X International Conference on Computational Methods for Coupled Problems, COUPLED 2023
June 5-7, 2023, Chania, Crete, Greece

COMPLEXITY REDUCTION OF LARGE-SCALE PARAMETRIC PROBLEMS: DOMAIN DECOMPOSITION, REDUCED ORDER MODELS AND MACHINE LEARNING

MATTEO GIACOMINI[*,♮], GIOVANNI STABILE[†] AND MARCO DISCACCIATI[□]

* Laboratori de Càlcul Numèric (LaCàN), E.T.S. de Ingeniería de Caminos, Canales y Puertos, Universitat Politècnica de Catalunya, Barcelona, Spain

♮ Centre Internacional de Mètodes Numèrics en Enginyeria (CIMNE), Barcelona, Spain
matteo.giacomini@upc.edu,
https://www.lacan.upc.edu/user/matteo.giacomini/

† International School for Advanced Studies, Via Bonomea 265, 34135, Trieste, Italy
giovanni.stabile@sissa.it,
https://www.giovannistabile.com

□ Department of Mathematical Sciences, Loughborough University, Epinal Way, Loughborough LE11 3TU, UK
M.Discacciati@lboro.ac.uk,
https://www.lboro.ac.uk/departments/maths/staff/marco-discacciati/

ABSTRACT

Coupled problems such as fluid-structure interaction, thermo-mechanics, thermo-fluids, electro-magneto-mechanics and aerodynamic noise are ubiquitous in engineering applications and they require complex interdisciplinary modelling skills. The numerical discretisation of these problems, e.g. via finite element or finite volume methods, leads to large systems of (non)linear equations for which monolithic solvers struggle to provide solutions in a reasonable computing time.

This issue becomes especially critical when multiple queries of the same problem need to be solved for different configurations of the system (e.g. geometry of the domain, material parameters, …). This is the case of many sensitivity and parametric studies performed on a daily basis by engineers and scientists in the framework of optimal control and optimisation, inverse analysis, data assimilation and uncertainty quantification.

This session aims to gather contributions on the most recent advances in domain decomposition, partitioned iterative solvers, preconditioning, reduced order models, scientific machine learning and physics-informed deep learning to address the current challenge of solving large-scale parametric problems arising from the discretisation of (possibly coupled) high-dimensional partial differential equations.

Contributions on emerging techniques in physics-based surrogate and data-assisted models bridging the above topics towards the construction of hybrid models and digital twins of large-scale industrial problems are particularly welcome.