Journal of *Marine Science and Engineering*

MDPI

Article

Structural Model Updating Method of Medium-Deep Water Jacket Platform Based on Sensitivity Clustering

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Abstract

As offshore oil and gas exploration extends into deeper waters and platforms operate over extended service lives, accurate and timely structural health monitoring of deepwater jacket platforms becomes increasingly critical. Rapid construction of a high-fidelity numerical twin model is therefore essential, yet existing structural model correction methods are largely designed for simple or low-dimensional systems and are inadequate for large-scale marine structures with high-dimensional parameters. To address these challenges, this study proposes a sensitivity-based clustering method for structural model correction of jacket platforms. First, a novel numerical sensitivity index of correction parameters is established, and these parameters are clustered into representative groups. An optimization objective function based on modal characteristics is then formulated, converting the model correction problem into a minimization problem, which is solved using a multi-objective optimization algorithm. To verify the effectiveness and noise robustness of the proposed method, numerical simulations of a jacket platform in the Weizhou Oilfield were performed. Here, maximum errors are reduced to 0.05% and 0.12% under low- and high-noise conditions, respectively, showing significant reductions in relative errors and improved modal confidence. The proposed methodology effectively enables rapid and accurate updating of numerical twin models for deepwater jacket platforms.

Keywords: jacket platform; model correction; sensitivity analysis; cluster analysis; structural health monitoring

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Academic Editor: Bang-Fuh Chen

Received: 21 January 2026
Revised: 7 February 2026
Accepted: 12 February 2026
Published: 15 February 2026

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1. Introduction

Subsea components of deepwater jacket platforms endure prolonged exposure to highly complex and harsh marine environments. The strong corrosivity of seawater continuously degrades material surfaces, resulting in progressive material deterioration. In addition, cyclic actions induced by waves, currents, and tides pose long-term alternating loads on structural components, significantly increasing their susceptibility to fatigue damage. The high hydrostatic pressure characteristic of deepwater environments further places stringent requirements on structural strength and sealing performance. Moreover, seabed sediment scouring, biofouling by marine organisms, and extreme natural events such as earthquakes and typhoons collectively exacerbate structural deterioration and damage accumulation. Under these combined effects of long-term environmental loading, operational stresses, and accidental loads, subsea components are prone to a variety of defects,

including corrosion-induced wall thinning, initiation and propagation of fatigue cracks caused by alternating loads, structural deformation, and loosening of connection joints. If these defects are not identified and mitigated in a timely manner, they may progressively intensify and deteriorate, ultimately leading to component failures. Such incidents may potentially trigger catastrophic accidents, such as the collapse of the entire jacket platform. These failures not only result in substantial economic losses but also pose severe threats to the marine environment through large-scale pollution. The use of in situ measurement data for model updating and structural health monitoring is therefore crucial to ensuring operational safety, maintenance, and inspection of offshore structures, including jacket platforms and offshore wind turbines [1–5].

As offshore oil and gas development progresses toward deeper waters and longer service lifetimes, increasingly stringent requirements are imposed on the timeliness, accuracy, and comprehensiveness of structural health monitoring for deepwater jacket platforms. Structural model updating constitutes the core of platform health monitoring, and the establishment of a numerical model that accurately represents the in-service structure provides a fundamental basis for structural inspection, condition assessment, operation and maintenance decision-making. These model updating approaches can be broadly categorized into two primary strategies. The first one is the sensitivity-based model updating technique. For instance, Jiang et al. [6] proposed a novel multistage approach for structural model updating based on sensitivity ranking. These parameters to be corrected with similar sensitivity levels are updated simultaneously at the same stage, and the complete procedure continues sequentially at several stages, from large to small, according to the predefined levels of the updating parameters. These numerical and experimental results demonstrate that the multistage approach is more effective for structural model updating of offshore platform structures even with limited information and measured noise. Baybordi and Esfandiari [7] presented an exact sensitivity equation that establishes a direct and linear relationship between changes in structural parameters and structural response variations, which has high computational efficiency in calculating the sensitivity of time domain responses. Furthermore, Helalat and Esfandiari [8] presented a novel sensitivity equation for estimating structural parameters using autocorrelation function (ACF) data of dynamic responses. The method reduced the need for extensive excitation frequencies, making structural parameter identification more practical and cost-effective, especially for large-scale offshore jacket platform structures. These methods relying on local derivatives or one-at-a-time parameter variations fail to capture non-linear interactions and synergies between parameters, which are prevalent in complex structural systems. It can lead to incomplete or misleading identification of influential parameters.

The second one is the data-driven structural model updating technique. For instance, Li et al. [9] proposed a finite element model correction method based on an improved ResNet50 network with a jacket platform as the engineering background. The results showed that the error after correction is less than 4%, which can reflect the real marine platform state well. Sha et al. [10] proposed a multi-source data synchronous updating framework for FE models based on the Genetic Aggregated Response Surface (GARS) and the Non-dominated Sorting Genetic Algorithm III (NSGA-III). GARS was employed to construct response surface models describing the relationship between structural responses (natural frequencies and local strains) and the parameters to be updated, replacing FE analyses during optimization. These errors in the first three frequencies of the FE model were reduced from 3.44%, −7.31%, and 5.88% to −0.02%, −0.43%, and 0.08%, respectively. Strain errors in the local region decreased from 12.96% and 10.33% to 1.4% and 2.1%. The framework can be regarded as the most promising strategy, and it could provide an effective reference for model updating of in-service offshore structures. Furthermore, Shrivastava

et al. [11] presented a Gaussian Process Emulator (GPE) framework developed as a surrogate model to predict the dynamic characteristics of welded joints efficiently. It reduced computational time by nearly 80% compared to the inverse eigen sensitivity method (IESM). Thus, it is suitable for the design and monitoring of ship and offshore structures. Recently, Wang et al. [12] proposed a novel stochastic model updating method for offshore platforms based on the Kriging model with active learning to improve accuracy and robustness under uncertainty. The updated model showed excellent agreement with measured natural frequencies in both mean and variance. These methods, like machine learning models and response surface methodology trained purely on measurement data, may identify patterns but offer little to no insight into the underlying physical mechanisms. This hinders engineer confidence and limits the transferability of findings. Their performance and reliability often hinge on the availability of large, high-quality datasets, which are costly and difficult to obtain in full-scale offshore engineering applications.

In conclusion, there is a gap between these two paradigms: physics-based methods lack the sophistication to handle complex parameter interactions holistically, while data-driven methods lack physical grounding. Furthermore, most existing studies are focused on simple cantilever beam structures or laboratory-scale jacket platform models and typically consider only a limited number of correction parameters. Consequently, these methods are insufficient for the efficient and accurate correction of large-scale offshore platform structures, which typically involve high-dimensional parameter spaces and complex structural interactions.

To address the previously mentioned challenges, this study proposes a new structural model updating method for medium-deep water jacket platforms based on sensitivity clustering. It leverages the physical grounding of global sensitivity analysis to create informative feature vectors, then uses statistical clustering analysis and multi-objective evolutionary algorithms to reveal interaction patterns in a way that is both quantitatively robust and physically interpretable. Specifically, numerical sensitivity indices are established to quantify the influence of individual correction parameters on the structural response of the jacket platform. Second, hierarchical cluster analysis is performed according to parameter sensitivity, enabling the aggregation of all correction parameters into several representative parameter groups, which are subsequently defined as new clustered correction parameters. Third, an optimization objective function is formulated based on modal characteristics, including natural frequencies and mode shapes, thereby transforming the structural model correction problem into a constrained minimization optimization problem. A multi-objective optimization algorithm is then employed to determine the optimal correction coefficients for each parameter cluster. Finally, the obtained optimal coefficients are incorporated into the benchmark FEM of the jacket platform, yielding an updated and corrected structural model. The main contributions of this study include:

- Proposing numerical sensitivity indices of modal parameters to correction parameters, which are used to quantitatively analyze the sensitivity of different types of correction parameters for medium-deep water jacket platform.
- Introducing cluster analysis to establish a classification approach for correction parameters based on sensitivity clustering. This approach significantly reduces the computational dimensionality of structural model updating process and enhances computational accuracy and efficiency, particularly for deep water jacket platforms comprising numerous structural members.

Systematic research on platform structural model correction, together with the development of efficient, accurate, and reliable monitoring and detection technologies, enables the timely identification of potential structural safety hazards. This capability is critical for ensuring the safe operation of offshore platform structures, extending their service life, and

reducing operational risks. It represents an essential technical foundation for promoting the sustainable development of the offshore oil and gas industry.

2. Theoretical Framework for Sensitivity Clustering Analysis of Model Correction Parameters

The fundamental objective of structural model correction for jacket platforms is to adjust physical parameters, material properties, geometric dimensions, and boundary conditions, such that the numerical FEM closely represents the actual structural behavior. Structural modal characteristics, specifically natural frequencies and mode shapes, are key indicators of global structural properties. These features are therefore commonly adopted as quantitative metrics for evaluating the effectiveness of model correction. To establish a theoretical basis for sensitivity clustering analysis, it is necessary to calculate sensitivity indices of modal frequencies and mode shapes with respect to the selected correction parameters.

2.1. Traditional Sensitivity Indicators

Fox and Kapoor [13] firstly define sensitivity measures for eigenvalues (modal frequencies) and eigenvectors (mode shapes). The sensitivity of the i-th eigenvalue λ_i with respect to the n-th correction parameter p_n can be obtained by differentiating the undamped eigenvalue equation, yielding

$$\frac{\partial \lambda_i}{\partial p_n} = \boldsymbol{\phi}_i^{\mathrm{T}} \left(\frac{\partial \Delta \mathbf{K}}{\partial p_n} - \lambda_i \frac{\partial \Delta \mathbf{M}}{\partial p_n} \right) \boldsymbol{\phi}_i \tag{1}$$

Furthermore, the eigenvalue sensitivity of the stiffness correction coefficient α_n with respect to the i-th eigenvalue λ_i can be expressed as

$$\frac{\partial \lambda_i}{\partial \alpha_n} = \boldsymbol{\phi}_i^{\mathrm{T}} \mathbf{K}_n \boldsymbol{\phi}_i; \frac{\partial \lambda_i}{\partial \beta_n} = -\lambda_i \boldsymbol{\phi}_i^{\mathrm{T}} \mathbf{M}_n \boldsymbol{\phi}_i \tag{2}$$

From Equation (2), it can be observed that the computation of eigenvalue sensitivities is relatively straightforward. Specifically, the sensitivity of the eigenvalue with respect to the stiffness correction parameter $\frac{\partial \lambda_i}{\partial \alpha_n}$ corresponds to the modal strain energy of the structure, given by $\boldsymbol{\phi}_i^{\mathrm{T}} \mathbf{K}_n \boldsymbol{\phi}_i$. In contrast, the sensitivity of the eigenvalue with respect to the mass correction parameter $\frac{\partial \lambda_i}{\partial \beta_n}$ is proportional to the modal kinetic energy, expressed twice as much as the modal kinetic energy $1/2 \lambda_i \boldsymbol{\phi}_i^{\mathrm{T}} \mathbf{M}_n \boldsymbol{\phi}_i$.

