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# Prediction of Interpreted Failure Loads of Rock-Socketed Piles in Mumbai Region using Hybrid Artificial Neural Networks with Genetic Algorithm

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***Abstract*— The pile capacity can be estimated using empirical, semi-empirical, numerical, analytical or experimental methods. Nevertheless, the capacities thus derived, vary depending upon the underlying assumptions. The static pile load test is the most accepted method for determining the failure load. However, due to time and cost constraints, a limited number of pile load tests are conducted. In the present study, the rock-socketed pile capacity is estimated using a hybrid model of Artificial Neural Network with Genetic Algorithm. The pile load test dataset of 148 patterns collected from the various sites of Mumbai region is used. The results obtained using the proposed method show an excellent agreement with the interpreted failure loads estimated using Paikowsky and Tolosko method.**

***Keywords*— Pile Load Test; Interpreted Failure Load; Artificial Neural Network; Genetic Algorithm; rock-socketed pile***

## I. INTRODUCTION

Several methods are available to compute the pile capacity based on analytical (Serrano and Olalla, 2002), empirical (Rosenberg and Journeaux, 1976; Horvath and Kenney,1979; Kulhawy and Goodman, 1980; Williams and Pells, 1981; Kodikara and Johnston, 1994; Zhang and Einstein, 1998; Basarkar and Dewaikar. 2005; Vipulanandan et al., 2007; Kulkarni and Dewaikar, 2016b), semi-empirical (Reese and O'Neill, 1989; Charles et al., 2001), numerical (Van der Veen, 1953; Hansen, 1963; De Beer, 1968; Chin, 1970; Davisson, 1972; Hirany and Kulhawy, 1988; Ahmad and Pise, 1997; De Court, 1999; Paikowsky and Tolosko, 1999) or experimental techniques (Rehnman and Broms, 1971; Benmokrane et al., 1994). Nevertheless, the capacities estimated using these methods would be different and hence, the static pile load test is perhaps the most accepted way of gauging the pile capacity.

The capacity is determined from the pile load test response based on distinct plunge or using various interpretation methods available in the case of non-plunging pile responses. The choice of a proper method for interpretation of the failure load based on pile load test plays a significant role (Fellenius, 2015). Kulkarni and Dewaikar (2016a) analysed a dataset of 53 cases collected from various sites of Mumbai region. They have reported that, Paikowsky and Tolosko (1999) method is suitable for the estimation of interpreted failure load as it gives optimum factor of safety. Hence, the results obtained using the proposed methodology are compared with those obtained using Paikowsky and Tolosko (1999) method.

However, owing to time and cost constraints, a limited number of pile load tests are conducted. Hence, need is felt to seek alternatives to estimate pile capacity. A hybrid model is proposed in the present analysis, using Artificial Neural Network (ANN) with the optimization tool of Genetic Algorithm (GA) to achieve this objective. Several researchers have reported pile capacity prediction using ANN and hybrid ANN techniques (Goh, 1994; Chan et al., 1995; Goh, 1995; Lee and Lee, 1995; Teh et al., 1997; Patil, 2000; Shahin et al., 2001; Basarkar, 2004; Goh et al., 2005; Maizir and Kassim, 2013; Benali et al., 2013 and Momeni et al., 2014). A detailed review of some of these methods is reported by Shahin (2016).

As of now, ANN models developed for the prediction of interpreted failure loads of rock-socketed piles have employed intact rock properties. However, the rock-socketed piles are supported by the surrounding rock mass and it would be rational to consider the effect of discontinuities (Pells and Turner, 1980; Zhang, 2005 and Zhang, 2010). The present study is distinct from the previous work in which, an attempt is made to arrive at interpreted failure load based on the rock mechanics principles.

A rock-socketed pile load test dataset of 148 cases is collected from various sites of Mumbai region. The dataset is analyzed and validated using the proposed hybrid model using supervised learning technique.

