

AI Agentic Selective Laser Sintering Process Optimization

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Abstract

Agentic systems enable the intelligent automation of complex workflows, specific to additive manufacturing this is applicable for complex tasks such as process parameter optimization for mechanical properties. This work investigates the AI enabled agentic process optimization within Selective Laser Sintering (SLS) to iteratively improve the tensile and flexural properties of 3 different materials on the Inova Mk1. These materials include PA12 GF, PA11 Onyx, and PA12 Blend (volume mixture of 25% PA12 GF and 75% PA12 White) and with using knowledge from previous builds and minimal guidance from the user, the agentic system was able to optimize process parameters over a small number of iterations to achieve comparable TDS specified mechanical properties. This work showcases the ability for an agentic system to continually learn from updated data, enabling the intelligent automation of complex tasks such as process parameter optimization for selective laser sintering.

1 Introduction

Additive Manufacturing (AM) enables rapid iteration and development cycles, alleviating the need for rigid tooling, specialized fixtures, and traditional manufacturing requirements.¹⁻³ Within additive manufacturing each process presents its own unique set of advantages such as relatively minimal postprocessing for Fused Deposition Modeling (FDM),⁴ high precision and functional materials of Laser Powder Bed Fusion (LPBF)² and E-Beam,⁵ and large form factor of Wire Arc Additive Manufacturing (WAAM).⁶ These advantages are effectively realized under ideal process parameters, however, nuances between environments and machines prohibit simple utilization of recommended settings.⁷

Agentic systems enable the intelligent automation of complex tasks such as the development of functional assemblies,^{8,9} drug discovery,¹⁰ computational materials science,¹¹ software development,¹² and alloy design.¹³⁻¹⁵ These agentic systems are particularly capable of search and optimization by enabling Large Language Models (LLMs) to operate within dynamic environments through the use of tools and data resources.^{8,13} Tools can include software platforms, Application Programming Interfaces (APIs), or system level commands which provide the LLM with greater capability to interact with its environment. With these capabilities, agentic systems not only enable tool orchestration and reasoning but further augment the user’s ability to execute upon complex and multi-faceted challenges.

Additive Manufacturing (AM) is a suitable domain where agentic systems are quite applicable.^{13,16} Existing work for build planning, defect mitigation, and process optimization rely on multi-physics simulations,^{17,18} machine learning,¹⁹⁻²¹ and specialized domain knowledge. Powder based processes such as Selective Laser Sintering (SLS) and Laser Powder Bed Fusion (LPBF) require precision controlled environments where parameters such as chamber temperature, laser power, scanning velocity, and numerous other factors can have an affect on part quality.^{2,3,22} With the proper process parameters, LPBF and SLS achieve micron level precision and are uniquely capable of producing complex geometric features that are otherwise impossible through other manufacturing processes.^{2,3} However, the search for op-

timal process parameters is a tedious undertaking since factors such as varying hardware components like optics introduce an additional source of variability. Calibration of a single set of process parameters requires multiple cycles of fabrication, testing, and analysis; presenting a gap where agentic systems can execute in a more efficient manner.^{23,24}

This work introduces an agentic system for the optimization of process parameters in selective laser sintering evaluated to the ASTM standard on a variety of materials. The system is capable of operating with a human-in-the-loop approach where utilizing ASTM test data from previous builds, firmware level tool calls, and reasoning enabled by Large Language Models (LLM), an optimal set of process parameters which result in desired mechanical properties can be efficiently determined. Samples are fabricated using the SLS4All Inova Mk1, an open source SLS machine built from kit, allowing for the collection of telmetry data in the form of optical image, surface temperature, and positional data. The collected data is compiled into a dataset utilized for further training of ancillary models and granting additional reasoning context enabling a continual learning agentic system (Figure 1).

2 Related Work

LLM-3D Print by Jadhav et al.¹⁶ is an early work that explores the application of a large language model to the task of process monitoring within the additive manufacturing process of Fused Deposition Modeling (FDM). This work developed a LangChain based agentic system which through a top down optical camera image data regarding the immediately printed layer using a 1.0 mm nozzle.¹⁶ The system utilized these top down images to detect layer defects and address with corrective parameter changes in subsequent layers with various agents orchestrated by GPT-4o. These agents are responsible for actions such as gathering information, planning, and executing solutions.¹⁶ With this system authors were able to show that an LLM is effective in detecting and compensating major defect factors such as stringing, oozing, and layer separation on par of that of a human. Furthermore, compression

