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Ship maneuvering model optimization for improved identification with less excitation

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ABSTRACT

The precise model of a ship is the foundation for its operation and control. The traditional methods of building such models are time-consuming and require large amounts of simulation data, sea trial experiments, or calculating with professional computational fluid dynamics software. Usually, specific maneuvers are conducted to obtain the experimental data with full excitation. In this paper, we propose a ship maneuvering model optimization method that can lower the requirement on data excitation during model identification by simplification. First, the least squares method is used to identify the preliminary parameters of the ship mathematical model. Then, correlation analysis can determine the correlation among the parameters and divide the parameters with higher correlation into one group. Sensitivity analysis is used to detect the influence level of parameters and as a basis for selecting the more critical parameters. Based on the results of these two analyses, we set up a standard to simplify the ship maneuvering mathematical model. Finally, the simplified model and the complete model are tested under different levels of data excitation, and the experiment results verify that the simplified model can perform better than the complete model when identifying with less excitation data.

1. Introduction

The last decade has seen an increasing interest in intelligent ships. The maritime industry is critical to social and economic development, accounting for roughly 90% of the EU's external freight trade, with more than 400 million passengers embarking and disembarking in European ports each year (Sullivan et al., 2020). Digitization is seen as the process of modernization in the maritime industry. In recent years, we have seen increasing interest in developing and employing digital twins for maritime industrial system design and ship intelligence (Zhang et al., 2022), which can predict ship motion based on sensors. The ship model is potentially fundamental to intelligent ships from a digitalization perspective. Thus, a simple and effective ship model is of great significance to the safe use of intelligent ships (Kanazawa et al., 2022). Ship motion prediction can reduce risk by predicting the future motion trend of the ship according to historical motion data (Wang et al., 2022). Detailed vessel motion forecasts would support underway and deployment decisions for safer and more efficient vessel operation (Schirmann et al., 2022; Li et al., 2019).

System-based (SB) and computational fluid dynamics (CFD) methods are primary simulation methods to predict ship motion (Toxopeus et al., 2018). The simulation computation time of the SB is much shorter than that of CFD since such methods need only solve the equations of motion using a prescribed mathematical model and maneuvering coefficients. For ship motion prediction, the system is the ship mathematical model that can represent ship dynamics. Building an accurate ship mathematical model poses some challenges. Ships will be influenced by many forces, including hydrodynamics, environmental force, etc., on the ocean (Fossen, 2011). The Taylor expansion is conducted on hydrodynamics to express the forces on the ocean, and the expansion coefficients are called the hydrodynamic parameters. Parameter identification for ship maneuvering models involves determining the hydrodynamic parameters, which are often ambiguous.

It is vital to identify the hydrodynamic parameters accurately. The more accurate the hydrodynamic parameters are, the more precise the model is. Because Taylor expansion requires dozens of parameters to describe the complexity of the ship's shape and environmental force, the amount of data needed to identify these parameters to ensure the model's fidelity is substantial. If fully identifying all the hydrodynamic parameters is almost impossible, keeping the most important components and relinquishing the less relevant ones seems an efficient alternative. Given two explanations of the data, all other things being equal, the simpler explanation is preferable. From the practical application perspective, an overly complex model will make the model's inspection and maintenance more difficult.

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The traditional methods for parameter identification need to conduct sea trial experiments under particular maneuvers like zigzag, which are full excitation and can comprehensively show the force changes in all degrees of freedom and requires less interference from environmental forces. Too many parameters are difficult to identify without particular maneuvers. The difficulty is that, even if the history data has been collected, particular tests have to be conducted to set up a mathematical ship maneuvering model, and this is costly. However, in practice, there is no need for highly complex models in most cases. So a simplified model that can be identified by data with less excitation has significant utility. To this end, parameters can be identified by data with less excitation, such as a random trajectory, which reduces constraints on parameter identification.

This paper analyzes the ship maneuvering model using generic correlation analysis and data-driven sensitivity analysis, which can be applied to most ships without prior knowledge. A standard is proposed to simplify the model based on two analysis results. The proposed simplified model is verified under different maneuvers and compared with the complete model. This paper's contributions are as follows:

- The simplified model we proposed can be identified with less excitation data instead of relying on the full excitation data, such as zigzag maneuvers, which lowers the data requirement.
- The correlation and sensitivity of parameters are analyzed to simplify the ship maneuvering model.
- A standard is set to simplify the ship model based on the correlation and sensitivity analysis results.

The paper is organized as follows. The related work will be explored in Section 2, including parameter identification and model simplification. Section 3 elaborates on the methodology, mainly the experimental process, including the ship maneuvering model, parameter identification, and model simplification. This section also illustrates the algorithms, including the least square regression, correlation, and sensitivity analysis. In Section 4, the experiment results are shown. We set up a simplified mariner model with correlation and sensitivity analysis results and verify the simplified model under different maneuvers. Then, Section 5 discusses the limitations of the proposed method and possible solutions. Finally, Section 6 offers a summary of the paper.

2. Related work

2.1. Parameter identification

Methods that can be used to determine the hydrodynamic coefficients in the ship maneuvering mathematical model include empirical formula, captive model tests, CFD calculation, and system identification (SI) combined with free-running model tests (Randeni P. et al., 2018). SI combined with free-running model tests is the most plausible and direct manner to confirm ship maneuvering properties (Costa et al., 2021), as it does not need a harsh experimental environment. Some conventional methods are also applied to SI in the ship mathematical model, such as extended Kalman filter (Skulstad et al., 2021), maximum likelihood (Chen et al., 2018), support vector regression (SVR) (Xu et al., 2019), etc.

Seeking to make an accurate ship model, many researchers have studied parameter identification in different scenarios. Jian-Chuan et al. (2015) identified the hydrodynamic derivatives of the Abkowitz model in the 20–20 zigzag test. The identified results were compared with the planar motion mechanism test results to verify the effectiveness of the partial least square parameter identification method. Meng et al. (2022) proposed a parameter identification scheme based on SVR combined with a modified grey wolf optimizer using the full-scale trial data of the vessel YUKUN. The study uses 10–10 zigzag test data as identification data to obtain the parameters of ship response mathematical models. Wang et al. (2021) completed the identification procedure for a three-degree-of-freedom (DOF) hydrodynamic model under disturbance based on the SVR and conducted zigzag experiments in different sea states to investigate the effects of turbulence on the identification performance. Wang et al. (2019) used v("nu")- Support Vector algorithm to identify the parameters in different maneuvers of zigzag tests under polluted simulate data of three different levels, which verify the robustness and efficiency of the algorithm. Jiang et al. (2022) proposed a novel system identification scheme to obtain a multi-input multi-output model of ship maneuvering motion based on a long-short-term-memory deep neural network using simulated standard maneuvers, including zigzag and turn circle, which can leverage the temporal correlation from the constructed training data to learn the underlying feasible model robust to extraneous noise. Many studies have demonstrated the feasibility of parameter identification in the ship model. But most of the research on identifying parameters relied at least partially on the zigzag test, such ship trajectories never occur in reality.

2.2. Model simplification

Simplification can improve the efficiency of the ship model because identifying a model with multiple parameters requires a level of excitation in data, which costs resources. Too many parameters will also pose challenges for maintenance. Some researchers have already worked on model simplification based on experience for different purposes. For example, Fang et al. (2018) applied the second-order model proposed by Nomoto to simplify the turning characteristics of a large container ship for the collision avoidance model. And the simplified model can quickly determine the helm angle when the ship makes a collision avoidance maneuver, which is helpful for the safety of ship navigation in heavy traffic areas. Xie et al. (2019) proposed a simplified 3DOF Abkowitz model based on experience, which provided a model basis for real-time prediction of ship states and collision risks. Some researchers also studied simplifying by other methods in different situations. Luo (2016) simplified the structure of the maneuvering model based on correlation analysis to diminish the drift of hydrodynamic coefficients and found that there are couplings among the hydrodynamic derivatives. Gao et al. (2018) used statistical hypothesis and p-value to remove parameters that would lead to the most negligible impact on model accuracy in motion equations for the submariner model. Zhang et al. (2019) proposed a method of simplifying the complex mathematical modeling group (MMG) model with considerable accuracy for atypical ships such that it conforms to the standard of the International Electrotechnical Commission (IE62065), which calculated relevant parameters by designing a motion simulation experiment applying the complex MMG model to the atypical ship. In different scenarios, simplifying the model structure can improve the feasibility of the model using different methods. In this paper, a method of model simplification to improve the identification of the model is proposed.

