Prediction of pile-separation length under vertical vibration using ANN

Sarat Kumar Das
Department of Civil Engineering, National Institute of Technology Rourkela, India

B. Manna
Department of Civil Engineering, Indian Institute of Technology Delhi, India

D.K. Baidya
Department of Civil Engineering, Indian Institute of Technology Kharagpur, India

ABSTRACT: This paper attempts to study the nonlinear soil-pile interaction under vertical vibration by both experimental and theoretical study. The field test results of single and group piles subjected to different excitation intensities are presented. The measured response is compared by the continuum approach of Novak with nonlinear solution. The soil properties of boundary zone and separation length at pile-soil interface used in this numerical methodology are fine-tunned by trial and error in order to match the experimental results. Artificial neural network (ANN) models are developed based on field test results and the pile separation length considered in the analysis. Different ANN models are developed using evolutionary learning algorithm and Bayesian regularization algorithm. Various statistical performance criteria are used to compare the developed ANN models. A sensitivity analysis is also made showing the effects of input.

1 INTRODUCTON

Pile foundations are widely used in weak soil deposits for supporting various structures. In addition to static loads, pile-supported foundations and structures are exposed to dynamic loads such as machine-induced vibrations, moving traffic, ocean waves and earthquakes. In recent years, with the development in the offshore structures technology and the nuclear power industry and other applications, the dynamic behavior of pile foundation has received a renewed attention.

Many methods, such as (i) using the concept of elastic subgrade reaction for obtaining equivalent soil springs, (ii) treating the pile problem as a case of one dimensional wave propagation in a rod, (iii) using the approximate continuum approach determining the stiffness and damping of the soil-pile system, were developed to achieve a direct and complete analysis of piles under dynamic conditions. The pile-soil interaction analysis based on the approximate continuum approach was originally proposed by Novak (1974), using plane strain soil reactions. This approach was extended by Novak and Aboul-Ella (1978) for piles in layered media such that the soil and pile properties can be different in individual layers. A complete set of dynamic interaction factors was proposed by Kaynia and Kausel (1982).

The artificial neural networks (ANN) are becoming more reliable than statistical method due to its special attributes of identifying complex system when the input and output are known from either laboratory or field experimentation. The network needs to be equally efficient for new data during testing or validation, which is called as generalization. There are different methods for generalization like early stopping or cross validation (Shahin *et al.* 2002; Das and Basudhar 2006). The 'learning' or 'training' process in ANN in general, is a nonlinear optimization of an error function. The aim of the training is to minimize the error function to get the optimized weight vectors. This is equivalent to the parameter estimation phase in conventional statistical models. The error function, most commonly used is the mean squared error (MSE) function. The error associated with weights and sigmoid function is a highly non-linear optimization with many local minima. Local and global optimization methods are carried out for finding out the weight vectors. The steepest descent algorithm and Levenberg-Marquardt (LM) algorithm which are gradient search algorithms are mostly used in ANNs applied to geotechnical engineering problems. As the characteristic of traditional nonlinear programming based optimization method are initial point dependent, the results obtained using back propagation algorithm are sensitive to initial conditions (weight vector) (Shahin *et al.* 2002). The use of global optimization algorithms like genetic algorithm and simulated annealing though being widely used in other field of engineering (Morshed and Kaluarachchi 1998), in geotechnical engineering use of GA for training ANN is limited (Goh 2002). Goh (2002) used GA to find out the optimum spread of probabilistic network for liquefaction analysis. In recent past another heuristic global optimization called differential evolution

(DE), introduced by Storn and Price (1995) is being used successfully in different engineering problems.

The available literature on test results with piles and pile groups subjected to dynamic loading is very limited due to the difficulties in conducting such dynamic tests on pile foundation. Dynamic tests have been performed previously on small-scale piles by some researchers (Novak and Grigg 1976, El Sharnouby and Novak 1984, Manna and Baidya 2009). Full scale dynamic tests on pile were conducted in the field by some researchers (Vaziri and Han 1991).

