

Investigation of Error Sources in Frequency Identification of Double-Layer Truss Domes

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Abstract:

Double-layer truss domes, characterized by their spatial configuration and complex dynamic behavior, require accurate information about their dynamic properties as an essential basis for seismic analysis and performance optimization. This study investigates the influence of modeling and analysis parameters on the accuracy of natural frequencies extracted from numerical models of double-layer truss domes, and proposes a corresponding error-compensation model. The analysis employs the Least Squares Complex Frequency (LSCF) method to extract natural frequencies from numerical models developed in MATLAB and OpenSees and to examine the error variation trends associated with each parameter. The results indicate that while parameters such as mesh density, global dimensions, analysis integration rate, loading intensity, damping ratio, and modal order each influence frequency identification accuracy, their effects can be unified under a single governing mechanism, namely the proximity of the identified natural frequency to the analysis integration rate. Based on these parametric sensitivities, a unified predictive model is established to estimate and adjust for potential identification errors. Under the assumptions adopted in the numerical simulations, the proposed model reduces the mean absolute percentage error (MAPE) from 12.5% to 0.63%, providing a practical tool for correcting frequencies extracted from numerical simulations, such as those used for machine learning datasets, structural health monitoring through model updating, as well as for guiding the selection of analysis parameters in dynamic simulations, where the vibrational properties embedded in the computed response may deviate from conventional modal analysis results.

1. Introduction

1.1. Background

Socio-economic advancements, the evolution of construction technologies, and the architectural pursuit of innovation have collectively facilitated the emergence of spatial structures that satisfy the demands for lightweight design, economic efficiency, and rapid construction [1]. Despite their lightness, these structures possess sufficient strength and stiffness to withstand applied loads. Both single-layer and double-layer space truss structures are extensively employed in long-span public buildings [2, 3], serving as a preferred solution for covering vast areas such as exhibition halls and stadiums [4].

In large-span single-layer domes, elastic instability presents a primary design challenge, whereas double-layer domes, owing to their inherently higher stiffness, are largely exempt from this concern [3]. The structural behavior of double-layer truss domes is governed by various parameters, making accurate behavioral prediction of their response a complex task [5].

1.2. Literature Review

Since identifying vibrational properties constitutes the foundational step in structural health monitoring (SHM) [6], the development of a precise system identification methodology for such complex spatial configurations is of paramount importance. Recent vibration-based SHM studies have further highlighted the importance of accurate modal parameter identification for reliable damage assessment [7, 8]. In this context, Li et al. [9] investigated the dynamic

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behavior of large-span domes, noting that vibrational modes are predominantly symmetrical and that hoop-direction degradation may precipitate progressive collapse. Jafarzadeh et al. [3] demonstrated that an increase in the rise-to-span ratio of diamatic double-layer domes significantly alters their seismic response. Ji et al. [10] identified four distinct failure modes for reticulated domes under blast loading: localized vibration, local damage, widespread damage, and global collapse. Kaveh et al. [11] introduced a chaos-based optimization algorithm tailored for large-scale dome trusses, enabling lighter design configurations with accelerated convergence rates. Ahmad and Damatty [12] established that cable domes featuring negative Gaussian curvature exhibit superior stability characteristics. Liu et al. [13] confirmed that suspended domes employing cable and spoke-truss systems demonstrate safe, elastic behavior under uniform loading. Furthermore, Zhuang et al. [14] validated the effectiveness of multi-dimensional isolation systems in controlling the seismic response of long-span domes.

While the aforementioned studies have significantly advanced the understanding of dome mechanics and design, the accurate extraction of their dynamic properties remains a critical yet challenging prerequisite for effective SHM implementation. To address this need, system identification and modal parameter estimation have evolved into indispensable tools for vibration analysis and structural health assessment [15]. These methodologies represent the initial and crucial step in damage detection and condition evaluation of structures. A key technique within this domain is Operational Modal Analysis (OMA), which identifies the dynamic properties of a system solely from output response measurements. Golestaneh et al. [16], through a comparative study of various system identification methods applied to the Geisha Bridge, demonstrated acceptable consistency in the extracted modal parameters. Ramezani and Bahar [17] proposed an enhanced Hilbert-Huang Transform (HHT)-based method, employing the concept of Average Marginal Spectrum (AMS) to identify the natural frequencies of multi-degree-of-freedom structures. Maliar et al. [18] utilized Frequency Domain Decomposition (FDD) within the LabVIEW environment to determine the modes and frequencies of a steel truss structure, observing that operational loading conditions influence identification outcomes. Ghalehshoyan et al. [19] successfully estimated structural damping ratios with acceptable accuracy using an enhanced frequency domain decomposition method. Naderpour and Fakharian [20] presented a two-step algorithm integrating wavelet transforms and peak-picking techniques for damage identification through modal parameters. Kamali and Hadianfard [21] introduced a spectral optimization-based modal identification method that leverages advanced frequency domain decomposition to overcome limitations of prior approaches while maintaining

robust performance even under noisy measurement conditions. Further contributions in this area include SSI-based model updating of moment-resistant frames using ambient vibration data [22] and damage identification in double-layer diamatic domes via EMA and 2D continuous wavelet transform [23].

The Least Squares Complex Frequency (LSCF) method is widely recognized as an efficient and robust technique for modal parameter identification. Originally developed to provide computationally efficient initial estimates for Maximum Likelihood Estimation (MLE), the LSCF method has demonstrated exceptional accuracy in estimating structural natural frequencies [6]. Its successful applications are well-documented across a broad spectrum of operational and experimental modal analysis applications [24–27]. Despite its widespread adoption, the LSCF method has its own limitations. The selection of the appropriate model order remains a critical challenge, as underestimation may omit genuine structural modes while overestimation introduces spurious numerical poles [26, 28]. Furthermore, the method is susceptible to numerical conditioning issues arising from the ill-conditioned normal equations when high-order polynomials are employed, particularly in the presence of closely spaced modes or heavy damping [29, 30]. Recent advances have sought to address these limitations through the use of discrete-time stabilization diagrams, improved regularization schemes, and automated pole selection algorithms [25, 31]. Error compensation frameworks comparable to the one developed in this study have been previously explored for other modal identification techniques. In the context of Frequency Domain Decomposition (FDD), researchers have proposed bias-correction procedures to account for spectral leakage and finite record length effects [32]. Similarly, for Stochastic Subspace Identification (SSI), correction models based on the condition number of the Hankel matrix and the stabilization behavior across varying model orders have been introduced to reduce systematic estimation bias [33]. However, a unified error compensation model tailored specifically to LSCF-based identification in spatial structures remains lacking, motivating the present work.

1.3. Aims and Scope

The dynamic behavior of double-layer truss domes is inherently sensitive to structural geometry, excitation characteristics, analysis parameters, and data acquisition settings. The influence of these factors on the accuracy of retrieved dynamic characteristics remains largely unexplored in the context of such spatial structures. To bridge this gap, the present study investigates the parametric sensitivity of frequency identification accuracy in such spatial structures and, critically, proposes a predictive error-compensation model designed to mitigate identification

biases. To this end, a double-layer truss dome is modeled in MATLAB and OpenSees, and key parameters, including mesh density, global dimensions, loading intensity, analysis time step, sampling rate, damping ratio, sensor placement, and noise level, are varied. The observed error trends are shown to arise from a single governing mechanism, namely the proximity of the identified natural frequency to the frequency associated with the analysis time step. This model supports the correction of frequencies extracted from numerical simulations, such as those used for machine learning datasets, and informs the selection of analysis parameters in dynamic simulations, where the vibrational properties embedded in the computed response may deviate from conventional modal analysis results.

