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Uncertainty quantification in prediction of material properties during additive manufacturing

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ABSTRACT

Based on our experience gained from uncertainty quantification (UQ) of traditional manufacturing, this paper discusses UQ for additive manufacturing with a focus on the prediction of material properties. Applications of UQ methods in traditional manufacturing are briefly summarized first. Based on that, we investigate how the state of the art UQ techniques can be applied to AM process to quantify the uncertainty in the material properties due to various sources of uncertainty. The UQ of ultimate tensile strength of a structure obtained from laser sintering of nanoparticles is used as an example to illustrate the proposed UQ framework.

1. Introduction

Additive manufacturing has been successfully applied to the manufacturing of metal components with complicated geometries (e.g., engine rotor blades) [1]. It has a huge market potential of several billion dollars [2]. Current AM techniques for metal component manufacturing include stereolithography (SLA) [3], fused deposition modeling (FDM) [4], laminated object manufacturing (LOM) [5], selective laser sintering (SLS) [6], selective laser melting (SLM) [7], direct metal deposition (DMD) [8], laser metal deposition (LMD) [9], direct metal laser melting (DMLM) [10], and others. The most widely used ones are powder bed fusion-based AM processes (i.e., SLS, SLM, LMD, or DMLM), which are also the focus of this paper.

In the laser powder bed fusion process, the powders are delivered to the powder bed layer by layer and the powders are melted by the laser beam according to laser paths defined according to the 3D computer aided design (CAD) model. Due to various sources of uncertainty involved in the processes from powder bed forming to melting and solidification, variability is present in the properties of the manufactured metal components. As a result, it is hard to repeat the manufacturing of a high quality product and a trial-and-error approach needs to be employed to get a product with high quality. This becomes a major hurdle for the wide application of metal-based AM techniques. The fundamental reason for this limitation is that the variability in the manufacturing processes has not been properly captured.

A key to resolve the aforementioned problem is to use uncertainty quantification (UQ) techniques during the AM process. Despite the fact that UQ techniques have been studied for traditional manufacturing processes, their application in AM process is still at its early stage. Only a few examples have been reported in the literatures on UQ in AM [11–13]. In addition, currently reported UQ methods in AM are mainly based on experiments and are performed at the process level. This will result in excessive material wastage, increase product development cost, and delay the product development process [14]. A generic UQ framework built upon a good understanding of the fundamental principles of the AM process will significantly benefit the widespread use of the AM techniques. The understanding of the material properties resulting from additive manufacturing and the associated UQ is thus an important need in fully realizing the promise of AM.

This paper focuses on leveraging our experience in UQ of traditional manufacturing to UQ in the prediction of material properties during AM. Two examples of the UQ of traditional manufacturing process are presented first. Based on that, we discuss the challenges related to the UQ of the AM process. Solutions of these challenges will then be introduced through the employment of the state of the art UQ techniques. Finally, a laser sintering model of iron nanoparticles, which is an important example of a micro AM process, is used to illustrate the application of UQ techniques in AM of metal products.

The remainder of the paper is organized as follows. Section 2 provides a brief summary of our experience with UQ in traditional manufacturing. Section 3 discusses the UQ of material properties prediction in the AM process. A laser sintering example of nano-particles is given in Section 4 to demonstrate some of the discussed UQ techniques, and concluding remarks are given in Section 5.

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2. UQ in traditional manufacturing

Recent efforts in UQ of traditional manufacturing have been pursued along two interesting directions: (i) multi-scale modeling that links the manufacturing process parameters to the microstructure and to macro-scale properties, and (ii) macro-scale linkage of multiple manufacturing processes. The first direction is explained in details as below.

Cai and Mahadevan [15] used multi-scale modeling to investigate the effect of uncertainty in material initial condition and manufacturing process parameters on the microstructure. The uncertainty in the microstructure is then propagated to the uncertainty in the macro-level material properties as shown in Fig. 1.

As shown in Fig. 1 (a), a two-dimensional dual phase polycrystalline microstructure is simulated based on the initial condition of the grain cores (generated using stratified MCS) and the manufacturing environment. Then a homogenization method is applied to predict macro-level properties. The cooling schedule of the alloy is used to illustrate the methodology, and Young's modulus is the prediction quantity of interest. Even with a given cooling schedule, spatial variation of temperature affects the microstructure and properties as indicated in Fig. 1 (a); this variability is also incorporated through a random field representation of the temperature. Fig. 1 (b) shows the variability of Young's modulus obtained under different coefficients of variation of the temperature, which is presented as spatially varying random field (RF). It shows that the variation in the Young's modulus can be reduced significantly by reducing the uncertainty in the manufacturing process parameter (temperature). The UQ methodology uses a Kriging surrogate model [16] for computational efficiency, since a large number of runs of the multi-scale analysis are required corresponding to multiple realizations of the uncertain variables (i.e. uncertainty in the initial condition of the grain cores and temperature of manufacturing). The relative contributions of both aleatory and epistemic sources to the overall bulk property uncertainty are quantified using a global sensitivity analysis (GSA) approach (discussed in Section 3). The GSA method and surrogate modeling method is employed to identify the most important uncertainty sources and reduce the computational effort required during the UQ process. The sensitivity analysis also provides guidance for effective quality control of the manufacturing process in order to meet the desired uncertainty bounds in the bulk property estimates.

