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AUTOMATED MODAL PARAMETERS IDENTIFICATION DURING ICE-STRUCTURE INTERACTIONS

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ABSTRACT

Offshore structures are prone to damage caused by ice-induced vibrations. It is presently unknown to what extent different ice conditions change the properties of the structure, such as natural frequency, damping ratio, and mode shape. Understanding the dynamic interaction between ice and structures are important for the operational ability of offshore structures. In this study, the covariance-driven stochastic subspace identification algorithm (SSI-cov) is introduced to identify modal parameters of a scale-model structure during ice-structure interactions. In order to reduce the number of user interactions and inherent bias to the identified modal parameters, we therefore introduce an automated parameter identification approach. First, SSI-cov is used to obtain poles that describe the information: damping ratio, mode shape, etc. After that, a stable criterion is used to pick up stable poles. Finally, Hierarchical clustering is used to cluster poles to identify the natural frequency. The proposed method is able to reduce the many user-intervenes and enables efficient automatic parameter identification. The results show that Hierarchical clustering can render more successful identifications than the slack value-based method among different ice speeds. The results also show changes in the system frequencies for different ice conditions.

Keywords: Ice-structure interaction, SSI-cov, Automated parameter identification, Hierarchical clustering.

NOMENCLATURE

μ continuous time eigenvalue.
λ eigenvalue.
ϕ eigenvector.
f frequency.
ξ damping coefficient.
φ mode shape.
ω frequency in radian.
σ normalized standard deviation.
S_f variance of frequency.
S_ξ variance of damping.
S_{MAC} variance of MAC.

INTRODUCTION

The action of drifting ice may induce vibrations in offshore structures, posing a threat to the structural integrity. It is important to understand the system characteristics during ice-structure interaction for the operational ability of offshore structures. The presence of ice surrounding a structure may alter the system properties, such as natural frequencies, damping ratios, and mode shapes. Identifying the modal parameters under different ice conditions may therefore give insight into how the ice actions affect modal properties, and in turn provide uncertainty bounds to each parameter. Nord et al. further showed that for some ambient interaction types it was difficult to identify the system properties, and showed that there is a need for a controlled environment assessment of when to expect a successful modal parameter identification [1].

In order to avoid bias from the analyst to the identified parameters, the system identification should ideally be performed without too many user interactions. Unfortunately, traditional methods involve many user interactions, which results in large computational cost [2] and bias to the results. Therefore, it is necessary to develop an analysis method for automatic modal parameters identification.

In what follows, it is assumed that for a limited time window of ice-structure interaction, the process can be described by a linear time-invariant system. To obtain the structural properties, a covariance-driven stochastic subspace identification (SSI) algorithm is applied to estimate modal parameters. All identified modal parameters are afflicted with statistical uncertainty because of the finite number of data samples, undefined measurement noises, non-stationary excitation, etc. [3]. Hence, a covariance-driven SSI (SSI-cov) algorithm was proposed to estimate the frequencies, damping ratios and their uncertainties [4].

After SSI-cov analysis, poles at different system orders are obtained. A pole is considered stable if the deviances in frequency, damping and normalized standard deviation of the frequency fulfill the predefined stability criterion. After that, a stabilization diagram is constructed by stable poles via taking frequency as abscissa and system order as ordinate [5]. Physical modes should then show up as vertical lines in the diagram.

To date, there are many suggested methods to automatically determine the modal parameters. Magalhaes et al. applied hierarchical clustering to identify the modes successfully based on the data from concrete arch bridge [6]. Verboven et al. [7] and Vanlanduit et al. [8] employed fuzzy C-means clustering to classify the modes into two categories (physical and spurious). Reynders et al. introduced how to use hierarchical clustering to identify the physical modes based on single-mode validation criteria [2]. It does not require any user-specified parameter values. The validation example shows the hierarchical clustering has better robustness to identify modal parameters than the traditional identification approach. Inspired by this research, hierarchical clustering is used to identify the parameters of the ice-structure interaction model.

This study proposes a workflow of modal parameters identification which is made up of three parts: data preprocessing, SSI-cov analysis and physical mode identification. This analysis procedure could identify modal parameters with few users intervenes and achieve a better performance of parameters identification than the slack value-based identification method. The main contributions are shown as follows: 1) several validation experiments are carried out to choose proper parameters for the selection of stable poles in order to improve the accuracy of identified frequencies; 2) Hierarchical clustering is compared with slack value-based identification approach to estimate the parameters of ice-structure interaction model.

