

## KINEMATIC INTERACTION FACTORS OF PILES

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### ABSTRACT

The presence of rigid pile in soil diffracts the 1D vertically propagating seismic waves and thus subjects the base of the structure to a seismic excitation which is different than the free field motion and may generally include rotational in addition to translational component. This effect is more pronounced for fixed head piles than for free head piles. This study is aimed at providing Artificial Neural Network based solutions to find the kinematic interaction factors for fixed and free head piles in homogenous soil layer. The data for Artificial Neural Network training and testing is based on Beam on Dynamic Winkler Formulation which is coded in MATLAB. As a practical application, the kinematic interaction factors are simply multiplied with the free field design response spectrum to derive the design response spectrum to be input at the pile head for calculation of inertial interaction.

Keywords: pile, Winkler foundation, artificial neural network, kinematic interaction, interaction factor

### INTRODUCTION

The seismic behavior of a structure is strongly affected by the interactive nature between the soil, piles and the supported structure. Away from the structure and its foundation, the response of the soil medium to the seismic excitation is influenced by the characteristics of the soil profile, and is denoted as free field motion. The piles embedded in the soil are subjected to this free field motion and the ensuing interplay between soil and piles is termed “kinematic interaction”, and the resulting response at the base of the structure is denoted as foundation input motion. The base of the structure is excited by the foundation input motion. As a result, the structure undergoes dynamic displacements and accelerations, creating inertial forces that are transmitted back to the piles, affecting the wave field in the adjacent soil. This last phenomenon is termed as “inertial interaction”. To accurately evaluate the seismic performance of a structure, the foundation input motion must be found first.

The objective of this paper is to present simple calculation schemes based on the Artificial Neural Network (ANN) technique of function approximation to estimate kinematic interaction factors (KIFs). The kinematic interaction factors can be applied to either Fourier spectra or response of free field motion to derive the foundation input motion. The data for training the ANN models is based on Beam on Dynamic Winkler Foundation (BDWF) formulation. Three ANN models are developed namely ANNKDFix, ANNKDFree, and ANNKRFree as detailed below:

(1) ANNKDFix: to predict the kinematic displacement factor,  $KDFix = U_{ppo}/U_{ffo}$  for fixed head pile in homogenous soil, where  $U_{ppo}$  is the amplitude of pile head displacement, and  $U_{ffo}$  is the amplitude of free field surface displacement.

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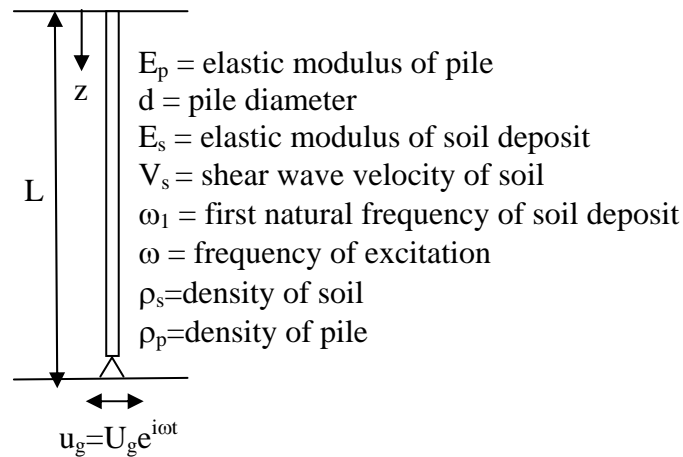
ANNKDFree: to predict the kinematic displacement factor,  $KDFree=U_{ppo}/U_{ffo}$ , for free head pile in homogenous soil.

ANNKRFree: to predict the kinematic rotation factor,  $KDFix=(d\phi_{ppo})/U_{ffo}$ , for free head pile in homogenous soil, where  $\phi_{ppo}$  is the rotation amplitude of the pile head and  $d$  is the pile diameter.

