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Parameter identification of nonlinear roll motion equation for floating structures in irregular waves

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ABSTRACT

In order to predict the roll motion of a floating structure in irregular waves accurately, it is crucial to estimate the unknown damping coefficients and restoring moment coefficients in the nonlinear roll motion equation. In this paper, a parameter identification method based on a combination of random decrement technique and support vector regression (SVR) is proposed to identify the coefficients in the roll motion equation of a floating structure by using the measured roll response in irregular waves. Case studies based on the simulation data and model test data respectively are designed to validate the applicability and validity of the identification method. Firstly, the roll motion of a vessel is simulated by using the known coefficients from literature, and the simulated data are used to identify the coefficients in the roll motion equation. The identified coefficients are compared with the known values to validate the applicability of the identification method. Then the roll motion is predicted by using the identified coefficients. The prediction results are compared with the simulated data, and good agreement is achieved. Secondly, the model test data of a FPSO are used to identify the coefficients in the roll motion equation. Then the random decrement signature of the roll motion is predicted by using the identified coefficients and compared with that obtained from the model test data, and satisfactory agreement is achieved. From this study, it is shown that the identification method can be effectively applied to identify the coefficients in the nonlinear roll motion equation in irregular waves.

1. Introduction

The roll motion of a floating structure at sea has a significant influence on its safety and operability; therefore, it is crucial to predict the roll motion of a floating structure accurately. Although the roll motion of floating structures has been investigated by many researchers for a long time, because of the strong nonlinear nature of the roll damping, it is still challenging to predict the roll motion correctly, and a universal method to predict the roll damping is still absent.

Traditionally, there are three kinds of methods available for predicting the roll damping, i.e., model test [1–3], semi-empirical method [4–7] and numerical calculation [8–10]. During the last decade, system identification techniques, which aim to find the best mathematical model that relates the output to the input of a system, have been applied to estimate the roll damping by analyzing the roll motion of floating structures. Unar [11] applied artificial neural network to identify the roll damping coefficient of a ship. Muñoz-Mansilla et al. [12] applied system identification method to estimate the parametric model of heave-pitch-roll dynamics of a high-speed craft. Xing and McCue [13] applied artificial neural network to identify the nonlinear roll motion of a ship by using experimental data. Jang et al. [14,15] applied an inverse formulism to identify the functional form of the nonlinear roll damping for a ship by using a free-roll decay experiment and the measured transient response, respectively. Jang [16] improved this identification method to simultaneously identify the nonlinear damping and the restoring characteristics of nonlinear oscillation systems. Han and Kinoshita [17–19] presented an application of stochastic inverse method for the nonlinear damping identification and applied this method to identify the nonlinear roll damping of a ship at zero forward speed and non-zero forward speed. Yin et al. [20] applied sequential learning RBF neural networks to on-line predict the roll motion of a ship during maneuvering.

Compared to the conventional learning methods based on large scale samples, support vector machine (SVM), as a new generation of machine study method, is very suitable for learning based on small scale samples. It was first proposed by Vapnik [21] in the 1990s. By taking advantage of the Lagrangian dual theorem and structural risk minimum principle to solve quadratic programming

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problems, SVM can achieve the global optimal solution of the quadratic programming problems. According to its application, SVM can be divided into two categories: one is support vector classifier (SVC) which is often used to solve classification problems; and the other is support vector regression (SVR) which is used to solve regressive problems. Because SVR can not only acquire the global optimum solution, but also can avoid the curse of dimensionality and the problem of data over-fitting to some extent, SVR has been successfully applied to parameter identification in ship and ocean engineering. Luo and Zou [22], Zhang and Zou [23,24] used least square SVR and ε-SVR respectively to identify the hydrodynamic derivatives in ship maneuvering motion equations. Xu et al. [25,26] applied least square SVR to identify the nonlinear coefficients in the dynamic model of underwater vehicles. Liu and Yang [27] applied varying parameters least square SVR to on-line predict the roll motion of a ship.

In the present study, a parameter identification method based on a combination of random decrement technique and SVR is proposed to identify the unknown coefficients in the nonlinear roll motion equation of a floating structure in irregular waves. Firstly, case studies based on the simulation data are designed to validate the applicability of this method. Secondly, the parameter identification method is applied to identify the unknown coefficients in the nonlinear roll motion equation by using the model test data of a FPSO. Then the roll motion is predicted based on the identified coefficients and the prediction results are compared with the measured data to demonstrate the validity of the identification method. Finally, some conclusions are drawn.

2. Equation of roll motion

The roll motion of a floating structure at sea can be described by a second-order nonlinear ordinary differential equation of the form

$$(I_{xx}+J_{xx})\ddot{\phi}+D(\dot{\phi})+C(\phi)=M \tag{1}$$

where ϕ is the roll angle (rad); I_{xx} is the mass moment of inertia (kg m^2); J_{xx} is the added mass moment of inertia (kg m^2); $D(\dot{\phi})$ is the damping moment (N m); $C(\phi)$ is the restoring moment (N m); M is the wave exciting moment (N m).

Various expressions of the damping and restoring moments are proposed [28,29]. In this paper, the most commonly used expression of a linear term plus a quadratic term is used to represent the nonlinear damping moment

$$D(\dot{\phi})=D_1\dot{\phi}+D_2\dot{\phi}|\dot{\phi}| \tag{2}$$

where D_1 and D_2 are the linear and nonlinear damping coefficients, respectively. The restoring moment is represented as an odd function of the roll angle by a linear term plus a cubic term in the form

$$C(\phi)=C_1\phi+C_3\phi^3 \tag{3}$$

where C_1 and C_3 are the linear and third-order restoring moment coefficients, respectively.

In irregular waves, the wave exciting moment M can be expressed by

$$M=\sum_{i=1}^{\infty}F_i\cos(\omega_i t+\theta_i) \tag{4}$$

where F_i and ω_i are the amplitude and frequency of the wave exciting moment component, respectively, and θ_i is the phase shift which is taken as a random variable uniformly distributed between 0 and 2π.