The rest of this paper is structured as follows: the next section describes the procedure on modal parameters identification, including data preprocessing, SSI-cov analysis, and physical mode identification. Case study compares two cases regarding optimal parameters selection and makes a comparison between the slack value and hierarchical clustering. Discussion and Conclusion are given finally.

Modal parameters identification procedure

This section introduces the main procedure of mode analysis. As shown in Fig. 1, The procedure includes three parts: data preprocessing, SSI-cov analysis, physical mode identification. Data preprocessing is to process the collected sensor data. Next, the processed data is analyzed by SSI-cov algorithm. Finally, physical modes could be clustered by the proposed algorithm.

Ice-structure interaction model testing

The ice-structure interaction model tests were carried out in the Hamburg Ship Model Basin's (HSVA) large ice model basin [1]. The setup consists of a flexible foundation with adjustable mass and stiffness to mimic certain dynamic characteristics of the structure and a rigid model. The flexible foundation was designed to have one or two natural frequencies in ice drift direction (21.36 and 29.53 rad/s). A cylindrical model (red) with a 500 mm diameter was used for the tests considered for the presented study. This model was equipped with tactile sensors to monitor local ice loads. Additionally, global loads were recorded by a 6-component load scale connecting the compliant basis and the model, and lasers and accelerometers monitored the ice-induced vibrations of the structure in x- and y-direction (loading direction and perpendicular in-plane motion). The setup is described in detail in [9]. The setup was instrumented by three Triax accelerometers to measure the structural response over different ice velocities as shown in Fig. 1. The data was obtained under different structural and ice related properties. These include the SDOF (one natural frequency) and MDOF (two natural frequencies) setup, both tested in two different ice thicknesses with constant compressive strength, and in two different ice types: standard model ice, and an alternative model ice type developed for crushing failure. Hence, eight ice-structure property combinations have been investigated. The full data set is described by Stange et al. [9]. Run 32010 investigated in the presented analysis was conducted in 41 mm thick standard model ice. HSVA's standard model ice is frozen from a 0.7% sodium chloride solution using a spraying technique which creates a fine grained fresh water ice top layer. Subsequently, the ice grows in the natural way with primarily columnar structure. During growth, air

[1] https://www.hsva.de/

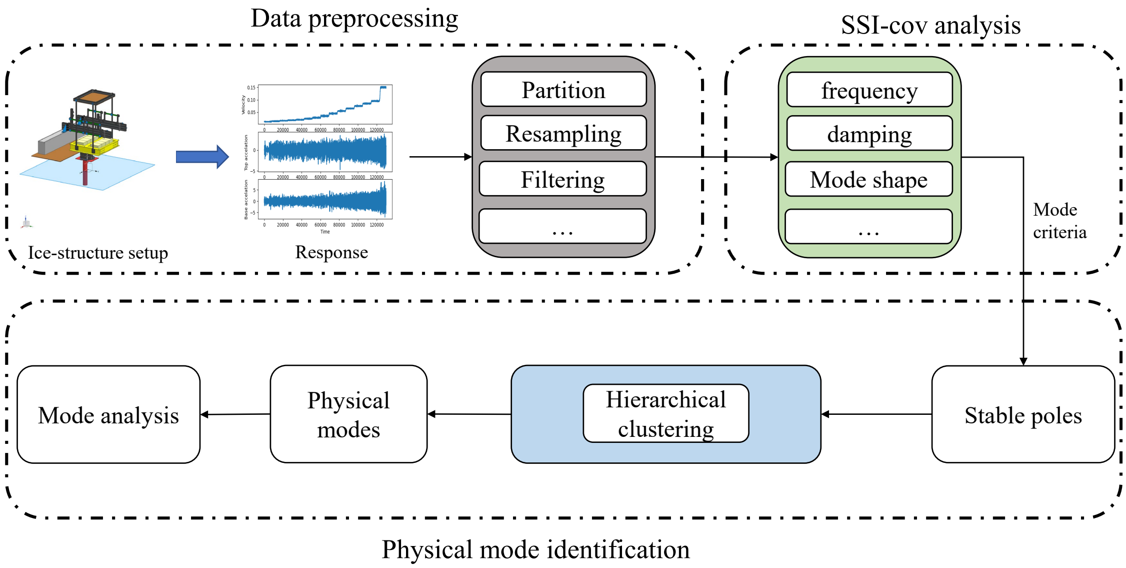


FIGURE 1: The procedure of automated modal parameters identification.