## PARAMETERS OF SEISMIC SOIL PILE INTERACTION

The layout of the pile soil system considered in this study is given in figure 1. The pile rests on rock formation, which is considered as a hinged support while the pile head may be rotationally fixed or free. The bedrock is excited by vertically propagating S-waves characterized by a harmonic displacement of  $u_g(t) = U_g e^{i\omega t}$ , where  $U_g$  is the ground displacement amplitude and  $\omega$  is the excitation circular frequency. The pile group effect is not considered as it plays a negligible role in kinematic interaction (Gazetas et al., 1992). Gazetas carried out extensive parametric study on free head piles and found that the kinematic interaction factors depend on the ratio of  $E_p/E_s$ ,  $L/d$ ,  $\nu$ ,  $\beta_s$ , and  $\rho_p/\rho_s$ . Out of these parameters,  $E_p/E_s$  and  $L/d$  are the most governing parameters (Pender, 1993).

Beam on Dynamic Winkler Formulation (BDWF) is adopted in this paper to generate data for ANN models training. The ranges of input parameters selected to generate data for ANN models are given in Table 1. The considered ranges cover most of the practical situations.



**Figure 1. Soil pile system**

**Table 1: Ranges of Parameters used for data generation**

	$E_p/E_s$	$L/d$	$\omega/\omega_1$	KDFix	KDFree	KRFree
Minimum	100	10	0.0637	0.0062	0.1962	0
Maximum	10000	40	12.7	1.0047	1.2743	0.4349

## BEAM-ON-DYNAMIC-WINKLER-FOUNDATION (BDWF) MODEL

Data for ANN models was generated by modeling the soil pile system as BDWF. The pile is connected to free field soil along its length through continuously distributed interface elements. The end of the

interface element that is connected to the free field soil is excited by the corresponding free field displacement  $u_{ff}(z,t)$ .

### Interface Element

Each interface element consists of a spring and a dashpot arranged in parallel. The spring stiffnesses ( $k_x$ ) is adopted from Kavvadas and Gazetas (1993). Thus  $k_x = \delta E_s$  where  $E_s$  soil modulus of elasticity of soil,  $\nu$  soil poisson's ratio, and

$$\delta = \frac{2}{1-\nu^2} \left( \frac{E_s d^4}{E_p I_p} \right) \left( \frac{L}{d} \right)^{1/8}$$

During soil pile interaction, the seismic energy is dissipated through hysteretic (material damping) and radiation (geometric damping). The former incorporates the internal energy dissipation in the soil, and is, thus related to soil damping ratio,  $\beta_s$  and the later is a geometric effect and represents the radiation of energy by waves spreading geometrically away from the pile soil interface. Hence the distributed dashpot/length of pile is,  $c_x = c_r + c_m$ , where  $c_r$ = distributed radiation dashpot coefficient and  $c_m$ = distributed material dashpot coefficient. In this study these coefficients are adopted from Gazetas & Dobry (1984a, b).

$$c_m = \frac{2k_x \beta_s}{\omega} \quad c_r = 2d\rho_s V_s \left( 1 + \left( \frac{V_c}{V_s} \right)^4 \right) a_o^{-1/4}$$

where  $V_c$  is the apparent velocity of the extension compression waves taken as the Lysmer's analog velocity  $V_{La}$  and  $V_s$  is the shear wave velocity of soil under consideration.

$V_c = V_{La} = \frac{3.4V_s}{\pi(1-\nu)}$  at all depths except near the ground surface ( $z \leq 2.5d$ ), where three-dimensional effects arising from the stress-free boundary are better reproduced by use of  $V_c \cong V_s$

### Solution of differential equation governing kinematic response of piles

The steady state pile displacement response to the harmonic excitation  $u_g(t)$  at the bedrock is governed by the following differential equation

$$U_{pp}''''(z) - \lambda^4 U_{pp}(z) = a U_{ff}(z), \text{ where}$$

$$\lambda^4 = \frac{m_p \omega^2 - S_x}{E_p I_p}, \alpha = \frac{S_x}{E_p I_p}, S_x = K_x + i c_x \omega$$

$S_x$  is complex impedance function,  $m_p$  is the pile mass per unit length,  $I_p$  is the second moment of inertia of pile, and  $U_{ff}(z)$  and  $U_{pp}(z)$  are displacement amplitudes of free field and pile at depth  $z$  respectively.