The sensitivity of the i-th eigenvector $\boldsymbol{\phi}_i$ with respect to the n-th correction parameter p_n can be represented by expanding its gradient as a weighted linear combination of all eigenvectors:

$$\frac{\partial \boldsymbol{\phi}_i}{\partial p_n} = \sum_{h=1}^{H} \sigma_{inh} \boldsymbol{\phi}_h \tag{3}$$

where σ_{inh}, the corresponding weighting coefficient is defined as

$$\sigma_{inh} = \begin{cases} \frac{\boldsymbol{\phi}_h^{\mathrm{T}} \left(\frac{\partial \mathbf{K}}{\partial p_n} - \lambda_i \frac{\partial \mathbf{M}}{\partial p_n} \right) \boldsymbol{\phi}_i}{\lambda_i - \lambda_h}, & h \neq i \\ -\frac{1}{2} \boldsymbol{\phi}_h^{\mathrm{T}} \frac{\partial \mathbf{M}}{\partial p_n} \boldsymbol{\phi}_i, & h = i \end{cases} \tag{4}$$

Accordingly, the eigenvector sensitivities with respect to the stiffness correction coefficient α_n and mass correction coefficient β_n can be expressed as

$$\begin{aligned} \frac{\partial \boldsymbol{\phi}_i}{\partial \alpha_n} &= \sum_{h=1}^{H} \begin{cases} \frac{\boldsymbol{\phi}_h^{\mathrm{T}} \mathbf{K}_n \boldsymbol{\phi}_i}{\lambda_i - \lambda_h} \boldsymbol{\phi}_h, & h \neq i \\ 0, & h = i \end{cases} \\ \frac{\partial \boldsymbol{\phi}_i}{\partial \beta_n} &= \sum_{h=1}^{H} \begin{cases} \frac{-\lambda_i \boldsymbol{\phi}_h^{\mathrm{T}} \mathbf{M}_n \boldsymbol{\phi}_i}{\lambda_i - \lambda_h} \boldsymbol{\phi}_h, & h \neq i \\ -\frac{1}{2} \boldsymbol{\phi}_h^{\mathrm{T}} \mathbf{M}_n \boldsymbol{\phi}_i \boldsymbol{\phi}_h, & h = i \end{cases} \end{aligned} \tag{5}$$

From the above formulations, it is evident that the computation of eigenvector sensitivities is considerably more complex. As discussed in the previous section, the eigenvalue sensitivities $\frac{\partial \lambda_i}{\partial \alpha_n}$ and $\frac{\partial \lambda_i}{\partial \beta_n}$ are scalar types and straightforward, whereas the eigenvector sensitivities $\frac{\partial \boldsymbol{\phi}_i}{\partial \alpha_n}$ and $\frac{\partial \boldsymbol{\phi}_i}{\partial \beta_n}$ are vectors and explicitly contain modal shape vectors $\boldsymbol{\phi}_h$. Thus, it is challenging to quantify the combined influence of modal frequencies and mode shapes on the correction parameters, calling for a more concise equation.

2.2. Novel Numerical Sensitivity Indicators

According to the principle of modal shape superposition, the sensitivity of the i-th eigenvector with respect to the stiffness correction coefficient α_n can be expanded as

$$\frac{\partial \boldsymbol{\phi}_i}{\partial \alpha_n} = \frac{\boldsymbol{\phi}_1^{\mathrm{T}} \mathbf{K}_n \boldsymbol{\phi}_i}{\lambda_i - \lambda_1} \boldsymbol{\phi}_1 + \frac{\boldsymbol{\phi}_2^{\mathrm{T}} \mathbf{K}_n \boldsymbol{\phi}_i}{\lambda_i - \lambda_2} \boldsymbol{\phi}_2 + \ldots + 0 + \ldots + \frac{\boldsymbol{\phi}_h^{\mathrm{T}} \mathbf{K}_n \boldsymbol{\phi}_i}{\lambda_i - \lambda_h} \boldsymbol{\phi}_h \tag{6}$$

which can be equivalently rewritten in matrix form as

$$\frac{\partial \boldsymbol{\phi}_i}{\partial \alpha_n} = \left[\frac{\boldsymbol{\phi}_1^{\mathrm{T}} \mathbf{K}_n \boldsymbol{\phi}_i}{\lambda_i - \lambda_1}, \frac{\boldsymbol{\phi}_2^{\mathrm{T}} \mathbf{K}_n \boldsymbol{\phi}_i}{\lambda_i - \lambda_2}, \ldots, 0, \ldots, \frac{\boldsymbol{\phi}_h^{\mathrm{T}} \mathbf{K}_n \boldsymbol{\phi}_i}{\lambda_i - \lambda_h} \right] \begin{bmatrix} \boldsymbol{\phi}_1 \\ \boldsymbol{\phi}_2 \\ \vdots \\ \boldsymbol{\phi}_i \\ \vdots \\ \boldsymbol{\phi}_h \end{bmatrix} \tag{7}$$

Similarly, the eigenvector sensitivity with respect to the mass correction coefficient β_n can be expressed as

$$\frac{\partial \boldsymbol{\phi}_i}{\partial \beta_n} = -\left[\frac{\boldsymbol{\phi}_1^{\mathrm{T}} \mathbf{M}_n \boldsymbol{\phi}_i}{1 - \frac{\lambda_1}{\lambda_i}}, \frac{\boldsymbol{\phi}_2^{\mathrm{T}} \mathbf{M}_n \boldsymbol{\phi}_i}{1 - \frac{\lambda_2}{\lambda_i}}, \ldots, \frac{1}{2} \boldsymbol{\phi}_i^{\mathrm{T}} \mathbf{M}_n \boldsymbol{\phi}_i, \ldots, \frac{\boldsymbol{\phi}_h^{\mathrm{T}} \mathbf{M}_n \boldsymbol{\phi}_i}{1 - \frac{\lambda_h}{\lambda_i}} \right] \begin{bmatrix} \boldsymbol{\phi}_1 \\ \boldsymbol{\phi}_2 \\ \vdots \\ \boldsymbol{\phi}_i \\ \vdots \\ \boldsymbol{\phi}_h \end{bmatrix} \tag{8}$$

From the above formulations, it is evident that the eigenvector sensitivities with respect to both stiffness and mass correction coefficients share identical modal vector components. By neglecting the explicit modal shape vectors, the remaining sensitivity coefficients can be adopted as new numerical sensitivity indicators, defined as

$$\frac{\partial \boldsymbol{\phi}_i^{\varkappa}}{\partial \alpha_n} = \left[\frac{\boldsymbol{\phi}_1^{\mathrm{T}} \mathbf{K}_n \boldsymbol{\phi}_i}{\lambda_i - \lambda_1}, \frac{\boldsymbol{\phi}_2^{\mathrm{T}} \mathbf{K}_n \boldsymbol{\phi}_i}{\lambda_i - \lambda_2}, \ldots, 0, \ldots, \frac{\boldsymbol{\phi}_h^{\mathrm{T}} \mathbf{K}_n \boldsymbol{\phi}_i}{\lambda_i - \lambda_h} \right] \tag{9}$$

$$\frac{\partial \boldsymbol{\phi}_i^{\varkappa}}{\partial \beta_n} = -\left[\frac{\boldsymbol{\phi}_1^{\mathrm{T}}\mathbf{M}_n\boldsymbol{\phi}_i}{1-\frac{\lambda_1}{\lambda_i}}, \frac{\boldsymbol{\phi}_2^{\mathrm{T}}\mathbf{M}_n\boldsymbol{\phi}_i}{1-\frac{\lambda_2}{\lambda_i}}, \ldots, \frac{1}{2}\boldsymbol{\phi}_i^{\mathrm{T}}\mathbf{M}_n\boldsymbol{\phi}_i, \ldots, \frac{\boldsymbol{\phi}_h^{\mathrm{T}}\mathbf{M}_n\boldsymbol{\phi}_i}{1-\frac{\lambda_h}{\lambda_i}}\right] \tag{10}$$

It follows that the eigenvector sensitivities $\frac{\partial \boldsymbol{\phi}_i^{\varkappa}}{\partial \alpha_n}$ and $\frac{\partial \boldsymbol{\phi}_i^{\varkappa}}{\partial \beta_n}$ consist of multiple sensitivity components. Vector norm measures, such as the Euclidean (2-) norm or other suitable norms, can be employed to quantify the magnitude of eigenvector sensitivity. Accordingly, the numerical sensitivity indicators of the eigenvector are defined as

$$SI_{\alpha_n i}^{\phi} = \left\| \frac{\partial \boldsymbol{\phi}_i^{\varkappa}}{\partial \alpha_n} \right\|_2; \quad SI_{\beta_n i}^{\phi} = \left\| \frac{\partial \boldsymbol{\phi}_i^{\varkappa}}{\partial \beta_n} \right\|_2 \tag{11}$$

where $SI_{\alpha_n i}^{\phi}$ and $SI_{\beta_n i}^{\phi}$ denote the numerical sensitivities of the i-th mode shape with respect to the stiffness and mass correction coefficients, respectively.

Similarly, the numerical sensitivity indicators of the eigenvalue, $SI_{\alpha_n i}^{\lambda}$ and $SI_{\beta_n i}^{\lambda}$, can be expressed as

$$SI_{\alpha_n i}^{\lambda} = \left\| \frac{\partial \lambda_i}{\partial \alpha_n} \right\|_2; \quad SI_{\beta_n i}^{\lambda} = \left\| \frac{\partial \lambda_i}{\partial \beta_n} \right\|_2 \tag{12}$$

When n_k stiffness correction coefficients and n_m mass correction coefficients are simultaneously considered, the aggregated eigenvalue numerical sensitivity SI_i^{λ} and eigenvector numerical sensitivity SI_i^{ϕ} for the i-th mode can be defined as

$$SI_i^{\lambda} = \left[SI_{\alpha_1 i}^{\lambda}, \ldots, SI_{\alpha_n i}^{\lambda}, \ldots, SI_{\alpha_{n_k} i}^{\lambda}, SI_{\beta_1 i}^{\lambda}, \ldots, SI_{\beta_n i}^{\lambda}, \ldots, SI_{\beta_{n_m} i}^{\lambda}\right] \tag{13}$$

$$SI_i^{\phi} = \left[SI_{\alpha_1 i}^{\phi}, \ldots, SI_{\alpha_n i}^{\phi}, \ldots, SI_{\alpha_{n_k} i}^{\phi}, SI_{\beta_1 i}^{\phi}, \ldots, SI_{\beta_n i}^{\phi}, \ldots, SI_{\beta_{n_m} i}^{\phi}\right] \tag{14}$$

