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Combined Geometrical and Modal Model Calibration via Reality Capture and Geometrical Modal Analysis: Application to a Steel Building

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ABSTRACT

Digital Twins (DTs) have gained significant attention for integrating real-time sensor data with digital models, yet their application in structural dynamics is often limited to calibrating idealized design models using modal data. In this study, we explore whether the incorporation of as-built geometry impacts the dynamic model calibration process for a two-story steel-timber hybrid building on the Virginia Tech campus. A 3D point cloud (3DPC) of the building was captured using LiDAR scans, and the geometric dimensions of the structure were refined by cross-referencing the LiDAR data with design drawings, ensuring an accurate representation of the as-built structure while identifying geometric inconsistencies between design and construction. Challenges such as noisy and occluded point clusters were addressed using statistical outlier removal and filtering methods to enhance the representation of structural components. An as-built finite element model was developed based on this processed data, while an as-designed model was constructed from the original plans. Simultaneously, operational vibration data were collected using accelerometers mounted on each steel beam-column connection, enabling modal shapes and frequencies to be identified through operational modal analysis (OMA). Model calibration was then performed by incorporating the as-built geometry obtained from LiDAR data, updating the model to reflect actual geometric characteristics such as member centerline alignments. After these refinements, the calibrated model closely matched the OMA results, demonstrating the impact of as-built geometry on structural behavior. By integrating LiDAR-based geometric data and vibration-derived modal parameters, we bridge the gap between as-built geometry and dynamic model calibration, contributing to advancements in reality capture, model updating, and decision support for structural dynamics.

Keywords: OMA, Digital Twin, Reality Capture, Model Updating, Instrumentation

1. INTRODUCTION

The concept of Digital Twins (DTs) has gained significant traction in structural engineering, serving as a powerful tool for integrating real-time sensor data with computational models to enhance structural health monitoring (SHM) and predictive analysis [1–3]. Although DTs are extensively used across different fields, their role in structural dynamics usually involves updating idealized finite element (FE) models with experimental modal analysis (EMA) or operational modal analysis (OMA), often ignoring the impact of as-built geometrical deviations [1]. This paper explores the potential of using reality capture technologies to incorporate as-built geometries into the model updating process to better align predictive models with real-world conditions.

LiDAR-based scanning has emerged as an effective tool in SHM by providing high-resolution geometric data for civil structures [1,4]. LiDAR-generated 3D point clouds (3DPC) make it possible to accurately assess structural dimensions and identify inconsistencies between design and construction. While advanced segmentation techniques such as region-growing methods and geometric slicing have been explored as a way to automate model geometry extraction [5–7], there has been limited exploration of the implications for vibration-based model updating. Traditionally, updating techniques focus on refining mass, stiffness, and damping properties to enhance modeling accuracy [8]. However, relying on idealized models overlooks as-built variations that influence dynamic behavior, which could lead to unrealistic updating results. Previous studies have integrated LiDAR-based data with modal analysis [9], but to the authors' knowledge, there are no examples of comparing the benefits of the as-built approach to the traditional as-designed approach.

This study examines the impact of as-built geometric data on dynamic model calibration for a two-story steel-timber hybrid building at Virginia Tech. A high-resolution 3DPC was obtained through LiDAR scanning, allowing for a detailed assessment of structural dimensions by comparing the as-built structure with design drawings. Geometric inconsistencies between the as-designed and as-built structures, such as beam centerline inconsistencies, skewed structural members, and slab thickness variations, were identified and refined to improve model accuracy. An as-built FE model was developed and compared with an as-designed model based on original plans. Experimental modal parameters extracted through accelerometer-based OMA measurements were used to evaluate both models, which were updated with dimensions and geometric properties from LiDAR data. After refinement, the calibrated as-built model closely aligned with the experimental results, highlighting the significance of incorporating as-built geometry in modal calibration and emphasizing the role of reality capture technologies in structural model updating.

2. CASE STUDY & METHODOLOGY

2.1. Building description

The HITT Steel-Timber Hybrid Building, shown in Figure 1, is a two-story prefabricated testbed structure developed to assess the integration of mass timber and structural steel systems. Located on the Virginia Tech campus, it serves as an experimental building for hybrid construction, investigating the use of cross-laminated timber (CLT) and dowel-laminated timber (DLT) floor panels in conjunction with structural steel beams and columns. The CLT and DLT slabs span between steel beams, supported by six steel columns anchored to the reinforced concrete foundation. The facade consists of a prefabricated cladding system.

