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Parameter identification of ship manoeuvring model under disturbance using support vector machine method

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ABSTRACT

Demanding marine operations increase the complexity of manoeuvring. A highly accurate ship model promotes predicting ship motions and advancing control safety. It is crucial to identify the unknown hydrodynamic coefficients under environmental disturbance to establish accurate mathematical models. In this paper, the identification procedure for a 3 degree of freedom hydrodynamic model under disturbance is completed based on the support vector machine with multiple manoeuvres datasets. The algorithm is validated on the clean ship model and the results present good fitness with the reference. Experiments in different sea states are conducted to investigate the effects of the turbulence on the identification performance. Generalisation results show that the models identified in the gentle and moderate environments have less than 10% deviations and are considered allowable. The higher perturbations, the lower fidelity the identified model has. Models identified under disturbance could provide different levels of reliable support for the operation decision system.

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Parameter identification; manoeuvring model; support vector machine; disturbance; nonlinear

1. Introduction

Obtaining a model that can accurately describe the ship dynamics and its interaction with the environment has always been of considerable interest to academic researchers and marine industries. The model is expected to be high fidelity so that can be used for designing high-performance model-based control strategies (Zheng et al. 2018), as well as developing computer-based simulators for virtual testing (Li et al. 2016).

However, the modelling process is found complex due to the nonlinear properties of ship dynamics. The models obtained from experiments are thought to be the most accurate and reliable, yet they can also be the most economically costly to develop. Only a limited number of hull ships have had any parameters determined experimentally. Although lots of empirical methods associated with various model series have been developed, they can only provide reliable estimates when the hull form fits some tested series well enough, so that they are suggested to be used with great care. An alternative of theoretical calculations appears to recourse to computer fluid dynamics (CFD). The CFD techniques are already matured enough to provide estimates that, in general, can be viewed even more credible than empirical methods (Martelli et al. 2021). However, building proper finite element models necessitates expert experience, and in addition, it often is computationally intensive for on-line use. System identification theory comes up for its efficiency and economy. When addressing the ship manoeuvring model configuration issue, in general, it has to deal with complicated hydrodynamic effects associated with nonlinear and coupled coefficients, which challenge the researchers a lot (Åström and Källström 1976; Skjetne et al. 2004).

To address the challenges in ship dynamics identification, researchers offer various methods, for example, least-square method (Ding 2014), Bayesian approach (Xue et al. 2020), the maximum likelihood method (Chen et al. 2018, july), extended Kalman filter method (Perera et al. 2015), and so on. These methods are demonstrated valid for a more or less wide range of hull forms and environment configurations. However, the conventional approaches are found sensitive to noise and initial estimations would influence the converging performance. Regarding the circumstances outlined it would be practically difficult to identify the model plant in a realistic environment. Given the technological and computational advances in instrumenting process, a branch of identification method by machine learning has been established.

The techniques in the form of neural networks (NNs) have been applied as a regression process to model the nonlinear ship dynamics and predict future trajectories. In the work of Rajesh and Bhattacharyya (2008), NN was employed to estimate the unknown time equation clubbed by all nonlinear hydrodynamic derivatives of large tankers. This experience shows that NNs work well on approaching nonlinearities, yet meanwhile, the exploration to parameters associated with the ship is kept out of reach. Similarly, in the work of Cheng et al. (2019), the NN was used to generate a surrogate model based on the ship motion data. Again, it is a black-box model, and the parameters are not correlated to specific physical properties of the ship.

In the cases where the hydrodynamic derivatives are preferred to be presented in detail, another machine learning technique – support vector machine (SVM) can help. This approach proposed by Vapnik (1999) features a kernel-based learning process and facilitates the possibility of acquiring regression coefficients. It is increasingly applied to estimate ship dynamics, for instance, in the work of Luo and Zou (2009), as well as Zhang and Zou (2011), the authors implemented the Abkowitz model identification of a benchmark ship. It is shown that the SVM approach works well when there is no disturbance accounted for in the system.

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However, the ship dynamics have always changing due to the interaction with environmental disturbance and load conditions. Developing a reliable model to a considerable extent under such interference to provide onboard decision support for autonomous vessels where no human expertise could dominate, is practically pivotal. Inspired by the pragmatic challenge, increasing attention has been drawn to the system identification problem in random environments. The SVM-based identification is found to be insensitive to instrumental noise and capable of achieving high generalisation performance (Sutulo and Soares 2014; Wang et al. 2019). Examples of identifying ship model in waves are reported in the work by Hou and Zou (2016) and Selvam and Bhattacharyya (2010). In their work, the excitation forces and moments of waves are estimated first by numerical calculation or experiment measurements. Whereas the instant signals of waves or ocean currents are always not available onboard, which consequently limits the assessment of environmental loads. An alternative solution is modelling the slow-varying environmental forces as a stochastic process to compensate for the lack of realistic ship manoeuvring data. Achieving reliable estimation under such disturbance is the target of this study. The extent of perturbations varies to simulate different sea states. Within this context, the authors intend to address the impact of external disturbance on the parameter identification performance and seek estimations to a considerable accuracy by using the SVM-based identification approach so that they can be used in different operating scenarios according to their fidelities.

The structure of this paper is organised as follows. Section 2 formulates the parameter identification problem and procedure. This is followed by a review of the ship manoeuvring model and the concept of SVM algorithms. In Section 3, the identification algorithm is implemented for a clean system, aiming to verify the fidelity of the numerical model. Section 4 focuses on the disturbance experiment design and results discussion. The marine ship is assumed to expose to different levels of environmental perturbations, and the fidelity of the identified model is of particular concern. Conclusions and future work are presented in the final section.

2. Parameter identification

The parameter identification of the ship manoeuvring model is complex due to the respective hydrodynamic effects. Normally, the ship dynamics are described by a group of derivative equations, associated with linear and nonlinear terms. Specifically, the identification process is described in Figure 1. The regression model, derived from the ship manoeuvring model, determines the input and output features of the SVM. After preparing the data containing ship motion and propulsion commands, the SVM is extensively trained and optimal coefficients are then generated. By substituting the identified results back into the ship manoeuvring model, the estimated model is obtained and could be further examined. Particularly, the generalisation capability of the identified model should be stressed properly.

