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# Toward a Digital Twin Framework: Finite Element Modeling and Optimal Sensor Placement for Calatrava's Città Dello Sport in Rome

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## Abstract

This work presents the initial development of a digital twin framework for structural health monitoring and predictive maintenance of the Città dello Sport in Rome, designed by Santiago Calatrava. A high-fidelity finite element model is constructed from detailed geometric and material data derived from BIM and survey information. Modal analysis is performed to extract the structural dynamic features, forming the basis for a preliminary optimal sensor placement strategy. Sensor locations are determined using a sparse sensing approach based on QR factorization with column pivoting applied to a reduced-order basis of mode shapes. Two configurations are considered, targeting the reconstruction of the first ten and twenty modes. The results indicate that the method concentrates sensors in dynamically informative regions, enabling accurate reconstruction of the global structural response.

**Keywords:** digital twins, finite element modeling, computer-aided engineering, structural health monitoring, optimal sensor placement, modal analysis

# 1 Introduction

A computational model that fails to account for the inherent uncertainty and evolving behavior of engineering systems restricts its ability to be tailored to specific cases. This limitation reduces both its predictive accuracy and the usefulness of the insights it generates [1, 2]. As highlighted in the 2024 report by the *National Academies of Engineering, Science, and Medicine* [3], a digital twin (DT) differs from conventional digital models, which map input parameters to outputs, or digital shadows, which focus on data assimilation and model updating [4]. Instead, a DT is characterized as a customized virtual counterpart representing key features of a physical or engineered system or process. It is built upon computational models that continuously integrate real-time sensor data, allowing the virtual representation to evolve alongside its physical counterpart. This ongoing synchronization supports the exploration of hypothetical scenarios, enabling forward-looking decisions aimed at maximizing value. Crucially, the two-way exchange of information between the physical system and its digital replica establishes a feedback loop characterizing the DT paradigm toward increasing levels of autonomy beyond basic automation.

Originating within aerospace engineering [5, 6], DT technology has extended into a wide range of fields. These applications span structural health monitoring and predictive maintenance [7–10], additive manufacturing [11], smart cities [12], energy systems [13], urban sustainability [14], geotechnical engineering [15], tsunami modeling [16], railway infrastructure management [17], aerial vehicles [18], spacecraft operations [19], and climate science [20].

Managing aging structural systems is an increasingly demanding task in modern engineering. As requirements for performance, reliability, resilience, durability, and safety grow, inadequate maintenance or system failure can lead to substantial economic, safety, and societal consequences. In this setting, virtual tools capable of reproducing system behavior with sufficient accuracy, efficiency, and detail offer a pathway to mitigate such risks. Within a structural health monitoring (SHM) framework, a twinning approach can be implemented by integrating sensor data through data-driven diagnostics, enabling a *from-physical-to-digital* flow of information while accounting for both aleatory and epistemic uncertainties. The continuously updated digital representation can then be used to predict system evolution and guide optimal maintenance and management decisions, establishing a complementary *from-digital-to-physical* flow. This perspective is essential for enabling predictive maintenance strategies, moving beyond traditional time- or condition-based approaches [21, 22].

Modeling damage as a microstructural internal variable is impractical for large-scale systems; in practice, damage is inferred from changes in stiffness, mass, damping, or boundary conditions, which alter the structure's dynamic response. Vibration-based SHM addresses this by continuously collecting and analyzing multivariate timeseries data (e.g., displacements or accelerations) from sensor networks.

Damage identification is typically framed hierarchically: detection, localization, quantification, and prognosis [23]. Since acquiring real-world data across multiple damage states is generally infeasible for civil structures, vibration-based methods rely heavily on physics-based simulations [24]. These simulations are commonly built on discretized partial differential equations solved via numerical methods. This simulation-driven paradigm [25] enables the systematic exploration of hypothetical damage scenarios, linking simulated responses to the underlying damage parameters.

As structural and geometric complexity increases, a wider range of localized damage patterns may arise. Beyond requiring more refined models, accurately capturing their magnitude, shape, and location makes optimal sensor placement essential. Carefully designed sensor layouts enhance sensitivity to damage and maximize the effectiveness of the collected information [26]. Notable contributions in this field include approaches based on the Fisher information matrix and related metrics [27, 28], information entropy [29, 30], value of information [31, 32], and data-drive classifiers [33, 34].

This work presents the initial steps toward the development of a comprehensive DT framework for SHM and predictive maintenance of Città dello Sport in Rome, designed by Calatrava. The focus is on the construction of a high-fidelity finite element (FE) model based on detailed geometric and material data. This physics-based model provides the core simulation platform for optimal sensor placement. The resulting sensing network will support future SHM tasks, including modal characterization and data assimilation strategies.

