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Active Control of Offshore Structures for Wave Response Reduction Using Probabilistic Neural Network

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KEY WORDS: Fixed offshore structure, Random ocean wave, Probabilistic neural network, Active control

ABSTRACT: *Offshore structures are subjected to wave, wind, and earthquake loads. The failure of offshore structures can cause sea pollution, as well as losses of property and lives. Therefore, safety of the structure is an important issue. The reduction of the dynamic response of offshore towers, subjected wind generated random ocean waves, is a critical problem with respect to serviceability, fatigue life and safety of the structure. In this paper, a structural control method is proposed to control the vibration of offshore structures by the probabilistic neural network (PNN). The state vectors of the structure and control forces are used for training patterns of the PNN, in which control forces are prepared by linear quadratic regulator (LQR) control algorithm. The proposed algorithm is applied to a fixed offshore structure under random ocean waves. Active control of the fixed offshore structure using the PNN control algorithm shows good results.*

1. Introduction

Offshore structures are subjected to wave, wind and earthquake loads. The failure of offshoreructures can cause sea pollution, as well as losses of property and lives. Therefore, the safety of offshore structures is an important problem. The reduction of the dynamic response of offshore towers subjected to random ocean waves has been a critical issue in the aspect of serviceability, fatigue life and safety of the structure. Therefore, a number of studies have been conducted to control vibrations of the offshore structure.

Bang (1994) performed the vibration control usingpassive tuned mass damper (TMD) and an active tuned mass damper (ATMD) for offshore structural vibration control. He measured only top velocities and accelerations of a structure to estimate the states of all other degrees of freedom (DOFs) using Kalman Filtering. Then, he evaluated the control force by minimizing the cost function of instantaneous optimal control. Li et al. (1999) changed the multi-DOFs offshore structures into single DOF structures and proposed the method of designing optimal TMD. In the above studies, the optimal damping and stiffness are determined from the optimal problem, which places the cost function with standard deviation ofexpectations of response using the probabilistic spectrum of an abnormal wave motion in the long term. Wang (2002) showed the optimal design method of TMD, maximizing vibration energy to control offshore structural response generated by the impulse load. Mohamed (1996) verified the vibration control effect of regular waves using AMD. Terro et al. (1999) introduced the vibration control method using a feedback signal. Suhardjo and Kareem (2001) performed the vibration control of offshore structure under random waves using the feedback control method. Recently, Kim et al. (2001) proposed an artificial neural network (ANN) learning method, using the cost function, and performed the structural vibration control for three DOF structure. The control of artificial neural networks can be effectively realized without deriving complicated equations. Also, it can be adapted to a new environment through a re-training process. However, artificial neural networks need much effort in determining the optimal structure, such as hidden layer node, activation function, etc. and consume considerable time in training the network. Moreover, the estimated results from neuralnetworks are not probabilistic, but deterministic. The probabilistic neural network (PNN), therefore, could be an effective and reasonable alternative, because PNN needs less time to determine the architecture of the network and to train the network. Probabilistic neural network (PNN) has been widely used for pattern recognition problems, such as texture recognition (Touretzky et al., 1997; Raghu and Yegnanarayana, 1998), image recognition (Lin et al., 1997), medical/biochemical field (Wang et al., 1998; Holmes et al., 2001), signal processing (Zaknich, 1998), finance (Yang et al., 1999), civil/geotechnical engineering (Goh, 2002; Aoki et al., 2002; Sinha and Pandey, 2002), etc.

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In this paper, a structural control method using the probabilistic neural network (PNN) is proposed to control vibrations of the offshore structure. The state vectors of the structure and control forces are used to set training patterns of the PNN, in which control forces are composed by a linear quadratic regulator (LQR) control algorithm under random ocean waves, and other random ocean waves are used to verify the proposed structural control. Active control of the fixed offshore structure using the PNN control shows good results.