Furthermore, the numerical sensitivity indicators are further normalized using maximum-value normalization:

$$nSI_i^{\lambda} = \left[nSI_{\alpha_1 i}^{\lambda}, \ldots, nSI_{\alpha_n i}^{\lambda}, \ldots, nSI_{\alpha_{n_k} i}^{\lambda}, nSI_{\beta_1 i}^{\lambda}, \ldots, nSI_{\beta_n i}^{\lambda}, \ldots, nSI_{\beta_{n_m} i}^{\lambda}\right] \tag{15}$$

$$nSI_i^{\phi} = \left[nSI_{\alpha_1 i}^{\phi}, \ldots, nSI_{\alpha_n i}^{\phi}, \ldots, nSI_{\alpha_{n_k} i}^{\phi}, nSI_{\beta_1 i}^{\phi}, \ldots, nSI_{\beta_n i}^{\phi}, \ldots, nSI_{\beta_{n_m} i}^{\phi}\right] \tag{16}$$

where

$$nSI_{\alpha_n i}^{\lambda} = \frac{ln\left(SI_{\alpha_n i}^{\lambda}\right)}{\max\left\{ln\left(SI_{\alpha_1 i}^{\lambda}\right), \ldots, ln\left(SI_{\alpha_{ni}}^{\lambda}\right), \ldots, ln\left(SI_{\beta_n i}^{\lambda}\right) \ldots, ln\left(SI_{\beta_{n_m} i}^{\lambda}\right)\right\}} \tag{17}$$

$$nSI_{\beta_n i}^{\lambda} = \frac{ln\left(SI_{\beta_n i}^{\lambda}\right)}{\max\left\{ln\left(SI_{\alpha_1 i}^{\lambda}\right), \ldots, ln\left(SI_{\alpha_n i}^{\lambda}\right), \ldots, ln\left(SI_{\beta_n i}^{\lambda}\right) \ldots, ln\left(SI_{\beta_{n_m} i}^{\lambda}\right)\right\}} \tag{18}$$

$$nSI_{\alpha_n i}^{\phi} = \frac{ln\left(SI_{\alpha_n i}^{\phi}\right)}{\max\left\{ln\left(SI_{\alpha_1 i}^{\phi}\right), \ldots, ln\left(SI_{\alpha_n i}^{\phi}\right), \ldots, ln\left(SI_{\beta_n i}^{\phi}\right) \ldots, ln\left(SI_{\beta_{n_m} i}^{\phi}\right)\right\}} \tag{19}$$

$$nSI_{\beta_n i}^{\phi} = \frac{ln\left(SI_{\beta_n i}^{\phi}\right)}{\max\left\{ln\left(SI_{\alpha_1 i}^{\phi}\right), \ldots, ln\left(SI_{\alpha_n i}^{\phi}\right), \ldots, ln\left(SI_{\beta_n i}^{\phi}\right) \ldots, ln\left(SI_{\beta_{n_m} i}^{\phi}\right)\right\}} \tag{20}$$

When considering the n_i-th mode, the mean value of the normalized numerical sensitivity across all selected modes can be adopted as a comprehensive numerical sensitivity indicator, expressed as

$$nSI^{\lambda} = \left[nSI^{\lambda}_{\alpha_1}, \ldots, nSI^{\lambda}_{\alpha_n}, \ldots, nSI^{\lambda}_{\alpha_{n_k}}, nSI^{\lambda}_{\beta_1}, \ldots, nSI^{\lambda}_{\beta_n}, \ldots, nSI^{\lambda}_{\beta_{n_m}} \right] \tag{21}$$

$$nSI^{\phi} = \left[nSI^{\phi}_{\alpha_1}, \ldots, nSI^{\phi}_{\alpha_n}, \ldots, nSI^{\phi}_{\alpha_{n_k}}, nSI^{\phi}_{\beta_1}, \ldots, nSI^{\phi}_{\beta_n}, \ldots, nSI^{\phi}_{\beta_{n_m}} \right] \tag{22}$$

where

$$nSI^{\lambda}_{\alpha_n} = \frac{1}{n_i}\sum_{i=1}^{n_i} nSI^{\lambda}_{\alpha_n i}; \quad nSI^{\lambda}_{\beta_n} = \frac{1}{n_i}\sum_{i=1}^{n_i} nSI^{\lambda}_{\beta_n i} \tag{23}$$

$$nSI^{\phi}_{\alpha_n} = \frac{1}{n_i}\sum_{i=1}^{n_i} nSI^{\phi}_{\alpha_n i}; \quad nSI^{\phi}_{\beta_n} = \frac{1}{n_i}\sum_{i=1}^{n_i} nSI^{\phi}_{\beta_n i} \tag{24}$$

The numerical sensitivity indicators defined above provide a basis for evaluating the influence of correction parameters on both eigenvalues and eigenvectors.

2.3. Clustering Analysis of Numerical Sensitivity

Previous studies have shown that disparities in parameter sensitivities constitute a primary source of ill-conditioning in structural model correction problems [6,12,14]. Classifying correction parameters according to the principle of equal or similar numerical sensitivity can effectively reduce the dimensionality and computational complexity of structural model correction for deepwater jacket platforms. This strategy improves the accuracy of model correction solutions and addresses the pressing demands of structural health monitoring, model updating, and operation and maintenance inspections for deepwater jacket platforms.

Hierarchical clustering is a widely used and representative clustering technique that constructs a multilevel, nested clustering structure by evaluating the similarity between data points. The clustering results are typically visualized in the form of a dendrogram, where individual data points constitute the lowest-level nodes and progressively merge into higher-level clusters, ultimately forming a single root node. Compared with other clustering algorithms, hierarchical clustering offers the advantage of revealing clustering patterns at multiple scales.

As shown in Figure 1, the hierarchical clustering procedure is implemented with an inconsistency coefficient threshold set at C = 0.5. The process begins at the root of the dendrogram and traverses downward until a node is encountered whose inconsistency coefficient is below the threshold C, and for which all descendant nodes also exhibit inconsistency coefficients below C. All leaf nodes (i.e., individual parameters) under such a node are then grouped into a single cluster.

In hierarchical clustering, the agglomerative algorithm iteratively merges the two most similar data points or clusters based on a predefined similarity measure. At each iteration, the similarity between all pairs of clusters is evaluated, and the pair with the smallest distance, indicating the highest similarity, is combined into a new cluster. This merging process is repeated until a specified termination criterion is satisfied, such as reaching a single cluster or a predefined number of clusters. In practice, similarity D is commonly quantified using the Euclidean distance between data points or cluster representatives, where smaller distances correspond to greater similarity. The Euclidean distance between two data points is defined as

$$D = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \tag{25}$$

The hierarchical clustering procedure can be summarized as follows:

S11: Initialize by assigning each data point to an individual cluster and computing the distances between all pairs of clusters.

S12: Identify and merge the two clusters with the minimum distance to form a new cluster.

S13: Update the distance between the newly formed cluster and all remaining clusters.

S14: Repeat Steps S12 and S13 until all clusters are merged into a single cluster or the predefined termination criterion is reached.

By computing the numerical sensitivity indicators of both eigenvalues and eigenvectors, all correction parameters are classified according to their sensitivity levels using hierarchical clustering analysis. Parameters exhibiting identical or similar sensitivities within the same cluster are subsequently redefined as new aggregated correction parameters. This sensitivity-based clustering strategy significantly reduces the dimensionality of the correction parameter space, thereby enhancing computational efficiency and accuracy.

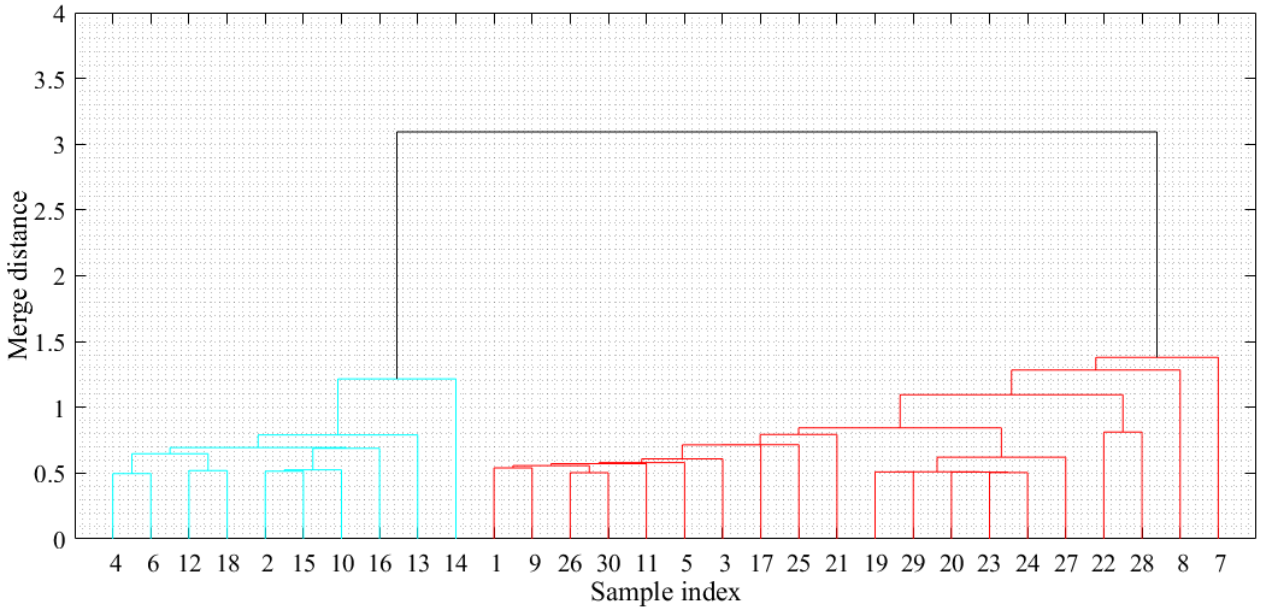


Figure 1. Hierarchical clustering tree.

3. Proposed Method for Correcting Jacket Platform Structural Models Based on Sensitivity Clustering

The primary objective of structural FEM correction is to minimize discrepancies between the numerical model predictions and the measured structural modal parameters. This objective can be formulated as a minimization optimization problem by constructing appropriate objective functions that quantify the differences between modal parameters obtained from the FEM and those identified from the actual structure. Among the various components of the model correction framework, the selection of the optimization objective function and the optimization algorithm play a decisive role in obtaining the correction results.

3.1. Optimization Objective Function

Over the past decade, objective functions based on modal parameters have been extensively developed and applied in structural model correction, including formulations based on eigenvalues and modal strain energy [15], as well as mode shapes [16]. In this

study, objective functions constructed from frequencies and mode shapes are adopted and defined as follows:

$$f_1 = \frac{1}{n_i}\sum_{j=1}^{n_i}\left|\frac{\lambda_i^{\mathrm{e}}}{\lambda_i^{*}} - 1\right| \tag{26}$$

$$f_2 = \frac{1}{n_i}\sum_{j=1}^{n_i}\left|mac\left(\boldsymbol{\phi}_i^{\mathrm{e}}, \boldsymbol{\phi}_i^{*}\right) - 1\right| \tag{27}$$

where λ_i^{e} and $\boldsymbol{\phi}_i^{\mathrm{e}}$ denote the i-th eigenvalue and eigenvector obtained from the FEM corresponding to the correction coefficient vector $\boldsymbol{x}$, respectively.

In practice, researchers can also combine different modal parameters into a single objective function by assigning appropriate weighting coefficients and solving single-objective intelligent optimization algorithms. But, during model refinement, determining precise and optimal weighting coefficients remains challenging. Conventional approaches typically rely on trial-and-error strategies, whereby multiple candidate solutions are generated by assigning different weighting coefficients and subsequently evaluated to identify the optimal result. This process inevitably leads to a substantial increase in computational cost and time consumption.

3.2. Multi-Objective Optimization Algorithms

The development of multi-objective optimization algorithms provides an effective framework for addressing the previously mentioned limitations. By simultaneously optimizing two or more objective functions, these algorithms eliminate the need for empirical trial-and-error procedures to determine weighting coefficients among different modal indicators.

$$\text{minimizing} f(\boldsymbol{x}) = \{f_1(\boldsymbol{x}), f_2(\boldsymbol{x})\} \tag{28}$$

Given the high dimensionality and nonlinear characteristics of jacket platform structural models, this study adopts a multi-objective optimization strategy based on the Non-dominated Sorting Genetic Algorithm with an elitism strategy (NSGA-II). The specific implementation procedure is outlined as follows:

S21: Randomly generate N candidate solutions for the correction coefficients to form the initial parent population $\boldsymbol{X}_0$.