is embedded into the growing ice sheet to adjust its density, increase its brittleness, and give the ice a white appearance. When the target thickness has been reached, cooling is switched off, and heat is released into the ice tank room. Consequently, the ice is weakened until the target strength is reached. Detailed information on HSVA's standard model ice, as well as the alternative ice type mentioned above, is given by Ziemer et al. [10].
All eight test runs contain several different ice drift speeds from 4 to 150 mm/s. Therefore, for test data analysis the measurements are subdivided into segments with constant velocity first. Second, segments are grouped for different ice failure types (intermittent crushing (IC), frequency lock-in (FLI), continuous crushing (CC)). The ice failure types strongly affect the dynamic response of the structure: In IC, the ice load is sawtooth-shaped with irregular loading periods which are much longer than the natural periods of the structure. The model, therefore, follows the ice load in a quasi-static manner. IC occurs at low ice speed. When the speed increases, the interaction changes to FLI. This failure mode is characterized by quasi-synchronized local ice failures that cause large oscillation amplitudes in a frequency close to the natural frequency of the structure. As the ice drift speed increases further, the failure mode changes to CC and creates an irregular, broadband excitation. After subdividing the data, it is resampled with 100Hz. Finally, a high pass filter whose cutoff is 0.2 HZ is used to remove the noise from the data. The processed data is used as the input of SSI-cov algorithm.

Covariance-driven stochastic subspace identification algorithm

The linear time-invariant system is described by a discrete time stat-space model

$$\begin{cases} x_{k+1} = Ax_k + w_k \\ y_k = Cx_k + v_k \end{cases} \tag{1}$$

where w_k and v_k are the process and output noise, respectively. In order to identify matrices A and C from which the modal frequencies, damping and mode shapes can be obtained, the eigenvalues and eigenvectors of the system in Eqn.1 is calculated by the following equations

$$\begin{cases} (A - \lambda_i I)\phi_i = 0 \\ \varphi_i = C\phi_i \end{cases} \tag{2}$$

from which the μ_i, f_i, and ξ_i can be obtained:

$$\mu_i = \frac{ln\lambda_i}{T}, f_i = \frac{|\mu_i|}{2\pi}, \xi_i = -100\frac{\Re(\mu_i)}{|\mu_i|} \tag{3}$$

where T is the sampling period. SSI is a prevalent method to estimate the matrices A and C. The algorithm uses the output data to build a subspace matrix $H_{p+1,q} \in \mathbb{R}^{(p+1)r \times qr_0}$. Therein, r is the number of sensors, r_0 is the number of reference sensors, and p and q are the parameters chosen such that $pr \geq qr_0 \geq n$, where n is the model order. The subspace matrix $H_{p+1,q}$ can be truncated at a user-defined model order n via singular value decomposition (SVD)

$$H_{p+1,q} = \begin{bmatrix} U_1 & U_0 \end{bmatrix} \begin{bmatrix} \Sigma_1 & 0 \\ 0 & \Sigma_0 \end{bmatrix} \begin{bmatrix} V_1^T \\ V_0^T \end{bmatrix} \quad (4)$$

and

$$O_{p+1} = U_1 \Sigma_1^{1/2} \quad (5)$$

The C matrix can be directly extracted from the first block of r rows of the observability matrix O_{p+1}, while the A matrix can be obtained from a least-squares solution of

$$O_{p+1}^{\uparrow} A = O_{p+1}^{\downarrow} \quad (6)$$

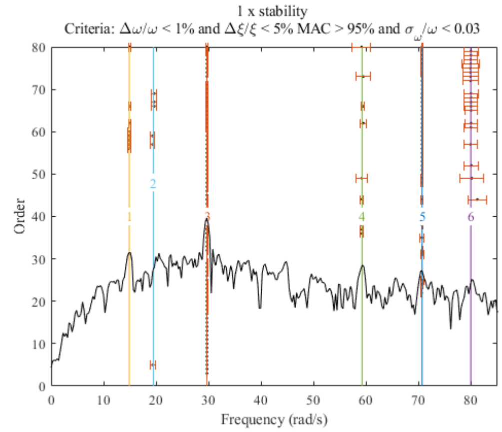
where $O_{p+1}^{\uparrow} = \begin{bmatrix} C \\ CA \\ \vdots \\ CA^{p-1} \end{bmatrix}$, $O_{p+1}^{\downarrow} = \begin{bmatrix} C \\ CA \\ \vdots \\ CA^{p} \end{bmatrix}$