# 2 Case study: Città dello Sport in Rome by Calatrava

**Project origins and evolution.** Città dello Sport in Rome Tor Vergata, designed by architect and engineer Santiago Calatrava, is a major example of contemporary monumental structural architecture in Italy and a well-known case of unfinished public project. Originally conceived to host the 2009 Swimming World Championships, the complex includes two twin facilities: the Palanuoto, with Olympic-size pools and about 5000 seats, and the Palasport, designed for up to 15,000 spectators. Both buildings were intended to be covered by symmetrical steel roofs, known as the "Vele" – Italian for "sails" – forming two geometrically identical structures connected by a central foyer. The design is defined by transverse arches and a main longitudinal spine arch spanning approximately 150 m.

Construction began in 2006 but soon experienced delays due to the high building complexity, design changes, and escalating costs. By 2009, it became clear that the project would not be completed in time, leading to the relocation of the Championships and the suspension of works. For over a decade, the complex remained un-

Figure 1: Città dello Sport in Rome as it appears today.

finished and exposed to deterioration. While the reinforced concrete structures were completed, only the Palanuoto was partially covered by the steel “Vela”, whereas the Palasport roof was never realized.

Despite years of abandonment, Città dello Sport has retained significant architectural and structural value, becoming an iconic element of the Roman landscape. Initial recovery works were included in the Jubilee 2025 interventions program, which introduced key safety measures, actions to arrest structural deterioration, and interventions to prevent further water infiltration. During this phase, the Palasport stands were also completed, temporarily converting it into an open-air arena (see Figure 1), and marking the first concrete step toward the recovery of the complex.

The history of degradation and incompleteness, together with the goal of resorting the complex and extending its life span, makes Città dello Sport an ideal case study for the development of a large scale SHM and predictive maintenance framework. This aligns perfectly the DT persepective, enabling early damage detection, improved maintenance planning, and enhanced public safety for future use. Given the high structural complexity of the system, this work focuses on defining an optimal sensor placement strategy for structural monitoring, enabling to balance SHM performance with the economic feasibility of designing and deploying the sensing network.

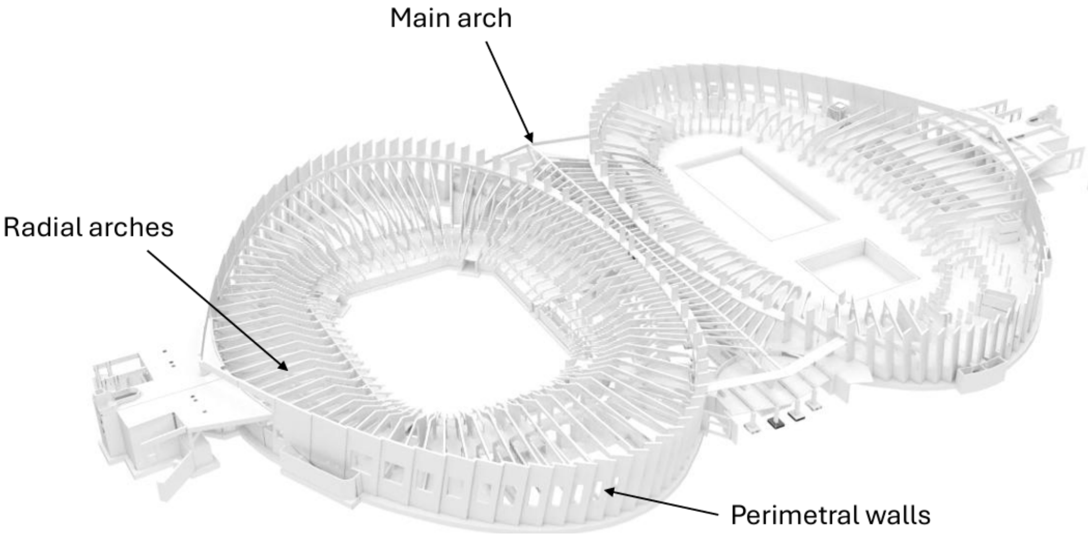



Figure 2: Detail of the concrete basement.