2. Active Control of Offshore Structures Using PNN

2.1 Equation of motion

The equation of motion of a structural system with n degrees of freedom subjected to external wave loads and the control forces can be expressed as (Kim, 2005)

$$[M]\{\ddot{u}\}+[C]\{\dot{u}\}+[K]\{u\}=[\overline{L_c}]\{f_c\}+[\overline{L_e}]\{f_e\} \tag{1}$$

where $\{u\}$, $\{\dot{u}\}$, $\{\ddot{u}\}$ are the displacement, the velocity and the acceleration of the structure, respectively; $\{f_c\}$ and $\{f_e\}$ are the control forces and external wave loads; $[M]$, $[C]$, $[K]$ are the mass, damping and stiffness matrices of the structure, respectively. $[\overline{L_c}]$ and $[\overline{L_e}]$ are location matrices respectively, corresponding to the locations of controllers and wave loads.

Wave forcevector $\{f_e\}$ can be expressed using Morison's equation, as follows (Morison et al. 1950)

$$\{f_e\}=[\rho(C_M-1)\nabla]\{\ddot{V}-\ddot{u}\}+[\rho\nabla]\{\ddot{V}\} + \left[\frac{1}{2}\rho C_D A\right]\{(\dot{V}-\dot{u})|\dot{V}-\dot{u}|\} \tag{2}$$

where $\{\dot{V}\}$ and $\{\ddot{V}\}$ are the velocity and the acceleration vector of water particles in the horizontal direction, respectively; A is the diagonal matrices, indicating the area projected in the direction of the flow; ∇ is the diagonal matrices, indicating the volume displaced by the structure $[C_D]=\rho K_D A$ and $[C_M]=\rho K_M \nabla$ ρ is the mass density of water; K_M is the empirical coefficient of inertia; K_D is the empirical coefficient of drag. In this study, K_M and K_D are set to be 2.0 and 1.4, respectively.

As can be observed from Eq.(2), the nonlinear fluid damping is introduced through the drag term. Therefore, the equation of motion isbut it is linearized, as follows:

$$C_{D_j}|\dot{V}_j-\dot{u}_j|(\dot{V}_j-\dot{u}_j)=\overline{C_{D_j}}(\dot{V}_j-\dot{u}_j) = C_{D_j}\sqrt{\frac{8}{\pi}}\,\sigma_{(\dot{V}_j-\dot{u}_j)}(\dot{V}_j-\dot{u}_j) \tag{3}$$

where $\overline{C_{D_j}}$ is the linearized coefficient; $\sigma_{(\dot{V}_j-\dot{u}_j)}$ is the standard deviation of relative velocity between water particles and structure in each node. In the paper, Each time the values are obtained from relative velocity up to time of pre-step (Yun et al., 1985).

When the state-space variable, $\{\dot{z}\}$, is introduced as follow,

$$\{\dot{z}\}=\begin{Bmatrix} u(t) \\ \dot{u}(t) \end{Bmatrix} \tag{4}$$

Eq. (1) and (2) can be transformedthe state-space equation form as [22]

$$\{\dot{z}\}=[A]\{z\}+[L_c]\{f_c\}+[L_e]\{f_e\}$$

$$[A]=\begin{bmatrix} 0 & 1 \\ -M^{-1}K & -M^{-1}C \end{bmatrix}$$

$$[L_c]=\begin{bmatrix} 0 \\ M^{-1}\overline{L_c} \end{bmatrix},\quad [L_e]=\begin{bmatrix} 0 \\ M^{-1}\overline{L_e} \end{bmatrix} \tag{5}$$

where $\{z(t)\}$ is a state vector; $[A]$ is a system matrix and $[M]$ is the sum of the mass and the added mass matrices; $[L_e]$ and $[L_c]$ are location matrices, respectively, corresponding to the locations of controllers and wave loadsthe state space; $\{f_e\}$ is the linearized wave force vector, as $C_M\ddot{V}+\overline{C_D}\dot{V}$. $\dot{V}$ and $\ddot{V}$ are described in section 2.2.

