Simulation-as-a-Service in the Loop -- Enhancing Rapid Prototyping of Complex Industrial Machines with Automatic Data Synthesis based on Numerical Simulation of Fluid Flow and Machine Learning

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Industrial machines based on complex technical flow can be designed and/or optimised using rapid prototyping based on numerical simulation e.g. with higher-order Finite Element methods and fast multigrid solvers. In many cases the operator needs to be alleviated from manually processing the workload data needed by these numerical components. This can be achieved by a Simulation-as-a-Service (Sim-a-a-S) [1] approach that automizes the processing of geometric (and process-) data of the digital twin to provide the discretisation and manages the processing jobs on high-end computers both in order to provide a competitive, low-latency workflow. The often resource-demanding simulation pipeline can be enhanced in terms of performance by using Machine Learning (ML) approaches that accelerate the critical components [2]. In this industry/university joint work however we go one step further using ML for rapid forecasting of relevant target function values that indicate the quality of the prototype (e.g. characteristic curves for pressure) at interactive rates in order to enable pre-selection of promising variations for rigorous simulation. Those characteristics can be derived from simulation results and thus a Sim-a-a-S core is employed to efficiently synthesise the training data. The system approach uses parameterizations of the geometric layer of the digital twin in order to reduce complexity in the training of neural network models for the target function regression, see Figure 1. Besides system architecture, in this talk we demonstrate the effectivity of a prototype in an early alpha stage of development.

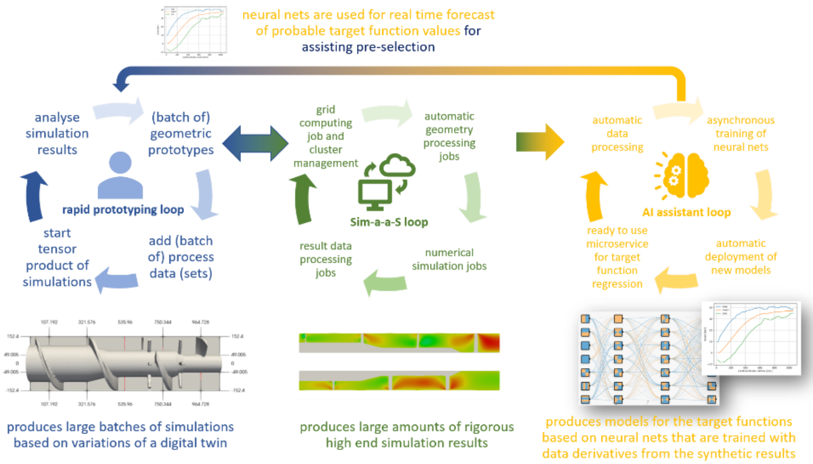

Figure 1: Asynchronous system solution for rapid prototyping with a Sim-a-a-S core. Users are assisted by real time predictions of process characteristics to pre-select (probably) good designs.

References

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