The training datasets include the vessel's multiple different manoeuvres. Note that the ship motion data should be taken extra cleaning treatment to eliminate the measurement noise if it is collected from the onboard sensors.

Models to describe ship dynamics can take many forms. To highlight the ship hydrodynamic properties, the Abkowitz model expressed in form of Taylor series is selected. A benchmark ship – a Mariner class vessel acts as research platform. The major steps concerning identification as shown in the dash box are expanded in the following subsections.

2.1. Ship manoeuvring model

For an offshore surface vessel performing manoeuvring tasks, its horizontal 3 degree of freedom (DOF) behaviour in non-dimensional form can be expressed as

$$\begin{bmatrix} m' - X_{\dot u}' & 0 & 0 \\ 0 & m' - Y_{\dot v}' & m'x_g' - Y_{\dot r}' \\ 0 & m'x_g' - N_{\dot v}' & I_{zz}' - N_{\dot r}' \end{bmatrix} \begin{bmatrix} \dot u' \\ \dot v' \\ \dot r' \end{bmatrix} = \begin{bmatrix} X' \\ Y' \\ N' \end{bmatrix} \tag{1}$$

where the superscript represents dimensionless variables. m' is the ship mass, x_g' is the position of gravity centre in the longitudinal direction of the body-fixed coordinate system. $\dot u'$, $\dot v'$, $\dot r'$ are the accelerations in surge, sway, and yaw directions. X', Y' and N' represent forces along the ship longitudinal and lateral directions, as well as the moments about the vertical axis, respectively. $X_{\dot u}'$, $Y_{\dot v}'$, $Y_{\dot r}'$, $N_{\dot v}'$, $N_{\dot r}'$ are non-dimensional added mass coefficients. $I_{zz'}$ is the inertia moment about the vertical axis.

The non-dimensional variables are defined as

$$\dot u' = \frac{\dot u L}{U^2}, \dot v' = \frac{\dot v L}{U^2}, \dot r' = \frac{\dot r L^2}{U^2}, u' = \frac{u}{U}, v' = \frac{v}{U}, r' = \frac{rL}{U}, U = \sqrt{(U_0 + u)^2 + v^2}$$

$$X' = \frac{X}{0.5\rho L^2 U^2}, \quad Y' = \frac{Y}{0.5\rho L^2 U^2}, \quad N' = \frac{N}{0.5\rho L^2 U^2}$$

where ρ is the density of water, L is the ship length, U is registered as the instantaneous ship speed, u refers to perturbed surge velocity about nominal speed U_0.

The non-dimensional forms of hydrodynamic forces/moments in the Abkowitz model are represented as Equation (2).

$$\begin{aligned} X' =& X_u'u' + X_{uu}'u'^2 + X_{uuu}'u'^3 + X_{vv}'v'^2 + X_{rr}'r'^2 + X_{rv}'r'v' \\ &+ X_{dd}'\delta'^2 + X_{udd}'u'\delta'^2 + X_{vd}'v'\delta' + X_{uvd}'u'v'\delta' + X_{uvv}'u'v'^2 \\ &+ X_{urr}'u'r'^2 + X_{uvr}'u'v'r' + X_{r\delta}'r'\delta' + X_{ur\delta}'u'r'\delta' + X_0' \end{aligned} \tag{2-a}$$

$$\begin{aligned} Y' =& Y_v'v' + Y_r'r' + Y_{vvv}'v'^3 + Y_{vvr}'v'^2r' + Y_{rrr}'r'^3 \\ &+ Y_{vrr}'v'r'^2 + Y_{vuu}'v'u'^2 + Y_{ruu}'r'u'^2 \\ &+ Y_{vu}'v'u' + Y_{ru}'r'u' + Y_d'\delta' + Y_{ddd}'\delta'^3 + Y_{ud}'u'\delta' \\ &+ Y_{uud}'u'^2\delta' + Y_{vdd}'v'\delta'^2 + Y_{vvd}'v'^2\delta' + Y_{r\delta\delta}'r'\delta'^2 \\ &+ Y_{rr\delta}'r'^2\delta' + Y_{rv\delta}'r'v'\delta' + (Y_0' + Y_{0u}'u' + Y_{0uu}'u'^2) \end{aligned} \tag{2-b}$$

$$\begin{aligned} N' =& N_v'v' + N_r'r' + N_{vvv}'v'^3 + N_{vvr}'v'^2r' + N_{rrr}'r'^3 \\ &+ N_{vrr}'v'r'^2 + N_{vuu}'v'u'^2 + N_{ruu}'r'u'^2 + N_{vu}'v'u' \\ &+ N_{ru}'r'u' + N_d'\delta' + N_{ddd}'\delta'^3 + N_{ud}'u'\delta' + N_{uud}'u'^2\delta' \\ &+ N_{rr\delta}'r'^2\delta' + N_{rv\delta}'r'v'\delta' + N_{vdd}'v'\delta'^2 + N_{r\delta\delta}'r'\delta'^2 \\ &+ N_{vvd}'v'^2\delta' + (N_0 + N_{0u}'u' + N_{0uu}'u'^2) \end{aligned} \tag{2-c}$$

The hydrodynamic derivatives $\{X'_{(\cdot)}, Y'_{(\cdot)}, N'_{((\cdot))}\}$ are the parameters that need to be identified.

