

pyOMA2: A Python module for conducting operational modal analysis

Dag P. Pasca¹ and Diego Federico Margoni²

¹ Norsk Treteknisk Institutt, Oslo, Norway ² Politecnico di Torino, Italy ¶ Corresponding author

DOI: [10.xxxxxx/draft](https://doi.org/10.xxxxxx/draft)

Software

- [Review](#)
- [Repository](#)
- [Archive](#)

Editor: [Fabian-Robert Stöter](#)

Reviewers:

- [@Nitnelav](#)
- [@e-dub](#)

Submitted: 12 September 2024

Published: unpublished

License

Authors of papers retain copyright and release the work under a Creative Commons Attribution 4.0 International License ([CC BY 4.0](#))

Summary

Operational Modal Analysis (OMA) has garnered considerable attention from the engineering community in recent years and has established itself as the preferred method for estimating the modal properties of structures in Structural Health Monitoring (SHM) applications, particularly in civil engineering. The key advantage of OMA over Experimental Modal Analysis (EMA) is its ability to derive modal parameters solely from output measurements taken during the structure's normal operation. This makes OMA a more practical and efficient approach, as opposed to the traditional EMA, which requires both input and output data.

Statement of need

pyOMA2 is the latest and improved version of the pyOMA module ([Pasca et al., 2022](#)), a Python library specifically designed for conducting operational modal analysis. While its predecessor relied on procedural workflows, pyOMA2 fully utilises Python's object-oriented capabilities to offer a comprehensive suite of tools for performing OMA.

Notable improvements over the previous version include support for single- and multi-setup measurements, allowing users to handle multiple acquisitions that combine reference and roving sensors; enhanced user-friendliness through a broad range of tools for pre-processing and visualising data; interactive plotting that enables users to select desired modes directly from algorithm-generated graphs; a geometry-definition feature to visualise mode shapes on tested structures; and, since version 1.1.1, the possibility to estimate uncertainty bounds of modal properties for the SSI family of algorithms.

The following algorithms are included in the module:

- Frequency domain decomposition (FDD) ([Brincker, Zhang, et al., 2001](#));
- Enhanced frequency domain decomposition (EFDD) ([Brincker, Ventura, et al., 2001](#));
- Frequency spatial domain decomposition (FSDD) ([Zhang et al., 2010](#));
- Reference based covariance driven stochastic subspace identification (SSlcov) ([Peeters & De Roeck, 1999](#); [Reynders, 2012](#); [Van Overschee & De Moor, 2012](#));
- Reference based data driven stochastic subspace identification (SSIdat) ([Peeters & De Roeck, 1999](#); [Reynders, 2012](#); [Van Overschee & De Moor, 2012](#));
- Poly-reference Least Square Frequency Domain (pLSFC) ([Peeters et al., 2004](#));

The multi-setup analyzes can be performed according the so-called Post Separate Estimation Re-Scaling (PoSER) approach as well as with the so-called Pre-Global Estimation Re-Scaling (PreGER) approach ([Amador & Brincker, 2021](#); [Brincker & Ventura, 2015](#); [Döhler & Mevel, 2013](#); [Rainieri & Fabbrocino, 2014](#)). The calculation of the uncertainty bounds for the SSI family of algorithms follows the efficient implementation by Döhler ([Döhler, 2011](#); [Döhler et al., 2013](#); [Döhler & Mevel, 2013](#)). The interested reader may refer to the extensive scientific literature on the subject for further information.

A few commercial software programs implements the algorithms mentioned above. The most

well-known presumably are ARTEMIS (Solutions, 2001), by Structural Vibration Solutions, and MACEC, a Matlab toolbox for modal testing and OMA (Reynders et al., 2014). When it comes to open source modules the only ones available to the authors best knowledge are the first version of pyOMA (Pasca et al., 2022) and Koma (Kvåle, 2024), which is also an open-source Python library available on GitHub. It provides tools for OMA, focusing on simplicity and ease of use. Koma is designed to be a lightweight alternative to more general libraries like pyOMA, making it suitable for smaller projects.