In the first part of the paper, the methodology and the dynamic test results on small prototype reinforced concrete pile groups (2 × 2) under vertical vibration are presented. Frequency versus amplitude curves of piles was experimentally established in the field. The test results are then compared with Novak's continuum approach (Novak and Aboul-Ella 1978) using nonlinear pile-soil model. In order to match the observed resonant frequency and amplitude, the soil properties of boundary zone and separation length at pile-soil interface used in this numerical methodology are fine-tunned by trial and error. In the second part, the artificial neural networks are used to develop a mathematical model based on the set of dynamic test results. In this study, ANN models using different training processes using DE algorithm and Bayesian regularization algorithm for training process are used for prediction of the separation length of pile.

2 SITE CONDITIONS AND PILE DATA

The field tests were conducted at the site which was located adjacent to Hangar, at Indian Institute of Technology, Kharagpur Campus, India. First soil samples were collected from three bore holes (BH) located at different places of the site. The subsurface investigation indicated that the test site was underlain by three different soil layers up to a depth of 2.80 m. Both laboratory and in situ tests were performed (Manna and Baidya 2009) to characterize the static and dynamic properties of the soil. In the in situ test consisted of standard penetration tests (SPT) to determine N value and cross-shole seismic tests for determining the shear wave velocity (V_s) of soil layer. The different soil profile and the variation of shear wave velocity of different soil strata are presented in Fig. 1.

The piles were constructed in the field by bored cast-in-situ method. The diameter of all the piles was 0.1 m and dimension of pile caps was 0.57 m × 0.57 m × 0.25 m. In total, twelve sets of pile were constructed. Three sets of single pile of three different lengths (L = 1.0 m, 1.5 m and 2.0 m) and nine sets of 2 × 2 group piles (Spacing s = 2d, 3d and 4d for each pile length L, where L = 1.0 m, 1.5 m and 2.0 m) were used for the investigation.
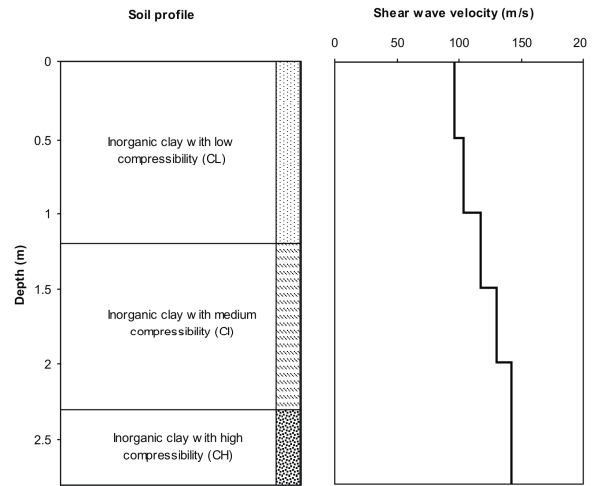

Fig. 1 Soil profile and the shear wave velocity profile with depth

3 VERTICAL VIBRATION TEST

Forced vibration tests were conducted on model piles subjected to vertical vibration. Lazan type mechanical oscillator was used to produce vibration. To ensure that the resonance peaks were well pronounced and within the frequency range of the exciting mechanism, mild steel ingots or test bodies were rigidly bolted on the top of the oscillator. The test body was comprised of steel ingots each weighing 650 N (8 nos) and 450 N (10 nos). Whole set up was then connected so that it acts as a single unit. Proper care was taken to keep the center of gravity of loading system and that of the pile cap in the same vertical line. A flexible shaft was used to connect the mechanical oscillator to a DC motor. The motor was connected to a speed control unit to control the speed of the DC motor. The vibration measuring equipment consisted of a two piezoelectric acceleration pickup and vibration meter. The schematic diagram of the experimental setup is shown in Fig 2. The methodology of vertical vibration tests of piles was described in Manna and Baidya (2009).

