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Application of lattice probabilistic neural network for active response control of offshore structures

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Abstract. The reduction of the dynamic response of an offshore structure subjected to wind-generated random ocean waves is of extreme significance in the aspects of serviceability, fatigue life and safety of the structure. In this study, a new neuro-control scheme is applied to the vibration control of a fixed offshore platform under random wave loads to examine the applicability of the proposed method. It is called the Lattice Probabilistic Neural Network (LPNN), as it utilizes lattice pattern of state vectors as the training data of PNN. When control results of the LPNN are compared with those of the NN and PNN, LPNN showed better performance in effectively suppressing the structural responses in a shorter computational time.

Keywords: active control; probabilistic neural network; lattice; training pattern; wave load.

1. Introduction

During the last three decades, various response control methods have been developed and applied to suppress the vibration of various structures. One of them, the control of offshore structures using tuned mass dampers (TMD), has been studied by Petersen (1980), Bang (1994), and Li *et al.* (1999). Then, Wang *et al.* (2002) has proposed the improved optimal design method of TMD maximizing vibration energy to control offshore structural response generated by the impulse load. However, the ability of the TMD to control the response of a structure is limited, and the TMD can generally be tuned to only one of the structure's natural frequencies.

Recently, Kim *et al.* (2001) proposed a neural network (NN) learning method using the cost function and performed the structural vibration control for a three-DOF structure. Kim *et al.* (2004)

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applied NN to the nonlinear benchmark structural control problem using a sensitivity evaluation scheme. NN control can be effectively realized without complicated equations being derived. However, the NN takes a long time to be trained (Madan 2005). To avoid the time-consuming problem in training the NN, Probabilistic Neural Network (PNN) was proposed for offshore structure control by Kim *et al.* (2007). Even if PNN control has greatly decreased the learning time, it still requires considerable computational efforts in calculating the control force at any instant of time. It basically calculates all the Euclidean distances of invoked input from all the patterns saved in the memory, and the most adjacent output pattern is selected as the control force output. If the training pattern of PNN is increased for better resolution, calculation time also increases in proportion to the number of patterns.

In order to make up for the weak point of PNN, Kim *et al.* (2008) proposed the lattice probabilistic neural network (LPNN) and applied it to a single degree of freedom system. Unlike the training pattern of PNN, those of the proposed LPNN were uniformly distributed at the lattice point in state space. Because of this, the position of the invoked input could be known and the output of the LPNN could be simply calculated by using only the adjacent pattern. However, since LPNN was only applied to a single degree of freedom system, its applicability still needs to be further verified.

In this study, the LPNN is applied for the vibration control of a real nonlinear fixed offshore tower under random wave loads to examine its applicability. Then, control results of the LPNN are compared with those of NN and PNN (Kim *et al.*, 2007a) to verify the validity of the LPNN control. Results proved that the vibrations of the fixed offshore tower under the random wave loads are more effectively controlled by LPNN than NN and PNN within a shorter computational time.

2. Active control method using LPNN

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)

$$[M]\{\ddot{u}\} + [C]\{\dot{u}\} + [K]\{u\} = [\bar{L}_c]\{f_c\} + [\bar{L}_e]\{f_e\} \tag{1}$$

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; and $[M], [C], [K]$ are the mass, damping and stiffness matrices of the structure, respectively. $[\bar{L}_c]$ and $[\bar{L}_e]$ are location matrices respectively, corresponding to the locations of the controllers and wave loads.

The wave force vector $\{f_e\}$ 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 matrix indicating the area projected in the direction of the flow; ∇ is the diagonal matrix indicating the volume displaced by the structure; $[C_M] = \rho K_M \nabla$ and $[C_D] = \rho K_D A$; ρ is the mass density of water; K_M is the empirical coefficient of inertia; and 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 what can be observed from Eq. (2), the nonlinear fluid damping is introduced through the drag term. Therefore, the equation of motion is nonlinear but it is linearized as follows

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

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

The state-space variable, $\{\dot{z}\}$, is introduced as follows

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

Eqs. (1) and (2) can be transformed into the state-space equation form as (Soong 1990)