2. Numerical Modelling Details

2.1 Geometry of models

Geometry plays a crucial role in the structural behavior of double-layer space truss domes. The overall form, dimensional proportions, and spatial distribution of elements within these configurations directly influence their load-bearing capacity, stability, and force transmission paths. To systematically investigate these effects and characterize the behavior of domes with varying geometric attributes, a parametric description of the geometry is employed in this study (Fig. 1).

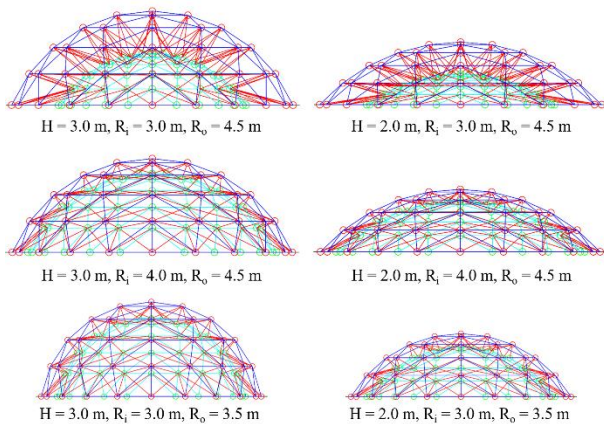


Fig. 1: Double-layer dome defined by varying inner radius (R_i), outer radius (R_o), and rise (H)

This approach facilitates the generation and analysis of diverse dome configurations through the controlled variation of key geometric parameters, allowing a systematic assessment of the relationship between geometric form and structural performance. The primary geometric parameters governing the configuration of the investigated domes include the inner radius, R_i , the outer radius, R_o , and the dome rise, H . As illustrated in Fig. 1, these parameters collectively define the clear span, the depth between layers, and the overall curvature of the dome. In addition to these

parameters, the structural topology and mesh density of the dome are governed by two discretization parameters: the number of circumferential (angular) divisions (N_θ) and the number of radial divisions (N_r), as illustrated in Fig. 2 and Fig. 3, respectively.

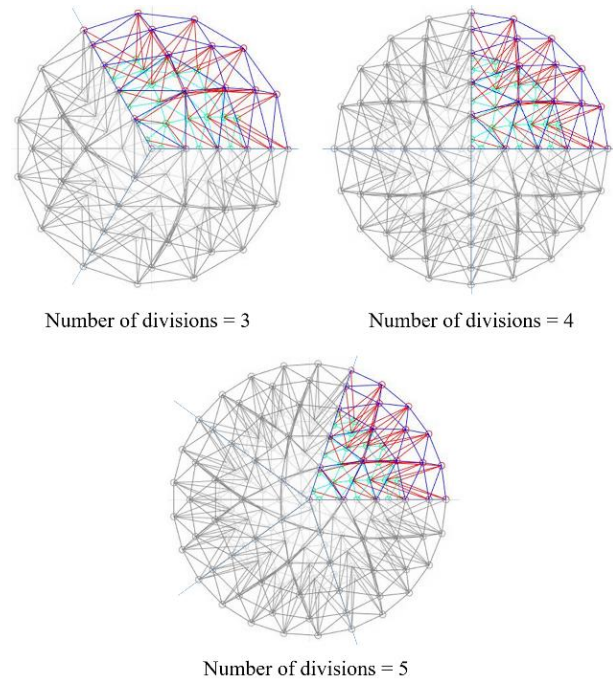


Fig. 2: Double-layer dome with varying angular divisions (N_θ)

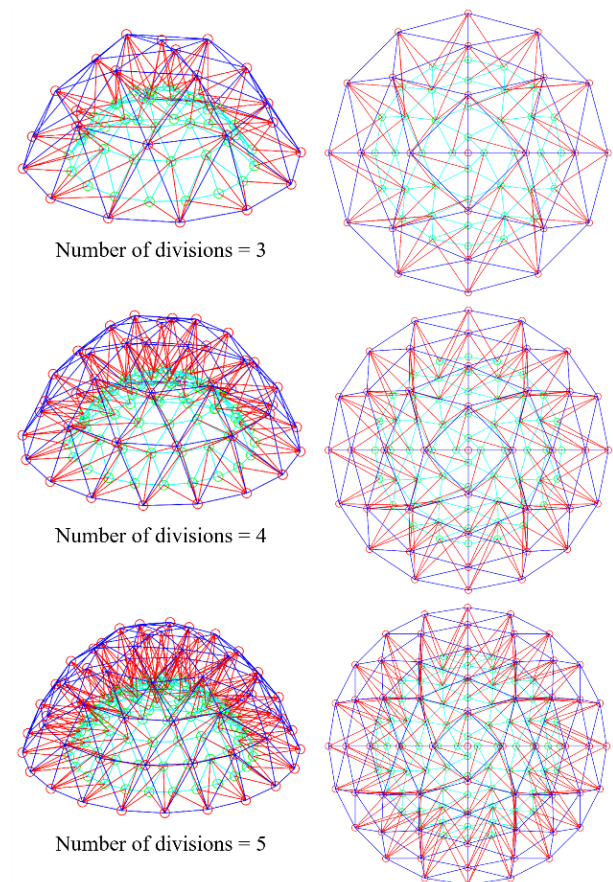


Fig. 3: Double-layer dome with varying radial divisions (N_r)

2.2. Material Properties

A linear-elastic model was adopted, and the mechanical properties of St37 structural steel were adopted for the modelling and design of all structural members comprising the double-layer truss dome. The specific mechanical parameters adopted in the numerical simulations are as follows: elastic modulus $E=200$ GPa, yield stress $F_y=240$ MPa, and Poisson's ratio $\nu=0.3$.

2.3. Constraints and Boundary Conditions

All member-to-member connections within the studied truss domes were idealized as perfectly pinned joints, permitting free relative rotation while fully transferring translational forces. To justify this assumption, a preliminary comparative analysis was conducted in which the double-layer dome was modeled using both truss elements with pinned connections and beam elements with rigid connections. The results indicated that the difference in natural frequencies between the two idealizations was negligible. This outcome is attributed to the slender cross-sections of the members and their inherently low flexural stiffness relative to their axial stiffness, which renders the rotational restraint at the joints practically insignificant for the global dynamic response. Based on this observation, the pinned truss idealization was adopted throughout the parametric study for computational efficiency and model simplicity. However this idealization is adequate for the slender members considered in this study, the influence of gusset plates and connection mass may become more pronounced in domes with stockier members or heavier connection detailing.

At the perimeter, pinned supports were applied by restraining all translational degrees of freedom (global x, y, and z directions) at the designated boundary nodes (green nodes in Fig. 4).

2.4. Analysis Procedure and Loading Protocol

To enhance computational efficiency and modelling flexibility, an integrated workflow was established between MATLAB and OpenSees. In this framework, the parametric geometry of each dome configuration is first generated and pre-processed within MATLAB. Subsequently, analysis scripts, including node definitions, element connectivity, boundary conditions, and loading specifications, are automatically written and executed in OpenSees. Structural loading was applied as a uniformly distributed area load of specified intensity, $q_u=3.8$ kN, acting over the entire surface of the dome. This distributed load was subsequently converted to equivalent concentrated nodal forces and applied exclusively to the nodes located on the upper layer of the dome, with magnitudes proportional to the tributary area associated with each node. The lumped mass at each node was determined by combining the mass equivalent of

the applied gravity load with one-half of the mass of the adjoining structural elements.

Following an initial static analysis, member sections were proportioned using the LRFD methodology in accordance with AISC specifications. All members were selected from standard hollow circular steel tube sections with a diameter-to-thickness ratio (D/t) fixed at 12. In compliance with code-based stability provisions, slenderness ratios were limited to a maximum of $\lambda_{max}=300$ for tension members and $\lambda_{max}=200$ for compression members.