The above discussed research is about UQ of only one process model. Manufacturing of any product requires multiple processes and sub-processes, and UQ for such a network of processes is not straightforward. The uncertainty sources occur at different stages of the manufacturing process and do not combine in a straightforward manner; the combination could be linear, nonlinear, iterative, or nested. Nannapnaneni et al. [17] found a Bayesian Network (BN) approach to be advantageous in the uncertainty aggregation of such a complicated manufacturing network. The Bayesian network approach can also incorporate GSA and surrogate modeling techniques to reduce both the number of variables and the computational cost.

The above discussions briefly summarize successful applications of the UQ techniques to traditional manufacturing process. Next, we will discuss the UQ of material properties prediction during the AM process.

3. Uncertainty quantification during additive manufacturing

In this section, we first briefly introduce the models in the AM process. Following that, we will discuss the UQ of AM process.

3.1. AM process models

During the AM process, the models used to predict the process performance can be roughly classified into five models as shown in Fig. 2. The outputs of the heat source model and powder bed model will act as inputs of the melting pool model. The output of the melting model will be used as input of the solidification model to study the evolution of the microstructure during the AM process. The solidification model and the melting pool model will provide information for the residual stress analysis model and other macro-level analysis models [18]. The analysis and simulation methods used in each model are also given in Fig. 2. Since there are connections between different simulation models, the uncertainty at lower levels such as that in the powder bed model will propagate to the uncertainty in the solidification model, which will then be presented in the residual stress model. This brings more challenges to the UQ of AM process than in traditional manufacturing.

In the subsequent sections, we will first identify various sources of uncertainty in the AM process and then discuss the challenges in UQ of AM and provide potential solutions.

3.2. Identification of uncertainty sources

Similar to the UQ of traditional manufacturing, the uncertainty sources in the AM process can be classified into two categories: *aleatory uncertainty* and *epistemic uncertainty* [19]. Aleatory uncertainty refers to natural variability, which is irreducible. Epistemic uncertainty refers to the uncertainty due to lack of knowledge regarding model inputs and

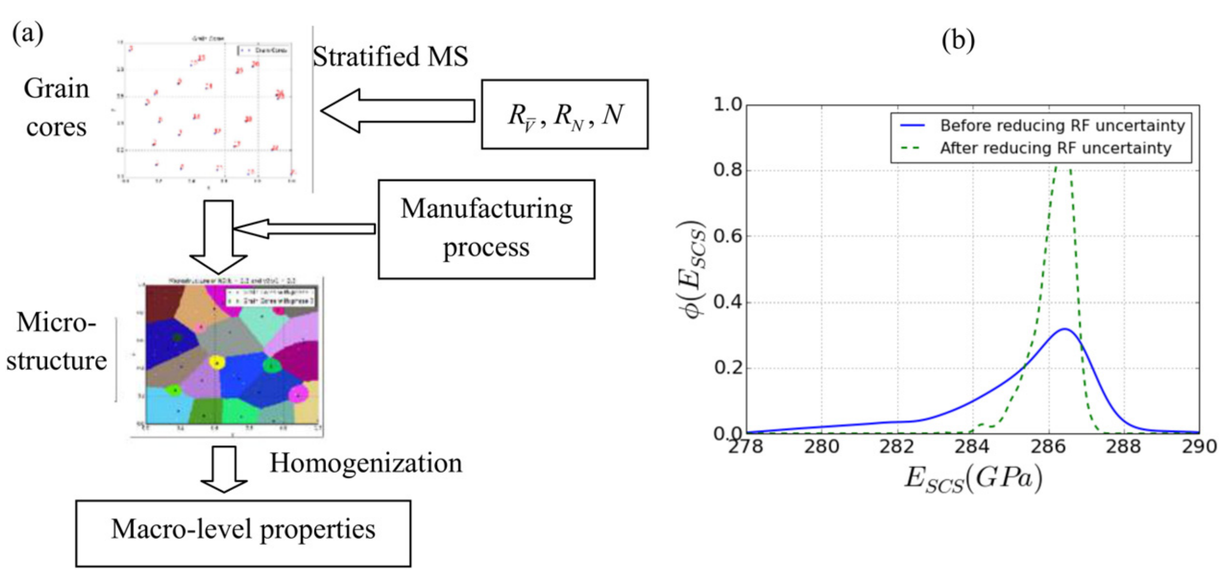

Fig. 1. UQ of Young's modulus for two-phase polycrystalline alloy [15].