Substituting Eqs. (2), (3) and (4) into Eq. (1), the second-order nonlinear ordinary differential equation of roll motion for a floating structure in irregular waves is derived:

$$(I_{xx}+J_{xx})\ddot{\phi}+D_1\dot{\phi}+D_2\dot{\phi}|\dot{\phi}|+C_1\phi+C_3\phi^3=\sum_{i=1}^{\infty}F_i\cos(\omega_i t+\theta_i) \tag{5}$$

Dividing Eq. (5) by the total moment of inertia $(I_{xx}+J_{xx})$, the normalized roll motion equation is obtained:

$$\ddot{\phi}+p_1\dot{\phi}+p_2\dot{\phi}|\dot{\phi}|+r_1\phi+r_3\phi^3=\sum_{i=1}^{\infty}A_i\cos(\omega_i t+\theta_i) \tag{6}$$

where $p_1=D_1/(I_{xx}+J_{xx})$, $p_2=D_2/(I_{xx}+J_{xx})$; $r_1=C_1/(I_{xx}+J_{xx})$, $r_3=C_3/(I_{xx}+J_{xx})$ and $A_i=F_i/(I_{xx}+J_{xx})$.

3. Identification method

The identification method consists of two parts: one is the random decrement technique which is applied to obtain the random decrement signature from the steady roll response of a floating structure in irregular waves; the other is SVR which is applied to identify the unknown coefficients in the nonlinear roll motion equation based on the obtained random decrement signature.

3.1. Random decrement technique

Random decrement technique, as an averaging technique, has been successfully applied in parameter or nonparametric identification in ship and ocean engineering in combination of conventional identification methods [30,31]. The basic concept of the random decrement technique is that the random response of a floating structure in irregular waves can be divided into two components: one is the deterministic component which is dependent on the initial state; the other is the random component which is dependent on the external excitation. By applying the random decrement technique, the random component is removed and the deterministic component, named as random decrement signature, is kept.

To derive the random decrement equation of the nonlinear roll motion in irregular waves, the following two variable substitutions are used:

$$y_1=\phi,\quad y_2=\dot{\phi} \tag{7}$$

Substituting Eq. (7) into Eq. (6), the following equation is obtained:

$$\begin{cases}\dot{y}_1=y_2\\ \dot{y}_2=-p_1y_2-p_2y_2|y_2|-r_1y_1-r_3y_1^3+\displaystyle\sum_{i=1}^{\infty}A_i\cos(\omega_i t+\theta_i)\end{cases} \tag{8}$$

When the random decrement technique is used to analyze the roll motion, the wave excitation is assumed to be a white noise random process which satisfies the following conditions

$$E[M(t)]=0,\quad E[M(t_1)M(t_2)]=\psi_0\delta(t_1-t_2) \tag{9}$$

where $E[\cdot]$ denotes the ensemble average of variables; ψ_0 is the zero-order spectral moment of the excitation; δ is the Dirac delta function [32,30].

Then the random process $Y(t)=[y_1, y_2]^T$ is a Markov process, and its conditional probability density function can be described by virtue of the Fokker–Planck equation

$$\frac{\partial P}{\partial t}=-\frac{\partial}{\partial y_1}(y_2P)+\frac{\partial}{\partial y_2}[(p_1y_2+p_2y_2|y_2|+r_1y_1+r_3y_1^3)P]+\frac{\psi_0}{2}\frac{\partial^2 P}{\partial y_2^2} \tag{10}$$

where $P = P(y_1, y_2, t|y_{10}, y_{20})$ is the conditional probability density of the random process $Y(t)$ and its initial condition is

$$\lim_{t\to 0} P(y_1, y_2, t|y_{10}, y_{20}) = \delta(y_1 - y_{10})\delta(y_2 - y_{20}) \tag{11}$$

where y_{10} and y_{20} are the initial roll angle and roll rate, respectively.

Multiplying Eq. (10) by the variables y_1 and y_2, respectively, and integrating the equation with respect to these two variables in the interval $[-\infty, \infty]$, the following equation is obtained:

$$\begin{cases} \dot{\mu}_1 = \mu_2 \\ \dot{\mu}_2 = -p_1\mu_2 - p_2 E[y_2|y_2|] - r_1\mu_1 - r_3 E[y_1^3] \end{cases} \tag{12}$$

where μ_1 and μ_2 are the mean values of the roll angle and roll rate, respectively.

The above formulae can be rewritten into a second-order nonlinear differential equation of the form

$$\ddot{\mu}_1 + p_1\dot{\mu}_1 + r_1\mu_1 + p_2\mu_3 + r_3\mu_4 = 0 \tag{13}$$

where $\mu_3 = E[y_2|y_2|]$, $\mu_4 = E[y_1^3]$.

According to Eq. (6), the free roll motion equation can be written as

$$\ddot{\phi} + p_1\dot{\phi} + p_2\dot{\phi}|\dot{\phi}| + r_1\phi + r_3\phi^3 = 0 \tag{14}$$

Comparing Eq. (13) with Eq. (14), it is obvious that these two equations are similar in the sense that the structure is similar and the coefficients in these equations are same. Thus, the damping coefficients and the restoring moment coefficients in the nonlinear roll motion equation can be determined based on the identification method by using the random decrement signature.

In order to obtain the random decrement signature, firstly, a constant roll angle value is selected as the threshold value, and the abscissa axis of the time history of roll response is divided into N segments of equal length, and every segment begins at the moment at which the roll angle value is equal to the selected threshold value. Meanwhile, the overlapping which may happen between the sequential segments is allowed, and the initial slopes of these segments alternate between positive value and negative value so that one half starts with positive slope and the other half starts with negative slope. Secondly, every segment is discretized with the same time step and the roll angle values at discrete points are obtained by interpolation technique. Then the random decrement signature of the roll response is obtained by superposing all the roll angle values at the discrete points with the same sequence number and dividing them by the number of segments N. See Elshafey et al. [30] for more details about how to obtain the random decrement signature.

3.2. Support vector regression

SVR, as a new generation of machine learning method, is based on the statistic learning theory. The basic concept of SVR is briefly introduced in this subsection, and more details can be found in Smola and Schölkopf [33].

The training data are given as

$$T = \{(x_i, y_i), i = 1, 2, \ldots, l\} \in (\Re^n \times \Re)_l \tag{15}$$

where $x_i \in \Re^n$ is the ith n-dimensional training input vector and $y_i \in \Re$ is the corresponding training output value; l is the number of training sample; $\Re^n$ is the n-dimensional Euclidean space and $\Re$ is the set of real numbers.

The goal is to find a feature function $g(x)$ which is often described as

$$g(x) = w^T\Phi(x) + b \quad (x \in \Re^n) \tag{16}$$

where $\Phi(x)$ is a transformation function which transforms the input vector x in the Euclidean space into $X = \Phi(x)$ in the feature space; $w \in \Re^n$ is a weight matrix; $b \in \Re$ is a bias.

