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Predictive control theory and design for offshore platforms

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Abstract. In order to achieve the best performance, the automatic control with advanced technology is made of sheathed steel to withstand a wide range of wave loads. This model shows how to control the vibration of the fiber panel as a solution using the new results from the Lyapunov stability question, a modification of the bat that making it easy to calculate and easy to use. It is used to reduce the storage space required in this system. The results show that the planned worker can compensate effectively for the unplanned delay. The results show that the proposed controller can compensate for delays and errors. Fuzzy control (predictive control) demonstrated the external vibration can be reduced.

Keywords: evolved control systems; offshore platforms; predictive control; time delays

1. Introduction

Offshore drilling rigs are structures commonly used to drill and produce oil and gas at offshore engineering sites. These offshore drilling rigs are inevitably exposed to external stressors from extreme environmental conditions such as weather, earthquakes, winds and waves (Hasan *et al.* 2010), causing vibrations and potential environmental impacts. there is. Sea level monitoring in particular is one of the most important processes in the field of control systems. There is a risk of accidents because input control is required. Many of these issues occur when an operation fails. It can lead to serious consequences such as death, injury and financial loss. Factors that cause this include a lack of system equipment. Lack of trained inexperienced staff Poor communication and common hardware failures Active control is preferred for high efficiency among existing control mechanisms (Sakthivel *et al*. 2014). For jacket types with active damping devices (AMD), time delays (Sakthivel *et al.* 2014, Chen 2014) should be considered to correct these defect. The most famous learning structure is proposed. This is called an intelligent algorithm to prevent local resolution (Goldberg 1989). The revised algorithm can also be applied to various neural networks. The algorithm does not need to develop new formulas to train the variables of the structure. Therefore, in neural networks, training variables in neural networks is better than using traditional algorithms.

Recently, several evolutionary algorithms have been used to adjust the parameters of neural

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networks. To increase the likelihood of responding to the optimal solution (Chen *et al.* 2019, Hsiao *et al*. 2005, Yeh *et al.* 2007), such algorithms not only provide parallel search technology, but also. We also offer a unique approach to find a solution. To find a solution. Not only will you rate different points in the search area. Various evolutionary algorithms such as genetic algorithm (GA) (Goldberg 1989), NN (Chen *et al.* 2019), fuzzy theory (Hsiao *et al.* 2005), LMI strategy (Yeh *et al.* 2007). The parameters were used to train the neural network. Several papers show the history of applying artificial intelligence tools to engineering problems. For example, Chiang *et al.* (2001, 2002, 2004) set new standards for systems. Chengwu *et al*. (2002), Systems and Hsiao *et al*. (2003, 2005) Utilizing the theory of artificial intelligence, Hsieh *et al*. (2006) published a stability analysis of artificial intelligence. Linetal *et al*. (2010). Provided the app. TLP system control application, Chen *et al.* (2006, 2007, 2009) also demonstrated the effectiveness of the neural network-based LDI theory. Liuetal (2009) developed the NN model. Structural biology algorithm. Meanwhile, Sakthivel *et al*. (2014) use reliable sample data control for the system. Chen *et al*. (2019, 2020) recently published some research findings on engineering applications for evolutionary models. Such algorithms do more than just provide parallelization and search techniques for finding solutions. Not only will you rate different points in the search area at the same time. This allows you to effectively train the parameters of your network's neural keys. Improves the output accuracy of the neural key network. Purpose is to investigate variables that affect stability under external wave power using a new evolutionary algorithm based on the evolutionary algorithm. He then proposed a distributed control set using parallel distributed compensation (PDC) technology and a powerful neurofuzzy algorithm (NFA) to overcome the effects of model errors. Make sure that stability is provided and there are no symptoms. The results are simulated and explained. And some conclusions were drawn.

2. System description

This paper presents research on active vibration compensation systems suitable for buildings. First, we focused on point-to-point management of jacketed offshore platforms. Fig. 1 shows a schematic diagram of a system that combines a traditional tension platform (TLP) with an active mass damper (AMD). The platform can be designed from the beginning as a single-level independent system (SDOF). Maximum movement boost mode You can suppress vibration in this way.

