Towards Data-Driven Computational Mechanics
Manifold Learning and Digital Twins

PhD thesis proposal

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Keywords: computational mechanics, machine learning, digital twins, reduced-order modeling

The goal of the thesis is to propose a set of numerical tools allowing to build data-driven computational models combining reduced-order modeling computation with machine learning for data-driven prediction and decision making.

The modern-day experimental techniques produce high volumes of data, giving access to unprecedented detail when observing material microstructure and its evolution under service loads. However, existing constitutive models are not always able to fit the experimental data due to measurement and modeling errors. Machine learning techniques are increasingly used to manage massive quantities of experimental data. However, there are two reasons, preventing their use as replacement for the traditional physical modeling approaches. The first reason is the cost of experiments. The second reason is the lack of physical bases in ML. Therefore, rather than to replace models by data, the idea proposed in this thesis is to enrich existing models by the data, possibly leading to implicit models, and in fine to simulation from data only.

The work will develop on top of three technologies actively researched at the Roberval Laboratory of UTC. The manifold learning, initially developed by computer scientists for image recognition, is extended to computational mechanics field, giving rise to a series of applications in shape optimization and identification. The Diffuse Approximation is a flexible approximation/interpolation technique able to treat data sparsely and irregularly distributed in space. Finally, the reduced order modeling allows to dramatically improve the efficiency of simulation by finite elements, by Galerkin projection of motion equations on a reduced basis. The proposed approach is meant to be general and will be tested on actual experimental data to be defined in collaboration with research/industry partners of Roberval Laboratory.

The successful candidate will have a background in applied mathematics, mechanical engineering or computer science. Competence in linear algebra, programming skills (Matlab) are expected. Finite element modeling is a plus.

References

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