2.3. Identification under weak excitation

Identification under weak excitation can improve identification efficiency and reduce experiment costs. Nouri et al. (2018) designed input by the amplitude-modulated pseudo-random binary signal in order to estimate the hydrodynamic derivatives of an autonomous underwater vehicle's nonlinear dynamic model and use the genetic algorithm to solve the constraint optimization problem. Wang et al. (2020) presented an optimal design scheme of excitation signals to determine the training data that provides the maximum dynamic information to improve the stability and accuracy of the identification of ship maneuvering models. Yue et al. (2022) proposed an online adaptive parameter identification method for the unmanned surface vehicle to identify its model parameters without the condition of persistence of excitation. The researchers focus on input optimization or online adaptive method, but we try to optimize the model to improve the identification under weak excitation.

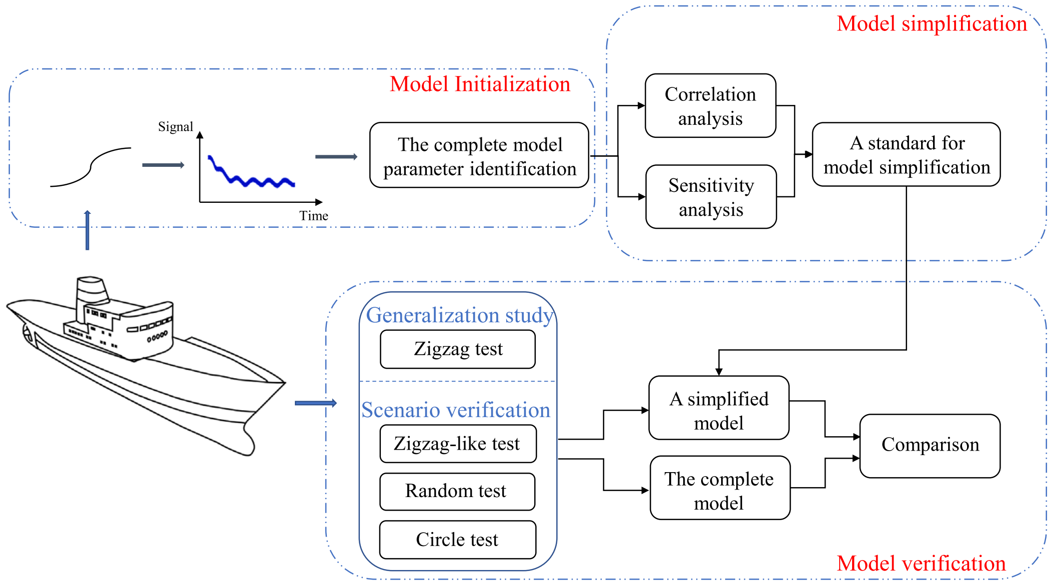


Fig. 1. The workflow of implementing model initialization, simplification, and verification.

3. Methodology

The ship maneuvering mathematical model will decompose hydrodynamics by Taylor expansion. Due to the many influencing factors and rapid changes in hydrodynamics, identifying the hydrodynamics parameters accurately to describe the hydrodynamics of ships is challenging.

3.1. Overview

This paper aims to set up a reliable ship mathematical model with fewer parameters than existent models and that can be implemented with less excitation data. The workflow of implementing model initialization, simplification, and verification is shown in Fig. 1. The first step is model initialization because an accurate mathematical model is almost impossible to obtain directly in practice. Therefore, a preliminary model needs to be built using parameter identification methods. The data is acquired by the ship maneuvering model, explained in Section 3.2, which outputs the following ship motion under control commands. And then the data are artificially polluted to simulate the data obtained in practice because most sensors will introduce noise when measuring. The second step is to analyze and simplify the ship mathematical model. The correlation analysis and sensitivity analysis are then chosen. Correlation analysis is a method to discover the relationship among parameters and the strength of that relationship. Sensitivity analysis is used to determine the importance of the parameters that have the same effect on the output. The more important parameters will be left, and others will be eliminated. This way, a mathematical model with fewer parameters can be set up. Finally, the simplified model is verified under different maneuvers and compared with the complete model.

3.2. Ship maneuvering model

The ship maneuvering model is the data generator, which can output the following ship motion with the current ship motion and control commands. There are two common methods of building up a ship maneuvering model, the Abkowitz model (Abkowitz, 1964) proposed by Prof. Abkowitz and the MMG (Models et al., 2005) proposed by a Japanese research committee. The first one involves expanding the hydrodynamic forces acting on the hull into the Taylor series of various motion variables from the overall point of view. Compared with the linear mathematical model, the third-order nonlinear terms are considered. The second method is to decompose the hydrodynamic forces and moments that act on the ship according to the physical meaning.

The 3DOF Abkowitz mariner model is chosen in this paper, as shown in Eq. (1). The experiments are performed in the Marine System Simulator (MSS) (Perez et al., 2006). The dynamics associated with the motion in heave, roll, and pitch are neglected, and the model has been simplified from the original. Only 10, 12, and 12 parameters are considered in the surge, sway, and yaw motion equation, respectively.

$$\begin{bmatrix} m' - X'_{\dot{u}} & 0 & 0 \\ 0 & m' - Y'_{\dot{v}} & m'x'_g - Y'_{\dot{r}} \\ 0 & m'x'_g - N'_{\dot{v}} & I'_{zz} - N'_{\dot{r}} \end{bmatrix} \begin{bmatrix} \dot{u}' \\ \dot{v}' \\ \dot{r}' \end{bmatrix} = \begin{bmatrix} X' \\ Y' \\ N' \end{bmatrix} \tag{1}$$

where m' is the non-dimensional mess of the ship. x'_g is center of gravity. $X'_{\dot{u}}, Y'_{\dot{v}}, Y'_{\dot{r}}, N'_{\dot{v}}, N'_{\dot{r}}$ represent hydrodynamic added mass. I'_{zz} is a non-dimensional inertia moment about the vertical axis. $\dot{u}', \dot{v}', \dot{r}'$ are the accelerations in surge, sway, and yaw. X', Y', N' denote the longitudinal force, the transverse force, and the yaw moment, respectively. Many factors will affect the values in the Abkowitz model, such as the ship size, speed, and the fluid medium's physical parameters. According to the similarity principle, the dimensionless hydrodynamic derivatives are used to facilitate the direct use of ship experimental data for prototypes, which are expressed as superscripts. The most commonly used normalization forms for marine craft are the prime system (Fossen, 2011). The accelerations and velocities can be described as shown in Eq. (2).

$$\dot{u}' = \frac{\dot{u}L}{U^2}, \dot{v}' = \frac{\dot{v}L}{U^2}, \dot{r}' = \frac{\dot{r}L^2}{U^2}, u' = \frac{u}{U}, v' = \frac{v}{U}, r' = \frac{rL}{U}, \tag{2}$$

where $\dot{u}, \dot{v}, \dot{r}$ are the velocities in three directions. $U = \sqrt{\left(U_0 + u\right)^2 + v^2}$ is the ship speed. u is the small perturbations from nominal surge U_0. The forces and moments X', Y', N' can be expressed as shown in Eq. (3).

$$X' = \frac{X}{\frac{1}{2}\rho L^2 U^2}, \quad Y' = \frac{Y}{\frac{1}{2}\rho L^2 U^2}, \quad N' = \frac{N}{\frac{1}{2}\rho L^3 U^2} \tag{3}$$

where L is the ship's length, and ρ is the density of the fluid.