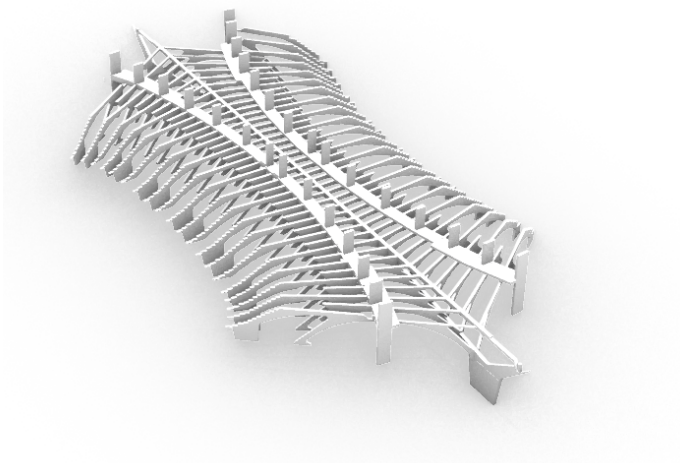


Figure 3: Detail of the central arch in the concrete basement.

**Description of the built structures.** The base of the complex, shared by the Palanuoto and Palasport, consists of a large reinforced concrete system comprising three main categories of elements (see Figure 2). The 132 inclined perimeter walls, 60 cm thick, define the outline of the two buildings, separate interior and exterior spaces, and provide the main support points for the roof. These are complemented by 136 radial arches of varying geometries, which support the stands and slabs, converging toward the central area where the two volumes meet. The final, yet fundamental, element is the central prestressed concrete spine arch (see Figure 3), which connects the two buildings, transfers the thrust of the radial arches, supports part of the foyer slab, and carries walls that sustain the central portion of the roof.

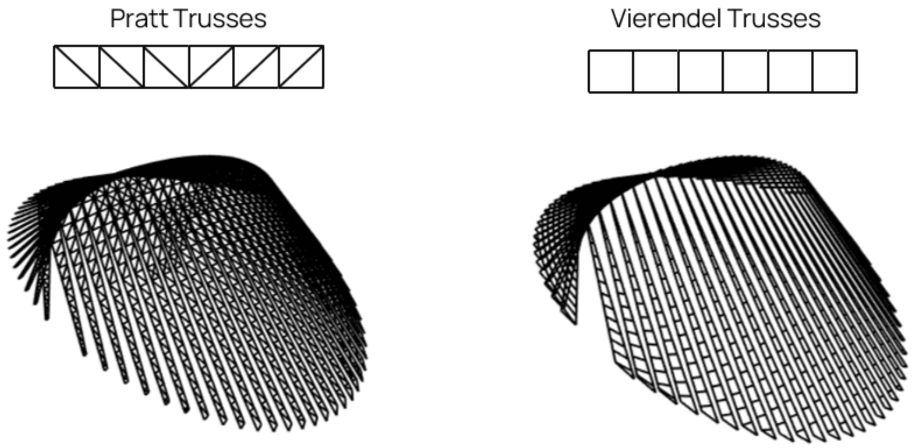



Figure 4: Detail of the steel roof with Pratt and Vierendeel truss systems.

The steel roof above the Palanuoto, known as “Vela”, is one of the most complex steel structures ever constructed in Italy. Rising nearly 70 m above ground level, it features a double-curvature geometry achieved through an alternating system of Vierendeel and Pratt trusses, as shown in Figure 4. These trusses connect on one side to the central spine arch and on the other to a perimeter ring that transfers loads to the reinforced-concrete walls. The corresponding “Vela” for the Palasport, originally designed as an identical counterpart, was never built. As a result, the Palasport remains an open reinforced-concrete volume, characterized primarily by its radial arches.

# 3 Finite element modeling

The structural geometry has been derived from a 3D BIM model created in `Autodesk Revit`. The BIM geometry has been in turn reconstructed from laser scanning surveys and subsequently validated against the original design drawings, which also provide the dimensions of the reinforced-concrete and steel components. The project documentation further specifies the nominal material classes: structural steels S460 and S335, and concrete C32/40, with mechanical properties listed in Table 1.

The FE model is implemented in the commercial software `SAP2000 v26`. The roof system is modeled using linear beam elements with six degrees of freedom per node (three translations and three rotations). Flexural releases are assigned to the diagonal and vertical members of the Pratt trusses. The concrete slabs, arches, and walls are instead modeled using four-node shell elements based on a Mindlin–Reissner thick-plate formulation, also featuring six degrees of freedom per node and accounting for transverse shear deformation.

| **Material** | **Young Modulus** $E$ [GPa] | **Poisson Ratio** $\nu$ [-] | **Density** [ton/m$^3$] |
|---|---|---|---|
| Reinforced Concrete | 30 | 0.2 | 2.5 |
| Structural Steel | 210 | 0.3 | 7.85 |

Table 1: Mechanical properties of the employed structural materials.

