Machine learning in precision engineering

Chair: Richard Leach, University of Nottingham

Fueled by the advent of high-speed parallel computing, the field of machine learning has ceased to be a mere research curiosity and has begun to be deployed in real industrial applications. At eu**spen**'s 21st International Conference & Exhibition, we are pleased to present an industrially focused workshop covering the current state of the art in machine learning for precision engineering. This workshop will comprise a series of industrial and academic speakers covering current applications of machine learning to precision engineering and challenges for the future.

1400 – 1410 Chairman's introduction

1410 – 1430 Some challenges for machine learning in industrial metrology

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At its root industrial metrology can be viewed as the actions required to control sources of variation in processes such that specifications are known to be met, in an industrial setting. This is self-evidently a very large field, so the choice of where to apply machine learning (ML) to best effect is an interesting problem. This session will discuss what factors influence where machine learning might be usefully applied within industrial metrology, looks at challenges the current state of practice in ML faces, and how industrial metrology might be used to advance ML applications. A "toy" application of ML within the field will be described as a case study.

1430 – 1450 The progression of AI for manufacturing from demonstration to production

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When we speak about data, we mean actionable insights and data driven intelligence, this is where Artificial Intelligence (AI) and machine learning (ML) comes into picture. The application of AI and ML is vast, and the potential of applying them in manufacturing use cases is immense. However, bringing ML into industrial processes is not as easy as buying a new piece of equipment or buying a new robot. There is a fair amount of work that needs to be done to ensure that the intelligence is embedded in the processes appropriately. This talk will use manufacturing case studies to explain the research progression that the MTC has been through over the last 6 years. Taking AI and ML research question from an initial state of: 'What data needs to be captured for the realization of process benefits in demonstrators?' to a state of 'How can we deploy these models to bring the benefits to industrial end users in production?' While highlighting many of the key challenges and opportunities faced by organizations adopting AI and ML in manufacturing.

1450 – 1510 JARVIS-DGL: Universal deep graph library for atomistic predictions, image recognition and natural language processing in materials science

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Graphs are a powerful non-Euclidean data structure method for establishing connections between features (nodes) and their relationships (edges). Graph neural networks (GNNs) have been used for a wide range of applications. In this work, we develop a library of GNN models and related tools for materials science applications, with particular focus on forward atomistic predictions, image recognition, and natural language processing (NLP). We predict atomistic properties such as formation energies, bandgaps, and 15 other material properties at the state of art accuracy levels. We use such models to identify candidate hosts for quantum defects for quantum computing applications. We use scanning tunneling microscopy images to identify atoms and lattice-types based on GNN based machine-vision techniques. We use GNN based NLP for identifying citation network for 2D materials in the arXiv dataset. The JARVIS-DGL tools will be made publicly available through GitHub repository. JARVIS-DGL is a part of NIST-JARVIS infrastructure (https://jarvis.nist.gov/).

1510 – 1540 Coffee Break

1540 – 1600 Machine learning for data processing in acoustic monitoring of laser powder bed fusion

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Currently, the laser powder bed fusion (L-PBF) process cannot offer a reproducible and predefined quality of the processed parts. Recent research on process monitoring focuses strongly on integrated optical measurement technology. Besides optical sensors, acoustic sensors also seem promising. Previous studies have shown the potential of analyzing structure-borne and air-borne acoustic emissions in laser welding. Only a few works evaluate the potential that lies in the L-PBF process. This work shows how the approach to structure-borne acoustic process monitoring can be elaborated by correlating acoustic signals to statistical values indicating part quality. Density measurements according to Archimedes' principle are used to label the layer-based acoustic data and to measure part quality. The data set is then treated as a classification and regression problem while investigating the applicability of existing artificial neural network algorithms, such as the TensorFlow in the Python language, to match acoustic data with density measurements. Furthermore, different methods for feature extraction are used and compared. Overall, the approach shows the potential to use machine learning for the data processing of process integrated sensor signals to evaluate part quality of manufactured products.

1600 – 1620 Machine learning for in-line quality data in advanced manufacturing: opportunities and challenges

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Thanks to the large amount of data that are nowadays available in-line (signals, images and videos), machine learning paves the way to a paradigm shift in quality inspection, monitoring and control for advanced manufacturing. However, additional effort is needed to answer many open questions, namely: How can machine learning support the analysis of highly unstructured, multi-stream, high-speed data in real time? How can data fusion be implemented in this framework? How can machine learning support small-data, one-of-a-kind, customized production? How can machine learning aid understanding the relationship between process signatures and product quality? How can uncertainty be included in the analysis? Starting from real case studies, this contribution provides a critical discussion on open issues that need to be solved to take full advantage of machine learning for in-line quality data modeling monitoring and control in advanced manufacturing.

1620 – 1640 Towards fully automated optical form measurement

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Optical form measurement techniques, including close-range photogrammetry and fringe projection profilometry, are increasing in popularity due to high-speed data acquisition and the non-contact nature of the measurement. However, these techniques are often labour intensive, computationally expensive and user dependent. A system wherein an object can be placed within and measured with the press of a button is therefore highly desirable but has thus far been a pipedream. However, potential paths towards this fully automated measurement pipeline are slowly coming into view due to the maturity of machine learning (ML) techniques. Developments within other sectors of research, such as the huge research effort in computer vision, have huge potential to be modified to be exploited within the optical metrology sector. In this presentation we discuss how ML can be applied to many different parts of the measurement and data post-processing pipeline to move toward full automation. We present our own contribution to this effort which has thus far included work on camera characterisation, object pose-estimation, view planning, and surface data synthesis.