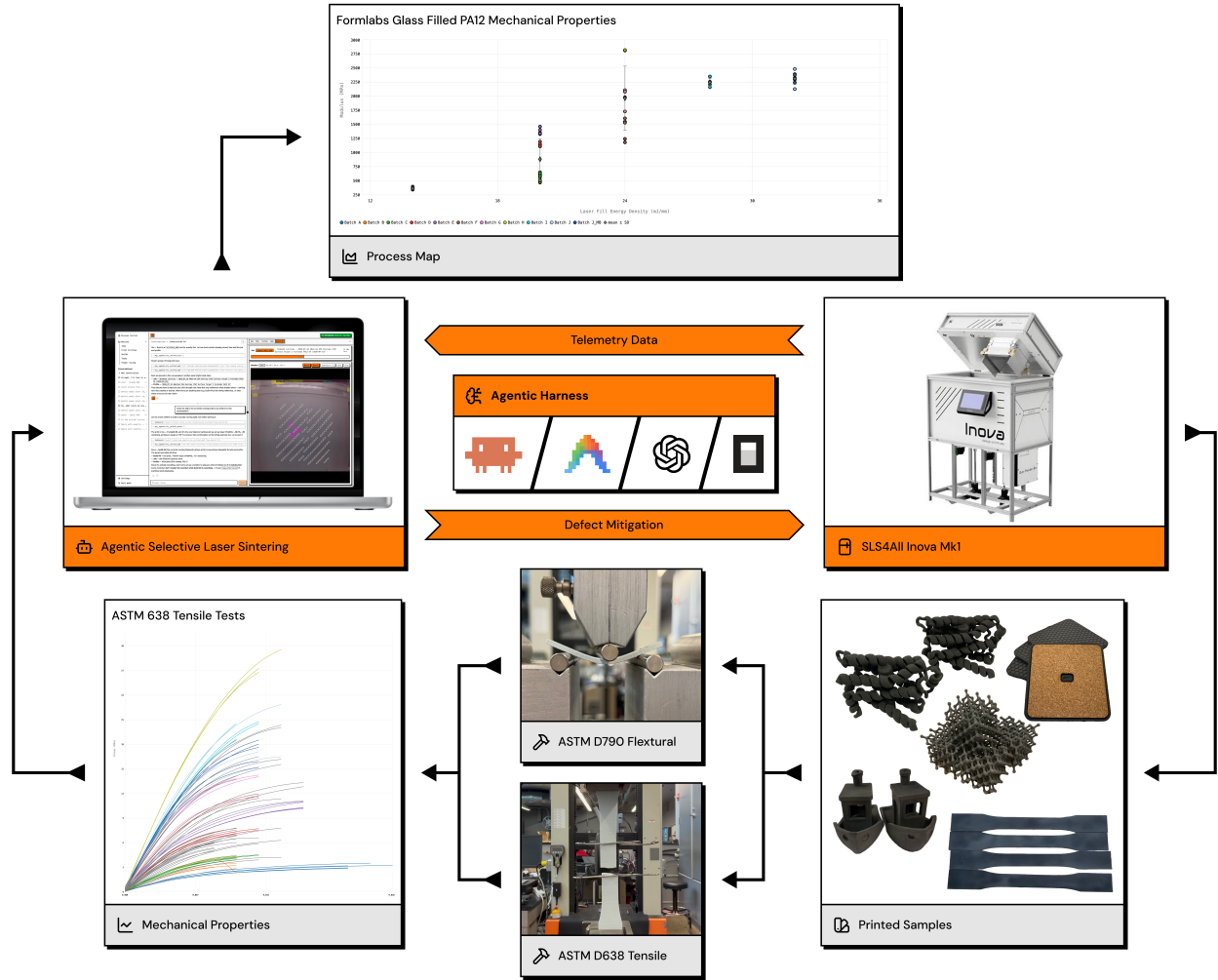


Figure 1: Agentic system for selective laser sintering capable of process parameter optimization and continual learning through evaluation of printed ASTM samples.

tests on samples constructed with and without the multi-agent system achieved a max peak load 5x greater than the same sample constructed without the system.¹⁶ This work provides the groundwork for an agentic system in additive manufacturing capable of addressing build layer defects through in-situ monitoring realized through superior mechanical properties in the final part.

Agentic additive manufacturing alloy evaluation focuses on the use of LLM enabled tool calling for the task of developing a lack of fusion process map within laser powder bed fusion for a proposed alloy composition.¹³ This work enables an agentic system to utilize software platforms such as Thermo-Calc to generate material properties for various alloy compositions which are then utilized in a Rosenthal based thermal model to determine melt pool dimensions utilized in lack of fusion process map calculations.¹³ For known materials such as Inconel 718 and Stainless Steel 316L, the system exhibited good alignment of the lack of fusion process regimes of various layer heights with the values found in the literature.¹³ For unknown alloy composition, the predicted lack of fusion process regimes displayed a general trend to match the general lack of fusion defect regime expected with compositions such as 99% Iron & 1%, Copper, and Al-Si-10Mg.¹³ This agentic system showcases the large language model’s ability to reason through complex user queries for and ultimately generate concrete, data based process maps.

Specific to materials science, Chaudhari et al.¹¹ developed a multi-agent framework named MatSciAgent composed of 4 different agents capable of materials retrieval, continuum simulation, crystal structure generation, and molecular dynamics simulation. The authors utilize GPT-3.5-Turbo as the core orchestrator of each agent and demonstrates the capability of each with a number of case studies. AtomAgents¹⁴ investigates the use of a multi-agent system equipped with physics based simulation tools to overcome the limitations the LLM’s training data. The authors explore this within 4 different case studies regarding materials property calculation, dislocation analysis, multi-scale mechanical problem solving, and hypothesis generation and validation. Ghafarollahi et al.¹⁵ extends upon this and explores

the use of a Graph Neural Network (GNN) enabled agentic system for the discovery of new potential alloy candidates within the NbMoTa family of alloys. In this search, candidates are optimized under the properties of Peierls barrier and screw dislocation energy which their GNN model predicts allowing the system to autonomously navigate through the design space of alloys considering both atomic-scale material properties and macro-scale mechanical properties.¹⁵