Model parameters for SDOF systems are represented by m_1, m_1, and m . x_1 The relevant coordinates associated with each and offshore platform movement are *represented by x1* . Mass natural frequency. Also, the AMD displacement ratio is represented by m_2, u_2, and $x_{2\text{, respectively}}$, and the AMD displacement is represented by x_2. The controlled non-uniform variation is indicated by u and f by physical analysis. Get the movement of the unified system (2.1). This can be described by the following interrelated derivative variables

$$\ddot{x}_1(t) = -(\omega_1^2 + \omega_2^2 m_2 / m_1)x_1(t) + (\omega_2^2 m_2 / m_1)x_2(t) - 2(\xi_1\omega_1 + \xi_2\omega_2 m_2 / m_1)\dot{x}_1(t) + (2\xi_2\omega_2 m_2 / m_1)\dot{x}_2(t)$$
$$+1/m_1(f(t) - u(t)) \qquad \ddot{x}_2(t) = \omega_2^2(x_1(t) - x_2(t)) + 2\xi_2\omega_2(\dot{x}_1(t) - \dot{x}_2(t)) + u(t)/m_2 \tag{2.1}$$

Neural networks are primarily used to represent network rules. This allows you to use well-known neural network algorithms to practice the rules. The core process of a neural network consists of fuzzy rules, inference, and a knowledge base (Terroa *et al*. 1999, Reyes *et al*. 2010, Tsai *et al.* 2012, 2015, Tim *et al.* 2019). The fuzzy defined by its predecessor and its result are used to determine the relationship between the input and the output. The inference process is primarily used

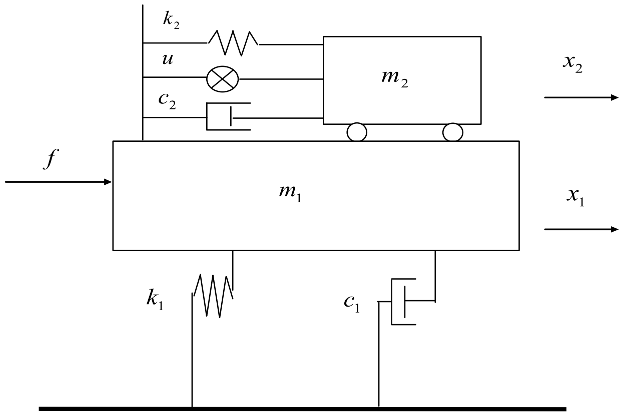

Fig. 1 Sketch of the TLP-AMD system

to determine connections and inference methods (Chen 2011, 2014, Tim *et al*. 2020, Chen *et al*. 2020, Tim *et al*. 2021, Zhen *et al*. 2021). Compared to Mamdani, TS neural types provide more meaning and integration. The first two processes This includes fuzzy rendering and manipulation similar to tick-type processes. In addition, the result of each rule is a function related to network input variables. To achieve this goal, we will use Neural TS. In other words, an evolutionary algorithm proposed for training variables (Chen *et al*. 2022, Hsiao *et al*. 2004, 2005, Chiang *et al*. 2007, Liu *et al*. 2009, Liu *et al*. 2010, Hung *et al*. 2019).

Defines a non- linear division pattern. I will explain as follows

$$N_j : \left\{ \begin{array}{c} \dot{x}_j(t)\psi_j(x_j(t),u_j(t))+\sum_{k=1}^{N_j} g_{kj}(x_j(t-\tau_{kj}))+\varphi j(t) \\ \varphi_j(t)=\sum_{\substack{n=1 \\ n\neq j}}^{J} C_{nj}x_n(t) \end{array} \right\} \tag{2.2}$$

Where $\psi_j(\cdot)$ and $g_{kj}(\cdot)$ is a nonlinear vector-valued function and $x_j(t)$ is a $x_j(t-\tau_{kj})$ state. τ_{kj} It means the $u_j(t)$ delay as an input and is C_{nj} the connection matrix between the *n* and *j subsystems* .