According to the structural risk minimum principle [21,33], the function estimation problem of finding the feature function in Eq. (16) according to the training data in Eq. (15) is transformed to a quadratic optimization problem which is described by

$$\begin{aligned} &\min_{w,\xi^{(*)}} J(w, \xi^{(*)}) = \frac{1}{2}w^T w + C\sum_{i=1}^{l}(\xi_i + \xi_i^*) \\ &s.t. \quad [\langle w, \Phi(x_i)\rangle + b] - y_i \le \varepsilon + \xi_i; \\ &\quad [\langle w, \Phi(x_i)\rangle + b] - y_i \ge -\varepsilon - \xi_i^*; \\ &\quad \xi_i, \quad \xi_i^* \ge 0; \quad i = 1, 2, \ldots, l \end{aligned} \tag{17}$$

where C is the penalty factor; $\xi^{(*)} = [\xi_1, \xi_1^*, \xi_2, \xi_2^*, \ldots, \xi_l, \xi_l^*]$ is the slack factor vector; $\langle\cdot,\cdot\rangle$ denotes the inner product; ε is the insensitive loss factor.

The key idea is to construct a Lagrangian function from the objective function in Eq. (17) by introducing a dual set of variables. According to the dual theorem, the Lagrangian function is given by

$$\begin{aligned} L := \frac{1}{2}||w||^2 + C\sum_{i=1}^{l}(\xi_i + \xi_i^*) - \sum_{i=1}^{l}(\eta_i\xi_i + \eta_i^*\xi_i^*) - \sum_{i=1}^{l}\alpha_i(\varepsilon + \xi_i + y_i \\ - \langle w, \Phi(x_i)\rangle - b) - \sum_{i=1}^{l}\alpha_i^*(\varepsilon + \xi_i^* - y_i + \langle w, \Phi(x_i)\rangle + b) \end{aligned} \tag{18}$$

where $\alpha_i, \alpha_i^*, \eta_i, \eta_i^*$ are the Lagrangian multipliers.

The partial derivatives of L with respect to the primal variables (w, b, ξ_i, ξ_i^*) have to vanish for optimality. It follows

$$\begin{cases} \dfrac{\partial L}{\partial w} = 0 \to w = \sum_{i=1}^{l}(\alpha_i^* - \alpha_i)\Phi(x_i) \\ \dfrac{\partial L}{\partial b} = 0 \to \sum_{i=1}^{l}(\alpha_i - \alpha_i^*) = 0 \\ \dfrac{\partial L}{\partial \xi_i} = 0 \to \eta_i = C - \alpha_i \\ \dfrac{\partial L}{\partial \xi_i^*} = 0 \to \eta_i^* = C - \alpha_i^* \end{cases} \tag{19}$$

Substituting Eq. (19) into Eq. (18), the dual problem of the primal optimization in Eq. (17) is obtained:

$$\begin{aligned} &\min_{\alpha,\alpha^*} \quad W(\alpha, \alpha^*) = \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l}(\alpha_i^* - \alpha_i)(\alpha_j^* - \alpha_j)K(x_i, x_j) + \varepsilon\sum_{i=1}^{l}(\alpha_i^* + \alpha_i) - \sum_{i=1}^{l}y_i(\alpha_i^* - \alpha_i) \\ &s.t. \quad \sum_{i=1}^{l}(\alpha_i - \alpha_i^*) = 0; \quad \alpha_i, \alpha_i^* \in [0, C] \end{aligned} \tag{20}$$

where K is the kernel function matrix and its element $K(x_i, x_j)$ equals to the inner product of the input vectors in the feature space, i.e., $K(x_i, x_j) = \langle \Phi(x_i), \Phi(x_j) \rangle$.

Solving Eq. (20) to obtain the optimal solution of the convex programming problem and the bias b, the feature function of SVR in Eq. (16) can be rewritten as

$$g(x) = \sum_{i=1}^{n} (\alpha_i^* - \alpha_i) K(x_i, x) + b \tag{21}$$

Generally, any kind of function can be taken as kernel function of SVR, such as linear function $K(x, x') = \langle x, x' \rangle$, polynomial function $K(x, x') = (1 + \langle x, x' \rangle)^d$, Gauss radial basis function $K(x, x') = \exp(-||x - x'||^2/2\sigma^2)$ and so on, only if the function satisfies the Mercer kernel theorem. Therein, $x' \in \Re^n$ is a vector which has the same dimension as x.

Because the essence of training SVR is to solve the convex quadratic programming problem in Eq. (20), any kind of optimization algorithms for solving quadratic programming problem can be applied to train SVR, such as interior point algorithms, subset selection algorithms and so on. In this paper, in order to improve the efficiency of training SVR, a novel optimization algorithm, called sequential minimum optimization (SMO) algorithm [34], is applied to train SVR. Compared with the traditional optimization algorithms for quadratic programming, the greatest merit of the SMO algorithm is to train SVR analytically instead of explicitly invoking a time-consuming numerical quadratic programming optimizer. The key idea of the SMO algorithm is to break the large quadratic programming problem into a series of smallest possible quadratic programming sub-problems by repeatedly finding two Lagrangian multipliers that can be optimized with respect to each other. After that, the smallest quadratic programming problems can be solved analytically. If no two Lagrangian multipliers can be optimized, the original quadratic programming problem is solved. The SMO algorithm actually consists of two steps: (1) a set of heuristics for efficiently choosing pairs of Lagrangian multipliers to work on, and (2) the analytical solution to a quadratic programming problem of size two.

4. Parameter identification

To validate the applicability of the identification method in identifying the damping coefficients and the restoring moment coefficients in the nonlinear roll motion equation, case studies based on the simulation data and model test data respectively are designed.

4.1. Identification example based on the simulation data

In order to simulate the roll motion, a vessel model is considered and the damping coefficients and restoring moment coefficients in Eq. (6) are pre-determined and given in Table 1 [35]. Then case studies with the white noise and the JONSWAP spectrum as the excitation respectively are carried out to test the validity of the identification method.