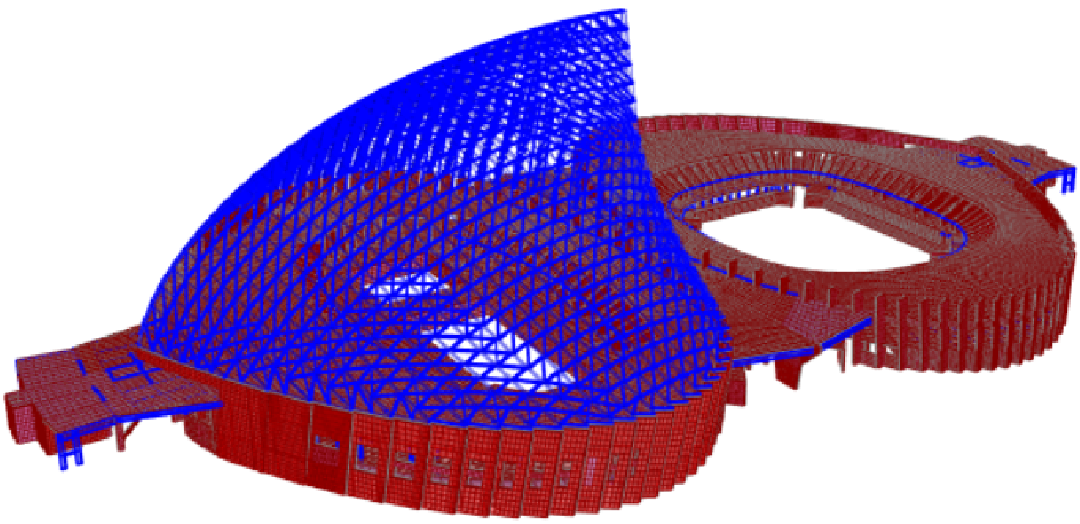


Figure 5: 3D view of the finite element model of Città dello Sport.

Figure 5 shows the resulting FE model, consisting of 165,810 shell elements, 7138 beam elements, and 193,207 nodes in total. Following an initial static validation, a modal analysis has been performed to extract the first 200 vibration modes. The analysis considers only the dead load, which currently represents the sole permanent load acting on the structure, and fully clamped boundary conditions at the base. Table 2 summarizes the modal properties for the first twenty modes, while two representative mode shapes (1st and 6th) are shown in Figure 6.

# 4 Preliminary results for optimal sensor placement

In this study, optimal sensor placement is performed using QR factorization with column pivoting applied to a reduced-order basis, following the sparse sensing framework in [35]. The basis is constructed from mode shapes obtained through FE modal analysis. The method selects measurement locations that optimally condition the reconstruction operator associated with this basis.

Two configurations are considered: reconstruction using the first 10 modes with 10 sensors, and the first 20 modes with 20 sensors. Figure 7a shows the 10 optimal

| **Mode** | **Period** $T$ [s] | **Frequency** $f$ [Hz] |
|---|---|---|
| 1 | 1.068 | 0.936 |
| 2 | 1.066 | 0.938 |
| 3 | 1.020 | 0.980 |
| 4 | 1.011 | 0.990 |
| 5 | 0.748 | 1.337 |
| 6 | 0.729 | 1.372 |
| 7 | 0.707 | 1.415 |
| 8 | 0.667 | 1.499 |
| 9 | 0.607 | 1.647 |
| 10 | 0.595 | 1.681 |
| 11 | 0.592 | 1.688 |
| 12 | 0.572 | 1.747 |
| 13 | 0.568 | 1.759 |
| 14 | 0.554 | 1.806 |
| 15 | 0.541 | 1.848 |
| 16 | 0.512 | 1.953 |
| 17 | 0.505 | 1.979 |
| 18 | 0.477 | 2.095 |
| 19 | 0.463 | 2.159 |
| 20 | 0.456 | 2.192 |

Table 2: Modal periods and frequencies for the first twenty modes.