The hydrodynamic forces and moments X', Y', and N' expressions can be established after a Taylor expansion, as shown in Eqs. (4), (5), (6). X'_*, Y'_*, N'_* represent hydrodynamic parameters. There are in total respectively 10, 12, and 12 hydrodynamic parameters in the complete model to express hydrodynamic forces and moments X', Y', N'.

$$\begin{aligned} X' &= X'_u u' + X'_{uu} u'^2 + X'_{uuu} u'^3 + X'_{vv} v'^2 + X'_{rr} r'^2 + X'_{rv} r' v' \\ &\quad + X'_{dd} \delta^2 + X'_{udd} u' \delta'^2 + X'_{vd} v' \delta' + X'_{uvd} u' v' \delta' \end{aligned} \tag{4}$$

$$\begin{aligned} Y' &= Y'_v v' + Y'_r r' + Y'_{vvv} v'^3 + Y'_{vvr} v'^2 r' + Y'_{vu} v' u' + Y'_{ru} r' u' + Y'_d \delta' \\ &\quad + Y'_{ddd} \delta'^3 + Y'_{ud} u' \delta' + Y'_{uud} u'^2 \delta' + Y'_{vdd} v' \delta'^2 + Y'_{vvd} v'^2 \delta' \end{aligned} \tag{5}$$

$$\begin{aligned} N' &= N'_v v' + N'_r r' + N'_{vvv} v'^3 + N'_{vvr} v'^2 r' + N'_{vu} v' u' + N'_{ru} r' u' + N'_d \delta' \\ &\quad + N'_{ddd} \delta'^3 + N'_{ud} u' \delta' + N'_{uud} u'^2 \delta' + N'_{vdd} v' \delta'^2 + N'_{vvd} v'^2 \delta' \end{aligned} \tag{6}$$

3.3. Parameter identification

With the ship maneuvering model, the data can be generated under zigzag or other maneuvers. When there are enough data, the parameters can be identified. The least square regression is a method of parameter identification, which can find a set of parameters to fit linearly. The least square method is based on the minimization mean square error. Thus it is designed to select unknown parameters to minimize the sum of the squares of the difference between the theoretical value and the observed value. The fitting function can be supposed as shown in Eq. (7).

$$h_\theta = \theta_0 + \theta_1 x + \theta_2 x^2 + \cdots + \theta_n x^n \tag{7}$$

The least square regression will find $\theta_0, \theta_1, \ldots, \theta_n$ to minimize $\sum_{i=1}^{n} (h_\theta(x_i) - y_i)^2$, where y_i is primitive function. So the Sum of Square Error (SSE), as shown in Eq. (8), is used to set up the cost function.

$$SSE = E(\hat{\omega}) = \|y - X(\hat{\omega})\|_2^2 = (y - X(\hat{\omega}))^T (y - X(\hat{\omega})) \tag{8}$$

To get the minimum value of the equation, we can take the derivative of $\hat{\omega}$ and let it be zero, as shown in Eq. (9).

$$\frac{\partial E}{\partial \hat{\omega}} = 0 \tag{9}$$

Then ω can be calculated as shown in Eq. (10).

$$\hat{\omega}^T = (X^T X)^{-1} X^T y \tag{10}$$

The least square regression achieves curve fitting and calculates very fast, so it is used in the ship mathematical model. From Eq. (1), it can also be expressed as Eq. (11) for Y and N directions.

$$\begin{cases} m_{22} \dot{v}' + m_{23} \dot{r}' = Y' \\ m_{32} \dot{v}' + m_{33} \dot{r}' = N' \end{cases} \tag{11}$$

It can be seen that the forces Y in sway are coupling with the moments N in yaw, so β_v, β_r as shown in Eqs. (12), (13) are used to fit the forces and moments to calculate the hydrodynamic coefficients of Y', N'.

$$\beta_v = \frac{m_{33} Y' - m_{23} N'}{m_{22} m_{33} - m_{23} m_{32}} \tag{12}$$

$$\beta_r = \frac{m_{22} N' - m_{32} Y'}{m_{22} m_{33} - m_{23} m_{32}} \tag{13}$$

Then, Eqs. (12), (13) can be decoupled to obtain the hydrodynamic coefficients of Y', N', as shown in Eqs. (14), (15).

$$Y' = \frac{m_{22} \beta_v - m_{23} \beta_r}{m_{22} m_{33} - m_{23} m_{32}} \tag{14}$$

$$N' = \frac{m_{32} \beta_v - m_{33} \beta_r}{m_{22} m_{33} - m_{23} m_{32}} \tag{15}$$

Parameter identification is needed to identify the parameters in the ship maneuvering model with historical data. This is because, in practice, only the physical parameters of the ships can be known, and the mathematical model cannot be obtained directly.

3.4. Correlation analysis

The correlation analysis is performed on the complete model to analyze the correlation of parameters and group the parameters. The correlation means the degree of linear relationship among variables. There are two usual methods to analyze the correlation of parameters, Pearson and Spearman. The covariance is used to measure the overall error of variables, as Eq. (16).

$$\mathrm{cov}(W, Z) = \frac{\sum_{i=1}^{n} \left(W_i - \bar{W}\right)\left(Z_i - \bar{Z}\right)}{n - 1} \tag{16}$$

where $\bar{W}$ and $\bar{Z}$ respectively express the mean of variance W and Z. n represents the number of samples. If coefficients have the same trend, the covariance will be positive, which means they are positively correlated. On the contrary, if they have an opposite tendency, the covariance will be negative, which means they are negatively correlated. Finally, if the covariance equals zero, they will be independent of others, which means they are not associated.

Pearson uses the correlation coefficients as shown in Eq. (17) to respond to the closeness and measure the linear relationship among variables.

$$\rho_{W,Z} = \frac{\mathrm{cov}(W, Z)}{\sigma_W \sigma_Z} = \frac{E\left[\left(W - \mu_W\right)\left(Z - \mu_Z\right)\right]}{\sigma_W \sigma_Z} \tag{17}$$

where σ_W means the standard deviation of variables. E expresses the mean of variables. But when the data do not meet the normal distribution, Spearman correlation analysis is chosen, introducing rank into the correlation analysis. In other words, variances need to be sorted to obtain the corresponding grade numbers first. Following this, the grade numbers are used to replace the original data and brought into the Pearson correlation coefficient formula to get the Spearman correlation coefficients as shown in Eq. (18).

$$\rho = \frac{\sum_i \left(W_i - \bar{W}\right)\left(Z_i - \bar{Z}\right)}{\sqrt{\sum_i \left(W_i - \bar{W}\right)^2 \sum_i \left(Z_i - \bar{Z}\right)^2}} \tag{18}$$

It can also be transformed to Eq. (19).

$$\rho = 1 - \frac{6 \sum_{i=1}^{n} (w_i - z_i)^2}{n\left(n^2 - 1\right)} \tag{19}$$

The correlation results are the basis for grouping the parameters. Parameters with high correlation have a similar effect on the output, so they can be removed.

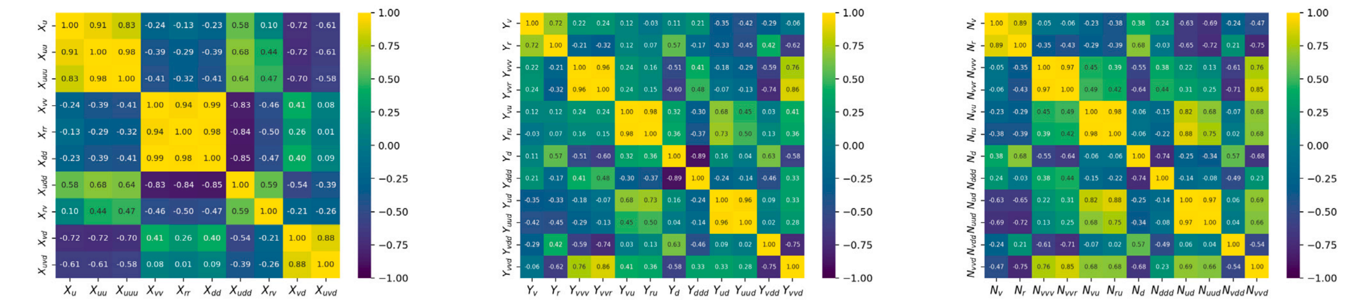
3.5. Sensitivity analysis

The sensitivity analysis can identify and prioritize the most influential inputs based on the relationships between the input variables and the output. The global sensitivity analysis (GSA) method aims at ranking input random variables according to their importance in the output uncertainty, or even quantifying the global influence of a particular input on the output (Antoniadis et al., 2021). The PAWN sensitivity analysis (Pianosi and Wagener, 2015) proposed by Pianosi and Wagener considers the entire probability density function of the model output instead of its variance only. It uses the Kolmogorov–Smirnov statistics, as shown in Eq. (20) to measure the difference between unconditional and conditional cumulative distribution functions.

