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Enhancing Dynamic Identification in Heritage Buildings: A Comparative Study of Optimal Sensor Placement Metrics

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ABSTRACT

Structural Health Monitoring (SHM) plays a crucial role in the preservation of heritage structures, enabling the early detection of damage and supporting informed conservation strategies. The effectiveness of SHM depends on the quality of sensor placement, which should maximise the information collected while minimizing the number of sensors. Various optimisation strategies have been developed for Optimal Sensor Placement (OSP), relying on different metrics to identify the most informative sensor locations. However, most of these methods have been applied primarily to modern structures, with very limited validation in historical buildings, which present unique challenges due to their complex geometries, material heterogeneity, and structural evolution over time.

This study aims to bridge this gap by implementing and comparing multiple OSP metrics within the context of a real heritage structure. A data-driven approach is adopted, using experimentally identified modal shapes from an Operational Modal Analysis (OMA) campaign, to mitigate the uncertainties associated with numerical models. The Church of Santa Ana in Seville, Spain, serves as a representative case study due to its architectural complexity and historical significance. The findings reveal notable variations in the performance of the metrics, clearly underscoring the need for tailored optimisation criteria to address the unique challenges of heritage buildings.

Keywords: Historical buildings, masonry structures, Structural Health Monitoring, Optimal Sensor Placement, preventive conservation, heuristic algorithms, energy-based metrics

1. INTRODUCTION

The assessment and conservation of heritage structures require advanced investigation and analysis techniques due to their architectural complexity, historical evolution, and material heterogeneity, making it challenging to define their structural properties and mechanical behaviour accurately [1]. Structural Health Monitoring (SHM) plays a crucial role in preserving these structures by enabling continuous assessment and early damage detection. However, implementing an effective SHM system in heritage buildings requires addressing relevant issues, particularly regarding the optimal placement of sensors to maximize the information obtained from a limited number of measurement points.

Optimal Sensor Placement (OSP) methodologies address this challenge by identifying strategic locations that enhance the quality of collected data while minimizing the number of required sensors. A wide range of optimisation metrics has been developed for this purpose, including criteria based on modal energy distribution or modal linear independence. Despite their extensive application in numerical models and laboratory settings, these metrics have been scarcely tested in real heritage structures and studies evaluating their effectiveness in this context are limited [2]. The irregular geometries, interacting macro-elements, and heterogeneous materials of historical buildings may affect their performance, raising questions about their suitability for complex cases.

Another critical limitation of many OSP strategies is their reliance on numerical models to estimate modal shapes and dynamic properties. In heritage structures, where material characteristics and boundary conditions are often uncertain, model-based approaches can introduce significant inaccuracies. A data-driven methodology based on experimentally identified modal parameters provides an alternative, ensuring that optimisation strategies reflect the actual structural behaviour rather than an idealized numerical representation.

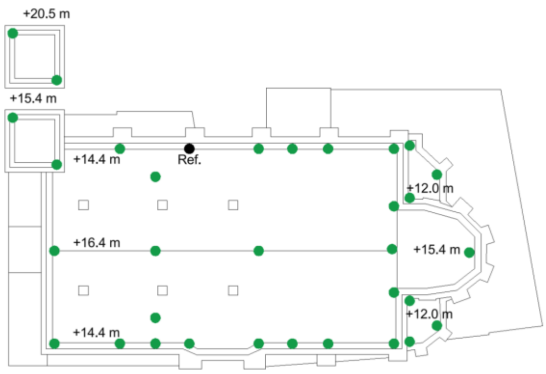
This study investigates the implementation and comparative analysis of multiple OSP metrics for a heritage masonry structure using a data-driven approach, that considers the modal shapes identified from an Operational Modal Analysis (OMA) campaign as input for the optimisation process. The Church of Santa Ana in Seville, Spain, is selected as a case study due to its architectural significance and complex structural configuration. The research evaluates the effectiveness of different optimisation criteria in capturing the building's dynamic response. The findings contribute to refining SHM strategies for heritage structures, supporting more effective conservation and risk mitigation efforts.