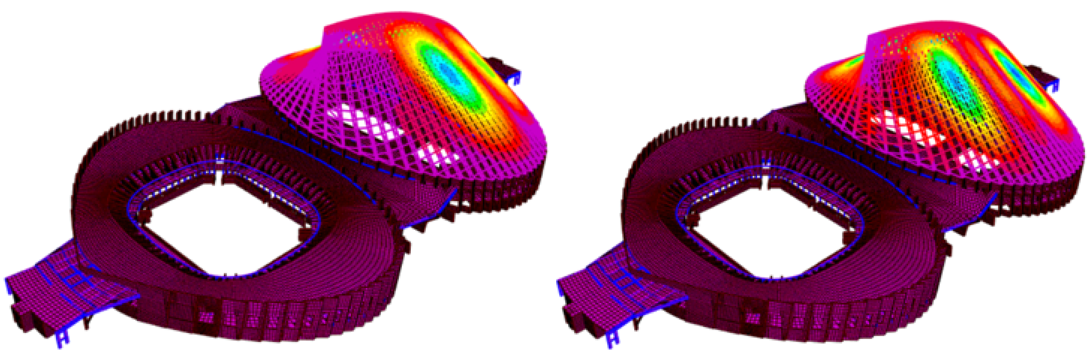
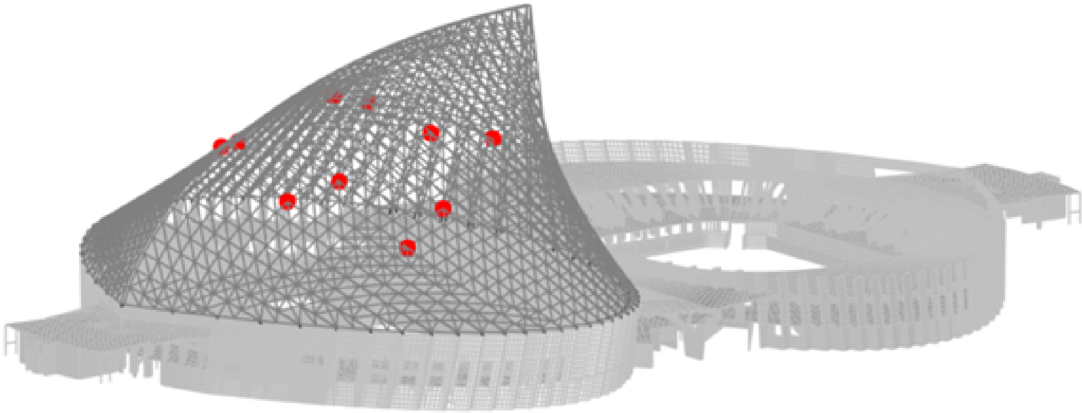


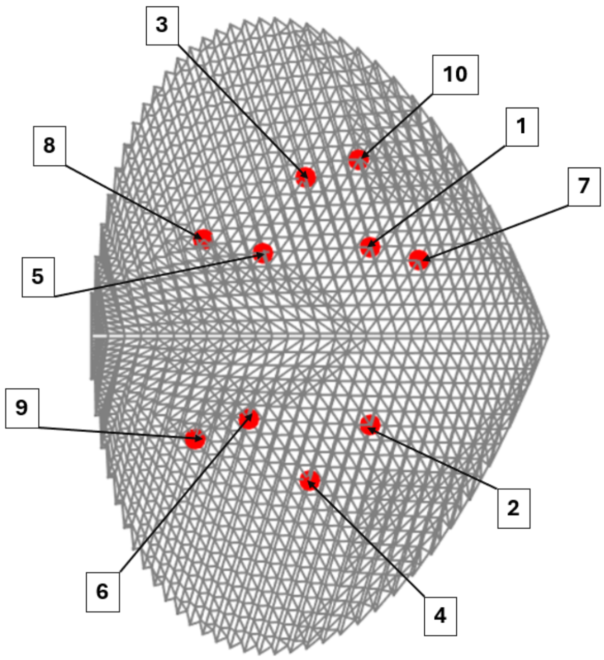
Figure 6: Finite element analysis - 1st and 6th vibration modes.

sensor locations for the first case, while Figure 7b reports the corresponding selection order. The results for the 20-mode configuration are presented in Figure 8a, with the selection sequence shown in Figure 8b.

In the 10-sensor configuration, all sensors are located on the steel roof, reflecting its higher compliance compared to the concrete substructure. When more modes are included, an additional sensor is placed in the concrete basement, in a region characterized by localized dynamic behavior. This spurious selection arises from the absence