Over the last decade, the local linear input / output relationships of nonlinear systems using fuzzy dynamic models have evolved significantly from Takagi and Suke's pioneering work (Tsai and Chen 2014, Tsai *et al*. 2016, Chen *et al*. 2000). The isolated *j (no interconnect)* subsystem of ***N*** was estimated by the fuzzy TS model with multiple delays. This is explained by the fuzzy IF-THEN rule. An important function of the TS model is to represent each linear law as follows

Rule *1* : IF $x_{1j}(t)$ is M_{i1j} and $\cdots$ and $x_{\eta j}(t)$ is $M_{i\eta j}$

already $\dot{x}_j(t)=A_{ij}x_j(t)+\sum_{k=1}^{N_j}A_{ikj}x_j(t-\tau_{kj})+B_{ij}u_j(t)$

Here $x_j^T(t)=[x_{1j}(t), x_{2j}(t),\cdots, x_{\eta j}(t)]$, $u_j^T(t)=[u_{1j}(t), u_{2j}(t),\cdots, u_{mj}(t)]$

($i = 1, 2, \cdots, r_j$) Is the IF-THEN rule number, $x_{1j}(t) \sim x_{\eta j}(t)$ an initial variable with A_{ij}, the B_{ij} appropriate M_{ipj} size and membership A_{ikj} . The final state of this dynamic model (2.3) is summarized as follows

$$\dot{x}_j(t) = \frac{\sum_{i=1}^{r_j} w_{ij}(t)[A_{ij}x_j(t) + \sum_{k=1}^{N_j} A_{ikj}x_j(t-\tau_{kj}) + B_{ij}u_j(t)]}{\sum_{i=1}^{r_j} w_{ij}(t)}$$
$$= \sum_{i=1}^{r_j} h_{ij}(t)[A_{ij}x_j(t) + \sum_{k=1}^{N_j} A_{ikj}x_j(t-\tau_{kj}) + B_{ij}u_j(t)] \tag{2.3}$$

When

$$w_{ij}(t) = \prod_{p=1}^{\eta} M_{ipj}(x_{pj}(t)), \quad h_{ij}(t) = \frac{w_{ij}(t)}{\sum_{i=1}^{r_j} w_{ij}(t)} \tag{2.4}$$

Where is the $M_{ipj}(x_{pj}(t))$ membership $\sum_{i=1}^{r_j} h_{ij}(t) = 1$ level M_{ipj} of $x_{pj}(t)$ let ,,, $w_{ij}(t) \geq 0$ and , $h_{ij}(t) \geq 0$ and $\sum_{i=1}^{r_j} w_{ij}(t) > 0$ Eq. (2.5) is obtained.

$$N_j : \begin{cases} \dot{x}_j(t) = \sum_{i=1}^{r_j} h_{ij}(t)(A_{ij}x_j(t) + B_{ij}u_j(t) + \sum_{k=1}^{N_j} A_{ikj}x_j(t-\tau_{kj})) + [\psi_j(x_j(t), u_j(t)) + \sum_{k=1}^{N_j} g_{kj}(x_j(t-\tau_{kj})) \\ \qquad - \sum_{i=1}^{r_j} h_{ij}(t)(A_{ij}x_j(t) + B_{ij}u_j(t)) - \sum_{i=1}^{r_j}\sum_{k=1}^{N_j} h_{ij}(t)(A_{ikj}x_j(t-\tau_{kj}))] + \phi_j(t) \\ \phi_j(t) = \sum_{\substack{n=1 \\ n \neq j}}^{J} C_{nj}x_n(t) \end{cases} \tag{2.5}$$

To discuss the stability of equation (2.5), we design fuzzy controls using the NFA calculus in Section 3.

3. Neural-fuzzy linear differential inclusion

A neural-network-based model (3.1) can be described as follows (Hsaio *et al.* 2005)

$$\dot{X}(t) = \Psi^S(W^S\Psi^{S-1}(W^{S-1}\Psi^{S-2}(\cdots\cdots\Psi^2(W^2\Psi^1(W^1\Lambda(t)))\cdots\cdots))) \tag{3.1}$$

A neural network differential inclusion (NNDI) system can be a representation of state space and described as follows

$$\dot{Y}(t) = A(a(t))Y(t),$$

The interpolation technique is reviewed in Eq. (3.2)

$$\begin{aligned}\dot{X}(t) &= [\sum_{\varsigma^S=1}^{2} h_{\varsigma^S}(t)G_{\varsigma}^{S}(W^S[\cdots[\sum_{\varsigma^2=1}^{2} h_{\varsigma^2}(t)G_{\varsigma}^{2}(W^2[\sum_{\varsigma^1=1}^{2} h_{\varsigma^1}(t)G_{\varsigma}^{1}(W^1\Lambda(t))])]\cdots])] \\ &= \sum_{\varsigma^S=1}^{2}\cdots\sum_{\varsigma^2=1}^{2}\sum_{\varsigma^1=1}^{2} h_{\varsigma^S}(t)\cdots h_{\varsigma^2}(t)h_{\varsigma^1}(t)G_{\varsigma}^{S}W^S\cdots G_{\varsigma}^{2}W^2G_{\varsigma}^{1}W^1\Lambda(t) \\ &= \sum_{\Omega^\sigma} h_{\Omega^\sigma}(t)E_{\Omega^\sigma}\Lambda(t)\end{aligned} \tag{3.2}$$