2.2. Reality capture and as-built geometry extraction

2.2.1. LiDAR scanning

LiDAR scanning was performed using a FARO Focus M70 terrestrial laser scanner, strategically placed within the HITT Steel-Timber Hybrid Building to capture a high-precision 3DPC. The scanner is capable of recording 3D reality data at distances up to 70 meters, ensuring detailed geometric documentation of the structure. The scanner has a range noise of about 0.8 mm at a distance of 10 meters, indicating its measurement resolution. To minimize occlusions and optimize scan coverage, multiple scanning stations were positioned at key vantage points, following a structured placement strategy designed to reduce data loss in critical structural regions. The LiDAR placement configuration for both stories is shown in Figure 2. Each scan was conducted with overlapping coverage, enabling accurate point cloud registration.

(a) (b)

Figure 1. (a) Steel-timber hybrid building; (b) The second story of the building.

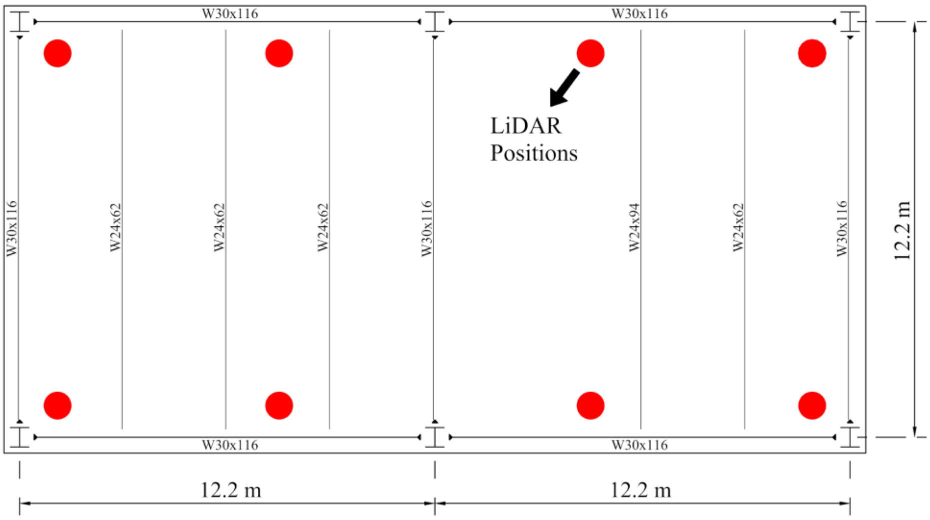


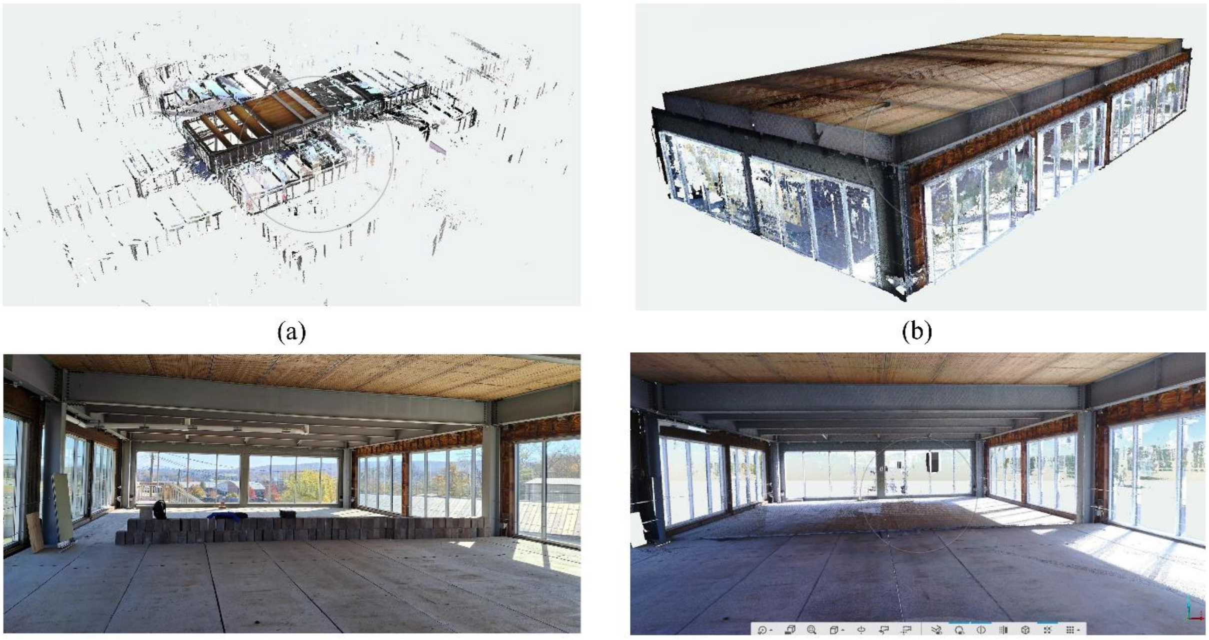
Figure 2. LiDAR placement configuration in plan view.