$$KS\left(w_i\right) = \max_z \left| F_z(z) - F_{z|w_i}(z) \right| \tag{20}$$

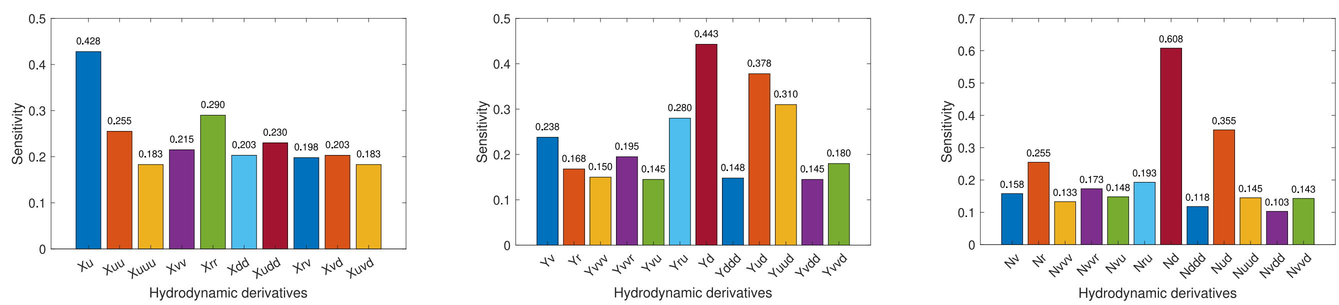
where $F_z(z)$ denotes the unconditional cumulative distribution function of the output z. $F_{z|w_i}(z)$ denotes the conditional cumulative distribution function when w_i is fixed. The PAWN index T_i considers the statistic over all possible values of w_i. So the definition of T_i is shown in Eq. (21).

$$T_i = \underset{w_i}{stat}[KS(w_i)] \tag{21}$$



(a) (b) (c)

Fig. 2. The results of the correlation analysis. (a) The correlation matrix of X hydrodynamic parameters. (b) The correlation matrix of Y hydrodynamic parameters. (c) The correlation matrix of N hydrodynamic parameters.



(a) (b) (c)

Fig. 3. The results of the sensitivity analysis. (a) The sensitivity analysis result of X hydrodynamic parameters. (b) The sensitivity analysis result of Y hydrodynamic parameters. (c) The sensitivity analysis result of N hydrodynamic parameters.

Table 1
Specifications of the ship.

Description	Value
Length between perpendiculars	160.93 m
Design draft	8.23 m
Design speed	20 *knots*
Nominal speed	15 *knots*
Maximum beam	23.17 m
Aspect ratio	1.88
Area of rudder	30.012 m^2
Design displacement	18541 m^3
Block coefficient	0.57

T_i varies between 0 and 1. The lower the value of T_i, the less influential w_i. If $T_i = 0$, then w_i has no influence on z. In this paper, the hydrodynamic parameters are set as the input, and the changes in trajectory are used to measure the influence degree of the hydrodynamic parameters on the ship model.

4. Experimental results

4.1. Experiment setting

The experiments are performed in MSS (Perez et al., 2006). Table 1 shows the specifications of the ship. The type of vessel is a fast cargo vessel. In the actual measurement, the sensors will involve noise, so the output of the data generator is polluted by artificial noise to simulate this situation. The method of adding noise refers to Sutulo and Guedes Soares (2014). The calculation method is as shown in Eq. (22).

$$\zeta_i = \zeta_{0i} + \zeta^{\max} k_0 k_\zeta \xi_i \tag{22}$$

where the output $\zeta = U, u, v, r, \delta$ can be recorded. ζ_{0i} indicates the actual output, which is a clean model response. $\zeta^{\max}$ is the maximum absolute value of the clean response. k_0 means the degree of the noise. To fit the actual operation, it is set to 5%. k_ζ is for the specific reduction factor. Usually, there is less noise in records for the rudder angle and the velocity than for the yaw and drift angle. So, it is set to 0.05 for the rudder angle and the surge's velocity and 1 for others. ξ_i is a Gauss-distributed random variable.

The output of the data generator with 5% noise under 20–20 zigzag maneuver is utilized, including nominal speed U_0, the perturbed surge velocity about U_0, the perturbed sway velocity about zero, the perturbed yaw velocity about zero, the perturbed yaw angle about zero, and the actual rudder angle to identify the parameters. A Savitzky–Golay filter is chosen to smooth the signals. At each position, the smoothed output value obtained by sampling the fitted polynomial is identical to a fixed linear combination of the local set of input samples; i.e., the set of $2M + 1$ input samples within the approximation interval are effectively combined by a fixed set of weighting coefficients that can be computed once for a given polynomial order N and approximation interval of length $2M + 1$.

4.2. Simplification results

A simplified model will be built to improve identification with less excitation. The correlation analysis is executed at first. The identified parameters with different degrees of noise are collected using the Spearman correlation. The results are shown in Fig. 2. The heat maps use the change in color to indicate the strength of the correlation, where yellow and blue, respectively, indicate positive and negative correlations. The value of correlation means the relevance among parameters. There are three different degrees of correlations: weak,

Table 2
Grouping results of X, Y, N directions.

	X	Value ($\times 10^{-5}$)	Y	Value ($\times 10^{-5}$)	N	Value ($\times 10^{-5}$)
1	X_u, X_{uu}, X_{uuu}	−184, −110, −215	Y_v	−1160	N_v, N_r	−264, −166
2	$X_{vv}, X_{rr}, X_{dd}, X_{udd}$	−899, 18, −95, −190	Y_r	−499	N_{vvv}, N_{vvr}	1636, −5438
3	X_{rv}	798	Y_{vvv}, Y_{vvr}	−8078, 15256	N_{vu}, N_{ru}	−264, −166
4	X_{vd}, X_{uvd}	93, 93	Y_{vu}, Y_{ru}	−1160, −499	N_d, N_{ddd}	−139, 45
5			Y_d, Y_{ddd}	278, −90	N_{ud}, N_{uud}	−278,−139
6			Y_{ud}, Y_{uud}	556, 278	N_{vdd}	13
7			Y_{vdd}, Y_{vvd}	−4, 1190	N_{vvd}	−489

Table 3
The complete model and the simplified model.

Direction	The complete model	The simplified model
X	$X'_u, X'_{uu}, X'_{uuu}, X'_{vv}, Xrr', Xdd', Xudd', Xrv', X'_{vd}, X'_{uvd}$	X_u, Xrr
Y	$Y'_v, Y'_r, Y'_{vvv}, Y'_{vvr}, Y'_{vu}, Y'_{ru}, Y'_d, Y'_{ddd}, Y'_{ud}, Y'_{uud}, Y'_{vdd}, Y'_{vvd}$	$Y'_v, Y'_r, Y'_{ru}, Y'_d, Y'_{ud}$
N	$N'_v, N'_r, N'_{vvv}, N'_{vvr}, N'_{vu}, N'_{ru}, N'_d, N'_{ddd}, N'_{ud}, N'_{uud}, Nvdd', N'_{vvd}$	$N'_v, N'_r, N'_{ru}, N'_d, N'_{ud}$

moderate, and strong (Ratner, 2009). If values are between 0 and 0.3 (0 and −0.3), a weak positive (negative) linear relationship is indicated through a shaky linear rule. If values are between 0.3 and 0.7 (0 and −0.7), a moderate positive (negative) linear relationship is indicated through a fuzzy-firm linear rule. Finally, if values are between 0.7 and 1.0 (−0.7 and −1.0), a strong positive (negative) linear relationship is indicated through a firm linear rule. The parameters with a strong positive (negative) indicate a strong correlation, which can be divided into one group. The correlation value of all parameters in one group must be greater than 0.7. Based on these conditions, the result of grouping parameters is shown in Table 2. The X, Y, and N parameters are divided into 4, 7, and 7 groups of strongly correlated parameters, respectively.

PAWN is used to analyze the sensitivity of hydrodynamic parameters in three directions, surge, sway, and yaw, as shown in Fig. 3. The higher the sensitivity value is, the more critical the parameters are. The mean of sensitivity values is the basis for measuring parameters' importance. The mean sensitivity values of hydrodynamic parameters in the X, Y, and N directions are 0.239, 0.232, and 0.211, respectively. If the values are over the mean, the parameters will remain.

The mathematical model can be simplified using correlation and sensitivity results. The correlation analysis determines which parameters are strongly correlated, so only one parameter for each group will remain. The sensitivity analysis shows the importance of parameters, so the most critical parameters for each group will be retained. If the most significant sensitivity value in the group is less than the mean of the sensitivity in that direction, the whole group will be discarded. The standard of simplifying is shown as follows.

