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Title: Machine Learning in the small data regime – from additive manufacturing to Li-ion battery cell production

Place: Seminar room 915

Machine learning techniques are increasingly applied in physics and engineering, in particular in the field of process monitoring, control or predictive maintenance. Machine learning is well established whenever big data is available for analysis. However, in many fields of experimental research and in collaboration with small or medium sized companies, the available data often represents just a small number of independent data points. This requires improved strategies to use machine learning techniques in a small data regime.

In additive manufacturing (3D printing) of metals, in particular for the laser powder bed fusion process, limited process control can cause metallurgical defect formation and inhomogeneous relative density in manufactured parts. This requires substantial quality control, such that, for instance, μ-computer tomography has been applied. For cost reasons, the substitution of expensive non-destructive material testing by data-based process monitoring is intensively explored. Machine learning show promising results for defect detection but require conceptual adaption to layer-wise manufacturing and line scanning patterns in laser powder bed fusion. A multi-layer volumetric approach to co-register μ-computer tomography measurements with process monitoring data has been developed and a workflow for automatic data set generation has been implemented. The volumetric approach differs from conventional approaches where data is analyzed in a layer-by-layer scheme. It has been benchmarked with respect to other approaches for data driven defect detection. Analysis of experimental data sets has shown that production process monitoring, based on optical melt-pool signal analysis, is capable of tracing relative density variations: Unsupervised machine learning, applied to cluster multiple-slice monitoring data, reveals characteristic correlations between such patterns. Careful analysis has revealed indications for an increased local relative density at the edge of the specimen. A possible interpretation based on thermal histories will be presented.

In physics and engineering, applying machine learning has to be done with care to avoid trivial results, re-discovering effects which have already been known, and incorrect predictions, which may violate physical laws. For this reason, physics informed neural networks (PINNs) have been developed which allow to incorporate physical laws into the objective functional and ensure physical consistency. Applying PINNS to the heat transport problem in laser material processing starts with modelling a time dependent heat source (laser focus at the surface) and heat propagation through a 3D structure in real time. For a straightforward example setting PINNs and heat flow simulation agree, which opens new possibilities to include further sensor data into the PINNs architecture and to model more complex heat transport phenomena in additive manufacturing.

Finally, applications of machine learning to battery cell production are of paramount interest in Europe, where a strong (expected) demand for electric vehicles stimulates the massive build-up of battery cell fabrication plants. In collaboration with Fraunhofer ISC in Würzburg, which runs an experimental model production line, real production data is recorded. AI modules are applied to perform data compression and extract relevant features for both data from production monitoring and data from electrochemical quality assessment. The extracted features will be correlated to search for early indicators of future battery failure already in early process steps. Unfortunately, while many different errors may occur, only few experimentally produced samples are available. Despites huge data volumes, this defines the problem as a small data problem. An adapted approach for dataset generation focusing on the particular requirements of machine learning tools may mitigate this problem by combining strategies from design of experiments (DOE) and active learning.