2.2.2. *Processing and registration*

The LiDAR point cloud data were processed and registered using FARO SCENE software to ensure a consistent and accurate representation of the as-built structure. The registration process involved aligning 8 scans per floor through an overlapping configuration, allowing precise stitching of individual scans into a unified 3DPC. Initial alignment was performed using the scanner's onboard positioning data, followed by fine-tuning through cloud-to-cloud registration to enhance accuracy. The registration process achieved approximately 60% overlap between merged scans. After registration, bounding boxes were applied to isolate the building interior and exterior, removing extraneous points and refining the dataset.

2.2.3. *Noise and occlusion handling methods*

FARO SCENE software was used to process the LiDAR data, focusing on removing unwanted points and refining the dataset. Initially, all data points outside the building were eliminated to retain only relevant structural information. Radius-based filtering was then applied to remove isolated points that did not contribute to meaningful geometric structures. To further clean the dataset, bounding boxes were created both inside and outside the building, enabling the systematic removal of remaining noise. Figures 3a and 3b illustrate the LiDAR data for the scan of the second floor, before and after noise removal, demonstrating the effectiveness of the applied filtering techniques. Furthermore, Figures 3c and 3d compare the density of collected points by presenting the same viewpoint in both a photograph and the corresponding LiDAR dataset.



(a) (b) (c) (d)

Figure 3. (a) Before noise removal; (b) After noise removal; (c) Picture of 2nd floor; (d) 3DPC of 2nd floor.

2.3. Finite element model development

2.3.1. *As-designed model*

The as-designed finite element model (FEM) was developed using the original construction plans and design documents. Structural components, including steel beams, columns, CLT and DLT floor panels, were modeled with their nominal dimensions and material properties as specified in the design documents. Standard boundary conditions and load assumptions were applied to ensure consistency with conventional structural analysis procedures. Element connectivity and support conditions were implemented as per the design intent, ensuring that the model accurately reflected the theoretical behavior of the structure. As shown in Figure 4, this model served as the baseline for comparative analysis against the as-built model.

2.3.2. *As-built model*

The as-built finite element model (FEM) was developed by incorporating LiDAR-derived geometric data, ensuring that the model accurately represents the constructed state of the building. The processed point cloud was used to refine member dimensions and positioning by comparing the as-built structure with the original design drawings. Geometric inconsistencies between the as-designed and as-built structures were identified and corrected to improve model accuracy. Material properties were kept consistent with the as-designed model.

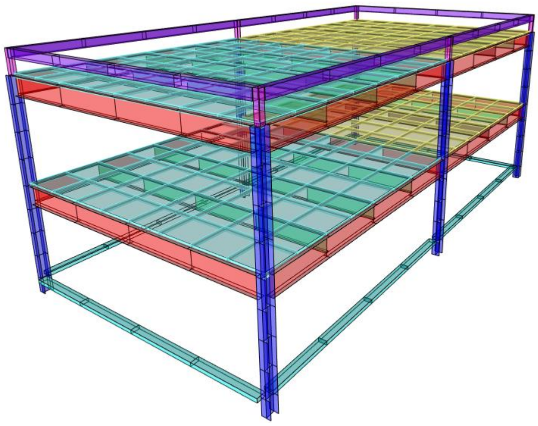


Figure 4. As-designed SAP2000 model.

