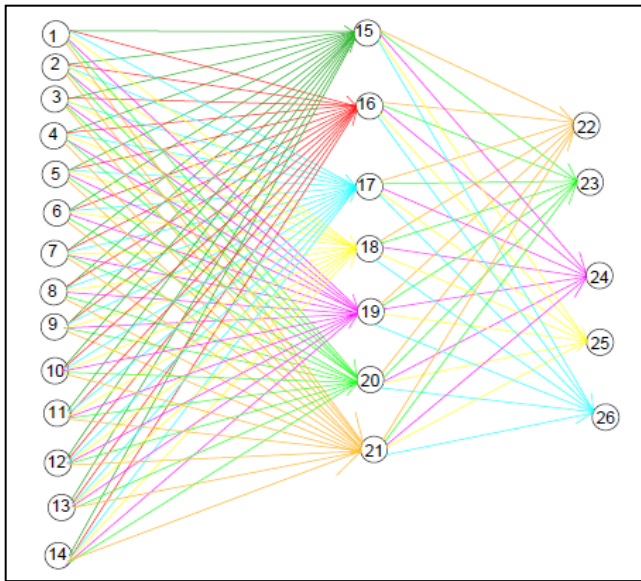
Fig. 4. A typical topology 14-7-5 adopted in the present study

E. Optimisation by Genetic Algorithm

The neural network is trained through the presentation of a series of input patterns and associated target output values using GA. The main operators are initialization, evaluation, selection, cross-over and mutation. Random population of chromosomes is generated and selected for reproduction based on survival of the fittest theory. The population size, the number of generations and the number of genes (decision variables) are problem-specific. Various iterations are performed for the population sizes of 20, 50, 75, 100 and 200. A smaller population size leads the solution to converge to local minima. The number of generations was varied at 50, 100, 200, 500 and 1000.

The unknowns, synaptic weights and biases are determined using the fitness function. The Root Mean Square Error (RMSE) value is defined as the fitness function and is calculated using the following expression for a total number of 'n' patterns.

$$RMSE = \frac{1}{n}\sqrt{\sum_{i=1}^{n}\left((y_m - y_p)^2\right)} \qquad (27)$$

Where,

d_{Actual} = settlement measured from PLT

$d_{Predicted}$ = settlement estimated using proposed model

The probability of being selected is given by its fitness. The higher the fitness, the higher is the chance of being selected. In the selection process, solutions are selected for progression to the next generation. Roulette by Rank is adopted in which, the population is first sorted. Based on the rank of the individual, it is assigned a probability of selection. The selected individuals are determined as the wheel is spun. The larger proportion of the wheel indicates higher rank of the individual, thus indicating greater chance of the individual to undertake mating. Roulette by Rank was utilized to produce

two off springs from two parents to have a robust and consistent network.

The chromosome gene range is varied between -1 to 1; -2 to 2; -5 to 5; -8 to 8 and -15 to 15. Generational Elitist algorithm is adopted in the analyses in which entire population is created using selection, crossover and mutation for candidate chromosomes and the top one or two solutions are retained.

Simple multi-point cross over is adopted to retain the resemblance to head and tails of the robust parents. The child gets the genes of the parents of chromosome A before the multiple points selected along the chromosome. After this cross-over point, the child gets the genes of parents of chromosome B. Based on the cross-over rate, the parents to mate is randomly selected. The crossover probability of 0.95 is applied.

Mutation simulates the errors in the transmission of a genetic material from one generation to the next. Mutation operator is performed on the number of chromosomes based on the mutation rate. The mutation rate is chosen as 0.05 having the mutator as simple by gene. The number of chromosomes that have mutations in a population is determined by the mutation rate parameter.

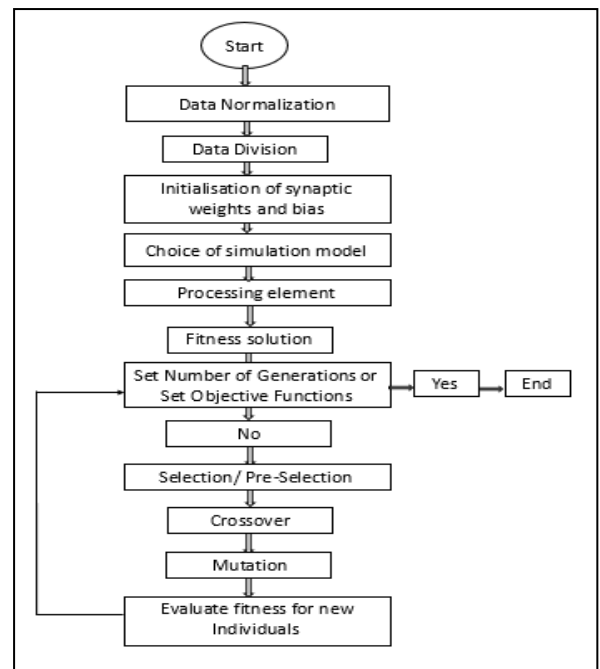A flowchart showing the steps adopted in the current methodology is shown in Fig. 5.