2. CASE STUDY: SANTA ANA CHURCH

The Church of Santa Ana in Seville, built in the 13th century, follows a rectangular layout with three naves and a main apse. A bell tower is attached to one side of the façade (Figure 1a) [3]. The masonry is predominantly brick, with stone reserved for critical structural elements. More information about the building can be found in [4].

An ambient vibration test for the operational modal analysis was conducted and used as the basis for the data-driven optimisation process. Figure 1b shows the 33 instrumented nodes of the OMA campaign that are considered for the data-driven optimisation analysis.

(a)



(b)

Figure 1. Santa Ana Church: (a) aerial view; (b) plan view of the accelerometer locations.

The data was processed using ARTeMIS software [5]. Six modal shapes were identified and considered for the OSP problem. They are presented in Figure 2. The first two modes are diagonal bending modes of the tower. The third mode combines a transverse bending shape of the nave with a tower bending mode. The fourth mode is a longitudinal mode of the nave while the fifth mode is a torsional mode. The sixth mode is a vertical mode of the nave's roof. More datil about the OMA campaign and the modal identification can be found in [4].

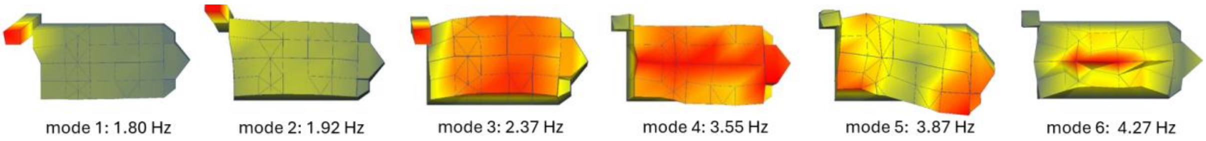


Figure 2. Six experimental vibration modes.

3. OPTIMAL SENSOR PLACEMENT PROBLEM

OSP is a combinatorial optimisation problem, where the objective is to determine the most informative sensor locations to identify a set of target modes given a predefined number of sensors to be selected among a larger number of candidates. Due to the exponential growth in the number of possible sensor combinations, evaluating all configurations of sensors out of the available candidates is computationally impractical. Consequently, different optimisation approaches have been developed based on specific objective functions that quantify the effectiveness of a given sensor configuration [6].

These objective functions can be broadly classified into two categories. The first category consists of metrics that evaluate the performance of individual sensors independently, allowing for a straightforward ranking-based selection [7]. The second category includes metrics that assess the quality of a sensor set as a whole, making their evaluation dependent on the specific combination of selected sensors. These metrics are often related to maximising the linear independence of modal information, minimising redundancy, or improving numerical stability [8] [9].

Since an exhaustive evaluation of all possible configurations is not feasible, alternative strategies must be considered to efficiently determine an optimised sensor configuration. For metrics in the first category, a simple ranking-based selection is sufficient, whereas for metrics in the second category, an iterative heuristic approach is usually implemented. In this work, the Backward Sensor Sequential Placement (BSSP) method is adopted, where sensors are sequentially removed from an initial candidate set until the desired number of sensors is reached [10]. This allows for a computationally feasible yet effective optimisation process, ensuring a balance between accuracy and efficiency.