Differential equation has the general solution

$$U_{pp}(z) = [e^{-\lambda z} e^{\lambda z} e^{-i\lambda z} e^{i\lambda z}] \left\{ \begin{matrix} D1 \\ D2 \\ D3 \\ D4 \end{matrix} \right\} + s U_{ff}(z)$$

$$s = \frac{\alpha}{q^{*4} - \lambda^4}, \text{ where } q^* \text{ is complex wave number} = \sqrt{\frac{\omega}{V_s + i\beta_s}}$$

$D_1, D_2, D_3$ , and  $D_4$  are arbitrary constants to be evaluated through pile boundary conditions.

## Boundary Conditions

### *Boundary conditions at pile base*

Moment at pile base is zero,  $M(L,t)=0$ ; and displacement at pile base is equal to ground displacement at bedrock i.e.  $u_p(L,t)=u_g(t)$ .

### *Boundary conditions at pile head*

Shear force and moment at pile head is zero i.e.  $V(0,t)=0$ ,  $M(0,t)=0$  for rotationally free head piles where as for rotationally fixed head piles the shear force and rotation at pile head are zero i.e.  $V(0,t)=0$ ,  $\theta(0,t)=0$ .

The solution of the differential equation is coded in MATLAB which first evaluates the free field displacements as a function of depth, their first, second, and third derivative. Determine four arbitrary constants through four boundary conditions and then evaluates kinematic interaction factors.

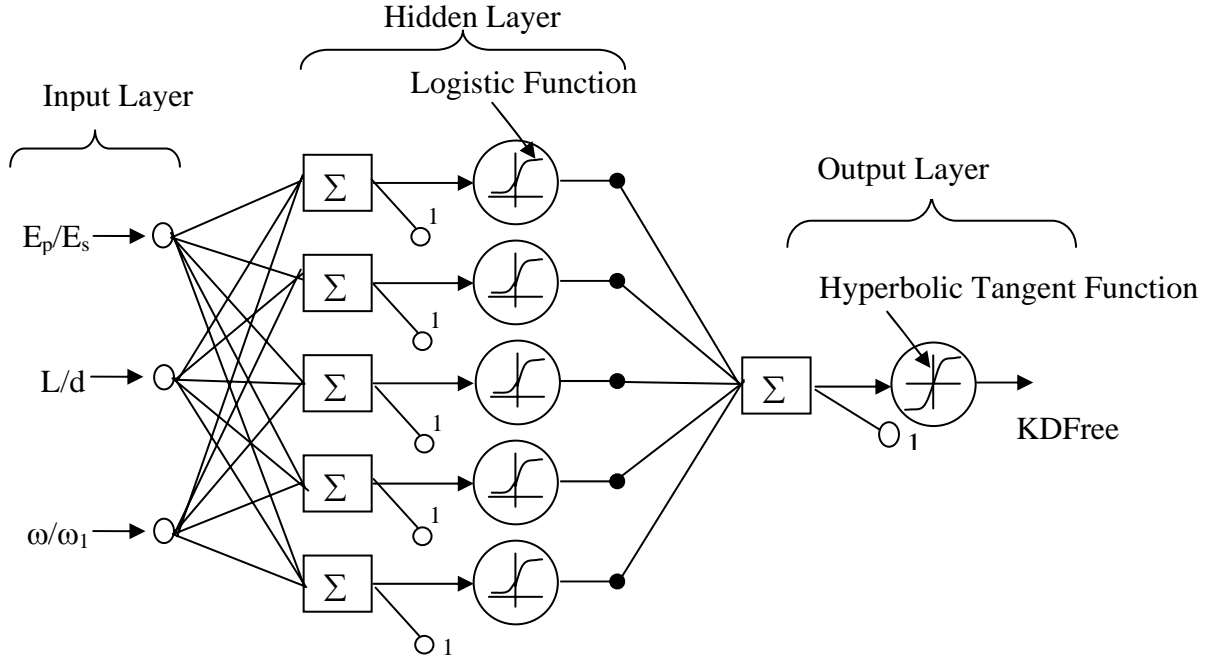
## ARTIFICIAL NEURAL NETWORK (ANN) MODEL

### Design of ANN Models

Artificial neural network is a computational mechanism able to acquire, represent, and compute a mapping from one multivariate space of information to another, given a set of data representing that mapping (Garrett, 1994). The applications of the ANN can broadly be categorized as classification, data association, data conceptualization, and data filtering. One of the most common engineering applications of ANN is to use inputs to predict certain outputs. About 80% of neural network applications utilize back-propagation neural network for prediction. Back-propagation ANN has been applied to various problems of civil engineering like predicting concrete shear capacity (Ahmad, 2005; Bohigas & Mari, 2004; Seleemah, 2005; El-Chabib, 2005), seismic liquefaction potential (Najjar and Ali, 1998), friction capacity of driven piles (Goh, 1995), overturning response of rigid block under near-fault type excitation (Gerolymos et al., 2005).