Two different static loads (W_s = 10 kN and 12 kN including the weight of the pile cap and oscillator) were used in both the cases. For each static load, tests were conducted at four different eccentric moments (M_e = $W \cdot e$ = 0.187, 0.278, 0.366, and 0.450 N m, where W is the weight of eccentric ro-

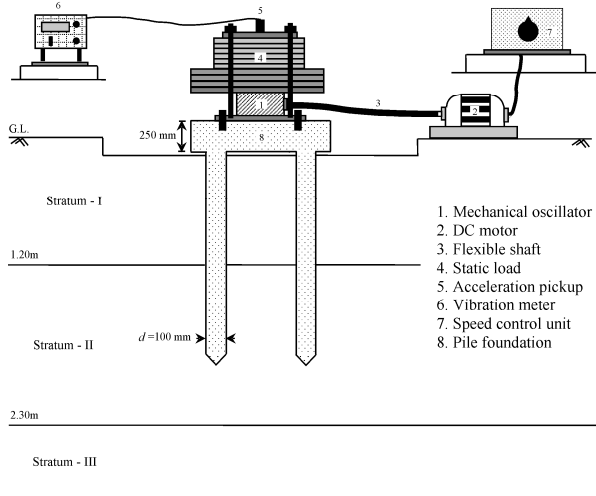tating part in oscillator and e is the eccentricity of the masses).

Fig. 2 Schematic diagram of test setup for vertical vibration

Steady state dynamic response to harmonic excitation was measured under different frequencies for all eccentric moments at each static load. All the tests were carried out for the following two different embedded depths (h) of pile cap: Case 1 - Pile cap embedded into soil ($h = 0.175$ m) and Case 2 - No contact of pile cap with soil ($h = 0$).

The observed response curves display nonlinearity as the resonant frequencies (f_r) decreases with increasing excitation intensity and also the amplitudes are not proportional to the excitation intensity. The complete vertical vibration test results of piles were presented in Manna and Baidya (2009).

4 COMPARISON WITH NOVAK'S CONTINUUM APPROACH

In this study the continuum approach proposed by Novak and Aboul-Ella (1978) are used to obtain the impedance of single pile embedded in layered medium. The pile group interaction analysis incorporated in this analysis is based on the practical concept of "interaction factors" proposed by Kaynia and Kausel (1982) for dynamic loading. The pile group impedances are calculated from the single pile impedances and the dynamic interaction factors in a rigorous manner, using closed-form formulae derived by Novak and Mitwally (1990). To account approximately for the effects of nonlinearity and slippage (Novak and Sheta 1980), it is assumed that an embedded cylindrical body is surrounded by a linear viscoelastic medium composed of two parts - an outer infinite region and an inner weak layer surrounding the cylindrical body. Soil nonlinearity, as well as the weakened bond and slippage are presumed to be accounted for by a reduced soil shear modulus and increased soil damping of the inner soil layer. The continuum model provides for the gradual expansion of the yielded zone around the pile and also the separation of pile and top layer of soil as the excitation level increase. For different excitation intensities, the soil parameter in the weakened zone and soil-pile separations are adjusted or fine-tuned so that the nonlinear theoretical response curves approach the observed results (Manna and Baidya 2010). The depth of anticipated separation (l_s) ranges from $1.8d$ ($= 0.18$ m) for $W \cdot e = 0.187$ N m to $2.4d$ ($= 0.24$ m) for $W \cdot e = 0.450$ N m. Comparison between the observed results and theoretical solutions for pile group ($L/d = 15$, $s/d = 2$, $W_s = 12$ kN, Case 2) are shown in Fig. 3.
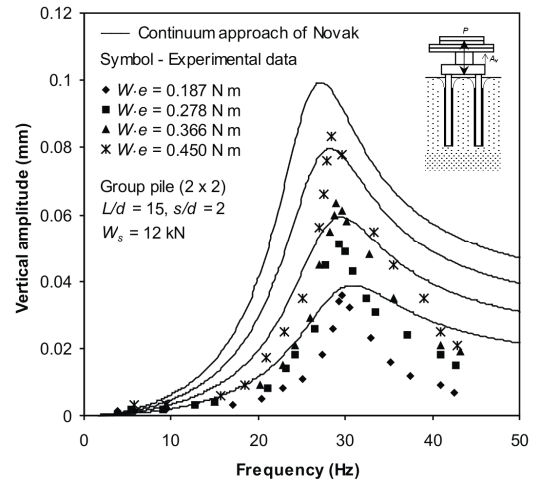

Fig. 3 Comparison of experimental results with Novak's continuum approach

It is observed that the predicted resonant frequency and amplitude are close to the experimental results. It can be said that Novak's model with varying boundary-zone parameters with depth and using the appropriate pile separation with soil, is capable to predict the resonant frequency and amplitude values accurately at all excitation levels.