3.1. Metrics and formulation

A large number of metrics found in the literature for OSP applied to different types of structures are compiled and considered for application to this case study. From the first group of metrics mentioned above, the following energy-based metrics are included: Non-Optimal Driving Point (NODP) [11], Mode Shape Summation Plot (MSSP) [12], Eigenvalue Vector Product (EVP)[13], Average Driving Point Residue (ADPR), and Weighted ADPR (WADPR)[14], including also in this group the variance method (VM) [15]. The second group of metrics, which depend on the specific combination of selected sensors, includes some metrics based on the Fisher Information Matrix (FIM), as the Effective Independence method (EfI) [8] and its variant EfI DPR [16], the Estimation Error Minimisation (EEM) [17] and the Information Entropy Index (IEI) [10]. Other metrics in this group are the modified VM (MVM) [18], QR-Decomposition (QRD) [19], Singular Value Decomposition ratio (SVDr) [9] and three metrics based on the minimisation of the off-diagonal values of the Modal Assurance Criterion (MAC): minMAC1 (maximum value) [20], minMAC2 (mean) [21], and minMAC3 (root-mean-square) [9]. The objective functions for all these metrics are presented in Table 1, where $\mathbf{\Phi}$ is the modal matrix (for EEM and IEI $\mathbf{\Phi}$ representing the full set of candidates and $\mathbf{\Phi}_{\mathrm{m}}$ considering just the partition to the measure locations), $\mathbf{\Lambda}$ the frequency vector, σ_{max} the largest singular value, σ_{min} the smallest singular value of the modal matrix, and c_{ij} are the $\mathbf{\Phi}$ covariance matrix coefficients.

Table 1. OSP metrics objective functions.

MSSP	EVP	NODP
$f_{MSSP}(\mathbf{\Phi}) = max\left(\sum_{j=1}^{N} \lvert \mathbf{\Phi}_{ij} \rvert\right)$	$f_{EVP}(\mathbf{\Phi}) = max\left(\prod_{j=1}^{N} \lvert \mathbf{\Phi}_{ij} \rvert\right)$	$f_{NODP}(\mathbf{\Phi}) = max\left(\min_{j} \lvert \mathbf{\Phi}_{ij} \rvert\right)$

ADPR	WADPR
$f_{ADPR}(\mathbf{\Phi}) = max(\mathbf{ADPR})$ $\mathbf{ADPR}_j = \frac{1}{n}\sum_{i=1}^{n} \mathbf{DPR}_{ij}$	$f_{WDPR}(\mathbf{\Phi}) = max(\mathbf{DPR}_{min} \otimes \mathbf{ADPR})$ $\mathbf{DPR} = \mathbf{\Phi}_{ij} \otimes \mathbf{\Phi}_{ij}\mathbf{\Lambda}^{-1}$

EfI and EfI DPR	IEI
$f_{EfI}(\mathbf{\Phi}) = max\left(min(\mathrm{diag}(\mathbf{E}))\right)$ $\mathbf{E} = \mathbf{\Phi}\left(\mathbf{\Phi}^{\mathrm{T}}\mathbf{\Phi}\right)^{-1}\mathbf{\Phi}^{\mathrm{T}}$ $f_{EfIDPR}(\mathbf{\Phi}) = max\left(min(\mathrm{diag}(\mathbf{E}) \otimes \mathbf{DPR})\right)$	$f_{\mathrm{IEI}}(\mathbf{\Phi}, \mathbf{\Phi}_m) = min\sqrt{\frac{\det(\mathbf{\Phi}^T\mathbf{\Phi})}{\det(\mathbf{\Phi}_m^T\mathbf{\Phi}_m)}}$

VM	MVM
$f_{VM}(\mathbf{\Phi}) = max\left(\sum_{j=1}^{N} \frac{c_{ii}}{\mathrm{Dep}_i}\right)$ $\mathrm{Dep}_i = \sum_{i \neq j} c_{ij}$	$f_{MVM}(\mathbf{\Phi}) = max\left(\min_{i}(\mathrm{pc}_i)\right)$ $pc_i = \frac{c_{ii}}{\sqrt{\sum_{j=1, j\neq i} c_{ij}^2}}$