After static analysis followed by the design of truss members, dynamic excitation was applied as a white noise acceleration with an amplitude of $A_w=0.1g$ at all support nodes in the three translational directions. Structural response was recorded using triaxial accelerometers placed at selected nodes of the upper layer, with a baseline sampling frequency of $f_s=100\text{Hz}$ (red nodes in Fig. 4). The loading and analysis integration rates are also set to 100 Hz. In the reference sensor layout, five accelerometers were positioned on the upper layer, with one at the central apex node and four at the first row of nodes located at the mid-height of the truss, symmetrically distributed around the dome circumference. For configurations with a larger number of sensors, a second row was introduced, with twice the number of sensors compared to the first row. For example, the 10-sensor layout follows a 1+3+6 arrangement comprising one apex sensor, three sensors in the first row, and six in the second, while the 13-sensor layout follows a 1+4+8 arrangement.

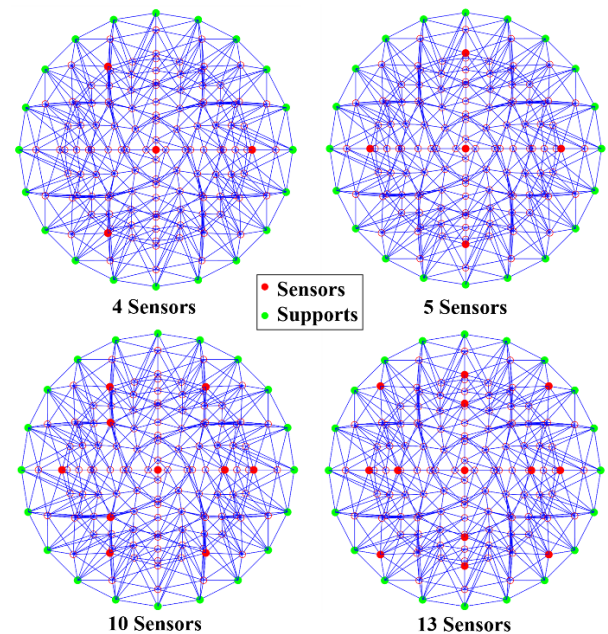


Fig. 4: Support locations and sensor layout configurations

Energy dissipation was modeled using Rayleigh damping, expressed as $[C]=\alpha[M]+\beta[K]$, where $[C]$, $[M]$, and $[K]$ denote the damping, mass, and stiffness matrices of the structure, and α and β are the mass- and stiffness-proportional damping coefficients, respectively. The

coefficients α and β were determined by solving the two-mode Rayleigh damping formulation using the natural frequencies of the first and second modes, ensuring that the specified damping ratio was achieved at these modes while varying gradually across the remaining frequency range. The baseline modal damping ratio was set to zero, corresponding to the undamped condition adopted for the primary parametric analyses. To examine the sensitivity of the identification results to energy dissipation, ξ was varied from 0 to 0.15, covering the range of typical damping ratios recommended for steel space structures [34], as detailed in Section 4.8. Upon completion of the structural analysis, the resulting response data are transferred back to the MATLAB environment, where the LSCF algorithm is employed to extract the natural frequencies of the system.

2.5. Validation of the Numerical Model

To validate the numerical model developed in OpenSees, a verification process was conducted using experimental data from a dome model reported by Lu et al. [34]. This process involved comparing the dynamic responses of the numerical model with results obtained from practical tests on a physical specimen. The structure employed for validation was a 1:25-scale single-layer spherical space truss dome fabricated from T6-6061 aluminum alloy, comprising 73 nodes and 204 members with cross-sectional dimensions of 18×8×1 mm. The rise-to-span ratio of the structure is 0.4, and the total mass of the model includes 3.88 kg of structural weight and 15.06 kg of additional weights. The geometry and key specifications of the physical model used for this validation are illustrated in Fig. 5. A comparison of the natural frequencies obtained from the experimental tests and the numerical model is presented in Table 1. As shown, the maximum prediction error of the numerical model is approximately 5%, confirming the acceptable accuracy of the developed model.

Table 1: Comparison of the natural frequencies obtained from the experimental and numerical models

Mode	Natural Frequency (Hz)		Deviation (%)
	Experimental	Numerical	
1	87.45	92.42	5.68
2	87.10	92.46	5.66
3	124.92	132.21	5.84
4	125.34	132.22	5.49
5	133.76	138.49	3.54

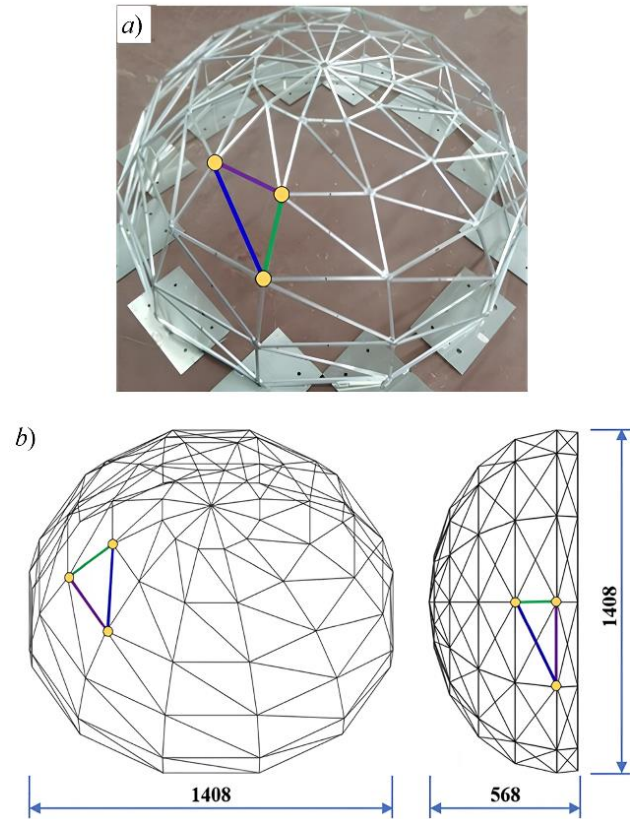


Fig. 5: Dimensions of the tested structure [34]: (a) actual experimental model; (b) schematic view

3. Frequency Identification Framework

3.1. Fundamentals of the LSCF Method

The LSCF method is a parametric frequency-domain estimator designed to extract modal parameters with high precision by identifying the system poles. In this approach, the time-domain data recorded from l sensors are transformed into the frequency domain using the Fourier transform, yielding a frequency vector of length N_f for each output channel. The auto- and cross-spectral density functions are then assembled into a power spectral density (PSD) matrix of dimensions $l \times l \times N_f$. Then, the analytical model is represented by a polynomial fraction of order n , fitted to the PSD matrix. Subsequently, the denominator coefficients are determined by minimizing the fitting error in a least-squares sense. The system poles, λ_r , are obtained as the roots of the denominator polynomial, from which the natural frequencies and damping ratios are computed as follows [15]:

$$f_r = \frac{|\lambda_r|}{2\pi} \quad (1)$$

$$\xi_r = -\frac{\text{Re}(\lambda_r)}{|\lambda_r|} \quad (2)$$

Where f_r and ξ_r denote the natural frequency and damping ratio associated with the r^{th} system pole, respectively. Assuming numerator and denominator polynomials of order

n , the denominator coefficients, θ_d , governing the pole locations are determined via:

$$\{\theta_d\} = \begin{bmatrix} -[M_{(1:n,1:n)}]^{-1}[M_{(1:n,n+1)}] \\ 1 \end{bmatrix} \quad (3)$$