2.2. Regression model

The Abkowitz model is generally considered as a nonlinear hydrodynamic model, whereas it can be viewed as a linear model with respect to the hydrodynamic parameters. The motion equations are discretised by using Euler's stepping method and the derived

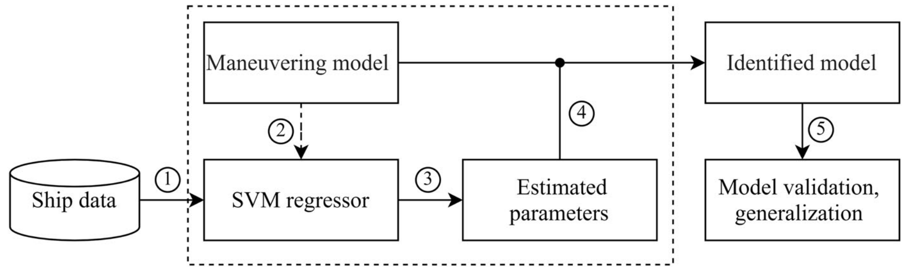

Figure 1. Scheme of parameter identification for ship manoeuvring model.

regression model is

$$\begin{aligned} u'(n+1) - u'(n) &= AX(n) \\ v'(n+1) - v'(n) &= BY(n) \\ r'(n+1) - r'(n) &= CN(n) \end{aligned} \tag{3}$$

where A, B, C are parameter vectors formed by hydrodynamic derivatives to be identified, given as

$$A = [a_1, a_2, \cdots a_{16}]_{1\times 16}$$

$$B = [b_1, b_2, \cdots b_{22}]_{1\times 22}$$

$$C = [c_1, c_2, \cdots c_{22}]_{1\times 22}$$

where $X(n)$, $Y(n)$, $N(n)$ are the variables vectors, n and $n+1$ are the adjacent sampling time steps. By solving the governing model Equation (1), one can get the variable vectors given as Equation (4), compounding by ship velocities and rudder angle.

$$\begin{aligned} X(n) =& [u', u'^2, u'^3, v'^2, r'^2, r'v', \delta'^2, u'\delta'^2, v'\delta', u'v'\delta', u'v'^2, u'r'^2, \\ & u'v'r', r'\delta', u'r'\delta', 1]^T \times \frac{U^2}{L} \times \frac{\Delta t}{m' - X'_{\dot{u}}} \end{aligned}$$

(4–a)

$$\begin{aligned} Y(n) = & [v', r', v'^3, v'^2 r', r'^3, v' r'^2, v' u'^2, r' u'^2, v' u', r' u', \delta', \delta'^3, u'\delta', \\ & u'^2\delta', v'\delta'^2, v'^2\delta', r'\delta'^2, r'2\delta', r'v'\delta', \ 1, \ u', u'^2]^T \\ & \times \frac{U^2}{L} \times \frac{\Delta t}{S} \end{aligned}$$

(4–b)

$$\begin{aligned} N(n) = & [v', r', v'^3, v'^2 r', r'^3, v' r'^2, v' u'^2, r' u'^2, v' u', r' u', \delta', \delta'^3, u'\delta', \\ & u'^2\delta', v'\delta'^2, v'^2\delta', r'\delta'^2, r'2\delta', r'v'\delta', \ 1, \ u', u'^2]^T \\ & \times \frac{U^2}{L^2} \times \frac{\Delta t}{S} \end{aligned}$$

(4–c) where $S = (m' - Y'_{\dot{v}})(I'_{zz} - N'_{\dot{r}}) - (m'x'_g - Y'_{\dot{r}})(m'x'_g - N'_{\dot{v}})$. The rudder angle is represented by δ and $\delta\prime = \delta$. It should be mentioned that the five zeros frequency added mass derivatives $X'_{\dot{u}}$, $Y'_{\dot{v}}$, $Y'_{\dot{r}}$, $N'_{\dot{v}}$ and $N'_{\dot{r}}$ usually have enough preciseness, which can be found in semi-empirical formulas or calculated through strip theory. They can always be estimated beforehand. Only the parameter sets A, B, and C are unknown and they will be identified by the SVM algorithm. Mention that the hydrodynamic derivatives $X'_{(\cdot)}$ in surge equation are simply obtained by Equation (5) once the vector A is determined. While b_i and c_i $(i = 1, \ 2, \ \ldots, 22)$ are not direct hydrodynamic coefficients in sway and yaw motion equation, they need further treatment by Equation (6).

$$X'_{(\cdot)} = \frac{L(m' - X'_{\dot{u}})}{\Delta t} A \tag{5}$$

$$\begin{bmatrix} Y'_{(\cdot)} \\ N'_{(\cdot)} \end{bmatrix} = \begin{bmatrix} \dfrac{(I'_{zz} - N'_{\dot{r}})\Delta t}{SL} & -\dfrac{(m'x'_g - Y'_{\dot{r}})\Delta t}{SL} \\ -\dfrac{(m'x'_g - N'_{\dot{v}})\Delta t}{SL^2} & \dfrac{(m\prime - Y'_{\dot{v}})\Delta t}{SL^2} \end{bmatrix}^{-1} \begin{bmatrix} B \\ C \end{bmatrix} \tag{6}$$

2.3. Support vector machine algorithm

Support vector machine (SVM) learning strategy was formally proposed in the 1900s by Vapnik (1999). As mentioned before, this approach is widely used in system engineering and is considered to be a powerful tool in system identification. As a batch technique, it does not require any initial estimation values and avoids lengthy iterations. It also has a better global optimal extremum, compared with traditional neural networks.

Generally, SVM used for regression is also called SVR. Given the training dataset $\{(x_i, y_i), x_i \in \mathbb{R}^n, y_i \in \mathbb{R}\}$, x_i is the input vector and y_i is the output. For regression purposes, the general approximation function of SVM is shown as

$$f(x) = \boldsymbol{W}^T \Phi(x) + b \tag{7}$$

where $\boldsymbol{W}$ is the weight matrix and b is the bias term. $\boldsymbol{\Phi}(\cdot)$ is the nonlinear function, which is mapping the input data to a high dimensional feature space. The goal is to find the optimal weights and threshold that best fit the data. It is proposed to do so by defining the criteria Equation (8) that simultaneously measures structure risk and empirical risk. It differs from conventional neural networks, which rely on only the empirical risk minimisation so that the SVM features a sparse solution.

$$\min_{w,b,e} \left(\frac{1}{2} \boldsymbol{W}^2 + \gamma \sum_{i=1}^{l} (\xi_i + \hat{\xi}_i) \right) \tag{8}$$