EEM	SVDr	minMAC1
$f_{\mathrm{EEM}}(\mathbf{\Phi}, \mathbf{\Phi}_m) = min\ \mathrm{tr}\ (\mathbf{\Gamma})$ $\mathbf{\Gamma} = \mathbf{\Phi}\left(\mathbf{\Phi}_{\mathrm{m}}^{\mathrm{T}}\mathbf{\Phi}_{\mathrm{m}}\right)^{-1}\mathbf{\Phi}^{\mathrm{T}}$	$f_{\mathrm{SVDr}}(\mathbf{\Phi}) = min\left(\frac{\sigma_{max}}{\sigma_{min}}\right)$	$f_{\mathrm{minMAC1}}(\mathbf{\Phi}) = min\left(\max_{i \neq j} \mathrm{MAC}_{ij}\right)$

minMAC2	minMAC3
$f_{\mathrm{minMAC2}}(\mathbf{\Phi}) = min\left(\frac{1}{k(k-1)}\sum_{i \neq j} \mathrm{MAC}_{ij}\right)$	$f_{\mathrm{minMAC3}}(\mathbf{\Phi}) = min\sqrt{\frac{1}{k(k-1)}\sum_{i \neq j} \mathrm{MAC}_{ij}^2}$

3.2. Implementation and results

The OSP problem is formulated considering the 99 degrees of freedom (DOFs) measured during the experimental campaign and the six target modes identified. The number of sensors is set between the minimum required, which equals the number of modal shapes to be identified (six), and a maximum of ten. These configurations are referred to as sensor sets (SS). The results obtained for the different metrics are presented in Figure 3 and analysed qualitatively, focusing on the distribution of sensors across macroelements, namely the tower (T), nave (N), and apse (A), as well as their orientation in the longitudinal (X), transversal (Y), and vertical (Z) directions.

For a correct interpretation of the six modal shapes based on a reduced number of sensors, at least one sensor in TX and TY at the top (modes 1 and 2), two sensors in NY (modes 3 and 5), one in NX (mode 4), and one in NZ (mode 6) are considered necessary. Additionally, the distribution of sensors within each macroelement is examined to ensure adequate coverage.

The methods based on the selection of the more suitable sensors based on a rank, namely NODP, MSSP, EVP, ADPR and WDPR, present some differences for the minimum sensor configuration but they tend to converge as the number of sensors increases. They generally follow a pattern with 2-4 sensors at the top of the tower, while the remaining are NY sensors located on the lateral wall opposite to the tower side. For these five optimisation metrics, no NX or NZ sensors are considered, nor are any placed in the apse.