where

$$\sum_{\varsigma^\sigma} h_{\varsigma^\sigma}(t) \equiv \sum_{q_1^\sigma=1}^{2}\sum_{q_2^\sigma=1}^{2}\cdots\sum_{q_{R^\sigma}^\sigma=1}^{2} h_{q_1^\sigma}(t)h_{q_2^\sigma}(t)\cdots h_{q_{R^\sigma}^\sigma}(t) \quad \text{for} \quad \varsigma = 1, 2, \cdots, R^\sigma \quad ; \quad E_{\Omega^\sigma} \equiv G_{\varsigma}^{S}W^S\cdots G_{\varsigma}^{2}W^2G_{\varsigma}^{1}W^1,$$

$$\sum_{\Omega^\sigma} h_{\Omega^\sigma}(t) \equiv \sum_{\varsigma^S=1}^{2}\cdots\sum_{\varsigma^2=1}^{2}\sum_{\varsigma^1=1}^{2} h_{\varsigma^S}(t)\cdots h_{\varsigma^2}(t)h_{\varsigma^1}(t).$$

Finally, based on Eq. (3.2), the NN dynamic was rewritten in NNDI of Eq. (3.3)

$$\dot{X}(t) = \sum_{i=1}^{r} h_i(t)\overline{E}_i\Lambda(t) \tag{3.3}$$

where constant matrix is with an dimension. The NNDI form becomes

$$\dot{X}(t) = \sum_{i=1}^{r} h_i(t)\{A_i X(t)\} \tag{3.4}$$

Based on the above model scheme, nonlinear systems can be represented as NNDI, a flexible and mathematical analysis tool for machine learning. To ensure the stability of the offshore platform, the TS machine learning model and stability analysis were modified. Furthermore, TS machine learning fuzzy models representing nonlinear systems can be described in the next section.

4. Fuzzy control design and evolved NFA

By improving the hybrid damping control, you can achieve the required movement. Please note that the hybrid damper control is genuine. I haven't designed the controller. The actual delay factor is given as a control signal.

Pay attention to how you monitor, including tracking errors and rates, in other words, it is related to ideal and actual conditions. Only the actual signal can be predicted for actual use, further improving performance. The gray system theory DGM model (2.1) is used to design the predictions. It can be easily implemented in a microcomputer based on little known information. It is assumed that the sequence number n can be described as DGM. Gray Model as follows

$$\alpha^{(1)}x^{(0)}(k)+px^{(0)}(k) = q, \qquad Bh = Y \tag{4.1}$$

Once the prediction is complete, the actual value of the signal will be measured over time. It is difficult to guarantee absolute accuracy. This is due to the large effect of resting motion on random stimuli. Compare the predicted value with the actual value. If the error is allowed, the predicted value is output. Otherwise, the actual signal will be sent directly. We assume that the short-term situation will not change significantly. The absolute difference between the current signal and the previous signal is 5 times the error limit.

The next motion prediction $x_1, \dot{x}_1, x_3, \dot{x}_3$ adds $x^{(0)}$ a measurement to the footer and $x^{(0)}(n+1)$ subtracts it $x^{(0)}(1)$ to create a new sequence in the same order. Repeat the above steps to create a DGM (4.1) model based on the dynamics of the NN model using the control.

$$x(k+1) = \sum_{i=1}^{r_l} \sum_{j=1}^{J} h_i(k)\bar{h}_j(k) H_{ij} x(k) + e(k) \tag{4.2}$$

Where $H_{ij} = A_i - B_i K_j$,, $\Re(x(k)) \equiv f(x(k), u(k))$ _ $e(k) = [\Re(x(k)) - \sum_{i=1}^{r_l} \sum_{j=1}^{J} h_i(k)\bar{h}_j(k) H_{ij} x(k)]$