For the white noise excitation, the wave exciting moment is assumed to be composed of 70 sinusoidal components of constant amplitude 0.07 rad/s^2. The frequency range of the excitation is taken between 2.0 and 5.0 rad/s. The wave exciting moment is expressed as

$$M = \sum_{i=1}^{70} 0.07 \cos(\omega_i t + \theta_i) \tag{22}$$

For the JONSWAP spectrum excitation, the wave exciting moment is assumed to be composed of 70 sinusoidal components of variable amplitudes. The amplitudes A_i are determined by

$$A_i = \sqrt{2S(\omega_i)\Delta\omega} \tag{23}$$

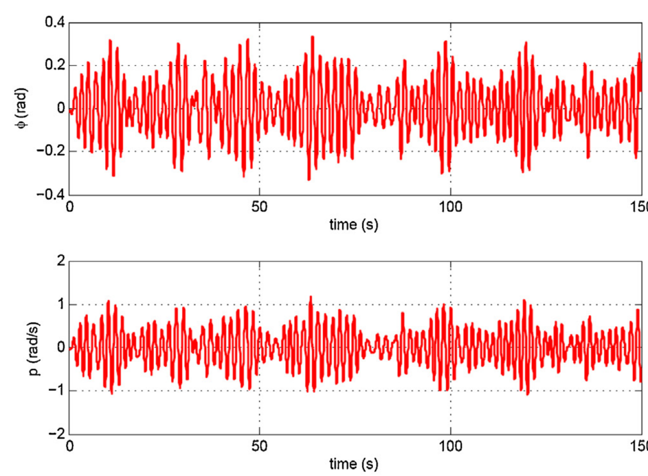
where $S(\omega_i)$ is the spectrum density corresponding to the wave frequency ω_i; $\Delta\omega$ is the frequency increment. The significant height and the modal frequency of the exciting spectrum are assumed to be 0.07 rad/s^2 and 3.14 rad/s, respectively. The frequency range of the excitation is taken between 2.0 and 8.0 rad/s.

Then the fourth-order Runge–Kutta method with the time step size of 0.05 s is applied to simulate the roll motion. The simulated roll responses for the two cases are shown in Fig. 1(a) and (b), respectively.

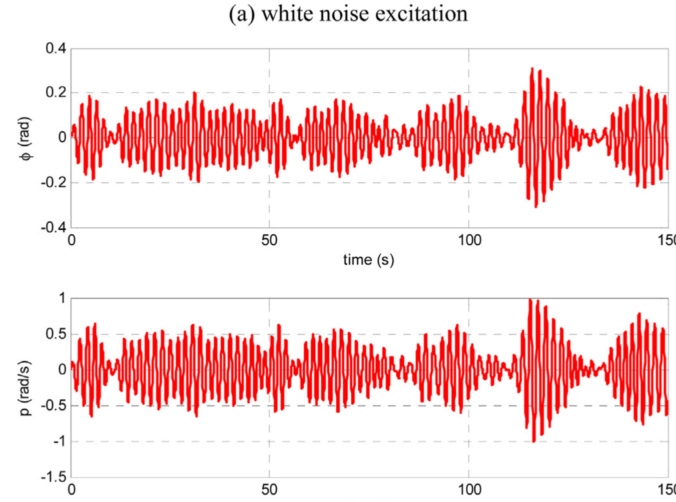
Based on the simulated roll response, the random decrement signature is obtained by virtue of the random decrement technique. The significant value of the roll angle, which is the arithmetic mean of the one-third maximum roll angle of the simulated data, is selected as the threshold value of random decrement signature.

Table 1
Comparison of the identified coefficients with the known values for white noise excitation.

Coefficient	Known	SVR		LS method	
		Identified	Error (%)	Identified	Error (%)
p_1	0.1627	0.1620	0.43	0.1620	0.43
p_2	0.5214	0.4947	5.12	0.5126	1.69
r_1	11.492	11.4887	0.03	11.4891	0.025
r_3	1.7008	1.7402	2.32	1.7013	0.05

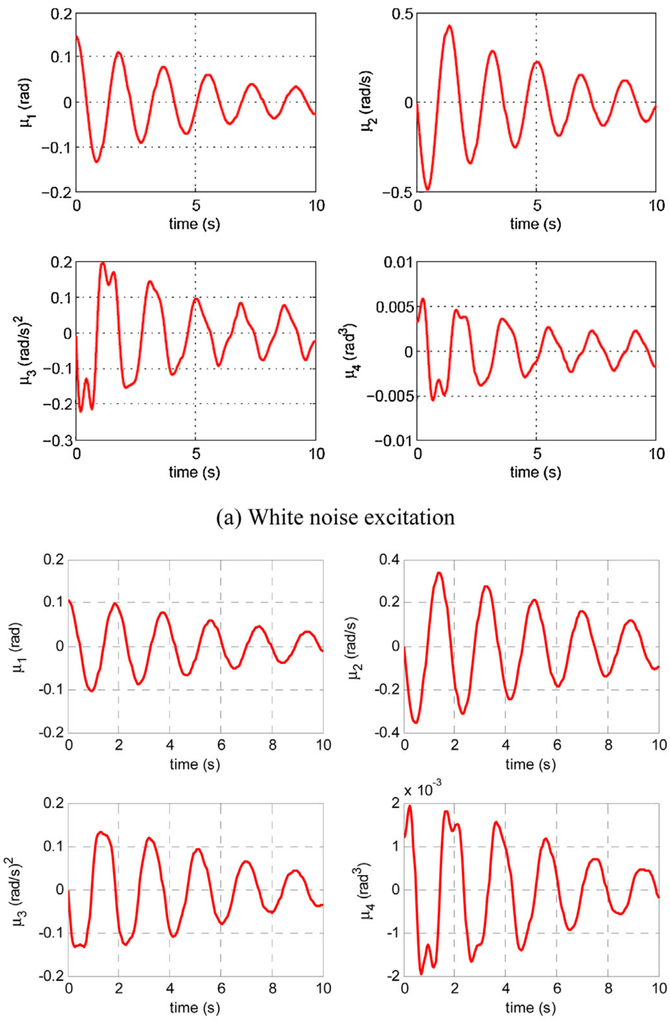


(a) white noise excitation



(b) JONSWAP spectrum excitation

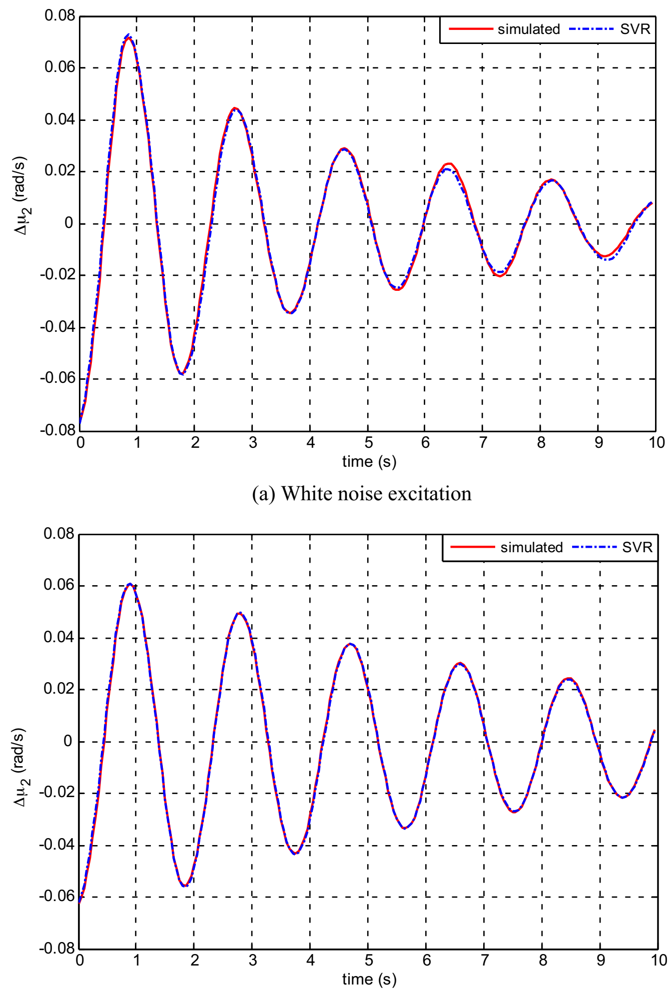
Fig. 1. Simulated roll responses.



