**9th European Congress on Computational Methods in Applied Sciences and Engineering (ECCOMA2024)**
***June 3-7, 2024, Lisbon, Portugal***

# PHYSICS-INFORMED MACHINE LEARNING FOR STRUCTURAL HEALTH MONITORING: EMERGING TRENDS AND OPEN ISSUES

**600**

**ALBERTO BARONTINI*, FILIPPO UBERTINI† AND ELENI CHATZI§**

* Department of Civil Engineering, University of Minho, ISISE, ARISE
Campus de Azurém, Avenida da Universidade, 4800-058 Guimarães, Portugal
albertobarontini@civil.uminho.pt and https://www.researchgate.net/profile/Alberto-Barontini

† Department of Civil and Environmental Engineering, University of Perugia
via G. Duranti, 93, 06125 Perugia, Italy
filippo.ubertini@unipg.it and https://ing1.unipg.it/ricerca/gruppi-di-ricerca/tecnica-delle-costruzioni/filippo-ubertini

§ Institute of Structural Engineering, ETH Zürich
Stefano-Franscini-Platz 5 CH-8093 Zürich, Switzerland
chatzi@ibk.baug.ethz.ch and https://baug.ethz.ch/en/department/people/professors/personen-detail.MTc1MDE1.TGlzdC8xOTA4LDE1NjE3MjkzNDM=.html

**Key words:** Deep Learning, Digital Twins, Surrogate Models, Structural Health Monitoring, Damage Identification, Physics-Informed Machine Learning, Grey-box Modelling, System Identification, Bayesian Inference, Scientific Machine Learning.

## ABSTRACT

Nowadays, high-performance and relatively inexpensive hardware components are capable of supporting advanced Structural Health Monitoring (SHM) paradigms, enabling large scale continuous acquisition of several sensor types with high and distinct sampling rates. However, the volume of the produced datasets grows in size and complexity, making them unmanageable with traditional approaches [1]. Machine learning (ML) allows dealing with large amounts of data and ensures learning from them, even when no prior knowledge of the investigated phenomena is available, alleviating the practical shortcomings linked to complex physics-based models [2-4]. However, purely data-driven approaches can mostly learn and predict behavioural patterns that were somehow experienced or simply provide evidence of deviations from baseline conditions. Thus, they require training on data that are representative across a broad range of possible environmental and operational conditions, are prone to overfitting and poorly generalise to out-of-sample scenarios [2,5]. Furthermore, they are, by construction, less interpretable than physics-based models, which, despite their limitations, allow for a more transparent understanding of the relationships between variables and the reasoning behind the applied inference.

The integration of physics-based modelling, which is more intuitive for engineers, with ML techniques allows for the combination of the advantages of data-driven methods with the insights delivered by physics-based principles. This ensures an enhanced learning and predictive capability, particularly when training data are limited, by leveraging domain-specific knowledge [2,5]. Various degrees of combination can be pursued within hybrid architectures

(e.g. surrogate models, residual models, constrained ML, etc.), depending on the specific characteristics and objectives of the application [2,3,6,7].

The scope of this mini-symposium is to present advancements and emerging trends in physics-informed SHM, discussing open challenges and promising solutions to tackle them. It aims to constitute a platform for the exchange of ideas and experiences and foster more coordinated and interdisciplinary research on the wide spectrum of modelling strategies to enforce physical laws or constraints within the learning process.

We welcome contributions on the integration of physics-based with data-driven approaches focused on, but not limited to:

- Advanced Bayesian approaches for the fusion of SHM and non-destructive evaluation data.
- Empowering model-based SHM approaches with surrogate models.
- Leveraging digital twins to enhance SHM strategies.
- Network-level SHM using transfer learning techniques.
- Cutting-edge methods for computation-physical domain adaptation in SHM.
- Integrating physics and ML for enhanced SHM.

## REFERENCES

[1] C. Cremona and J. Santos, ‘Structural Health Monitoring as a Big-Data Problem’, *Structural Engineering International*, vol. 28, no. 3, pp. 243–254, 2018.

[2] E.J. Cross, S.J. Gibson, M.R. Jones, D.J. Pitchforth, S. Zhang and T.J. Rogers, ‘Physics-Informed Machine Learning for Structural Health Monitoring’, in *Structural Health Monitoring Based on Data Science Techniques*, A. Cury, D. Ribeiro, F. Ubertini and M.D. Todd, Eds., Springer International Publishing, 2022, pp. 347–367.

[3] E. García-Macías and F. Ubertini, ‘Real-time Bayesian damage identification enabled by sparse PCE-Kriging meta-modelling for continuous SHM of large-scale civil engineering structures’, *Journal of Building Engineering*, 59, 105004, 2022.

[4] A. Barontini, M.G. Masciotta, P. Amado-Mendes, L.F. Ramos and P.B. Lourenço, ‘Negative selection algorithm based methodology for online structural health monitoring’, *Engineering Structures*, 229, 111662, 2021.

[5] A. Karpatne *et al.*, ‘Theory-Guided Data Science: A New Paradigm for Scientific Discovery from Data’, *IEEE Transactions on Knowledge and Data Engineering*, vol. 29, no. 10, pp. 2318–2331, 2017.

[6] G. Kerschen, K. Worden, A. F. Vakakis, and J.-C. Golinval, ‘Past, present and future of nonlinear system identification in structural dynamics’, *Mechanical Systems and Signal Processing*, vol. 20, no. 3, pp. 505–592, 2006.

[7] Z. Lai,C. Mylonas, S. Nagarajaiah, and E. Chatzi, Structural identification with physics-informed neural ordinary differential equations’, *Journal of Sound and Vibration*, 508, 116196, 2021.