- The correlation between any two parameters in a group is greater than 0.7.
- The parameters with the greatest sensitivity value will be left in the group unless it is less than the mean of that direction.
- Because Y, N are coupled, the union of parameters in these two directions needs to be left. That is to say, $\theta_{y,n} = \theta_y \cup \theta_y$

Based on the correlation results shown in Table 2 and the results of the sensitivity analysis shown in Fig. 3, the simplified model can be expressed as Eq. (23), (24), (25). The hydrodynamic parameters of the two models are listed in Table 3. So the numbers of hydrodynamic coefficients are reduced from 10 to 2 in the surge and from 12 to 5 in the sway and yaw.

$$X' = X'_u u' + X'_{rr} r'^2 \tag{23}$$

$$Y' = Y'_v v' + Y'_r r' + Y'_{ru} r'u' + Y'_d \delta' + Y'_{ud} u'\delta' \tag{24}$$

$$N' = N'_v v' + N'_r r' + N'_{ru} r'u' + N'_d \delta' + N'_{ud} u'\delta' \tag{25}$$

4.3. Generalization study

To verify the generalization of the simplified model, the simplified model with the parameters identified from the zigzag test is tested in other maneuvers, including the circle test and the random test. The zigzag tests are usually chosen for parameter identification, where features can be easily identified because of the drastic changes in the forces and moment. The 20–20 zigzag test is conducted, as shown in Fig. 4. In this paper, the noise-polluted and filtered output of the data generator is set as the benchmark, as shown in the red dotted line in Fig. 4(a). The simplified model shown in Eq. (23), (24), (25) is performed parameter identification with contaminated data obtained from the data generator. The trajectory under the same control command as the complete mathematical model is shown in the green line in Fig. 4(a). The outputs of the data generator with artificial noise are input for parameter identification, which simulates model identification in real conditions. The identified parameters are used as the parameters of the complete model, and the trajectory under the same control command as the data generator is shown in the green dotted line in Fig. 4(a). The red dot represents the origin, which is the starting point.

In addition to the trajectory, the fitting results of velocity terms, including surge, sway, and yaw, are shown in Fig. 4(b). The surge term has greater deviation than the sway and yaw terms because only two parameters are left for the surge term. However, the impact on the trajectory prediction of the ship is minimal. The surge term differs between the simplified and complete models in the first 200 s, probably due to the lower departure speed and thus more noise interference. The simplified model and the benchmark have similar sway and yaw, which can prove that the simplified model can represent the mariner well.

The simplified model and the complete model obtained from the 20–20 zigzag tests are tested in the circle and random test to assess their generalization, the results as shown in Fig. 5. In most cases, the ships will not conduct the zigzag in reality, but it is likely to have less excitation data, such as turning to avoid obstacles. In Fig. 5(a), the simplified model is more accurate than the complete model in the beginning, which indicates that the simplified model can be considered for short-term prediction. But the simplified model does not provide reliable long-term prediction and needs to be corrected. In Fig. 5(c), both the complete model and the simplified model can predict the trajectory accurately to some extent.

4.4. Identification on less excitation maneuvers

Three trajectories, including the zigzag-like, random, and circle test, which contain different levels of excitation, are generated to verify the effectiveness of the simplified model in identifying under less excitation data. The details of the tests are as shown in Table 4. Note that the outputs of the data generator for each trajectory are the training data for

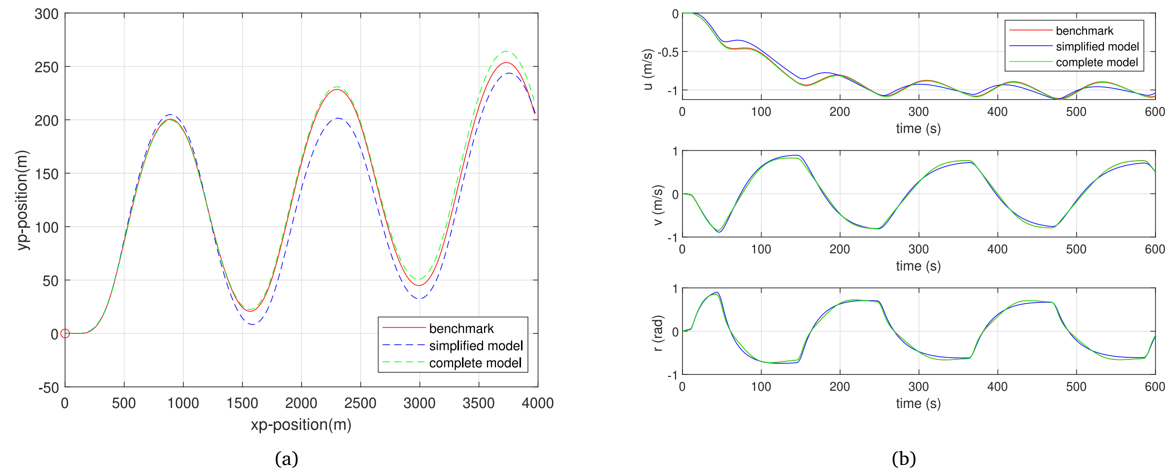


Fig. 4. The results of the 20–20 zigzag test. (a) The trajectory of the simplified model and the complete model. (b) The velocity comparison of the simplified model and the complete model.

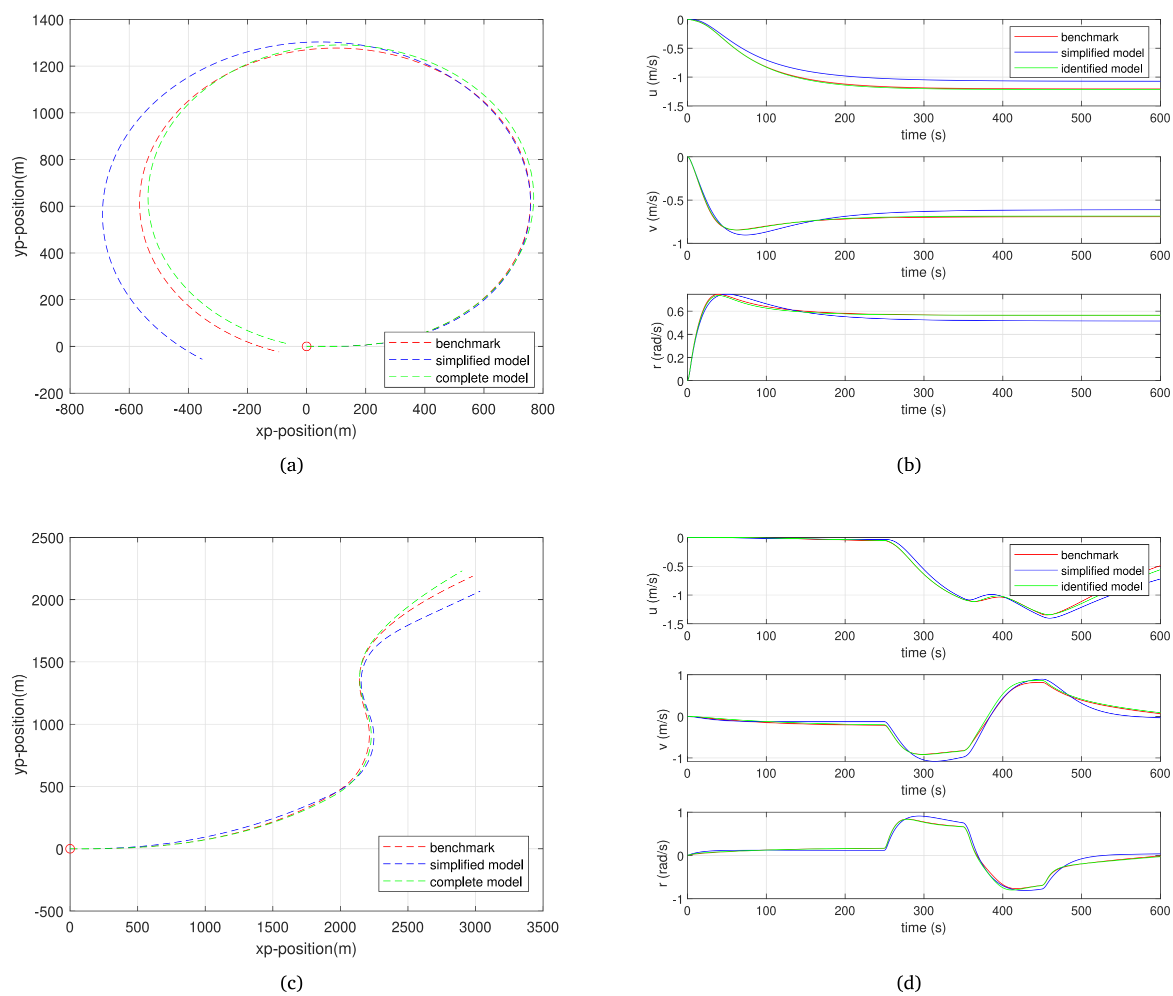
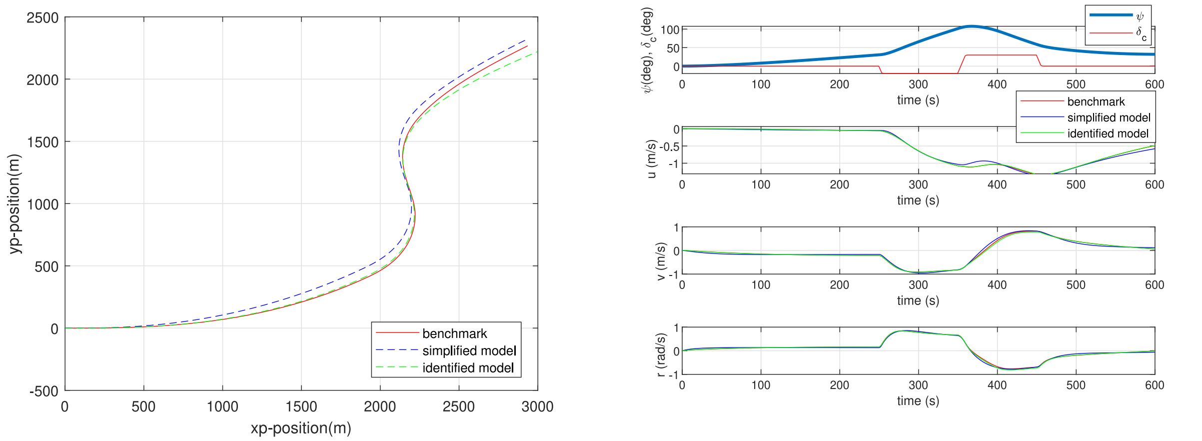