## II. GEOLOGY OF MUMBAI

Deccan trap forms the major geologic formation of Mumbai region. Basalt is the predominant rock-type. Mumbai region comprises considerable amounts of evolved rock types such as Breccia, Rhyolite, Trachyte and Felsic and basic Tuff. The Deccan basaltic flow and associated pyroclastic and plutonic rocks evolved under the geologic formation of Mumbai region are classified under the Sahyadri Group (Sethna 1999). 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.

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. 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. Overview of the methods used for development of the proposed model

The hybrid method adopted for developing the proposed GA-based ANN model for the estimation of interpreted failure load are detailed below.

*A. Interpreted failure load*

Interpreted failure loads computed using the proposed hybrid model is compared with the interpreted failure loads estimated using Paikowsky and Tolosko (1999) method since it gave optimum Factor of Safety (FOS) as mentioned earlier. However, this method requires pile load test data.

Nevertheless, in order to train the network using input parameters obtained from routine Geotechnical investigation, Kulkarni and Dewaikar (2016b) method is employed.

The methods are described in this section.

*1) Paikowsky and Tolosko (1999) method using pile load test data*

Paikowsky and Tolosko (1999) method is derived based on following two assumptions.

- The inverse of the slope of settlement ($\Delta$)/load ($P$) vs. $\Delta$ yields the failure load (Chin, 1970).
- The failure corresponds to the settlement at the point of intersection of Davisson offset line with the load-settlement curve (Davisson, 1972).

In Fig. 1, the linear response generated from a typical plot of $\Delta/P$ vs. $\Delta$ is shown. This linear relationship is expressed by Eq. (1).

$$\frac{\Delta}{P} = a\Delta + b \tag{1}$$

Where,

$a$ = slope of the line

$b$ = intercept of the line

Fig. 2 shows Davisson (1972) offset line represented by Eq. (2) for a pile diameter, $D$, pile length, $L$, pile cross-sectional area, $A_p$ for a pile material with modulus of elasticity, $E_p$.

$$\Delta = X + S\,P \tag{2}$$

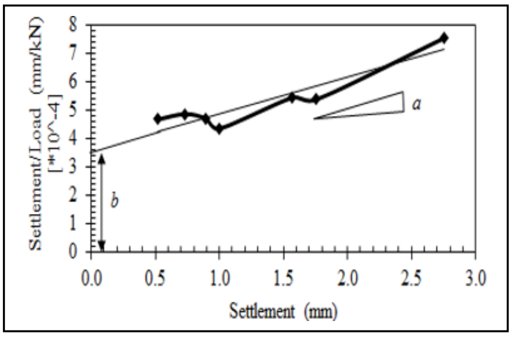


Fig. 1. A typical plot of Paikowsky and Tolosko (1999) method

The slope, $S$ and intercept, $X$ of Davissons's (1972) offset line are represented in Eqs. (3) and (4) or (5).

$$S = L/E_pA_p \tag{3}$$

Kyfor et al. (1992) recommend Eqs. (4) and (5) for $D$ < 610 mm and $D$ > 610 mm respectively

$$X = 3.8 + \frac{D}{120} \tag{4}$$

$$X = 3.8 + \frac{D}{30} \tag{5}$$

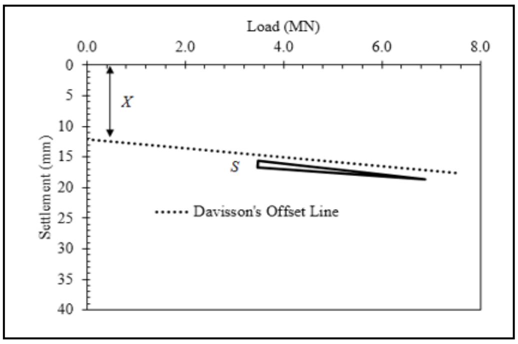


Fig. 2. A typical plot showing offset and slope of Davisson's (1972) method

The interpreted failure load, $P_{METH}$ is expressed by Eq. (3).

