Self-Driven Process Optimization in Pneumatic 3D Printing: From Static Ensemble Learning to Autonomous Bayesian Method

Maxime Goulet[1], Audrey Laventure[1]
[1]*[Département de Chimie, Institut Courtois, Université de Montréal, 1375 Avenue Thérèse-Lavoie-Roux, Montréal, Québec H2V 0B3, Canada]*

Correspondence to: [Maxime Goulet] maxime.goulet.3@umontreal.ca

1. Introduction

Pneumatic extrusion-based 3D printing enables the fabrication of complex architectures with materials ranging from low-viscosity solutions to high-viscosity molten polymers. However, optimizing the multi-dimensional parameter space, encompassing pressure, temperature, speed and others, remains a persistent bottleneck, typically requiring laborious trial-and-error or exhaustive dataset generation [1]. Standard open-loop printers lack the adaptability required to navigate these complex process windows, particularly when transitioning between solution-based and melt-based extrusion modes. This work presents the development of a novel, self-optimizing 3D printing architecture designed to autonomously identify optimal processing conditions. We propose a transition from static, data-heavy machine learning models to an active learning framework utilizing Bayesian Optimization [2], implemented on a custom, open-source heated pneumatic print head.

2. Foundational Data and Processing Characterization

To validate the necessity and accuracy of the proposed autonomous system, an extensive foundational study was first conducted using poly(caprolactone) (PCL) on a commercial Hot Melt Extrusion (HME) system. Comprehensive material characterization, including Thermogravimetric Analysis (TGA) and Differential Scanning Calorimetry (DSC), defined the safe thermal processing window (60 °C to 265 °C) and crystallization kinetics. The upper limit was strictly enforced to prevent oxidative degradation mechanisms common in polyesters [3]. Rheological studies helped identify the shear-thinning behaviour critical for extrusion, mapping a viscosity range from 80 Pa·s to 750 Pa·s. A static dataset of 840 samples was generated via a fixed-interval grid search, analysing print fidelity through stereomicroscopy and stylus profilometry. While ensemble learning models trained on this data successfully predicted optimal printing parameters (minimizing height, width and filament deviation from the 0.2 mm nozzle target), the process highlighted the inefficiency of static data collection, necessitating a more agile hardware-software solution.

3. Self-Optimizing Hardware Architecture

One of the core contributions of this work is the introduction of a custom-engineered, open-source pneumatic printing head capable of distinct thermal management and pressure control. Unlike standard commercial heads, this system is designed to process a broad rheological spectrum, transitioning seamlessly between liquid solutions and viscous melts while being easily interchangeable. The hardware is coupled with a Bayesian optimization algorithm that replaces the exhaustive grid-search method. Instead of relying on a pre-existing database, the system utilizes a gaussian process surrogate model to actively select the next set of printing parameters based on an acquisition function. This process allows for a self-driven intelligent exploration and exploitation of the parameter space in real-time.

4. Methodological Synthesis and Validation

The efficacy of the new Bayesian system is validated against the ground-truth data established in our foundational PCL study. We demonstrate that the self-optimizing printer converges on the optimal print fidelity metrics defined by specific filament height, width, and surface topology targets using a fraction of the samples required by the static ensemble approach. By integrating the material constraints identified via thermal and rheological characterization directly into the optimization loop, the system avoids material degradation while maximizing print speed and fidelity.

5. Conclusion

This research bridges the gap between material science and autonomous robotics. By moving beyond static datasets to an active, Bayesian-driven approach, we demonstrate a scalable method for rapidly adopting novel polymers in additive manufacturing. The proposed open-source hardware and control framework signif-

icantly reduce material waste and characterization time, paving the way for truly autonomous, multi-material 3D printers.

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