(a) White noise excitation

(b) JONSWAP spectrum excitation

Fig. 2. Random decrement signatures.



(a) White noise excitation

(b) JONSWAP spectrum excitation

Fig. 3. Training results of SVR.

For white noise excitation, the threshold value is $\phi_s = 0.136$ rad. For JONSWAP spectrum excitation, the threshold value is $\phi_s = 0.106$ rad. The random decrement signatures obtained for the two cases are shown in Fig. 2(a) and (b), respectively.

Integrating Eq. (13) in the interval $[t_n, t_{n+1}]$, and applying the trapezoidal method to approximately calculate the integration of the last three terms in the left-hand side of the equation, it follows

$$\dot{\mu}_{1,n+1} - \dot{\mu}_{1,n} = -p_1(\mu_{1,n+1} - \mu_{1,n}) - \frac{hp_2}{2}(\mu_{3,n+1} + \mu_{3,n}) - \frac{hr_1}{2}(\mu_{1,n+1} + \mu_{1,n}) - \frac{hr_3}{2}(\mu_{4,n+1} + \mu_{4,n}) \quad (24)$$

where $\dot{\mu}_{1,n}$ and $\mu_{1,n}$ denote the random decrements of roll rate and roll angle at the nth time step, respectively; h is the integration time step.

Since Eq. (24) is linear with respect to the unknown coefficients, when applying SVR to identify the unknown coefficients, the linear function $K(x, x') = \langle x, x' \rangle$ is selected as the kernel function. Compared with the feature function of SVR in Eq. (21), if SVR has been trained (which means that the bias b approximates to zero), then $\sum_{i=1}^{n}(\alpha_i^* - \alpha_i)x_i$ are the identified parameters.

In order to train SVR, both the input and output are needed. According to Eq. (24), the input and output of SVR are defined as

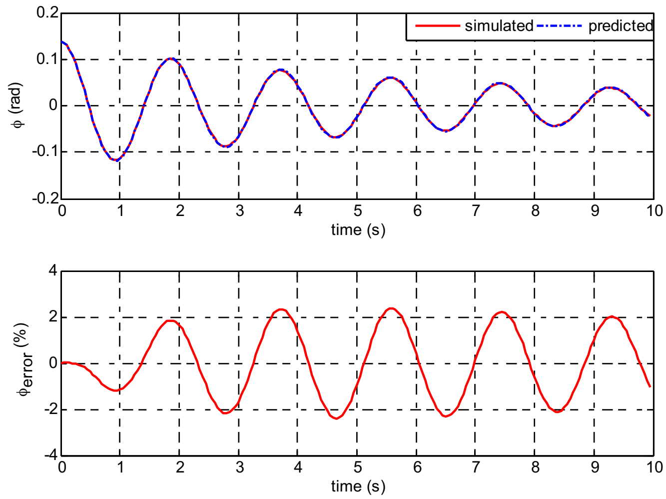
$$\begin{aligned} &\text{Input} = \{\mu_{1,n+1} - \mu_{1,n}; \mu_{3,n+1} + \mu_{3,n}; \mu_{1,n+1} + \mu_{1,n}; \mu_{4,n+1} + \mu_{4,n}\} \\ &\text{Output} = \{\dot{\mu}_{1,n+1} - \dot{\mu}_{1,n}\} \end{aligned} \quad (25)$$

The training sample couples constructed according to Eq. (25) are used to train SVR and the training results of SVR for the two cases are shown in Fig. 3(a) and (b), respectively.

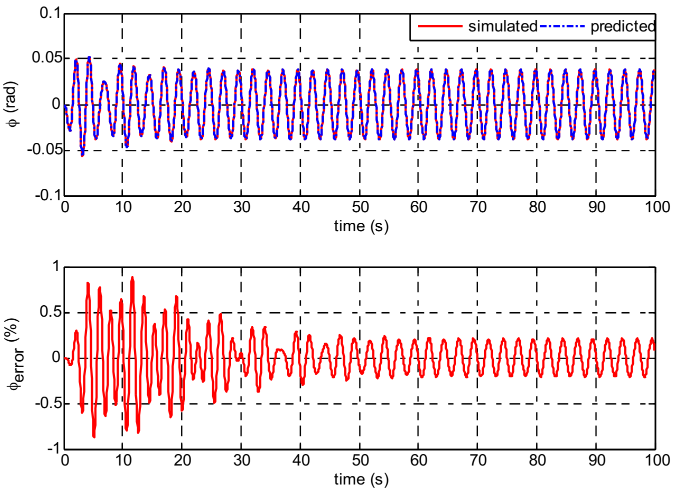
Once SVR is trained, the unknown coefficients in Eq. (24) can be identified. The identified coefficients for the two cases are given in Tables 1 and 2 respectively in comparison with the known values. Also the identified values by the standard least square (LS) method are given in Tables 1 and 2 for the purpose of comparison.

Table 2
Comparison of the identified coefficients with the known values for JONSWAP spectrum excitation.

