

Mission

Mission Statement:

• We plan to investigate how variations in 3D printing parameters influence the quality of printed part. By systematically analyzing these factors, we aim to enhance the reliability and consistency of FDM printing processes.

Goals:

- Investigate correlations between in-line data and physical properties
- Establish a data-driven approach to improve quality assurance in additive manufacturing

Significance:

- Address limitations in traditional quality control methods
- Enhance the reliability of 3D-printed parts through better process understanding

Research

Printer Types:

• Investigated various 3D printers to determine the most suitable model for this study

Data-Gathering Technology:

• Researched the best platforms for integrating sensors and collecting real-time data

Sensor Selection:

• Identified key process parameters (vibrations, temperatures) that influence print quality

Coding and Data Integration:

• Explored programming solutions to handle multi-sensor data streams in real-time

Surface Roughness and Tensile Testing:

• Studied methods to measure post-print quality parameters

Future Work

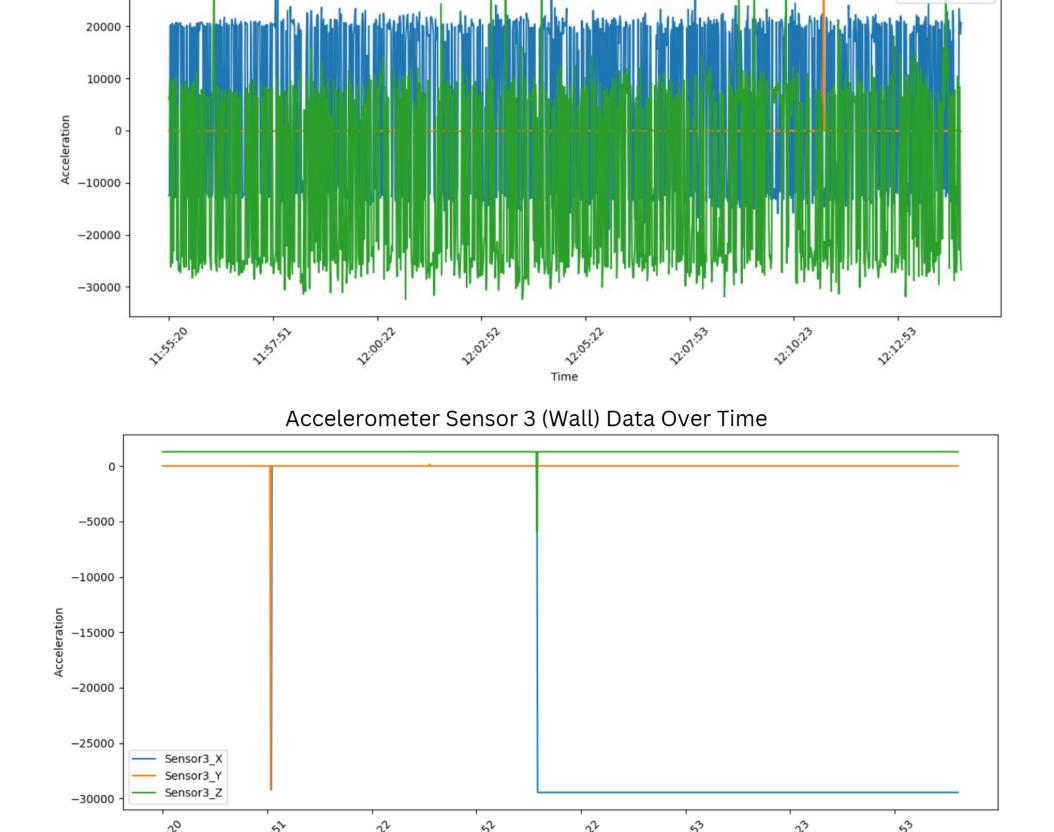
- Refine data collection methodology by increasing time resolutions and frequency to capture more detailed trends
- Explore the use of machine learning algorithms to predict quality, including strength and stiffness
- Expand data set by testing additional print parameters and sample designs to improve correlation reliability