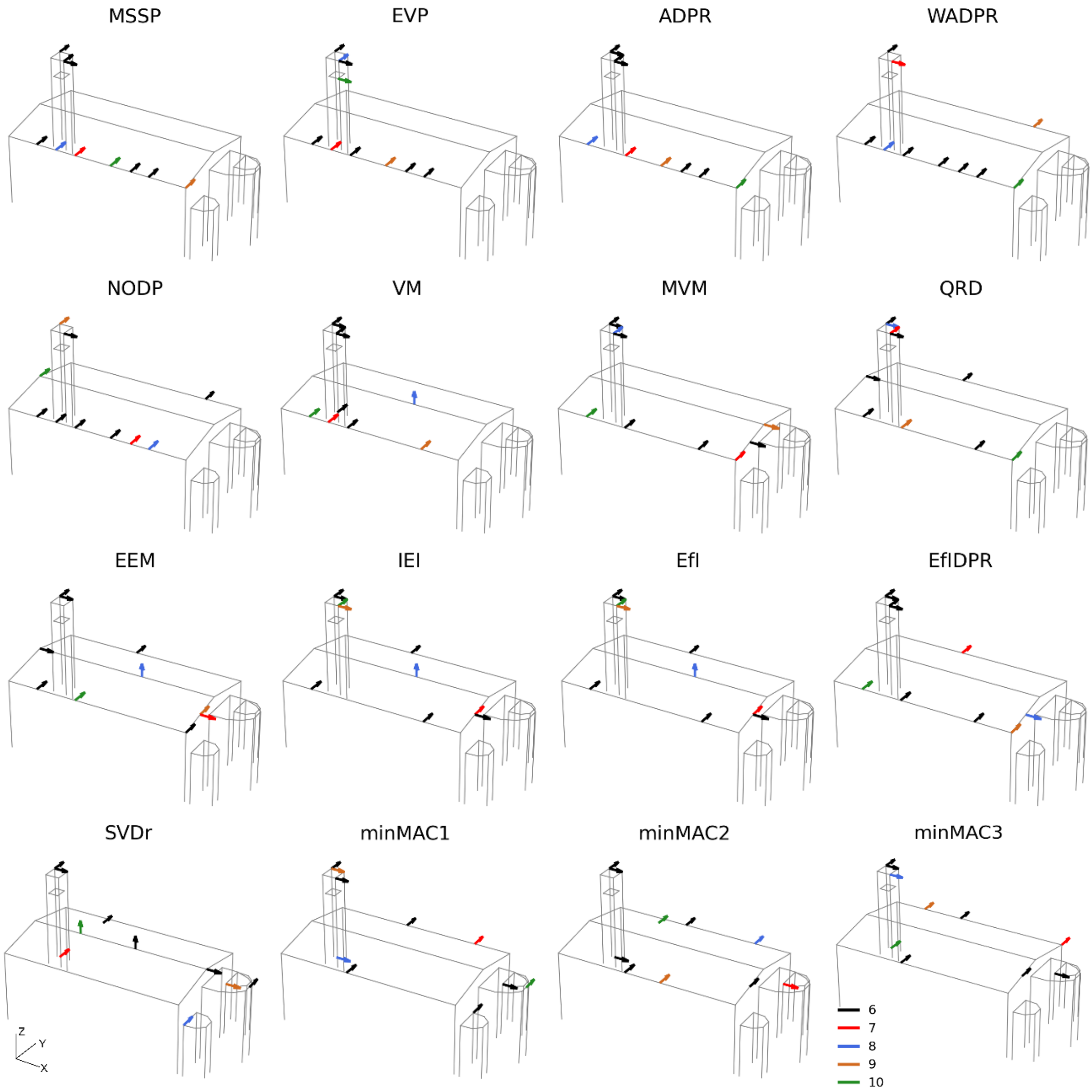


Figure 3. OSP results: black basic 6 sensor configuration (6-SS), red 7th sensor (7-SS), blue 8th sensor (8-SS), orange 9th sensor (9-SS), green 10th sensor (10-SS).

MVM presents similar results to ADPR, with the four sensors at the top of the tower and several transversal sensors on the same lateral wall. The main difference is that MVM also includes sensors in the longitudinal direction. The VM also places four sensors at the top of the tower and several NY sensors, but with some clustering. Additionally, the eighth sensor is a NZ. The results for the QRD method show a more widely distributed pattern. The 6-SS pattern proposes a TX and TY at the top, three NY sensors distributed and a NX sensor. The additional sensors are located in the tower and the transversal direction at the nave.

The EEM method follows a similar 6-SS pattern with the two horizontal sensors on the tower, a triangular distribution of NY sensors, and the same NX sensor. Two additional NY sensors are included, however, instead of placing four sensors at the tower for the final configuration, a NZ and an additional NX are added. The IEI yields the same results as the EfI. Similar to the EEM, this proposal presents an equilibrated combination of sensors, starting with the TX and TY sensors at the top level, one NX and three NY distributed spatially in the longitudinal walls of the nave. The vertical direction is included in 8-SS case. For the 9-SS and 10-SS configurations, additional TX and TY sensors are placed in the other top level corner. The EfI-DPR presents similarities but places four sensors at the top in the initial configuration, adds an NX sensor in the 8-SS case, and does not include sensors in the vertical direction, resulting in a final configuration similar to QRD.