2.2 Simulation of random waves

For a linear wave theory, the horizontal component of wave particle velocity, ($\dot{V}$ and $\ddot{V}$), for deep water waves can be represented by

$$\dot{V}(y,t)=\sqrt{2}\sum_{i=1}^{N}[S_{hh}(\omega_i)\Delta\omega]^{\frac{1}{2}}\omega_i \times \exp\left(-\frac{\omega_i^2 y}{g}\right)\cos(\omega_i t+\phi_i) \tag{6}$$

in which $\omega_i = i\Delta\omega$ ϕ_i is random phase angles uniformly distributed between 0 and 2π y is the depth from sea level; g is gravitational acceleration and N is the number of data; $S_{hh}(\omega)$ is the one-sided wave spectrum

$$\ddot{V}(y,t) = -\sqrt{2}\sum_{i=1}^{N}[S_{hh}(\omega_i)\Delta\omega]^{\frac{1}{2}}\omega_i^2 \times \exp(-\frac{\omega_i^2 y}{g})\sin(\omega_i t+\phi_i) \tag{7}$$

For the purpose of this study, we assume the offshore tower to be excited by waves under fully developed sea conditions, for which the one-sided wave spectrum is suggested by Pierson-Moscowitz.

$$S_{hh}(\omega) = \frac{\alpha g^2}{\omega^5} exp[-\beta(\frac{\omega}{\omega_0})^4] \tag{8}$$

where $\alpha = 0.0081$, $\beta = 1.25$, $\omega_0 = \sqrt{0.161g/H_s}$, $H_s = 0.5m$ is significant wave height. In this paper, random waves are generated using the one-sided wave spectrum suggested by Pierson-Moscowitz.

2.3 LQR control algorithm

In this paper, the linear quadratic regulator (LQR) is used to obtain training patterns for PNN. According to the LQR control method, the control force $\{f_c(t)\}$ is to be chosen in such a way that minimizes a performance index (J), defined as

$$J(f_c) = \int_0^t (\{Z\}^T[Q]\{Z\} + \{f_c\}[R]\{f_c\})dt \tag{9}$$

In Eq. (9), $[Q]$ is a $2n \times 2n$ positive semi-definite matrix; $[R]$ is a $m \times m$ positive semi-definite matrix; and control forces with m degrees of freedom are applied. $[Q]$ and $[R]$ are referred as weighting matrices. The optimal control force for LQR is denoted as follows:

$$\{f_c\} = -[G]\{Z\} = -[R]^{-1}[L_c^T][S]\{z\} \tag{10}$$

in which $[G]$ is the control gain, and the solution of Riccati equation $[S]$ is obtained from the following:

$$[A^T][S] + [S][A] - [S][L_c][R]^{-1}[L_c]^T[S] + [Q] = 0 \tag{11}$$

Therefore, the control force is calculated by the product of the control gain ($[G]$) and the state vector of system ($\{Z\}$) (Soong, 1990).

2.4 Probabilistic neural networks

The PNN is basically a pattern classifier that combines the well-known Bayes decision strategy with the Parzen non-parametric estimator of the probability density functions of different classes (Specht, 1990). PNN has gained interest because it offers a way to interpret the network's structure in the form of a probability density function, and it is also easy to implement. Such strategies are called "Bayes strategies" and can be applied to problems containing any number of classes (Fig. 1).

For M-category situation, the p-dimensional input vector $X = [X_1, ..., X_j, ...X_p]^T$ can be classified by the Bayes decision rule, as follows:

$$d(X) = \theta_k \text{ for arg max}\{h_k l_k f_k(X)\}\ k = 1, \cdots, M \tag{12}$$

where $f_k(X)$ is the probability density functions for categories M, respectively; l_k is the loss function associated with the decision $d(X) = \theta_{others}$ when $\theta = \theta_k$ (the losses associated with correct decisions are taken to be equal to zero); h_k is the priori probability of occurrence of patterns from category k. In the simplified case, it is assumed that both loss functions and priori probabilities are equal to each other, and the Bayes rule classifies an input pattern to the class that has its probabilistic density functions (PDF) greater than the PDF of the other class. Therefore, the accuracy of the decision boundaries depends upon the accuracy with which the underlying PDFs are estimated. Parzen (1962) showed how one may construct a family of estimates of $f_k(X)$, and Cacoullos (1966) has also extended Parzen's results to estimates in the special ease that the multivariate kernel is a product of univariate kernels. In the particular case of the Gaussian kernel, the multivariate estimates can be expressed as