3 Methodology

3.1 Experimental Platform

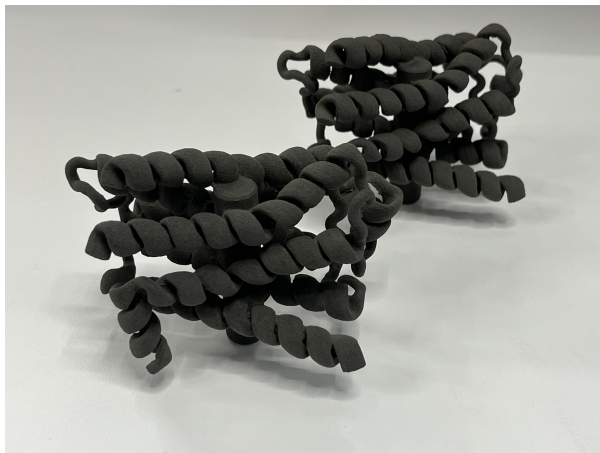
3.1.1 SLS4All Inova Mk1

The selective laser sintering process will be performed using the Inova Mk1 (Fig. 2a) for a range of materials such as PA12, PA12 GF, and other experimental powder compositions. The Inova Mk1 is an open source, low cost, selective laser sintering machine developed by SLS4All founders Tomas Starek and Pavel Dyntera.²⁵ This machine was purchased as kit from SLS4All and assembled over the course of several months producing successful prints (Fig. 2b) using Formlabs' PA12 GF.²⁶ The Inova Mk1 utilizes a 450 nm blue diode laser capable of delivering 10 watts of power.²⁵ The machine is capable of an effective build volume of 150 mm x 150 mm x 185 mm and utilizes an array of 4 halogen lamps for surface heating control and a 5 heating elements for build chamber temperature control.²⁵ Surface temperature monitoring and control is achieved with a *ThermoCam Waveshare MLX90640* capable of producing a 32 x 24 pixel thermal image for temperatures ranging from 0 °C to 300 °C. The optical camera utilizes an Omnicision OV5647 sensor capable of streaming a 1920 x 1080 pixel image at 30 frames per second. Average scan speed is around 1,650 mm/s at 5 watts (250 μ m spot size) and 2,800 mm/s at 10 watts (350 μ m spot size).²⁵ The firmware controlling the hardware components such as the galvanometers, laser, stepper motors, sensors,

and heating elements runs off a combination of open-source software programs including Klipper,²⁷ SLS4All.Compact.²⁸



(a) SLS4All Inova Mk1



(b) Printed $\beta 2$ Protein Model

Figure 2: Inova Mk1 (a) assembled from kit prints complex geometries, such as the $\beta 2$ protein molecule (b), only capable through the SLS process.

3.1.2 Platform Limitations

The Inova Mk1 system presents several software and hardware limitations. Although the software is primarily open-source, modules disclosing specific feature implementations such as part slicing and tool path generation are considered proprietary and only provided in a compiled state. In addition, there is little documentation regarding the machine's exposed Application Programming Interface (API) as the dashboard web interface is streamed from the host. The maintainers do offer an option for utilizing custom firmware plugins and this is the primary method in which the agentic system communicates with the Inova Mk1. With regard to the installed sensors, relative to thermal and optical imaging equipment used in other in-situ process monitoring works,^{19–21,29,30} the resolution and frame rate that these sensors provide is comparatively coarse. This adds a potential constraint to the quality of real-time information that can be utilized by the agentic system when testing process parameters and executing builds. The manufacturer also suggest material restrictions to primarily polymer based powders with a melting temperature of 200 °C.²⁵

3.2 Agentic System

The agentic system (Figure 3) enables the intelligent automation of parameter selection and process monitoring through the guidance of large language model. Integration with a relational database (i.e. PostgreSQL) enables the use of dynamic memory such that previous system outputs and tool call results can be recalled for future prompts, providing additional context for the large language model to use during reasoning. Lastly, the system is able to interact with its environment through agentic tool calls following the Model Context Protocol (MCP). This includes general knowledge tools such as those specific to material properties, previous builds, print profile configuration, and ASTM testing data. In addition, the system is also capable of executing machine firmware level tool calls which allow for the creation and adjustment of process parameters for the next ASTM build and runtime overrides for surface temperature, recoating, and energy.

3.2.1 Agent Harness

The agent harness is the framework which implements the functionality overhead for enabling the LLM to communicate and execute tool calls, create and maintain user conversations, and other various system level tasks. For this agentic system a collection of model harnesses including Claude Code, Antigravity CLI, OpenAI Codex, and OpenCode are implemented with the Claude Fable model used to execute process parameter optimization. Through the standard of the Model Context Protocol, all of the tools and implemented functionality can be utilized interchangeably with each of the agent harnesses enabling a modular system which can easily replace the system’s current LLM with one that better suits the need of the user.

3.2.2 MCP Enabled Tool Calling

Tool calling is orchestrated by the LLM and enabled through the model harness via the Model Context Protocol. For this agentic system the tools can be organized into several