Fig. 5. Flowchart for simulation of load-settlement response using GA-based ANN

F. Validation

The optimized synaptic weights and biases obtained from the trained network are multiplied with a chosen set of 49 patterns and the network is tested for the prediction of target. The values of RMSE of the network at the testing stage are obtained by comparison between load-settlement response predicted by the proposed model with that of PLT to measure the performance of the proposed network.

VI. DATABASE

The load-settlement data of the pile load tests is collected from Basarkar (2004) and from various pile testing agencies namely, M/S Composites Combine Technocrats Pvt. Ltd., M/S STUP, M/S MMRDA, M/S Stephon, M/S SAFE and M/S Marina Pile Foundation.

The range of data considered for the study is presented in Table 1

TABLE I. RANGE OF INPUT PARAMETERS CONSIDERED FOR THE STUDY

Input Parameters	Maximum	Minimum	Average
L_s/D	10.0	0.5	3.8
L_w/D	12.0	0.0	3.4
L/D	36.4	6.6	16.7
σ_{cm} (MPa)	27.4	0.4	4.4
E_p (MPa)	33541.0	1750.0	26756.2
E_m (MPa)	2662.2	364.8	1183.1
D (m)	1.2	0.3	0.8
X (m)	0.044	0.0063	0.015
f_w (MPa)	0.3	0.1	0.2

VII. NETWORK PERFORMANCE

This section presents a comparison of P-δ obtained by PLT with the proposed method for various trials. The generations, population size and the range for variation of synaptic weights and bias are varied during these trials. The generations analyzed during the combinations are 50, 100, 150, 200 and 500. The population sizes are varied at 20, 50, 75, 100 and 200 for various models.

A. Population

Table 2 presents the variation of RMSE values for various trials of population sizes. It is seen that; the model is optimum with RMSE value of 0.0043 for population size of 200 individuals. This analysis is for chromosome limit set as -10 to 10.

TABLE II. VARIATION OF POPULATION FOR 14-5-5 MODEL WITH 500 GENERATIONS

Model	Population	RMSE
ANN14-C20	20	0.0055
ANN14-C50	50	0.0051
ANN14-C75	75	0.0053
ANN14-C100	100	0.0049
ANN14-C200	200	0.0043

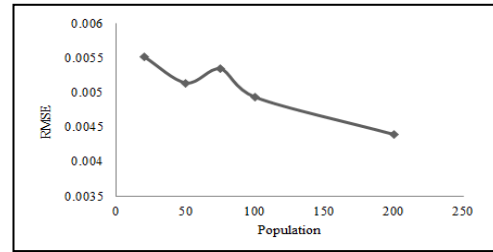Fig. 6 shows that, the model is optimum for the population size of 200 individuals.

Fig. 6. Variation of RMSE forvarious population sizes

Table 3 presents the variation of generations at 50, 100, 200 500 and 1000 individuals for the topology of 14-5-5. The population size for all the models is considered as 100 individuals. It is seen that, RMSE values for 500 and 1000 generations are about 0.0049. These values for 50, 100 and 200 generations are higher and hence, generations of 500 is considered to be the optimum.

TABLE III. VARIATION OF GENERATIONS

Model	Generations	RMSE
ANN14-D50	50	0.0057
ANN14-D100	100	0.0054
ANN14-D200	150	0.0056
ANN14-D500	200	0.0052
ANN14-D1000	500	0.0049

Fig. 7 shows suitability of the adopted model for 500 generations.
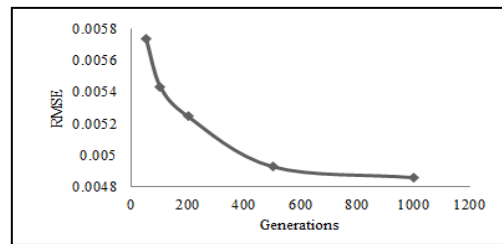

Fig. 7. Variation of RMSE for various trials of generations

B. Chromosome gene range

Table 4 shows the variation of chromosome gene range for the model 14-5-5. A population size of 100 individuals and 500 generations is considered for the analyses. It is seen that value of RMSE decreases to about 0.0044 for chromosome gene range of -5 to 5 thus indicating its suitability.