If P is positive, it is a κ model error and $e(k)$ has the following inequality

$$\boldsymbol{H}_{ij}^T \boldsymbol{P} \boldsymbol{H}_{ij} - \boldsymbol{P} < 0 \tag{4.3}$$

If satisfied, the system will be symptom-free and stable, which is valid by Eq. (4.3).

$$\begin{aligned}
\Delta V(k) &= V(k+1) - V(k) = x^T(k+1) P x(k+1) - x^T(k) P x(k) \\
&= [\sum_{i=1}^{r} \sum_{l=1}^{r} h_i(k) h_l(k) \{A_i - B_i K_l\} x(k)]^T P_j [\sum_{i=1}^{r} \sum_{l=1}^{r} h_i(k) h_l(k) \{A_i - B_i K_l\} x(k)] \\
&\quad - x^T(k) P x(k) \\
&= \sum_{i=l=1}^{r} h_i^2(k)\, x^T(k) [(A_i - B_i K_i)^T P (A_i - B_i K_i) - P] x(k) \\
&\quad + 2 \sum_{i<l}^{r} h_i(k) h_l(k) x^T(k) [H_{il}^T P H_{il} - P] x(k),
\end{aligned}$$

we have ΔV <0, and the proof is thereby completed. A fuzzy evolutionary algorithm (NFA) based on nature has been proposed. First, the fitness program randomly selects raw R rules from the R subpopulation to generate a TNFN. Repeat the above steps in SelectionTimes using try and errors.

5. Algorithm

The overall design process can be summarized as the following algorithm.

Step 1: The following equation shows how to generate TNFN.

$$TNFN_i = \{Ind_{1sel}, Ind_{2sel}, \ldots. Ind_{Rsel}\} \tag{5.1}$$

where i is selection times, TNFNi is the ith generated TNFN, Ind represents the individual to form the TNFN, Sel means the selected index of the individual in the th j subpopulation.

Step 2: The fitness program evaluates each TNFN prepared from step 1 to obtain a fitness value. The capacitance value is primarily used to indicate the performance of each TNFN. In other words, it is the main process of development, because the exercise of value plays an important role in determining whether to seek the best solution. The value of the ability to conceive can help individuals make effective assessments, and vice versa. In this study, the well-known mean squared error (RMS) (Reyes et al., 2010) was used to assess the performance of TNFN because it can more effectively reflect the performance of the model. Eq. (5.2) describes the fitness function designed in this study.

$$FitnessValue = 1/\ TNFN_i \tag{5.2}$$

It can be seen from Eq. (5.2) means higher fitness value, which means TNFN output is close to output, and vice versa.

Step 3: After receiving the fitness value of each selected TNFN, the fitness program will calculate the fitness value of each individual containing TNFN. Specifically, divide the fitness value obtained in step 2 by the number of cycles (i.e., R). After that, talent sharing value will be collected for selected individuals. To examine how each individual relates to the others, we discuss how the ability to choose values in a set behaves on the overall solution. Primarily used to prevent overpopulation of the best performers, allowing the overall solution to address the underperformers. This will maintain the best mix of individuals.

Step 4: In the last step, each person's cumulative value will be divided by the number of times they have been selected. Subsequently, average competence represents the value of individual performance. equation. (5.3) shows the calculation of the average fitness value.

$$fitness\ value_{\mathrm{Ind}} = FitnessValue_{\mathrm{Industry}} / \ Select\ Value_{\mathrm{Industry}} \tag{5.3}$$

where i=1, 2… R ; j=1, 2… SP

In short, the proposed AEA can help address the various criteria by which individuals in each subgroup are assessed. More precisely, one can consider achieving such criteria for hybridization and mutation. Therefore, when the solution is far from the optimal solution, this step of development is not only to find a larger research space, but when the solution is closer to the optimal solution, the development can also narrow the search space to be searched. Therefore, AEA can provide a powerful method for assessing subgroups.

6. Example

In this section, we study network vibration controllers for jacketed offshore platforms. First, we describe the variables of wave structure and strength. Then discuss the impact of the time delays. Finally, compare the performance of the proposed controllers with the performance of different literatures.