Where $M_{(1:n, 1:n)}$ represents the sub-matrix formed by the first n rows and n columns of matrix $[M]$, and sub-matrix $M_{(1:n, n+1)}$ denotes the first n rows of the last column. The matrix $[M]$ is assembled as:

$$[M] = \sum_{k=1}^{l,l} ([T_k] - [S_k]^H [R_k]^{-1} [S_k]) \quad (4)$$

With the constituent matrices defined by:

$$[R_k] = [\Gamma_k]^H [\Gamma_k] \quad (5)$$

$$[S_k] = [\Gamma_k]^H [Y_k] \quad (6)$$

$$[T_k] = [Y_k]^H [Y_k] \quad (7)$$

In the above expressions, l denotes the number of measurement sensors, k indexes the output channel pairs ($k=1, \dots, l,l$), and H signifies the Hermitian (conjugate) transpose. The matrices $[\Gamma_k]$ and $[Y_k]$ are constructed as:

$$[\Gamma_k] = \begin{bmatrix} z^0(\omega_1) & \cdots & z^n(\omega_1) \\ \vdots & \ddots & \vdots \\ z^0(\omega_{N_f}) & \cdots & z^n(\omega_{N_f}) \end{bmatrix} \quad (8)$$

$$[Y_k] = \begin{bmatrix} -\hat{G}_k(\omega_1)z^0(\omega_1) & \cdots & -\hat{G}_k(\omega_1)z^n(\omega_1) \\ \vdots & \ddots & \vdots \\ -\hat{G}_k(\omega_{N_f})z^0(\omega_{N_f}) & \cdots & -\hat{G}_k(\omega_{N_f})z^n(\omega_{N_f}) \end{bmatrix} \quad (9)$$

Where $e^{i\omega_f \Delta t}$ is the generalized transform variable, $\hat{G}_k(\omega_f)$ represents the cross-spectral density of the recorded signal pair at frequency ω_f , and N_f is the length of the frequency vector.

3.2. Neighborhood Radius Clustering for Stabilization

The neighborhood radius technique is a distance-based clustering method employed to refine the stabilization diagram and automate the selection of structural frequencies. Each data point is treated as a potential cluster center, and points falling within a prescribed radius are assigned to that cluster. The objective is to isolate stable, physically meaningful poles within the frequency dataset. In the present implementation, non-zero frequencies extracted via LSCF are sorted and subsequently grouped based on proximity using two controlling parameters: the neighborhood radius and the minimum occurrence threshold required to declare a frequency as stable (see Fig. 6). Through systematic adjustment of these parameters, the clustering algorithm effectively filters out spurious modes that arise from numerical errors.

As illustrated in Fig. 7, the application of neighborhood radius clustering substantially enhances the clarity of the stabilization diagram and automates the selection of structural frequencies. Fig. 7a presents the raw LSCF stabilization output, while Fig. 7b demonstrates the refined diagram following clustering, where the elimination of

outliers reveals a distinct and interpretable set of stable frequency poles, thereby facilitating more reliable and automated modal parameter extraction.

3.3 Definition of Identification Error

The frequency identification error is defined as the relative deviation between the actual frequency, f_{act} , and the identified frequency, f_{id} , expressed as:

$$\varepsilon = \frac{f_{act} - f_{id}}{f_{act}} \quad (10)$$

In Section 5, where the compensation model is applied, the actual frequency can be recovered from the identified frequency using the inverse relationship:

$$f_{act} = \frac{f_{id}}{1 - \varepsilon} \quad (11)$$

It is worthy to note that in the subsequent plots, ε is expressed as a percentage.

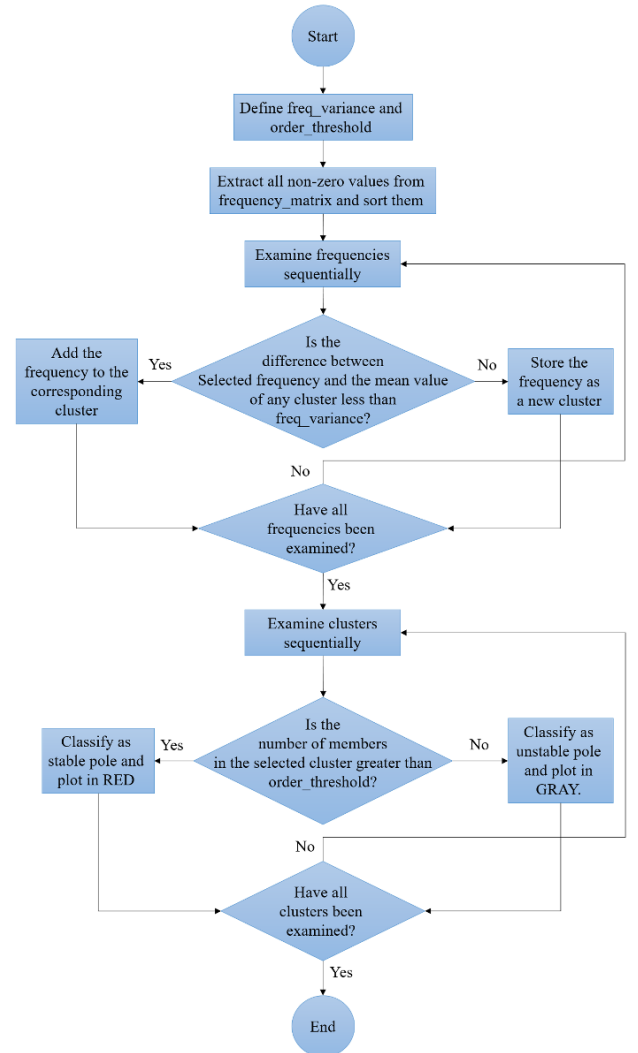


Fig. 6: Neighborhood Radius Clustering flowchart

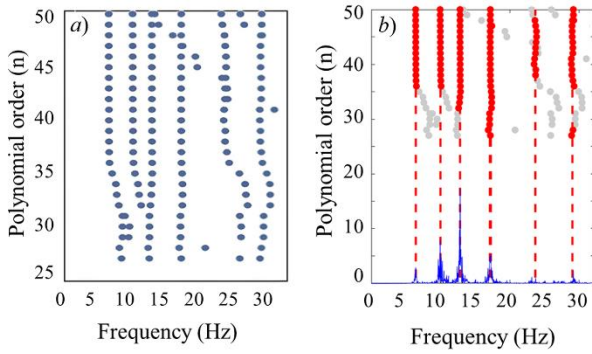


Fig. 7: Stabilization diagrams: (a) raw LSCF output, and (b) refined diagram following neighborhood radius clustering

4. Parametric Sensitivity Analysis

4.1. Effect of Radial and Circumferential Divisions

To investigate the influence of geometric mesh density on the accuracy of frequency identification, a series of models was developed in which the global geometric parameters were held constant (i.e., the inner radius, $R_i=3$ m; outer radius, $R_o=4.5$ m; and rise, $H=3$ m). The sensor layout, consisting of one central accelerometer and four peripheral accelerometers deployed on the upper layer, was fixed across all models. All other parameters, including material properties, boundary conditions, and loading intensity, remained unchanged in accordance with the baseline configuration established in Section 2.

