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A Neural-Network-Based Sensitivity Analysis Approach for Data-Driven Modeling of Ship Motion

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***Abstract*—Researchers have been investigating data-driven modeling as a key way to achieve ship intelligence for years. This paper presents a novel data analysis approach to data-driven modeling of ship motion. We propose a global sensitivity analysis (GSA) approach combining artificial neural network (ANN) and sparse polynomial chaos expansion (SPCE) techniques to accommodate high-dimensional sensor data collected from ship motion. An ANN is constructed as a surrogate model to associate ship sensor data with a certain type of ship motion. To account for the computational efficiency of GSA, an SPCE is integrated into the GSA to decrease the need for Monte Carlo (MC) samples generated by the ANN. A probe variable is designed to couple with the MC samples, which plays a role in determining the degree of convergence of variable importance. A test on benchmark function demonstrates the efficiency and accuracy of the proposed approach. A case study of ship heading with and without environment effects is conducted. The experimental results show that the proposed approach can identify and rank the most sensitive factors of ship motion. The proposed approach highlights the application of GSA in data-driven modeling for ship intelligence.**

***Index Terms*—Data-driven modeling, environment effect, global sensitivity analysis (GSA), ship intelligence, ship motion.**

I. Introduction

THE digital agenda is one of the pillars of the European strategy for growth, which proposes to increase Europe's exploitation of the potential of information and communication technologies to foster innovation, economic growth, and progress. The strategy lists "ship intelligence" as one of the main areas through which to achieve growth. Ship intelligence has become a key aspect of making the maritime and offshore industries more innovative, efficient, and fit for future operations. Interest in developing and employing digital twins [1], big data [2], and cloud computing [3] for ship intelligence, particularly autonomous ships, has recently increased. Autonomy will require various technologies, including data collection, modeling, and intelligent applications. Data-driven modeling is a fundamental component of this innovation, which can provide support for higher level applications, such as ship motion prediction, onboard support, and autopilot.

To date, various novel intelligent data-driven techniques, such as extended Kalman filtering, Bayesian network, fuzzy logic, regression analysis, and artificial neural network (ANN) have been applied to ship motion modeling. In general, data-driven models have been highly dependent on sensor data. Regarding to data-driven modeling of ship motion, it is necessary to consider the ship sensor data that contains the characteristics of ship motion [4]. First, ship motion is highly nonlinear. This is caused by ship propulsion, together with environmental disturbances [5], [6], such as wind, wave, and current. Second, a variety of types of sensors are equipped with ships will generate data with varying sampling frequency. Third, the data of ship motion is highly dimensional, which originate from various sources of sensors. Mining the valuable information from massive ship sensor data to create useful ship motion models is important but challenging.

Sensitivity analysis (SA) is one of the potential solutions to figure out the intrinsic relationship of ship sensor data for data-driven modeling of ship motion [7]. SA is widely used for a wide range of industrial applications, including assessing the uncertainty, calibrating the model, and making robust decisions. SA reveals the relationship between changes in a data-driven model's output and variations in its input parameters [8]. SA has two main categories: local sensitivity analysis (LSA) and global sensitivity analysis (GSA). LSA explores the influence of an individual input parameter on the model output once at a time, while the other inputs remain fixed. LSA methods are not very applicable to the practical problems of models of ship motion because they are usually nonlinear [7]. GSA measures the sensitivity from the entire range of each input space, which not only can help to identify the key input variables, but also identify the model processes [9], [10]. To the best of our knowledge, studies of the application of GSA to data-driven modeling have been limited for the following challenges.

1) It is not easy to conduct GSA on sensor data directly because of the importance of input using numerical simulations.

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2) GSA methods usually are computationally expensive.
3) In practical engineering applications, it is hard to determine when GSA will achieve a convergent result.

Our on-going project aims to develop intelligent systems to support decision making in various maritime operations. A new integrated platform for planning and execution of real-time support to autonomous or semiautonomous ship operations based on data analysis tools, and data-driven modeling technique is designed, which will serve the maritime industry's interest in improving operational effectiveness and safety. In this paper, we focus on variance-based GSA of data-based modeling of ship motion. Considering the GSA cannot be applicable to the sensor data directly, an ANN is employed to construct the surrogate model. To accelerate the computation of variance-based GSA methods, sparse polynomial chaos expansion (SPCE) [11] is adopted. The main contributions of this paper are: first, it proposes a new SA method based on ANN and SPCE, making the variance-based GSA applicable to systematically analyze ship motion under the influence of environment; second, it introduces a probe variable to the variance-based GSA method, making it possible to examine the sensitivity and convergence of the proposed algorithm itself in the real engineering applications; and third, by means of a GSA with SPCE techniques, it investigates influences of the environmental factors (wave, wind).

The remainder of this paper is organized as follows. Section II is a brief review of previous work, primarily the introduction of SA and its application to ship motion. Section III describes the framework that explains how to combine the Sobol method and SPCE and apply it to ship sensor data sets. The proposed method is examined on both analytical benchmark and sensor data set of ship motion in Section IV. Section V provides the discussion and conclusion.