Fig. 5. The results of the generalization test for the complete model and simplified model with parameters identified in the zigzag test. (a) The circle test of the simplified model and the complete model. (b) The comparison of the surge, sway, and yaw speed in the circle test. (c) The random test of the simplified model and the complete model. (d) The comparison of the surge, sway, and yaw speed in the random test.

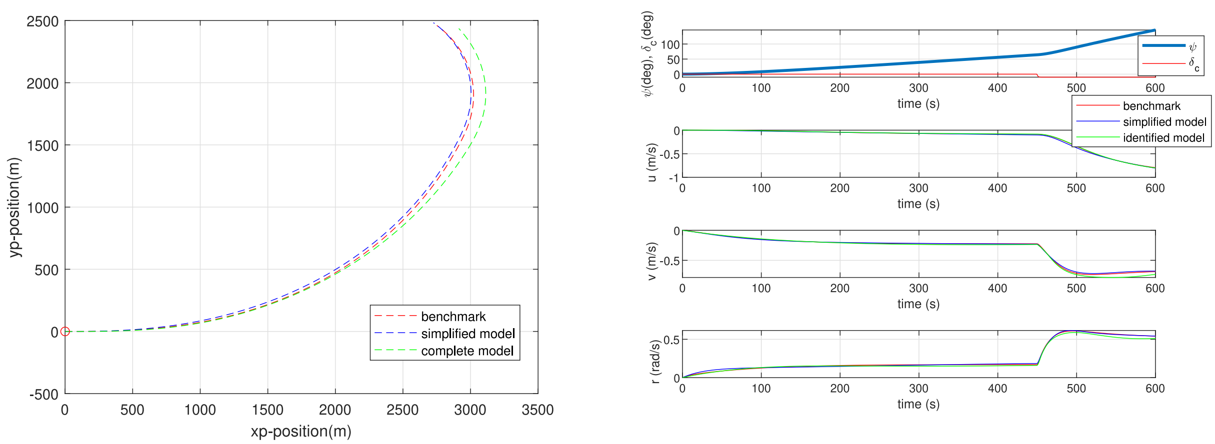
identifying parameters respectively. The simplified model and complete model with parameters obtained from different levels of excitation are tested with the same command as the data generator, as follows.

- The zigzag-like test. A more excitation trajectory is shown in Fig. 6. The running time is 600 s. The mariner makes a 20° turn at 250 s for 100 s and a −30° turn at 350 s for 100 s. The rudder angle



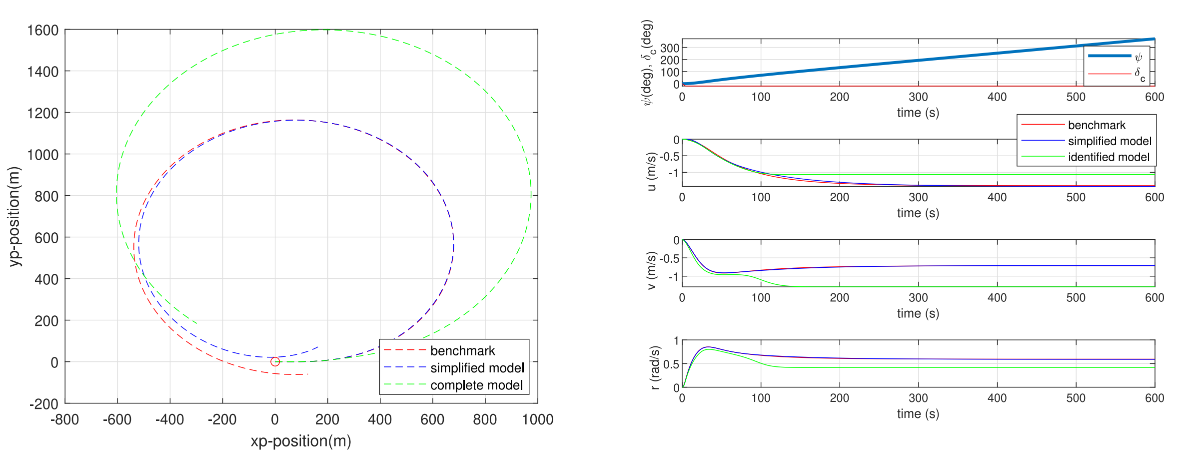
(a) (b)

Fig. 6. The results for models with the parameters identified from the zigzag-like test. (a) The trajectory of the complete model and the simplified model in the zigzag-like test. (b) The changing trend of command and yaw angle and the comparison of the surge, sway, and yaw speed in the zigzag-like test.



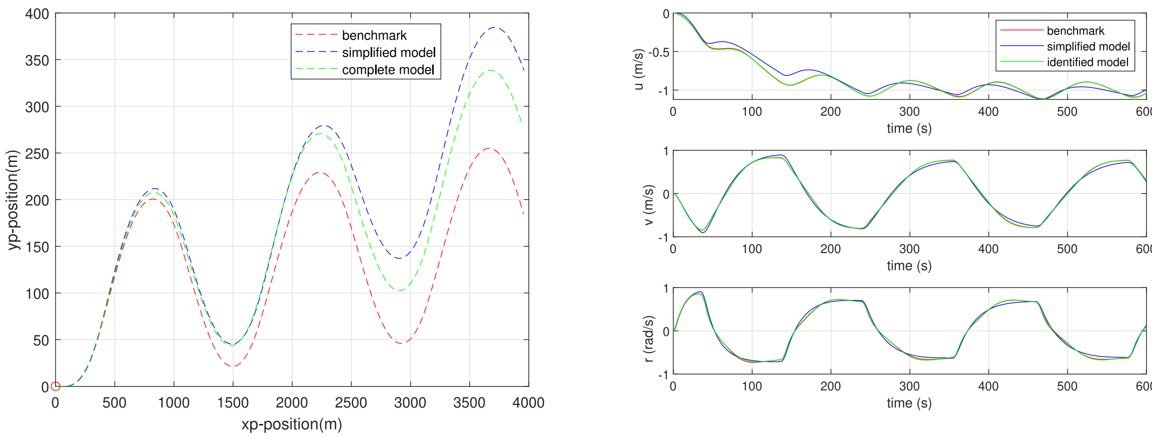
(a) (b)

Fig. 7. The results for models with the parameters identified from the random test. (a) The trajectory of the complete model and the simplified model in the random test. (b) The changing trend of command and yaw angle and the comparison of the surge, sway, and yaw speed in the random test.



(a) (b)

Fig. 8. The results for models with the parameters identified from the circle test. (a) The trajectory of the identified model and the simplified model in the circle test. (b) The changing trend of command and yaw angle and the comparison of the surge, sway, and yaw speed in the circle test.



(a) (b)

Fig. 9. (a) The trajectory of the simplified model and the complete model in the 20–20 zigzag test with 10% noise. (b) The changing trend of command and yaw angle and the comparison of the surge, sway, and yaw speed in the zigzag test.