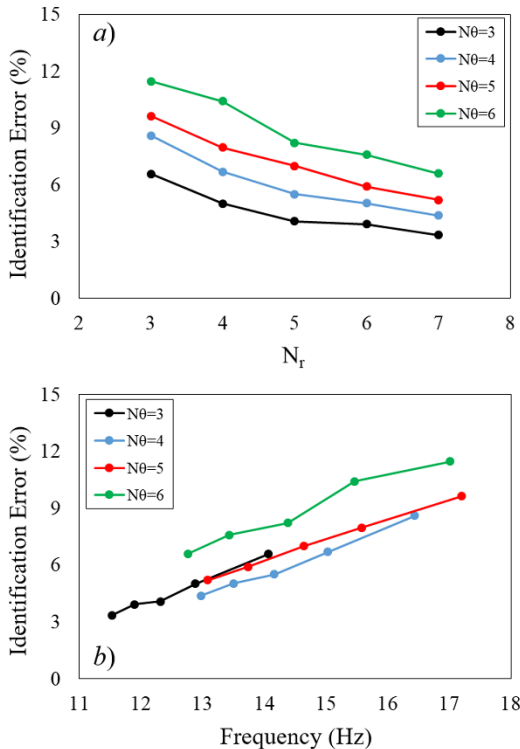


Fig. 8: Effect of radial and circumferential divisions on identification error; a) as a function of mesh density; b) as a function of corresponding frequency

The radial divisions (N_r) were varied from 3 to 7, while the circumferential divisions (N_θ) were increased from 3 to 6.

These ranges were selected to encompass sparse to moderately dense grid configurations, enabling a systematic assessment of how member density influences the system identification. **Fig. 8a** illustrates the frequency identification error as a function of the geometric refinement level. It should be noted that the results presented in this section pertain solely to the first mode frequency. The results consistently demonstrate that increasing the density of radial and hoop members leads to a notable reduction in the identification error of natural frequencies. This improvement can be partly attributed to the richer spatial distribution of members, which enhances the transfer of dynamic characteristics between adjacent nodes and provides a more complete representation of the system's global response.

The reduced error may also be linked to the lower natural frequencies resulting from increased mesh density (**Fig. 8b**). As the number of radial and circumferential divisions increases, the natural frequencies systematically decrease due to two concurrent mechanisms:

- A reduction in effective stiffness, since the cross-sectional dimensions of the elements are constrained by AISC slenderness limits, preventing proportional stiffness increases with grid refinement.
- An increase in effective mass, as a greater number of divisions leads to a larger total count of structural elements.

4.2. Effect of Rise and Outer Radius

To investigate the simultaneous influence of the dome rise (H) and outer radius (R_o) on frequency identification accuracy, a parametric set of numerical models was constructed. All models shared a fixed inner radius ($R_i=4$ m), constant radial and circumferential divisions ($N_r=5$, $N_\theta=4$), and identical material properties, boundary conditions, and loading protocol as established in Section 2. The sensor layout was also held fixed (i.e., one central and four peripheral accelerometers on the upper layer) to isolate geometric effects. The rise was varied across four levels ($H=1, 2, 3, 4$ m), while the outer radius was incrementally increased from $R_o=4.5$ m to 8.5 m.

Again, the investigation is focused on the fundamental frequency. **Fig. 9a** presents the resulting frequency identification error as a function of the combined geometric variation. According to the figure, increasing either the rise or the outer radius of the dome leads to a notable reduction in identification error. The corresponding variation in the natural frequencies is shown in **Fig. 9b**. As both the rise and outer radius increase, the fundamental natural frequency exhibits a continuous downward shift. This behavior is consistent with the two governing mechanisms identified earlier. The greater mass and reduced stiffness drive the observed reduction in natural frequencies. Importantly, and

consistent with the relationship established in Section 4.1, this frequency reduction also contributes to the decrease of identification error by shifting the dominant spectral peak farther from the analysis and sampling frequencies.

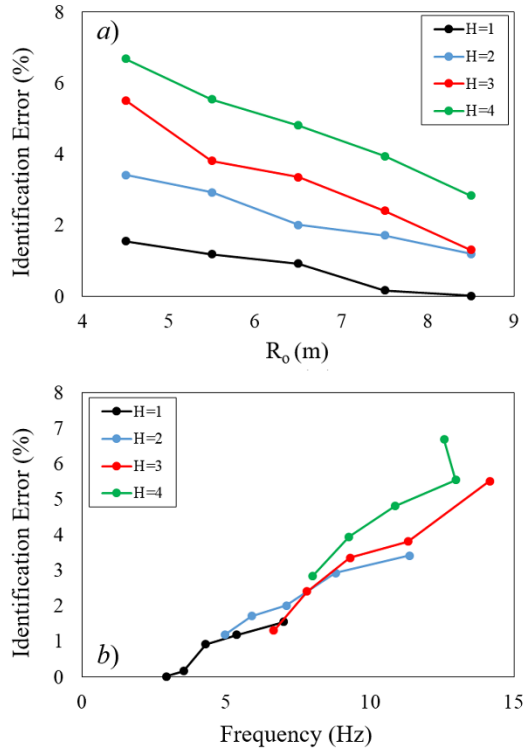


Fig. 9: Variation of identification error; a) as a function of rise and outer radius; b) as a function of corresponding frequency

4.3. Effect of Loading Intensity

To evaluate the influence of loading intensity, all structural parameters were held constant at their baseline values while the uniformly distributed load was varied between $q_u=2$ kPa and $q_u=7$ kPa. For each loading case, the LSCF procedure was executed, and results were plotted in **Fig. 10a**. The results reveal that increasing the applied load leads to a monotonic reduction in identification error across all models. The corresponding variation in natural frequency is illustrated in **Fig. 10b**. As loading intensity increases, the fundamental frequency decreases systematically (a direct consequence of the added mass effect). Consistent with earlier observations, decreasing the fundamental frequency of the structure causes the lower identification error, the underlying reason for which is further examined in the following section. It should be noted that additional nodal masses, such as those arising from gusset plates at the joints, are not explicitly modeled in this study. However, their effect on the identification error is expected to be analogous to that of the applied loading, since both contribute to the total nodal mass and thereby shift the natural frequencies without altering the underlying error trend.

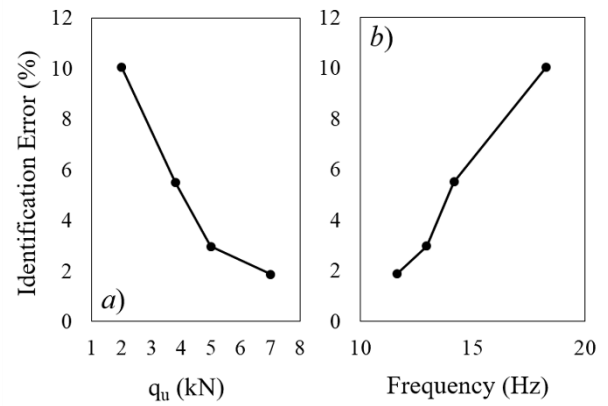


Fig. 10: Variation of identification error; a) as a function of loading intensity; b) as a function of corresponding frequency

4.4. Effect of Time Resolution Settings

The time resolution settings are governed by three distinct time steps, namely the excitation time step, Δt_i , which controls the rate at which the input excitation is applied to the structure, the analysis time step, Δt_a , which defines the integration increment used by the solver in OpenSees, and the data acquisition time step, Δt_s , which determines the interval at which the structural response is recorded. The corresponding frequencies are defined as $f_i=1/\Delta t_i$, $f_a=1/\Delta t_a$, and $f_s=1/\Delta t_s$, respectively. To assess the influence of these parameters on identification error, the dome geometry and sensor layout were held constant (i.e., the inner radius, $R_i=3$ m; outer radius, $R_o=4.5$ m; and rise, $H=3$ m), while the time resolution settings were varied. In the first step, f_a and f_s were kept constant at 100 Hz, while f_i was reduced from 100 to 25 Hz. **Fig. 11a** presents the first singular value of the PSD matrix as a function of frequency for selected values of f_i . As shown, although reducing f_i , which effectively lowers the cutoff frequency of the white noise excitation, diminishes the spectral peaks at higher frequencies, the peaks remain sufficiently distinct, and the LSCF method is still capable of correctly identifying the vibrational frequencies.