The module's reliability and applicability for research purposes have been demonstrated by the authors through various studies, such as (Alaggio et al., 2021; Aloisio et al., 2020; Simoncelli et al., 2023). Additionally, the module has gained traction within the research community, as evidenced by its use in studies by (Abuodeh et al., 2023; Croce et al., 2023; Saharan et al., 2023; Talebi et al., 2023), and others.

Module's structure

The module is structured into three primary levels:

1. At the first level are the setup classes. Users instantiate these classes by providing a data array and the sampling frequency for a single setup scenario, or a list of data arrays and their respective sampling frequencies, and reference indices, for a multi-setup scenario.
2. The second level comprises the algorithms classes. Users can instantiate the algorithms they wish to run and then add them to the setup class.
3. The third level contains the support classes, which serve as auxiliary components to the first two levels. This level includes various specialized classes:
 - result classes, where outcomes are stored.
 - geometry classes, for storing geometric data.
 - run_param classes, where parameters used for running the algorithms are kept.
 - Dedicated classes for animating mode shapes and interacting with plots generated by the algorithm classes.

In addition to the levels depicted in the figure, there is a further level not shown, comprised of the set of functions internally called by the class methods. Many of these functions represent an updated version of those available in our previous release, pyOMA.

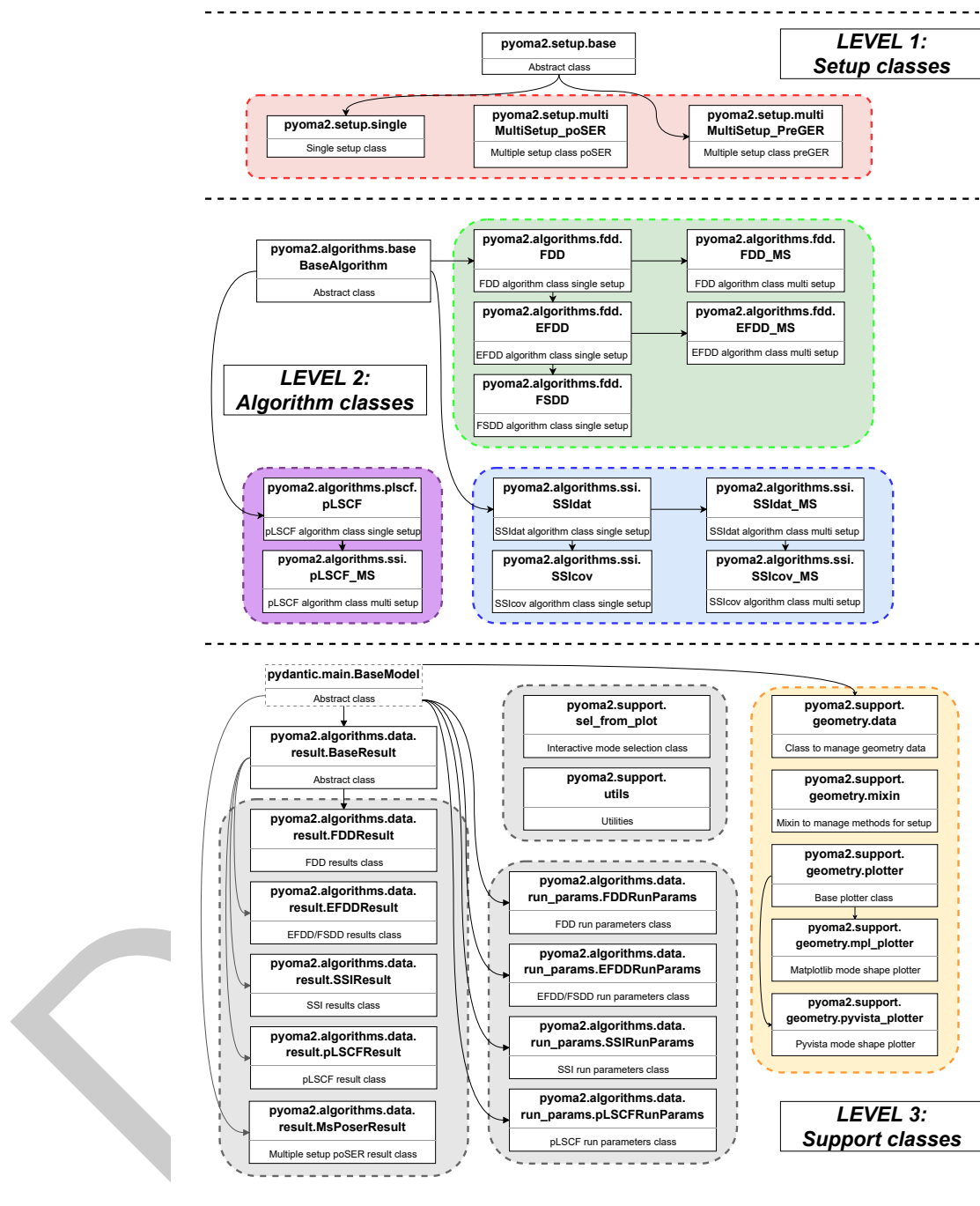


Figure 1: Schematic organisation of the module showing inheritance between classes

71 Documentation

72 A comprehensive documentation for pyOMA2, including examples, is available at [https://pyoma.](https://pyoma.readthedocs.io/en/main/)
73 [readthedocs.io/en/main/](https://pyoma.readthedocs.io/en/main/).

74 Acknowledgements

75 We acknowledge contributions from Angelo Aloisio and Marco Martino Rosso.

76 References

- 77 Abuodeh, O., Locke, W., Redmond, L., Sreenivasulu, R. V., & Schmid, M. (2023). Examining
78 methods for modeling road surface roughness effects in vehicle–bridge interaction models
79 via physical testing. *Society for Experimental Mechanics Annual Conference and Exposition*,
80 33–47. https://doi.org/10.1007/978-3-031-36663-5_5
- 81 Alaggio, R., Aloisio, A., Antonacci, E., & Cirella, R. (2021). Two-years static and dynamic
82 monitoring of the santa maria di collemaggio basilica. *Construction and Building Materials*,
83 268, 121069. <https://doi.org/10.1016/j.conbuildmat.2020.121069>