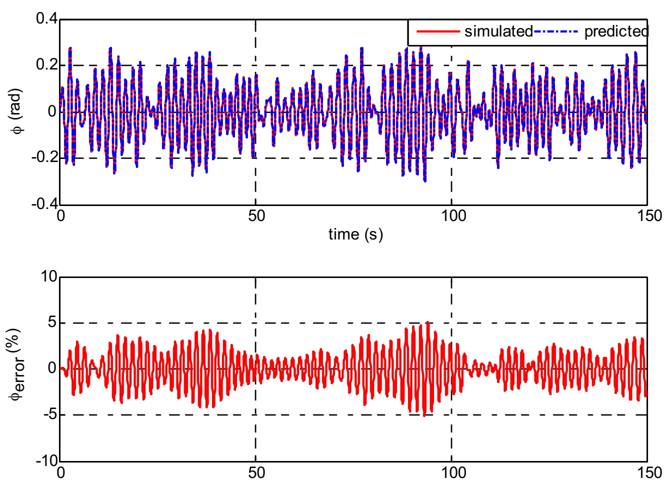
Coefficient	Known	SVR		LS method	
		Identified	Error (%)	Identified	Error (%)
p_1	0.1627	0.1583	2.70	0.1547	4.92
p_2	0.5214	0.4772	8.48	0.4571	12.33
r_1	11.492	11.2791	1.85	11.1715	2.79
r_3	1.7008	1.8140	6.65	1.8137	6.64



(a) Roll angle and the prediction error in the free decay test

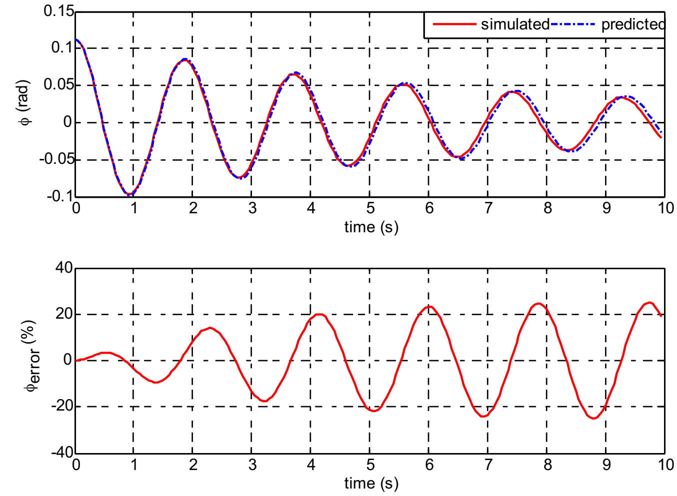


(b) Roll angle and the prediction error in regular waves

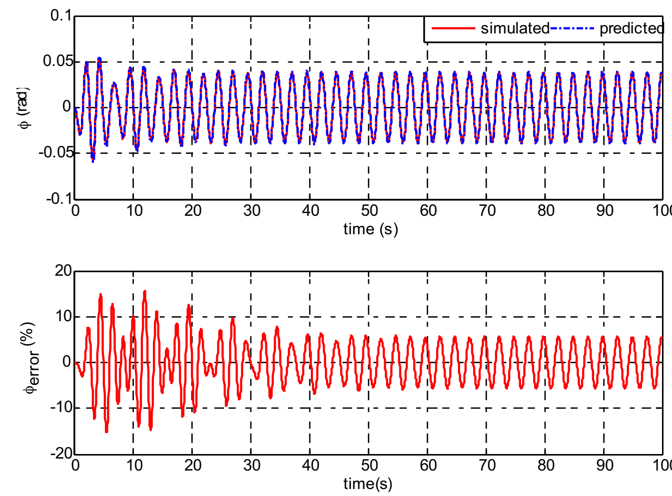


(c) Roll angle and the prediction error in irregular waves

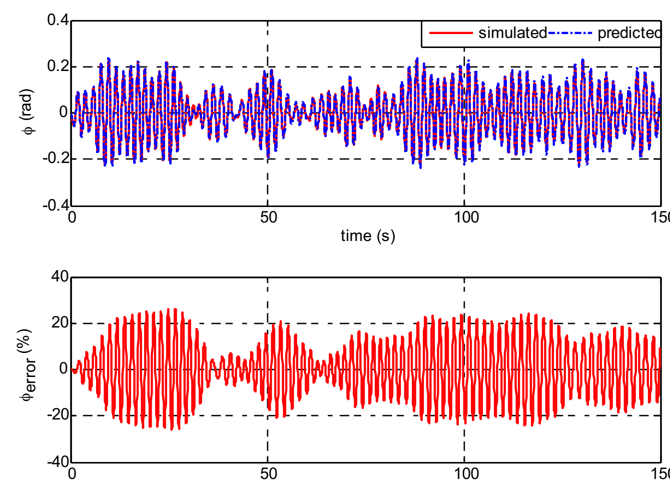
Fig. 4. Comparison between the predicted and simulated roll angles, white noise excitation.