Subject to:

$$\begin{aligned} f(x_i) - y_i &\le \epsilon + \xi_i, \\ y_i - f(x_i) &\le \epsilon + \hat{\xi}_i, \\ \xi_i \ge 0, & \ \ \hat{\xi}_i \ge 0 \end{aligned}$$

where $i = 1 \cdots l$, l is the number of samples, and γ is the penalty factor with positive values. ξ_i and $\hat{\xi}_i$ are non-negative slack variables. ϵ is the tube size referring to the precision by which the function is to be approximated. Errors are to be accepted when the samples are located in the tube. The introduction of tube and slack variables in the SVM algorithm promotes its robustness to noise and generalisation performance. Solving for the optimal weights and bias is a process of convex optimisation, which is made simpler by using Lagrange multipliers and formulating the dual optimisation problem given as

$$\max_{\alpha,\alpha^*} \sum_{i=1}^{l} y_i(\alpha-\alpha^*) - \sum_{i=1}^{l} \epsilon(\alpha-\alpha^*) - \frac{1}{2}\sum_{i,j=1}^{l}(\alpha_i-\alpha_i^*)(\alpha_j-\alpha_j^*)x_i, x_j \tag{9}$$

Subject to:

$$\sum_{i=1}^{l}(\alpha_i-\alpha_i^*)=0,\ \ \alpha,\alpha^*\in[0,\gamma]$$

where α, α^* are the Lagrangian multipliers. x_i, x_j refers to the kernel function. The solution for the weights is based on the Karsh-Kuhn-Tucker conditions. Finally, the approximation of the function $f(x)$ is given as

$$f(x)=\sum_{i=1}^{l}(\alpha_i-\alpha_i^*)x, x_i+b \tag{10}$$

The support vectors are those data on or outside the tube with non-zero Lagrange multipliers. To carry out parameter identification using SVM, the linear kernel function is then adopted, representing an inner product between its operands. So, the identified parameter θ can be regressed as

$$\theta=\sum_{i=1}^{l}(\alpha_i-\alpha_i^*)x_i \tag{11}$$

In general, the identification process is conducted as the following steps:

1. Collect the sample experiment data $\{(t_i, u_i, v_i, r_i, \delta_i),\ i=1,\ldots .l\}$ based on full-scale sea trials or simulation.
2. Construct the input and output vectors for each SVM regressor according to Equations (3) and (4).
3. Train the SVM regressor and optimise the hydrodynamic coefficients.
4. Substitute the identified results back into model Equation (2) to get identified ship model.
5. Verify the generalisation performance of the obtained model.

3. Model validation

In this section, the effectiveness of the SVM-based identification algorithm will be investigated in a clean vessel model without disturbance.

The experiments are performed in the Marine Systems Simulator (MSS) (Perez et al. 2006) developed by the Norwegian University of Science and Technology and cooperating groups. It handles different simulation scenarios and provides enough resources for the implementation of mathematical models of marine systems. The Mariner class vessel (Chislett and Strom-Tejsen 1965) is selected as a benchmark for verification in this study. It should be noted that in the hydrodynamic model of the Mariner class vessel, only 10 hydrodynamic coefficients in surge motion equation, 15 in sway equation, and 15 in yaw equation are considered, and the others are zeros. The SVM regressor is implemented by using Scikit-learn in Python. Following the procedure as shown in Figure 1, the parameters are identified and verified against the experimental values.

3.1. Training data preparation

To cover as much as dynamic features, multiple manoeuvres are conducted in the simulator at 15 knots (7.717 m/s). The multiple manoeuvring datasets, including 20°/20°, 15°/15°, and 10°/10° zigzag tests, are sequentially generated, and equally sampled at 2 Hz in 900 s. 1800 samples are collected in total as the training data.

3.2. Identification results

Once the samples are extracted, the SVM is trained to fit the approximation function. The hyperparameters γ and ϵ in the SVM regression model with linear kernel are determined by grid search and cross validation. In this regression model, the regularisation factor γ is obtained as 10^4, and ϵ is 0. The unknown non-dimensional hydrodynamic coefficients in Equation (2) are identified and the results are listed in Table 1, in comparison with the planar motion mechanism (PMM) experimental values. It can be seen that most of the numerical coefficients agree well with the real experimental values. Although some of them, for instance the coefficients N_0, N'_{0u}, N'_{ouu} in yaw direction, have relatively obvious discrepancies, they have a limited effect on the accuracy of the numerical model as their values are quite small.

3.3. Identified model validation

To verify the obtained hydrodynamic models, the prediction of the same multiple zigzag maneuver tests – 20°/20°, 15°/15°, and 10°/10°, is performed by the numerical model. Figure 2 shows that the model predicted velocities in three directions, as well as the angular displacement, achieve a satisfactory agreement with the references. The consistency in parameter value and prediction

Table 1. Identified non-dimensional hydrodynamic coefficients ($\times 10^{-5}$).

X-Coef	SVM	PMM	Y-Coef	SVM	PMM	N-Coef	SVM	PMM
X'_u	−185.2	−184.0	Y'_v	−1158.2	−1159.9	N'_v	−262.4	−264.0
X'_{uu}	−116.6	−110.0	Y'_r	−498.1	−498.9	N'_r	−165.4	−166.0
X'_{uuu}	−220.0	−215.0	Y'_{vvv}	−8150.4	−8078.5	N'_{vvv}	1667.5	1636.0
X'_{vv}	−923.0	−899.0	Y'_{vvr}	15312.0	15358.0	N'_{vvr}	−5484.0	−5483.0
X'_{rr}	13.8	18.0	Y'_{vu}	−1156.2	−1160.0	N'_{vu}	−250.6	−264.0
X'_{rv}	779.3	798.0	Y'_{ru}	−497.3	−498.9	N'_{ru}	−162.2	−166.0
X'_{dd}	−94.6	−95.0	Y'_d	277.6	278.0	N'_d	−139.0	−139.0
X'_{udd}	−190.2	−190.0	Y'_{ddd}	−89.6	−90.0	N'_{ddd}	42.3	45.0
X'_{vd}	92.3	93.0	Y'_{ud}	554.3	556.1	N'_{ud}	−270.0	−278.0
X'_{uvd}	86.1	93.0	Y'_{uud}	271.7	278.0	N'_{uud}	−87.8	−139.0
			Y'_{vdd}	−3.6	−4.0	N'_{vdd}	17.5	13.0
			Y'_{vvd}	1213.1	1190.1	N'_{vvd}	−476.2	−489.0
			Y_0	−3.6	−4.0	N_0	1.6	3.0
			Y'_{0u}	−8.6	−8.0	N'_{0u}	8.0	6.0
			Y'_{ouu}	−2.7	−4.0	N'_{ouu}	−0.4	3.0