The principle of SSI-cov is to propagate the covariance of the subspace matrix, Σ_H, to the modal parameters through first-order perturbations. The covariance of the modal parameters are obtained as

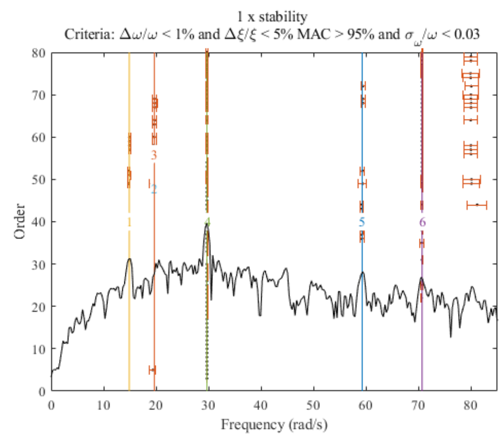
$$\begin{aligned} cov(\begin{bmatrix} f_i \\ \xi_i \end{bmatrix}, \begin{bmatrix} f_j \\ \xi_j \end{bmatrix}) &= \begin{bmatrix} J_{f_i,A} & 0_{1,rn} \\ J_{\xi_i,A} & 0_{1,rn} \end{bmatrix} \Sigma_{AC} \begin{bmatrix} J_{f_i,A} & 0_{1,rn} \\ J_{\xi_i,A} & 0_{1,rn} \end{bmatrix}^T \\ cov(\begin{bmatrix} \Re(\phi_i) \\ \Im(\phi_i) \end{bmatrix}, \begin{bmatrix} \Re(\phi_j) \\ \Im(\phi_j) \end{bmatrix}) &= \begin{bmatrix} \Re(J_{\phi_i,A,C}) \\ \Im(J_{\phi_i,A,C}) \end{bmatrix} \Sigma_{AC} \begin{bmatrix} \Re(J_{\phi_i,A,C}) \\ \Im(J_{\phi_i,A,C}) \end{bmatrix}^T \end{aligned} \quad (7)$$

The detailed computational process can be referred to [4] After SSI-cov analysis, the modal parameters are derived. Next, the mode stability criterion is employed to pick stable poles. The selected stable poles are further analyzed to obtain physical modes in the following step.

Physical mode identification Once poles that are stable/unstable are identified, one must group poles with similar modal characteristics. This is commonly performed in a stabilization diagram, which shows the frequency of the poles on the horizontal axis and the order of the system on the vertical axis. A



(a) Two accelerations



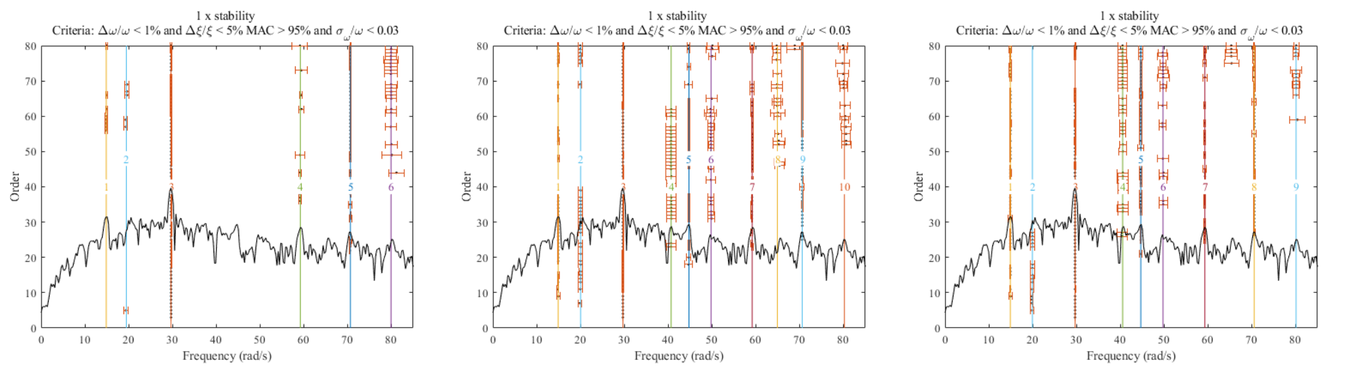
(b) Three accelerations

FIGURE 2: Mode frequency under the different number of structural response signals.

