

Additive Manufacturing

How AI can enhance Additive Manufacturing (AM) quality in harsh environments

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Additive Manufacturing (AM) enables for the fabrication of multiple material types on various machine architectures for numerous application use cases. Along with this diversity that AM offers, the capability for rapid fabrication of complex part geometries is an area of extreme interest in field service environments. However, the AM process exhibits high variability and is susceptible to numerous uncertainty factors. For example, a printed part produced with the same machine, material, and process parameters may exhibit high variability in terms of its performance. In this framework, Artificial Intelligence (AI), as an emerging and disruptive technology is leveraged to enhance the AM outcome. AI efficiently detects statistical patterns in each set of data and simplifies complex studies with reduced-order and surrogate modelling. In addition, the built AI model establishes the link between the input parameters and the output performance, enabling an optimisation loop.

Wichita State University National Institute of Aviation Research (NIAR), Hexagon, Edison Welding Institute (EWI), Rapid Prototype & Manufacturing (rp+m), Auburn University, and ASTM International undertook a joint modelling endeavour under the framework of the ATRQ (Advanced Tools for Rapid Qualification) program investigating Service Life of Additive Manufacturing (SLAM). The primary objective is to evaluate the quality of AM parts, printed with Stratasys Ultem™ 9085 material and exposed to service life environmental conditions such as UV or Xenon. An integrated solution and workflow combining experimental data, virtual testing through micromechanics, and AI needs to be identified and implemented to fine-tune the solution and deploy it. The National Center for Defense Manufacturing and Machining (NCDMM) provided program management throughout the investigation. This program was scoped under the America Makes consortium and sponsored by the Air Force Research Laboratory (AFRL).

The modelling strategy includes tools such as MaterialCenter for data management, Digimat for micromechanical modelling of the AM process, ODYSSEE and Python for AI, reduced order modelling, uncertainty quantification

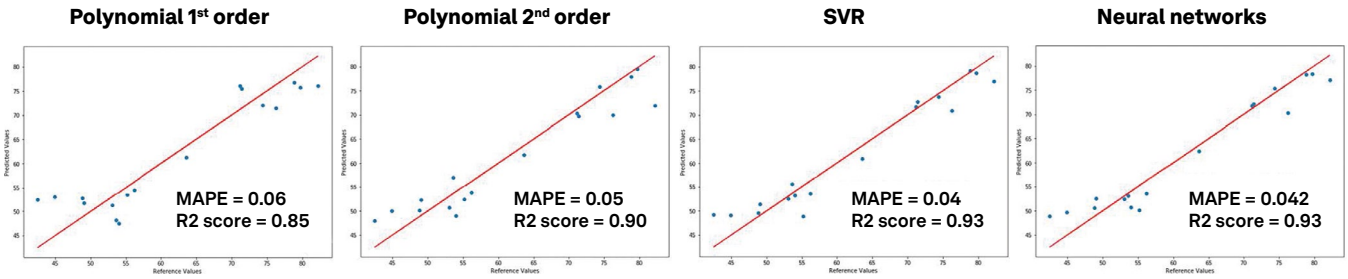


Figure 1: Different AI models evaluating the performance of printed samples: (a) Polynomial 1st order, (b) Ploynomial 2nd order, (c) SVR, (d) Neural networks.

and reliability analysis, and a Django Web Framework for web development of the deployed solutions.

Modelling methodology at sample level

The experimental data is supplied from mechanical testing performed at NIAR and utilises standard specimen-level geometries, to provide the necessary mechanical performance data that can be leveraged in the predictive AI model development. The input parameters of the specimen-level geometries are stress-strain curves of printed samples for different printing directions, tests, and environmental conditions. These stress-strain curves can be described through reduced descriptors, which consist of the Young's modulus, yield stress, hardening and failure parameters. The experimental data is used to train the AI model to predict the reduced descriptors and rebuild the stress-strain curve corresponding to the printing direction, test, and environmental condition of the printed sample. AI plays the role of establishing an efficient link between the input parameters and the output stress-strain curve at the sample level. Different AI models can be used to predict these reduced descriptors. Figure 1 shows the performance of different tested AI models in evaluating the strength of the printed sample for different conditions and configurations. The reliability index quantifies the extent to which a configuration adheres to a given design boundary.