5 BASIC PRINCIPLE OF ARTIFICIAL NEURAL NETWORK APPROACH

A typical structure of ANN consists of a number of processing elements or neurons that are usually arranged in layers; an input layer, an output layer and one or more hidden layers. The input from each processing element in the previous layer is

multiplied by an adjustable connection weight (w_{ji}). At each neuron, the weighted input signals are summed and a threshold value (b_j) is added. The combined input (I_j) is then passed through a nonlinear transfer function $\{f()\}$ to produce the output of processing element. Hence the output (y_k) from the output node can be written as

$$y_k = F(v_k) = F\left[\sum_{j=1}^{N_h} w_{kj} f\left[\sum_{l=1}^{N_l} w_{jl} x_1 + b_{j0}\right] + b_{k0}\right] \qquad (1)$$

The steepest descent algorithm and Levenberg-Marquardt (LM) algorithm which are gradient search algorithms are mostly used to minimize the error function to get the optimized weight vectors in geotechnical engineering problems (Das and Basudhar, 2006).

The test results presented in Manna and Baidya (2009) is used to develop models using artificial neural network (ANN). In the present study, the ANN models are trained with differential evolution and Bayesian regularization method and are defined as DENN and BRNN respectively. The results are compared with that obtained from commonly used Levenberg-Marquardt trained neural networks (LMNN) to discuss the prediction efficiency of the networks. The above neural network models have been developed using MATLAB tool boxes (Math Works 2001). A brief description about the BRNN and DENN is presented here for completeness.

5.1 Bayesian regularization neural network

The Bayesian regularization method the performance function is changed by adding a term that consist of mean square error of weights and biases as given below

$$\mathrm{MSEREG} = \gamma\,\mathrm{MSE} + (1 - \gamma)\,\mathrm{MSW} \qquad (2)$$

Where MSE is the mean square error of the network, γ is the performance ratio and

$$\mathrm{MSW} = \frac{1}{n}\sum_{j=1}^{n} w_j^2 \qquad (3)$$

This performance function will cause the network to have smaller weights and biases there by forcing networks less likely to be overfit. The optimal regularization parameter λ is determined through Bayesian framework (Demuth and Beale 2000). The above combination works best when the inputs and targets area scaled in the range [-1, 1] (Demuth and Beale 2000).

Based on field test results and the pile separation length considered in the continuum approach of Novak, artificial neural network (ANN) models are developed.

6 RESULTS AND DISCUSSION

The data base consists of dynamic parameters M_e, L/d, h and G_{s2}/G_{s1} (where, G_{s1} and G_{s2} are the shear modulus of soil at top layer and at pile tip respectively) as input parameters with separation length (l_s) as the output. The total number of data points considered was 144 out of which 100 were taken for training and 44 were taken for testing. Different ANN models were developed and results were compared in terms of correlation coefficient (R) and coefficient of determination (E). The correlation coefficient (R) and root means square error (RMSE) were mostly for performance criteria evaluation of ANN models. However, R was a biased parameter and sometimes, higher values of R might not necessarily indicate better performance of the model because of the tendency of the model to be biased towards higher or lower values (Das and Basudhar 2006), the coefficient of determination (E) was also considered. The E value compares the modeled and measured values of the variable and evaluates how far the network is able to explain total variance in the data set.

Fig. 4 shows the relationship between predicted and observed values for two trials using LMNN. It can be seen that it needs some trials before getting the best results and it is therefore needs number of iteration selection of proper epoch value. But, finally it was observed that the LMNN could predict the separation length l_s accurately with R and E values as 1.0 and 1.0 respectively as shown in Table 1.