$$P_{METH} = \frac{-B \pm \sqrt{B^2 + 4AX}}{2A} \tag{6}$$

Where,

$B = aX+b-S$ and

$A = aS$

*2) Kulkarni and Dewaikar (2016b) method using Geotechnical Investigations data*

The following expression is employed for estimating the interpreted failure load, $Q_i$ (Kulkarni and Dewaikar, 2016b).

$$Q_i = A_wf_w+A_sf_s+A_pq_p \tag{7}$$

Where,

$A_w$ = surface area of pile in the weathered stratum

$A_s$ = surface area of pile in the socket material

$f_w$ = unit skin friction in the weathered stratum

$f_s$ = unit skin friction in the socket material

$q_p$ = unit pile tip resistance

The chart prepared by Cole and Stroud (1977) is used for estimating $f_w$. Eqs. (8) and (9) represent the expressions for estimating $f_s$ and $q_p$ (Kulkarni and Dewaikar, 2016b).

$$f_s = 0.2\sigma_{cm}^{0.5} \tag{8}$$

$$q_p = 3\sigma_{cm}^{0.5} \tag{9}$$

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In Eqs. (8) and (9), the value of $\sigma_{cm}$ is estimated using the relationship as per the following expression (Zhang, 2010).

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

Where,

$\sigma_{cm}$ = compressive strength of rock mass

$\sigma_c$ = compressive strength of intact rock

## B. *Artificial Neural Network*

ANN is a type of machine learning technique which finds applications for non-linear input-output relationships. In this, the nervous system is simulated to seek solutions to problems in terms of supervised, unsupervised or reinforced learning. It comprises mainly two components: neurons and connection weights (Zurada, 1992).

### 1) *Processing element*

A neuron is necessarily the processing element. The normalized value of the input neurons are multiplied with the synaptic weights and bias is added to this product (Maizir and Kassim, 2013). In Fig. 3, a pictorial representation of a typical neuron is shown.

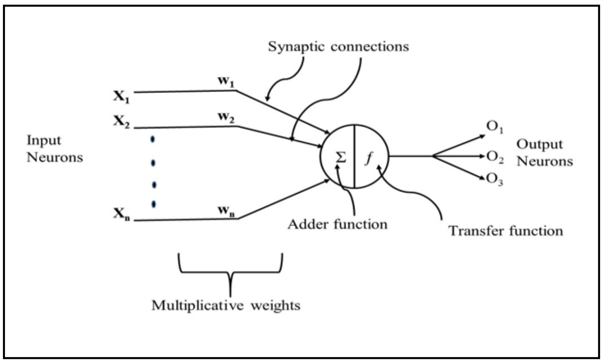


Fig. 3. A typical neuron

### 2) *Adder Function*

An adder function is operated as the matrix multiplication between the input neurons and synaptic weights. A bias is added to this product so that, it is transferred from the origin. Eq. (11) represents these two operations.

$$I_j = \left( \sum_{i=1}^{n} w_{ji} x_i \right) + \theta_j \tag{11}$$

Where,

$I_j$ =activation level at node $j$

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

$x_i$ = normalised input at node $i$

$\theta_j$ =bias at node $j$

### 3) *Transfer (activation) function*

An activation (squashing or transfer) function is operated in order to squash the amplitude of the output neuron. The transfer function, $f\,(I_j)$ performs the operation of introducing nonlinearity. Eq. (12) shows the output of the neuron derived by performing transfer function operation on adder function.

$$y_j = f\left(I_j\right) \tag{12}$$

Where,

$y_j$ = output at node $j$

In this paper, the activation functions of log-sigmoid or hyperbolic tangent are used as transfer functions. The two main attributes of activation function are the existence of the threshold and setting upper and lower boundaries. Eqs. (13) and (14) present the types of transfer functions adopted in the present study.