II. Related Work

The SA is defined as the investigation of "how uncertainty in the output of a model (numerical or otherwise) can be apportioned to different sources of uncertainty in the model input factors" [12]. The SA approaches have been increasingly employed to address all kinds of problems in ship motion applications. Li *et al.* applied input and output derivatives to simplify the three-layer structure of the NARX neural network for ship motion prediction [13], [14]. Zhang and Liu utilized the sum of square derivatives to select the network inputs for the NARMAX model, which was also used for ship motion prediction [15]. Hwang proposed an indirect SA method to study the hydrodynamic derivatives of a ship [16]. Rhee and Kim proposed a direct method of conducting SA using the differentiation of the mathematical ship model. Their methods can give more efficient estimation results [17]. Dong and Rhee [18] employed SA to study the maneuverability of submersibles, examining the hydrodynamic coefficients on the basis of several different types of sea trials. Using a similar approach to Dong, Wang *et al.* [19] performed an SA of hydrodynamic coefficients in a 4-DOF mathematical model based on simulated data. Xu *et al.* [20] used numerical simulation as a basis for a simple sensitivity study analyzing the sensitivity of an autonomous underwater vehicle. Santhakumar *et al.* [21] performed an SA of hydrodynamic parameters on the basis of an underwater robot. Shenoi *et al.* conducted an SA of all hydrodynamic derivatives in a 4-DOF of container ship [22]. Matsuura *et al.* performed the SA on a mooring system to optimize the hydrodynamic coefficients [23]. To reduce the influence of model complexity on simultaneous drift, Luo and Zou [24] analyzed the sensitivity of a single hydrodynamic derivative on its maneuverability prediction and hydrodynamic modeling. Kim *et al.* conducted an SA of an Abkowitz-type mathematical model and determined the influence of the hydrodynamic derivatives on KVLCC2 maneuverability [25]. Mizythras *et al.* proposed an SA to investigate the various performance parameters that affect the propulsion and maneuvering abilities of a ship [26]. The analysis results can act as a supplementary study to assess the influence of performance parameters on the performance of the test vessel. However, the literature offers few SA studies relating to ship motion modeling under environment effects. State-of-the-art SA methods in ship motion application currently follow the theory of LSA. Although traditional LSA methods can be used for ship motion analysis, such as the simplification of ship motion prediction model, importance rank of the parameters, and risk reduction, LSA is not suitable for nonlinear systems such as those that include environment disturbance [27]. Hence, we propose a GSA-based approach for ship motion analysis under environmental effects.

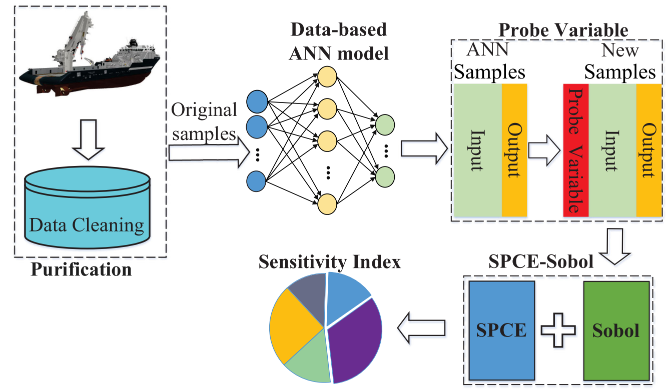

Fig. 1. Framework of ANN-SPCE-Sobol.

III. Proposed Approach

An offshore ship may have hundreds of sensors that cumulatively collect enormous amounts of data. Using the variance-based Sobol method to assess the data is computationally expensive. We propose the application of SPCE to the Sobol approach to ship sensor data to accelerate the computation speed.

A. *Framework of ANN-SPCE-Sobol*

The use of SA combining SPCE and Sobol for data-based model is proposed. The ship sensor data system features flexible and versatile data that can be easily imported into the system to obtain the compact structure. Fig. 1 illustrates the proposed framework and the original structure. The framework consists of four components.

1) *Purification*: Considering that raw sensor data may contain noisy, discontinuous, and superfluous information, it is essential to purify it to minimize the effect on further modeling and analysis. The first step of the data cleaning process is the noise reduction, which uses the median filtering technique. The details of purification are described in Section III-B.
2) *Data-based ANN model*: Data-based ANN is an important part of the scheme, for two reasons. First, this approach builds a bridge between the modeler and the sensor data that will make it easier to improve the model and understand the behavior of the ship. Second, the data-based ANN model will generate a number of input parameters using Latin hypercube sampling [28] technique to calculate the corresponding output. Here, the group of a set of input parameters and the corresponding output is called a *sample* [29]. The data-based ANN model contains all the relevant input parameters after cleaning, and is trained by these data to achieve certain accuracy in advance. The model would be reconstructed using those selected input variables through SPCE-Sobol method. In this paper, a three-layer feed-forward neural network is built for ANN-SPCE-Sobol and ANN-Sobol. The back-propagation algorithm is used as the learning algorithm. The Sigmoid function and linear function are employed as the activation function of a hidden layer and output layer, respectively. During the training phase, 80% of sensor data is employed for training and the remaining 20% for testing and validation.
3) *Probe variable*: The use of a probe variable has two purposes: The first is to help reveal the convergence of sensitivity index of input parameters. The second is to perform parameter screening and access the results of the sensitivity index. Ideally, the sensitivity index of the probe variable should be zero, because the probe variable does not occur in the representations of model and it would not affect the model in any other fashion. The probe variable will be added to the samples, which is shown in Fig. 1. Section III-D introduces the computation of the sensitivity index of the probe variable.
4) *SPCE-Sobol*: This paper combines the SPCE algorithm with the Sobol method to perform GSA on the input selection for a data-based ANN model. Taking advantage of SPCE to achieve fast convergence, the sensitivity index can be calculated directly. SPCE is trained using the sample generated by the ANN model, conducting Sobol SA using the well-trained SPCE.

B. Data Preprocessing

The data comes from the Offshore Simulator Centre AS (OSC), Aalesund, Norway [30]. Developed by Norwegian University of Science and Technology and its research partners from industry, OSC is an advanced training platform for offshore operation personnel. It allows users to produce solutions based on a very powerful physical engine existing in changeable wind, wave, and current conditions. Fig. 2 shows a true ship model in OSC.

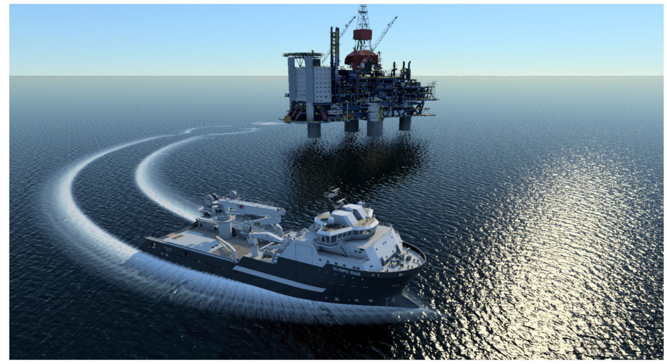

Fig. 2. Maneuver scenario in OSC.