TABLE IV. VARIATION OF CHROMOSOME SETTING

Model	Chromosome settings	RMSE
ANN14-B1	-1 to +1	0.0053
ANN14-B2	-2 to +2	0.0051
ANN14-B5	-5 to +5	0.0044
ANN14-B8	-8 to +8	0.051
ANN14-B15	-15 to 15	0.0051

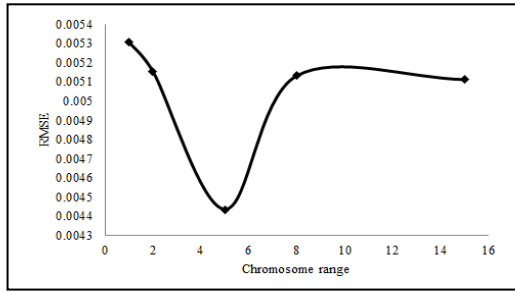Fig. 8 depicts the suitability of chromosome range of -5 to 5.

Fig. 8.   Variation of MARE with chromosome gene range

C. Number of neurons in the hidden layer

The topologies of 14-3-5, 14-5-5, 14-7-5, 14-9-5 and 14-11-5 are analyzed. In Table 5, the performances of these topologies are presented. The values of RMSE are varying in the range, 0.0049 to 0.0053. It is seen that these values drop till the number of neurons is 5; after which the values show an increase. This analysis is for chromosome limit set as -10 to 10. This indicates the suitability of the model 14-5-5.

TABLE V.   SUMMARY OF VARIATION OF NEURONS

Model	Topology	RMSE
ANN3	14-3-5	0.0051
ANN5	14-5-5	0.0049
ANN7	14-7-5	0.0049
ANN9	14-9-5	0.0053
ANN11	14-9-5	0.0049

D. Predicted Response

In Fig. 9, a good agreement is seen between P-δ response obtained by PLT and proposed method for the optimum model 14-5-5 at the training stage indicated by the RMSE value of 0.0043. The population size and number of generations are 100 and 500 respectively. The chromosome gene range is -10 to 10. Fig. 10 presents the P-δ response obtained by PLT and proposed method for the optimum model 14-5-5 at the testing stage. A close match is seen as indicated by the RMSE of 0.0095 at the recall stage.

VIII.   CONCLUSION

This study proposes a hybrid ANN model employing optimization tools of GA for the prediction of load-settlement response of rock-socketed piles in Mumbai region in the absence of pile load test data. The dataset of 148 pile load tests is used for the analyses. Based on the results, the topology of 14-5-5 is recommended. The data division is conducted using 67% of the data for training and 33% of the data for recall stage. The model is optimum for the chromosome gene range of -5 to +5 for the optimization of synaptic weights and biases. It is observed that the model ANN14-C200 gives the optimum RMSE values of 0.0043 and 0.0095 for training and recall stages respectively. Thus, a reliable performance of the proposed model is observed.
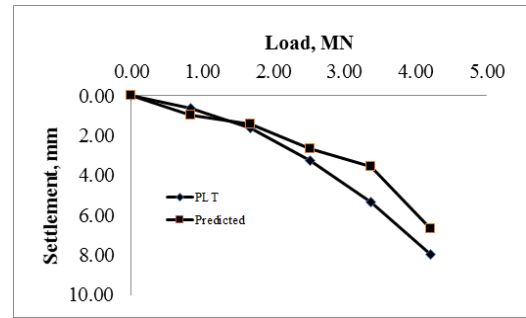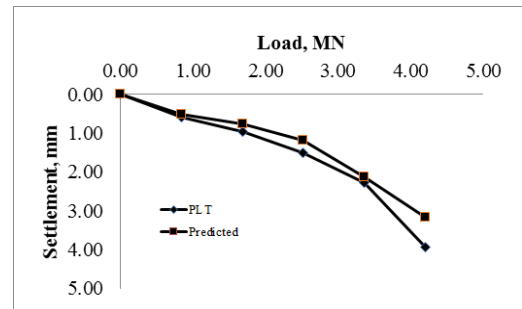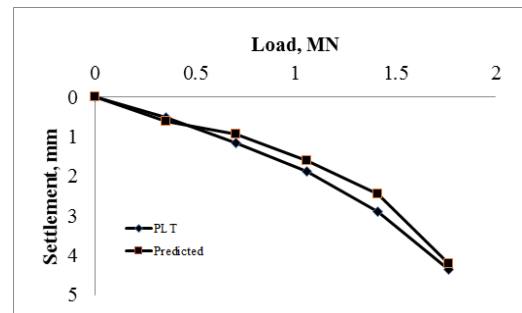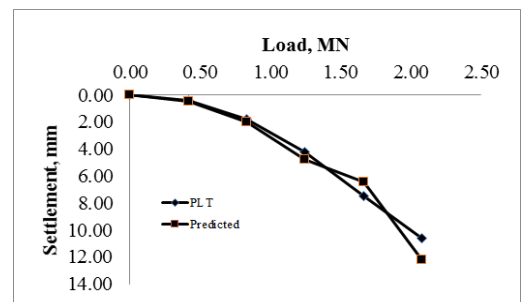