2.4. Operational modal analysis

Operational Modal Analysis (OMA) was conducted to extract the dynamic characteristics of the HITT Steel-Timber Hybrid Building under ambient conditions. Unlike traditional experimental modal analysis, OMA does not require controlled external excitation and instead relies on natural environmental loads, such as wind and minor ground vibrations, to induce structural response. The goal of this analysis was to determine the modal parameters, including natural frequencies and mode shapes, which would be used to validate and refine the finite element models (as-designed and as-built).

2.4.1. Data collection using accelerometers

The accelerometers used in this study are Micron Optics os7520 fiber optic accelerometers, specifically designed for high-sensitivity vibration measurements. The os7520 offers a high sensitivity of up to 2500 nm/g, making it effective for capturing low-frequency structural vibrations. The accelerometers are placed as detailed in Figure 5, with four sensors per column, two per floor, where the first floor is denoted as Floor A and the second floor as Floor B. Each accelerometer on a given floor is aligned with either the X-axis or Y-axis, following the notation 1xA, where "1" refers to the first column, "x" indicates the X-axis direction, and "A" represents Floor A. Data were collected for 30 minutes at 50 Hz, then downsampled to 25 Hz. From the 24 total sensors deployed, 6 were removed due to poor signal quality or failure: 1yA, 3yB, 5yA, 5yB, 6yB, 6xB.

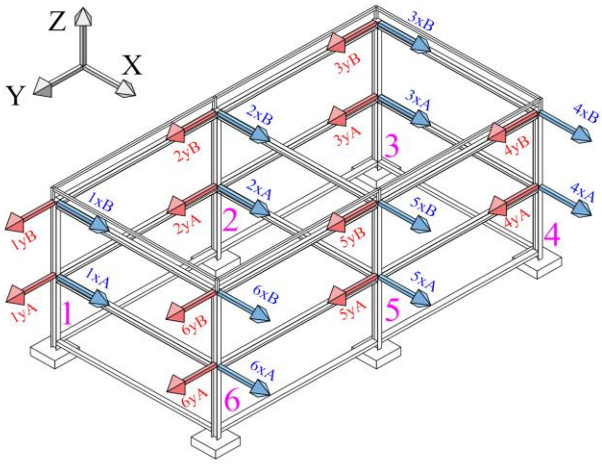


Figure 5. Accelerometer placement and orientation.

2.4.2. Modal parameters extraction

The raw data were high-pass filtered at 0.5 Hz and processed via the Covariance-Based Stochastic Subspace Identification method [10-12]. The open-source Modal Analysis Toolkit (https://code.vt.edu/vibes-lab/modal-analysis) was used for this analysis. Mode shapes and natural frequencies were manually extracted from the resulting stabilization diagram.

3. RESULTS & DISCUSSION

LiDAR data analysis revealed geometric imperfections that could impact structural behavior. One of the most prominent discrepancies was observed in the slab system, where the constructed CLT diaphragm deviated from the design intent by exhibiting a 3.5 cm increase in thickness relative to the adjacent DLT slab. Furthermore, significant misalignment was identified in a beam framing into the girders, with its two ends offset by 15 cm in the horizontal plane. While this beam was expected to be parallel to its neighboring members, one end was found to be skewed by 7.5 cm toward an adjacent beam, whereas the opposite end deviated by 7.5 cm in the opposite direction, as demonstrated in Figure 6. These differences were used to update the as-built finite element model accordingly.

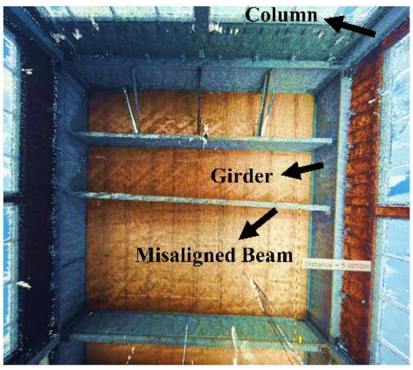


Figure 6. Misaligned beam example.

After the raw data was high-pass filtered at 0.5 Hz and processed via the Covariance-Based Stochastic Subspace Identification method mode shapes and natural frequencies were manually extracted from the resulting stabilization diagram, shown in Figure 7. From this diagram, it can be observed that the data were noisy but still sufficient to extract the first three modes: 2.15 Hz (transverse bending), 2.28 Hz (longitudinal bending), and 3.16 Hz (torsion). The extracted modal parameters are shown in Figure 8.