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

$$[A] = \begin{bmatrix} \mathbf{0} & \mathbf{I} \\ -\mathbf{M}^{-1}\mathbf{K} & -\mathbf{M}^{-1}\mathbf{C} \end{bmatrix} \tag{5}$$

$$[L_c] = \begin{bmatrix} \mathbf{0} \\ \mathbf{M}^{-1}\overline{\mathbf{L}}_c \end{bmatrix}, \quad [L_e] = \begin{bmatrix} \mathbf{0} \\ \mathbf{M}^{-1}\overline{\mathbf{L}}_e \end{bmatrix}$$

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; $[L_c]$ and $[L_e]$ are location matrices, respectively, corresponding to the locations of the controllers and the wave loads in the state space; and $\{f_e\}$ is the linearized wave force vector as $C_M\ddot{V} + \overline{C}_D\dot{V}$.

2.2 Simulation of irregular waves

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

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

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

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

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

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

where $\alpha = 0.0081$, $\beta = 1.25$, $\omega_0 = \sqrt{0.161g/H_s}$, and $H_s = 0.5$ m is the significant wave height. In this paper, irregular waves are generated using this method.

2.3 Training pattern and control force

Unlike the training pattern of PNN introduced by Specht (1990), the training pattern of the LPNN controller is composed of the lattice form of the control force $(f_{j,k})$ and the state vector $(u_k, \dot{u}_k)$ as shown in Fig. 1, in which the state vector is the uniform interval between the maximum and the minimum of the optional structural response. The control force is calculated by the product of the control gain (**G**) and state vector (**z**) of the system, as follows

$$f_{j,k} = -(\mathbf{G}\cdot z) = -(\mathbf{R}^{-1}\cdot\mathbf{L}_e^T\cdot\mathbf{S})\cdot z \qquad j,k = -3,\ldots,3 \tag{9}$$

where **G** is the control gain; and the solution of Riccati equation (**S**) is obtained through the following equation

$$\mathbf{A}^T\mathbf{S} + \mathbf{S}\mathbf{A} - \mathbf{S}\mathbf{L}_e\mathbf{R}^{-1}\mathbf{L}_e^T\mathbf{S} + \mathbf{Q} = 0 \tag{10}$$

where **Q** and **R** are referred to as the weighting matrices.

The process of calculating the LPNN controller will be described in Section 2.4.

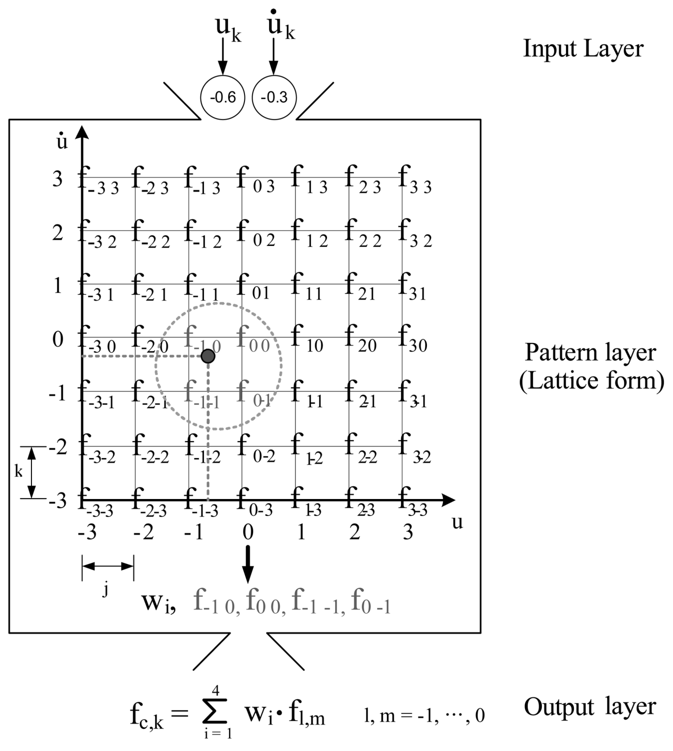


Fig. 1 Structure of LPNN

2.4 Lattice probabilistic neural network

Fig. 1 shows the structure of the LPNN with two inputs and a single output at the k^{th} time step. To reduce the output calculation time, the training patterns of the LPNN are uniformly distributed in state space (see Fig. 1). By doing so, one can easily know the position of any given input in state space, as follows