S22: Evaluate the fitness values of all solutions using the defined objective functions and rank them according to non-domination relationships.

S23: Apply genetic operators to the parent population $\boldsymbol{X}_0$ to generate an offspring population $\boldsymbol{X}_0^{\mathrm{s}}$.

S24: At iteration t, merge the parent population $\boldsymbol{X}_{t-1}$ and offspring population $\boldsymbol{X}_{t-1}^{\mathrm{s}}$ to form a combined population.

S25: Perform fast non-dominated sorting on the combined population to generate a hierarchical set of non-dominated fronts based on solution fitness.

S26: Compute the crowding distance for all solutions within the same non-dominated front to maintain population diversity.

S27: Select the top N solutions from the combined population based on non-domination rank and crowding distance to construct the new parent population $\boldsymbol{X}_t$.

S28: Generate a new offspring population $\boldsymbol{X}_t^{\mathrm{s}}$ through a genetic algorithm such as selection, crossover, and mutation.

S29: Repeat Steps S24–S28 iteratively until the predefined termination criteria are satisfied.

Through iterative multi-objective optimization, a set of Pareto non-inferior solutions with the highest dominance level is obtained, commonly referred to as the Pareto optimal front (POF). All solutions on the POF are non-dominated with respect to one another

and represent optimal trade-offs among competing objective functions. The POF can be expressed as

$$\widetilde{\mathbf{X}} = \left[\widetilde{\boldsymbol{x}}_1, \ldots, \widetilde{\boldsymbol{x}}_i, \ldots, \widetilde{\boldsymbol{x}}_m\right] \tag{29}$$

where $\widetilde{\boldsymbol{x}}_i$ denotes i-th non-inferior solution on the POF, and m is the total number of non-inferior solutions. In practical applications, the optimal set of structural correction coefficients can be determined by selecting the mean solution of the non-dominated set or by identifying the knee (inflection) point of the Pareto front, which provides a balanced compromise between competing objectives. Once the optimal solution is obtained, the corresponding correction coefficients are substituted into the reference FEM to update its stiffness and mass matrices. The correction process can be expressed as

$$\begin{aligned} \mathbf{K}^* &= \mathbf{K} + \Delta\mathbf{K} = \mathbf{K} + \textstyle\sum_{n=1}^{n_k} \widetilde{\alpha}_n \mathbf{K}_n; \\ \mathbf{M}^* &= \mathbf{M} + \Delta\mathbf{M} = \mathbf{M} + \textstyle\sum_{n=1}^{n_m} \widetilde{\beta}_n \mathbf{M}_n \end{aligned} \tag{30}$$

where $\widetilde{\alpha}_n$ and $\widetilde{\beta}_n$ denote the stiffness and mass correction coefficients of the n-th solution within $\widetilde{\boldsymbol{x}}_{best}$, which meets the require of $\widetilde{\boldsymbol{x}}_{best} = \left[\widetilde{\alpha}_1, \ldots, \widetilde{\alpha}_n, \ldots, \widetilde{\alpha}_{n_k}, \widetilde{\beta}_1, \ldots, \widetilde{\beta}_n, \ldots, \widetilde{\beta}_{n_m}\right]$.

The NSGA-II algorithm is one of the most widely recognized and applied multi-objective evolutionary algorithms (MOEAs) in engineering optimization, particularly for complex, non-linear problems like structural model updating. Its performance is well-documented and serves as a common benchmark. The multi-objective optimization is performed using the classic NSGA-II algorithm. A population size of 160 is initialized, and the evolution is run for 200 generations, which is determined sufficient for Pareto front convergence in preliminary trials. The simulated binary crossover and polynomial mutation operators are employed, with distribution indices set to 20 and 20, respectively. The crossover probability is set to 0.9, and the tournament selection based on the crowded-comparison operator was used. More detailed NSGA-II procedures can be found in the literature [14,16].

3.3. Proposed Correction Method Based on Sensitivity Clustering

Structural model correction methods based on multi-objective optimization algorithms [14–18] have been widely applied to overcome the limitations of single-objective intelligent algorithms, particularly in achieving balanced treatment of multiple modal parameters during the correction process. Intelligent algorithms are fundamentally probabilistic search methods designed to identify global optima among numerous local optima. However, numerical simulations and physical model experiments have shown that these algorithms are highly sensitive to the selection of initial correction parameters and often struggle to achieve accurate solutions when applied to high-dimensional optimization problems.

In response to these challenges, this study proposes a sensitivity-clustering-based structural model correction framework for jacket platforms. First, numerical sensitivity indicators are established to quantify the influence of each correction parameter on the structural modal responses. A hierarchical clustering algorithm is then applied to the sensitivity indicators, enabling the aggregation of correction parameters with similar sensitivities into a reduced set of consolidated correction parameters. This process significantly decreases the dimensionality of the optimization problem. Second, an optimization objective function is formulated based on modal characteristics, including natural frequencies and mode shapes, thereby transforming the structural model correction task into a minimization optimization problem. A multi-objective optimization algorithm is subsequently employed to determine the optimal values of the consolidated correction coefficients. Finally, the

identified optimal coefficients are incorporated into the baseline FEM of the jacket platform, resulting in an updated and corrected structural model. The overall workflow of the proposed sensitivity-based clustering correction method for jacket platform structures is summarized as follows:

S31: Deploy monitoring sensors at designated locations on the deepwater jacket platform to acquire real-time structural dynamic response data. Perform modal identification on the measured responses to obtain the low-order measured natural frequencies $\boldsymbol{\omega}^* = \left\{\omega_1^*, \omega_2^*, \ldots, \omega_i^*, \ldots, \omega_{N_m}^*\right\}$ and the corresponding incomplete mode shapes $\boldsymbol{\varphi}^* = \left\{\boldsymbol{\varphi}_1^*, \boldsymbol{\varphi}_2^*, \ldots, \boldsymbol{\varphi}_i^*, \ldots, \boldsymbol{\varphi}_{N_m}^*\right\}$. Modal expansion techniques are then employed to reconstruct the complete measured mode shapes $\boldsymbol{\phi}^* = \left\{\boldsymbol{\phi}_1^*, \boldsymbol{\phi}_2^*, \ldots, \boldsymbol{\phi}_i^*, \ldots, \boldsymbol{\phi}_{N_m}^*\right\}$. Here, ω_i^* denotes the measured natural frequency of the i-th mode, $\boldsymbol{\varphi}_i^*$ is the corresponding incomplete mode shape; $\boldsymbol{\phi}_i^*$ is the expanded complete mode shape $\boldsymbol{\varphi}_i^*$, and N_m is the number of identified modes.

S32: Based on the design documentation and structural drawings of the deepwater jacket platform, establish a baseline FEM using finite element analysis software. Perform eigenvalue analysis to obtain the simulated low-order natural frequencies $\boldsymbol{\omega} = \{\omega_1, \omega_2, \ldots, \omega_i, \ldots, \omega_{N_m}\}$ and the corresponding complete mode shapes $\boldsymbol{\phi} = \{\boldsymbol{\phi}_1, \boldsymbol{\phi}_2, \ldots, \boldsymbol{\phi}_i, \ldots, \boldsymbol{\phi}_{N_m}\}$, where ω_i and $\boldsymbol{\phi}_i$ represent the simulated natural frequency and mode shape of the i-th mode, respectively.

S33: Construct numerical sensitivity indicators nSI^{λ} and nSI^{ϕ} for the low-order natural frequencies and mode shapes with respect to the correction parameters of the deepwater jacket platform. Compute the corresponding frequency sensitivity values $\boldsymbol{S}_{\lambda}$ and $\boldsymbol{S}_{\phi}$.

S34: Integrate the frequency sensitivity $\boldsymbol{S}_{\lambda}$ and mode shape sensitivity $\boldsymbol{S}_{\phi}$ to obtain a comprehensive sensitivity index $\boldsymbol{S}$. Perform hierarchical clustering analysis on the comprehensive sensitivity values of all correction parameters, thereby grouping them into N_c categories of consolidated correction parameters.

S35: Establish an optimization objective function by minimizing the discrepancies between simulated and measured modal parameters. Employ a multi-objective optimization algorithm to solve the optimal values of the consolidated correction coefficients.

S36: Substitute the identified optimal correction coefficients into the baseline FEM to update its global and local stiffness and mass matrices, thereby obtaining a revised FEM of the jacket platform that closely matches the measured structural behavior.

4. Numerical Simulation Analysis of a Medium-Deep Water Jacket Platform

4.1. Establishment of the Numerical Model for the Medium-Deep Water Jacket Platform

The proposed structural model correction method was validated using a medium-deep water jacket platform located in the Weizhou oilfield. Based on the structural design documentation of the eight-leg jacket platform, a detailed FEM of the platform structure was developed. The model comprises 139 nodes and 328 elements, as illustrated in Figure 2. Using the horizontal plane as the reference datum, the top elevation of the jacket platform is set at 20 m, while the bottom elevation reaches −51.5 m. The structural material properties are assumed to be homogeneous and isotropic, with an elastic modulus of 206 GPa, a density of 7850 kg/m^3, and a Poisson's ratio of 0.30. The upper deck assembly and its associated operational loads, with a total mass of 2300 t, are simulated using mass elements. These masses are evenly distributed among the top eight nodes of the platform. The jacket pile foundation is represented by equivalent stiffness matrices applied to the bottom

nodes of the eight jacket legs, thereby achieving an equivalent boundary constraint at the platform base.

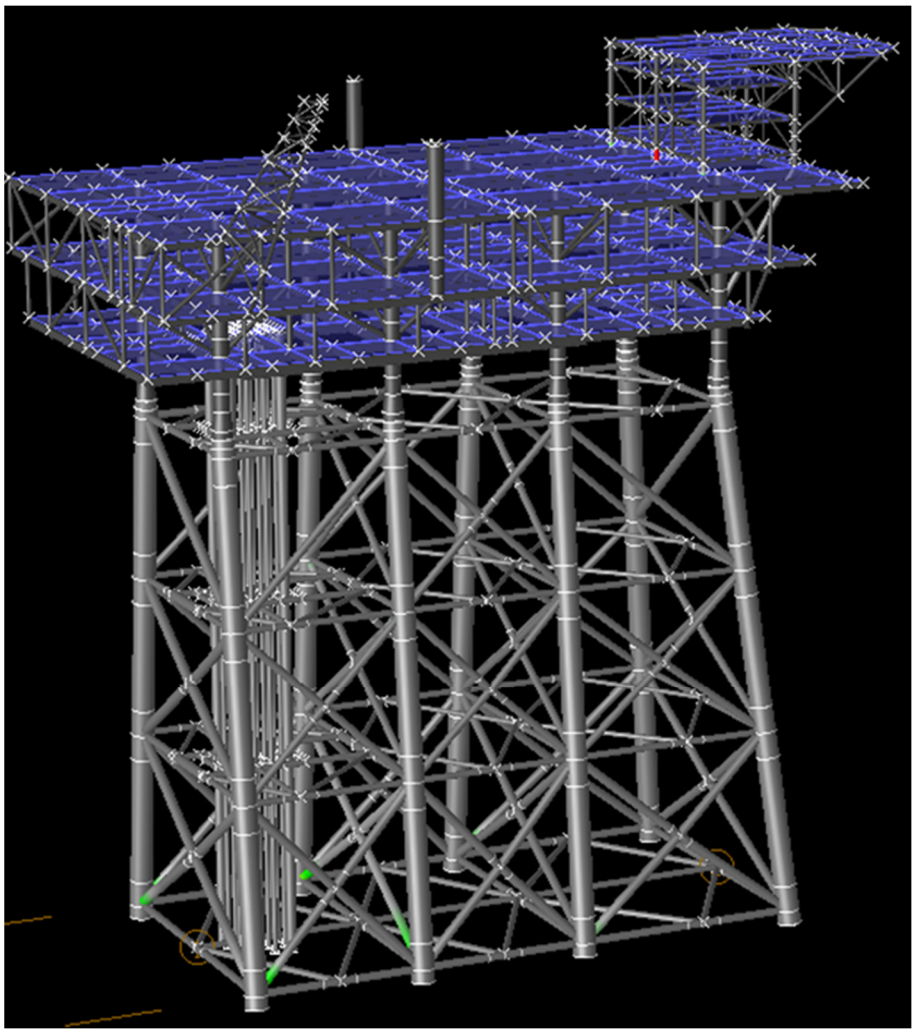


Figure 2. Structural model of the Weizhou medium-deep water jacket platform.

