Northeastern University
Predictive Informatics Research Lab
Young Scholars Program

Run to Run Quality Optimization for FDM Printing with Machine Learning for Manufacturing at Scale

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Abstract

Traditional large-scale plastic manufacturing processes often limit customization and complexity, impacting the user experience and product potential. Fused Deposition Modeling (FDM) offers significant advantages in customization and complexity, but with slower production speeds. This study introduces a **Bayesian optimization model designed to adjust FDM process parameters to enhance output quality while maintaining low production times**. To demonstrate its efficiency, the model was trained to optimize the surface quality of a thin thermoplastic polyurethane (TPU) wall; successfully, it identified a global optimum within **27 trials out of 256 parameter combinations**. Through this research, we aim to advance the adoption of FDM in mass manufacturing and enable the mass production of high-quality, customizable plastic products in smart manufacturing environments.

Background

Plastic products are traditionally mass manufactured through **invariant** and design-restrictive methods (e.g. injection molding). Conversely, Fused Deposition Modeling (FDM) is an additive manufacturing method that extrudes thermoplastic filament layerwise.

Pros of FDM:
- Designs can be rapidly iterated at low volumes
- Capable of producing complex design features

Cons of FDM:
- Higher production times for repetitive parts
- Production speeds and quality are typically inversely correlated

Our research aims to optimize the parameters of the FDM process to **maximize product quality within a certain range of production speeds** and bridge consumer needs with production capabilities.

Materials Used

Software:
Prusa Slicer, Blender, Onshape, Google Colaboratory, Google Sheets, Adobe Scan

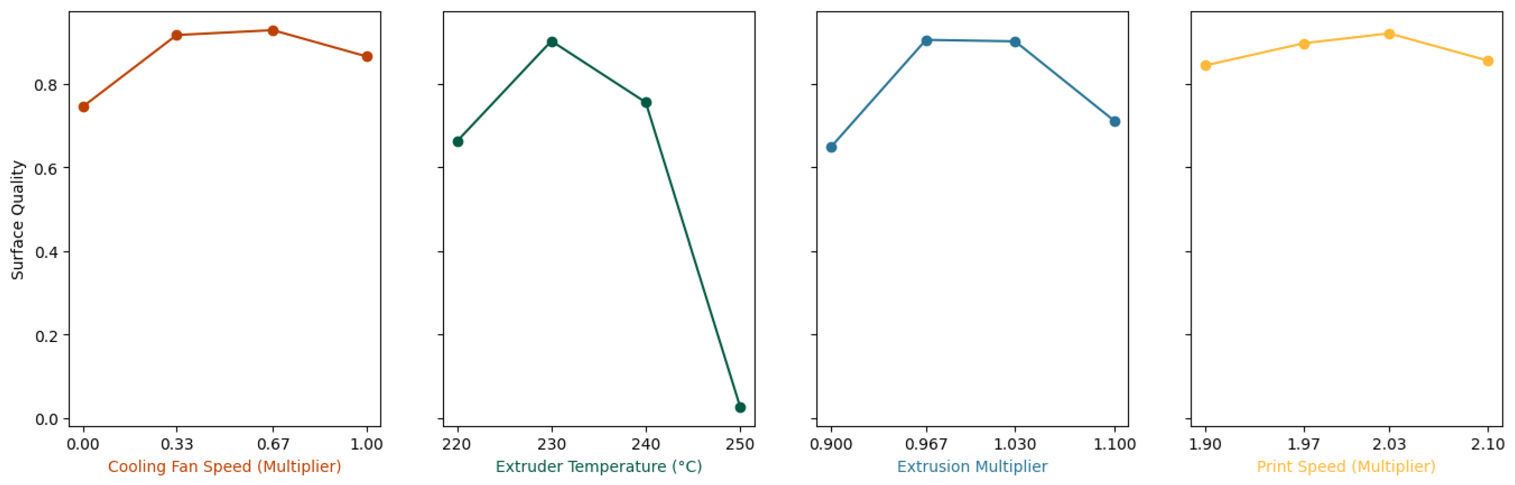
Python libraries and compiler:
Python 3.10, Pandas, NumPy, Scikit-Learn, OpenCV, Scikit-Image, SciPy, Gspread, Matplotlib

Equipment used:
Prusa Mk4 FDM 3d-printer, ESUN 95A Thermoplastic Polyurethane (TPU), Puluz Photo Light Box, Phone Camera

Preliminary Testing

Validation

Demonstrate a relation between our chosen parameters—cooling fan speed, extruder temperature, extrusion multiplier, print speed—and output quality.