Table 4
The experimental setting.

	Maneuver type	Rudder angle(°)	Course	Time(s)	Sampling rate(s)
1	The zigzag-like test	–	250–350 s 20° 350–450 s −30° 450–600 s 10°	600	1
2	The random test	–		600	1
3	The circle test	20	–	600	1

remains unchanged at other times. So there are three fluctuations in forces and moment, which can be seen as a zigzag-like test. The change is not as obvious as in the zigzag test, as shown in Fig. 6(b). Although there is still a gap between the trajectories of the simplified model and the benchmark, the results indicate the gap is narrower than those in the zigzag test.

- The random test. A random trajectory with less excitation is designed, as shown in Fig. 7. The running time is also 600 s. The mariner keeps going at full speed and only makes a 10° turn in 450 s for 150 s. So there is only one fluctuation in the whole trial. The results and command changes are shown in Fig. 7(b). The simplified model performs better than the complete model, especially in turning, probably because the fewer force changes in the trail, the less information can be extracted. The extracted information is not enough to identify as many parameters as the complete model, but it is enough for the simplified model.
- The circle test. The less excitation trajectory is the circle test, as shown in Fig. 8. The data of the circle test are hardly used to identify the parameters, as the changes in forces are very slight. The forces only change when starting, and they remain the same after that. The results and command changes in 20° turn are shown in Fig. 8(b). The simplified model can perform better than the complete model. The trajectory of the simplified model almost coincides with the trajectory of the data generator. But for the complete model, the deviation in trajectory is very large. Sometimes the parameters of the complete model cannot be identified with the circle test data alone, such that the trajectory diverges.

In three tests, as shown in Figs. 6, 7, 8, the velocity changes in three directions are gradually stable, and the data excitation gradually decreases. As the data excitation increases, the trajectory of the simplified model is gradually closer to the benchmark than that of the complete model. The experimental results show that the simplified model is easier to identify than the complete model. In the case of low data excitation, the simplified model can still be identified, which proves that the ship maneuvering model can be improved identification with less excitation by simplifying.

The data polluted by 10% white noise are also tested, as shown in Fig. 9(a). But the measuring methods are gradually improving, and the measuring noise will most likely be 5% and almost never reach 10%. From the result, we can see that the increasing noise significantly impacts the complete model, but the impact on the simplified model is less obvious. The differences in trajectory between the data generator and the identified model are greater than between the complete model and the simplified model.

We use the mean absolute error (MAE) to evaluate the performance of the simplified model.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \tag{26}$$

where y denotes the benchmark obtained by the original mathematical model. $\hat{y}$ denotes the estimated value of the parameters. n denotes the length of time. The speed MAE of the complete and simplified model in different maneuvers are shown in Fig. 10, which includes four experiments shown in Figs. 4, 6, 7, 8. The smaller the trajectory change, the more the simplified model is superior to the complete model. The complete model is hard to identify if using only the circle test. But for the common maneuvers such as zigzag and circle, the trajectory difference of the simplified model can be acceptable. So the simplified model can be identified with less excitation data.

5. Discussion

This study conducts experimental investigations by using different levels of excitation data to train and verify the effectiveness of the simplified model, described in Section 4.4. Therefore, it is plausible to say that the study would provide basic insight for parameter identification under less excitation. However, the method has certain limitations, which can be further studied.

From the point of the methodology, the proposed means can also be applied to other ship models. When faced with insufficient data,

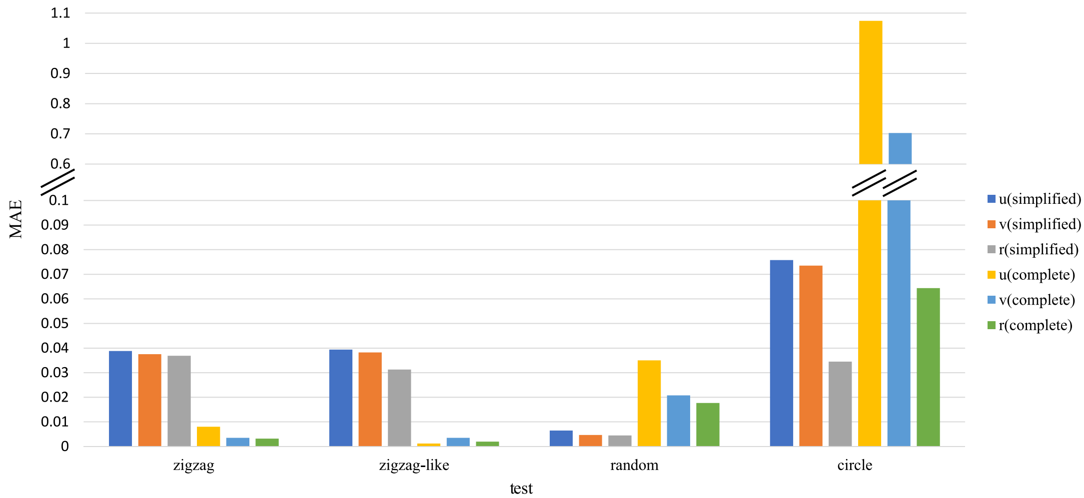
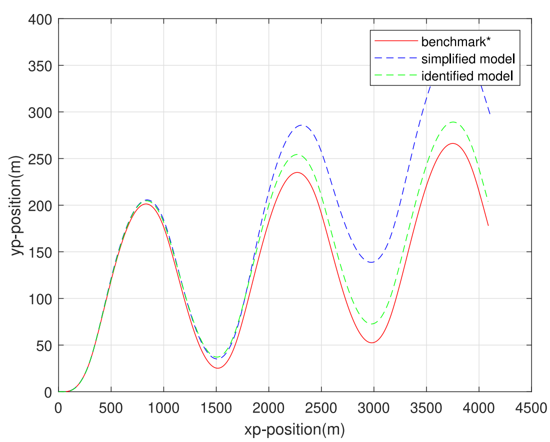
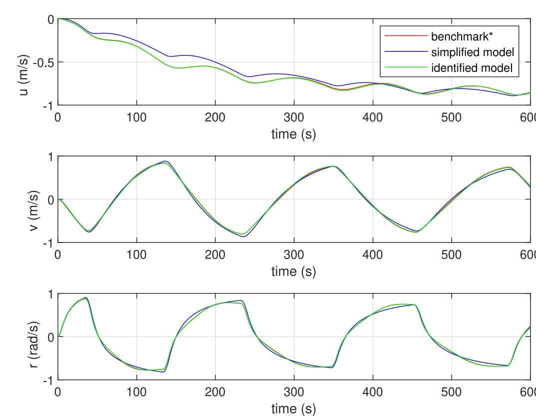


Fig. 10. The error histogram of the simplified model and the complete model.

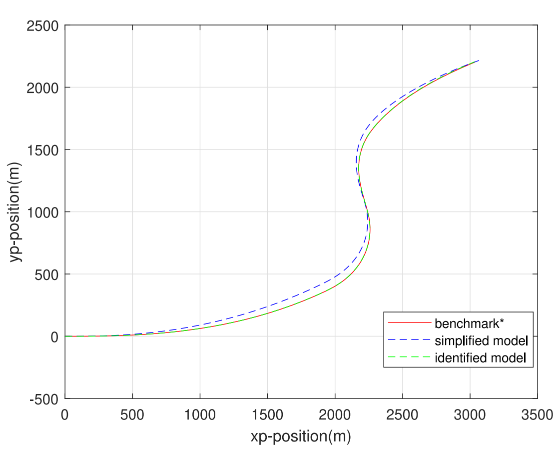


(a)

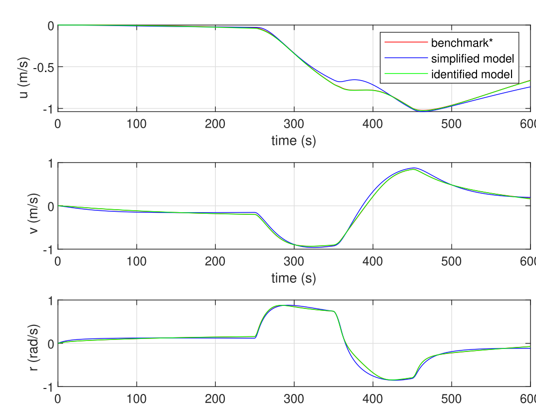


(b)

Fig. A.11. The results of the double mass vessel with the parameters identified from the zigzag test. (a) The trajectory of the complete model and the simplified model in the zigzag test. (b) The changing trend of command and yaw angle and the comparison of the surge, sway, and yaw speed in the zigzag test.