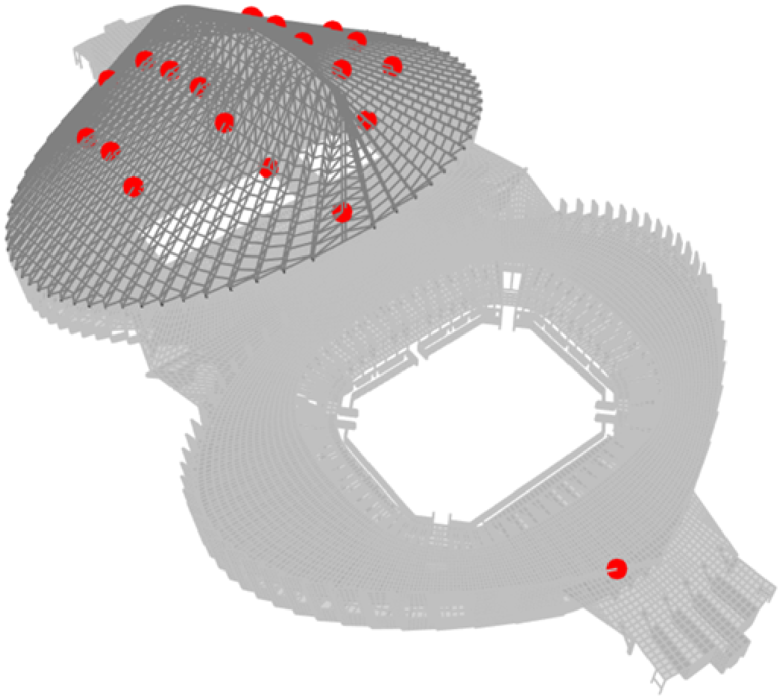
(a)



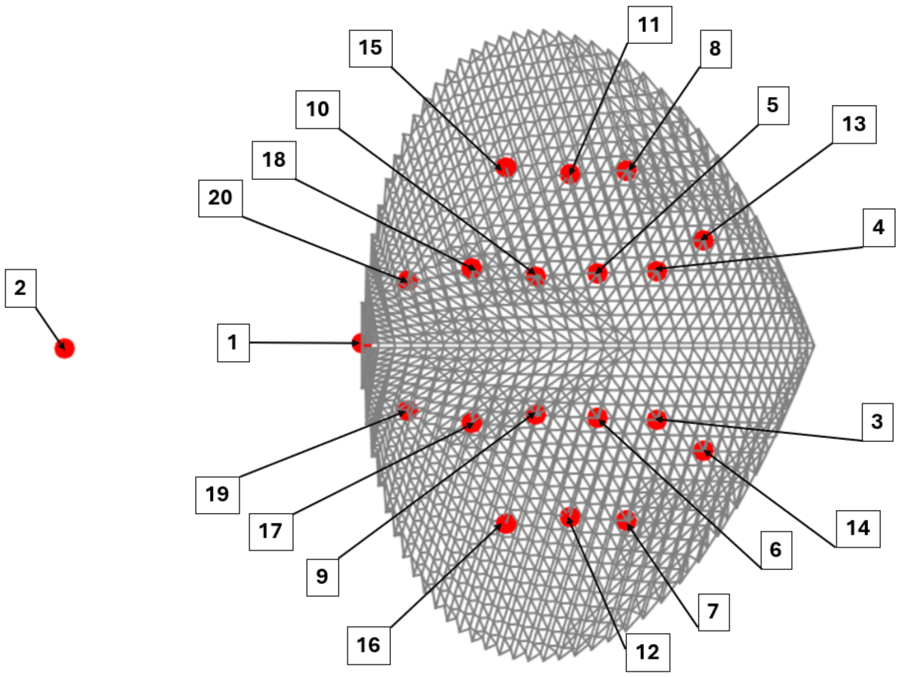

(b)

Figure 7: Optimal sensor placement results: (a) 3D view of the sensor layout corresponding to ten sensors selected for reconstructing the first ten structural modes; (b) detail of the order in which the sensors are selected.

of prior filtering of the mode shapes, which allows local modes with periods comparable to those of the roof to influence the placement. As a result, the algorithm also captures local dynamics not relevant for monitoring the global behavior of the roof.



(a)




(b)

Figure 8: Optimal sensor placement results: (a) 3D view of the sensor layout corresponding to twenty sensors selected for reconstructing the first twenty structural modes; (b) detail of the order in which the sensors are selected.

# 5 Conclusion and future developments

This work represents a first step toward a comprehensive digital twin framework for structural health monitoring and predictive maintenance of the Città dello Sport in Rome. A finite element model has been developed from detailed geometric data and used to perform a modal analysis. The resulting mode shapes have been employed for a preliminary optimal sensor placement using a sparse sensing strategy based on QR factorization with column pivoting. Two configurations have been considered, respectively targeting the reconstruction of the first ten and twenty mode shapes.