The data collected from the ship in OSC contains variables associated with varying environmental effects in terms of wind and wave. The simulation also includes ship motion reference units that account for the six degrees of freedom (sway, roll, yaw, heave, pitch, and surge). Due to the physical definition of raw, it has some jumping phenomena. For example, the definition of roll angle, yaw angle, and pitch angle is within $[0°, 360°]$. When the angle changes near the border, jumping is inevitable. To get rid of this type of discontinuity, we employ an algorithm that we defined in our previous paper [14]. There are also some control variables, such as rudders and thrusters. Analyzing these is problematic. For example, changing the rudder would affect the dynamics of the ship. Using the rudder angle directly would result in an incorrect influence estimation of the control signal.

In fact, both lift and drag forces reflect the rudder effect [31]. The thruster force can be conveniently separated into two parts: rudder lift L_i and drag forces D_i. $i = 1, 2$ represents different rudders

$$L_i = F_i(1 + k_{iLn\omega_i})(k_{iL\delta_1} + k_{iL\delta_2}|\delta_i|)\delta_i \tag{1}$$

$$D_i = F_i(1 + k_{iDn\omega_i})(k_{iD\delta_1}|\delta_i| + k_{iD\delta_2}|\delta_i^2|) \tag{2}$$

where ω_i stands for the shaft speeds of thrusters. δ_i represents the angle of rudder. The parameters of lift and drag can refer to [31].

In addition, as the ANN is employed to construct the metamodel of the raw data, it is necessary to normalize all parameters to speed up the training convergence and improve accuracy of the ANN model. All the parameters would be normalized based on the following:

$$\widehat{\boldsymbol{x}} = \frac{\boldsymbol{x} - E(\boldsymbol{x})}{\sqrt{\mathrm{Var}(\boldsymbol{x}) + \epsilon}} \tag{3}$$

where $E(\boldsymbol{x})$ represents the mean of $\boldsymbol{x}$. $\mathrm{Var}(\boldsymbol{x})$ stands for the variance of $\boldsymbol{x}$. ϵ is a positive infinitesimal to make the calculation possible when $\boldsymbol{x}$ is a constant. ϵ is set to 10^{-6} in this paper. Apart from the above-mentioned, this paper also considers synchronizing those data with different sampling frequency.

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C. Sobol Method Based on SPCE

Assuming the model form is $f(\boldsymbol{X}) = f(x_1, \ldots, x_M)$, where $\boldsymbol{X} = (x_1, \ldots, x_M)$ represents the model input, which contains M independent parameters. Based on the theory of Sobol [32], the model output can be decomposed by different effects [33], which is shown as follows:

$$f(\boldsymbol{X}) = f_0 + \sum_{i=1}^{M} f_i(x_i) + \sum_{1\le i\le j\le M} f_{ij}(x_i, x_j) + \cdots + f_{1,2,\ldots,M}(x_1, x_2, \ldots, x_M). \tag{4}$$

Some literatures [34], [35] have argued that only the lower order terms are important. So, this paper considers only the two higher orders. Equation (4) can be rewritten as follows:

$$f(\boldsymbol{X}) = f_0 + \sum_{i=1}^{M} f_i(x_i) + \sum_{1\le i\le j\le M} f_{ij}(x_i, x_j). \tag{5}$$

Assume the $f(\boldsymbol{X})$ is square integrable. Squaring (5) and integrating over the input space, the following equation can be obtained:

$$\int f^2(\boldsymbol{X})d\boldsymbol{X} - f_0^2 = \sum_{i=1}^{M}\int f_i^2(x_i) + \sum_{1\le i\le j\le M}\int f_{ij}^2(x_i, x_j). \tag{6}$$

The left part in (6) is called the total variance

$$V = \int f^2(\boldsymbol{X})d\boldsymbol{X} - f_0^2. \tag{7}$$

The right part in (6) is called the partial variance

$$V_i = \sum_{i=1}^{M}\int f_i^2(x_i)$$
$$V_{ij} = \sum_{1\le i\le j\le M}\int f_{ij}^2(x_i, x_j). \tag{8}$$

Generally, the global sensitivity index would be described by the ratio of partial variance and total variance [33]. The first-order (main effect) sensitivity index for the ith variable x_i can be defined by

$$S_i = \frac{V_i}{V}. \tag{9}$$

The total-order sensitivity index is calculated as follows:

$$S_{Ti} = 1 - \frac{V_{\sim i}}{V}. \tag{10}$$

The Sobol method employs Monte Carlo methods to calculate the sensitivity index, which brings very expensive computational complexity [36], [37]. To reduce the computational complexity of Sobol's method, the idea of polynomial chaotic expansion (PCE) is adopted.

The technique of PCE is to decompose the model output using the Hilbertian polynomial basis (such as the Hermite polynomial) as follows:

$$g(\boldsymbol{X}) = \sum_{i=0}^{\infty} b_i \Psi_i(\boldsymbol{X}) \tag{11}$$

where b_i represents the ith polynomial coefficient. $\Psi_i(\boldsymbol{X})$ stands for the multivariate Hermite basis. In practical applications, it is suggested to be truncated to a certain number of terms. The strategy of truncation is shown as follows:

$$p = \frac{(M+d)!}{M!d!} - 1 \tag{12}$$

in which d stands for the degree of polynomial meta-model and p represents the total number of PCE terms. Imagine the number of random input M increases linearly, the conventional PCE will meet the problem which is the well-known curse of dimensionality in some literature [38]. To overcome this problem, Blatman proposes a sparse-adaptive scheme [11]. The range of d is set by users, and selecting the proper d is problem-dependent. The adaptive algorithm would select the best d from the preset candidates based on the accuracy runs of SPCE.

After constructing the truncation strategy, the weights b_i should be determined by minimizing the following equation:

$$\underset{b}{\operatorname{argmin}} \left(\sum_{i=1}^{N'} [f(\boldsymbol{x}_i) - \boldsymbol{b}^T \boldsymbol{K}(\boldsymbol{x}_i)]^2 + \eta \sum_{i=1}^{N'} b_i \right) \tag{13}$$

where N' is the design space of SPCE, $\boldsymbol{b}$ is the coefficients vector, $\boldsymbol{K}$ is the design matrix [37], and $\eta > 0$ is a penalty coefficient. To get the optimal solution, least angle regression [39] can be adopted.