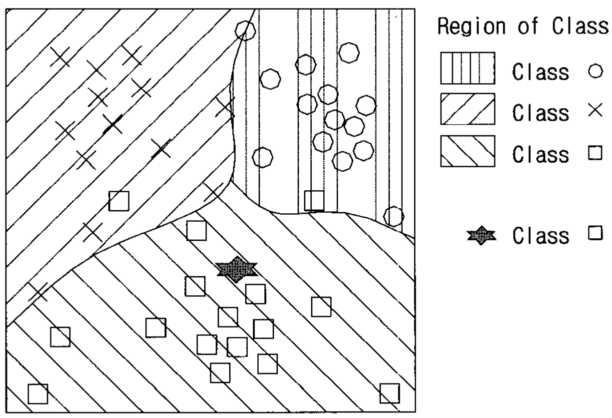

Fig. 1 Pattern classification by PNN

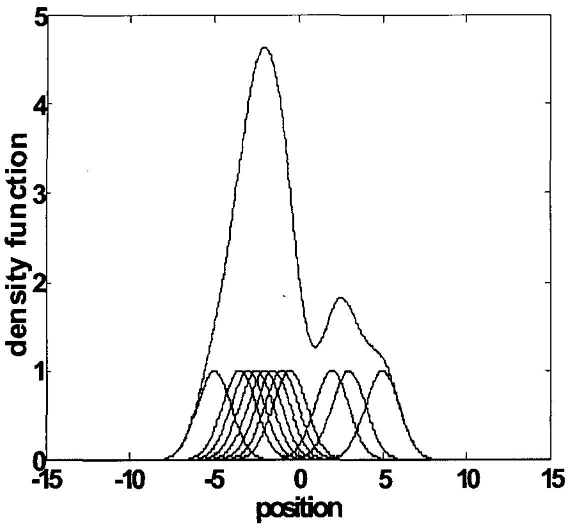

Fig. 2 Parzen's density estimation

$$f_k(X) = \frac{1}{(2\pi)^{p/2}\sigma^p}\frac{1}{m}\sum_{i=1}^{m}\exp\left(\frac{|X-X_{ki}|}{2\sigma^2}\right) \quad (13)$$

where X is the test vector to be classified; $f_k(X)$ is the value of the PDF of category K at point X; m is the number of training vectors in category K; P is the dimensionality of the training vectors; X_{ki} is the ith training vector for category K and σ is the smoothing parameter. Note that although $f_k(X)$ is simply the sum of small multivariate Gaussian distributions, centered at each training sample, the sum is not limited to being Gaussian (Fig. 2).

Figure 3 shows the PNN organization for classification of input patterns X into m-categories.

In Fig. 3, the input units are merely distribution units that supply the same input values to all of the pattern units. Input values are the displacements and velocities in this study. The second layer consists of a number of pattern units, which are training samples grouped according to the specified control force. Each pattern unit forms a dot product of the input pattern vector X with a weight vector W_i $Z_i = X \cdot W_i$, and then performs a nonlinear operation on $Z_i$before outputting its activation level to the summation unit. Instead of the sigmoid activation function commonly used for the back-propagation neural network, the nonlinear operation used here is $\exp[(Z_i - 1)/\sigma^2]$. Assuming that both X and W_i are normalized to unit length, this is equivalent to using (the same form as Eq. 13). The third layer is called a summation layer and is used to calculate the class PDFs. The