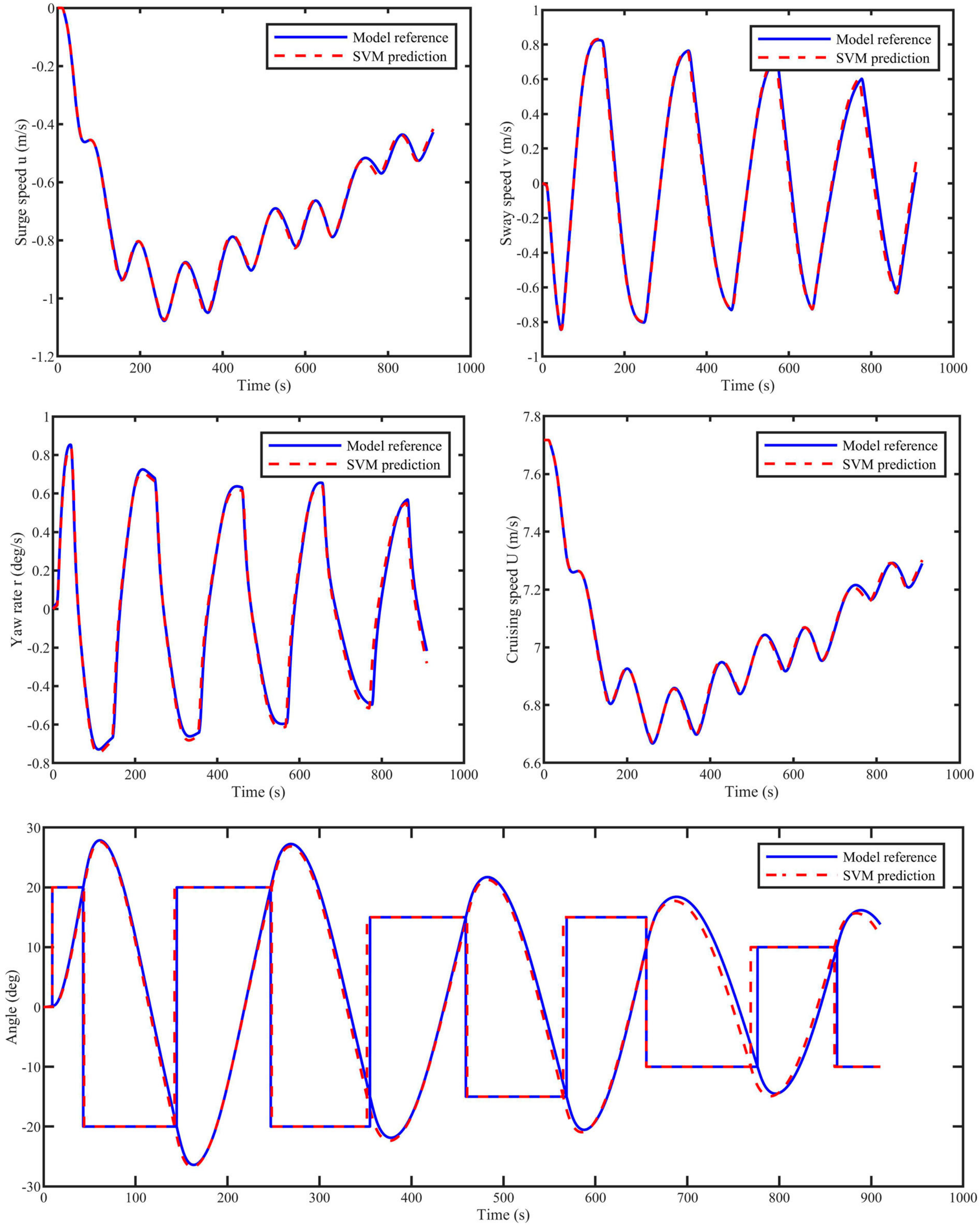

Figure 2. The validation between the SVM predictions and the model reference zigzag tests. (This figure is available in colour online.)

performance demonstrates the effectiveness and reproducibility of the SVM-based identification method.

4. Disturbance experiment

To estimate the hydrodynamic parameters under environmental disturbance, and investigate the influence on the model fidelity, disturbance experiments are conducted, and identification results are discussed in this section.

4.1. Disturbed manoeuvring models

The ship motion is always influenced by variations of wind, waves, and ocean currents in real world. These forces are not accounted for in the Abkowitz model presented in Section 2. A reasonable way to describe the environmental effects is modelling them as a stochastic process (Fossen 2011). Such a process can represent the slow-varying environmental forces and moments due to wind loads, second-order wave drift forces, and current forces. These effects are lumped