physical mode appears as a straight vertical line of poles, and the line with the corresponding lowest frequency is the first eigenfrequency, the column with the corresponding second lowest frequency is the second natural frequency, and so on. Poles that are not stacked on a vertical line are usually what is referred to as spurious poles/modes, i.e. modes without physical interpretation. Once one has determined which poles that should be counted as part of one column, it is common to compute the average value of these poles, from which we find the corresponding natural frequency, damping and mode shape. The major challenge lies in the process of choosing the poles that should be counted as part of the column of poles (mode), due to the fact that some lie at a slightly different frequency, have different damping values or mode shape, and different corresponding uncertainties. Therefore different techniques have emerged to handle the physical mode selection, where clustering algorithms have been suggested

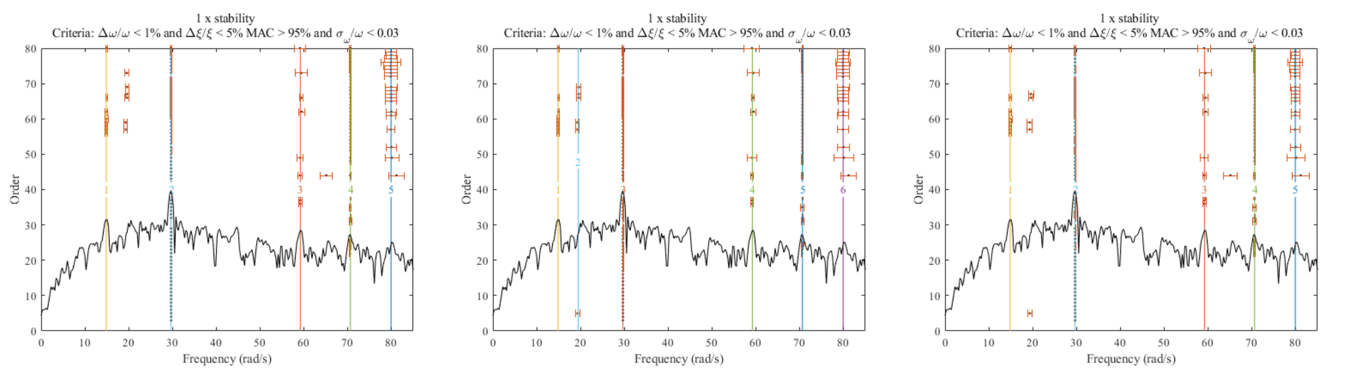
TABLE 1: THE EXPERIMENT SETTINGS FOR ICE-STRUCTURE INTERACTION ANALYSIS.

Test	Model	Ice type	Ice speed	Ice thickness	Flexural strength
32010	9500MDOF	Model ice	4-150mm/s	41mm	56kPa



(a) rb=100 (b) rb=150 (c) rb=200

FIGURE 3: The comparison of identified modes for different choices of blockrows.



(a) nb=10 (b) nb=20 (c) nb=30

FIGURE 4: The comparison of identified modes among different number of blocks.

as an efficient technique to determine the physical modes. One of the popular methods is Hierarchical clustering [2, 11]. Hierarchical clustering is a recursive partitioning of a dataset into successively smaller clusters. The input is a weighted graph whose edge weights represent pairwise similarities or dissimilarities between data points. Hierarchical clustering is represented by a rooted tree where each leaf represents a data point and each internal node represents a cluster containing its descendant leaves. The tree is constructed based on the distance information between different data points [12]. It is suitable for the data set with arbitrary shapes and attributes of arbitrary type. And the hierarchical relationship among clusters is easily detected, and relatively high scalability in general [13].