The SVDr method presents a distributed pattern. The 6-SS includes the top level TX and TY sensors, one NX, one NZ, one NY sensor in the nave and one AY sensor in the apse. Subsequent selections include a NY sensor, two sensors in the apse (one transversal and one longitudinal), and an additional NZ sensor. This makes SVDr the only metric to define two NZ sensors and the only one not placing sensors on the longitudinal side walls.

Metrics defined by the off-diagonal elements of the MAC present a TX and TY sensor on the top in the 6-SS case, but minMAC3 includes an additional sensor from the 8-SS configuration, while minMAC1 adds one in the 9-SS configuration. In the nave, all three metrics include a pair of aligned sensors in the central area. For the 10-SS configuration, minMAC2 and minMAC3 include up to six NY sensors, whereas minMAC1 includes only three NY sensors but adds two AY sensors. Both minMAC1 and minMAC2 consider the longitudinal direction in the nave, placing an NX sensor on the roof near one of the lateral walls; however, in minMAC1, this sensor appears only in the 8-SS configuration. All three metrics place the same longitudinal sensor in the apse, but none includes any NZ sensor.

To assess and compare the results quantitative, the optimisation metrics are used as performance metrics (PM). Furthermore, three performance metric indexes (PMI) are defined. PMI1 corresponds to the average of all PMs. Based on the analysis of the individual values and the nature of the metrics, two additional PMIs are considered. PMI2 involves three energy-based metrics (EVP, ADPR and NODP) and three iterative metrics (the determinant of the FIM, the SVDr and the minMAC3) aiming to provide a balanced PMI. PMI3 is defined using only the last three metrics, as they are commonly used as performance metrics. The results are plotted in Figure 4 for the 6-SS and the 10-SS case.

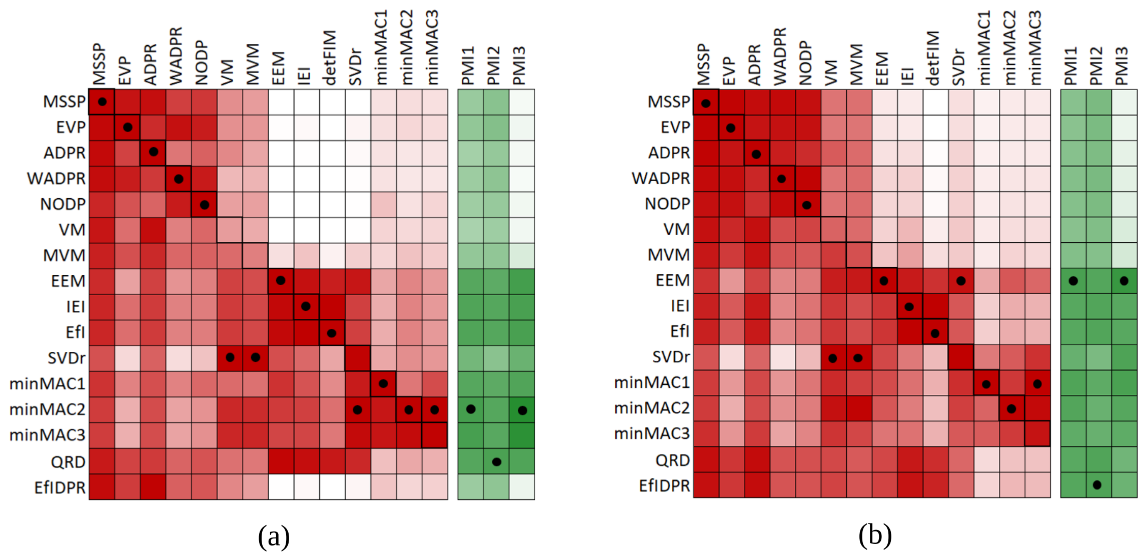


Figure 4. PMs analysis of the normalised values. Red individual PMs, green PMIs. Colour scales from 0 in white to 1 for the darkest tone. Black dot indicating best value for each PM or PMI: (a) 6-SS; (b) 10-SS.