A Levenberg–Marquardt back-propagation algorithm was used in this research. It is one of the fastest methods available for training moderate-sized feed-forward neural networks (Hagan et al. 1996). The architecture of ANNKDFree model consisting of an input layer of three input neurons, a hidden layer of five neurons, and an output layer consisting of one output neuron is shown in Figure 2. The symbols  $w$  and  $b$  in figure 2 represent connection and bias weights with subscripts representing the corresponding neurons between two layers.

The input to the ANN models includes  $E_p/E_s$ ,  $L/d$ , and  $\omega/\omega_1$ , and therefore, the input layers consisted of three input neurons. The outputs of the ANN models are the corresponding kinematic interaction factor (KIF). Therefore each ANN model has one output neuron in the output layer. The output neuron is assigned a tan-sigmoidal (hyperbolic tangent) function. The transfer function used for hidden neurons is logistic sigmoid function. The number of neurons in hidden layer was varied from three to seven. Optimum numbers of hidden neurons were found to be four for ANNKDFix, and five for ANNKDFree and ANNKRFree. These neurons avoid underfitting i.e. large training and testing errors and prevent overfitting i.e. low training error but high testing error. All ANN models use 50% of the total data for training, and the remaining 50% is reserved for testing the performance of the trained ANN.



**Figure 2: Artificial Neural Network Architecture for ANN1**

The data generated to train ANN models are first randomized and then divided into two sets namely the training data set and the testing data set. The data was so divided so as to give comparable statistical properties for training and testing.

### Scaling of Training Data

Preprocessing of the training data is performed so that the processed data was in the range of -1 to +1. The training data sets (inputs and targets outputs) are scaled (preprocessed) according to

$$P_n = 2 \times \frac{(P - \min P)}{(\max P - \min P)} - 1 \quad (1)$$

$$T_n = 2 \times \frac{(T - \min T)}{(\max T - \min T)} - 1 \quad (2)$$

P = matrix of the input vectors; T= matrix of the target output vectors; P<sub>n</sub>=matrix of scaled input vectors; T<sub>n</sub>= matrix of scaled target output vectors; minP= vector containing minimum values of the original input; maxP = vector containing maximum values of the original input; minT = vector containing the minimum value of the target output; maxT = vector containing the maximum value of the target output. The scaled data was then used to train the neural network. The data from the output neuron have to be postprocessed to convert the data back into unscaled units to get actual kinematic interaction factor according to

$$T = 0.5 \times (T_n + 1)(\max T - \min T) + \min T \quad (3)$$

The maximum and minimum values of input and output vectors are given in table 1.

The training was carried out until the average sum squared error over all the training patterns was minimized. This occurred after about 1500 cycles of training. The connection and bias weights obtained after ANN training can be used to estimate the kinematic interaction factors. The weight and bias matrices obtained after the training phase of ANN models are W<sub>1</sub>= weight matrix representing connection weights between the input layer neurons and hidden layer; W<sub>2</sub>= weight matrix representing

connection weights between the hidden layer neurons and the output neuron;  $B_1$ =bias vector for the hidden layer neurons;  $B_2$ = bias vector for the output layer neuron. These weight matrices for ANN models are given below.