Modelling methodology at micromechanical level

The modelling step at the micromechanical level establishes the connection between the specimen level and the structural level. Information from the specimen and microstructural levels are considered to perform the analysis at structural level. For instance, it enables evaluating the impact of a given process parameter on the final performance of the product. Figure 2 depicts how the printing direction influences the local orientation of the microstructure which can affect the final performance of the printed part. At this micromechanical level, AI facilitates the creation of material cards that are used in the structural analysis. The micromechanical material cards consist of different parameters that are evaluated and calibrated by the AI model for a specific configuration, such as an exposure to UV or Xenon.

Modelling methodology at structural level

In addition to the specimen-level geometries, the fabrication and investigation of a more complex model is used as a proof of concept in expanding the developed model's predictive capabilities to a higher level in the building block approach. For the structural level, the printing of an aerospace rocker is considered, and its performance is evaluated with respect to specific environmental conditions that have a that has uncertainty. Two main environmental conditions are considered for this validation, which are exposures to UV and Xenon. By building a reduced order model, AI reduces high-fidelity analysis at the structural level. This makes it possible to efficiently evaluate the reliability index of the printed part for a given exposure level of UV and Xenon, as shown in Figure 3.

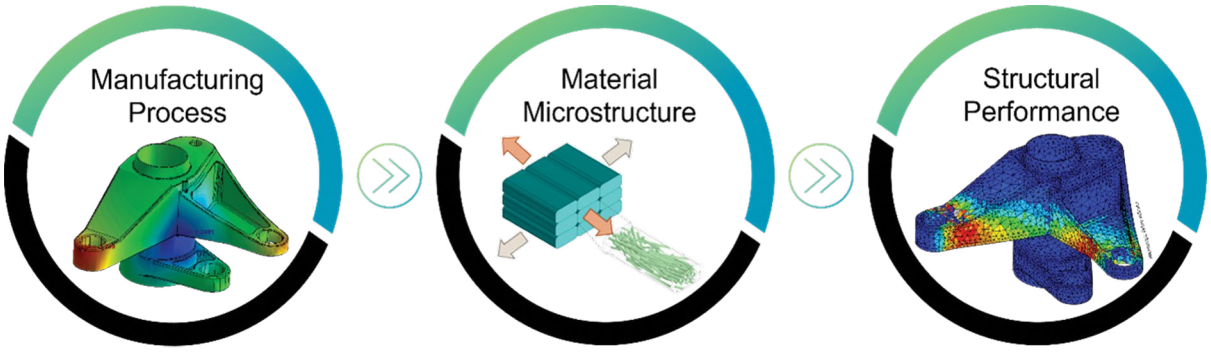


Figure 2: Micromechanical modelling.