$$position = \left(\frac{u_k}{j} + \frac{s}{2}, \frac{\dot{u}_k}{k} + \frac{v}{2}\right) \tag{11}$$

where u_k and $\dot{u}_k$ are the displacement and velocity at the k^{th} time step, respectively; j and k are the uniform widths of the training pattern in state space; s and v are the sizes of the u_k and $\dot{u}_k$ axes, respectively; and *position* is the position of a given input in state space. Then, those adjacent patterns can be directly identified by Eqs. (12)-(15).

$$j_1 = ceil\left[\frac{u_k}{j} + \frac{s}{2}\right] \tag{12}$$

$$j_2 = ceil\left[\frac{u_k}{j} + \frac{s}{2}\right] - 1 \tag{13}$$

$$k_1 = ceil\left[\frac{\dot{u}_k}{j} + \frac{v}{2}\right] \tag{14}$$

$$k_2 = ceil\left[\frac{\dot{u}_k}{j} + \frac{v}{2}\right] - 1 \tag{15}$$

where the $ceil(\cdot)$ operator means the smallest integer greater than the input value. Since the adjacent pattern can be identified, there is no need to calculate the hamming distances of all patterns. However, PNN calculates the distance of the input patterns (displacement and velocity of the structure) from all training patterns since it cannot identify which ones are around the given input pattern. The total number of operations for the hamming distance calculation in PNN is $n \times m$, where n is the number of patterns in each dimension and m is the degrees of freedom of state space; whereas in LPNN, only $4 \times m$ operations are needed. LPNN is very simple and fast in calculating the control output.

The distance between the input pattern (response of structure) and the training pattern (lattice type) for LPNN can be expressed as

$$dist_i = \sqrt{\sum(\mathbf{X}-\mathbf{Y})^2} \quad i = 1, \ldots, 4 \tag{16}$$

where $\mathbf{X}$ is the input pattern $(u_k, \dot{u}_k)$ at the k^{th} time step; and $\mathbf{Y}$ represents the four training patterns $([u_l, \dot{u}_m])$ around the input pattern (see Fig. 1). The calculated distance in the pattern layer is converted to a weight value, as follows

$$w_i = \frac{pd_i}{sp}, \quad pd_i = \frac{(sd - dist_i)}{2} \quad i = 1, \ldots, 4 \tag{17}$$

where sd is the sum of the distances; pd_i is the participated rate of the weight of the training pattern; sp is the sum of pd_i; and w_i is the weight of the training pattern corresponding to the distance. In the output layer, the control force $(f_{c,k})$ is calculated by the product of the weight (w_i) and the control forces ($f_{l,m}$) corresponding to the training pattern, as follows

$$f_{c,k} = \sum_{i=1}^{4} w_i \cdot f_{l,m} \quad i = 1, \ldots, 4 \tag{18}$$

3. Numerical application

A numerical analysis is carried out for a fixed offshore tower with a height of 184 m. This tower is idealized as a seven discrete mass system as shown in Fig. 2. The structural properties of the

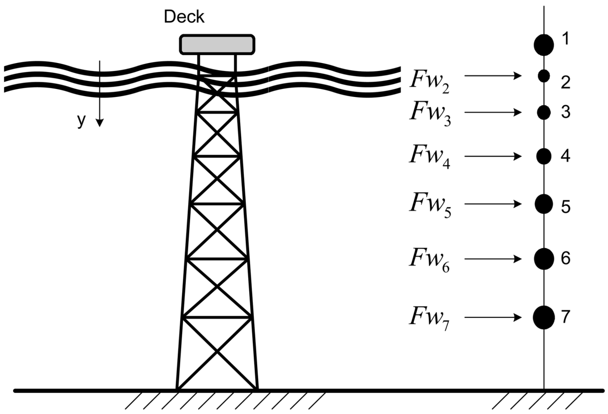


Fig. 2 Fixed offshore tower and its model

Table 1 Structural properties

Level	Y (m)	M (ton)	$\rho\nabla K_M$ (ton)	$\frac{1}{2}\rho A K_D$ (ton)	∇	A
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

