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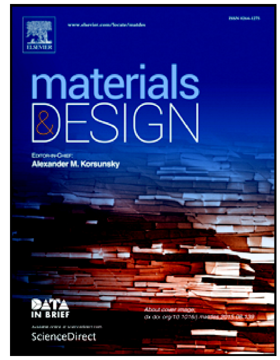

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Integration of Physically-based and Data-driven Approaches for Thermal Field Prediction in Additive Manufacturing

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Abstract

A quantitative understanding of thermal field evolution is vital for quality control in additive manufacturing (AM). Because of the unknown material parameters, high computational costs, and imperfect understanding of the underlying science, physically-based approaches alone are insufficient for component-scale thermal field prediction. Here, we present a new framework that integrates physically-based and data-driven approaches with quasi *in situ* thermal imaging to address this problem. The framework consists of (i) thermal modeling using 3D finite element analysis (FEA), (ii) surrogate modeling using functional Gaussian process, and (iii) Bayesian calibration based on the thermal imaging data. According to heat transfer laws, we first investigate the transient thermal behavior during AM using 3D FEA. A functional Gaussian process-based surrogate model is then constructed to reduce the computational costs from the high-fidelity, physically-based model. We finally employ a Bayesian calibration method, which incorporates the surrogate modeling results and thermal measurements, to enable layer-to-layer thermal field prediction across the whole component. A case study on fused deposition modeling is conducted for components with 7 to 16 layers. The cross-validation results show that the proposed framework allows for accurate and fast thermal field prediction for components with different process settings and geometric designs.

Keywords: additive manufacturing, thermal field, geometry of freeform, finite element modeling, Bayesian calibration.