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Guest Editorial

Special Issue on Uncertainty Quantification and Management in Additive Manufacturing

Additive manufacturing (AM) represents a new paradigm of manufacturing where parts are manufactured using their 3D models (such as CAD models) by joining materials in a layer-by-layer manner. Widespread implementation of additive manufacturing requires robust techniques for performance evaluation, quality control, and certification. AM product quality is impacted by multiple uncertainty sources that are present at various stages of the manufacturing process, such as raw materials, process equipment, process parameters, process simulation models, and sensor measurements. Therefore, techniques of uncertainty quantification and management (UQ&M) are essential for the quality control and certification of additive manufacturing processes. With the development of advanced simulation techniques, artificial intelligence, and big data analytics, new UQ&M approaches are emerging to enable model-based quality control and certification, data-driven quality monitoring, and AI-based quality assurance in additive manufacturing. This special issue covers various recent advances in the field of UQ&M with a focus on additive manufacturing.

The Call for Papers was announced in November 2020 with a submission deadline of Feb. 1, 2021. We would like to express our sincere gratitude to Prof. Ayyub and the editorial board for their support. There are 13 full papers in this special issue, which includes a review paper and 12 research papers. The review paper by *Mahadevan*, *Nath*, and *Hu* provides a comprehensive literature review on UQ methodologies focusing on model uncertainty, discusses the corresponding activities of calibration, verification and validation, and examines their applications reported in the AM literature.

The 12 full research papers highlight recent advances in uncertainty modeling, surrogate modeling, Bayesian calibration, uncertainty propagation, process optimization under uncertainty, and process control and monitoring under uncertainty, and their applications in additive manufacturing. They can be classified into two groups, namely, (1) UQ&M in AM modeling, and (2) AM process optimization and control under uncertainty. Below are highlights of the papers in this special issue.

In order to model various uncertainty sources in the AM modeling, *Moges* et al. characterize several sources of laser powder bed fusion (L-PBF) model uncertainty for low, medium, and high-fidelity thermal models. The studied uncertainty sources include model assumption, numerical discretization error, and input parameter uncertainty. The propagation of these uncertainty sources to the melt pool provides guidance for measuring model fidelity and model selection in different applications. *Dey* and *Yodo* propose a linear optimization-based approach to predict conservative confidence intervals for linear and polynomial regression models and demonstrate the approach on a fused deposition experimental dataset. *Sharma* et al. propose a data-driven approach to investigate the influence of major fabrication parameters in the laser-based additively manufactured Ti–6Al–4V. They consider four fabrication parameters—scanning speed, laser power, hatch spacing, and powder layer thickness, and investigate their impact on three postfabrication parameters - heating temperature, heating time, and hot isostatically pressed or not.

With a goal to reduce the required computational effort for UQ, *Huang* et al. propose a transfer learning-based multifidelity point-cloud neural network method (MF-PointNN) for surrogate modeling of melt pool in AM. The application of the developed multifidelity surrogate modeling method to electron-beam additive manufacturing of Ti–6Al–4V shows that it outperforms the current Gaussian process-based multifidelity surrogate modeling methods. *Batabyal* et al. present a Gaussian process-based approach to quantify the variability of the size of the neck region of two particles modeled using the phase-field approach. Based on the uncertainty propagation and associated sensitivity analysis, they observe that variation in neck size is more sensitive to the uncertainty in the interparticle distance than that of surface diffusivity. Similarly, *Zheng and Wang* perform UQ on the silicon electrodeposition process using Gaussian process regression to evaluate the impacts of various experimental operation parameters on the thickness variation of the coated silicon layer and to find the optimal experimental conditions. *Zhang* et al. study the role of predictive modeling to accelerate the design of additively manufactured parts. Specifically, they discuss forward prediction with cross-validation, global sensitivity analyses to understand the effects of various parameters, inverse prediction and optimization, and intelligent data addition for a direct energy deposition process. *Ye* et al. study uncertainty quantification (UQ) analysis for multiple hierarchical models to establish process-microstructure relationships in LPBF process using a Bayesian network, which is later used to calibrate and analyze simulation models that have experimentally unmeasurable variables.

Aiming to design a reliable structure for AM, *Kulkarni* et al. investigate the design, fabrication, mechanics, and reliability of additively-manufactured lattice structures with repeating cubic unit cells using probabilistic analysis. *Kapusuzoglu* et al. develop an approach for multi-objective robust design optimization under uncertainty to design the parameters of a fused filament fabrication process, in order to minimize both the mean and variance of two quality metrics: porosity and geometric inaccuracy. They consider both aleatory and epistemic uncertainty sources and construct a Bayesian deep learning model for use in uncertainty quantification and optimization. *Pandita* et al. focus on demonstrating the impact of probabilistic modeling and uncertainty quantification for modeling process maps on powder-bed fusion additive manufacturing. Specifically, they discuss techniques for accelerating the parameter development processes, quantifying uncertainty and identifying missing physical correlations in the process computational model, and transferring learned process maps from a source to a target process. For AM process quality control, *Xi* study the control effectiveness of the proportional-integral-derivative control and the model predictive control for the LPBF process based on a physics-based machine learning model. The control objective is to maintain the melt pool width and depth at required levels under process uncertainties from the powder and laser.

We hope that the research community benefits from these papers. We also hope that the papers stimulate further advances in the application of UQ&M techniques to additive manufacturing. We thank all the authors who responded to our call for papers and

contributed excellent research articles. We also thank all the reviewers for spending time reviewing the papers. Last but not least, we thank Ms. Deena Ziadeh who helped us with logistical details.

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