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DATA-DRIVEN SIMULATION FOR AM

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ABSTRACT

The complexity of additive manufacturing (AM) processes and additively manufactured materials is extremely demanding for conventional numerical methods. This may hinder their application within control applications or engineering design loops, where multiple evaluations of a specific model are required, e.g. in the context of process and component optimization. Even more, already part-scale simulations of AM structures can be challenging due to their multiscale and multiphysics nature, e.g., when microstructures or functional behaviour are to be considered. Thus, the freedom of design offered by AM in terms of geometry, material, meso- and microstructure can hardly be explored by conventional, simulation-based design and optimization approaches.

Recent advances in machine learning demonstrate that reliable empirical approaches can increasingly be obtained from Big Data. While a data-driven approach is – once trained – fast at prediction, the generation of Big Data in AM processes requires complex, expensive sensor technology or abundant fine-grained and thus time-consuming simulations. At high speeds and thermal gradients, however, it is sometimes simply not possible to reliably generate certain data even with the best sensor technology at hand. Moreover, certain process and final part characteristics are hidden to the observer and can only be quantified using destructive testing methods.

This session deals with (physics-informed) data-driven approaches in the context of

simulation for AM. Applications may be real-time simulation, process-structure-property linkage, computational homogenization and surrogate modelling, automated calibration and optimization of process and component models, model management, etc. with the ultimate goal of creating digital or hybrid twins for AM.