- 84 Aloisio, A., Pasca, D., Tomasi, R., & Fragiaco, M. (2020). Dynamic identification and
85 model updating of an eight-storey CLT building. *Engineering Structures*, 213, 110593.
86 <https://doi.org/10.1016/j.engstruct.2020.110593>
- 87 Amador, S. D., & Brincker, R. (2021). Robust multi-dataset identification with frequency
88 domain decomposition. *Journal of Sound and Vibration*, 508, 116207. <https://doi.org/10.1016/j.jsv.2021.116207>
- 89 Brincker, R., & Ventura, C. (2015). *Introduction to operational modal analysis*. John Wiley &
90 Sons.
- 91 Brincker, R., Ventura, C. E., & Andersen, P. (2001). Damping estimation by frequency domain
92 decomposition. *Proceedings of IMAC 19: A Conference on Structural Dynamics: Februar*
93 *5-8, 2001, Hyatt Orlando, Kissimmee, Florida, 2001*, 698–703.
- 94 Brincker, R., Zhang, L., & Andersen, P. (2001). Modal identification of output-only systems
95 using frequency domain decomposition. *Smart Materials and Structures*, 10(3), 441.
- 96 Croce, T., Girardi, M., Gurioli, G., Padovani, C., & Pellegrini, D. (2023). Towards a cloud-
97 based platform for structural health monitoring: Implementation and numerical issues.
98 *International Conference on Experimental Vibration Analysis for Civil Engineering Structures*,
99 610–619.
- 100 Döhler, M. (2011). *Subspace-based system identification and fault detection: Algorithms*
101 *for large systems and application to structural vibration analysis* [PhD thesis]. Université
102 Rennes 1.
- 103 Döhler, M., Lam, X.-B., & Mevel, L. (2013). Uncertainty quantification for modal parameters
104 from stochastic subspace identification on multi-setup measurements. *Mechanical Systems*
105 *and Signal Processing*, 36(2), 562–581. <https://doi.org/10.1016/j.ymssp.2012.11.011>
- 106 Döhler, M., & Mevel, L. (2013). Efficient multi-order uncertainty computation for stochastic
107 subspace identification. *Mechanical Systems and Signal Processing*, 38(2), 346–366.
108 <https://doi.org/10.1016/j.ymssp.2013.01.012>
- 109 Kvåle, K. A. (2024). *KOMA: Knut's operational modal analysis toolbox for python*. <https://doi.org/10.5281/zenodo.14446286>
- 110 Pasca, D. P., Aloisio, A., Rosso, M. M., & Sotiropoulos, S. (2022). PyOMA and PyOMA_GUI:
111 A python module and software for operational modal analysis. *SoftwareX*, 20, 101216.
- 112 Peeters, B., & De Roeck, G. (1999). Reference-based stochastic subspace identification for
113 output-only modal analysis. *Mechanical Systems and Signal Processing*, 13(6), 855–878.
114 <https://doi.org/10.1006/mssp.1999.1249>
- 115 Peeters, B., Van der Auweraer, H., Guillaume, P., & Leuridan, J. (2004). The PolyMAX
116 frequency-domain method: A new standard for modal parameter estimation? *Shock and*