(a) Roll angle and the prediction error in the free decay test

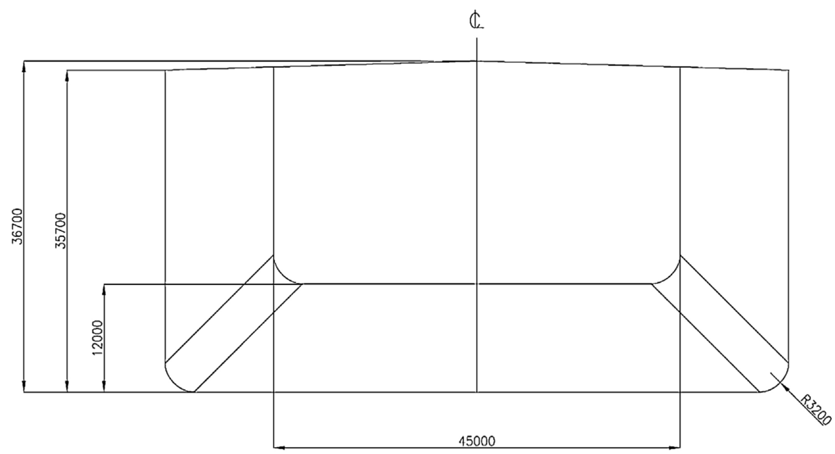


(b) Roll angle and the prediction error in regular waves

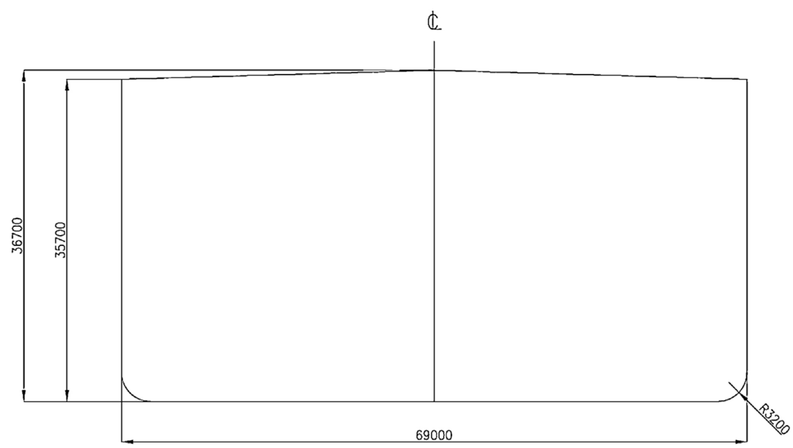


(c) Roll angle and the prediction error in irregular waves

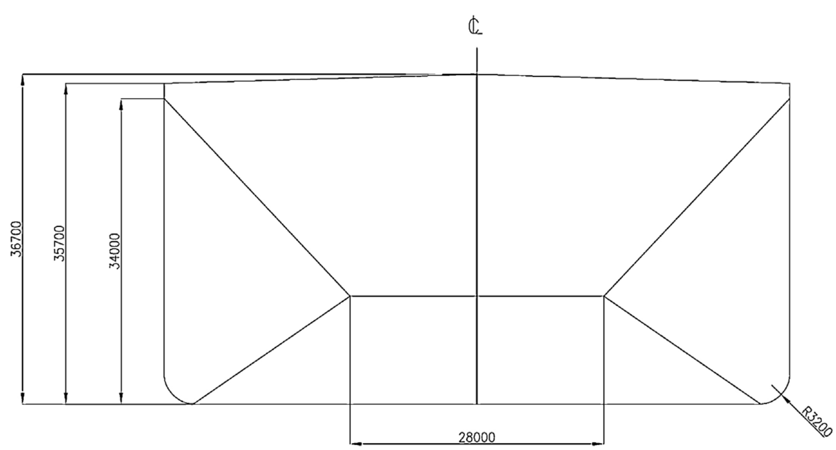
Fig. 5. Comparison between the predicted and simulated roll angles, JONSWAP spectrum excitation.



(a) Stern view



(b) Typical frame



(c) Bow view

Fig. 6. Body plan of the FPSO.

For the white noise excitation, it can be seen from Table 1 that the maximum error of SVR is only about 5%, which indicates that SVR can be applied to identify effectively the coefficients in the nonlinear roll motion equation based on the random decrement analysis. Besides, it can be seen that the standard LS method has higher identification accuracy than SVR. On the other hand, for the JONSWAP spectrum excitation, it can be seen from Table 2 that the maximum error of SVR is about 8.5% and the identification accuracy of SVR is higher than that of the standard LS method. Considering that the wave exciting moment of roll motion in irregular waves is actually colored noise rather than white noise, it can be concluded that SVR is more suitable for the parameter identification of the nonlinear roll motion equation than the standard LS method.

Then the roll motions in the free roll decay test, in regular waves with the wave excitation $f(t)=0.2\sin(2.5t+\pi)$ and in irregular waves with the white noise excitation and the JONSWAP spectrum excitation are respectively predicted by using the identified coefficients. In Fig. 4(a)–(c), the predicted roll angles in the free roll decay test, in regular waves and in irregular waves with the white noise excitation by using the identified coefficients in Table 1 are compared with the simulated roll angles by using the known coefficients, respectively. In Fig. 5(a)–(c), the predicted roll angles in the free roll decay test, in regular waves and in irregular waves with the JONSWAP spectrum excitation by using the identified coefficients in Table 2 are compared with the simulated roll angles by using the known coefficients, respectively. In these figures, the time histories of the prediction errors of roll angle are also shown. The prediction error is calculated by

$$\phi_{error} = \frac{\phi_P - \phi_S}{\phi_{rms}} \times 100\% \tag{26}$$

where ϕ_{error} is the prediction error; ϕ_P is the predicted roll angle; ϕ_S is the simulated roll angle; ϕ_{rms} is the root-mean-square of the simulated roll angle.

From Figs. 4 and 5, it can be clearly seen that though some discrepancies exist, the agreement between the simulated and predicted roll angles is acceptable. It can be concluded that the identification method based on the combination of random decrement technique and SVR can be applied to identify the coefficients in the nonlinear roll motion equation by using the simulation data. However, it should be noted that in the simulation process, the wave exciting moment is directly generated by using the JONSWAP spectrum, rather than determined by the transfer function of wave exciting moment in the linear theory. Although it makes this simulation example not realistic, the conclusion of the simulation study is not influenced seriously.

4.2. Identification example based on the model test data

In order to verify the applicability of the identification method in identifying the unknown coefficients in the nonlinear roll motion equation of floating structures by analyzing the experimental data, model tests are carried out for a FPSO model and the roll response to irregular wave excitation is measured. The model scale is 1:81 and the principal particulars of the model are given in Table 3. Fig. 6 shows the body plans of the FPSO. The model is subjected to the irregular waves of JONSWAP spectrum. The significant height of the wave spectrum is 0.1852 m and the peak spectral period is 1.68 s. The model test condition corresponds to the 100-year survival condition at full scale, where the significant height of the wave spectrum is 15 m and the peak spectral period is 15.1 s. The measured roll angle and the roll rate obtained by numerical difference are shown in Fig. 7.

The identification procedure is applied to the model test data. The significant value of the roll angle ϕ_s = 0.028 rad, which is the arithmetic mean of the one-third maximum roll angle of the measured data, is selected as the threshold value of the random decrement signature. The random decrement signature is obtained by the random decrement technique, as shown in Fig. 8.

Table 3
Principal particulars of the FPSO model.

Item	Symbol	Unit	Value
Length over all	L_{oa}	m	3.82
Length between perpendiculars	L_{pp}	m	3.71
Breadth	B	m	0.67
Depth	D	m	0.32
Mean draft	T	m	0.15
Displacement volume	∇	m^3	0.363
Dry radius of roll gyration	i_x	m	0.23
Bilge keel	$L_k \times B_k$	m^2	2.85 × 0.01

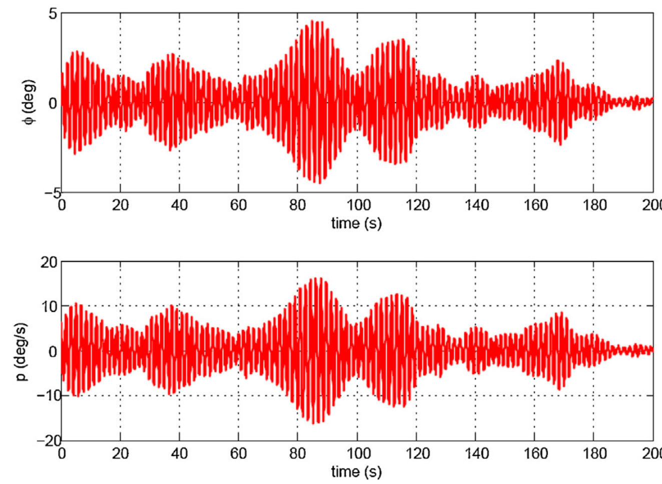


Fig. 7. Roll response of the FPSO model in irregular waves.