The sensitivity index of SPCE-Sobol can be obtained as follows:

$$S_{i1,\ldots,iq} = \frac{\sum_{k\in R_{i1,\ldots,iq}} b_k^2 \Psi_k^2(\boldsymbol{X}_{i1}, \ldots, \boldsymbol{X}_{iq})}{\sum_{i=0}^{d} b_i^2 E[\Psi_i^2(\boldsymbol{X})]}. \tag{14}$$

Since the summands in (14) could be derived from the coefficients obtained from (13), the analytical solutions of Sobol index could be estimated with insignificant computational time.

D. Determining Unimportant Parameters by Employing a Probe Variable

The probe variable, which Stoppiglia *et al.* [40] proposed, is widely used in the literature. It has been employed to select input parameters using Gram–Schmidt procedure. Fock [41] combined the probe variable and variance-based EFAST method to select the input parameters for the feed-forward neural networks. Using probe variable as the tool for parameter screening can reliably classify the important variable. Based on [41], this paper combined the idea of probe variable and variance-based Sobol method to select input variables for a data-based ship motion prediction model.

In our framework, the probe variable is added to the ANN samples. As mentioned in Section III-A, the combination of input and output is called a sample. To have no influence on the output of the model, the probe variable would be added to the ANN samples generated by the data-based model. The probe variable would be added into the input part, creating a combination of new input and output called new samples. The sensitivity index of probe variable would calculate numerically using the new samples. To make the probe variable different from the other input parameters, the probe variable would be sampled uniformly, while the other inputs are sampled in Gaussian distribution.

Ideally, the influence of the probe variable to the model output is zero. Under current technical conditions, the calculation of SA often employs numerical approximations, which often bring calculation error. The purposes of using probe variable is to estimate those errors. Referring to [41], if the sensitivity index of the input factor is below the sensitivity index of the probe variable, this input parameter should be considered unimportant; otherwise, it is influential. In our proposed method, there is no need to change the model output, and the sensitivity index of probe variable can be calculated based on the samples directly.

Sobol [42] proposed a method that can estimate the sensitivity index directly from the model output $f(X)$ only. In this paper, we refer his work and derive the calculation process of the sensitivity index of probe variable. The calculation may require two independent sample matrices A and B, whose dimensions are $N \times M$, in which N stands for the number of samples and M represents the number of input variables.

The first-order sensitivity index can be described as follows [42]:

$$S_i = \frac{V_i}{V} = \frac{\frac{1}{N}\sum_{j=1}^{N} f(B)_j (f(A_B^{(i)})_j - f(A)_j)}{V(y)}. \tag{15}$$

The total sensitivity index can be expressed as

$$S_{Ti} = 1 - \frac{V_{\sim i}}{V} = \frac{\frac{1}{2N}\sum_{j=1}^{N} (f(A)_j - f(A_B^{(i)})_j)^2}{V(y)}. \tag{16}$$

$A_B^{(i)}$ and $B_A^{(i)}$ in (15) and (16) can be obtained to exchange the ith column in B/A, which are introduced by Saltelli *et al.* [43].

The definition of probe parameter can be shown as follows:

$$f(x_1, x_2, \ldots, x_M, \boldsymbol{x}_{\text{probe}}) = f(x_1, x_2, \ldots, \ldots, x_M). \tag{17}$$

From (15), the key problem of the calculation of first-order sensitivity index is to get the three resample matrices A, B, and $A_B^{(i)}$. Suppose A is $f(x_1, x_2, \ldots, x_i, \ldots, x_M)$, B is $f(x_1^{'}, x_2^{'} \ldots, x_i^{'}, \ldots, x_M^{'})$. So, the $A_B^{(i)}$ can be obtained to exchange the ith column, $A_B^{(i)} = f(x_1, x_2, \ldots, x_i^{'}, \ldots, x_M)$. If the ith input parameter corresponds to the probe variable, $f(A_B^{(i)}) - f(A)$ can be described as follows:

$$\begin{aligned} f(A_B^{(i)}) - f(A) &= f(x_1, x_2, \ldots, x_{i-1}, x_i^{'}, x_{i+1}, \ldots, x_M) \\ &\quad - f(x_1, x_2, \ldots, x_{i-1}, x_i, x_{i+1}, \ldots, x_M) \\ &= f(x_1, x_2, \ldots, x_{i-1}, x_{i+1}, \ldots, x_M) \\ &\quad - f(x_1, x_2, \ldots, x_{i-1}, x_{i+1}, \ldots, x_M) \\ &= 0. \end{aligned} \tag{18}$$

So, the first-order sensitivity index of the probe input variable is zero. As with the total sensitivity index of the probe input variable, $f(A) - f(A_B^{(i)})$ can be calculated based on (18), which has a value of zero. The high-order interaction sensitivity index of probe variable is equal to $S_{Ti} - S_i = 0 - 0 = 0$.

In this paper, the original Sobol method is extended to the SPCE-Sobol; although the formation of the sensitivity has changed, the nature of Sobol is still the same. That is to say, the sensitivity index of probe parameter is still zero in the new method. The convergence of the probe variable will be verified in the analytical benchmark function in Section IV-A2.

IV. Experiment

Section IV-A is dedicated to the validation of the proposed approach. The widely used benchmark Sobol function in variance-based GSA is employed to test the performance of the proposed approach compared with other methods. And then the proposed method is applied to the ship sensor data set. The experiments are conducted in MATLAB R2017a with a computer equipped with 4.20 GHz i7-7700K CPU and 32 GB RAM. To construct the SPCE, the UQLab toolbox [44] is employed.

A. High-Dimension Benchmark—Sobol Function

The performance of the proposed approach is first tested with a high dimension problem to investigate its analytical stability and robustness. The benchmark test here is the Sobol function with M inputs whose expression is

$$f(\boldsymbol{x}) = \prod_{i=1}^{M} \frac{|4x_i - 2| + a_i}{1 + a_i} \quad \boldsymbol{x} \in [0,1]^M. \tag{19}$$

Here, three scenarios are tested to illustrate the performance of the proposed method. The value of M is set to 10, 15, and 25 respectively. a_1–a_6 are set to 1, 2, 5, 10, 20, and 50, and the rest are set to a constant value of 500. First, the original samples are set big enough to generate a high accuracy ANN model, and ten ANN models are created, and the best model is chosen from the ten models based on the performance test using MSE. The performance of the ANN-Sobol and ANN-SPCE-Sobol would be compared based on the number of ANN-samples. Second, the convergence analysis would be analyzed on the basis of number of ANN-Samples.

