Associate Professorship of Computational Solid Mechanics
TUM School of Engineering and Design
Technical University of Munich

Master thesis

Simulation-based surrogate modelling and machine learning

Background

In computational mechanics, high-fidelity numerical simulations of solid materials and structures under various loading conditions are typically computationally expensive. This is especially the case for complex geometries, nonlinear materials and time-dependent phenomena. In the context of multi-query tasks such as optimization, uncertainty quantification and such, the computational effort becomes prohibitive.

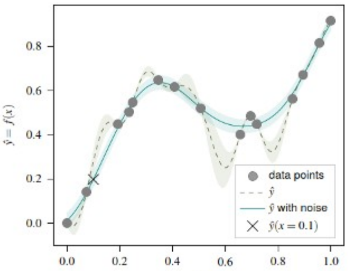

Figure 1: Gaussian process regression [1]

This challenge has led to the increasing use of surrogate models as efficient alternatives to predict quantities of interest. Surrogate modelling involves constructing an approximate model (e.g. Gaussian process regression) that emulates the behavior of the high-fidelity simulation but at a fraction of the computational cost.
For instance, in a structural optimization, a surrogate model might be used to predict the structure's compliance as a function of design parameters, thereby enabling the identification of a design that minimizes this target while adhering to constraints.
The integration of surrogate modelling into optimization workflows is particularly beneficial in fields such as aerospace, automotive, biomechanics, and civil engineering, where high-performance requirements and complex loading conditions necessitate extensive computational analyses.

Tasks

Within this master's thesis a python framework for simulation-based surrogate modeling and Machine Learning (ML) should be created. The aim is to create modular pipeline to test varying methods in a plug and play manner. Moreover, the implementation should be made accessible via a Jupyter notebook to nicely illustrate the workflow. Main topics are Design of Experiments and sampling, regression and ML models and (robust) optimization. Whereby, specific interest is set on techniques for a large parameter space. Based on python libraries different methods should be implemented. A strategy for comparing the varying methods should be developed and realized.

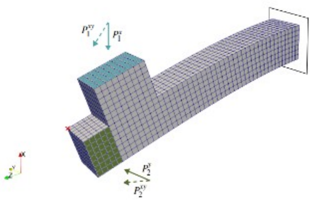

Figure 2: Exemplary FEM problem [1]

In a first step a suitable example must be created and set up in the FEM software OpenRadioss. Next, the python implementation with comprehensive documentation should be created.

Organizational information

The master thesis is offered at TUM in cooperation with Siemens.

Basic knowledge about solid mechanics, finite element modelling, optimization, machine learning and python programming is preferred.

If interested, please send an up-to-date CV as well as a transcript of records to catharina.czech@siemens.com and philippa.weissinger@tum.de

References

[1] C. Czech, **A modular multi-fidelity scheme combining data-driven reduced order models for structural analysis under uncertainty**, PhD-Thesis, Technical University of Munich, Germany, 2024.