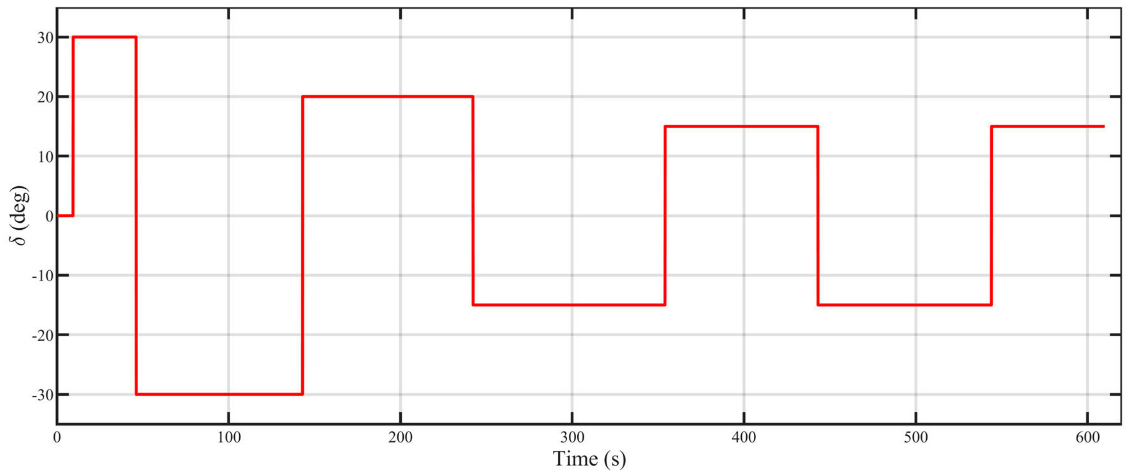

Figure 3. The excitation signal of multiple zigzag tests. (This figure is available in colour online.)

into a bias term $\boldsymbol{b} \in \mathbb{R}^3$ acting on the ship. The disturbed model is given as

$$\begin{bmatrix} m' - X'_{\dot{u}} & 0 & 0 \\ 0 & m' - Y'_{\dot{v}} & m'x'_g - Y'_{\dot{r}} \\ 0 & m'x'_g - N'_{\dot{v}} & I'_{zz} - N'_{\dot{r}} \end{bmatrix} \begin{bmatrix} \dot{u}' \\ \dot{v}' \\ \dot{r}' \end{bmatrix} = \begin{bmatrix} X' \\ Y' \\ N' \end{bmatrix} + \boldsymbol{R}^T(\psi)b + \boldsymbol{w}_2 \tag{12}$$

where $\dot{\boldsymbol{b}} = \boldsymbol{w}_1$ represents the stochastic disturbances, and it is usually modelled as a Wiener process. The variables $\boldsymbol{w}_i (i = 1, 2)$ are zero-mean Gaussian noise vectors, referring to bias, and process noise respectively. $\boldsymbol{R}$ is the rotation matrix shown as follows, transforming the ship motion from the body-fixed frame to the earth-fixed frame. ψ is to the ship heading.

$$\boldsymbol{R} = \begin{bmatrix} \cos\psi & -\sin\psi & 0 \\ \sin\psi & \cos\psi & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Note the measurement noise is not accounted for in this model, for the reason that we mainly focus on the effects of environmental effects and progress noise on the performance, which are practically meaningful and have not been closely studied. From Equation (12), the regression function is derived in a form as

$$\begin{bmatrix} \dot{\boldsymbol{v}} \\ \dot{\boldsymbol{b}} \end{bmatrix} = \begin{bmatrix} \boldsymbol{M}^{-1}\boldsymbol{\tau} \\ 0 \end{bmatrix} + \begin{bmatrix} 0 & \boldsymbol{M}^{-1}\boldsymbol{R}^T(\psi) \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \boldsymbol{v} \\ \boldsymbol{b} \end{bmatrix} + \begin{bmatrix} \boldsymbol{M}^{-1}\boldsymbol{w}_2 \\ \boldsymbol{w}_1 \end{bmatrix} \tag{13}$$

where $\boldsymbol{M} \in \mathbb{R}^{3\times3}$ is the vessel mass matrix including added mass. $\boldsymbol{v} = [u, v, r]^T$ is the ship velocity vector, and $\boldsymbol{\tau} = [X, Y, N]^T$ represents hydrodynamic forces and moment, as described in Equation (2). The parameters inside the expression are the ones that need to be identified.

By applying the SVM method validated in Section 3, hydrodynamic coefficients in three directions are estimated, and the corresponding model fidelity is examined in detail.

4.2. Disturbance set up

When preparing the training data, more rudder commands are added to cover ship dynamic characteristics. Figure 3 shows the excitation signal distribution in the simulation period.

The bias $\boldsymbol{w}_1 \in \mathbb{R}^{3\times1}$ and process noise $\boldsymbol{w}_2 \in \mathbb{R}^{3\times1}$ are defined according to the rule proposed by Sutulo and Soares (2014):

$$w_i = \max(\varphi_i) k_{0i} k_i \zeta \tag{14}$$

Table 2. Disturbance/noise level set up.

Noise level (NL)	k_0
NL0	0%
NL1	5%
NL2	10%
NL3	20%

where ζ is the discrete zero-mean Gaussian white noise process. φ is the primary clean reference response. $\max(\varphi_i)$ refers to the maximum absolute value of the clean response and it scales the noise signal to the origin response. k is a response specific reduction factor, which is set to be 0.05 for rudder angle response, 0.2 for the surge velocity, and 1.0 for other remaining responses. k_0 is the general reduction factor used to label the noisy extent, which is assumed to be 5%, 10%, and 20% as listed in Table 2.

4.3. Identification results under disturbance

To investigate the effect of disturbance level on the identification results, a group of experiments is designed as listed in Table 3. The disturbance bias level is set varying from NL1 to NL3, while the process noise level is set constant at NL1. To eliminate the outliers in the random process, each experiment case is executed one hundred trials. The Savitzky–Golay filter is applied to preprocess and smooth the training data.

One trial of the disturbed accelerations in surge, sway, and yaw directions are presented in Figure 4. This example shows that the disturbance level in general has a more obvious consequence on the surge acceleration than on the sway and yaw directions. It is not unreasonable that the coupling between sway and yaw direction decreases the perturbation effects to some extent.

After the training datasets are prepared after hundreds of trials, the SVM algorithm is applied to train the regressor for the 3-DOF dynamic model. The identified parameters are found normally distributed and thus the average is chosen as the general solution. By

Table 3. Experiment case set up.