1) Comparison Between ANN-Sobol and ANN-SPCE-Sobol: As Tables I–III show, the ANN-SPCE-Sobol is competent to improve the computational efficiency but not sacrificing precision, compared with the ANN-Sobol. From the experiment results, the probe variable has a sensitivity index of almost zero as expected, and the ANN-SPCE-Sobol achieves a better performance in terms of both the estimate results and number of samples. The proposed approach dramatically reduces the computational complexity regarding the number of ANN samples. Taking Table III for instance, the ANN-Samples of ANN-Sobol is almost 20 (20 000/1024) times than that of ANN-SPCE-Sobol. Considering the complexity of a model, the proposed approach does not raise the computational complexity of conducting the variance-based GSA. Therefore, the more complex the model is, the more computation time would be reduced by using SPCE. In addition, in the three test scenarios, the performance of ANN-SPCE-Sobol varies with the growing of input size, the result of ANN-SPCE-Sobol is more accurate, whereas the computation time increases moderately.

TABLE I
COMPARISON OF FIRST-ORDER BETWEEN ANN-SOBOL AND ANN-SPCE-SOBOL (M = 10)

Input	True	ANN-SPCE-Sobol	ANN-Sobol
1	0.604	0.595	0.597
2	0.268	0.265	0.261
3	0.067	0.063	0.064
4	0.020	0.015	0.013
5	0.010	0.011	0.009
6	0.000	0.011	0.010
probe	0.000	0.009	0.011
ANN samples	—	**200**	**5000**

TABLE II
COMPARISON OF FIRST-ORDER BETWEEN ANN-SOBOL AND ANN-SPCE-SOBOL (M = 15)

Input	True	ANN-SPCE-Sobol	ANN-Sobol
1	0.604	0.595	0.597
2	0.268	0.274	0.267
3	0.067	0.066	0.064
4	0.020	0.017	0.015
5	0.010	0.012	0.013
6	0.000	0.008	0.009
probe	0.000	0.009	0.009
ANN samples	—	**512**	**8192**

TABLE III
COMPARISON OF FIRST-ORDER BETWEEN ANN-SOBOL AND ANN-SPCE-SOBOL (M = 25)

Input	True	ANN-SPCE-Sobol	ANN-Sobol
1	0.604	0.597	0.596
2	0.268	0.268	0.268
3	0.067	0.067	0.064
4	0.020	0.019	0.018
5	0.010	0.012	0.013
6	0.000	0.007	0.008
probe	0.000	0.009	0.008
ANN samples	—	**1024**	**20000**

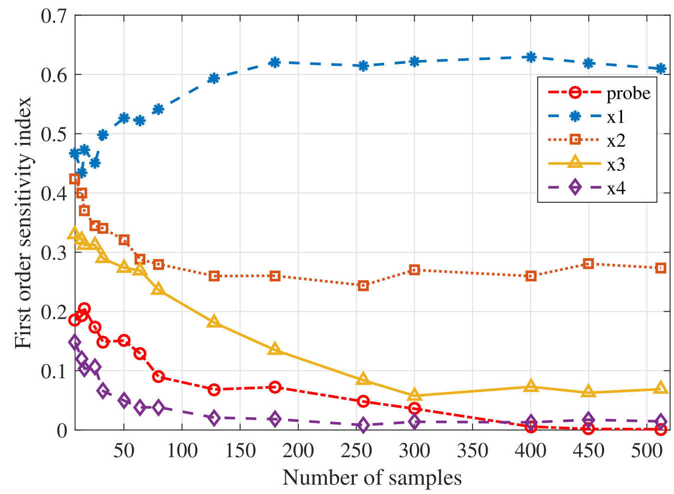

Fig. 3. Convergence analysis of the proposed method.

2) Convergence Analysis of the Proposed Method: To examine the sensitivity of the algorithm itself and to observe the convergence of sensitivity index of input, the convergence analysis is also conducted. Fig. 3 presents the convergence of the biggest first-order sensitivity index S_i of four inputs and the probe variable, and presents the evolution of the parameter convergence with growing sample size for the five parameters. It is noticed that the final sensitivity indices are reached very quickly, whereas more fluctuations are observed with a smaller number of samples. In this paper, the sensitivity index of our proposed approach is calculated on the basis of numerical approximations (Monte Carlo (MC) simulations). Thus, the key issue is the convergence analysis to ensure a reliable estimation of sensitivity index and robust parameter ranking. To study the convergence, the first-order sensitivity index are conducted with an increasing samples. Fig. 3 also shows that the S_i for most of the input variables converge to 500 ANN samples. For some parameters, more than 300 ANN samples are enough to reach a steady value.

Section III-D has proved that the total, first-order sensitivity index of probe variables are all zero. From the experimental result, ANN-SPCE-Sobol assigns a nonzero but very small first-order sensitivity index to the probe parameter. The reason the sensitivity index is small may be insufficient sampling, aliasing, or the interference effect. The result also shows that the sensitivity index of the probe variable is bigger than the sensitivity index of x_4 for the small samples, and increasing the number of samples almost equalizes both values. The x_4 can be identified as an unimportant parameter with the help of probe variable even for insufficient samples. Therefore, the parameters for which the first-order sensitivity index is less than or equal to the probe variable should be considered insignificant.

The assignment of an artificial value to the first-order sensitivity index would not require much additional calculation. It is hard to determine when the results would achieve a relatively convergent result in practical engineering applications. Employing the probe parameter as the parameter of interest makes it easier to quantify those significant parameters clearly.