*Weight and Bias Matrices for ANNKDFix*

$$W_1 = \begin{bmatrix} 0.1575 & 0.6526 & 0.1622 \\ 0.1462 & 0.6481 & 0.1342 \\ -0.0119 & 0.1868 & -3.1880 \\ 4.0713 & -0.0556 & -0.0599 \end{bmatrix} \quad B_1 = \begin{bmatrix} 0.1908 \\ 0.2222 \\ -8.8738 \\ 10.3919 \end{bmatrix}$$

$$W_2 = [275.3 \quad 285.7 \quad 1165.1 \quad -860.8] \quad B_2 = [852.3121]$$

*Weight and Bias Matrices for ANNKDFree*

$$W_1 = \begin{bmatrix} -0.7951 & -3.2456 & 6.9741 \\ 1.7072 & -3.6850 & 14.9470 \\ 0.8041 & 3.2436 & -6.9865 \\ -1.2705 & 2.3714 & -6.4716 \\ -4.9902 & -2.3568 & 5.2564 \end{bmatrix} \quad B_1 = \begin{bmatrix} -0.6999 \\ 9.3396 \\ 0.7018 \\ -1.5968 \\ -5.5271 \end{bmatrix}$$

$$W_2 = [-338.083 \quad 1.6118 \quad -336.9977 \quad 2.1119 \quad 2.2238] \quad B_2 = [335.4918]$$

*Weight and Bias Matrices for ANNKRFree*

$$W_1 = \begin{bmatrix} -0.0466 & 0.6654 & -8.0697 \\ 1.0610 & -1.7342 & 2.6758 \\ -0.8282 & 1.9736 & -5.9451 \\ -1.1908 & 1.7099 & -2.6744 \\ 1.1245 & -1.7225 & 2.6786 \end{bmatrix} \quad B_1 = \begin{bmatrix} -13.0827 \\ 1.2521 \\ -0.4956 \\ -1.2072 \\ 1.2315 \end{bmatrix}$$

$$W_2 = [-470.7 \quad -765 \quad 1.5 \quad 755.8 \quad 1522.3] \quad B_2 = [-758.05]$$

### Procedure for estimating KIF

The ANN model described in this paper can be used to predict the kinematic interaction factors. The procedure can easily be programmed into a calculator capable of performing simple matrix operations. The input data is first preprocessed according to equation 1 to get scaled input vector  $P_n$ . The KIF is then obtained through the network as follows:

$$T_n = \tanh[W_2 \{ \text{logsig}(W_1 \times P_n + B_1) \} + B_2] \quad (4)$$

$$\text{logsig}(x) = \frac{1}{1 + \exp(-x)}$$

The scaled output  $T_n$  is then unscaled using equation 3 to obtain corresponding KIF.

### ANN Model Prediction

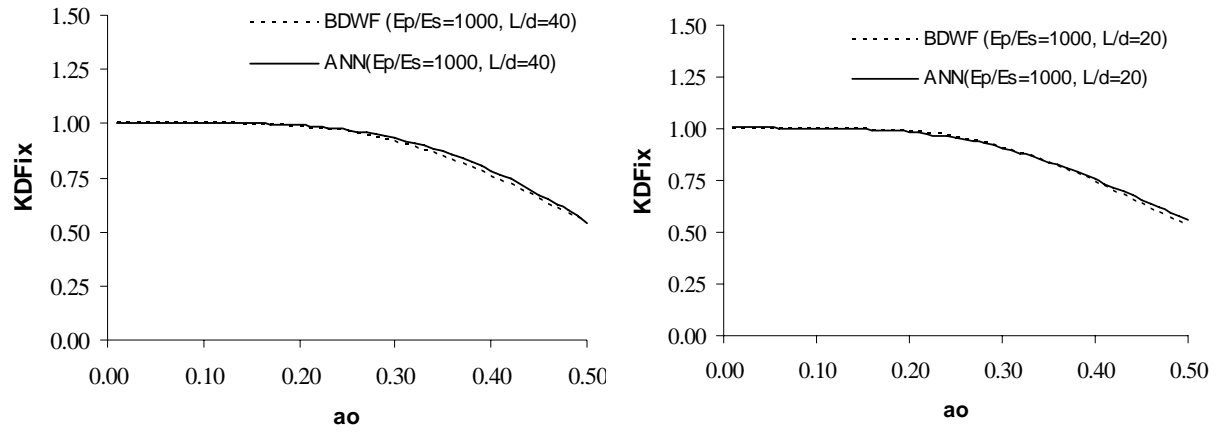
The ANN models were used to predict the KIF for four cases of soil/pile properties and for a range of frequencies. As shown in figures 3 to 8, the predictions of the ANN models are reasonable from engineering point of view. It is evident from the figures that as the rigidity of the pile relative to the soil increases, the free field motion is strongly altered. The kinematic interaction effect is more pronounced in fixed head piles than for free head piles (figures 3 and 4). Figures 5 and 6 show that the kinematic displacement factor for free head piles may be greater than 1.0 for certain frequency ranges. The kinematic displacement factor for free head piles is also accompanied with kinematic rotation (figures 7 and 8), and should not be neglected in the design.