In the next step, the influence of sampling frequency, f_s , was examined by keeping f_i and f_a constant at 100 Hz. The corresponding results are presented in **Fig. 11b**. As f_s decreases, the Nyquist frequency, defined as $f_{Nyq}=f_s/2$, decreases accordingly, and frequency content above this threshold can no longer be directly represented in the recorded signal. As a result, spectral peaks associated with structural modes above the Nyquist limit become unidentifiable. However, peaks corresponding to frequencies below the Nyquist limit remain clearly distinguishable, and the LSCF method continues to correctly identify the system frequencies within this range. It should also be noted that, for frequencies exceeding the Nyquist limit, the phenomenon of aliasing causes these higher-frequency components to be reflected into the lower-frequency region of the spectrum, appearing as spurious

peaks at mirrored positions. Specifically, a structural frequency f above f_{Nyq} manifests as an aliased frequency $f_{alias}=|f-f_s|$, which may be misinterpreted as a genuine structural mode.

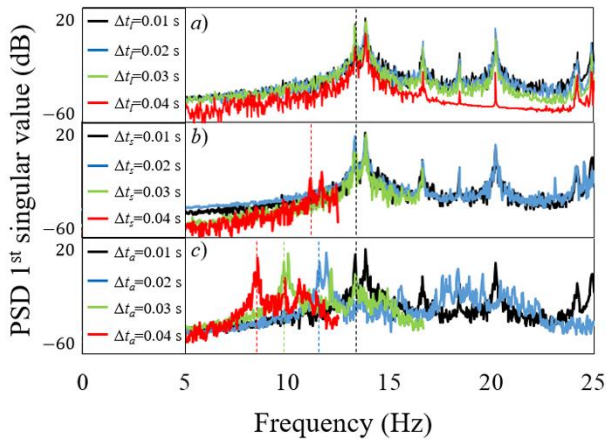


Fig. 11: First singular value of the PSD matrix under varying; a) excitation rate; b) sampling rate; c) analysis integration rate

In the third step, the influence of the analysis time step, Δt_a (and its corresponding frequency f_a) was examined. Since varying f_a independently of the other two parameters is not feasible within the numerical framework, all three frequencies were simultaneously reduced from 100 Hz to 25 Hz, and the results are presented in **Fig. 11c**. As shown, reducing f_a not only produces effects similar to those observed for f_i and f_s , but also introduces a systematic error that results in the underestimation of the identified system frequencies. To investigate this behavior further, the identification errors obtained from the LSCF method are presented in **Fig. 12a** as a function of the analysis integration frequency, f_a . According to the figure, as f_a increases, the identification error decreases at an accelerating rate. This increased accuracy stems from the enhancement of temporal resolution in the calculated and recorded dynamic response. Although smaller f_a reduces computational effort, it may also suppress higher-frequency content and lead to the omission of certain modes. **Fig. 12b** presents the resulting frequency–error relationship. It is important to note that the actual natural frequency of the structure under investigation remained constant throughout this analysis. However, as the analysis integration rate changes relative to this fixed structural frequency, the proximity of the natural frequency to f_a varies accordingly. Hence, the horizontal axis of **Fig. 12b** is expressed as the ratio of the actual natural frequency to the analysis integration frequency (f/f_a). According to the figure, as the normalized frequency ratio increases the identification error grows systematically. This trend is fully consistent with the general recommendations emphasizing the need for adequate separation between the analysis rate and the system frequency.

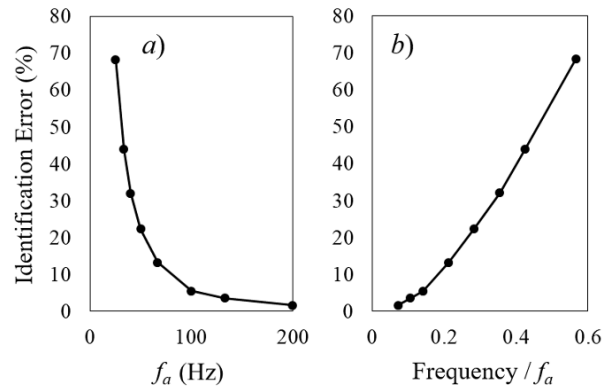


Fig. 12: Variation of identification error; a) as a function of analysis integration rate; b) as a function of frequency ratio

4.5. Effect of Excitation Time and Amplitude

To evaluate the influence of excitation characteristics on frequency identification accuracy, the amplitude and duration of the applied white-noise base excitation were varied parametrically while all structural parameters and the time resolution settings were held constant at their baseline values. The excitation amplitude, A_w , was set to 0.1g, 0.3g, and 0.5g, while the excitation duration was increased from 5 s to 30 s. **Fig. 13** presents the identification error as a function of both excitation amplitude and duration. The results indicate that neither parameter exerts a significant influence on the accuracy of the LSCF-based frequency extraction.

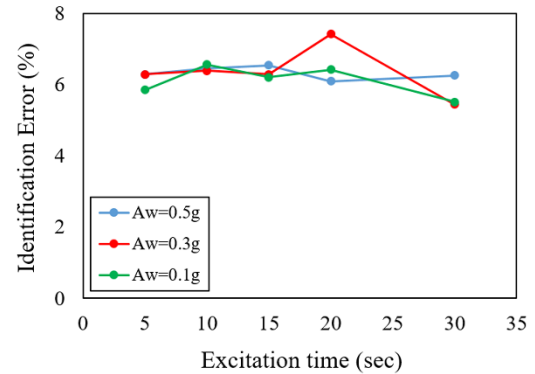


Fig. 13: Variation of identification error with respect to excitation time and amplitude

4.6. Effect of Sensor Placement

To evaluate the influence of sensor placement on LSCF accuracy, the number of accelerometers was varied from 4 to 25, placed either on the upper or lower layer. All structural parameters were held constant at their baseline values, with a fixed time resolution of $f_i = f_a = f_s = 100$ Hz. As shown in **Fig. 14**, increasing the number of sensors yields only a marginal improvement in identification accuracy, with the error remaining relatively stable. Furthermore, transferring the sensors from the upper to the lower layer results in a very slight increase in identification error. The marginal effect of both sensor count and placement stems from the high inherent stiffness of the double-layer configuration, in which the diagonal web members rigidly couple the two chords,

such that the spatial information required for resolving the fundamental mode is already adequately captured by a modest number of sensors on either layer.

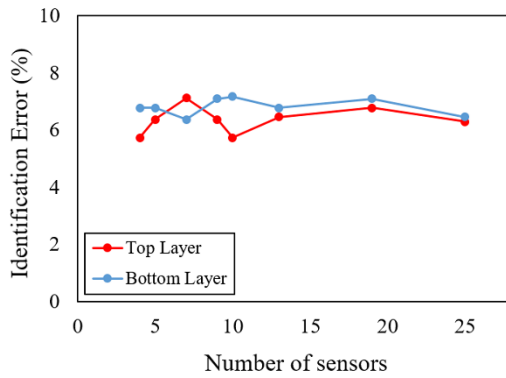


Fig. 14: Variation of identification error with respect to number and placement of sensors

4.7. Effect of Mode Number

To examine whether the parametric trends established for the fundamental mode extend to higher-order dynamics, the first two modes of two representative dome configurations, with a rise of $H=1$ m and $H=3$ m, each subjected to varying outer radius (R_o), were extracted and compared. All other parameters remained at their baseline values.

Fig. 15a presents the identification error as a function of the outer radius for both modes in both configurations. The results demonstrate that the second mode follows a qualitatively similar trend to the first mode, exhibiting a gradual reduction in error with increasing R_o . However, the second mode consistently yields a slightly higher identification error than the first mode across all cases.