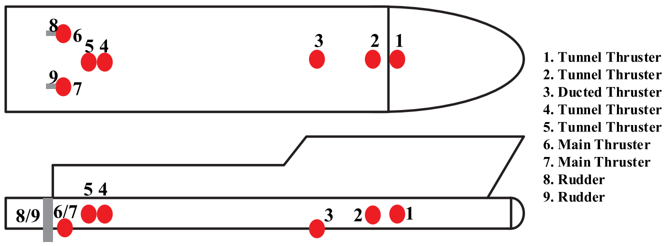

Fig. 4. Simplified simulation ship model.

TABLE IV
RECORDED SHIP DATA SPECIFICATION

Module	Parameter	Abbreviation	Range
Ship state Data	surge_velocity	surge_vel	Data
	sway_velocity	sway_vel	Data
	heave_velocity	heve_vel	Data
	roll_velocity	roll_vel	Data
	pitch_velocity	pith_vel	Data
	yaw_velocity	yaw_vel	Data
	roll	roll	[0°-360°]
	pitch	pitch	[0°-360°]
	yaw	yaw	[0°-360°]
Environment	wind_direction	wind_dir	Data
	wind_velocity	wind_vel	Data
	wave_height	wave_hgt	Data
	wave_direction	wave_dir	Data
Thrust Data	thrust6_force	thrust6_F	Data
	rudder8	rudder8	Data
	thrust7_force	thrust7_F	Data
	rudder9	rudder9	Data

B. Case Ship

The case ship is chosen from the OSC simulator, which is equipped with two tunnel thrusters and one ducted propeller in the bow and two tunnel thrusters and two main propellers with rudders at the stern, as shown in Fig. 4. In this vessel, ship state data, thruster data, and environment data are monitored and stored, as shown in Table IV. The ship state data is the status data of ship, and the environmental data includes the wind and the waves. In this paper, S-shape motion and circle motion are simulated in OSC. Fig. 5(a) shows the trajectory of S-type motion. Fig. 5(b) shows the trajectory of ship circle motion. In our experiment, the S-type and circle motion is simulated mainly by controlling the rudder of the two main thrusters. For the S-type motion, the control routine is as follows: when the heading angle reaches to X degree, the rudder angle is set to Y degrees; when the heading angle reaches to − X degrees, the rudder angle is set to − Y degrees. For the circle motion, a constant rudder angle is applied at all times. In the OSC simulation platform, it is convenient to employ the script to auto control the ship in all kinds of settings, such as waves, winds, and currents. The procedure of our simulation using script is as follows:

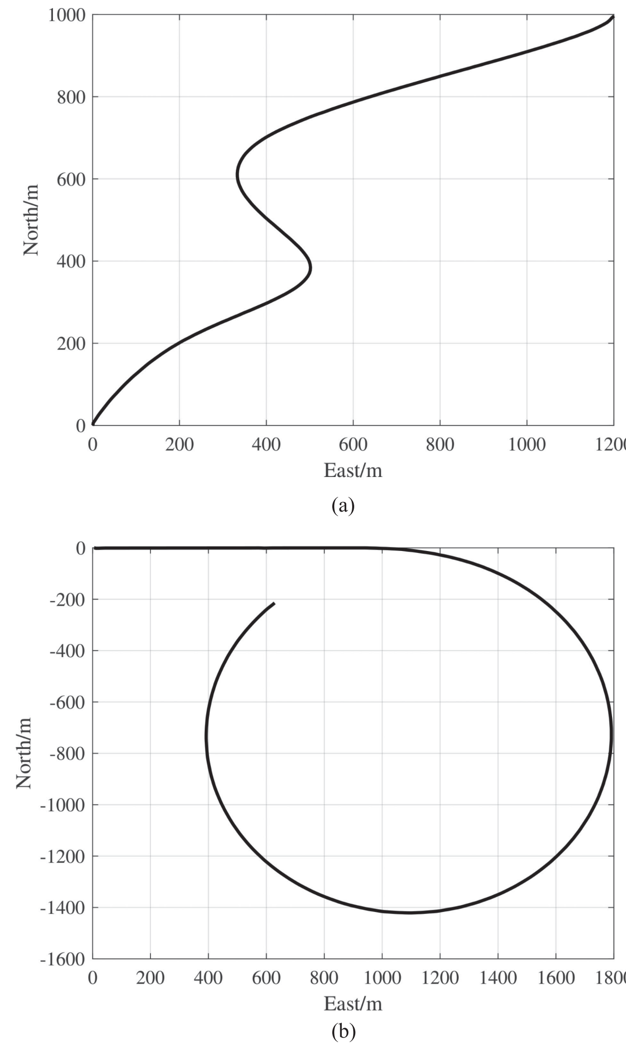

Fig. 5. Two types of ship motion. (a) Trajectory of S type. (b) Trajectory of circle type.

1) setting the wind and wave;
2) starting the control routine;
3) collecting the sensor data.

In our analysis, all parameters are assumed independent, and the distribution for each parameter is measured from the sensor data. The definition of the space of input variable then only to define the variation range of each input variable [45]. As reported in Table IV, the range of some parameters depends on their physical meaning, and the range of others is limited by the minimum and maximum observations of the parameter over the entire data set. To implement the SPCE-Sobol in both types of ship motion, the SPCE is configured with the design space, $N' = 1000$, and the degree, $d = 1:6$. In the applications of offshore operations, especially in the close-range maritime operations, heading is a key parameter to ship motion. Thus, the next two experiments

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TABLE V
SCENARIOS OF S-TYPE MOTION WITH/WITHOUT ENVIRONMENT EFFECTS

Scenarios	Main thruster output	Description
1	10%	no environmental disturbances.
2	30%	no environmental disturbances.
3	60%	no environmental disturbances.
4	30%	2.5m wave and 0∼12 m/s wind come from ship stern.
5	30%	2.5m wave coming from side (east to west).
6	30%	2.5m wave and 0∼12 m/s wind come from side (east to west).

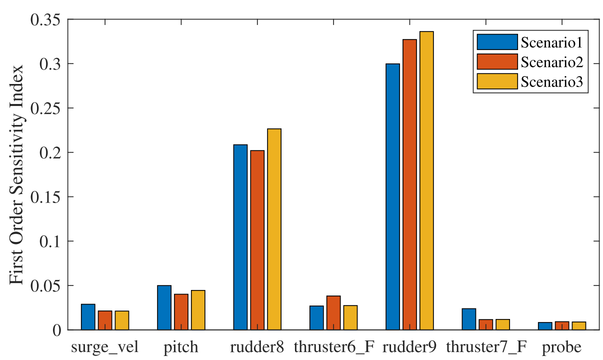

Fig. 6. First-order sensitivity index of heading in scenarios 1–3.