- Log-sigmoid

$$f(I_j) = \frac{1}{1+\exp(-I_j)} \tag{13}$$

- Hyperbolic tangent

$$f(I_j) = \tanh(I_j) \tag{14}$$

### 4) *Network Topology*

Feed Forward Network (FFN) is employed in the present study. The structure (topology) of the network consists 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 input neurons do not process any signals and perform the operation of passing information to the hidden layer. The neurons in the hidden layers receive the signals from input layer and process them through the adder and the activation functions and pass it to the output layer. The neurons in the output layer also process the signals through adder and activation functions.

The network receives the inputs which are multiplied by the connection weights. The bias is added to the product. The output is generated by passing the adder function through transfer function of log sigmoidal which produces a layer of hidden neurons. These are again multiplied by the connection weights and the product is added to the threshold value. The signal received from the hidden neurons is then operated by the transfer function, hyperbolic tangent, to produce the output. Here the FFN ends. The final output is compared with target for *n* patterns and the difference between the two values represents error, *E* estimated as:

$$E = y_m - y_p \tag{15}$$

Where,

$y_m$ = normalised predicted output

$y_p$ = normalised target output

This error is optimized (minimised) using GA.

## C. *Genetic Algorithm (GA)*

GA is a powerful technique developed by Holland (1975) based on the concept 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 (Mitchell, 1996). 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 for the acceptance of qualified individuals and their off-springs. The crossover stage marks the combination of genes of the parents to form off-springs by altering the values of genes. In

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mutation stage, the values of genes are flipped from 1 to 0 or vice-versa in order to safeguard the useful genes that may be lost in selection and/or cross-over stage. The termination criterion for this algorithm is reached either when the objective function is satisfied or at the end of 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.

## III. PROPOSED HYBRID MODEL

The proposed model is developed using FFN. The input parameters are chosen based on the analyses of data for Mumbai region (Kulkarni and Dewaikar, 2016a and Kulkarni and Dewaikar, 2016b). Their analyses recommend $P_{METH}$. The synaptic weights and bias are initialized in the first step. 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 minimised using GA.

### A. *Selection of input and output parameters*

The input and output parameters are selected based on the discussion of interpreted failure load given earlier.

As per Eq. (6), $P_{METH}$ is proportional to $X$ and $S$ and is represented as,

$$P_{METH} \propto X, S \tag{16}$$

Using the previously defined expression for the slope, $S$, of Davisson's offset line,

$$P_{METH} \propto X, \frac{L}{E_p A_p} \tag{17}$$

Or,

$$P_{METH} \propto X, \frac{L}{D}, E_p \tag{18}$$

Expanding Eq. (7),

$$Q_i = \frac{\Pi}{4} D^2 q_p + \Pi D L_s f_s + \Pi D L_w f_w \tag{19}$$

Substituting Eqs. (8) and (9), the above equation becomes,

$$Q_i = \frac{\Pi}{4} D^2 (3\sigma_{cm}^{\ 0.5}) + \Pi D L_s (0.2\sigma_{cm}^{\ 0.5}) + \Pi D L_w f_w \tag{20}$$

Or,

$$Q_i \propto D, \sigma_{cm}, \frac{L_s}{D}, \frac{L_w}{D}, f_w \tag{21}$$

Thus, the design variables are, $D$, $\sigma_{cm}$, $L_s/D$, $L_w/D$, $f_w$, $X$, $L/D$ and $E_p$. In addition to these, modulus, $E_{ms}$ of elasticity of rock mass in socket is included in the present study to give due weightage to rock-mass properties. The interpreted failure load, $P_i$ predicted by proposed hybrid model is the output parameter.

### B. *Data Normalization*

The input/output parameters are normalized using the following expression.

$$N = \frac{U - U_{min}}{U_{max} - U_{min}} \tag{22}$$

Where,

$N$ = normalised value

$U$ = actual value of an input/output parameter

$U_{min}$ = minimum value from the range of input/output parameter

$U_{max}$ = maximum value from the range of input/output parameter

### C. *Data Division*

Based on statistical significance, the data is divided and 54% of the patterns are considered for training of the network and 46% for testing for each pile diameter.