Modal analysis was subsequently performed on the established FEM in MATLAB R2016b [19] to obtain the first three natural modes of the medium-deep water jacket platform structure. The corresponding natural frequencies are 1.2784 Hz, 1.5697 Hz, and 1.6630 Hz, respectively. The associated mode shapes are presented in Figure 3.

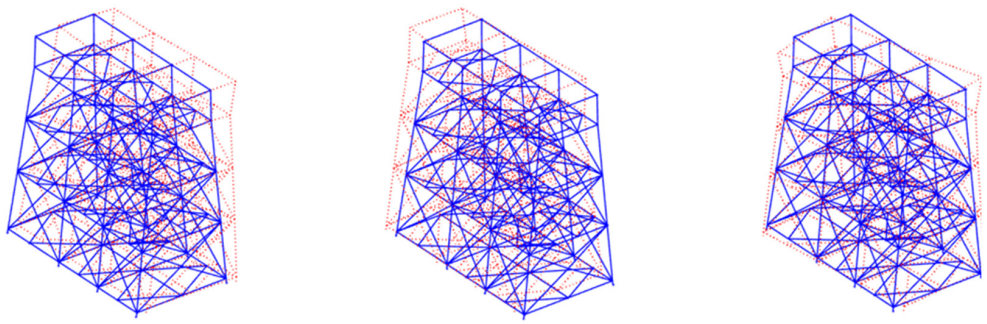


Figure 3. First three mode shapes of the Weizhou medium-deep water jacket platform.

4.2. Sensitivity Clustering Analysis Results

The sensitivities of the structural stiffness correction parameters with respect to the first three natural frequencies and corresponding mode shapes were computed. Figure 4 illustrates the numerical sensitivity distributions of the first three modes for the Weizhou medium-deep water jacket platform. The normalized numerical sensitivities of the stiffness parameters are shown in Figure 5, while the average numerical sensitivity values are presented in Figure 6.

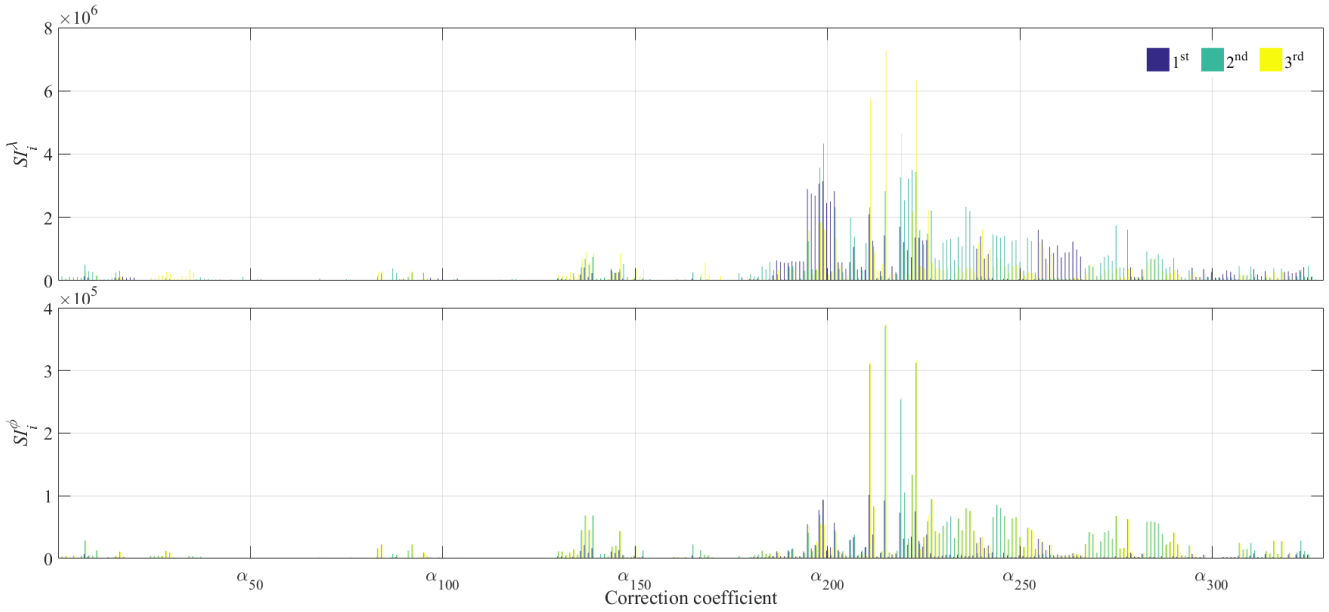


Figure 4. Numerical sensitivity of the first three modes of the jacket platform structure.

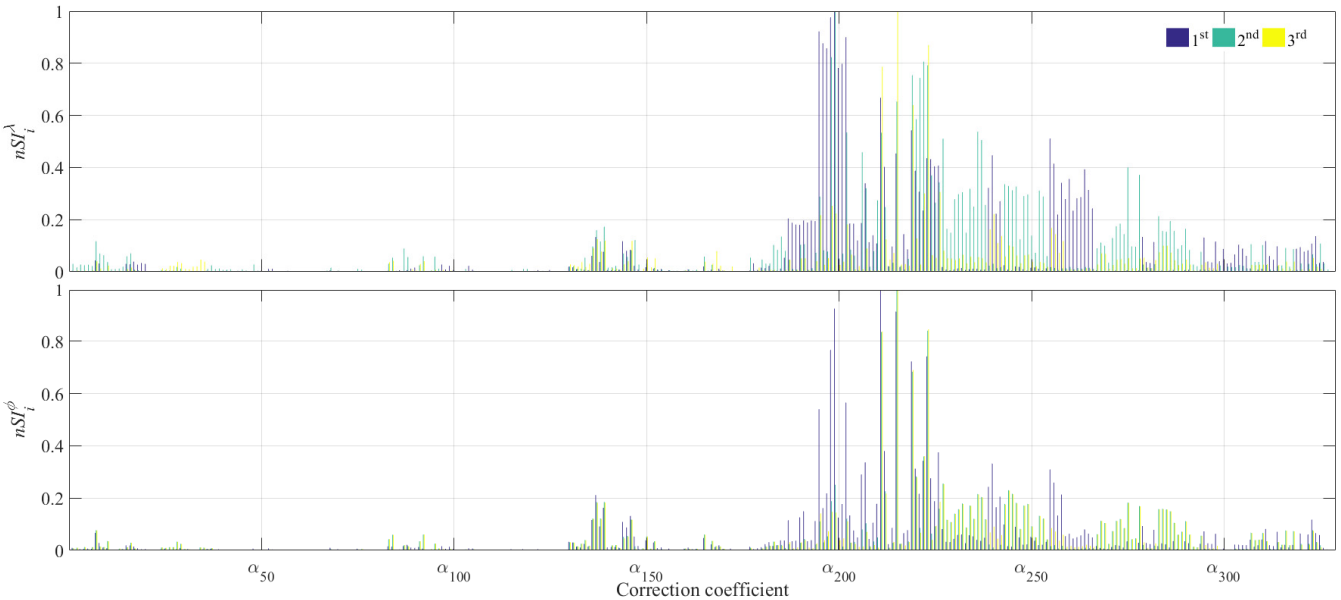


Figure 5. Normalized numerical sensitivity of the jacket platform structure.

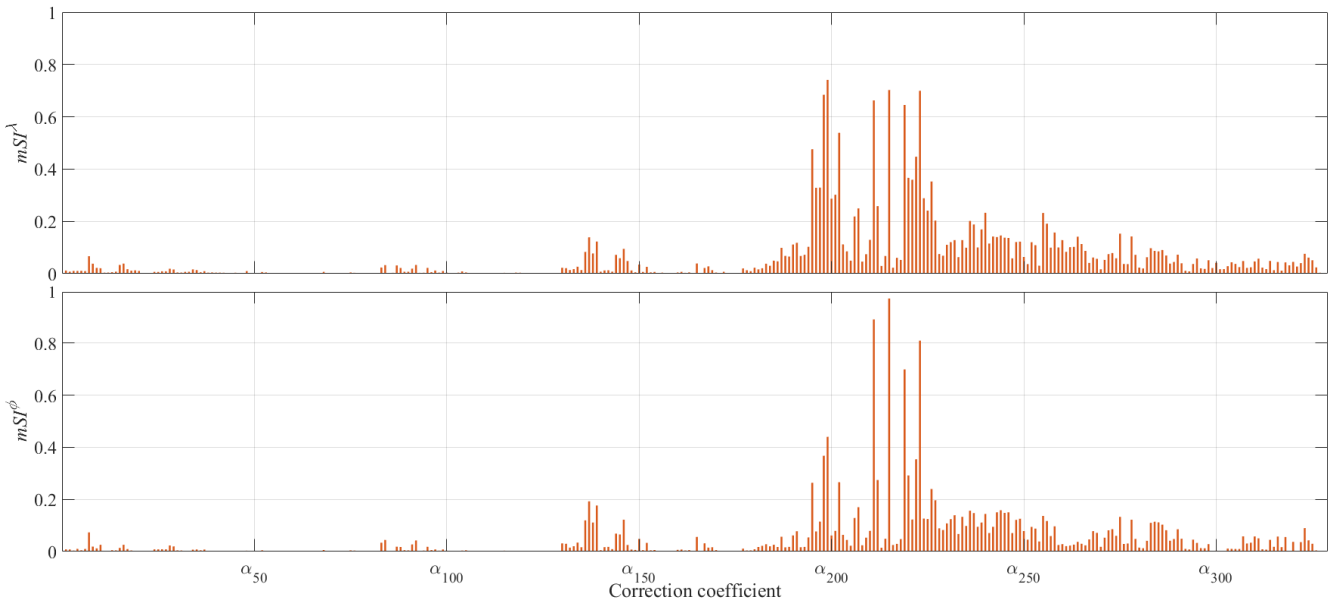


Figure 6. Averaged numerical sensitivity of the jacket platform structure.

By integrating the normalized sensitivity values of natural frequencies and modal shapes shown in Figure 5 and applying hierarchical cluster analysis to the stiffness correction parameters, the original 328 stiffness correction parameters are consolidated into 12 representative correction parameter categories, as summarized in Figures 7–9 and Table 1. This consolidation significantly reduces the dimensionality of the optimization problem.