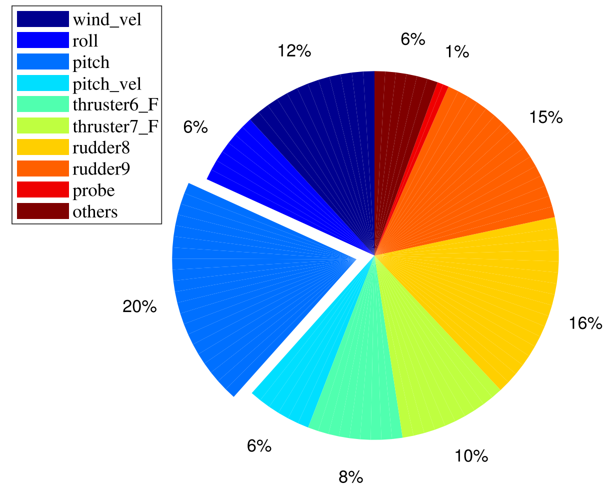

Fig. 7. Total-order sensitivity index of wind and wave in scenario 4.

mainly focus on the analysis of environmental factors to ship heading.

C. S-Type Motion

1) S-Type Motion Without Environment Effects: First, the S-type motion data set without environment effects is employed to investigate the performance of the proposed method. To illustrate the robustness of the proposed method and to explore the hidden relationship in the ship historical sensor data, three scenarios are compared, as listed in the first three rows of Table V. In the three scenarios, ship heading was chosen as the output variable, and the rest of the variables are the input variables.

In this section, the results of ANN-SPCE-Sobol first-order sensitivity index for three scenarios is presented and compared, and the six most influential inputs are shown in Fig. 6. From the figure, the sensitivity index of the probe variable is almost 0.01. For conciseness, those input parameters whose sensitivity index are less than or equal to the probe variable are not shown in the figure. The sensitivity results are estimated using original sensor data samples of 6000 and ANN samples of 512, respectively. In Fig. 6, it is noted that similar sensitivity index is obtained and rudder 9 is clearly the most important parameter, followed by rudder 8 for scenarios 1–3. In the three scenarios, the ship is commanded in a forward motion state, and the two main rudder are the key factors for heading. In this simulation, no environment factors are added, so the impact of other thrusters is not obvious. It is also noted from Fig. 6 that the sum of the first-order sensitivity index of all six most influential inputs is less than 1, which means the interaction of input variables is also obvious, as expected.

2) S-Type Motion With Environment Effects: As the ship motion is strongly related to the wind and wave, this section focuses on the influence of environment factors to the ship heading. In this test, three scenarios are taken into consideration, shown as the last three rows of Table V. In the fourth scenario, the ship heads toward north, 30% command on the main thrusters, 2.5 m swell +2.5 m wave (ITTC spectrum), 0∼12 m/s wind come from stern, so the wind and wave would increase the vessel velocity. In the fifth and sixth scenarios, the wave and wind come from side (east to west). In scenario 5, only wave is considered, but wave and wind are taken into consideration in scenario 6. The speed of wind is from 0∼12 m/s, and a sum of a sinusoidal wave with peak-to-peak value of 2.5 m and a wave spectrum with significant waveheight of 2.5 m. In this section, total sensitivity index is calculated.

In Section IV-C1, first-order sensitivity index is considered. In this section, total-order sensitivity index is used for identifying the influential factors, which is lower than the sensitivity index of probe parameter and are shown in the group of others. Fig. 7 shows the results of scenario 4, which includes eight important input variables with their total-order sensitivity index. This indicates that the pitch of the ship should be considered as the most important factor (20%) when wind and wave come from ship stern.

Similarly, in scenario 5, as shown in Fig. 8, it can be seen that eight parameters are important to the heading. From the figure we can know that when wave comes from east to west, the most important input variable is the roll. In the case of only waves, the height or wave direction may be the most important parameters to the heading. However, in the OSC simulator, the wave height and wave direction is set as a constant, and the proposed approach discards these two parameters. Fortunately, it should be noted that the roll reflects the wave when the wave

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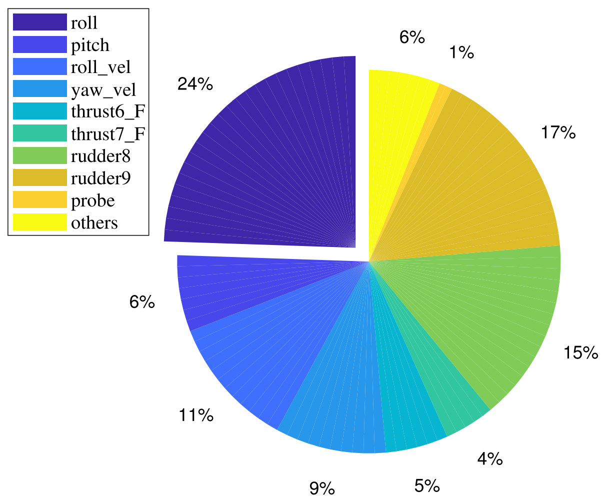

Fig. 8. Total-order sensitivity index of wave in scenario 5.

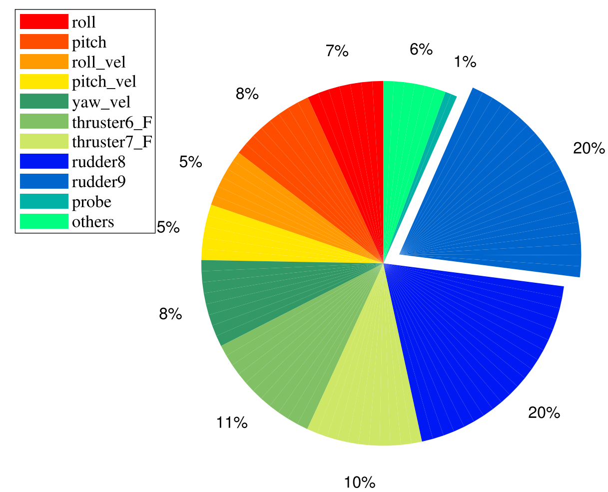

Fig. 10. Total-order sensitivity index of circle motion without environmental factors.