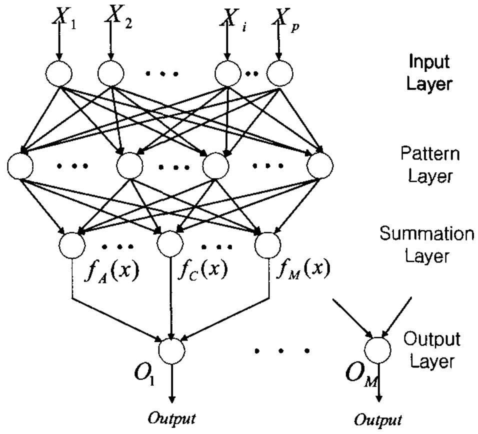

Fig. 3 Structure of PNN

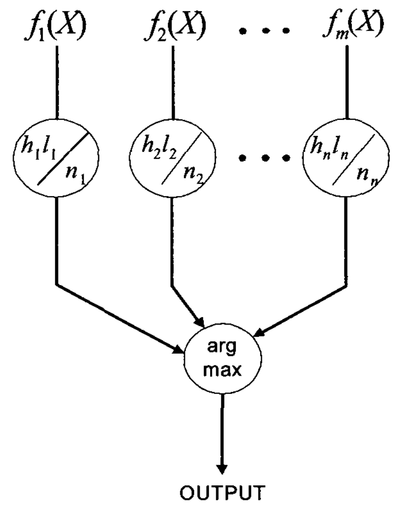

Fig. 4 Structure of output layer for m-category situation

$$\exp[-(W_i - X)^T(W_i - X)/2\sigma^2] \quad (14)$$

summation units sum the inputs from the pattern units that correspond to the category from which the training pattern was selected. The last layer is an output layer that classifiesan input pattern to one of the classes, based on the summation layer output, as well as the loss functions and a *priori* probabilities that are stored as weights to the output layer. These units produce binary outputs.

Decision units for m-input neurons are shown in Fig. 4. The PNN is trained by first assigning each training pattern to a pattern unit, according to its class, and setting the connecting weight vector equal to this training pattern. When all the training patterns in the training database have been presented to the network once, both input-to-pattern layer and pattern-to-summation layer weights are constructed. Weights of the output layer are assigned by loss functions and a priori probabilities of the M classes.

2.5 Active control using PNN

In order to apply the method in the vibration control of a structure, the rule base of the PNN needs to be composed. In this study, the rule base is made by a state vector in the deck and a control force as an input and an output, respectively. The state vector and control force are derived by the LQR control algorithm under random ocean waves, and then the proposed PNN control algorithm is introduced to another set of random ocean waves. PNN produce probabilistically the most suitable control force that measured the Euclidian distance between the training pattern and the state vector about another set of random ocean waves. Therefore, the structural vibration is reduced by the control force. Figure 5 and 7 show the block diagram and the basic control flowchart of the corresponding PNN controller.

3. Numerical Application and Results

A numerical analysis is carried out for the fixed offshore tower with heights of 184m. This tower is idealized as a seven discrete mass system, as shown in Fig 6. The structural properties of the tower are given in Table 1. The state vector of the structure and the control force are derived by LQR control under random waves, and they are used for the training pattern of the PNN. Then, another random wave was used to verify the proposed PNN control algorithm.

In this section, we compared the control capability of the PNN with that of the ANN. Time histories of simulated wave particle velocity and acceleration, generated by Eq. (6) and Eq. (7), are shown in Fig. 8. Controlled and uncontrolled responses of the PNN and the ANN under random ocean waves are shown in Figs. 9~10. From the figures, the deck displacement and velocity responses have been effectively suppressed by the both control algorithm, in which, the decreasing rates of the maximum displacement in the deck by the PNN and the ANN algorithm are 51.0% and 58.4%, respectively. Although the differences between the decreasing rates by the PNN and the ANN are not noticeable in these figures, the PNN control algorithm has many strong points over the ANN control algorithm.

Fig. 8 Time histories of simulated wave particle velocity and accelerationThe ANN needs a re-training process and more computational time in training the network. However, the PNN, as a pattern classifier, needs less time to determine the architecture of the network and to train the network. Moreover, the PNN provides the probabilistic viewpoints in order to consider the uncertainties in the control process as well as deterministic classification results.