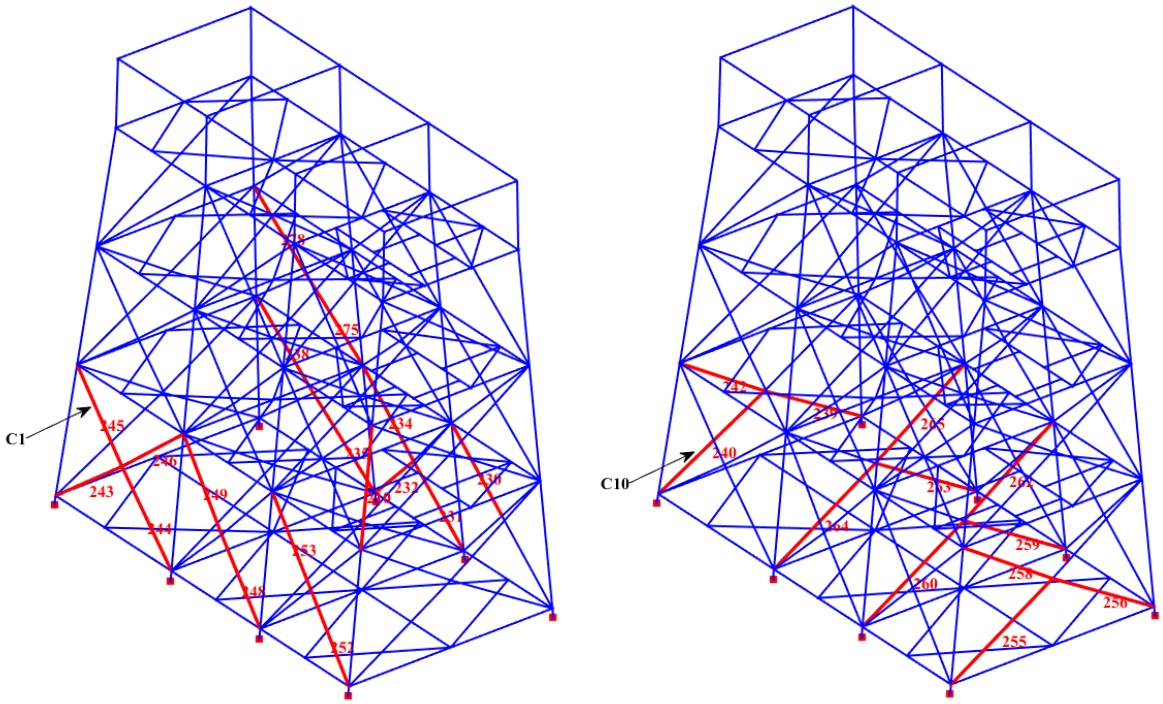


Figure 7. Hierarchical clustering analysis results of Category 1 and Category 10.

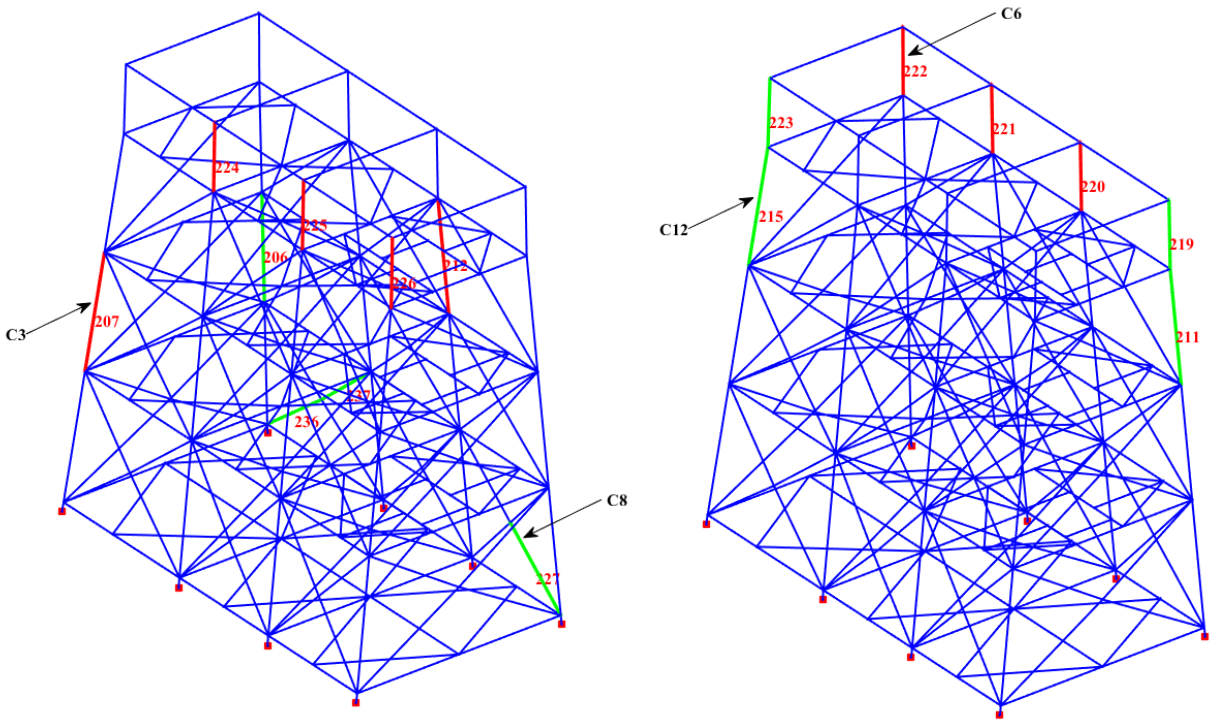


Figure 8. Hierarchical clustering analysis results of Category 3/8 and Category 6/12.

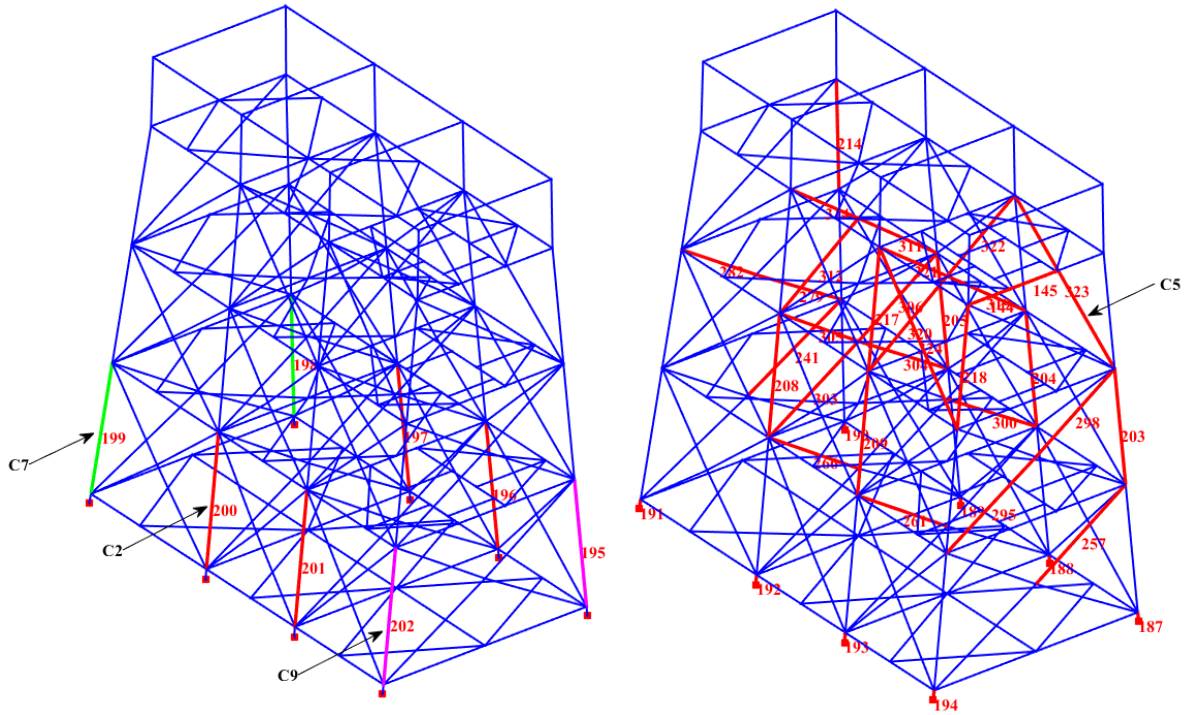


Figure 9. Hierarchical clustering analysis results of Category 2/7/9 and Category 5.

Table 1. Results of hierarchical clustering analysis for numerical sensitivity.

Category	Stiffness Correction Parameters	New Correction Parameters	Number
1	210 230 231 232 234 235 238 243 244 245 246 248 249 252 253 275 278	1	17
2	196 197 200 201	2	4
3	207 212 224 225 226	3	5
4	1 2 3 4 5 6 10 11 12 13 14 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55 56 57 58 59 60 61 62 63 64 65 66 67 68 69 70 71 72 73 74 75 76 77 78 79 80 81 82 83 85 86 89 90 91 93 94 96 97 98 99 100 101 102 103 104 105 106 107 108 109 110 111 112 113 114 115 116 117 118 119 120 121 122 123 124 125 126 127 128 129 130 131 132 133 135 140 141 142 143 148 149 150 151 152 153 154 155 156 157 158 159 160 161 162 163 164 166 167 168 169 170 171 172 173 174 175 176 178 179 180 181 182 213 216 270 280 281 292 293 296 297 299 301 302 308 309 313 315 317 326 327 328	4	181
5	144 145 187 188 189 190 191 192 193 194 203 204 205 208 209 214 217 218 241 257 261 266 279 282 295 298 300 303 304 305 306 311 312 314 319 320 321 322 323 324	5	40
6	220 221 222	6	3
7	198 199	7	2
8	206 227 236 237	8	4
9	195 202	9	2
10	239 240 242 255 256 258 259 260 262 263 264 265	10	12
11	7 8 9 15 16 84 87 88 92 95 134 136 137 138 139 146 147 165 177 183 184 185 186 228 229 233 247 250 251 254 267 268 269 271 272 273 274 276 277 283 284 285 286 287 288 289 290 291 294 307 310 316 318 325	11	54
12	211 215 219 223	12	4

As shown in Figure 7, the stiffness correction parameters for Category 1 are mainly applied to the lowest and second levels (E210/E275/E278) of the jacket platform structure.

Specifically, these include correction parameters for 16 diagonal bracing units along the long-side facades and for one leg unit (E210). Similarly, the stiffness correction parameters for Category 10 are concentrated on the lowest level, involving correction parameters for 12 diagonal bracing units along the short-side facades, with each facade containing parameters for three units.

As shown in Figure 8, the correction parameters for Category 3 are distributed across the second level (E207), the third level (E212), and the top level (E224/E225/E226). It is noteworthy that all five of these correction parameters correspond to leg/column units. Furthermore, the stiffness correction parameters for Category 6 are all concentrated on the top level, specifically involving three column units (E221/E222/E223). Interestingly, the correction parameters for Category 12 include the remaining two column units on the top level, along with the third-level leg units (E211/E215) connected to them.

