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Towards additive manufacturing process control using machine learning

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The project aimed to assess the feasibility of using semi-supervised machine learning for automatic certification and process control in additive manufacturing (AM). It succeeded in demonstrating that such an approach is able to classify built AM parts as ‘acceptable’ or ‘faulty’ with a success rate at least as good as more conventional approaches. This achievement is a move towards reducing the risks faced by industry when adopting AM technologies.

Additive manufacturing in the UK

Additive manufacturing (AM) is revolutionising UK industry. It is a tool-less digital approach in which 3D objects are built by applying successive layers of material. The possibility of using diverse materials and finely-tuned build instructions, controlled by Computer Aided Design (CAD) software, enables the production of highly bespoke products. Compared with conventional methods, AM can improve component performance, reduce whole lifecycle waste and create parts with superior mechanical properties.

The value of this is apparent for a wide range of sectors, from the production of lightweight components for aerospace to bespoke implants for medicine. These sectors are, however, highly regulated and sensitive to failure; uncertainties associated with the quality, reproducibility and material properties of AM parts are inhibiting significant adoption of AM. Reducing the risks of deploying AM technology will help to maximise the impact of AM.

Machine learning for the certification of parts

Machine learning is used to certify standardised parts that are produced in high volumes. Parts are accepted or rejected on the basis of process measurements. Decision criteria are generated by training an algorithm with 'labelled' data, from parts that are labelled as acceptable (certified) or faulty (rejected). This is known as **supervised machine learning** as illustrated in the schematic below.

100s of parts need to be manually certified before the algorithm can be trained.
This is far too expensive for Additive Manufacturing.

This method is not feasible for additive manufacturing due to the cost implications; as manufacturing errors occur internally, an expensive scan is required to certify a part. Sufficient labelled data for training an algorithm can amount to more than a hundred builds. To do this for every new bespoke product, often only produced in small volumes, renders the method prohibitively expensive. The project investigated overcoming this drawback by applying new techniques from machine learning to classify parts without the need for large numbers of previously certified parts.

The project is the first to develop a **semi-supervised machine learning** approach for the identification of faulty additively manufactured parts.

The project's industrial partner, Renishaw Plc, is a leading technology company that designs and makes machines to 'print' parts from metal powder (additive manufacturing). Whenever a new object is printed, data is collected on, for example, light emitted from the melt pool. The project took the novel approach of extracting features associated with build quality from this large, non-labelled data set which were combined with a small amount of data pre-labelled as certified or rejected. The assumption made here is that photodiode measurements, which are closely related to properties of the melt pool, are also associated with build quality. Recognition that the process-data falls into clusters allowed the identification of faulty parts on the basis of process measurements. The resulting algorithm determines

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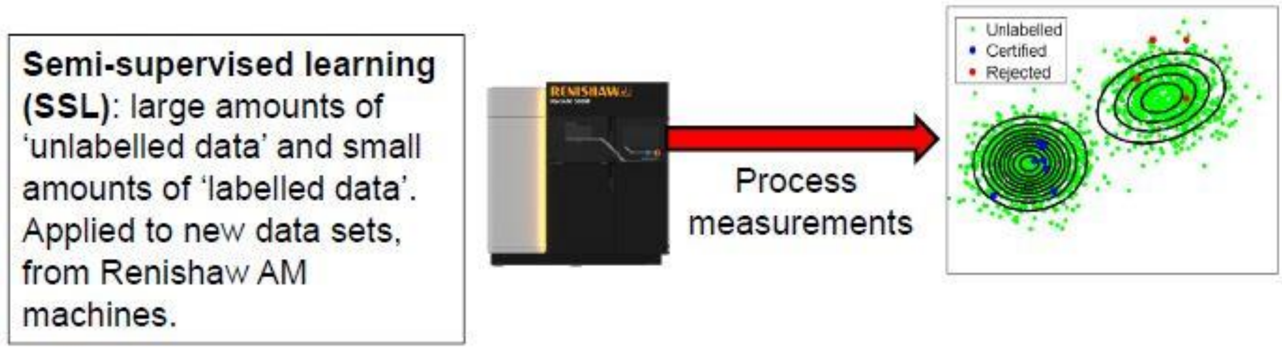
whether the part is ‘acceptable’ or ‘faulty’ using an approach known as **semi-supervised machine learning**.

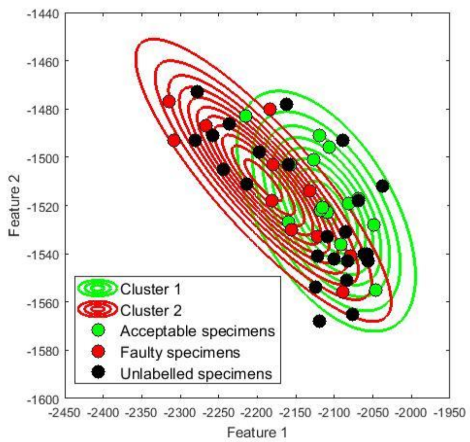


Implementing semi-supervised machine learning at Renishaw Plc

For the study, two builds were conducted using a Renishaw RenAM 500 L-PBF machine. Each build consisted of 25 individual tensile test bars. Throughout each build the laser position was measured and this was used to associate data with each individual test bar. After construction, each bar was tested and labelled as ‘acceptable’ or ‘faulty’. A data matrix was composed of 50 columns (one per test bar) which each contained the photodiode measurements corresponding to each test bar; producing approximately 3 million rows of data. Statistical methods extracted features from the process measurements. Specimen classification was subsequently repeated with different numbers of classified and unclassified test bars, to explore the ability of the semi-supervised learning approach to analyse different ratios of labelled and unlabelled builds.

Results

The results obtained, when half the test bars are labelled and half are unlabelled, are shown in the adjacent box. Green and red contours illustrate identified clusters that correspond, respectively, to ‘acceptable’ and ‘faulty’ specimens. The approach was consistently able to classify builds with a 77 percent success rate. By repeating these tests for different numbers of unclassified builds it was found that similar algorithm performance could be achieved using as little as one third of the classified builds.



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Key finding 1

The feasibility of identifying additive manufacturing (AM) build errors from photodiode measurements was demonstrated. Faulty builds can be identified with 77 percent accuracy, solely on the basis of measurements taken during the build process.

Key finding 2

By reducing the number of parts that require certification for training an algorithm, the benefits of a semi-supervised approach were demonstrated.

Wider applications

In this project, we focused on laser powder bed fusion applications. The approach is currently being extended to other forms of additive manufacturing techniques such as inkjet printing. The aim is to predict optimum process parameters to produce higher quality parts. Stereolithography is another potential area of application.

What next?

The outcomes of this study are being used to develop a graphical user interface for applications at Renishaw, UK. Since this study completed, we have developed our approach further and it is now possible to identify flaws, layer by layer, with improved accuracy.

Future work will find the limits within which process measurements must be to ensure quality and thereby implement machine-learnt process control. By using a semi-supervised approach to reduce the number of certification experiments needed to infer such a control mechanism, we expect to greatly reduce the costs and time associated with new materials innovation in additive manufacturing.

An ultimate goal is to use real-time measurements to monitor the manufacturing process as it is carried out and allow only good products to reach the end-point of manufacture.

Further funding achieved

Funder:	EPSRC Impact Acceleration Account
Amount:	£12,368
Project title:	Machine Learnt Fault Detection for Additive Manufacturing
Timeframe:	4 months

Funder:	University of Liverpool Knowledge Exchange Voucher
Amount:	£9,659
Project title:	Machine Learnt Process Control for Sustainable Paper Production
Timeframe:	3 months