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Manufacturing empowered by physics-aware digital twins

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Background

Virtual twins in the form of simulation tools that represent the physics of materials, processes and structures, making use of physics-based models, were the main protagonists of the XX century engineering. Thus, the virtual twin consists of the so-called nominal model, expected representing the observed reality, in general calibrated offline from the data provided by specific tests, enabling to predict the responses to given loadings, the last also nominal in the sense that they are expected representing the ones that the design will experience in service.

For that purpose, the mathematical models consisting of complex partial differential equations, generally strongly nonlinear and coupled, are discretized despite of the fact that in many cases the calculations are very costly in computational resources and computing time.

The XXI century engineering requests focusing on the real system (instead of on its nominal representation) in operation, subjected to the real loading that it experienced until the present time (instead of the nominal loading) in order to perform efficient diagnosis, prognosis and prescriptive decision making.

Here, usual modeling and simulation techniques are limited, the former because of the fact that a model is sometimes no more than a crude representation of the reality, and the last because of the computational cost that its solution using well experienced state-of-the-art discretization techniques entails.

Recent Model Order Reduction (MOR) techniques enable evaluating in almost real-time the solution of physics-based models. These techniques neither reduce nor modify the model itself, they simply reduce the complexity of its solution by employing more adapted approximations of the unknown fields [1].

Model Order Reduction techniques express the solution of a given problem (a PDE for instance) into a reduced basis with strong physical or mathematical content. Sometimes these bases are extracted from some offline solutions of the problem at hand, as the proper orthogonal decomposition (POD) or the reduced bases method (RB) perform. Now, when operating within the reduced basis, the solution complexity scales with the size of this basis, in general much smaller than the size of the multi-purpose approximation basis associated with the finite element method (FEM) whose size scales with the number of nodes involved in the mesh that covers the domain in which the problem is defined. Even if the use of a reduced basis implies a certain loss of generality, it enables impressive computing time savings while guaranteeing acceptable accuracy as soon as the problem solution continues living in the space spanned by the reduced basis.

The main drawbacks of those techniques are: (i) their limited generality when addressing situations far from the ones that allowed the reduced basis construction; (ii) the difficulties of addressing nonlinear models, that require the use of advanced strategies; and (iii) its intrusive character with respect to its use in well experienced and validated existing software.

For circumventing, or at least alleviating, the just referred computational issues, an appealing route consists of constructing the reduced basis at the same time that the problem is solved, as proper generalized decompositions (PGD) perform [2-4]. However, PGD is even more intrusive than POD and RB referred above. Thus, non-intrusive PGD procedures were proposed, that proceed by constructing the parametric solution of the parametric problem from a number of high-fidelity solutions performed offline, for different choices of the model parameters. Among these techniques we can mention the SSL-PGD, that considers hierarchical separated bases for interpolating the precomputed solutions [5], or its sparse counterparts [6,7].

Once the parametric solution of the problem at hand is available, it can be particularized online for any choice of the model parameters, enabling simulation, optimization, inverse analysis, uncertainty propagation, simulation-based control, ... all them under the stringent real-time constraint [3].

On the other hand, recent advances in data-science, artificial intelligence and machine learning make possible an alternative data-driven engineering. The data-driven route becomes especially appealing when:

- Physics-based models are unknown or the ones that exist remains too inaccurate in their predictions. In this case the physics-based model can be enriched by considering the data-driven model of the deviation, at the heart of the Hybrid Twin concept [8].
- Diagnosis can be performed in a very efficient from the solely use of data, however, its explanation requires deeper modelling approach.
- MOR becomes difficult to perform or employ, with the associated effects on the prognosis performances.

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