Let $Q = q_1, q_2, ..., q_n$ be a set of objects. The dendrogram is constructed by the following steps [11]:

1) Compute the proximity matrix containing the distance between each pair of objects (q_i, q_j).
2) Group the objects into a hierarchical cluster tree using the distance information.
3) Choose the cut off value to partition the hierarchical tree into clusters.

TABLE 2: The identified frequencies by slack value and hierarchical clustering based on the data in '32010' under the ice failures of IC, FLI, and CC.

Data file	Frequency	Method	ice velocity (mm/s)														
			4	6	8	10	12	14	16	18	20	28	45	65	80	95	150
			IC	IC	FLI	FLI	FLI	FLI	FLI	FLI	FLI	FLI	FLI	CC	CC	CC	CC
32010	First	Slack value	70.80	14.86	**20.25**	29.76	**21.02**	**21.07**	30.71	**21.06**	**21.19**	**21.27**	**21.57**	**21.38**	**21.50**	**21.38**	**21.61**
		Hierarchical	70.80	14.86	**20.24**	**20.99**	**21.02**	**21.07**	**21.03**	**21.06**	**21.19**	**21.27**	**21.57**	**21.43**	**21.51**	**21.50**	**21.61**
	Second	Slack value	119.20	**29.80**	61.01	41.85	**30.80**	**28.39**	**31.75**	**29.05**	**28.55**	**29.79**	**30.29**	**30.13**	**30.14**	21.41	**26.83**
		Hierarchical	120.38	**29.80**	24.90	**29.76**	**30.80**	**28.38**	**31.32**	**29.17**	**28.55**	**29.79**	**30.30**	**30.08**	**30.14**	25.96	**26.83**
	Third	Slack value	122.92	36.88	80.66	70.58	42.01	**31.30**	**31.79**	**29.22**	**31.61**	42.57	59.68	61.41	59.33	25.94	**30.39**
		Hierarchical	152.26	36.88	**29.95**	41.86	42.01	**31.26**	42.02	42.14	**31.61**	42.57	53.21	61.35	49.06	**30.08**	**30.39**

TABLE 3: The identified damping by slack value and hierarchical clustering based on the data in '32010' under the ice failures of IC, FLI, and CC.

Data file	Damping (%)	Method	ice velocity (mm/s)														
			4	6	8	10	12	14	16	18	20	28	45	65	80	95	150
			IC	IC	FLI	FLI	FLI	FLI	FLI	FLI	FLI	FLI	FLI	CC	CC	CC	CC
32010	First	Slack value	NULL	NULL	0.11	NULL	0.08	0.01	NULL	0.08	0.03	0.02	0.64	2.44	1.67	1.64	2.47
		Hierarchical	NULL	NULL	0.13	0.05	0.08	0.01	0.08	0.08	0.03	0.02	0.64	2.35	1.73	1.51	2.47
	Second	Slack value	NULL	0.54	0.65	2.57	3.23	1.82	2.69	3.69	1.89	2.53	0.92	0.79	1.17	1.02	0.37
		Hierarchical	NULL	0.54	1.02	2.57	3.23	1.57	3.26	3.58	1.89	2.51	0.91	0.82	1.17	1.09	0.38

In this study, eigenfrequency difference and MAC are used as distance measures in [14]. Its form is shown in Eq. (8)

$$d(k,l) = |f_k - f_l| + (1 - MAC(\phi_k, \phi_l)) \tag{8}$$

where f_k is the eigenfrequency of mode k; MAC is computed by Eq. (9)

$$MAC(\phi_k, \phi_l) = \frac{|\phi_k^T \phi_l|^2}{||\phi_k||_2^2 ||\phi_l||_2^2}, ||\phi_k||_2^2, ||\phi_l||_2^2 \neq 0 \tag{9}$$

where ϕ_k is the mode shape of mode k.

Through continuous iterations of evaluating the paired distance, the data points that are smaller than the cutoff value are partitioned into the same cluster. Finally, hierarchical clustering yields a set of similar mode sets from the cleared stabilization diagram. After that, the identified physical modes are evaluated and analyzed further based on natural frequencies and damping ratios.

Case study

This section mainly introduces two parts of the experiments. The first part is to pick up the optimal parameters for SSI-cov analysis. Next, hierarchical clustering is compared with a slack value-based approach in [1] to examine the efficiency of the automated modal analysis.