The resulting sensor layouts show that the algorithm concentrates measurement points in dynamically informative regions, where modal displacements are significant and spatially independent. This confirms the effectiveness of the unsupervised, modal-based approach in identifying locations suitable for reconstructing global dynamic features. However, when local modes are included in the basis, the algorithm may select sensor locations with limited relevance for the global response. This highlights a key limitation of unsupervised optimal sensor placement in large, complex structures, where local modes can bias the selection toward locations that are not informative for global behavior and damage detection.

Future work will address this limitation by developing a supervised sensor placement strategy based on explicitly modeled damage scenarios. By directly linking sensor selection to damage detection performance, the approach will identify configurations that are maximally informative for structural health monitoring while reducing the influence of spurious local effects.

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# References

[1] B. Moya, I. Alfaro, D. Gonzalez, F. Chinesta, and E. Cueto, "Physically sound, self-learning digital twins for sloshing fluids," *PLoS One*, vol. 15, no. 6, p. e0234569, 2020.

[2] D. A. Arcones, M. Weiser, P.-S. Koutsourelakis, and J. F. Unger, "Model Bias Identification for Bayesian Calibration of Stochastic Digital Twins of Bridges," *Applied Stochastic Models in Business and Industry*, vol. special issue article, 2024.

[3] National Academy of Engineering and National Academies of Sciences, Engineering, and Medicine, *Foundational Research Gaps and Future Directions for Digital Twins*. Washington, DC: The National Academies Press, 2024.

[4] W. Kritzinger, M. Karner, G. Traar, J. Henjes, and W. Sihn, "Digital Twin in manufacturing: A categorical literature review and classification," *IFAC-PapersOnLine*, vol. 51, no. 11, pp. 1016–1022, 2018. 16th IFAC Symposium on Information Control Problems in Manufacturing INCOM 2018.

[5] Shafto, Mike and Conroy, Mike and Doyle, Rich and Glaessgen, Ed and Kemp, Chris and LeMoigne, Jacqueline and Wang, Lui, "Technology Area 11: Modeling, Simulation, Information Technology & Processing," tech. rep., National Aeronautics and Space Administration, Washington, District of Columbia, 2020.

[6] Digital Twin: Definition & Value — An AIAA and AIA Position Paper, "AIAA Digital Engineering Integration Committee and others," tech. rep., AIAA: Reston, Virginia, 2020.

[7] M. Torzoni, M. Tezzele, S. Mariani, A. Manzoni, and K. E. Willcox, "A digital twin framework for civil engineering structures," *Computer Methods in Applied Mechanics and Engineering*, vol. 418, p. 116584, 2024.

[8] E. Varetti, M. Torzoni, M. Tezzele, and A. Manzoni, "Adaptive digital twins for predictive decision-making: Online Bayesian learning of transition dynamics." arXiv preprint arXiv:2512.13919, 2026.

[9] M. Torzoni, D. Maisto, A. Manzoni, F. Donnarumma, G. Pezzulo, and A. Corigliano, "Active digital twins via active inference," *Engineering Applications of Artificial Intelligence*, vol. 174, p. 114519, 2026.

[10] C. Li, S. Mahadevan, Y. Ling, S. Choze, and L. Wang, "Dynamic Bayesian Network for Aircraft Wing Health Monitoring Digital Twin," *AIAA Journal*, vol. 55, no. 3, pp. 930–941, 2017.

[11] A. Phua, C. Davies, and G. Delaney, "A digital twin hierarchy for metal additive manufacturing," *Computers in Industry*, vol. 140, p. 103667, 2022.

[12] M. Jans-Singh, K. Leeming, R. Choudhary, and M. Girolami, "Digital twin of an urban-integrated hydroponic farm," *Data-Centric Engineering*, vol. 1, p. 20, 2020.

[13] A. L. Reis, A. Andrade-Campos, P. Matos, C. Henggeler Antunes, and M. A. Lopes, "An energy and cost efficiency Model Predictive Control framework to optimize Water Supply Systems operation," *Applied Energy*, vol. 384, p. 125478, 2025.

[14] A. Tzachor, S. Sabri, C. E. Richards, A. Rajabifard, and M. Acuto, "Potential and limitations of digital twins to achieve the sustainable development goals," *Nature Sustainability*, vol. 5, no. 10, pp. 822–829, 2022.

[15] D. Cotoarbă, D. Straub, and I. F. Smith, "Probabilistic digital twins for geotechnical design and construction." arXiv preprint arXiv:2412.09432v1, 2024.