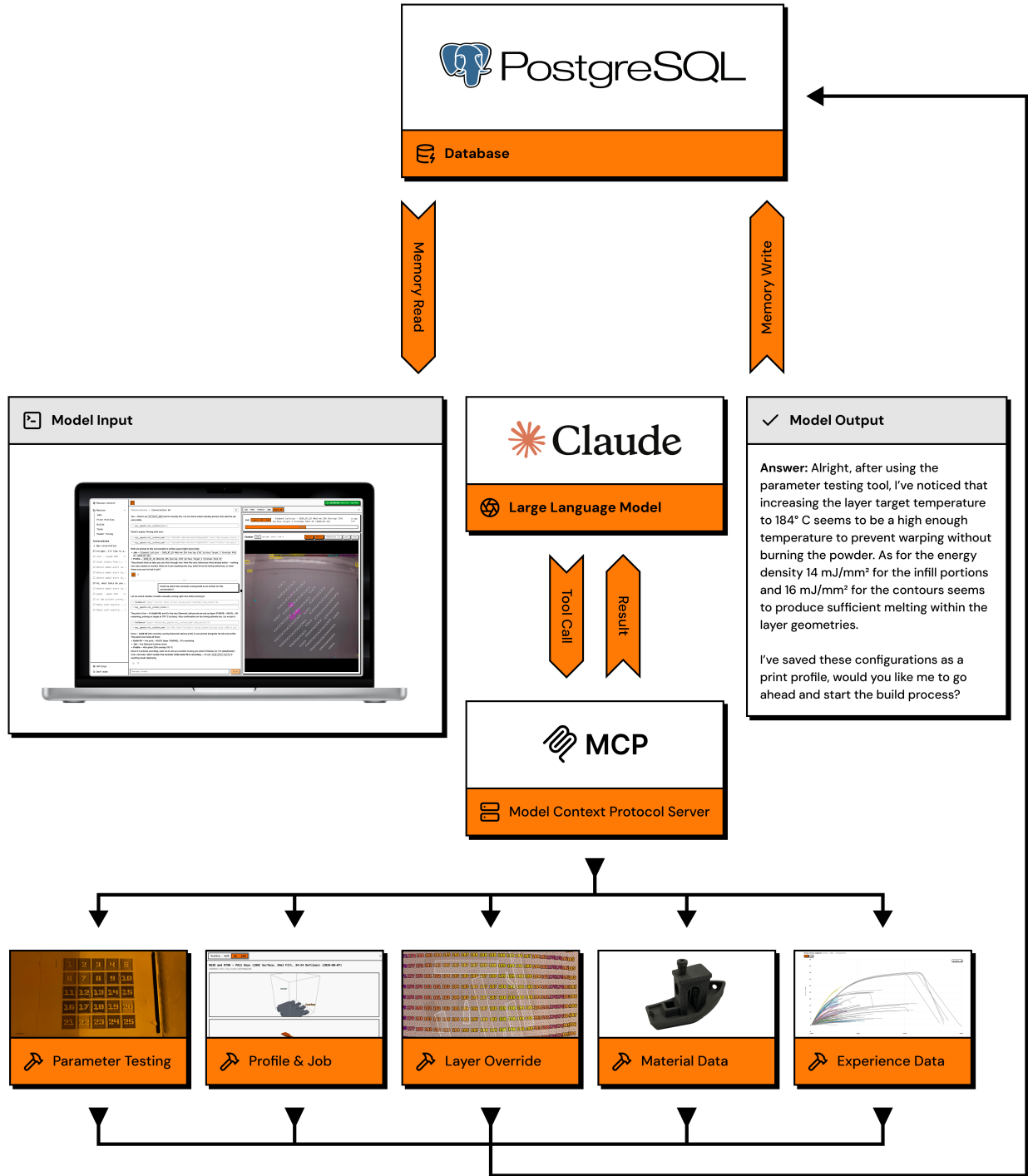


Figure 3: Agentic Selective Laser Sintering (SLS) process begins with user input for determining process parameters for a proposed material sent to the Large Language Model (Claude Fable). Query utilizes data from previous conversations stored in relational database (PostgreSQL) and selection of tools via Model Context Protocol (MCP) to investigate query. Model generates a response, saved for reference in future tasks enabling a continual learning environment.

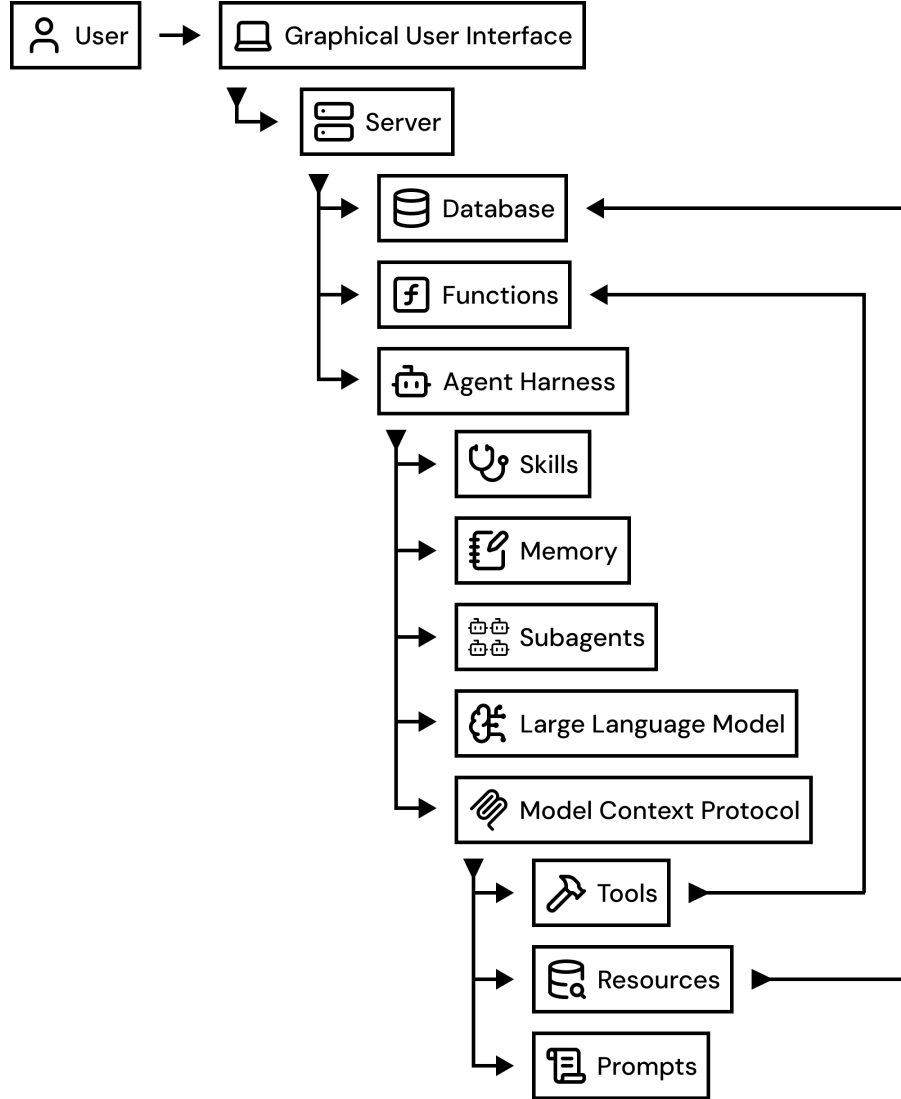
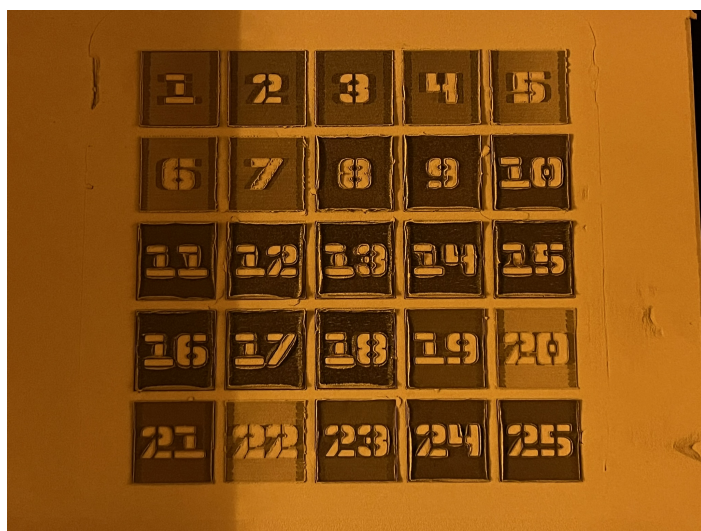