The matrix represents the PM values normalized based on the maximum result among all the optimisation metrics. In general, energy-based metrics do not perform well for PM that seek linear independence. However, for some energy-based PMs, acceptable results are achieved when optimising iterative metrics. Based on the results, a general classification can be made: energy-based metrics form one group, EEM, IEI, and EfI belong to another group, which may also include QRD. Finally, MAC-based metrics constitute a separate group. SVDr falls between the last two groups.

VM and its modified version (MVM) show poor performance in optimizing their own PM, with better results obtained using SVDr. EfIDPR is a hybrid between energy-based metrics and those focused on linear independence, tending to perform better as the number of sensors increases. Considering the three PMIs, minMAC2 and QRD show the highest values for the 6-SS case, while EEM and EfIDPR exhibit the best performance for the 10-SS case.

4. CONCLUSIONS

This paper has presented the implementation of a wide range of OSP metrics for a complex heritage masonry building using a data-driven approach. The problem formulation is based on data from an OMA campaign. The results have been thoroughly analysed and compared providing several relevant conclusions.

In general terms, it has been observed that the number of vital sensors is insufficient in a complex case such as this, where different macroelements and directions are involved in the modes to be identified. For this scenario, only the SVDr metric distributes sensors in a way that adequately covers the elements and directions involved in the modes to be identified.

Regarding the proposed metrics, the energy-based approaches yield poorer results. This is evident both in the analysis of sensor distribution, where two directions of the nave remain unexplored, and in the evaluation of PM based on linear independence. The VM and MVM methods also exhibit certain shortcomings; their performance analysis reveals that these two methods fail to properly optimise their objective function, as other methods achieve significantly better results.

EfI, IEI and EEM present balanced and consistent patterns, particularly in the 8-SS case, where a configuration is obtained that includes all macroelements and significant directions of the six modes. The SVDr metric also demonstrates a well-distributed configuration; however, the analysis of the PM matrix shows that the heuristic algorithm does not achieve the best solution. Although the values are quite similar, other metrics provide more optimal results.

Off-diagonal MAC-based metrics, despite presenting a distributed pattern, tend to over instrument the transverse direction of the nave while failing to include the vertical direction. Moreover, their optimisation using heuristic methods presents certain deficiencies, particularly in the case of minMAC3. Here, the same PM is optimised in both configurations by an alternative minMAC metric.

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REFERENCES

[1] M. G. Masciotta, J. C. A. Roque, L. F. Ramos, and P. B. Lourenço, "A multidisciplinary approach to assess the health state of heritage structures: The case study of the Church of Monastery of Jerónimos in Lisbon," *Constr. Build. Mater.*, vol. 116, pp. 169–187, 2016, doi: 10.1016/j.conbuildmat.2016.04.146.

[2] E. Chaves, A. Barontini, N. Mendes, V. Compán, and P. B. Lourenço, "Methodologies and Challenges for Optimal Sensor Placement in Historical Masonry Buildings," *Sensors 2023, Vol. 23, Page 9304*, vol. 23, no. 23, p. 9304, Nov. 2023, doi: 10.3390/S23239304.

[3] J. Aguilar Valseca, "Traza, Geometría Y Estructura De La Iglesia De Santa Ana De Sevilla," PhD Thesis. Universidad de Sevilla, 2023.

[4] E. Chaves, J. Aguilar, A. Barontini, N. Mendes, and V. Compán, "Digital Tools for the Preventive Conservation of Built Heritage: The Church of Santa Ana in Seville," *Herit. 2024, Vol. 7, Pages 3470-3494*, vol. 7, no. 7, pp. 3470–3494, Jun. 2024, doi:

10.3390/HERITAGE7070164.

[5] SVS, "ARTeMIS Modal Pro User Manual." Structural Vibration Solutions (SVS), Aalborg, Denmark, 2020.

