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PHYSICS-BASED MACHINE LEARNING FOR ENGINEERING SIMULATIONS AND DIGITAL TWIN

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ABSTRACT

Machine Learning (ML) models, which have already found tremendous success in several applications, are beginning to play an important role in advancing scientific discovery in several engineering domains, traditionally dominated by the numerical solution of PDEs [1]. The use of ML models is particularly promising in scientific problems involving processes that are not completely understood, or where it is computationally infeasible to run simulations at desired resolutions in space and time. Moreover, tasks such as inverse modeling, optimization, parameters identification and uncertainty quantification - necessary towards a Digital Twin approach - require advanced surrogate and reduced order models techniques.

Neither an *ML-only* nor a *Physics-based-only* approach can be considered sufficient for complex scientific and engineering applications, in particular in computational mechanics. Therefore, the research community is beginning to explore the continuum between ML and Physics-based models (PINN, Deep Learning ROM, Autoencoders just to name a few examples [2]), where both scientific knowledge and ML are integrated in a synergistic manner.

However, several challenges are still present and need to be addressed both from a theoretical and practical point of view. Indeed, these approaches have been so far mostly applied to address very simple benchmarks, but there are still many gaps to be filled to make these algorithms suitable for a production environment.

The aim of this Session is to present and share the latest improvements in this field, exploring future possible developments and applications, in particular involving real case industrial applications.

REFERENCES

[1] Willard, J., Jia, X., Xu, S., Steinbach, M., & Kumar, V. *Integrating physics-based modeling with machine learning: A survey.* arXiv preprint arXiv:2003.04919, 1(1), 1-34 (2020).

[2] Haghighat E., Juanes R. *SciANN: A Keras/TensorFlow wrapper for scientific computations and physics-informed deep learning using artificial neural networks*, Computer Methods in Applied Mechanics and Engineering, 373, 113552 (2021).