Case	Disturbance bias	Process noise
1	NL1	NL1
2	NL2	NL1
3	NL3	NL1

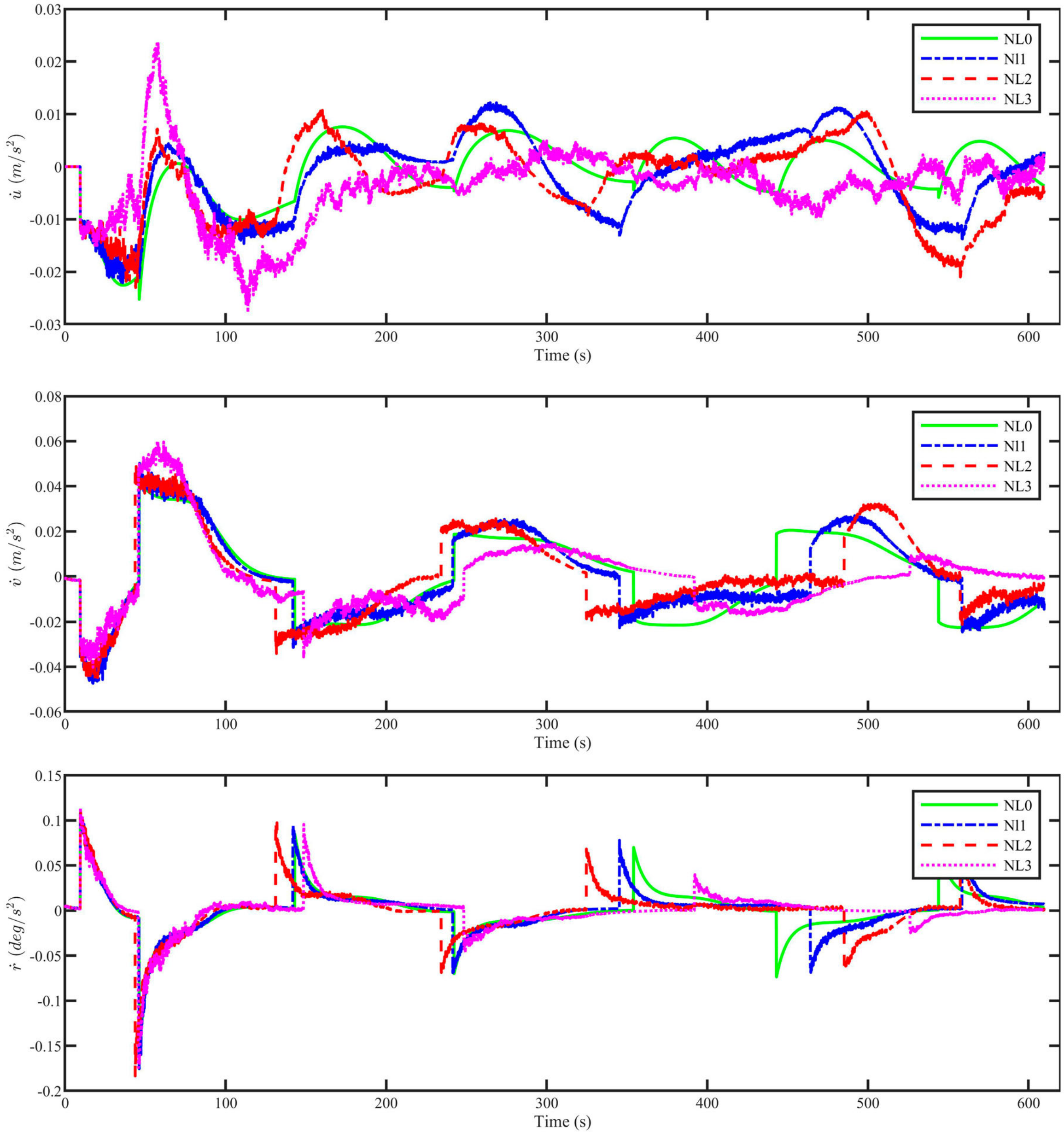

Figure 4. The disturbed accelerations in surge, sway, and yaw directions at different disturbance levels. (This figure is available in colour online.)

substituting those results into Equation (2), the identified models at different disturbance levels are then obtained.

Normally, the extensively trained SVM results are able to reprobude the training trajectory, therefore, a more critical evaluation of the model fidelity is that it should be capble of predicting other manoeuvres that the SVM has not been trained on. An 18° turning circle operation is then undertaken to examine its generalisation performance. The comparison between the SVM predictions and origin model reference in 3-DOF velocities, heading angle, and ship trajectory are shown in Figure 5. It can be seen that the model identified under disturbance and process noise could basically capture the ship's dynamic properties and generate a relative accurate response. The prediction errors at NL1 and NL2 are considered allowable. Generally, the deviation gets larger when the disturbance level is higher. Note that at the same disturbance level NL1, the deviation of surge speed is more obvious than that of sway and yaw speed, which is implied by the results from Figure 4.

To quantitatively measure the prediction errors, the manoeuvring characteristics for turning circles are calculated and listed in Table 4. The table shows that the predicted maneuver properties at different disturbance levels have various deviations from the model reference. More concretely, at NL1 and NL2, the discrepancies are almost lower than 10%, while at NL3, the errors are around 20%. It reveals that when the ship is exposed to gentle and moderate environments, the identified model is able to keep its key characteristics and its predictive capability could be considered acceptable. Although relatively obvious dispersions at NL3 scenario is observed, it could still indicate a potential path in the short future. These results reveal that the SVM-based approach could realise parameter identification in disturbed environment to a certain accuracy, which practically extends the applicable scope in kinds of scenarios.