Fig. 9.(a)

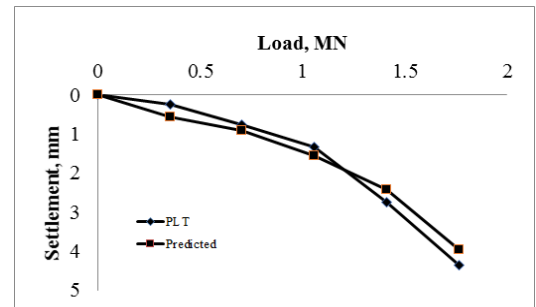Fig. 9. (b)

Fig 9 (C)

Fig. 9 (d)

Fig. 9 (e)

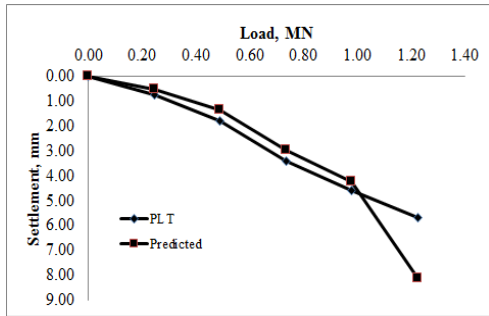Fig. 9.   Comparison of predicted and measured by PLT P-δ response for training stage for ANN14-C200

Fig. 10.(a)

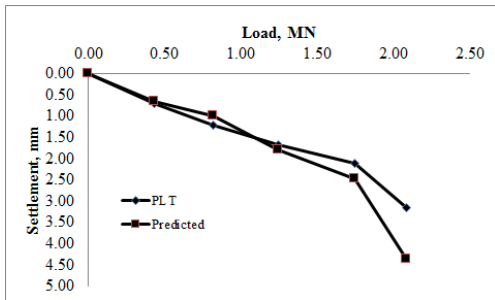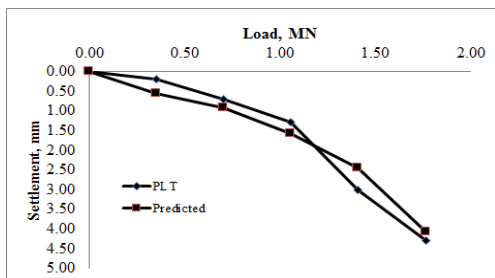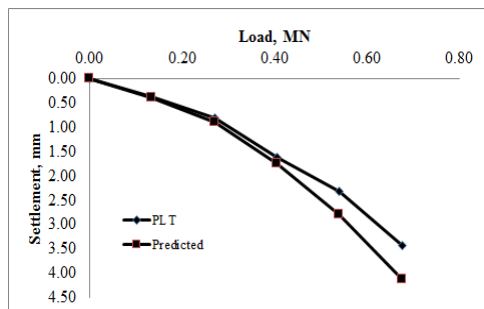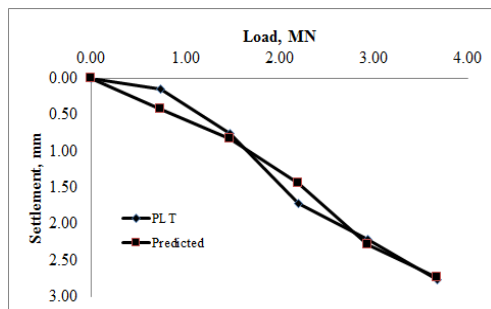Fig. 10 (b)

Fig. 10. (c)

Fig. 10 (d)

Fig.10 (e)

Fig. 10. Comparison of predicted and measured by PLT P-δ response for recall stage for ANN14-C200

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