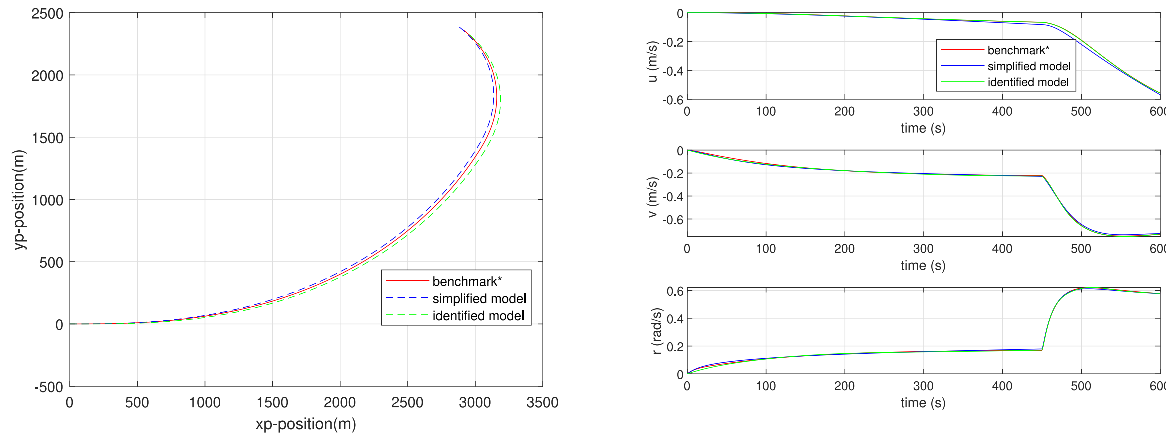


(a)



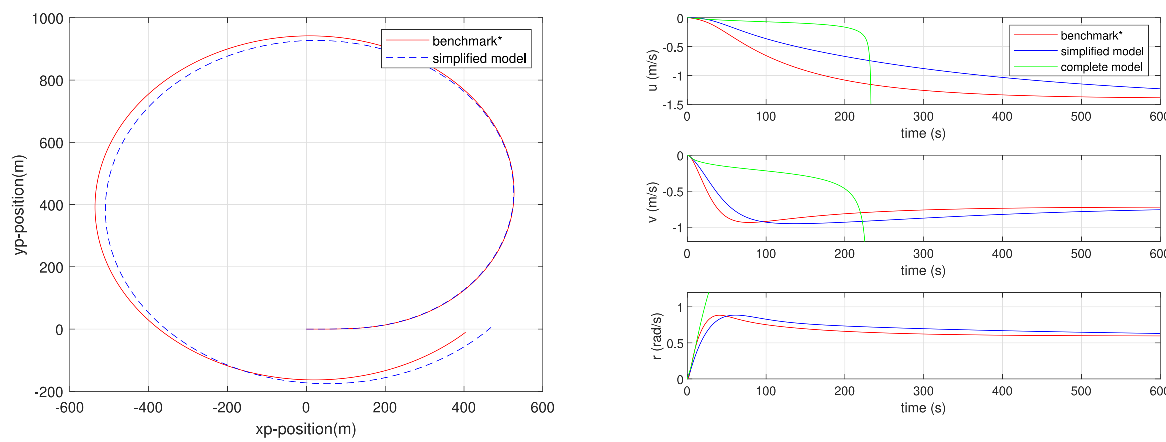
(b)

Fig. A.12. The results of the double mass vessel with the parameters identified from the zigzag-like test. (a) The trajectory of the complete model and the simplified model in the zigzag-like test. (b) The changing trend of command and yaw angle and the comparison of the surge, sway, and yaw speed in the zigzag-like test.



(a) (b)

Fig. A.13. The results of the double mass vessel with the parameters identified from the random test. (a) The trajectory of the identified model and the simplified model in the random test. (b) The changing trend of command and yaw angle and the comparison of the surge, sway, and yaw speed in the random test.



(a) (b)

Fig. A.14. The results of the double mass vessel with the parameters identified from the circle test. (a) The trajectory of the identified model and the simplified model in the circle test. (b) The changing trend of command and yaw angle and the comparison of the surge, sway, and yaw speed in the circle test.

model simplification can help us to obtain a ship model, reducing model complexity to fitting existing data. In Section 4.2, we can see that the data of the common maneuver, such as zigzag, can support building a simplified model. The simplified model can be identified with less required experimental data, which proves its stronger applicability. The simplified model can also be applied to other vessels with similar features like dimension, tonnage, and propulsion. We test the simplified model on the double-mass mariner as shown in Appendix. The accurate range of transfer learning should research in the future; however, the topic is out of the scope of this paper.

The standard we proposed for ship model simplification could be lower for other kinds of ships. For example, we can leave two parameters with the highest sensitivity values in one group with a high degree of correlation. In this paper, only two parameters of the surge are left, which may have a limited impact on the trajectory deviation, but can significantly affect the velocity, especially in the departure. We may use different retention methods in the future in line with the actual use motions.

Having redundant features in maneuvering models is a main cause of the so-called "parameter drift" problem, where some parameters end up with spurious values due to measurement noises (Luo and Li, 2017). Such a model with spurious parameters would not perform well in the model deployment with inexperienced inputs, which suggests that model simplification that involves removing redundant features has played a critical role in model identification. With limited data, the simplified model can perform better than the complex model because the simplified model can be identified more easily. The simplified model has a lower requirement for data, which is useful when not enough data can be obtained.

There are some questions about the PAWN index. It is gaining traction among the modeling community as a sensitivity measure, but little attention has been paid to its robustness (Puy et al., 2020). Though the PAWN index is more sensitive to the design parameters than that of Sobol, this sensitivity has a complex pattern that makes the use of PAWN, or better the tuning of the PAWN design parameters, a delicate task. So the method of sensitivity analysis could be changed. The global sensitivity analysis method is recommended, which considers the whole variation range of the inputs, such as Morris and Sobol.

6. Conclusions

This paper proposes a model simplification structure that can lower the requirement for data excitation during parameter identification. The white noises of various levels artificially pollute the outputs of the data generator for the mariner to simulate the measured value in reality. We use parameter identification to calculate the hydrodynamic parameters to build an identified model with the measured value. The least square regression is used to identify parameters. To simplify the mathematical model, we use correlation analysis and sensitivity analysis. Correlation analysis is used to group parameters with strong relationships, and sensitivity analysis is used to find the parameters that have the most significant impact on the output. We add different degrees of noise into the model's output and obtain a set of hydrodynamic parameters to test the correlation of parameters. The PAWN sensitivity analysis, which is a GSA method, is chosen. We set a standard and build a simplified model based on this knowledge. The simplified model has been tested under various scenarios in different levels of data excitation. Even though the accuracy of the simplified model is lower than that of the complete model under the zigzag and zigzag-like test, the simplified model has higher accuracy than the complete model in the random test designed in the paper. It implies that the simplified model will be more robust in real scenarios. In the circle test with less data excitation, the simplified model can be identified, while the opposite is true for a complete model. Results illustrate that the simplified model can outperform the complete model when there is less data excitation.

CRediT authorship contribution statement

Shiyang Li: Conceptualization, Methodology, Investigation, Writing – original draft. **Tongtong Wang:** Conceptualization, Writing – review & editing, Supervision. **Guoyuan Li:** Writing – review & editing, Supervision. **Houxiang Zhang:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix. The result of the double-mass vessel

To verify the generalization of the simplified model (Eqs. (23), (24), (25)), a doubled mass of the benchmark vessel (Table 1) is designed and conducted the same experiments as those in Section 4.4. The different levels of excitation data are generated by the data generator and as the train data for identifying the simplified and complete model separately. The simplified model and the complete model with the parameters identified from different levels of excitation tests are tested in the zigzag, zigzag-like, random, and circle test. The commands of the test are the same as shown in Table 4. In Figs. A.11,A.12,A.13,A.14, the red line presents the trajectory and the velocity comparison results of the double-mass data generator, and the blue and green lines express the simplified and identified models, respectively.

The results of the double-mass mariner have a similar trend to the original mariner. As the training data excitation decrease, the accuracy of the simplified model increase. In the circle test, as shown in Fig. A.14, the trajectory of the complete model diverges, which can be seen from the velocity comparison. The results of the double-mass vessel can prove that the simplified model can be used for similar ships.

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