However, while using BRNN model it was observed that different trials yielded the R and E values as 1.0 and 1.0 respectively as shown in Fig. 5. The variation and convergence of SSE, squared weights and number of effective parameters are also presented in Fig. 5. The number of effective parameters helps in avoiding the overfitting and hence BRNN has better generalization. The statistical performance criteria for BRNN are also shown in Table 1.

The variation of results of DENN with number of epoch (trials) found to vary similar to LMNN before getting the best results. It can be seen that all the ANN models developed for the prediction of l_s could exactly match with the observed values.

The weights and biases (parameters) for the BRNN models are shown in Table 2. Using the parameters presented here, a prediction model can be presented as per Eq. 1 and Das and Basudhar (2006). The parameters also can be used for the

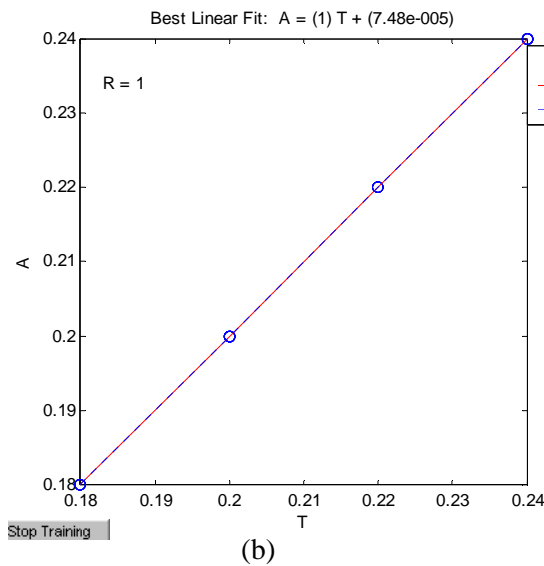sensitivity analysis to find out the important input parameters (Das and Basudhar 2006).
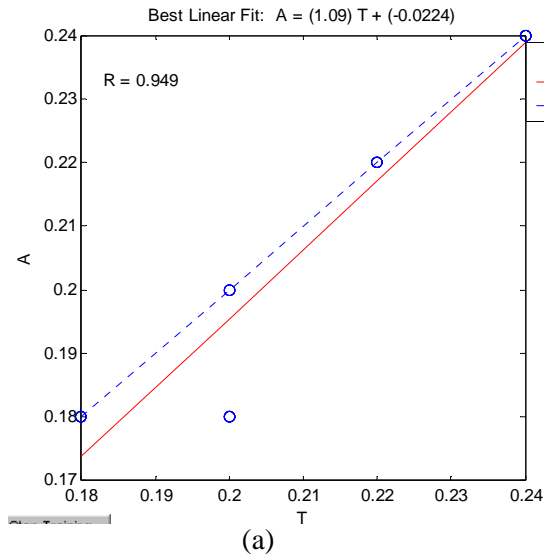

(a)

(b)

Fig. 4 The predicted and observed values l_s for the LMNN model for (a) 1st trial and (b) 2nd trial

Table 1. General performances of different neural network models for prediction of separation length

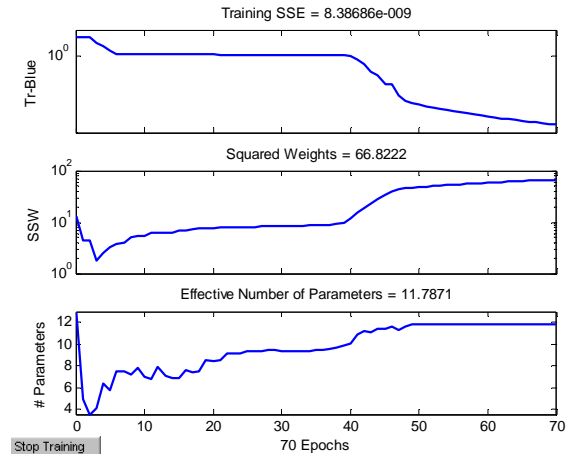| Model	Training Data		Testing Data	
	R	E	R	E
LMNN	1.000	1.000	1.000	1.000
BRNN	1.000	1.000	1.000	1.000
DENN	1.000	1.000	1.000	1.000