The hierarchical clustering analysis results for Categories 2/7/9 and Category 5 are presented in Figure 9. The stiffness correction parameters for Categories 2/7/9 mainly correspond to eight leg units at the lowest level and exhibit good symmetry. In contrast, the correction parameters for Category 5 are primarily concentrated on leg units and facade diagonal bracing units located on the second and third levels. Detailed unit clustering information can be found in Table 1.

4.3. Analysis of Modified Structural Models for Jacket Platforms

In this section, the performance of the proposed sensitivity-based clustering correction method under low-noise and high-noise numerical simulation conditions is investigated. The range and distribution (e.g., Gaussian with specified standard deviation) of the added noise are based on a review [2,6,20] of reported measurement errors and uncertainties from real-world offshore structural health monitoring (SHM) campaigns and metocean data acquisition. To further demonstrate the robustness of the proposed sensitivity-clustering approach, a sensitivity analysis has been included under different assumed noise levels 1% and 3%.

4.3.1. Analysis of Modified Results Under Low-Noise Conditions

Two representative operating conditions are considered. In Condition 1, the stiffness correction coefficient of Category 1 is set to -0.2. In Condition 2, stiffness correction coefficient errors of -0.2 are introduced for both Category 1 and Category 3. For both conditions, the noise level is fixed at 1%. The reference FEM of the jacket platform structure was corrected using the proposed sensitivity-based clustering model updating method. The results are summarized in Table 2, Figures 10 and 11.

Table 2. Model correction results under low-noise conditions.

Simulation/ Measurement	Reference FEM			Corrected FEM		
Frequency	**Frequency**	**Relative Error**	**MAC**	**Frequency**	**Relative Error**	**MAC**
			Condition 1			
1.2777 Hz	1.2784 Hz	0.06%	1.0000	1.2776 Hz	0.01%	1.0000
1.5562 Hz	1.5697 Hz	0.87%	0.9999	1.5560 Hz	0.01%	1.0000
1.6540 Hz	1.6630 Hz	0.54%	0.9998	1.6537 Hz	0.02%	1.0000
			Condition 2			
1.2717 Hz	1.2784 Hz	0.53%	0.9999	1.2703 Hz	0.11%	1.0000
1.5521 Hz	1.5697 Hz	1.13%	0.9998	1.5525 Hz	0.02%	1.0000
1.6475 Hz	1.6630 Hz	0.94%	0.9996	1.6470 Hz	0.03%	1.0000

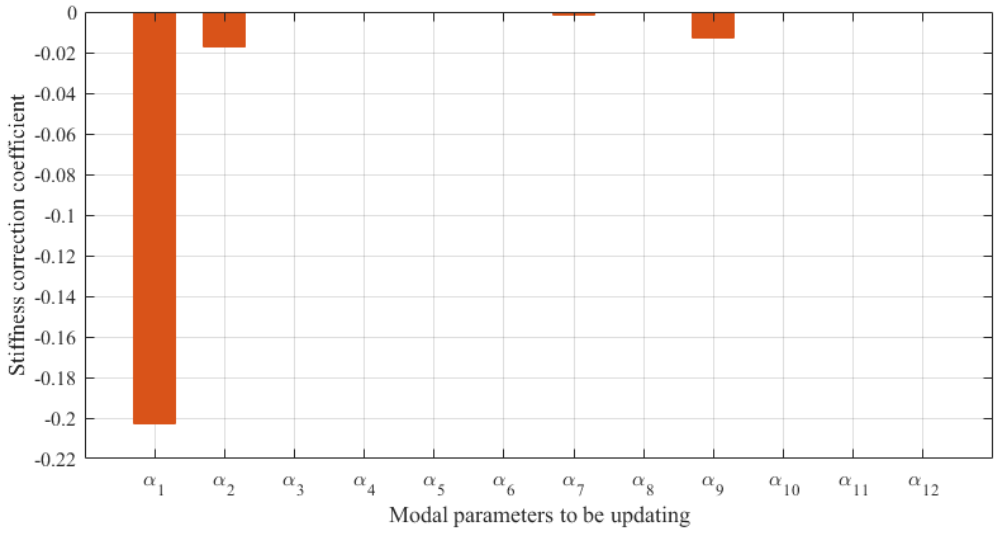


Figure 10. Stiffness correction coefficients obtained for Condition 1 under low-noise conditions.

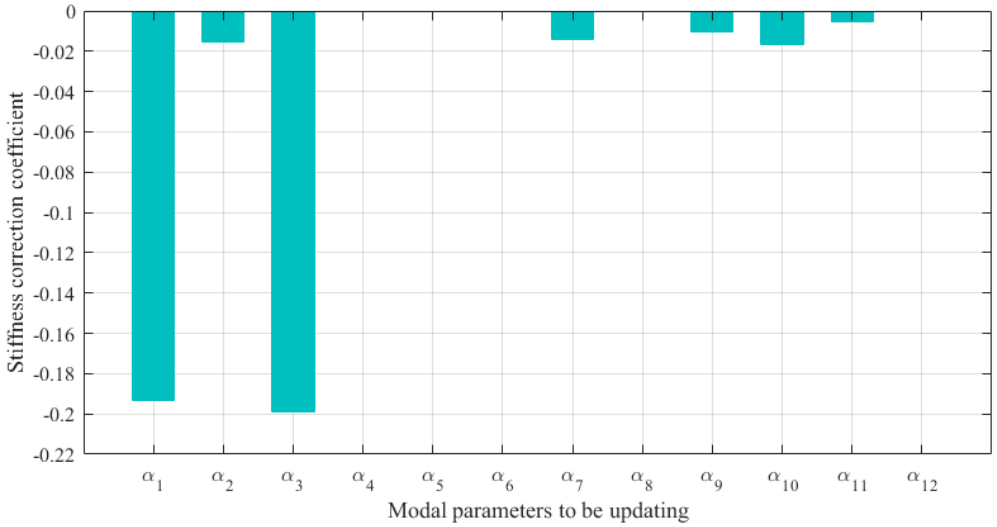


Figure 11. Stiffness correction coefficients for Operating Condition 2 under low-noise conditions.

For Condition 1, modal analysis of the reference FEM yielded the first three natural frequencies of 1.2784 Hz, 1.5697 Hz, and 1.6630 Hz. Compared with the simulated measured frequencies, the relative errors were 0.06%, 0.87%, and 0.54%, respectively. The Modal Assurance Criterion (MAC) values between the simulated measured mode shapes and those of the reference FEM were 1.0000, 0.9999, and 0.9998, indicating strong modal correlation prior to correction. Applying the proposed sensitivity-based clustering correction method, an optimal solution consisting of 12 consolidated stiffness correction coefficients was obtained, as shown in Figure 10. Based on these coefficients, all 328 original stiffness correction coefficients were recovered through numerical back-calculation. The reference FEM was subsequently updated to generate the corrected jacket platform structural model. Modal analysis of the corrected FEM produced the first three natural frequencies of 1.2776 Hz, 1.5560 Hz, and 1.6537 Hz. These values closely match the simulated measured frequencies, with relative errors reduced to 0.01%, 0.01%, and 0.02%, respectively. The MAC values between the corrected modal shapes and the simulated measured modal shapes reached 1.0000 for all three modes, demonstrating excellent agreement. Overall, the maximum relative error in natural frequencies decreased from 0.87% before correction to 0.02% after

correction, clearly validating the effectiveness and accuracy of the proposed sensitivity clustering model correction approach under low-noise conditions.

Further analysis of the 12 consolidated stiffness correction coefficients indicates that the coefficient corresponding to Category 1 converges to −0.2030, exhibiting a relative error of only 1.50% compared with the true preset value of −0.2. The correction coefficients for Categories 2 and 9 are both below −0.02, while those for the remaining categories are close to zero. In summary, the proposed sensitivity-based clustering method for structural model updating of jacket platforms enables accurate determination of structural correction coefficients.

Similarly, for Condition 2, the first three modal frequencies of the corrected conductor platform FEM are 1.2703 Hz, 1.5525 Hz, and 1.6470 Hz. These values closely match the simulated measured frequencies of 1.2717 Hz, 1.5521 Hz, and 1.6475 Hz, respectively. The maximum relative error after correction is 0.11%, which is approximately one-tenth of the maximum pre-correction relative error of 1.13%. Compared with the benchmark FEM, the modal confidence criteria (MAC values) for the first three modes exhibit slight improvements after correction. Overall, these results further validate the effectiveness of the proposed sensitivity-based clustering method.

Figure 11 illustrates the correction coefficients obtained for Condition 2 under low-noise conditions. The stiffness correction coefficients for Categories 1 and 3 are −0.1931 and −0.1991, respectively, corresponding to relative errors of 3.45% and 0.45% when compared with the preset true value of −0.2. The stiffness correction coefficients for all remaining categories are less than −0.02. These results demonstrate that the proposed sensitivity-based clustering method can accurately identify and quantify the dominant structural stiffness correction coefficients.

4.3.2. Analysis of Correction Results Under High-Noise Conditions

This section investigates the performance of the proposed method under high-noise numerical simulation conditions. In Condition 3, a stiffness correction coefficient error of −0.2 is introduced for Category 1, with a measurement noise level of 3%. In Condition 4, stiffness correction coefficient errors of −0.2 are applied to Categories 1, 3, and 8, also with 3% measurement noise. The benchmark FEM of the jacket platform structure is corrected using the proposed sensitivity-based clustering model correction method, and the corresponding results are summarized in Table 3.

Table 3. Model correction results under high-noise conditions.

Simulation/ Measurement	Reference FEM			Corrected FEM		
Frequency	**Frequency**	**Relative Error**	**Frequency**	**Frequency**	**Relative Error**	**Frequency**
			Condition 3			
1.2777 Hz	1.2784 Hz	0.06%	0.9998	1.2771 Hz	0.05%	1.0000
1.5562 Hz	1.5697 Hz	0.87%	0.9998	1.5567 Hz	0.03%	0.9999
1.6540 Hz	1.6630 Hz	0.54%	0.9996	1.6540 Hz	0.00%	0.9999
			Condition 4			
1.2711 Hz	1.2784 Hz	0.58%	0.9999	1.2695 Hz	0.12%	1.0000
1.5467 Hz	1.5697 Hz	1.49%	0.9995	1.5470 Hz	0.01%	1.0000
1.6455 Hz	1.6630 Hz	1.06%	0.9991	1.6450 Hz	0.03%	1.0000

Table 3 shows that the proposed method significantly improves the accuracy of the structural FEM under high-noise conditions. For Operating Conditions 3 and 4, the maximum relative errors of the corrected models are reduced to 0.05% and 0.12%, respectively,

compared with pre-correction maximum relative errors of 0.87% and 1.49%. This represents a substantial reduction in frequency prediction errors for the first three modal orders. Meanwhile, the MAC values of the corrected FEMs exhibit slight improvements relative to those of the benchmark models, indicating enhanced consistency between the corrected modal shapes and the simulated measured modal shapes.

Figures 12 and 13 present the consolidated 12-category stiffness correction coefficients obtained for Operating Conditions 3 and 4 under high-noise conditions, respectively. The results further demonstrate that the proposed sensitivity-based clustering method can reliably identify and estimate the dominant stiffness correction coefficients.