For offshore platforms (Tsai and Chen 2014), the water depth of the cover structure is d = 218 m, the total height of the platform is L = 249 m, the characteristic diameter D corresponding to the platforms at four legs is D=1.83 m, and modal mass $m1$ = 7,825,307 kg, then the natural frequency of the platform is u_1 = 2.0466 rad/s and the structural damping ratio is x_1 = 2%. As shown in Figure 1, the AMD equipment is installed on a panel platform. The characteristics of AMD equipment are as follows: mass m_2 = 78.253 kg, natural frequency u_2 = 2.0074 rad/s, damping rate x_2 = 20%. The system time sampling time is here T = 0.01 s, and its parameters are as follows (the wind and wave conditions are described in Tsai and Chen (2014))

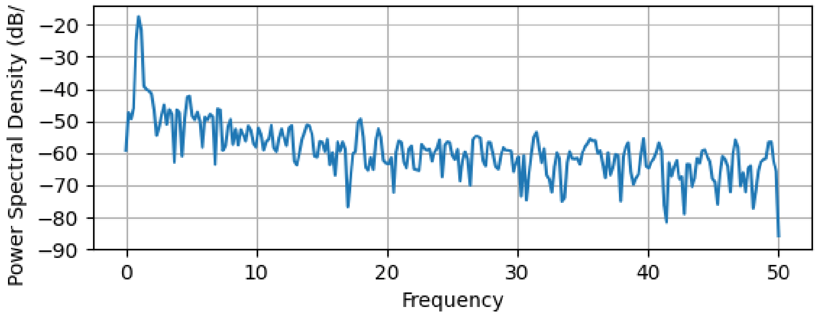

Fig. 2 Power spectrum density (PSD) of wave elevation

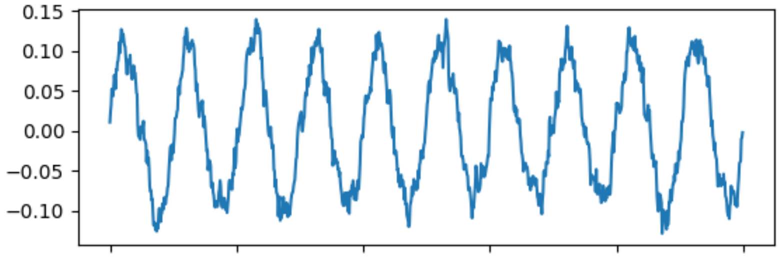

Fig. 3 Power spectrum density (PSD) of wave force.

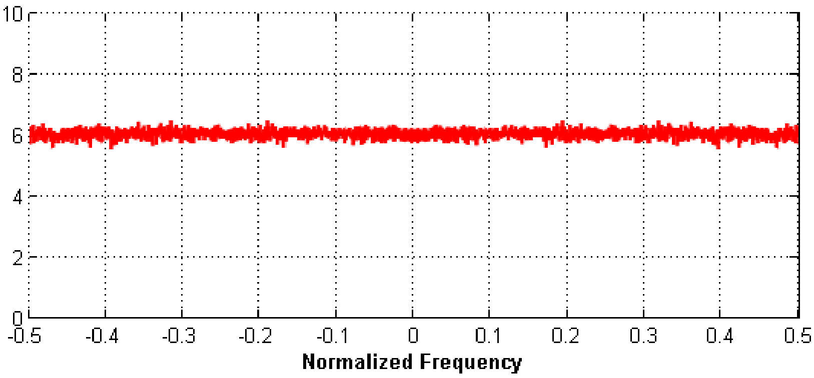

Fig. 4 Irregular wave force acting on the offshore structure

$$\mathbf{A} = \begin{bmatrix} 0.9998 & 0.0000 & 0.0100 & 0.0000 \\ 0.0002 & 0.9998 & 0.0000 & 0.0100 \\ -0.0423 & 0.0004 & 0.9989 & 0.0001 \\ 0.0400 & -0.0401 & 0.0082 & 0.9918 \end{bmatrix}, \quad \mathbf{B} = 10^{-6} * \begin{bmatrix} 0.0000 \\ 0.0006 \\ -0.0013 \\ 0.1273 \end{bmatrix}, \quad \mathbf{D} = 10^{-8} * \begin{bmatrix} 0.0006 \\ 0.0000 \\ 0.1277 \\ 0.0005 \end{bmatrix}$$

The wave height power and the wave power spectral density (PSD) are shown in Figs. 2 and 3. We get the force of the irregular waves acting on the offshore platform, as shown in