4. Conclusion

In this study, a control method using the PNN is proposed for the structural vibration subjected to random waves. The proposed algorithm is applied and verified for the vibration control ofthe fixed offshore structure under random waves. The PNN method does not need a training process as the back-propagation algorithm in the ANN, though the controlled responses by the PNN method still show good and quite similar performance to those of the ANN. The proposed PNN techniques can be represented as an experience-based control toolkit, since the training patterns are composed of the state vectors and the resulting control forces for random ocean waves already arose or are expected at a specific bridge site.

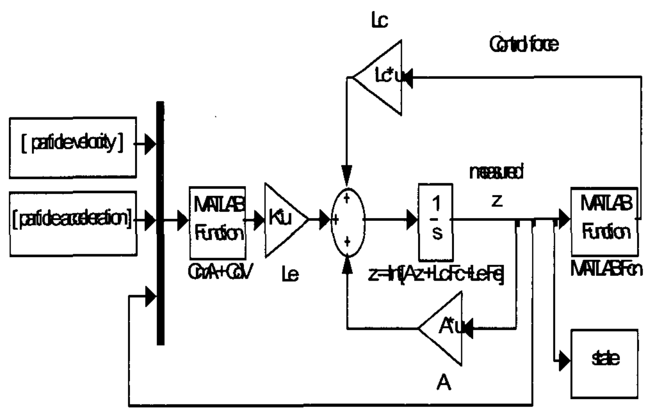

Fig. 5 Control flowchart

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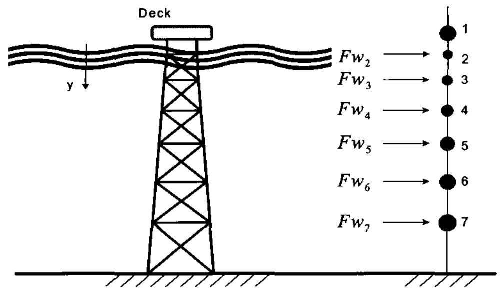

Fig. 6 A fixed offshore tower and its model.

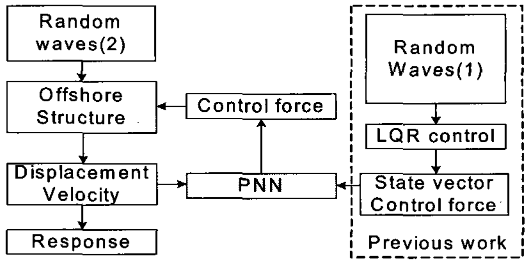

Fig. 7 Block diagram of PNN controller

Table 1 Structural properties

Level	Y (m)	M (ton)	$\rho\nabla K_M$ (ton)	$\frac{1}{2}\rho A K_D$ (ton)	∇ (m^3)	A (m^2)
1	-23	4,818	0	0	0	0
2	3	1,477	1,153	182	20,374	9,210
3	23	1,302	1,080	156	19,084	7,884
4	43	2,409	2,102	248	37,137	12,526
5	82	4,117	3,519	350	62,152	17,758
6	122	5,388	4,424	372	78,142	18,789
7	162	6,089	5,256	430	92,841	21,737
			Stiffness(N/m)			
4.E+08	-5.E+08	1.E+07	1.E+07	6.E+07	1.E+07	1.E+07
-5.E+08	1.E+09	-8.E+08	-1.E+07	-2.E+07	2.E+07	-3.E+06
1.E+07	-8.E+08	2.E+09	-8.E+08	-3.E+07	3.E+06	9.E+06
1.E+07	-1.E+07	-8.E+08	1.E+09	-4.E+08	-2.E+07	8.E+06
6.E+07	-2.E+07	-3.E+07	-4.E+08	1.E+09	-5.E+08	-4.E+06
1.E+07	2.E+07	3.E+06	-2.E+07	-5.E+08	1.E+09	-6.E+08
1.E+07	-3.E+06	9.E+06	8.E+06	-4.E+06	-6.E+08	3.E+09