### D. *Topology of FFN*

To develop this network, FFN is used comprising one input layer with nine neurons, one hidden layer with three to thirteen neurons and one output layer with one neuron. The bias is added to the neurons in hidden layers and output layer. In Fig. 4, a typical topology of 9-9-1 adopted in the present study is shown.

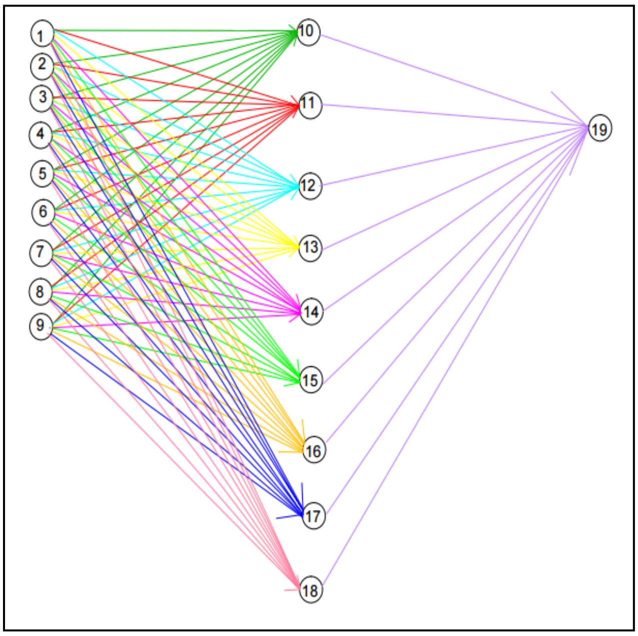


Fig. 4. Topology 9-9-1 adopted in the present study

### E. *Optimization by GA*

The learning of the hybrid network ANN with GA is based on the optimization of synaptic weights and bias. The output is compared with the target and the error is estimated. Further, back propagation to minimise the error is attempted using GA. The objective function is aimed to be minimized by optimization of synaptic weights and bias using GA.

Iterations are performed for the population size of 50 to 200. A smaller population size leads the solution to converge to local minima. In Table 1, the GA parameters adopted in the present study are shown. A decision variable contributes to a gene in GA. A chromosome is formed when all the genes are attached together. The gene type is adopted as Real bounded in SolveXL. The upper and lower bounds of the synaptic weights and bias are varied in the range of -1 to 1, -10 to 10 and -100 to 100 during various trials.

The interpreted failure load, $P_i$ is estimated by de-normalizing the output produced by the proposed model. $P_i$ is compared with $P_{METH}$ and the RMSE value is estimated. The performance of the proposed model is discussed later in this paper.

*F. The objective function : RMSE*

The RMSE is calculated using the following expression for *n* number of patterns.

$$\text{RMSE}=\frac{1}{n}\sqrt{\sum_{i=1}^{n}\left((y_m-y_p)^2\right)} \qquad (23)$$

In the training process, the network adjusts its weights on the basis of the patterns presented for learning, and finds a set of weights that produce input-output mapping with the least RMSE.

TABLE I. SUMMARY OF PARAMETERS ADOPTED IN THE SIMULATION MODEL

| Parameter | Trails performed for | Recommendations |
|---|---|---|
| Problem Type | Single/Multiple objectives | Single Objective |
| Population Size | 50,100,200 | 100 |
| Algorithm | Generational, Generational Elitist, Steady State, NSGA II | Generational Elitist |
| Cross-over | Simple one Point, Simple Multi-point, Uniform Random | Simple Multi-point |
| Cross-over Rate | | 0.95 |
| Mutator | Simple, Simple by Gene | Simple by Gene |
| Mutation Rate | | 0.05 |
| Mutation probability | | 0.25 |
| Chromosome Gene type | Integer Bounded, Real Bounded, Gray Integer Bounded, Gray Real Bounded | Real Bounded |
| Chromosome Range | -1 to 1<br>-10 to 10<br>-100 to 100 | -1 to 1 |
| Objective function | | Minimise Root Mean Square Error |
| Constraints | | - |
| Simulation | | - |
| Number of Generations | 50, 100, 500, 1000 | 500 |

*G. Validation*

The optimised synaptic weights and bias obtained from the trained network are multiplied with a chosen set of 67 patterns and the network is tested for the prediction of target. The RMSE of the network at the testing stage and the coefficient of determination, $R^2$ value obtained by comparison between $P_i$ and $P_{METH}$ measure the performance of the proposed network.