Fig. 15b presents the corresponding frequency–error relationship for the same models in **Fig. 15a**. Notably, despite the distinct geometric parameters and modal orders, all four curves collapse onto a single underlying trend, revealing that the identification error increases with the structural frequency in a consistent, nonlinear manner. This unified behavior across different dome geometries and mode numbers underscores the dominant role of the normalized frequency (f/f_a) in governing identified frequency accuracy.

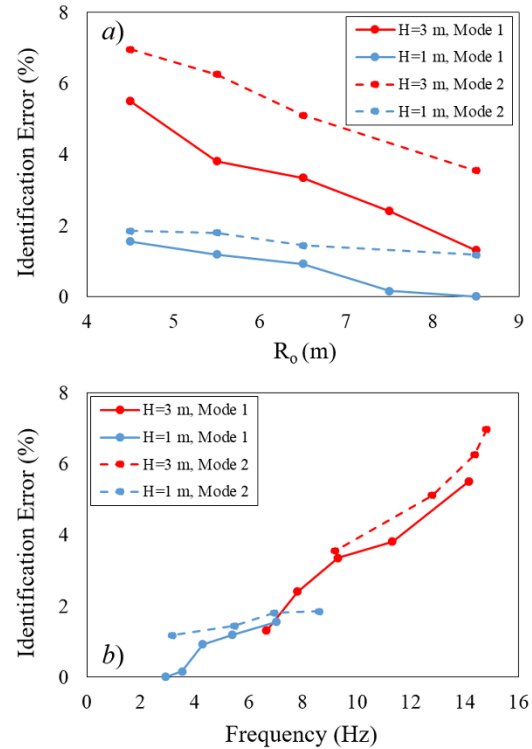


Fig. 15: Variation of identification error; a) as a function of outer radius; b) as a function of corresponding frequency

4.8. Effect of Damping Ratio

To assess the sensitivity of frequency identification to energy dissipation, the modal damping ratio, ξ , was varied from 0 to 0.15, while all geometric, loading, and sampling parameters remained at their baseline values. **Fig. 16** presents the identification error for the first two modes as a function of the damping ratio. The results reveal a slight increase in identification error with increasing damping for both modes. This trend is attributed to the broadening of the peaks in the PSD function at higher damping levels, which reduces the precision. Furthermore, the second mode consistently exhibits a marginally higher identification error than the first mode across the entire damping range. This is explained by its higher natural frequency, which places it closer to the analysis rate, f_a .

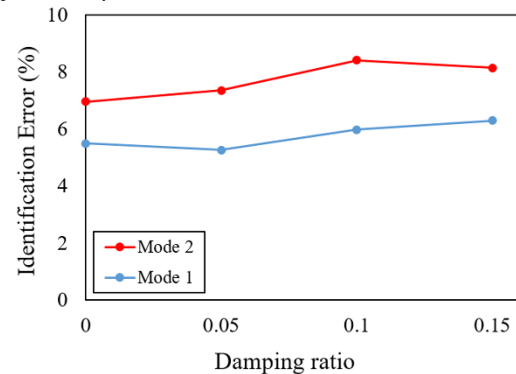


Fig. 16: Effect of damping ratio on identification error

4.9. Effect of Measurement Noise

To evaluate the robustness of frequency identification under more realistic conditions, Gaussian white noise was added to the recorded acceleration responses at signal-to-noise ratios (SNR) ranging from -20 dB to $+20$ dB. **Fig. 17** presents the first singular value of the PSD for selected SNR levels, illustrating that the spectral peaks become progressively less distinct as the noise level increases.

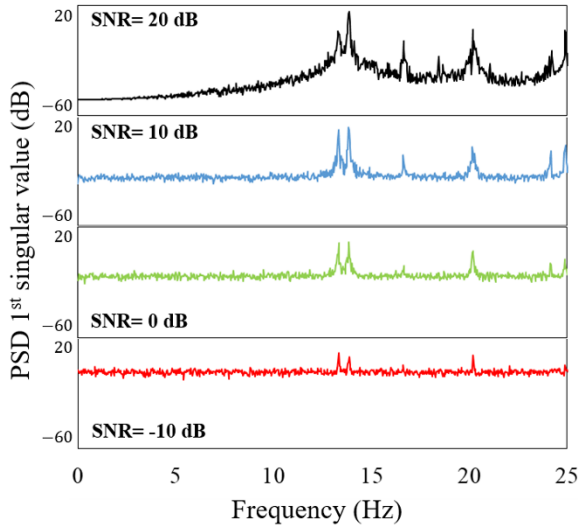


Fig. 17: First singular value of the PSD matrix at different SNR levels

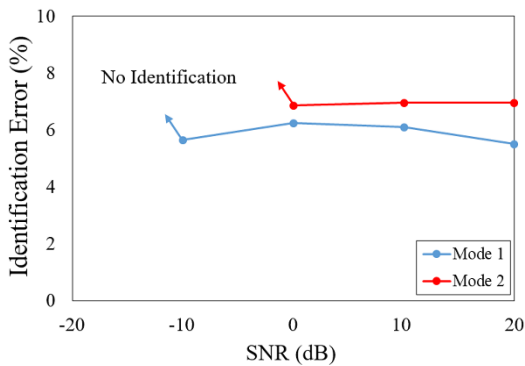


Fig. 18: Identification error versus SNR for the first and second modes of baseline model

Fig. 18 shows the identification error for the first and second modes as a function of SNR. The results indicate that the identification accuracy remains largely unaffected by noise down to a certain SNR threshold. However, below this threshold, the modal peaks are no longer reliably detectable. For the first mode, identification remains feasible down to approximately -10 dB, whereas the second mode becomes unidentifiable below approximately 0 dB. This earlier deterioration of the second mode is attributed to its lower spectral amplitude relative to the background noise, which causes it to be masked sooner than the fundamental mode. This observation raises the concern that higher modes, possessing lower participation in the measured response, are

more susceptible to both colored excitation spectra (finite-bandwidth white noise) and measurement noise. Consequently, under elevated noise levels, the second mode disappears before the first, confirming that the practical identifiability of higher modes is constrained not only by the excitation bandwidth but also by the signal-to-noise ratio of the acquisition system.

5. Error Prediction Model

The parametric sensitivity analysis presented in Section 4 revealed that the influence of various parameters on frequency identification error can be traced to their effect on the natural frequency of the system. Rather than treating each parameter independently, the observed trends suggest that the identification error can be expressed as a unified function of the system frequency itself. Motivated by the consistent observation throughout this study that the error scales with the proximity of the structural mode to the analysis integration rate, the normalized identified frequency, f_{id}/f_a , emerges as the most informative predictor of identification accuracy. Based on this reasoning, the identification error is modeled as a function of the normalized identified frequency. **Fig. 19** presents the error data points from all parametric cases investigated in this study, plotted against the normalized identified frequency (f_{id}/f_a), together with the fitted power-law curve. The regression yields a coefficient of determination $R^2=0.9941$ and a root mean square error of $RMSE=0.0077$, indicating a high-quality fit and low residual dispersion across the entire dataset. The fitted relationship is expressed analytically as:

$$\varepsilon = 3.81 \left(\frac{f_{id}}{f_a} \right)^{2.06} \quad (12)$$

It is evident from the collapse of the data that the normalized frequency ratio serves as a robust and parsimonious predictor, absorbing the effects of the diverse parameters examined in Section 4 into a single regression. To assess the effectiveness of the proposed compensation model, the correction procedure was applied to the entire dataset. **Fig. 20** compares the normalized identified frequency (f_{id}/f_a) against the normalized actual frequency (f/f_a) both before and after applying the error compensation. In the uncompensated case, the data points deviate systematically from the ideal 1:1 line, reflecting the persistent underestimation of natural frequencies by the LSCF estimator. After applying the proposed compensation, the corrected points align closely with the line of perfect agreement. Quantitatively, the mean absolute percentage error (MAPE) across all cases is reduced from 12.5% to 0.63%, confirming the efficacy of the model in substantially mitigating the systematic bias inherent in frequency extraction of double-layer truss domes.