Experimental Methods

Quantification

Image processing:

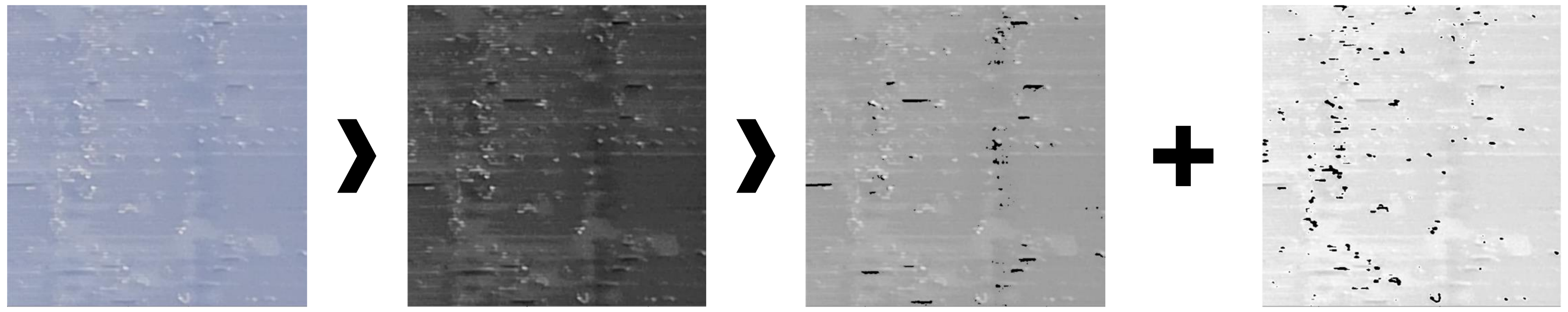
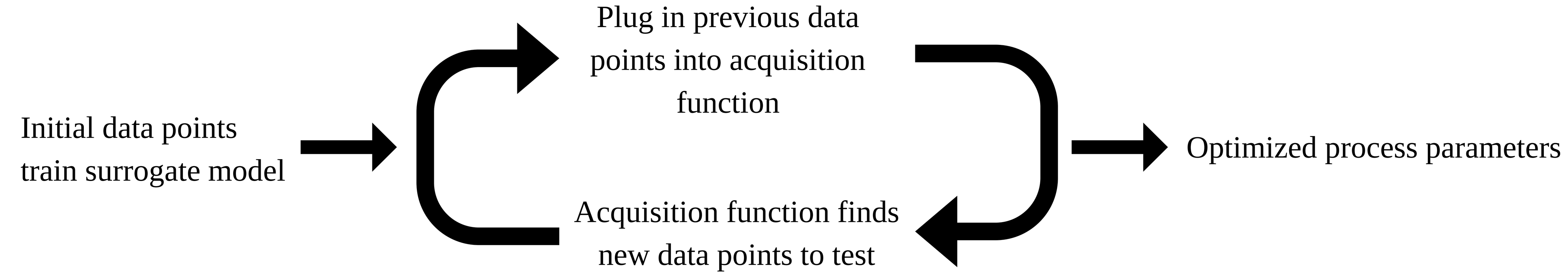


Image taken with a camera and light box
Grayscale cropped photo
Threshold processing

Calculation

$$\text{Quality} = 1 - \text{p(holes)} - \frac{\sigma_{\text{pixel grayscale}}}{6\mu_{\sigma_{\text{preliminary data}}}}$$