## IV. DATASET

The pile load test is conducted in Mumbai region in accordance with IS:2911, Part IV, (1985, Reaff. 2010). The database of 148 patterns 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. Table 2 provides the range of parameters considered in the study.

## V. NETWORK PERFORMANCE

This section presents a comparison of $P_i$ with $P_{METH}$ for various trials. The generations, the population size and the range are varied to optimize the synaptic weights and bias are varied during various trials. The generations analyzed during these combinations are 50, 100, 150, 200, 500 and 1000. The population size is varied at 20, 50, 75, 100 and 200.

TABLE II. 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 |
| $\sigma_{cm}$ (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 |

*A. Number of neurons*

The topologies of 9-3-1, 9-5-1, 9-7-1, 9-9-1 and 9-11-1 are analyzed. In Table 3, the performances of these topologies are presented. The values of RMSE are varying in the range, 0.01 to 0.0096. It is seen that these values drop till the number of neurons is 5; after which the value shows an increase for 11 number of neurons in the hidden layer. This analysis is for chromosome limit set as -5 to 5. The patterns are analyzed for population size of 100 individuals and 100 generations.

TABLE III. SUMMARY OF VARIATION OF NEURONS

| Model | Topology | RMSE | $R^2$ |
|---|---|---|---|
| ANN3 | 9-3-1 | 0.01 | 0.84 |
| ANN5 | 9-5-1 | 0.0093 | 0.86 |
| ANN7 | 9-7-1 | 0.01 | 0.84 |
| ANN9 | 9-9-1 | 0.0096 | 0.85 |
| ANN11 | 9-11-1 | 0.0096 | 0.85 |

Fig. 5 shows the variation of RMSE values with the number of neurons in hidden layer for population size of 200 individuals. Fig. 5 shows the variation of RMSE values with the number of neurons in hidden layer.

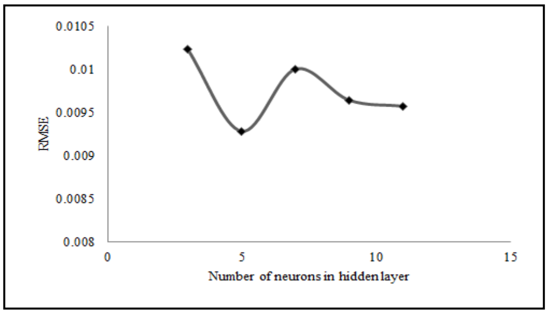


Fig. 5. Variation of RMSE with the number of neurons in hidden layer

Fig. 6 shows the variation of $R^2$ value with the number of neurons. The value of $R^2$ increases up to 5 neurons beyond which a decrease is observed. This indicates the suitability of the model 9-5-1.

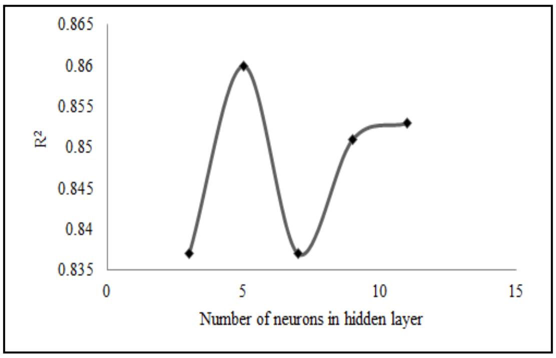


Fig. 6. Variation of $R^2$ with number of neurons in hidden layer

### B. Chromosome gene range

Table 4 shows the variation of chromosome gene range for the model 9-5-1. It is seen that the values of RMSE and $R^2$ decreases to 0.01 and 0.84 respectively for chromosome gene range of -10 to 10. The patterns are analyzed for population size of 100 individuals and 100 generations.