The kinematic interaction factors can be applied to either Fourier spectra or response of free field motion to find the foundation input motion. This is applied to free field response spectrum in the following example: a free head pile is considered with length,  $L = 20$  m; diameter,  $d = 1.5$ ; elastic modulus,  $E_p = 3.5 \times 10^{10}$  Pa. The pile is embedded in a homogenous soil layer with shear wave velocity,  $V_s = 60$  m/s, overlying bedrock. These properties yield:  $E_p/E_s = 1950$ , and  $L/d = 13.3$ . The predicted response spectrum using the kinematic displacement factors is compared in Figure 9 with that obtained from the BDWF as well as the spectrum of the free field motion. It is noted from the figure 9 that the predictions of the ANN model agree well with the BDWF predictions and that the foundation input acceleration is greater than the corresponding free field response spectrum for certain frequency range.

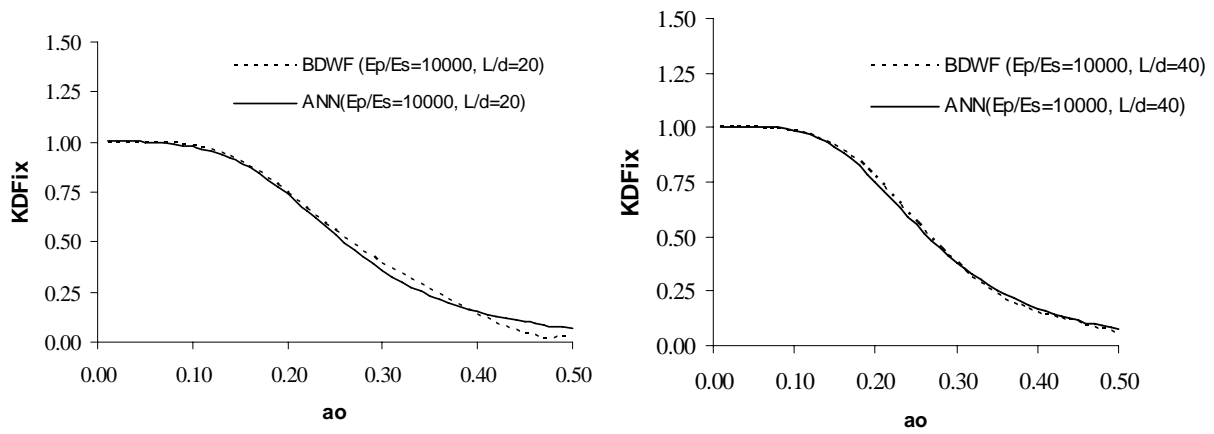
### CONCLUSION

The following conclusions are drawn:

- (i) ANN models have been developed for the prediction of the kinematic interaction factors. The ANN based solutions significantly reduce the amount of calculations, eliminating the need to carry out site response analysis and soil pile interaction analysis.
- (ii) The ordinates of the free field design response spectrum are simply multiplied by the corresponding kinematic response factors to derive the design response spectrum at the base of the structure to be used in the inertial interaction analysis.
- (iii) The rotational component in foundation input motion associated with free head pile is significantly small and can be neglected in general for computation convenience. However, the rotational component can be of significance for those structures having greater rotational moment of inertia.
- (iv) The fixed head pile suppresses the free field motion more than a free head pile. Therefore, it is generally conservative to use only the free head kinematic displacement factor in the analysis. However, for proper consideration, the relevant interaction factors shall be used.