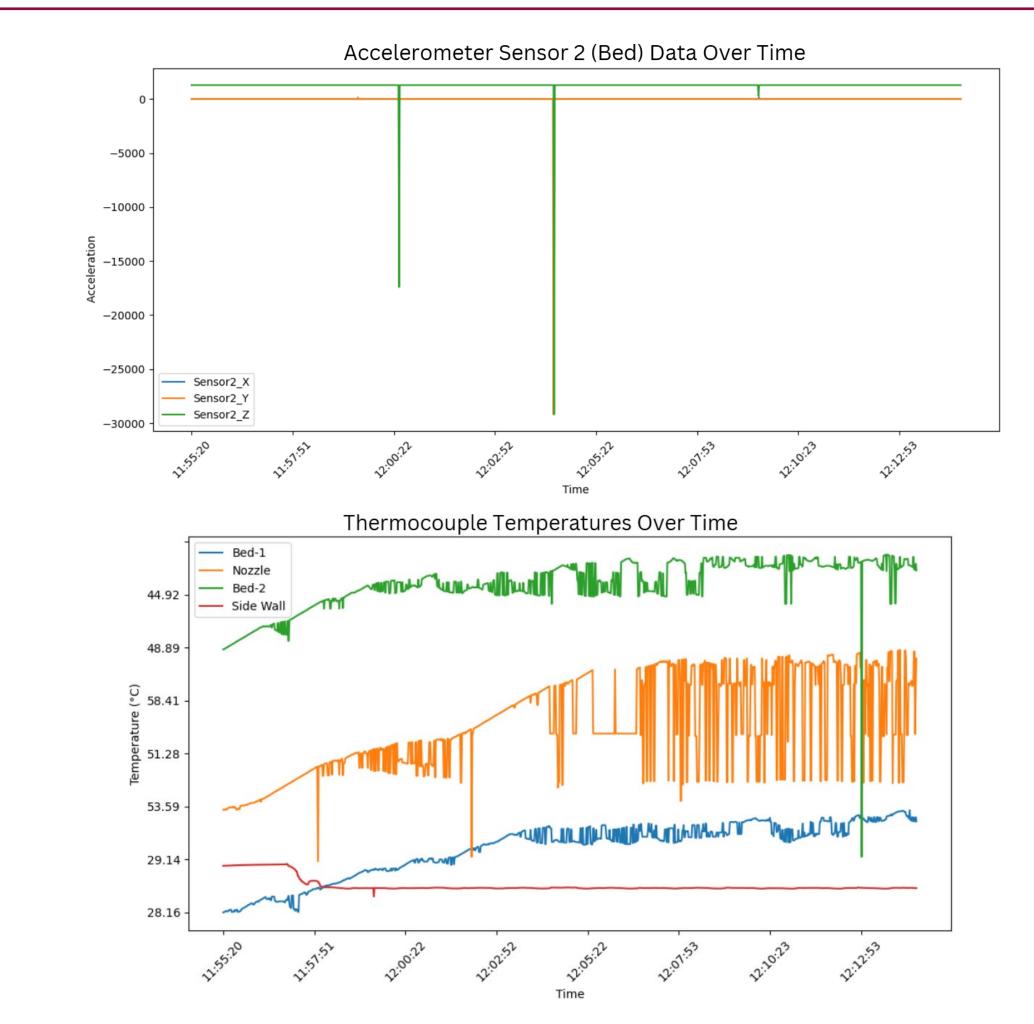
FDM Process Quality

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Final Design





Test 1:

Print Setting Overview:

- Bed Temperature: 60 °C (standard for PLA printing to ensure good adhesion)
- Nozzle Temperature: 200 °C (optimal extrusion temperature for PLA filament)
- Print Speed: 100% (default print speed to balance quality and efficiency

Sensor Data Collection

- Accelerometer Data can be found in the first 3 figures above which each display data collected along the X, Y, and Z axes.
- Thermocouples Data can be found in fourth, bottom right figure which displays data collected along the front bed, back bed, nozzle, and wall.

Key Observations:

Accelerometer Sensor 1 (Nozzle Data)

- Most Vibrant Data
- X and Z axes exhibit significant oscillations with the Y axis showing occasional spikes
- Can be caused due to higher levels of vibration on the nozzle in the X and Y direction and the occasional rapid movements in the Y direction

Accelerometer Sensor 3 (Wall Data)

- Minimal Activity
- X, Y, and Z axes exhibit a flat line with the exception of significant spikes at specific moments
- Can be caused by rapid movement changes including corners, infill patterns, or direction shifts

Accelerometer Sensor 2 (Bed Data)

- Moderate Activity, Few Spikes
- X, Y, and Z axes exhibit flat lines with a few abrupt drops typically seen in the Z direction.
- Can be caused due to abrupt movements or vibrations cause by the z-axis motor

Thermocouple Sensors

- Nozzle: Some fluctuation during print but remains relatively stable which indicates consistency during prints
- Beds: Some slight variations with one sensor maintaining stability while the other shows gradual heating which could indicate uneven heating across the bed surface
- Wall: negligible temperature changes which confirms no significant environmental interference



Concept Development

Experimental Framework:

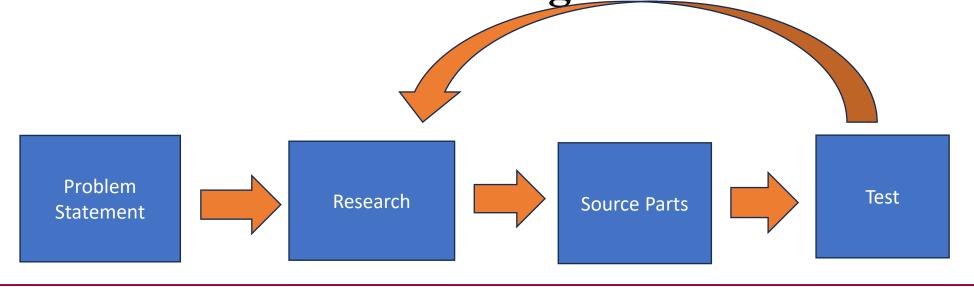
- Printer: Bambu Lab 3D Printer
- Sample Design: Dog bone specimens
- Sensors:
 - 3 accelerometers for vibration monitoring
- 4 thermocouples for temperature measurement

Variables:

- Parameters: bed temperature, nozzle temperature, and print speed
- Levels: 75%, 100%, and 125% of the baseline conditions

Data Collection:

- In-line metrics: temperature, vibrations, and nozzle position
- Post-process metrics: surface roughness and tensile stiffness and strength



Milestones

- Problem Statement and Scope Definition
- Material Acquisition and Setup
- Sensor Integration and System Assembly
- Software Development
- Initial System Validation
- Data Collection and Troubleshooting
- Iterative Refinement

References

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•Westphal, Erik & Seitz, Hermann. (2021). Machine Learning for the intelligent analysis of 3D printing conditions using environmental sensor data to support quality assurance. Additive Manufacturing. 50. 102535. 10.1016/j.addma.2021.102535.

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