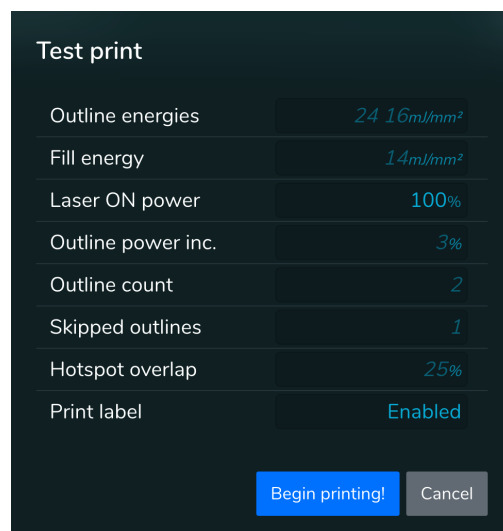
Figure 4: The agent harness provides the large language model with the functionality to utilize tools, data, and memory to better interact with its environment. A common architecture is outlined above where tools and resources allow for access into server hosted functions and database access respectively.

group based on their functionality, those being: material information, initial testing, print profile and build history, recorded data, and runtime overrides.

Within the realm of material information, tools here allow for inference on specified materials and their approximate properties. For example in the case of PA12 GF, tools repsective to materials would query upon manufacturer published technical data sheets, machine level process parameters, and other available data to provide the necessary information required to experiment with this material. The parameter testing tool is a feature specific to the Inova Mk1 such that when experimenting with new powders, a 5 x 5 grid of labeled patches (Figure 5a) can be printed on the surface of the print bed. This allows for the rapid testing of print parameters through patch specific configurations such as outline and fill energy densities (Figure 5b). In addition to executing patch prints, the tool will utilize the available sensors to extract quality information regarding each printed patch to determine which patch configuration to test next.



(a) Printed Parameter Testing Patches



(b) Patch Configuration

Figure 5: 5 x 5 grid of patches (a) printed for testing PA12 GF powder, each with their own parameter configuration (b).

For jobs and print profiles, the tools here set the various build parameters for a specific material within the Inova Mk1 for future use. Notable parameters include surface and chamber temperatures, energy densities for the fill and contours, hotspot overlape, desired

layer height, and recoater speed. The runtime overrides tools allow for the LLM to control various aspects of the build including surface temperature, recoating passes, and applied energy to address potential issues that may occur during the build. Lastly tools related to recorded data allows for the LLM to investigate the effectiveness of previous process parameter settings such that adjustments can be applied to improve mechanical performance measured through ASTM testing.

3.3 Manufacturing Process

With prescribed print parameters and job templates, each build will be printed with a consistent powder chamber preheat of 145 °C, 100 µm layer height, 100% recoater speed, and cooling procedure. Print parameters are maintained and executed by the Inova Mk1 firmware to the best of its ability. For example array of halogen lamps placed over the print surface to maintain a consistent even surface temperature (halogens are pulsed to increase and reduce surface temperature), however, the realized surface temperature may differ. After each build the print is left to cool down overnight (often 8+ hours) before the powder cake is removed for post processing. Powder is sifted and reclaimed during postprocessing and material is kept separated to the best ability of the author.

3.4 Sample Evaluation

Testing samples (Figure 6) were constructed to the standards outlined by the American Society for Testing and Materials (ASTM) and compared to measurements published by the manufacturer. With regard to tensile properties, specifications from the ASTM D638³¹ standard (Type 1 and Type 4) will be used to construct and test the samples. For bending stress analysis, specifications from the the ASTM D790³² standards will be followed. Apart from their respective batch-wise process parameters, all samples are fabricated with a layer height of 100 µm, powder chamber temperature of 145 C, and the major axis of each sample parallel to the print bed to minimize build height. For each batch, a minimum of 5 samples

were printed to adequately obtain a range of values for benchmarking. Tensile and flexural testing was conducted with the Instron 4469 Universal Testing System using a 50kN load cell following the prescribed methodology within the respective standard.

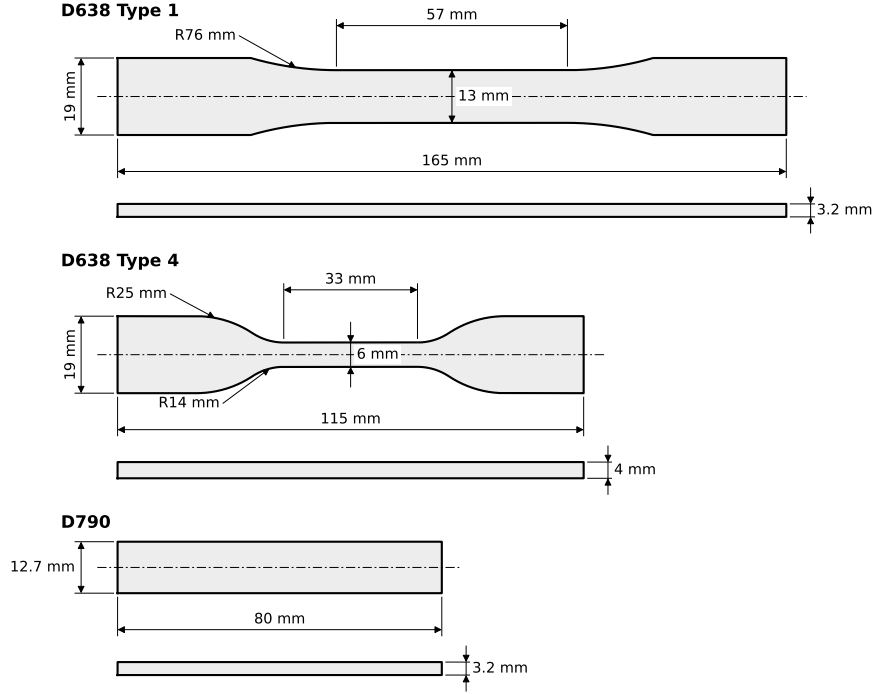


Figure 6: ASTM D638 and D790 samples dimensions used in the evaluation of mechanical properties.