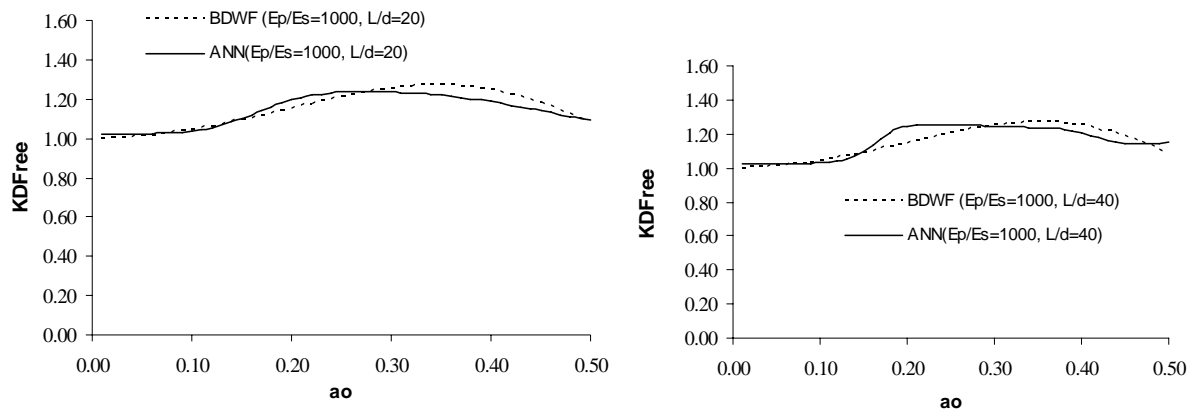


**Figure 3. Kinematic displacement factors for Fixed head piles ( $E_p/E_s=1000$ ,  $L/d=20, 40$ )**

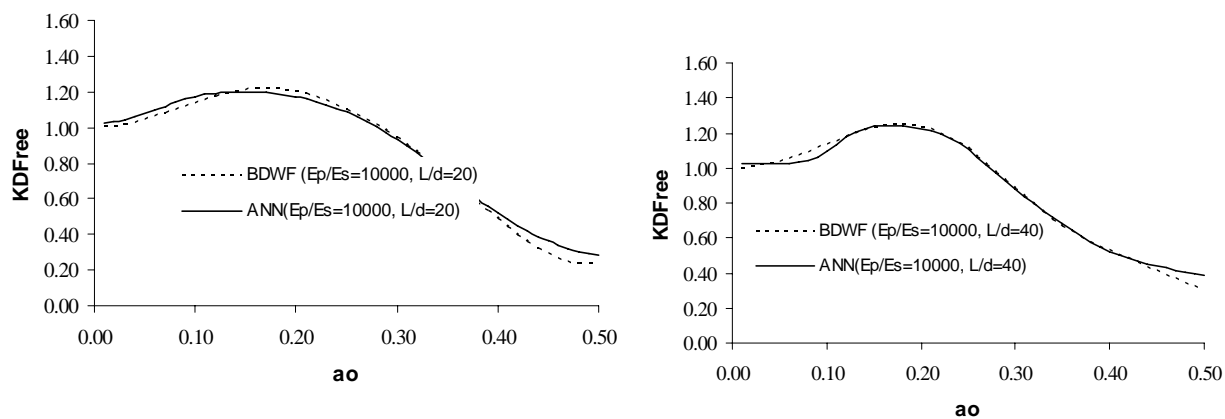


**Figure 4. Kinematic displacement factors for Fixed head piles ( $E_p/E_s=10000$ ,  $L/d=20, 40$ )**

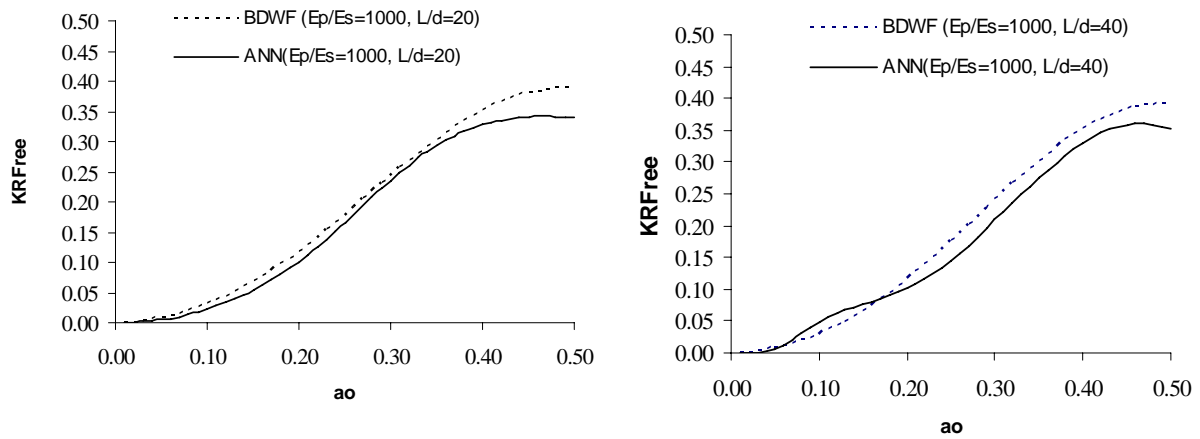




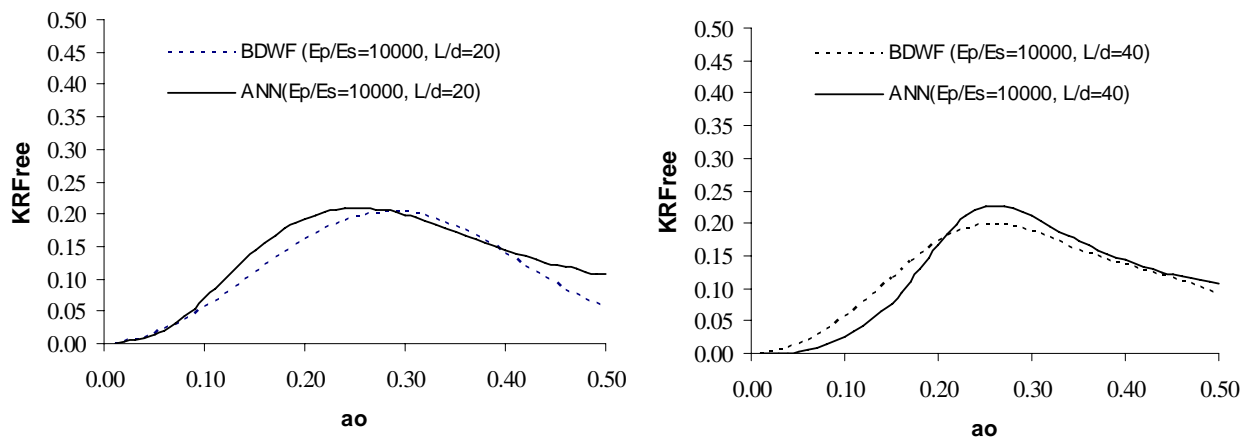
**Figure 5. Kinematic displacement factors for free head piles ( $E_p/E_s=1000$ ,  $L/d=20, 40$ )**



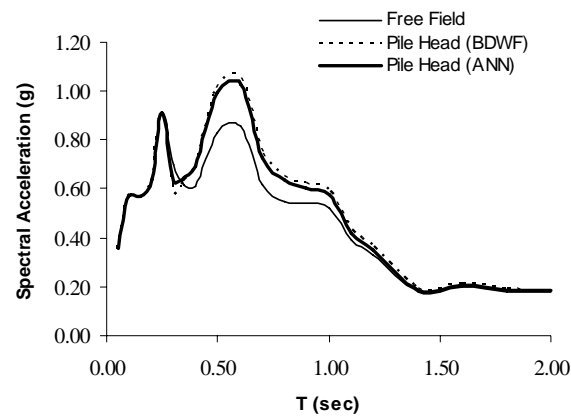
**Figure 6. Kinematic displacement factors for free head piles ( $E_p/E_s=10000$ ,  $L/d=20, 40$ )**



**Figure 7. Kinematic Rotation Factors for free head piles ( $E_p/E_s=1000$ ,  $L/d=20, 40$ )**



**Figure 8. Kinematic rotation factors for Free head piles ( $E_p/E_s=10000$ ,  $L/d=20, 40$ )**



**Figure 9. Free field and Pile head response spectra**

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