- 119 *Vibration*, 11(3-4), 395–409. <https://doi.org/10.1155/2004/523692>
- 120 Rainieri, C., & Fabbrocino, G. (2014). Operational modal analysis of civil engineering structures.
121 *Springer, New York*, 142, 143. <https://doi.org/10.1007/978-1-4939-0767-0>
- 122 Reynders, E. (2012). System identification methods for (operational) modal analysis: Review
123 and comparison. *Archives of Computational Methods in Engineering*, 19, 51–124. <https://doi.org/10.1007/s11831-012-9069-x>
- 124 <https://doi.org/10.1007/s11831-012-9069-x>
- 125 Reynders, E., Schevenels, M., & De Roeck, G. (2014). MACEC 3.2: A matlab toolbox for
126 experimental and operational modal analysis. *Department of Civil Engineering, KU Leuven*.
- 127 Saharan, N., Kumar, P., & Pal, J. (2023). Convolutional neural network–based structural
128 health monitoring framework for wind turbine blade. *Journal of Vibration and Control*,
129 10775463231213423. <https://doi.org/10.1177/10775463231213423>
- 130 Simoncelli, M., Aloisio, A., Zucca, M., Venturi, G., & Alaggio, R. (2023). Intensity and
131 location of corrosion on the reliability of a steel bridge. *Journal of Constructional Steel*
132 *Research*, 206, 107937. <https://doi.org/10.1016/j.jcsr.2023.107937>
- 133 Solutions, S. V. (2001). *ARTEMIS extractor: Ambient response testing and modal identification*
134 *software, user's manual*. Demark.
- 135 Talebi, A., Potenza, F., & Gattulli, V. (2023). Interoperability between BIM and FEM
136 for vibration-based model updating of a pedestrian bridge. *Structures*, 53, 1092–1107.
137 <https://doi.org/10.1016/j.istruc.2023.04.115>
- 138 Van Overschee, P., & De Moor, B. (2012). *Subspace identification for linear systems:*
139 *Theory—implementation—applications*. Springer Science & Business Media.
- 140 Zhang, L., Wang, T., & Tamura, Y. (2010). A frequency–spatial domain decomposition
141 (FSDD) method for operational modal analysis. *Mechanical Systems and Signal Processing*,
142 24(5), 1227–1239. <https://doi.org/10.1016/j.ymssp.2009.10.024>