Due to the correlation between the SVM input features, the parameter estimations may show a large dispersion from their experimental values. However, the model, as a whole, can still be able

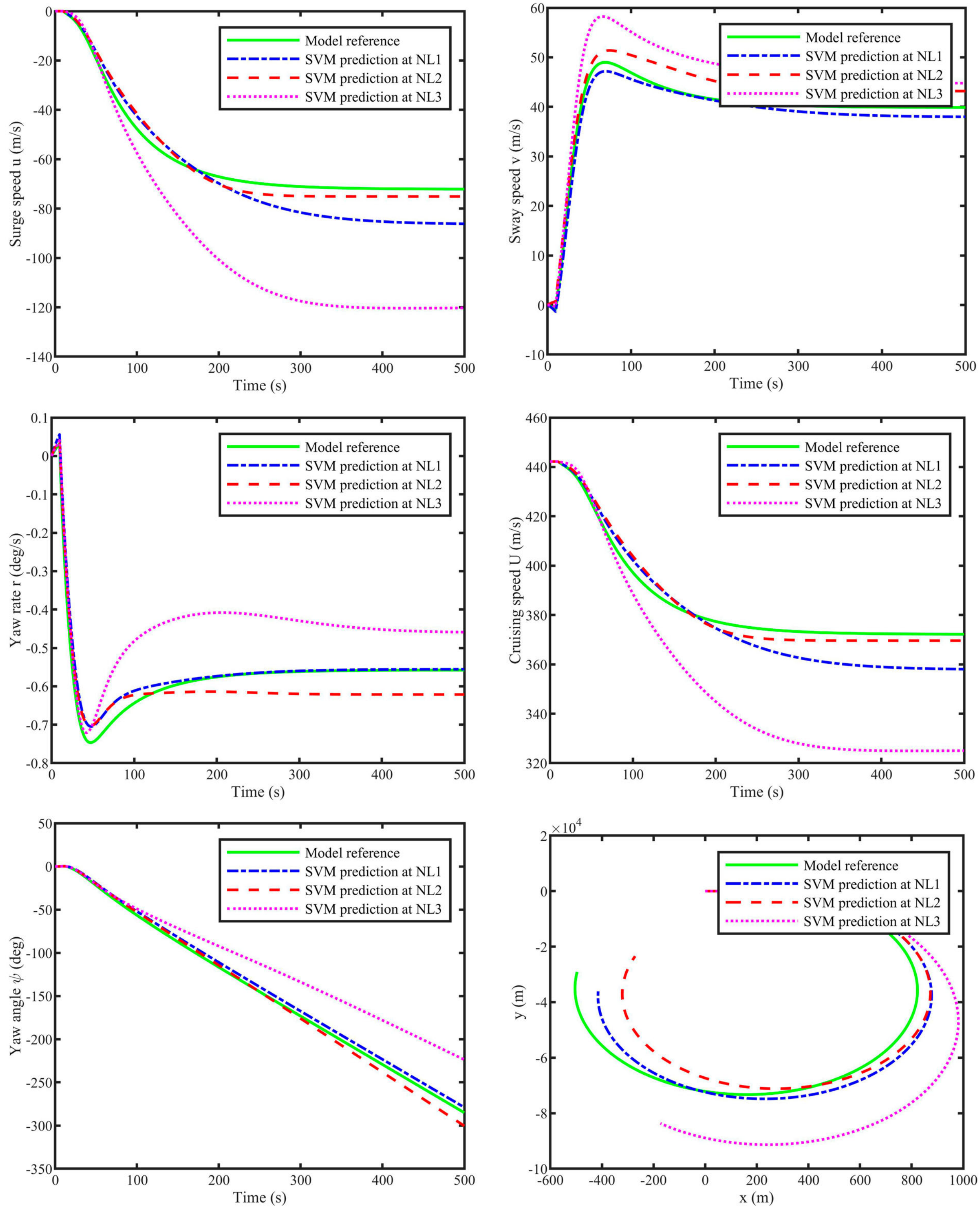

Figure 5. The SVM predictions at different disturbance levels compared with model reference of 18° turning circle. (This figure is available in colour online.)

Table 4. Manoeuvring characteristics comparison between SVM predictions and model reference.

Manoeuvring characteristics	Model reference	SVM_NL1		SVM_NL2		SVM_NL3	
	Value (m)	Value (m)	Deviation (%)	Value (m)	Deviation (%)	Value (m)	Deviation (%)
Steady turning radius	667	644	3.5	595	10.8	707	6.0
Maximum transfer	1279	1306	2.1	1242	2.9	1594	24.6
Maximum advance	746	801	7.4	796	6.7	905	21.3
Transfer at 90 (deg) heading	546	578	5.9	557	2.0	694	27.1
Advance at 90 (deg) heading	742	796	7.3	791	6.6	895	20.6
Tactical diameter at 180 (deg) heading	1275	1302	2.1	1237	3.0	1586	24.4

to predict new maneuver behaviour with different fidelities, even if the parameters cannot be assigned a physical interpretation. The generalisation capability of the identified model presented above is found evidence for this argument.

5. Conclusions

In this paper, an SVM-based parameter identification procedure is presented, which is applied to the scenario where ship manoeuvres in stochastic environments. The work focuses on the investigation of identification performance, as well as the model fidelity under different levels of perturbations. By taking multiple zigzag manoeuvres data in the MSS simulator, the SVM is well trained to get all hydrodynamic coefficients, linear and nonlinear, in a 3-DOF Abkowitz model. Satisfactory estimation results are achieved in the clean system, showing its approachability in marine domain. The method is then extended to incorporate stochastic process to the model plant to simulate real environment effects. Estimation results show that the fidelity is decreasing with respect to the interference levels. Models with prediction errors of the magnitude could be considered usable in 5% and 10% disturbance. Although the model dispersion is obvious under 20% perturbation, the intuitive predictions is still encouraging in which we could bring support to the operation decision system.

The main advantages of using the SVM identification method are the possible robustness to noise by tuning the penalty factor and width of the insensitive tube, so that being able to achieve better generalisation compared to traditional neural networks. Meanwhile, it offers an inspection of specific parameters associated with the vessel other than a grouped black-box model. Even if its strengths are obvious, its performance on a heavily polluted system is still limited. In addition, this approach is now validated on constant parameters, and it cannot be applied to time-varying coefficients. This drawback limits the on-line identifications that are always encountered in real life. For instance, for the operations that cause a large angular displacement of a vessel, such as takeoff and landing of autonomous aerial vehicles and helicopters, crane operations, and so on, the ship responses are changing associated with the operation status. Such cases push further research on time-varying parameter identification, which will be included in the future study. Furthermore, the presented identification procedure will be implemented in real-life sea trials to verify its adaptability in realistic scenarios. Efforts will also be paid to refine the SVM approach to improve the identification accuracy in strong environments.

Disclosure statement

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