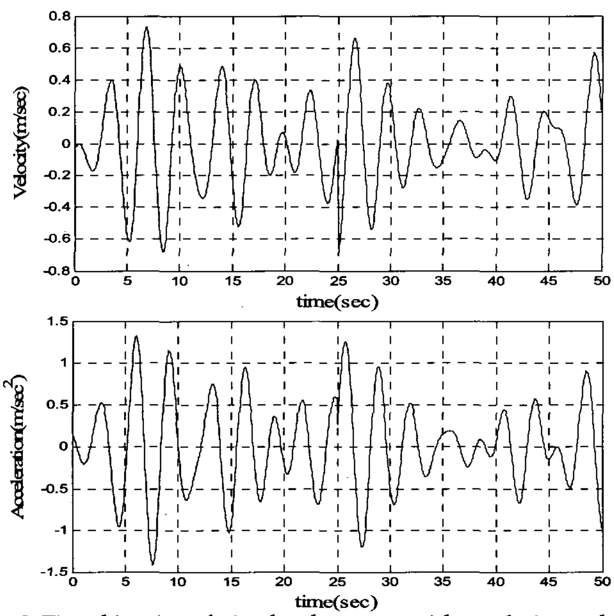

Fig. 8 Time histories of simulated wave particle velocity and acceleration

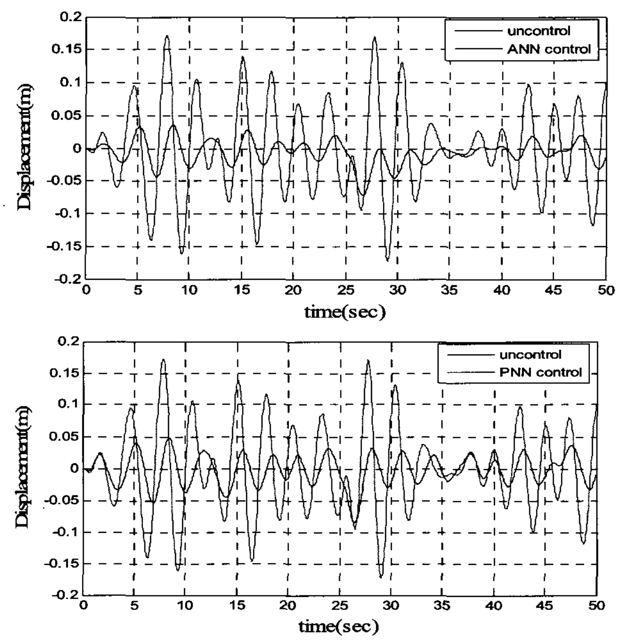

Fig. 9 Deck displacement

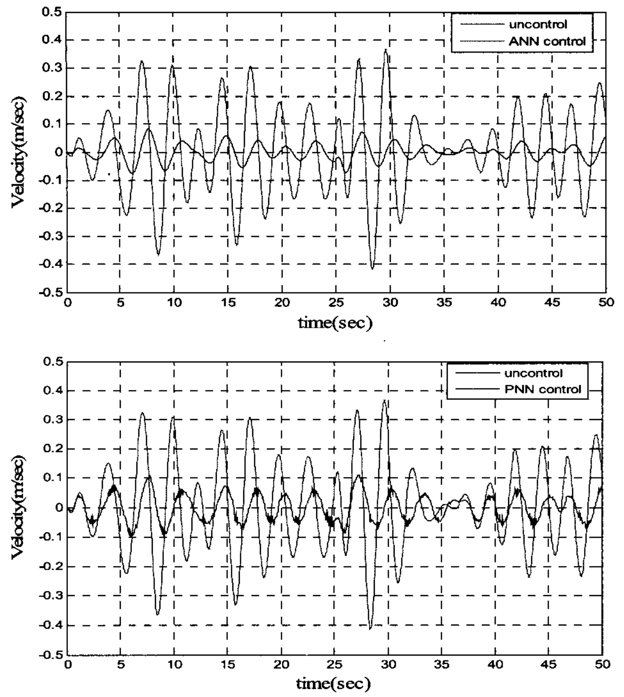

Fig. 10 Deck velocit

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