Automated Extraction of Symbolic Abstractions in Production and Materials Engineering

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Abstract

Machine learning offers a powerful route to modeling complex process–structure–property relationships in additively manufactured alloys, but achieving both predictive accuracy and interpretability remains a central challenge. Ensuring reliable AM performance therefore requires predictive models that are both accurate and interpretable. This study presents a hierarchical framework that combines Bayesian inference with symbolic regression to predict the mechanical properties of additively manufactured alloys. The approach first applies Maximum A Posteriori (MAP) optimization to Bayesian expressions to obtain reliable point estimates of material properties from first-principles modeling data while accounting for uncertainty from microstructural variation. These MAP-derived estimates are then used as a condensed dataset for symbolic regression, which identifies concise, physically interpretable equations. The resulting workflow addresses the need for predictive power and explainability in materials science, offering actionable insight for process optimization and alloy design.

The framework uses Bayesian statistics to quantify uncertainty arising from complex process-structure-property relationships in AM [Awd et al., 2022]. Deterministic models often overlook the stochastic nature of defect formation and microstructural evolution in processes such as laser powder bed fusion (PBF-LB/M) [Mayr et al., 2024]. In contrast, the Bayesian formulation incorporates prior knowledge and updates it with experimental observations. MAP optimization provides the posterior mode as a computationally efficient alternative to full Bayesian inference, preserving uncertainty awareness without the cost of sampling-based methods. By encoding domain knowledge, for example through priors on porosity and grain size, the MAP stage regularizes predictions and improves robustness for sparse or noisy mechanical testing data [Awd et al., 2024].

Because the Bayesian stage can remain difficult to interpret directly, the second stage applies symbolic regression to the MAP estimates [Kabliman et al., 2021; Kabliman and Kronberger, 2026]. This produces closed-form equations linking process parameters and microstructural features to the target property. Compared with more opaque models such as deep neural networks or large ensembles, these expressions provide greater transparency and align with the growing demand for Explainable AI (XAI) in critical engineering applications [Chaddad et al., 2023; Puthanveettil Madathil et al., 2024; Branco et al., 2023; Adegbola, 2025]. Their low computational cost also supports integration into engineering workflows for process control and materials design [Abouhabaga and El Shrief, 2026].

We validate the framework on experimental datasets for AM alloys including Ti-6Al-4V and AlSi10Mg, targeting fatigue strength and tensile properties. The MAP estimates provide robust inputs for symbolic regression, yielding models with high accuracy (often $R^2 > 0.95$) and consistency with established metallurgical principles. The discovered expressions recover relationships such as inverse dependence of fatigue strength on the largest defect size and Hall-Petch-like grain-size effects [Cappuccio et al., 2025]. Their interpretability supports expert trust, helps reveal overlooked parameter interactions, and can guide more efficient experimental campaigns [Abbaspour Onari et al., 2025]. By combining Bayesian rigor with symbolic regression, the proposed framework of-

fers an accurate and explainable tool for AM qualification, materials development, and industrial decision-making [Shahbazi et al., 2026; Awad et al., 2026].

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