4 Results

4.1 Material 1 (Nylon 12 Glass Filled)

The control series of tests were conducted using Formlabs Glass Filled Nylon 12 (PA12 GF) powder, manually tuned over the course of 15 different batches. After the initial assembly of the Inova Mk1, PA12 GF was utilized as the primary material used to calibrate the various sensors, optical configuration, and temperature control of the machine. During this period, the basic selective laser sintering capability was displayed through the fabrication of initial prints (Figure 2b), although these parts lacked the mechanical properties expected from

PA12 GF.

At this baseline, a laser fill energy density of 14 mJ/mm with outline of 24 mJ/mm and 16 mJ/mm was used to fabricate the part with a hotspot overlap of 25% and a surface bed temperature of 168 C. With these process parameter settings (Batch A) an initial tensile modulus of around 365 MPa was recorded, significantly lower than the published 2800 MPa from the manufacturer’s TDS. In addition to the properties listed in the TDS, reference samples were obtained from manufacturer (Form Now printing service from Formlabs) to physical verify the listed mechanical properties. These samples were printed on the Formlabs Fuse series of SLS machines which utilize a 30 W fiber laser in contrast to the Inova’s 10 W diode laser. These reference samples exhibited as tensile modulus of around 2599 MPa with a spread of 98 MPa and a flexural modulus of 1950 MPa with a spread of 271 MPa.

Process parameters and build testing layouts were then manually tuned over these series of batches as to match the mechanical properties of the reference samples with the Inova Mk1 (Table 1). Batch J achieves the highest tensile properties closest to that specified by the manufacturer at a fill energy density of 32 mJ/mm, a hotspot overlap of 50%, and a surface temperature of 178 °C. Batch H does achieve a higher tensile modulus of 2815 ± 4 MPa and a flexural modulus of 2272 ± 396 MPa, however these properties were not reproducible and attributed to potential measurement error. This build used a print surface temperature target of 173 C, fill energy density of 24 mJ/mm (outline energy densities of 28 mJ/mm and 18 mJ/mm), and a hotspot overlap of 50%. Through a set of manual tuning explorations, a collection of baseline data was obtained to further inform the agentic system in future parameter exploration tasks as seen with material 2 and material 3.

4.2 Material 2 (Nylon 11 Onyx)

Nylon 11 Onyx (PA11 Onyx) from Sinterit presents a unique challenge to for the task of process parameter optimization as the material exhibits ideal mechanical properties when printed in a nitrogen rich environment, intended for the Lisa series of printers. From the

Table 1: Manually tuned print profile settings and respective tensile and flexural properties obtained through ASTM tests Formlabs PA12 GF.

Batch	Select print parameters			Mechanical properties			
	Fill (mJ/mm)	Overlap (%)	T_{surface} (°C)	E_t^* (MPa)	UTS* (MPa)	E_f^* (MPa)	σ_f^* (MPa)
A	14	25	172	397	3.5	—	—
B	20	25	172	609	4.4	—	—
C	20	25	172	651	4.6	404	11.0
D	20	50	173	1193	8.0	938	22.4
E	20	50	173	1402	11.2	1232	26.9
F	24	50	173	1609	12.1	1560	32.3
G	24	50	173	1981	14.3	1634	34.0
H [‡]	24	50	173	2817	29.6	2773	68.5
I	28	50	173	2349	21.6	1684	43.7
J	32	50	178	2482	23.0	1177	24.2
K	32	50	173	2036	16.7	1233	28.1
L	40	25	173	1187	7.8 k 2130	55.4	
M	40	25	176	1002	6.9	915	20.6
N	24	50	173	1040	6.7	770	13.6

*Best-specimen value of tested ASTM D638 (E_t , UTS) and D790 (E_f , σ_f) samples.

[‡]Not reproducible, removed from consideration.

manufacturer specification, the powder is expected to exhibit a tensile and strength of 1680 MPa and 55 MPa respectively along with a flexural modulus and strength of 1290 MPa and 54.2 MPa. With these specifications, the agentic system presented with the task of searching for optimal process parameters to set for a build utilizing the material PA11 Onyx.

For each subsequent batch the system is prompted to recall previous builds and through a series of tool calls the LLM investigates the relationship between process parameters and the respective mechanical properties of the tested samples. A Graphical User Interface (GUI) is provided to the user to view the prescribed process parameters along with the model’s reasoning before starting the build (Figure 7).

After initial testing conducted using the parameter testing tool, batches investigating the process parameters and mechanical characteristics for PA11 Onyx were printed. These include batches O, P, Q, and R which are compiled in Table 2. Batch O investigated a