TABLE IV. VARIATION OF CHROMOSOME SETTING

| Model | Chromosome settings | RMSE | $R^2$ |
|---|---|---|---|
| ANN9-B1 | -1 to +1 | 0.0107 | 0.82 |
| ANN9-B2 | -2 to +2 | 0.0106 | 0.82 |
| ANN9-B5 | -5 to +5 | 0.011 | 0.83 |
| ANN9-B8 | -8 to +8 | 0.013 | 0.76 |
| ANN9-B10 | -10 to +10 | 0.01 | 0.84 |

### C. Population

Table 5 presents the variation of RMSE and $R^2$ values for various trials of population sizes. It is seen that; the model is optimum with RMSE and $R^2$ values of 0.0097 and 0.84 respectively for population size of 200 individuals.

TABLE V. VARIATION OF POPULATION

| Model | Population | RMSE | $R^2$ |
|---|---|---|---|
| ANN9-C20 | 20 | 0.011 | 0.801 |
| ANN9-C50 | 50 | 0.011 | 0.8 |
| ANN9-C75 | 75 | 0.0099 | 0.83 |
| ANN9-C100 | 100 | 0.0093 | 0.83 |
| ANN9-C200 | 200 | 0.0097 | 0.84 |

### D. Generation

Table 6 presents the variation of generations at 50, 100, 150, 200 and 250. It is seen that, RMSE value is least (0.0094) for 250 generations and the corresponding $R^2$ is maximum (0.86). Hence, the optimum number of generations is taken as 250. These analyses are for 9-5-1 for population size of 100 individuals and chromosome setting of -10 to 10.

TABLE VI. VARIATION OF GENERATIONS

| Model | Generations | RMSE | $R^2$ |
|---|---|---|---|
| ANN9-D50 | 50 | 0.014 | 0.77 |
| ANN9-D100 | 100 | 0.01 | 0.83 |
| ANN9-D150 | 150 | 0.0098 | 0.84 |
| ANN9-D200 | 200 | 0.0095 | 0.85 |
| ANN9-D500 | 250 | 0.0094 | 0.86 |

Based on these analyses, a model, A5B10C200D1000, with topology 9-5-1, population size of 200, 1000 generations and chromosome setting of -10 to 10 was developed. In Fig. 7, a good agreement is seen between $P_i$ and $P_{METH}$ ($RMSE$ = 0.0077) at training stage. The patterns where a large scatter is obtained beyond acceptable range are considered as bias cases.

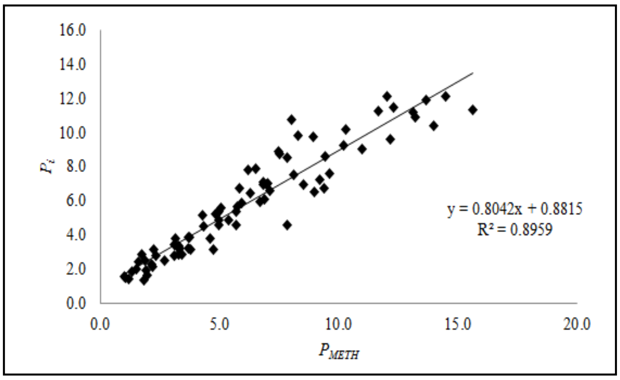


Fig. 7. Comparison of $P_{METH}$ with $P_i$ at training stage for model A5B10C200D1000

Fig. 8 shows a close match of $P_i$ with $P_{METH}$ at the recall stage. This is indicated by $R^2$ value of 0.8.