Parameters selection

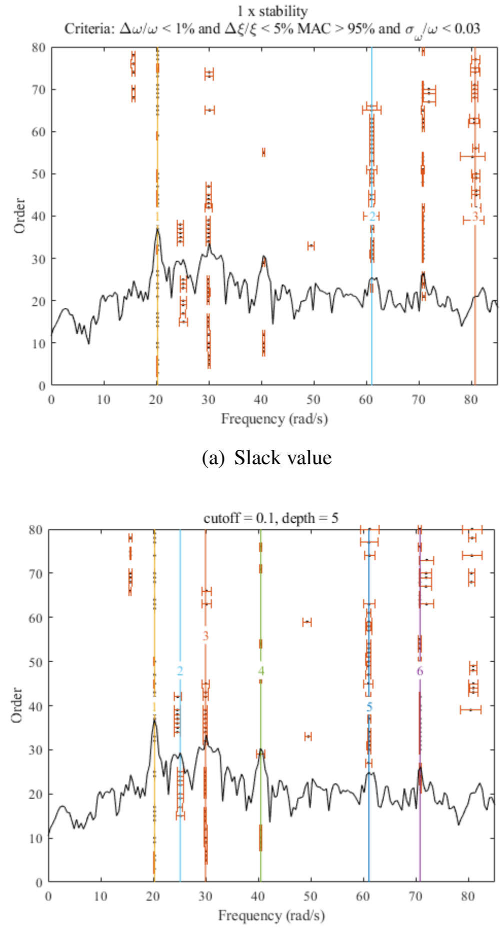
The SSI-cov algorithm involves user interaction to choose a couple of parameters that need to be selected. For example, there are three accelerometers to measure the acceleration of the structure. However, not all measured signals contribute to accurate parameters identification. In addition, the number of blocks (nb) of output data matrices, as well as the number of blockrows (rb), have influences to some extent. Other parameters such as sampling frequency, system orders, could affect the identified results, which are not our main concern in this study. Their settings can be referred to [1].

In order to select proper parameters for modal parameters identification, Test 32010 is used as a case and its corresponding settings are shown in Table 1. The test had a stepwise increasing ice speed, and therefore different regimes of ice-structure interaction would take place during the total time span. The data was cut to begin when the ice speed reached 4 mm/s. Thereafter the data was analyzed in time windows that each consisted of 2000 data points. The choice of data points was selected to have the sufficient number of data points for the SSI-cov algorithm to render consistent results, and few enough data points for the interaction regime to significantly change. Next, tolerance deviances to frequency, damping, and MAC-values, as well as the normalized standard deviation of the frequency ($\hat{\sigma}_{\omega_i}/\omega_i$) are leveraged to pick up stable poles. Based on [1], a pole at order n was considered stable if the deviances in frequency, damping ratio, and normalized standard deviation of the frequency between a pole at order n and n-1 were less than 0.01, 0.05 and 0.05, respectively, and corresponding MAC-values exceeded 0.95. After that, S_f, S_ξ and S_{MAC} are chosen to be 0.02, 0.3 and 0.5 respectively to select eigenmodes. Figure. 2(a) and Figure. 2(b) show the identified modes under the case of different accelerations. Therein, the black curve is the power spectrum whose peaks represent the possible physical modes. The stable poles with variance are plotted following their order. The formed straight lines represent the identified frequencies by stable poles. In Fig. 2(b), the identified second and third frequencies are overlapped while Fig. 2(a) presents a better identification result. Therefore, this study uses two accelerations as input data for SSI-cov analysis.

Figure. 3(a), Figure. 3(b), and Figure. 3(c) display the identified eigenfrequencies and their estimated standard deviations in the cases of 'rb = 100', 'rb = 150', 'rb = 200' separately. When rb equals to 150 or 200, there are more spurious modes that have larger standard deviations, as shown in Fig. 3(b) and Fig. 3(c). Compared with them, 'rb = 100' could obtain more accurate results which are in line with the position of the peaks of the power spectrum, as shown in Fig. 3(a). Hence, the study prefers 100 as blockrows. Figure. 4(a), Figure. 4(b), and Figure. 4(c) display the identified eigenfrequencies and their estimated standard deviations in the cases of 'nb = 10', 'nb = 20', 'nb = 30', separately. Through the comparison among these three figures, it is easy to find that 'nb = 20' could obtain better results as frequency (20) disappeared in other stability diagrams. For this reason, the number of blocks is selected as 20 in this study.

