ELECTRICAL, ELECTRONICS AND COMMUNICATIONS ENGINEERING

CRT/DET - Physics Informed AI for FEM Model Order Reduction

Funded By	FONDAZIONE CRT CASSA DI RISPARMIO DI TORINO [P.iva/CF:06655250014] Dipartimento DET

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Context of the research activity	In many engineering fields, the use of finite element methods (FEM) has become unavoidable to reduce the sim-to-real gap, a necessary condition for the development of Digital Twins that can lower design and testing costs. However, the high computational effort has made such High-Fidelity models unusable in real-time monitoring, estimation and control applications. In the recent scientific and industrial world, simulation data are used to generate "light" surrogate models of physical systems through the exclusive use of AI and statistical methods. However, these methods suffer from data shortage, over-fitting and poor generalization ability. The proposed research will hybridize machine learning technologies with physical models, increasing the robustness of surrogate models, allowing us to mitigate these issues.

	Order reduction (OR) in finite element methods (FEMs) refers to techniques that simplify high-order problems into lower-order ones, making them more computationally efficient while maintaining acceptable accuracy. This process is crucial for solving complex problems in engineering and physics, where high-order systems can be computationally expensive to solve directly. In this PhD project, some classical OR approaches will be first reviewed. These can be summarised as follows: - Static Condensation. This technique involves reducing the size of the system of equations by eliminating certain degrees of freedom (DOFs) associated with internal nodes of the elements. This is typically done for higher-order elements where internal DOFs can be condensed out, leaving only the boundary DOFs to be solved in the global system. - Proper Orthogonal Decomposition: It involves capturing the dominant modes of the system by decomposing it into orthogonal basis functions using singular value decomposition. - Reduced Basis Methods: These methods construct a reduced basis from a set of high-fidelity solutions and project the original high-dimensional problem

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<tr><td>Objectives</td><td>onto this reduced basis.
- Balanced Truncation: It balances the controllability and observability Gramians of the system and truncates the less important states.
- H-P Adaptivity: This technique combines the concepts of h-refinement (mesh refinement) and p-refinement (increasing the polynomial order of the basis functions) to achieve higher accuracy with fewer elements. By selectively refining the mesh or increasing the polynomial order where needed, the computational cost can be reduced while maintaining accuracy.
- Galerkin Projection: It involves projecting the high-dimensional system onto a lower-dimensional subspace. The choice of the subspace basis functions is crucial and can be derived from various methods such as POD, eigenfunctions, or other orthogonal functions.
- Multigrid methods: They solve the problem on a hierarchy of grids, from fine to coarse. The solution on the coarse grid is used to correct the solution on the finer grids, effectively reducing the computational effort by capturing the long-wavelength components of the solution on the coarser grids.

The research activity will then move to non-traditional OR approaches, based on artificial intelligence (AI). AI and, in particular, Machine learning (ML) methods have shown a great potential in enhancing FEM by providing new tools for model reduction, improving accuracy, speeding up simulations, and automating tasks. The methods that will be considered during the PhD project include the following ones:
- Surrogate Modeling: Surrogate models, or metamodels, approximate the behavior of complex FEM simulations with simpler, computationally efficient models.
- OR using ML: Machine learning can enhance traditional model order reduction techniques.
- Data-Driven FEM: ML techniques can directly leverage data to build or augment FEM models, e.g. using Physics-Informed Neural Networks, Generative Adversarial Networks.
- Parameter Identification and Inverse Problems: ML can be used to solve inverse problems where the goal is to identify model parameters that best fit the observed data.
- Mesh Generation and Adaptation: ML can improve mesh generation and adaptation processes, crucial for FEM accuracy and efficiency.

The goal of this PhD project is to hybridize machine learning technologies with known physical models, increasing the robustness of surrogate models, mitigating the relevant problems of ML techniques like data shortage, over-fitting and poor generalization ability. This will be achieved through intelligent parameterization of the system of interest, and the use of Reduced Order Modelling (ROM) techniques to optimize repetitive simulations. This technology would disrupt various engineering and natural science fields. Applications of interest, in fact, will include modeling and control of collaborative soft-robots in precision agriculture, as well as demonstrating the goodness of the techniques developed in the analysis and reduction of complex systems affected by high unpredictability, such as simulation of biological systems, Computational Fluid Dynamics (CFD) in meteorology and prediction of anomalous weather events, CFD in the automotive field.</td></tr>
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<tr><td>Skills and competencies for the development of the activity</td><td>Dynamic system theory; Automatic control; convex and nonlinear optimization; data analysis; data fusion; machine learning; fluid automation; multi-physics FEM; simulation of complex systems; Matlab/Simulink.</td></tr>
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