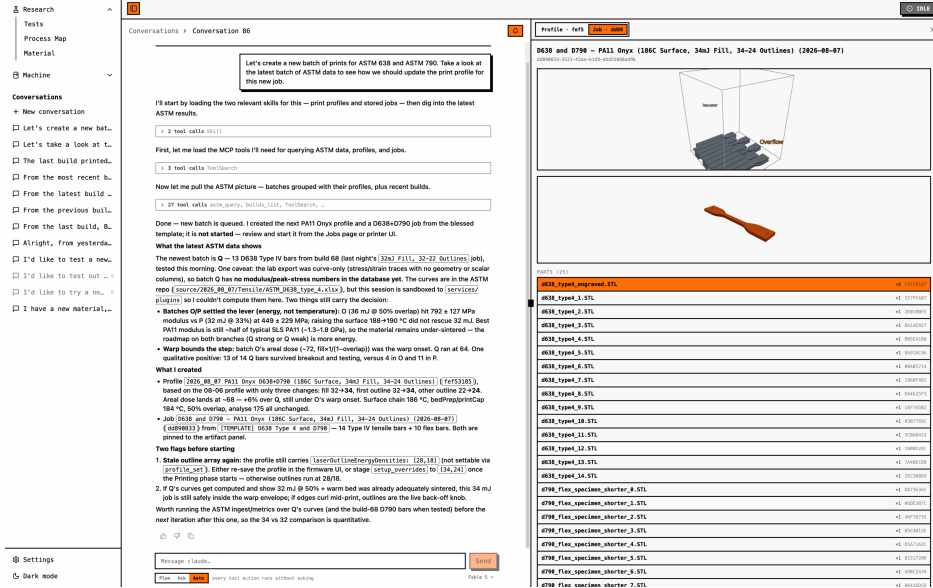


Figure 7: GUI showcasing the user flow of build planning to investigate a novel set of process parameters along with the reasoning from the agentic system.

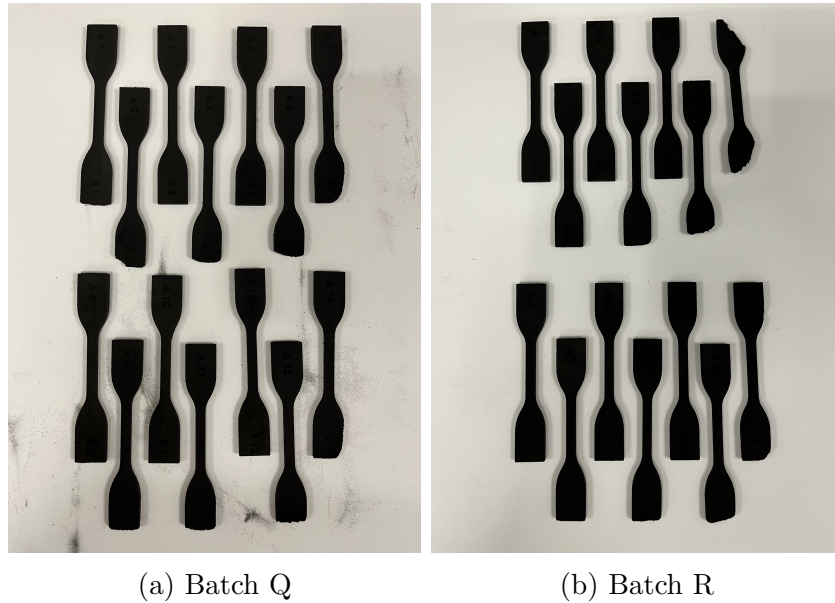


Figure 8: Tensile samples for Batch Q and R printed with PA11 Onyx. Top row includes samples 1 - 7 and bottom row showcases samples 8 - 14.

Table 2: Agentially optimized print profile settings and respective tensile properties for PA11 Onyx achieves similar mechanical properties outlined in TDS from Sinterit.

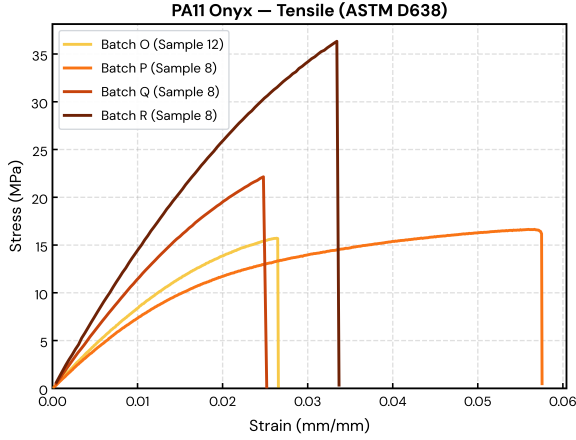
Batch	Select print parameters			Mechanical properties			
	Fill (mJ/mm)	Overlap (%)	T_{surface} (°C)	E_t^* (MPa)	UTS* (MPa)	E_f^* (MPa)	σ_f^* (MPa)
O	36	50	186	934	15.7	—	—
P	32	33	186	827	16.6	425	16.6
Q	32	50	186	1323	22.1	867	31.3
R	34	50	188	1571	36.3	1093	42.5

*Best-specimen value of tested ASTM D638 (E_t , UTS) and D790 (E_f , σ_f) samples.

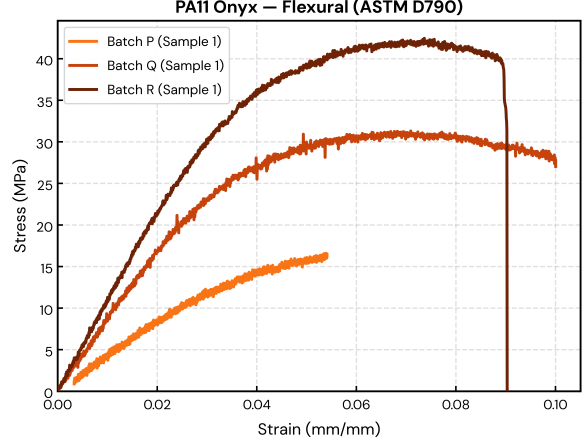
fill energy density of 36 mJ/mm along with outlines energy densities of 36 mJ/mm and 26 mJ/mm with a hotspot overlap of 50%. This print encountered significant warping during the build process and only 3 samples were successfully obtained and tested for this build with the highest tensile modulus of 934 MPa. The next batch of samples (P) were printed with a hotspot overlap of 33 % and a fill energy density of 32 mJ/mm and outline energy densities of 32 mJ/mm and 22 mJ/mm, a significant downstep from the previous sample. For the highest achieved values, this resulted in a lower tensile modulus of 827 MPa and flexural modulus of 425 MPa. Batch Q (Figure 8a) kept the same energy density configuration but revisited the hotspot overlap of 50% and achieved successful results with the highest achieved tensile modulus of 1323 MPa. Batch R (Figure 8b) further increases the fill energy density to 34 mJ/mm and increase the surface temperature from 186 C to 188 C and achieved a tensile modulus of 1571 MPa. With the results from each batch, the agentic system shows its capability to learn from the previous batch of results and improve the mechanical properties with subsequent prints (Figure 9).