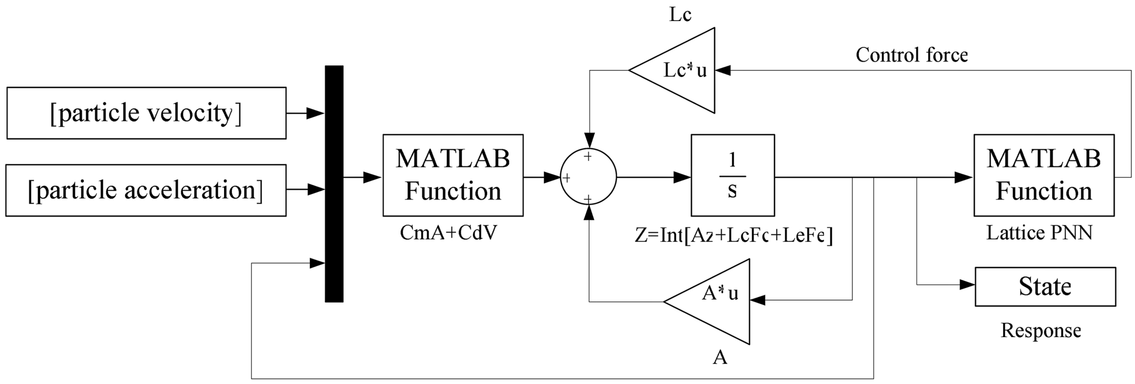


Fig. 3 Tim Block diagram of LPNN controllers

tower are given in Table 1. Fig. 3 shows the block diagram of the LPNN controller for the fixed offshore tower.

4. Control results

To use random ocean waves, time histories of simulated wave particle velocities and accelerations are generated by Eqs. (6)-(7), as shown in Figs. 4-5. Controlled and uncontrolled responses of the proposed algorithm under random ocean waves are shown in Fig. 6, wherein the decreasing rate of the maximum displacement at the deck is 79.05%. The figure shows that the displacement and velocity responses of the deck can be reduced considerably when the proposed method is used. Fig. 7 shows the control forces corresponding to random ocean waves.