[6] W. Ostachowicz, R. Soman, and P. Malinowski, "Optimization of sensor placement for structural health monitoring: a review," *Struct. Heal. Monit.*, vol. 18, no. 3, pp. 963–988, 2019, doi: 10.1177/1475921719825601.

[7] E. Vila-Chã, A. Barontini, and P. B. Lourenço, "Implementation of a Condition Monitoring Strategy for the Monastery of Salzedas, Portugal: Challenges and Optimisation," *Buildings*, vol. 13, no. 3, p. 719, 2023, doi: 10.3390/buildings13030719.

[8] D. C. Kammer and L. Yao, "Enhancement of on-orbit modal identification of large space structures through sensor placement," *Journal of Sound and Vibration*, vol. 171, no. 1. pp. 119–139, 1991. doi: 10.1006/jsvi.1994.1107.

[9] J. Li, X. Zhang, J. Xing, P. Wang, Q. Yang, and C. He, "Optimal sensor placement for long-span cable-stayed bridge using a novel particle swarm optimization algorithm," *J. Civ. Struct. Heal. Monit.*, vol. 5, no. 5, pp. 677–685, 2015, doi: 10.1007/s13349-015-0145-4.

[10] C. Papadimitriou, "Optimal sensor placement methodology for parametric identification of structural systems," *J. Sound Vib.*, vol. 278, no. 4–5, pp. 923–947, Dec. 2004, doi: 10.1016/j.jsv.2003.10.063.

[11] N. Imamovic, "Validation of Large Structural Dynamics Models Using Modal Test Data," 1998.

[12] J. P. DeClerck and P. Avitabile, "Development of several new tools for modal pre-test evaluation," in *Proceedings of the 14th international modal analysis conference*, 1996, p. 1272.

[13] C. B. Larson, D. C. Zimmerman, and E. L. Marek, "A Comparison of Modal Test Planning Techniques: Excitation and Sensor Placement Using the NASA 8-bay Truss," *SPIE*, vol. 2251, p. 205, 1994, Accessed: Mar. 19, 2024.

[14] Y.-T. Chung and J. D. Moore, "On-orbit sensor placement and system identification of space station with limited instrumentations," in *Proceedings of the international modal analysis conference*, 1993, p. 41.

[15] M. Meo and G. Zumpano, "On the optimal sensor placement techniques for a bridge structure," *Eng. Struct.*, vol. 27, no. 10, pp. 1488–1497, 2005, doi: 10.1016/j.engstruct.2005.03.015.

[16] M. Papadopoulos and E. Garcia, "Sensor placement methodologies for dynamic testing," *AIAA J.*, vol. 36, no. 2, pp. 256–263, May 1998, doi: 10.2514/2.7509.

[17] W. Chen, W. guang Zhao, H. ping Zhu, and J. feng Chen, "Optimal sensor placement for structural response estimation," *J. Cent. South Univ.*, vol. 21, no. 10, pp. 3993–4001, 2014, doi: 10.1007/s11771-014-2387-4.

[18] M. Chang and S. N. Pakzad, "Optimal Sensor Placement for Modal Identification of Bridge Systems Considering Number of Sensing Nodes," *J. Bridg. Eng.*, vol. 19, no. 6, pp. 1–10, 2014, doi: 10.1061/(asce)be.1943-5592.0000594.

[19] C. Schedlinski and M. Link, "An Approach to Optimal Pick-up and Exciter Placement," *4th Int. Modal Anal. Conf.*, pp. 376–382, 1996.

[20] D. S. Li, C. P. Fritzen, and H. N. Li, "Extended MinMAC algorithm and comparison of sensor placement methods," in *Conference Proceedings of the Society for Experimental Mechanics Series*, Orlando, 2008. Accessed: Dec. 23, 2021.

[21] B. Li, D. Li, X. Zhao, and J. Ou, "Optimal sensor placement in health monitoring of suspension bridge," *Sci. China Technol. Sci.*, vol. 55, no. 7, pp. 2039–2047, 2012, doi: 10.1007/s11431-012-4815-8.