[16] S. Henneking, S. Venkat, and O. Ghattas, "Goal-Oriented Real-Time Bayesian Inference for Linear Autonomous Dynamical Systems With Application to Digital Twins for Tsunami Early Warning." arXiv preprint arXiv:2501.14911v1, 2025.

[17] G. Arcieri, C. Hoelzl, O. Schwery, D. Straub, K. Papakonstantinou, and E. Chatzi, "POMDP inference and robust solution via deep reinforcement learning: An application to railway optimal maintenance," *Machine Learning*, 2024.

[18] M. Tezzele, S. Carr, U. Topcu, and K. E. Willcox, "Adaptive planning for risk-aware predictive digital twins." arXiv preprint arXiv:2407.20490v2, 2024.

[19] S. Henao-Garcia, M. Kapteyn, K. E. Willcox, M. Tezzele, M. Castroviejo-Fernandez, T. Kim, M. Ambrosino, I. Kolmanovsky, H. Basu, P. Jirwankar, and R. Sanfelice, "Digital-Twin-Enabled Multi-Spacecraft On-Orbit Operations," in *AIAA SCITECH 2025 Forum*, p. 1432, 2025.

[20] P. Bauer, B. Stevens, and W. Hazeleger, "A digital twin of Earth for the green transition," *Nature Climate Change*, vol. 11, no. 2, pp. 80–83, 2021.

[21] S. D. Glaser and A. Tolman, "Sense of Sensing: From Data to Informed Decisions for the Built Environment," *Journal of Infrastructure Systems*, vol. 14, no. 1, pp. 4–14, 2008.

[22] J. D. Achenbach, "Structural health monitoring – What is the prescription?," *Mechanics Research Communications*, vol. 36, no. 2, pp. 137–142, 2009.

[23] A. Rytter, *Vibrational Based Inspection of Civil Engineering Structures*. PhD thesis, University of Aalborg, Denmark, 1993.

[24] C. Farrar and K. Worden, *Structural Health Monitoring: A Machine Learning Perspective*. John Wiley & Sons, 2013.

[25] T. Taddei, J. D. Penn, M. Yano, and A. T. Patera, "Simulation-Based Classification; a Model-Order-Reduction Approach for Structural Health Monitoring," *Archives of Computational Methods in Engineering*, vol. 25, pp. 23–45, 2018.

[26] W. Ostachowicz, R. Soman, and P. Malinowski, "Optimization of sensor placement for structural health monitoring: A review," *Structural Health Monitoring*, vol. 18, no. 3, pp. 963–988, 2019.

[27] Z. Shi, S. Law, and L. Zhang, "Optimum Sensor Placement for StructuralDamage Detection," *Journal of Engineering Mechanics*, vol. 126, no. 11, pp. 1173–1179, 2000.

[28] J. Penny, M. Friswell, and S. Garvey, "Automatic choice of measurement locations for dynamic testing," *AIAA Journal*, vol. 32, no. 2, pp. 407–414, 1994.

[29] G. Capellari, E. Chatzi, and S. Mariani, "Structural Health Monitoring Sensor Network Optimization through Bayesian Experimental Design," *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering*, vol. 4, no. 2, p. 04018016, 2018.

[30] G. Capellari, E. Chatzi, and S. Mariani, "Cost–Benefit Optimization of Structural Health Monitoring Sensor Networks," *Sensors*, vol. 18, no. 7, p. 2174, 2018.

[31] A. Kamariotis, E. Chatzi, and D. Straub, "Value of information from vibration-based structural health monitoring extracted via Bayesian model updating," *Mechanical Systems and Signal Processing*, vol. 166, p. 108465, 2022.

[32] C. Malings and M. Pozzi, "Value-of-information in spatio-temporal systems: Sensor placement and scheduling," *Reliability Engineering & System Safety*, vol. 172, pp. 45–57, 2018.

[33] M. G. Kapteyn and K. E. Willcox, "Design of Digital Twin Sensing Strategies Via Predictive Modeling and Interpretable Machine Learning," *Journal of Mechanical Design*, vol. 144, no. 9, p. 091710, 2022.

[34] J.-W. Kim, M. Torzoni, A. Corigliano, and S. Mariani, "Attention Mechanism-Driven Sensor Placement Strategy for Structural Health Monitoring," *Engineering Proceedings*, vol. 27, no. 1, p. 43, 2022.

[35] K. Manohar, B. W. Brunton, J. N. Kutz, and S. L. Brunton, "Data-Driven Sparse Sensor Placement for Reconstruction: Demonstrating the Benefits of Exploiting Known Patterns," *IEEE Control Systems Magazine*, vol. 38, pp. 63–86, 2018.