Comparison between slack value and hierarchical clustering

This section compares the slack value-based parameters identification approach with hierarchical clustering. The data whose ice velocities are 8 mm/s and 95mm/s in datafile '32010' is chosen as two cases to compare these two methods. The benchmark values of the first two eigenfrequencies are 21.352 and 29.516 rad/s separately, which are estimated when the structure was moving in the open water [9]. Considering the uncertain



(a) Slack value

(b) Hierarchical clustering

FIGURE 5: The comparison of slack value and hierarchical clustering when ice velocity is 8 mm/s.

factors, the benchmark values are expanded by 10% deviation to an interval: [19.22, 23.49] for the first frequency, [26.56, 32.47] for the second frequency. The cutoff and depth of the Hierarchical clustering algorithm are chosen as 0.1 and 5 separately based on data characteristics.

The focus of this study falls on the first three natural frequencies that represent the most concerning modes. The ice velocities range from 4-150 mm/s. The identified frequencies are shown in Table. 2. The bold numbers represent the successful identifications of natural frequencies by two methods. For IC, the identified first frequencies by slack value and Hierarchical clustering are 70.8, 14.86, separately for different ice speeds. Results show that both methods fail to identify the first frequency. For FLI and CC, the first two natural frequencies identified by Hierarchical clustering are around 21 rad/s and 29 rad/s among different ice speeds. From this table, Hierarchical clustering renders more bold numbers than the slack value-based approach. Table. 3 shows the identified damping of the first two modes. 'NULL' means the corresponding damping can not be obtained due to the failure of parameters identification. It can be seen that both methods achieve similar results. For 'FLI', the damping of the first mode is quite lower than that of the second mode, whereas it is opposite for other cases. This trend probably results from the increase of ice velocity.

Figure. 5(a) and Figure. 5(b) show the identified frequencies by these two methods in the case of ice velocity being 8 mm/s. Based on the referenced values of the first two natural frequencies, it is easily found that hierarchical clustering can identify these two frequencies correctly while slack value can not. As shown in Fig. 5(a), some missing modes are supposed to be identified in the stabilization diagram. For example, at the position of frequency 30 rad/s, there is supposed to be a mode that appears on the peak of the power spectrum. Based on aforementioned analyses, it is concluded that hierarchical clustering outperforms the slack value-based approach as a whole.

Discussion

The section above introduced the Hierarchical clustering approach to identify the modal parameters of the structure when encountering ice-structure interaction. As shown in Table. 2, it often fails to identify the correct modal parameters for certain cases like IC failure and FLI at low ice velocities. For IC failure, likely the ice-structure interaction system is too time-variant and too nonlinear for the current method to identify the structural parameters inherently hidden in the measured signals. This phenomenon does probably depend on the severity of the ice-actions compared to the mass and stiffness of the structure. However, given that for a certain structure ice-actions are rare and operational parameters are to be extracted automatically as part of a structural health monitoring system at daily or hourly intervals, our results show that hierarchical clustering did have a better performance of parameters identification than the traditional slack-value method.

Another limitation lies in that input parameters impact results. For example, the change of nb and rb turns out to be different identification results. In other words, the uncertainty of input parameters would affect the accuracy of parameters identification. For the convenience of analysis, in this study, the limited numbers are compared based on previous research to obtain a relatively accurate result.

Conclusion

This study introduced a Hierarchical clustering method to automatically identify the parameters of the ice-structure interaction model. The proposed analysis workflow is shown in Fig. 1, including data preprocessing, SSI-cov analysis, modal parameters identification. In order to verify the superiority of the proposed method, the slack value-based parameter identification method is leveraged to make a comparison based on data file 32010. First of all, parameters such as rb and nb are selected based on contrast tests. Next, hierarchical clustering and slack value are compared under the difference ice velocities from 4 - 150 mm/s. The results show hierarchical clustering outperforms slack value in terms of the accuracy of parameters identification for the ice failures of 'FLI' and 'CC'.

Accurate parameter identification is pivotal to the operational ability of offshore structures. As the second limitation in the Discussion, however, it is hard to obtain an accurate result due to parameters uncertainty. Therefore, it is necessary to quantify the uncertainty of input parameters from the perspective of statistics to implement a more accurate estimation.

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