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

SCIENTIFIC MACHINE LEARNING FOR MODELLING AND SIMULATION

TRACK NUMBER 600

I. CORTES GARCIA* AND M. ABDELMALIK*

* Department of Mechanical Engineering, Eindhoven University of Technology
Groene Loper 15, 5612 AE Eindhoven, The Netherlands.

i.cortes.garcia@tue.nl and m.abdel.malik@tue.nl

Key words: scientific machine learning, structure-preserving methods, system identification, surrogate modelling, computational mechanics, differential equations

ABSTRACT

Scientific machine learning has gained large interest in the engineering community as a balance between classic, physics based approaches and emerging data based techniques [1]. On one hand, the robustness and reliability of the physical equations can be enhanced by the potentially fast machine learning methods, that further allow incorporation of experimental, real-life data. On the other hand, including physics information into the learning process enhances the training efficiency by e.g. imposing important physical properties such as conservation and symmetry laws.

Advances in scientific machine learning has also led to the development of hybrid computational methods where machine learning is used to aid classical solution methods such as finite elements, finite volumes, numerical time integration, etc. Amongst others, trained algorithms can serve as surrogate models that are fast to evaluate [2,3]. Furthermore, new or augmented models can be inferred, allowing to include or learn unknown physical behavior [4].

The aim of this mini-symposium is to bring together researchers in the field of scientific machine learning to enhance the modelling or simulation process in applications both from the engineering domain as well as natural sciences. Topics include (but are not limited to):

- Surrogate modelling with machine learning methods for uncertainty quantification
- Structure-preserving machine learning techniques
- System and parameter identification methods for differential equations

REFERENCES

[1] Strang, G. (2019). Linear algebra and learning from data. Wellesley-Cambridge Press.
[2] Lu, L., et al. (2021). Learning nonlinear operators via DeepONet based on the universal approximation theorem of operators. Nature machine intelligence, 3(3), 218-229.
[3] Kovachki, N., et al. (2021). Neural operator: Learning maps between function spaces. arXiv preprint arXiv:2108.08481.
[4] Prume, E., et al. (2023). Model-free data-driven inference in computational mechanics. Computer Methods in Applied Mechanics and Engineering, 403, 115704.