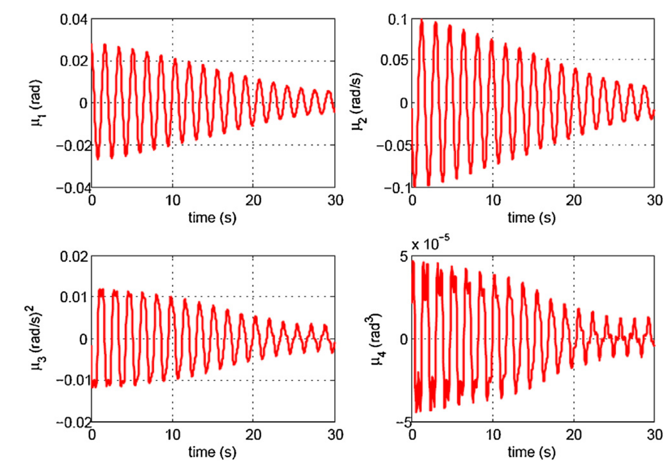


Fig. 8. Random decrement signature.

According to Eq. (25), the training sample couples of SVR are constructed and used to train SVR. The training results are shown in Fig. 9.

Once SVR is trained, the damping coefficients and the restoring moment coefficients can be obtained. The results are given in Table 4, where the identified coefficients by the standard LS method are also given for comparison.

Because the actual values of the damping coefficients and restoring moment coefficients of the FPSO model are not available,

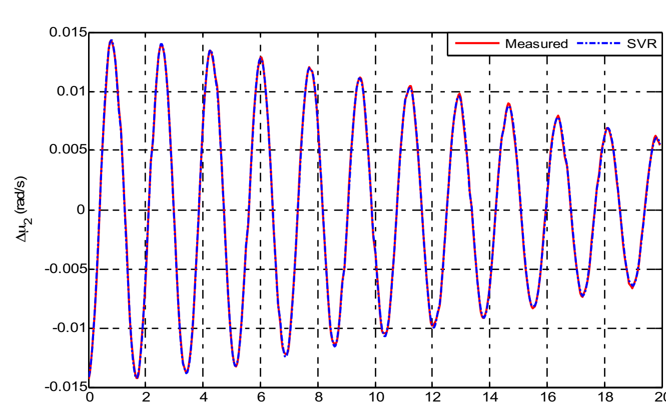


Fig. 9. Training results of SVR.

Table 4
Identified coefficients.

Coefficient	SVR	LS method
p_1	0.1624	0.2584
p_2	0.3505	0.5655
r_1	13.2541	13.2104
r_3	0.6602	0.8669

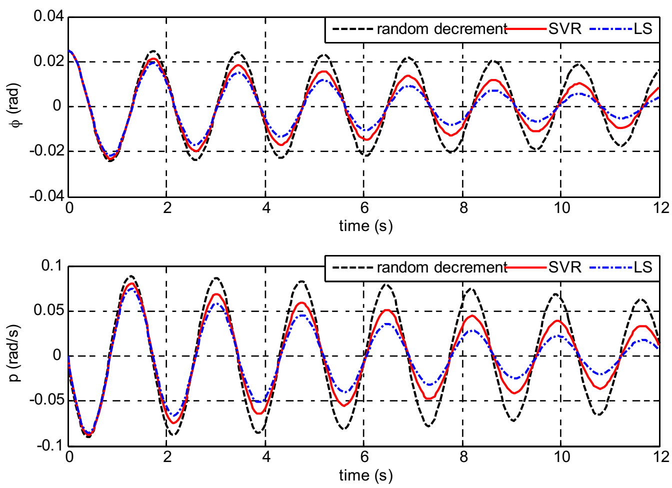


Fig. 10. Comparison of the predicted free roll motion with the random decrement signature.

comparisons between the identified values and the actual values are impossible. In order to validate the accuracy of the identified coefficients, the free roll motion is predicted by using the identified coefficients. Since the actual free decay data are experimentally not available, the random decrement signatures obtained from the measured roll response are used to approximate the free decay motion. Then the predicted results are compared with the random decrement signatures, as shown in Fig. 10.

From Fig. 10, it can be clearly seen that there are some discrepancies between the random decrement signature and the predicted free decay motion. The discrepancies may be caused by the following reasons: the random decrement signatures obtained from the measured roll response do not exactly represent the free decay motion, and there are some discrepancies between the identified coefficients and the actual ones.

Moreover, from Fig. 10 it can be seen that the discrepancy between the random decrement signature and the predicted free decay motion by SVR is less than that by the standard LS method; this means, the identification method proposed in this paper is better than the standard LS method. It is more suitable for identifying the unknown coefficients in the nonlinear roll motion equation, especially in the case where only the roll motion data are available.

5. Conclusions

In this paper, a novel identification method based on a combination of the random decrement technique and SVR is proposed for identifying the damping coefficients and restoring moment coefficients in the nonlinear roll motion equation of a floating structure in irregular waves. In order to verify the accuracy and applicability of the identification method, it is firstly applied to analyze the simulation data of a vessel to identify the unknown coefficients. The comparison between the predicted motion based on the identified coefficients and the simulated motion based on the known coefficients validates the identification ability of the proposed method. Then the identification method is applied to analyze the model test data of a FPSO model. The free roll motion is predicted by using the identified coefficients, and the prediction results are compared with the random decrement signatures obtained by the random decrement technique based on the measured data. The reasonable agreement demonstrates the applicability and validity of the identification method in identifying the coefficients in the nonlinear roll motion equation. Therefore, the method can be effectively applied to obtain the roll damping and restoring moment of a floating structure while operating at sea with only the motion responses measured. This is an especially meaningful merit, since the various coefficients in the nonlinear roll motion equation can be identified by analyzing only the roll motion data which are relatively easy to measure. Nevertheless, it should be pointed out that this identification method is not applicable in the initial design stage, because the roll response is usually not available at this stage.

The proposed identification method has been successfully applied to identify the damping coefficients and restoring moment coefficients in the nonlinear roll motion equation. However, the roll motion is often coupled with sway and yaw motions, hence it is more practical and desirable to identify the coupled equations of sway, roll and yaw motions simultaneously. In the future study, the focus will be on expanding the identification method to estimate the coefficients in the coupled equations of sway, roll and yaw motions simultaneously.

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