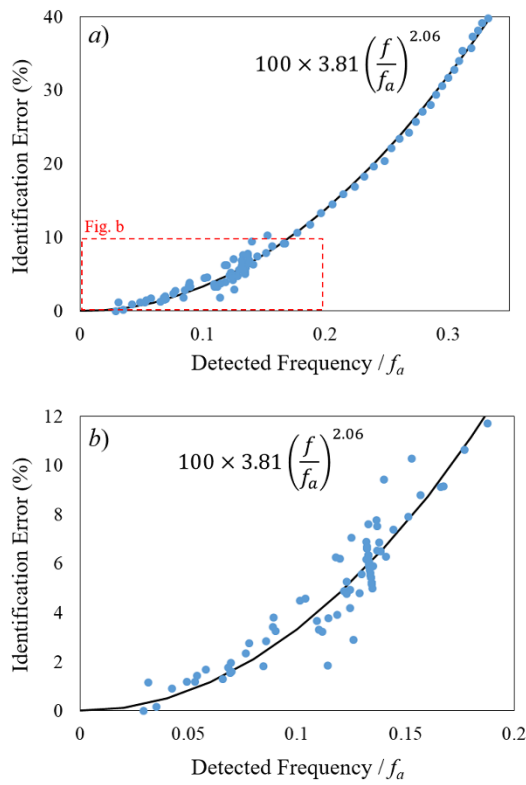


Fig. 19: Fitted error prediction model as a function of normalized identified frequency

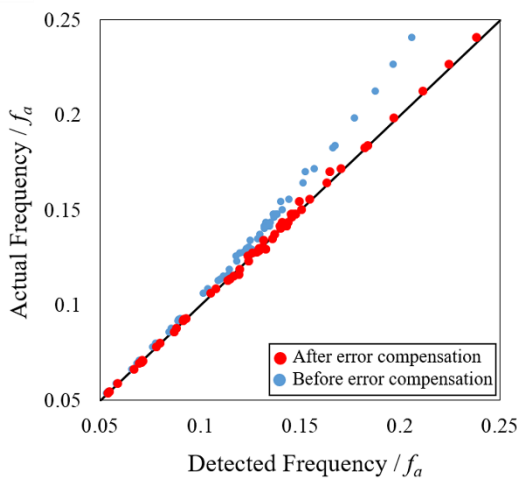


Fig. 20: Identified frequency ratio vs. actual frequency ratio

6. Discussion

The findings of this study are relevant to two distinct groups of practitioners. First, researchers who rely on numerical system identification, such as those generating training datasets for machine learning models, performing vibration-based damage identification, or calibrating finite element models through model updating for SHM, can use the proposed compensation model to correct the frequencies extracted from their simulations, since the identification error varies across modes depending on their proximity to the analysis rate. Second, engineers performing dynamic

simulations should be aware that the vibrational properties embedded in the computed response may deviate from those obtained via conventional modal analysis, and the results presented herein offer a practical basis for selecting appropriate analysis parameters to limit the resulting error. To examine whether the identified systematic error is specific to the LSCF method or inherent to the numerical discretization itself, two additional identification techniques were applied to the same dataset, namely Frequency Domain Decomposition (FDD) as a frequency-domain method and Stochastic Subspace Identification (SSI) as a time-domain method. **Fig. 21** presents the first singular value of the PSD matrix obtained from FDD together with the stabilization diagram derived from SSI for analysis integration rates f_a decreasing from 100 to 25 Hz. The results demonstrate that, as f_a decreases, the spectral peaks and stable poles in all four panels remain clearly identifiable but are systematically shifted toward lower frequencies, indicating a consistent compression of the frequency axis. This behavior confirms that the systematic bias observed in this study is not an artifact of the LSCF estimator but rather a consequence of the temporal discretization of the numerical model, affecting both frequency-domain and time-domain identification methods in a qualitatively similar manner. Minor differences in the appearance of the peaks arise from the inherent algorithmic characteristics of each method, yet the underlying error trend remains consistent across all three approaches. These observations suggest that the proposed compensation framework, while calibrated for LSCF in the present study, may be extended to other identification methods following appropriate recalibration.

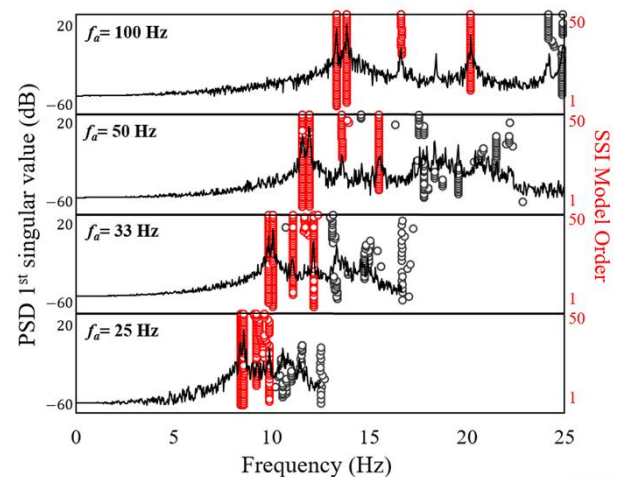


Fig. 21: Comparative identification results for FDD and SSI methods under decreasing analysis rates

The proposed compensation model is derived from the parametric ranges and idealized assumptions adopted in this study, including linear elastic material behavior, lumped mass representation, Rayleigh damping, and pinned joints. Its applicability to structures with characteristics falling outside the studied parametric domain, such as different

topologies, rise-to-span ratios, loading intensities, sampling rates, damping ratios, or connection detailing involving rigid joints with stocky members, should be treated with caution. For such cases, recalibration of the model using structure-specific data is recommended.

7. Conclusion

This study investigated the systematic errors arising in the extraction of natural frequencies from numerical models of double-layer truss domes. A parametric framework was developed in MATLAB and OpenSees to examine the influence of modeling and analysis parameters, including mesh density, global dimensions, loading intensity, analysis rate, sampling rate, damping ratio, and sensor placement, on the accuracy of the extracted frequencies.

The results demonstrate that the diverse parametric effects can be unified under a single governing mechanism, namely the degradation of spectral resolution as the structural frequency approaches the frequency associated with the analysis integration rate. This mechanism manifests as a systematic underestimation of the identified frequencies, which becomes more pronounced as the temporal discretization of the numerical model is coarsened. The proposed error compensation model, expressed as a function of the normalized extracted frequency, reduced the mean absolute percentage error from 12.5% to 0.63%, substantially mitigating the systematic bias inherent in frequency extraction from numerical simulations.

As the findings of this study are derived from numerical simulations under idealized assumptions, the model should be recalibrated using structure-specific data for applications beyond the studied parametric domain. Nevertheless, the framework offers a practical tool for researchers relying on numerical system identification, including those generating training datasets for machine learning, performing vibration-based damage identification, or applying SHM through model updating, as well as for engineers selecting analysis parameters in dynamic simulations. From a broader SHM perspective, the proposed framework enhances the reliability of frequency-based damage detection and model updating where numerical models serve as the primary source of dynamic information. Future work should extend these findings to alternative identification methods such as FDD and SSI, and explore configurations beyond the considered parametric domain.

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