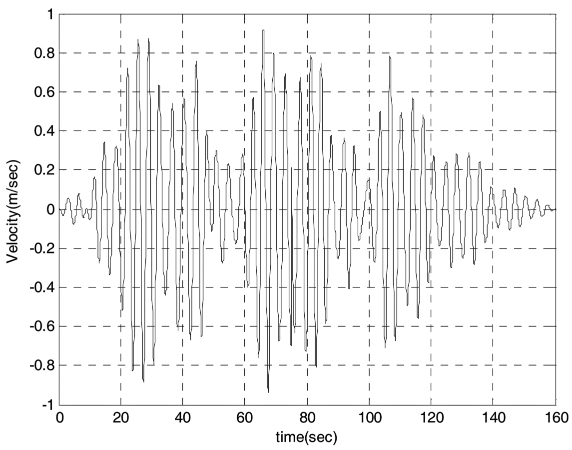


Fig. 4 Time histories of simulated wave particle velocity

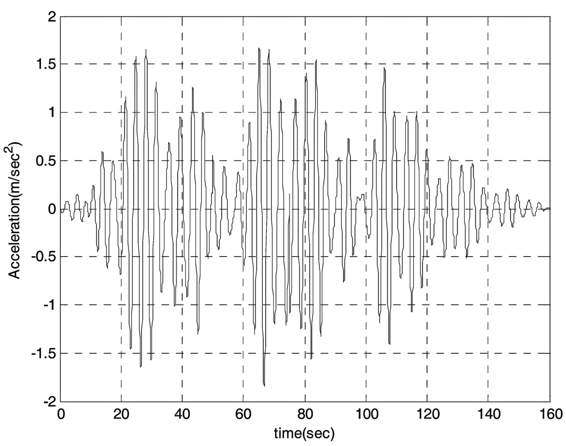
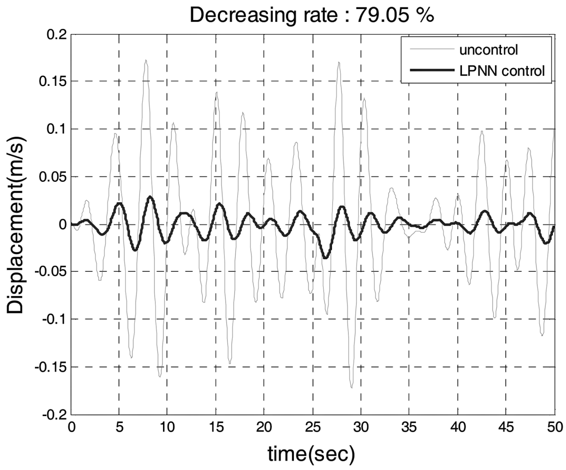
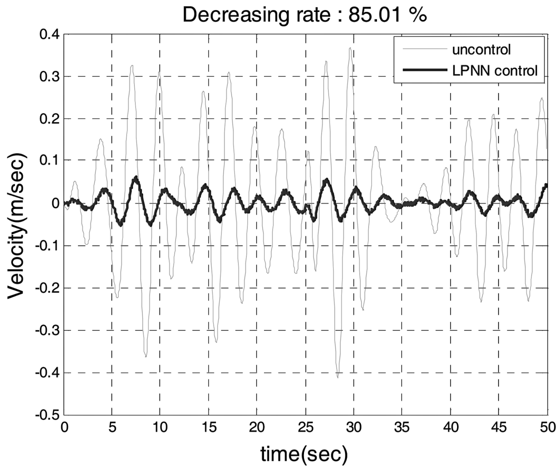


Fig. 5 Time histories of simulated wave particle acceleration



(a) Displacement



(b) Velocity

Fig. 6 Comparison between uncontrolled and controlled responses of the offshore structure

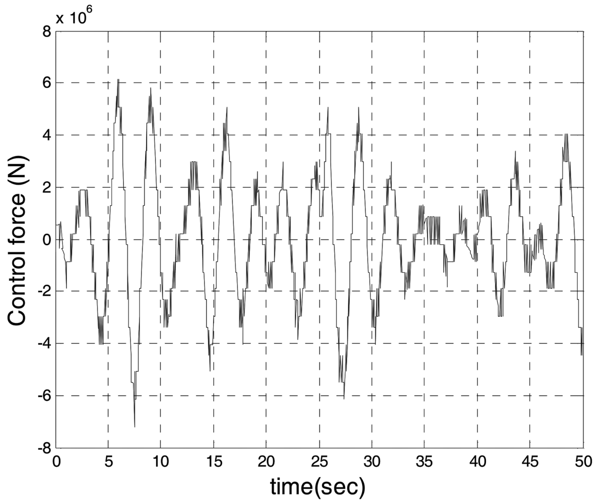
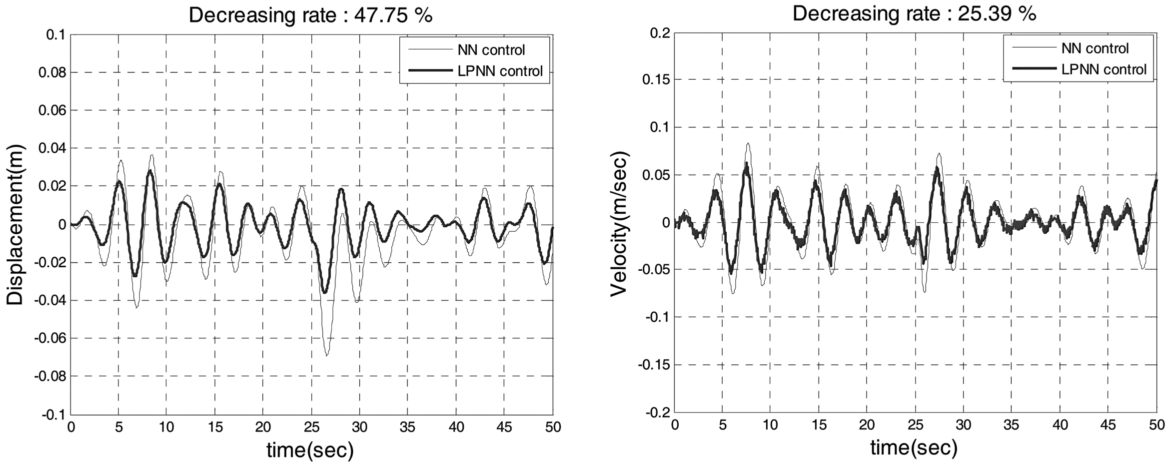