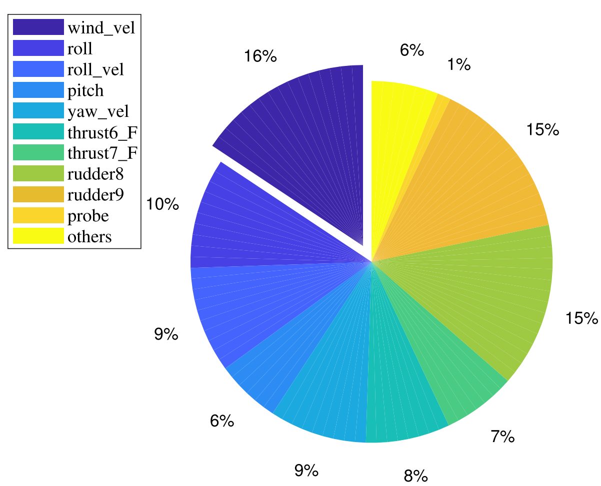

Fig. 9. Total-order sensitivity index of wave and wind in scenario 6.

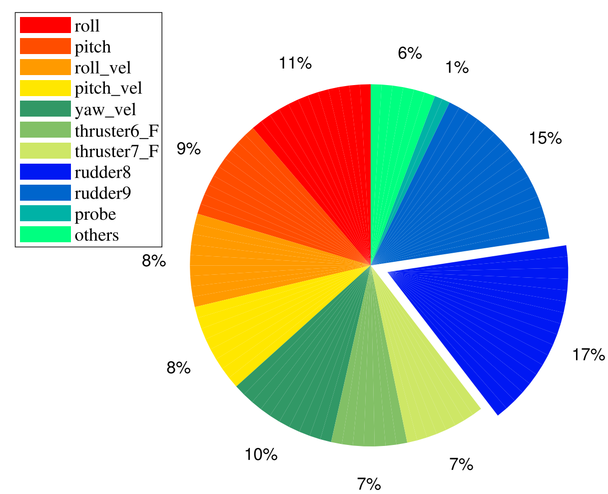

Fig. 11. Total-order sensitivity index of circle motion with environmental factors.

comes from east; that is to say, wave is the most important variable in this scenario.

Fig. 9 represents the influence of wave and wind with direction east to west on the ship heading in scenario 6. The figure shows that wind velocity is the most influential input. The parameters "roll," "rudder 8," and "rudder 9" have the almost same impact to the output. The result shows that the wave and wind would have significant impact on ship roll with the direction of east to west.

D. Ship Circle Motion

The proposed approach is also applied to the ship circle motion. In this section, the ship heading of circle motion with/without environment factors are also focused upon. In the test scenarios, the setting of wave and wind is the same with the scenario 6 described in Table V.

Fig. 10 shows the total-order sensitivity index of the ship heading in circle motion without environmental factors. This figure uncovers the most significant inputs. Specifically, the two rudders and two thrusters correspond to the four largest sensitivity indices, respectively, which should be taken care of to implement a high efficient data-based neural network.

Fig. 11 illustrates the total-order sensitivity index of the ship circle motion with environmental factors. It can be found that the two rudders, roll, and pitch, have a relatively larger sensitivity index among the inputs. From this figure, the global sensitivity of ship circle motion under environmental factors depends on many input parameters, which enables one to obtain more knowledge of the complex motion. In Figs. 10 and 11, one can notice that the roll and pitch under environmental factors are more sensitive than those without environmental factors. For instance, roll in Fig. 10 almost has a 7% effect on the model output; however, in Fig. 11 the effect of roll is up to 11%. It should also be noticed from Fig. 11 that the values of the total-order sensitivity index of each input variable are very close.

The results show that the most important parameters in the model of ship motion without environment factors are rudders (control signal). If ship heads under environment effects, the most important parameters could be environment factors, whether under wave or under wind and wave.

V. Discussion and Conclusion

The need for ship intelligence has recently been emphasized, as those intelligent models are powerful tools to understand complex system behavior and to point out key-processes involved in the control of traits, such as ship heading/rolling. The data-driven model of ship motion is very often hampered by the fact that obtaining appropriate parameters requires too much effort. In this study, an SPCE-based SA method was carried out to select those important model input factors. The benchmark test demonstrates that the efficiency and accuracy of the proposed approach compared to the conventional MC-based Sobol method, and the proposed probe variable can be used to identify the important parameters.

This paper builds a bridge between variance-based GSA and ship maneuvering applications. A novel approach has been represented to implement the GSA by applying the SPCE to reduce computational complexity. In the application of the proposed method, some input factors are grouped into influential, and the rest are considered as not influential. To help screen those important parameters, a probe variable has been proposed. In this fashion, we can infer the number of input variables that will represent the variability of model. In addition, the GSA can provide the key information to assess the loss in variability when building the data-based ship motion prediction model.

Contrary to traditional GSA, this proposed approach can effectively calculate the sensitivity index of a high number of independent input parameters of ship maneuvering applications. The experimental results indicate the advantages of this proposed approach in analyzing ship maneuvering models with a large number of input factors, especially under environmental effects. The analysis of accuracy and computational burden shows that this method can greatly improve computational efficiency compared to the ANN-Sobol method. The implementation of the SPCE within the Sobol makes the Sobol available for large, complex data-based models, such as a ship motion prediction model. It provides GSA with a broad range of practical applications in the field of ship intelligence.

The proposed approach depends heavily on ship motion data, and conclusion may be different for another type of ship motion simulations. It is necessarily to transform raw data to avoid discarding important variables. Future work will be focused on analyzing ship position in close-range maneuvering, and investigating other integrable neural network or regression functions to reduce computational complexity and improve the reliability of the variance-based GSA for ship motion modeling.

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