Fig. 5 The predicted and observed values l_s for the BRNN model

Table 2. Weights and biases for prediction of l_s as per BRNN

Neuron	Weights					Biases	
	M_e	L/d	h	G_{s2}/G_{s1}	l_s	b_{hk}	b_0
Hidden neuron 1 (k=1)	3.658	-0.613	2.716	0.362	3.568	-0.016	-0.054
Hidden neuron 2 (k=2)	3.642	0.151	-2.705	-0.210	3.570	-0.016	

Thus, the statistical performance of the different models were comparable, however, the performance of BRNN was found to better than DENN and LMNN in terms of generalization. The better performances of the BRNN were due to penalty for higher weight values to achieve good generalization.

7 CONCLUSION

This paper describes development of different ANN models to predict the separation length of pile subjected to vertical harmonic loading. A large number of dynamic tests with different exciting intensities are considered to study the frequency amplitude behavior of piles for vertical vibration. The observed data is used to develop ANN models using different training algorithms. All the developed ANN models are found to predict the separation length exactly using the given input parameters. However, BRNN model is found have better generalization in terms of its variation with different trials. The models parameters are presented which can be used to develop prediction model.

REFERENCES

Das, S. K., and Basudhar, P. K. (2006). "Undrained lateral load capacity of piles in clay using artificial neural network." *Computer and Geotechnics*, 33(8), 454 - 459.

Demuth, H., and Beale, M. (2000). "Neural network toolbox." The MathWorks Inc.USA.

El-Sharnouby, B., and Novak, M. (1984). "Dynamic experiments with group of piles." *J. Geotech. Eng.*, 110(6), 719-737.

Goh, A. T. C. (2002). "Probabilistic neural network for evaluating seismic liquefaction potential." *Canadian Geotech. J.*, 39, 219-232.

Kaynia, A. M., and Kausel, E. (1982). "Dynamic behavior of pile groups." *Proc.2nd Int Conf Num Meth Offshore Piling*, Austin, Texas, 509-532.

Manna, B., and Baidya, D. K. (2009). "Dynamic vertical response of model piles – experimental and analytical investigations." *Int J Geotech Eng*, 3, 271-287.

Manna, B., and Baidya, D. K. (2010). "Nonlinear dynamic response of pile foundations under vertical vibration." *Soil Dyn. and Earthq. Eng.*, 30(6), 456 - 469.

Math Work, Inc. (2001). "Matlab user's manual". Version 6.5." Natick, MA: The MathWorks, Inc.

Morshed, J. and Kaluarachchi, J. J. (1998). "Parameter estimation using artificial neural network and genetic algorithm for free-product migration and recovery." *Water resource research*, AGU, 34(5), 1101-1113.

Novak, M. (1974). "Dynamic stiffness and damping of piles." *Canadian Geotech. J.*, 11, 574-598.

Novak, M., and Aboul-Ella, F. (1978). "Impedance functions for piles embedded in layered medium." *J Eng. Mech.*, 104(3), 643-661.

Novak, M., and Grigg, R. F. (1976). "Dynamic experiments with small pile foundations." *Canadian Geotech. J.*, 13, 372-385.

Novak, M., and Mitwally, H. (1990). "Random response of offshore towers with pile-soil-pile interaction." *J. Offshore Mech. and Arctic Eng.*, 112, 35-41.

Novak, M., and Sheta, M. (1980). "Approximate approach to contact problems of piles." *Proc. Dynamic Response of Pile Foundations: Analytical Aspects*, ASCE, New York, 53-79.

Shahin, M. A., Maier, H. R., and Jaksa, M. B. (2002). "Predicting settlement of shallow foundations using neural network." *J. of Geotech. and Geoenviron. Eng.*, 128(9), 785-793.

Storn, R., and Price, K. (1995). "Differential evolution- A simple and efficient adaptive scheme for global optmization over continuous spaces." *Technical Report* TR-95-012, International Computer Science Institute, Berkeley, CA, USA.

Vaziri, H., and Han, Y. (1991). "Full-scale field studies of the dynamic response of piles embedded in partially frozen soils." *Canadian Geotech. J.*, 28, 708-718.