Fig. 7 Control force corresponding to wave load

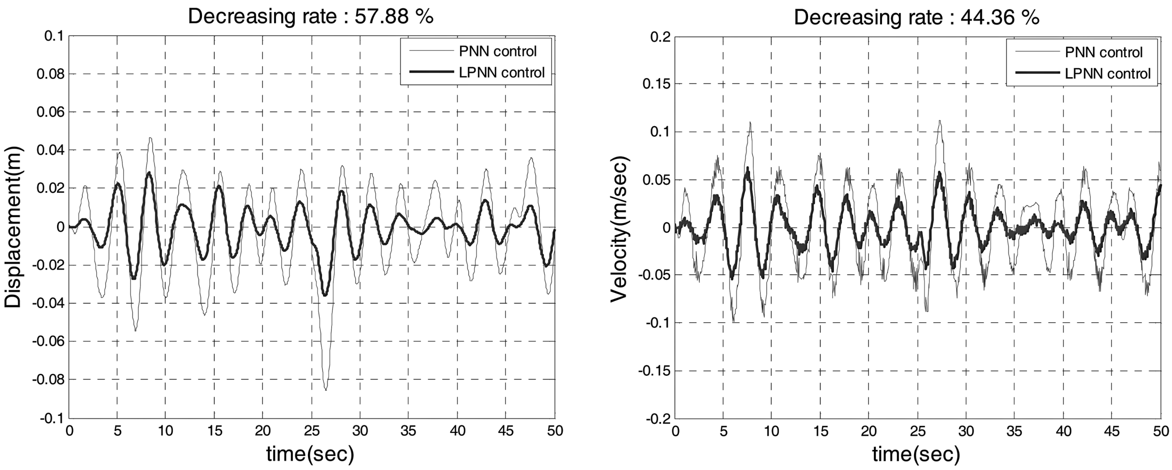
From Fig. 6, it can be found that the LPNN algorithm can effectively control the offshore structure under unknown random ocean waves. The results of the LPNN are compared with those of the NN and PNN (Kim *et al.* 2007a) to verify the control performance. Controlled responses of the offshore structure under random ocean waves using the NN and LPNN are shown in Fig. 8, while Fig. 9 shows the responses derived from using the PNN and LPNN. Comparing the NN and LPNN, the differences of the maximum displacement and velocity of both methods are 47.75% and 25.39%, respectively; while that between PNN and LPNN are 57.88% and 44.36%, respectively.

The computational times for one step control force calculation are 3.468×10^{-3} sec in NN, 0.021 sec in PNN, and 0.375×10^{-3} sec in LPNN.



(a) Displacement (b) Velocity

Fig. 8 Controlled responses by the NN and the LPNN



(a) Displacement (b) Velocity

Fig. 9 Controlled responses by the PNN and the LPNN

5. Conclusions

In this study, a simple and robust method using the LPNN is applied for the vibration control of a fixed offshore platform under random wave loads to examine the applicability of LPNN. The training pattern of the LPNN is prepared in lattice forms to save output calculation efforts. Due to this type of training pattern, adjacent patterns for any given input can be directly identified, and the output can be calculated from the weighted sum of the adjacent patterns only. In the numerical simulation of the fixed offshore tower control, LPNN takes almost no time in output calculation. And when the control results of the LPNN are compared with those of the NN and PNN to verify the control performance, the LPNN controller was more effective than the other two methods in decreasing the structural responses within a short computational time.

Acknowledgements

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