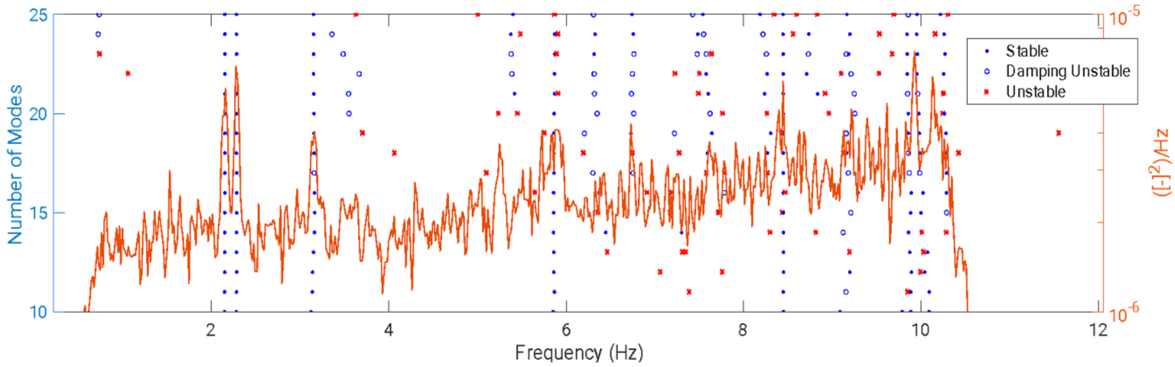


Figure 7. OMA stabilization diagram.

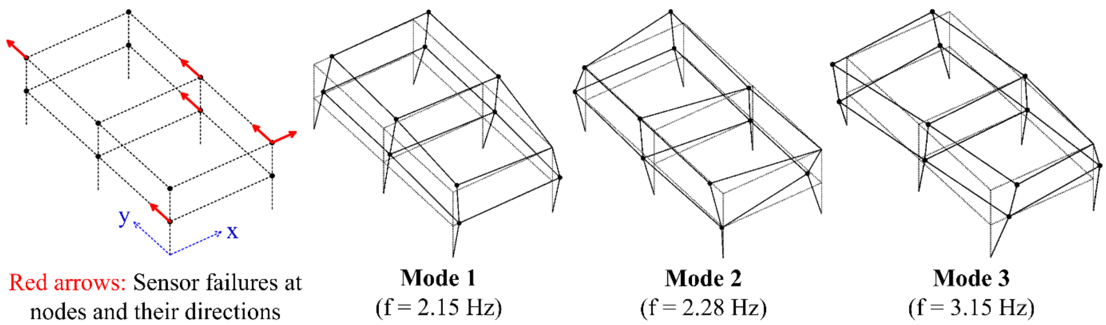


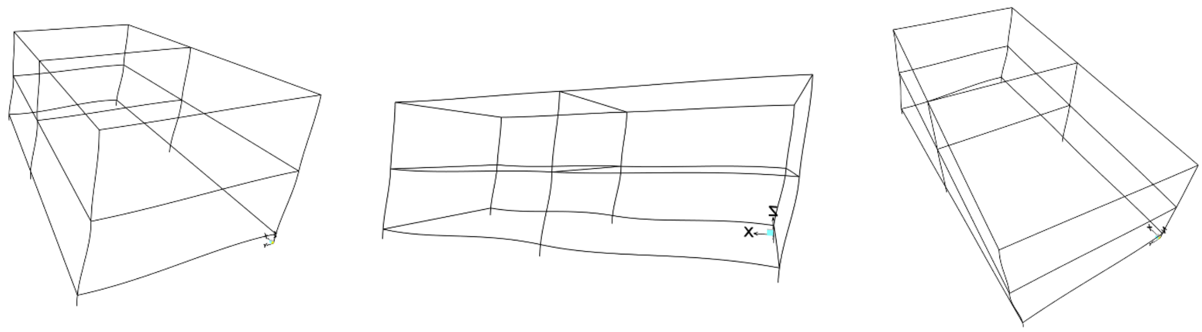
Figure 8. Representative mode shapes from the stable lines. Deflections appear as zero for missing sensors.