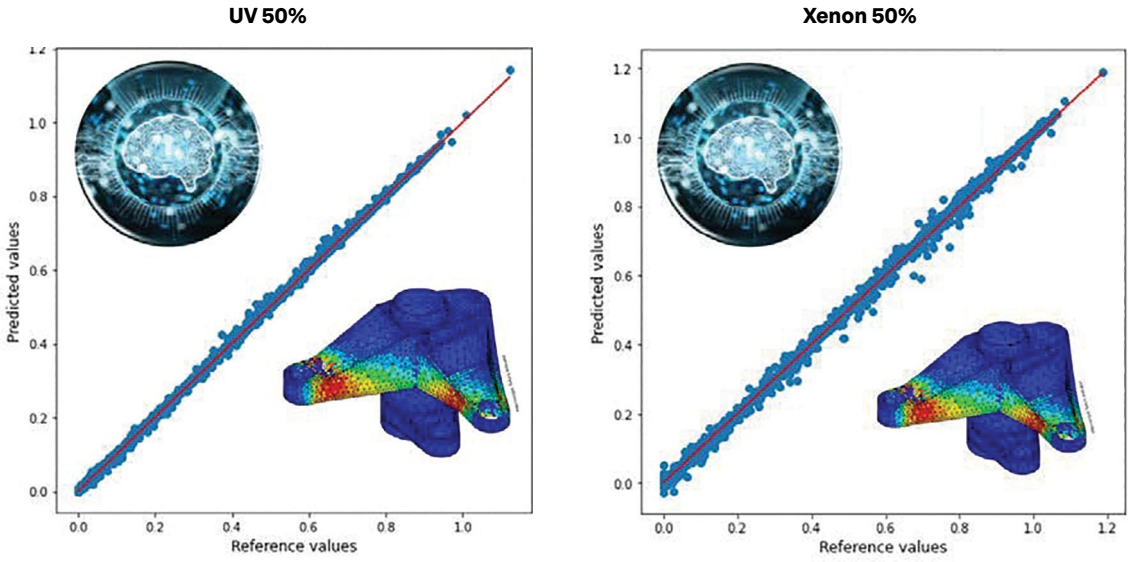


Figure 3: Reduced order model evaluating the performance of a printed aerospace rocker exposed to a 50% level of UV (left) and Xenon (right).

Results and next steps

The integrated approach assesses the reliability index of printed parts for different exposure levels to UV and Xenon. In Figure 4, the AI model at the structural level reveals that the reliability of the printed part increases with the exposure level to UV, whereas the overall reliability decreases with increasing exposure level to Xenon.

An integrated solution consists of experimental data at the sample level. The output is the prediction of the quality of a printed part as a function of a given set of input parameters.

The project demonstrated a high-confidence approach, on par with a building block philosophy, while minimising time, cost, and the number of specimens required to meet specific environmental demands. The effort carried out can be seen as an intermediate step towards the implementation of a complete virtual portal which aims to accelerate innovation and increase the quality of AM parts. The portal uses an integrated approach mixing different technologies like cloud computing, CT-scanning, real-time monitoring of the printed parts and micromechanics. AI plays the role of a binder and enabler, connecting the dots efficiently and in a user-friendly way, between these different components and technologies.

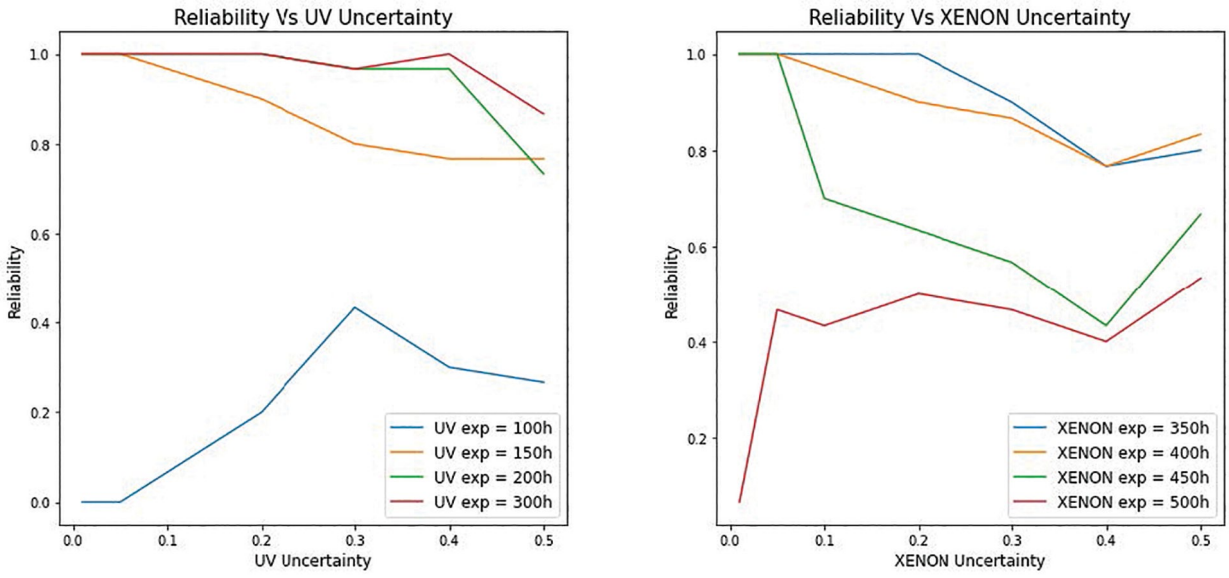


Figure 4: Reliability index as a function of the exposure to UV (left) and Xenon (right) uncertainty.