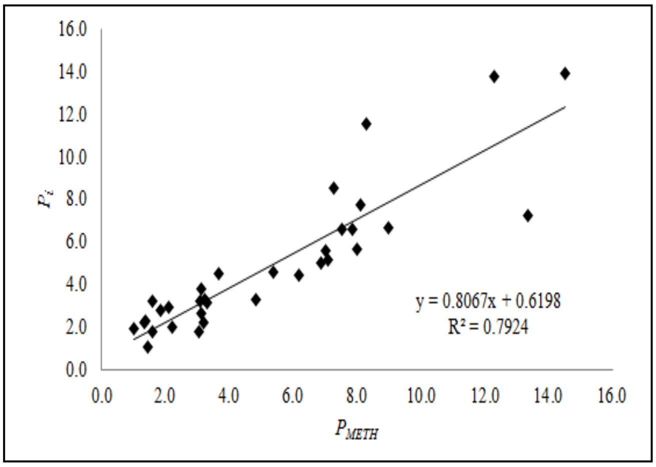


Fig. 8. Comparison of $P_{METH}$ with $P_i$ at recall stage for model A5B10C200D1000

### E. Sensitivity Analysis

The sensitivity analysis is performed to determine the influence of input parameters on the output. In the present study, the cosine amplitude method (Yang and Zang, 1997) is used. The following expression is used for the $k^{th}$ pattern to determine the most influential input parameters.

$$S_{ij} = \frac{\sum_{k=1}^{n}(x_{ij} * y_{jk})}{\sqrt{\sum_{k=1}^{n} x_{ik}^2 \sum_{k=1}^{n} y_{jk}^2}} \tag{24}$$

The value of $S_{ij}$ indicates the significance of the input parameter. If the value is zero, no relationship exists between input and output parameters and on the other hand, if the value is close to 1, a strong relationship is seen. Fig. 9 shows that, the parameters $D$ and the factor $X$ from Paikowsky and Tolosko (1999) method have a strong influence on the output based on output predicted by model A5B10C200D1000. The parameter $L_w/D$ shows least influence on the output.

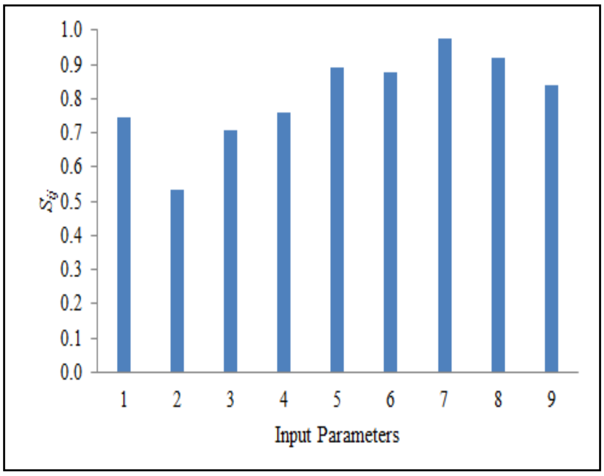


Fig. 9. Sensitivity Analysis based on predicted output by model ANN9-B10
Note: 1 = $L_s/D$; 2 = $L_w/D$; 3 = $L/D$, 4 = $\sigma_{cm}$; 5 =$E_p$; 6 =$E_{ms}$; 7 =$D$; 8 =$X$; 9 =$f_w$

## VI. CONCLUSIONS

This study proposes a hybrid ANN model employing optimization tools of GA for the prediction of interpreted failure load of rock-socketed piles in Mumbai region. The dataset of 148 pile load tests is used for the analysis. Based on the results, the topology of 9-5-1 is recommended. The data division is conducted using 54% of the data for training and 46% of the data for recall stage. The model is optimum for the chromosome gene range of -10 to +10 for the optimization of synaptic weights and bias. It is observed that the model A5B10C200D1000 gives the optimum RMSE value of 0.0077 and the value of $R^2$ is 0.9 for training stage thus indicating a reliable performance of the proposed model. The sensitivity analysis shows that, $L/D$, $L_w/D$ are least influential and $D$, $E_{ms}$, $E_p$, $X$, $\sigma_{cm}$, $f_w$ are contributing to $P_{METH}$ to a large extent.

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