After implementing geometric modifications based on observations from the LiDAR data, the primary focus was to adjust the as-designed and as-built models so that their first mode frequency matched the first mode obtained from the OMA analysis, which was 2.15 Hz. As a baseline comparison, every change applied to the as-built model was also incorporated into the as-designed model, except for the modifications directly influenced by the LiDAR data. This approach ensured that the only difference between the two finite element models was the inclusion of LiDAR-based geometric corrections, allowing for a clear assessment of how as-built geometry impacts the modal behavior of the structure relative to OMA results. The most critical parameters, with relatively higher uncertainties, are summarized in Table 1. These parameters were adjusted manually in the calibration process to align the first mode frequency of the models as closely as possible with the OMA-derived value of 2.15 Hz.

Table 1. Main parameters changed during model updating.

Parameter	Initial value	Final value		Unit
		For As-Built Model	For As-Designed Model	
Facade load	0.5	1	1	kPa
Acoustic topping load	1.44	1.92	1.92	kPa
CLT density	500	400	350	kg/m^3
DLT density	500	400	350	kg/m^3
Rigid zone factor	1	0.9	0.9	-

After completing the iterative model updating process on the as-built model, which required multiple iterations, the final mode shapes and corresponding modal frequencies, as presented in Figure 9, were obtained.



Mode 1 (f = 2.15 Hz) **Mode 2** (f = 3.13 Hz) **Mode 3** (f = 3.26 Hz)

Figure 9. Modal shapes and frequencies by as-built model.

By comparing the modal analysis results of the finite element (FE) model with those obtained from the OMA, the corresponding Modal Assurance Criterion (MAC) values are determined. These MAC values provide a quantitative measure of the correlation between the mode shapes derived from the FE model and those identified through OMA, helping to assess the accuracy of the numerical model in capturing the actual dynamic behavior of the structure. The obtained MAC values, modal frequencies and relative errors in frequencies are presented in Table 2.

Table 2. Comparison of modal analysis results.

Modes	f (Hz)			Relative error in f (%)		MAC	
	OMA	As-Designed	As-Built	As-Designed	As-Built	As-Designed	As-Built
1 (x-translational)	2.15	2.15	2.15	0	0	**0.91**	**0.92**
2 (y-translational)	2.28	3.04	3.13	33.3	37.3	**0.96**	**0.96**
3 (torsion)	3.15	3.29	3.26	4.4	3.5	**0.85**	**0.88**

The results show that as-built models help to correct some small discrepancies between the finite element model and true behavior. In particular, when compared to the as-designed model, the as-built model achieved slightly higher Modal Assurance Criterion (MAC) values for the first and third modes, with 1% and 3% improvements, respectively. With respect to frequency, both the as-designed and as-built models match the first mode frequency exactly as intended through the model calibration process. For the second mode, the as-designed model provides slightly better agreement, with a relative error of 33.3% compared to 37.3% in the as-built model. In contrast, the as-built model performs better for the third mode, with a lower relative error of 3.5% compared to 4.4%. These results do not indicate a clear advantage to using the as-built model, through the manual calibration process. It is, however, worth noting that greater change to the nominal CLT and DLT density parameters were needed to calibrate the as-designed model, which could be considered a disadvantage.

4. CONCLUSION & FUTURE WORK

In this study, the role of as-built geometry in dynamic model calibration is investigated by comparing as-designed and as-built structural models of a two-story steel-timber hybrid building. Using LiDAR data, the as-built model was updated to better reflect the actual geometry of the structure, accounting for deviations from design drawings. OMA was conducted to obtain experimental modal parameters. The results showed that incorporating as-built geometry helps to improve Modal Assurance Criterion (MAC) values by a few percentage values. The results with regard to frequency did not show a clear advantage for either model. As-designed model offered better frequency accuracy for the second mode, the as-built model achieved improved agreement for the third mode. Automated optimization of the model parameters, rather than manual, may yield more insight into the question of the advantages between as-built and as-designed modeling. Overall, these findings support the idea that geometric differences between design and construction can influence dynamic properties, namely mode shapes, even at building scale. While these differences account for only a small amount of the modal response, they could be a benefit for high-precision applications like Digital Twins and Structural Health Monitoring. As automated model extraction from reality capture techniques becomes more sophisticated, OMA model updating strategies should seek to leverage as-built geometric information as part of the process.

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