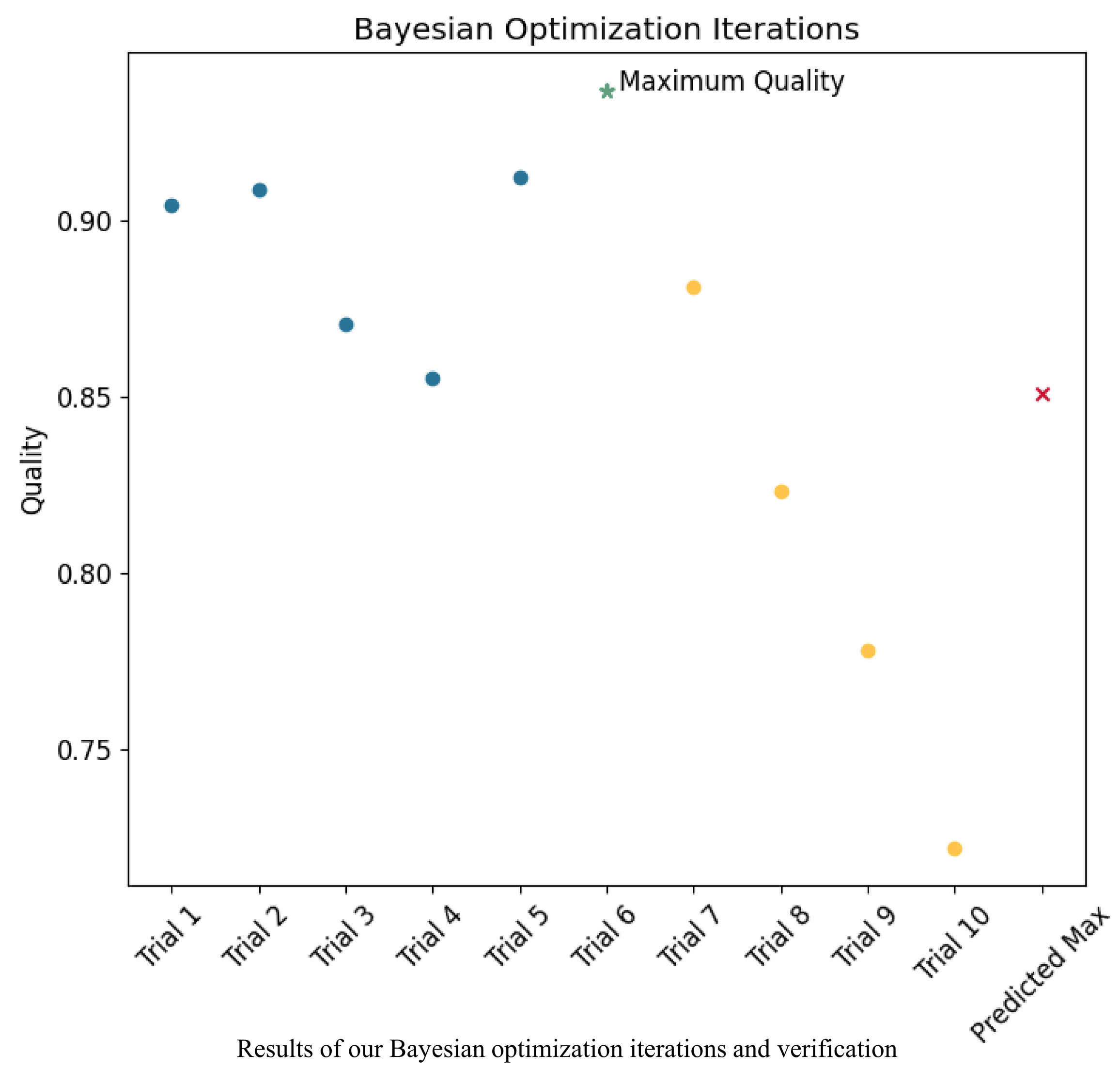
Optimization



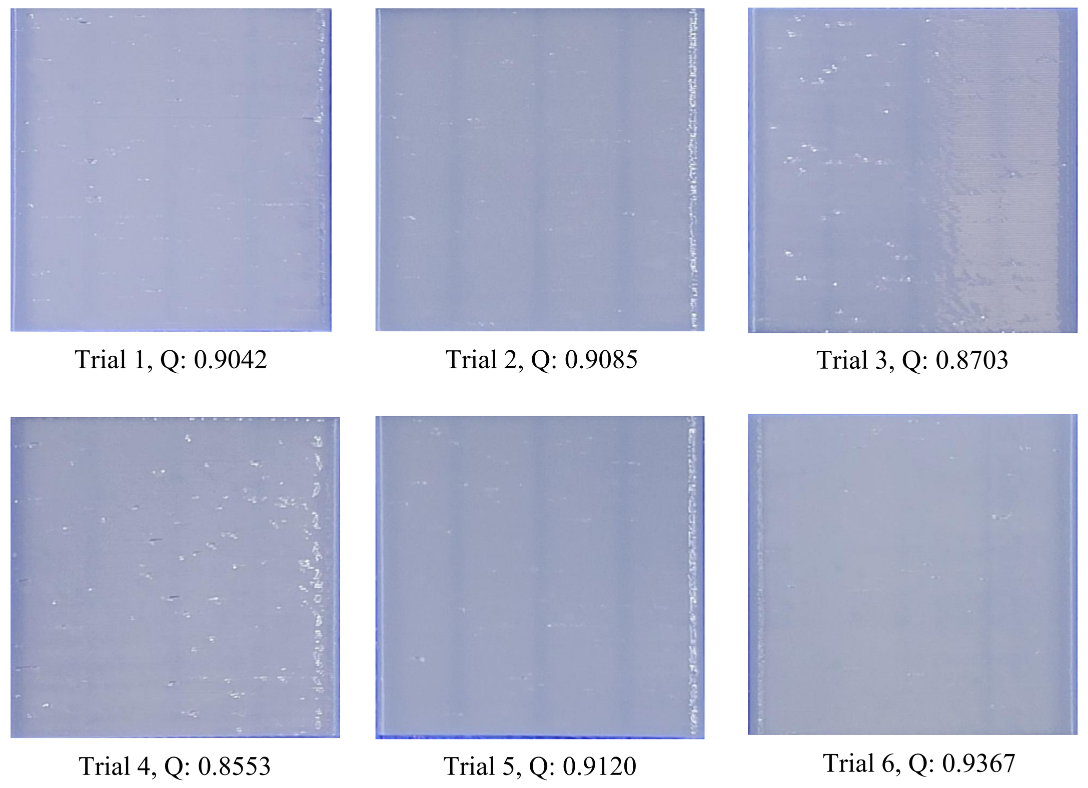
Analysis

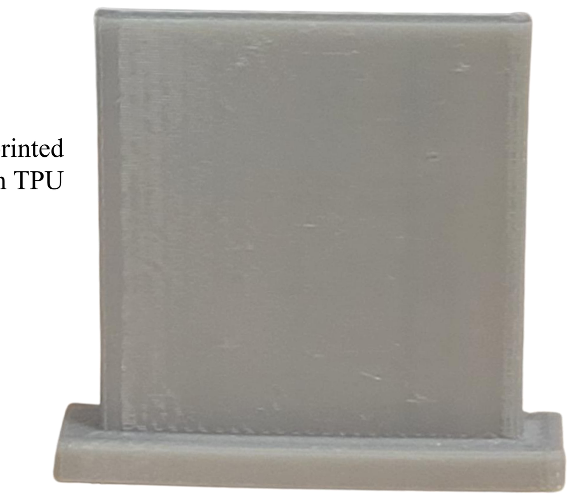
Verify the effectiveness of optimized parameters through 4 additional iterations and analysis of predicted maximum quality

Results



Results of our Bayesian optimization iterations and verification





Our 3mm case study printed with TPU

We concluded that Trial 6 was the global maximum based on four additional trials and a test print of the algorithm's predicted maximum. In total, we conducted 27 trials (16 preliminary, 6 optimizing, 4 verification, and 1 predicted maximum test)

Conclusion and Future Steps

Final Process parameters:

Cooling Fan Speed (% Multiplier)	Extruder Temperature (°C)	Extrusion Multiplier	Speed (% Multiplier)
100%	230	1.03	210%
Preliminary Mean Quality:	0.781	Optimized Quality	0.9367

With an improvement of **0.1557, or 20%,** from the mean quality of our preliminary trials, our algorithm successfully demonstrates the effectiveness of Bayesian optimization within the FDM process. In terms of time, **we saved 229 trials, or over 76 hours of printing** based on our average print time.

The adoption of optimized FDM techniques within mass manufacturing will improve user experiences and broaden manufacturing capabilities.

To further continue research into optimizing the FDM manufacturing process, an online model of machine learning could be developed to adapt parameters and adjust print quality during printing itself. Additional studies, potentially testing structural stability or dimensional accuracy, can also be done to explore the vast relationships between smart manufacturing and FDM printing.

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