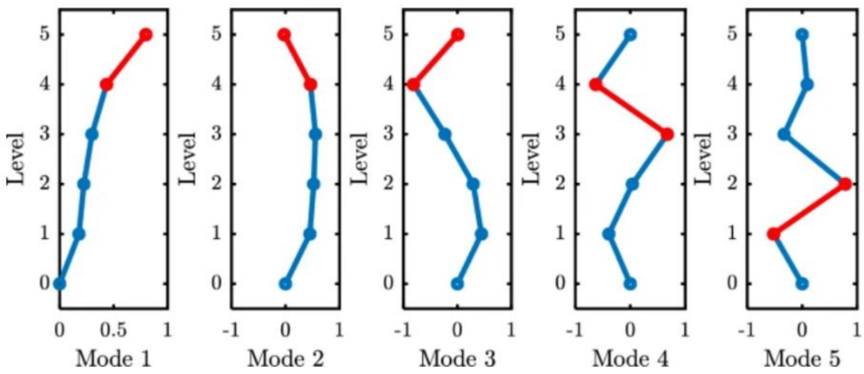

Fig. 5 The best installation location for the offshore platform when the target order is high

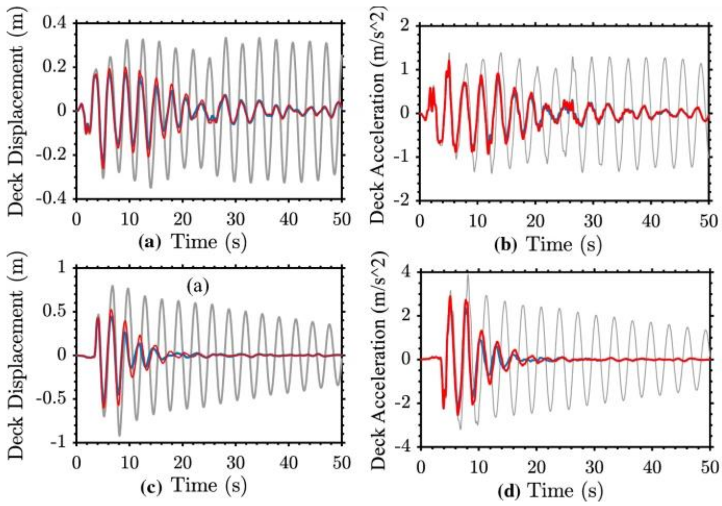

Fig. 6 Control results of the offshore platform structure

Fig. 4. The performance index of the vibration control system of the offshore platform is $R = 10^{-5}$, $N = 210/T$. The network between distributed equipment and offshore platforms differentiates from traditional point control systems. Due to the harsh environment, delays and loss of packages are usually unavoidable.

In addition, for this examples, other known genetic algorithms are compared to the proposed NFA to provide reasonable evidence of the practical application of the proposed controller design.

The Fig. 5 has this result is different from that for public buildings since the good position for public buildings, mainly focused on the first type, usually in the bottom of the building. This is because the size of the deck, i.e. the top floor, is more than that of the public structure. In addition, for the decision model, the best position for the offshore platform is neutral and this is the same for public buildings.

Compared to the vibration response in uncontrolled conditions, the control estimation can reduce the maximum deviation up to 40%, the average deviation up to 35%, the maximum varies from up to 45% and the average difference from 38%. The maximum control power is 10% of the object, and the average control power is 10%. In Figure 6, the control fails at 20 s. For the first 15 s, control has a 65% reduction in maximum control compared to instructions with a reduction of 70%. We only show 50 s in this experiment, and the whole experiment lasts for 16 minutes, with both controls standing still.

7. Conclusions

This paper proposes a model-related approach for designing efficient controllers for evolutionary algorithms to overcome the effects of model errors. Make sure your system is stable. Stability criteria are directly examined by the Lyapunov method. The NFA is based on a complex system of echolocation TS fuzzy TS models and solves problems based on this standard and distributed control system. A group that designs predictive signals and active controls. Finally, a numerical sample was provided to illustrate the stability analysis of the nonlinear response. And the application of this standard depends on the actual degree of vibration compensation of MDOF. The results of control strategies can also reduce the risk of industrial applications. The results of this paper also provide a practical perspective on risk analysis for the marine industry. Especially in the prevention of serious accidents in the design of large offshore drilling rigs.

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