Physics-Informed Machine Learning to Accelerate Process Modeling in AdditiveManufacturing of Structural Materials for Nuclear Application

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ABSTRACT:

The goal of this research is directed toward developing scientific and formalized physics-informed data-driven techniques toward accelerating the generation of both forward and inverse scaling laws that can be transferred across material systems or manufacturing processes to understand the fundamental linkages between processing and the properties of interest in metal additive manufacturing (AM). Among all metal AM processes, laser powder bed fusion (L-PBF) and laser directed energy deposition (L-DED) are extremely relevant to DoE-NE's mission because of the portfolio of products DoE-NE caters to. Both L-PBF and L-DED offer distinct advantages over traditional manufacturing processes in reducing lead time and material usage as well as enabling the fabrication of complex geometries. For example, to fabricate heat exchanges with intricate channels, L-PBF would be ideal while for building large parts such as pressure vessels, laser-wire DED (LW-DED) would be more economical. For repairing legacy components or to fabricate functionally-graded parts, laser-powder DED (LP-DED) could be used. However, the qualification of the L-LBF and L-DED processes is expensive and time-consuming. One of the greatest impediments is the amount of experimentation or computational modeling data it takes to develop scaling laws for new material systems (e.g., SS316L, IN718, etc.), manufacturing processes (e.g., L-PBF, LP-DED, LW-DED, etc.), and manufacturing equipment (e.g., large vs. small build volume, etc.). The state-of-the-art methods to develop scaling laws rely on performing the necessary experiments and modeling calculations for each combination of the material, manufacturing process, and manufacturing equipment of interest to develop them from scratch. Additionally, a sparse amount of work exists to developthe inverse scaling laws.

To address this critical requirement of generalizing both forward and inverse scaling laws across materials and manufacturing processes, I will start the investigation by blending the information obtained from high and low-fidelity simulation models as well as a limited amount of experimental data using probabilistic machine learning (ML) tools to develop a multi-fidelity (MF) surrogate. The MF surrogate will, thereafter, be used as a proxy to predict the desired properties (e.g., melt pool area, aspect ratio, etc.) as a function of process parameters at discrete time instants facilitating the design of temporal scaling laws as opposed to the current steady-state ones. Since I will use a probabilistic surrogate as opposed to a deterministic one, the scaling laws will be automatically associated with their uncertainties. Thereafter, I will use the emerging tools of transfer learning (TL) toward transferring the scaling laws across material systems and manufacturing methods. Finally, I will integrate the MF surrogate with an optimization framework to develop the inverse scaling laws and validate them via experimental demonstration. I will use two metallic alloys e.g., SS316L and IN718 as candidate materials and three manufacturing processes e.g., L-PBF, LP-DED, and LW-DED as candidate manufacturing processes.

The proposed work will transform the way scaling laws are currently developed for structural materials relevant to nuclear engineering applications via AM. A multidisciplinary approach, at the crossroads of manufacturing, modeling, characterization, and machine learning certainly involves risk because of the complex interrelationships that define the problem. However, without such an approach, the current issues of using AM for building components with repeatability cannot be adequately addressed using simple process- structure-property relationships. I have been working on computational modeling and manufacturing for about seven years and machine learning for about four years, and I have developed unique capabilities in my laboratory to tackle this challenge. Moreover, Penn State, with its world-class facilities, is an ideal place to conduct this investigation. I am looking to extensively collaborate with DOE NE researchers to develop this framework where some data may come from a different equipment located at a different geographical location to demonstrate the efficacy, versatility, and robustness of the proposed framework. The project will involve two full-time