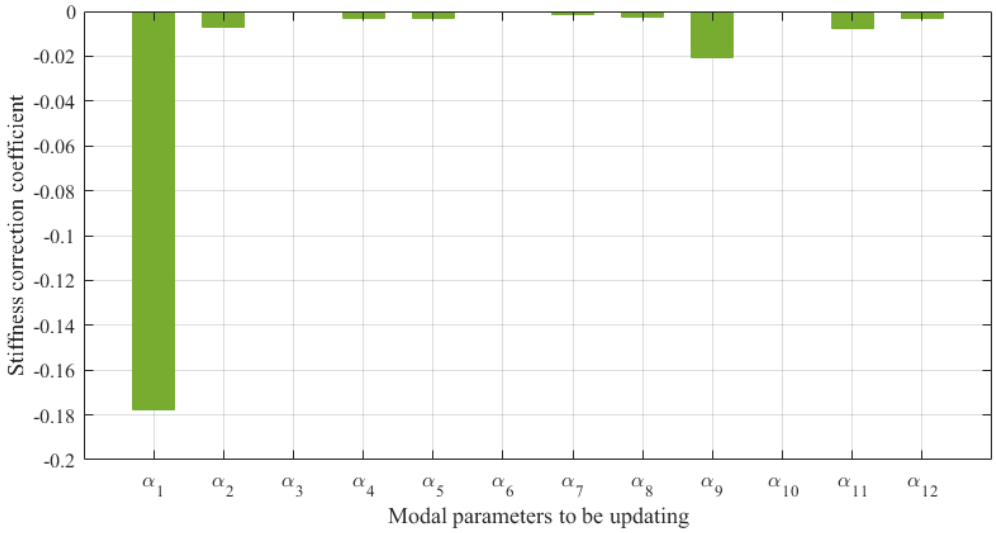


Figure 12. Stiffness correction coefficients for Condition 3 under high-noise conditions.

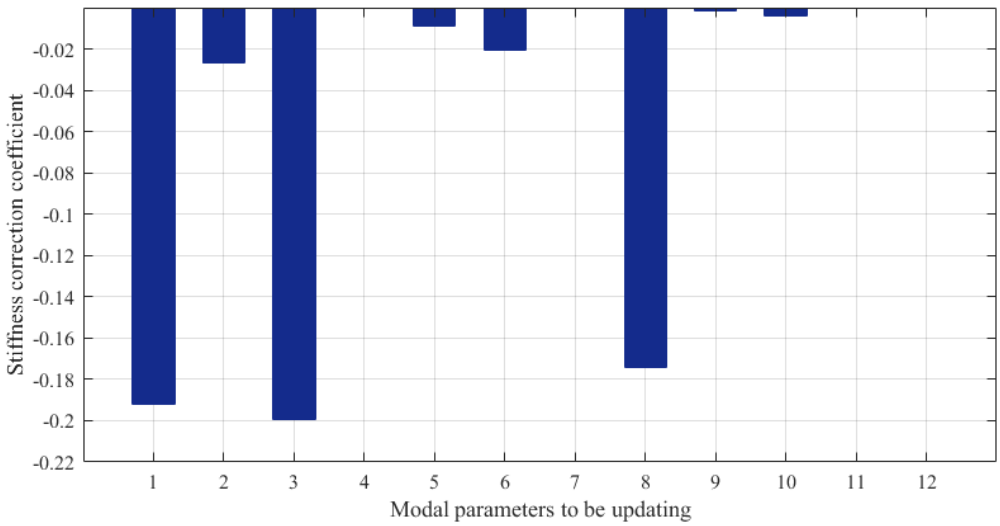


Figure 13. Stiffness correction coefficients for Condition 4 under high-noise conditions.

4.4. Comparison with Other Model Updating Methods

This section investigates the performance of the proposed novel sensitivity clustering strategy under high-noise numerical simulation conditions, as listed in Table 4.

Table 4. Model correction results with/without sensitivity clustering under high-noise conditions.

Simulation/ Measurement	Corrected FEM-Without Clustering			Corrected FEM-Sensitivity Clustering		
Frequency	Frequency	Relative Error	Frequency	Frequency	Relative Error	Frequency
			Condition 4			
1.2711 Hz	1.0216 Hz	19.6294%	0.9845	1.2695 Hz	0.12%	1.0000
1.5467 Hz	1.2845 Hz	16.9521%	0.9465	1.5470 Hz	0.01%	1.0000
1.6455 Hz	1.3180 Hz	19.9012%	0.9813	1.6450 Hz	0.03%	1.0000

Under Condition 4, the corrected model implemented without the sensitivity clustering strategy exhibited a maximum relative error of about 20%, which represents a considerable deterioration from the pre-correction level of 1.49%. This poor outcome indicates ineffective correction of frequency prediction errors for the initial three modal orders. Furthermore, a slight reduction is observed in the MAC values relative to the benchmark model, denoting a decrease in the consistency between the corrected modal shapes and the simulated experimental shapes. Conversely, applying the sensitivity clustering strategy reduced the maximum relative error to 0.12%, while the MAC values demonstrated a slight increase. Collectively, these findings validate the capability of the proposed sensitivity-based clustering approach to reliably identify and estimate the dominant stiffness correction coefficients.

Under high-noise Condition 4, the Pareto optimal fronts (POFs) obtained using the sensitivity clustering strategy are positioned ahead of those derived without clustering, as illustrated in Figure 14. A distinct gap is evident between the two sets of POFs, indicating that the proposed sensitivity clustering strategy yields more accurate and stable solutions. It is noteworthy that for multi-dimensional optimization problems–such as the 328-dimensional space considered in this study–relying solely on multi-objective optimization algorithms for model updating often fails to yield satisfactory results. This represents a core technical challenge in high-dimensional optimization. By reducing the dimensionality of space through sensitivity-based clustering, the proposed approach offers an effective and practical solution to this challenge.

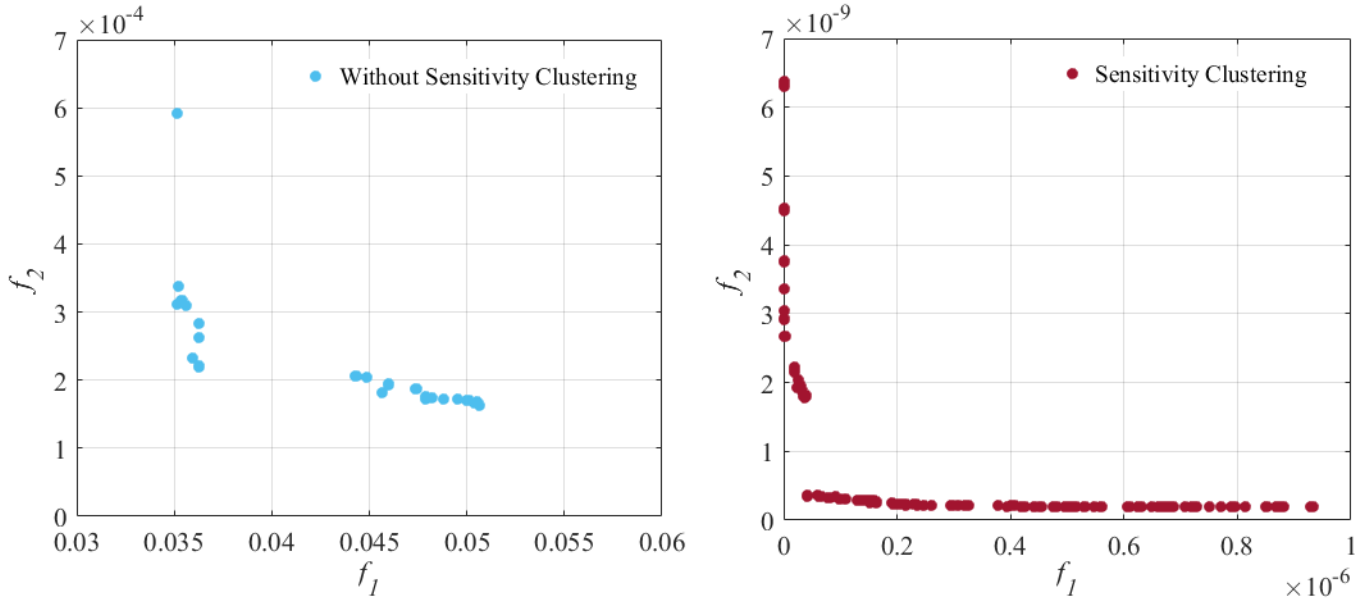


Figure 14. Pareto optimal fronts with/without sensitivity clustering under high-noise conditions.

5. Conclusions

Existing structural model correction methods for jacket platforms are primarily developed for simplified structures or scaled experimental models and are generally applicable only when the number of correction parameters is limited. As a result, these approaches are insufficient for the accurate correction and updating of numerical twin models for large-scale, full-size offshore structures, such as deepwater jacket platforms, which typically involve many parameters. To overcome these limitations, this study establishes numerical sensitivity indicators for the correction parameters of jacket platform structural models. A hierarchical clustering algorithm is introduced to classify correction parameters according to their sensitivity characteristics, thereby aggregating parameters with similar sensitivities into a reduced set of new correction variables. On this basis, a multi-objective optimization strategy is employed to solve for the aggregated correction coefficients, ultimately forming a structural model correction method for jacket platforms based on sensitivity clustering. Numerical simulation studies conducted on a deepwater jacket platform in the Weizhou Oilfield demonstrate the effectiveness and noise robustness of the proposed method. The results show that, after model correction, the maximum relative errors of the FEM are reduced to 0.05% and 0.12%, compared with 0.87% and 1.49% before correction. This represents a substantial reduction in frequency prediction errors. Meanwhile, the modal confidence criteria for the first three modes exhibit slight improvement. In addition, the proposed method accurately identifies and determines all relevant stiffness correction coefficients for the jacket platform structure.

With the continued expansion of global oil and gas exploration into deepwater regions, the number of deepwater jacket platforms is steadily increasing. The safe and stable operation of these platforms directly affects the efficiency and safety of offshore oil and gas production and is of significant strategic importance for ensuring energy security and promoting deep-sea resource development. Under complex and severe marine environmental conditions, guaranteeing the structural safety and reliability of deepwater jacket platforms remains a critical challenge in marine engineering. Future research will focus on extending the proposed sensitivity-clustering-based structural twin model correction framework toward the development of rapid identification technologies and intelligent inspection equipment for critical maintenance regions of deepwater jacket platform structures. Such advancements are expected to further enhance the capability for real-time condition assessment and early warning, thereby providing effective support for the long-term safe operation of deepwater offshore structures.

It should be noted that the present study demonstrates the proposed framework on a specific offshore platform structure. Future research should focus on applying the proposed sensitivity-clustering model updating approach to a wider range of structural systems (e.g., different offshore platforms, wind turbines, risers) to further verify its generality and to build a broader understanding of common interaction patterns.

Author Contributions: Conceptualization, Z.Z. (Zongfeng Zhang) and S.W.; methodology, Y.J.; software, L.W.; validation, J.M., T.C., and Y.J.; formal analysis, Y.J.; investigation, T.C.; resources, Z.Z. (Zepeng Zheng); data curation, S.W.; writing—original draft preparation, Y.J.; writing—review and editing, Z.Z. (Zepeng Zheng); visualization, Y.J.; supervision, S.W.; project administration, Z.Z. (Zongfeng Zhang); funding acquisition, S.W. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Sinopec Science and Technology Department Project "Research on key technologies for optimization of offshore facilities in Weizhou Oilfield" (Grant Nos. P24119).

Data Availability Statement: The original contributions presented in this study are included in the article material. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

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