4.3 Material 3 (Nylon 12 Blend)

Material 3 is a mixture of Formlabs Glass Filled Nylon 12 (PA12 GF) and Formlabs White Nylon 12 (PA12 White), approximately 25% and 75% respectively by volume. PA12 White exhibits lower absorptivity than its PA12 GF counterpart further observed in failed parame-



(a) PA11 Onyx Tensile Samples



(b) PA11 Onyx Flexural Samples

Figure 9: PA11 Onyx tensile and flexural properties show gradual improvement with each subsequent batch, best sample from Batch R.

Table 3: Agent optimized print profile settings along with respective tensile and flexural properties for the PA12 Blend (25% PA12 White and 75% PA12 GF by volume) exceeds TDS specified UTS and σ_f for PA12 GF displays comparable mechanical properties for PA12 White.

Batch	Select print parameters			Mechanical properties			
	Fill (mJ/mm)	Overlap (%)	T_{surface} (°C)	E_t^* (MPa)	UTS* (MPa)	E_f^* (MPa)	σ_f^* (MPa)
S	48	50	168	1092	14.4	—	—
T	56	50	168	1675	35.2	1439	47.3
U	56	50	172	1678	44.4	1830	60.6

*Best-specimen value of tested ASTM D638 (E_t , UTS) and D790 (E_f , σ_f) samples.

ter testing runs where sufficient sintering was not observed while utilizing the energy density settings of the Inova’s 450 nm blue laser. Previous trials with PA12 GF proved successful sintering with elevated temperatures and energy densities indicating this powder exhibits an absorptivity suitable for the Inova’s optical configuration. The Nylon 12 Blend (PA12 Blend) explores the utilization of PA12 GF as a dopant to increase the base absorptivity of PA12 White in order to achieve sintering and optimize to ideal mechanical properties.

Initial parameter testing of PA12 Blend exhibited visible sintering with an energy density of 46 mJ/mm. Batch S utilized a fill energy density of 48 mJ/mm, hotspot overlap of 50%

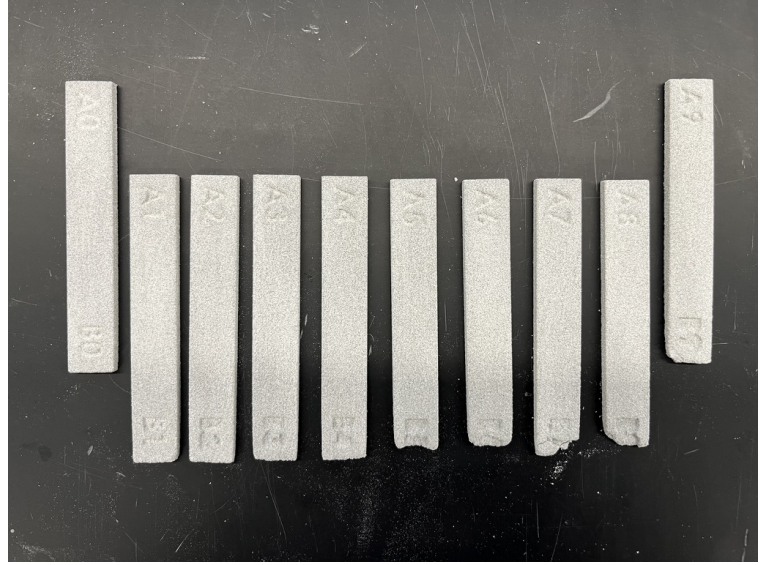
and surface temperature of 168 °C printing a total of 7 ASTM D638 type 4 samples at varying locations within the print bed. This batch was printed with the excess powder from the parameter testing print and ended early into the upper stack of ASTM D638 samples 8 - 14 resulting in only 7 testable samples (Figure 15). Obtained tensile properties were far below than that of the manufacturer advertised for either PA12 GF or PA12 White (flexural properties were not obtained due to print ending early). This however provided a sufficient starting point for the agentic system to utilize the obtained mechanical properties and recommend parameter adjustments for the next batch.

For the next print (Batch T) the agentic system was provided the results from the previous tensile tests and prompted to make adjustments to the print parameters to improve the resulting mechanical properties. The resulting print profile utilized a fill energy density of 56 mJ/mm, a hotspot overlap of 50%, and a consistent surface temperature of 168 °C. Samples obtained from this batch include two stacks of ASTM D638 tensile samples (Figure 10a) and ASTM D790 flexural samples (Figure 10b) arranged in the shown layout to provide adequate coverage to the print surface. With the adjustment to fill energy density, tested sample exhibited almost double the previous tensile properties of Batch S (Table 3) providing positive feedback to the agentic system.

With these findings, the agentic system was asked to further optimize the print parameters to provide a more even distribution of ideal tensile and flexural properties around the print surface (Batch U). For this the previous print parameters were kept the same with the only adjustment made to the print surface temperature, elevating it to 172 °C. Tensile (Figure 11a) and flexural (Figure 10b) exhibited ideal sintering specifically towards the bottom right of the print surface where the sample showed brittleness in previous Batch T. Obtained mechanical properties from the tensile samples showed a slight increase in the tensile modulus of the samples of around 3 MPa, however the greatest increase was observed in the ultimate tensile strength of 44.4 MPa from 35.2 MPa, approximately 25% increase from that of Batch T. Flexural properties also exhibited similar results increasing to 1830



(a) Batch T Tensile



(b) Batch T Flexural

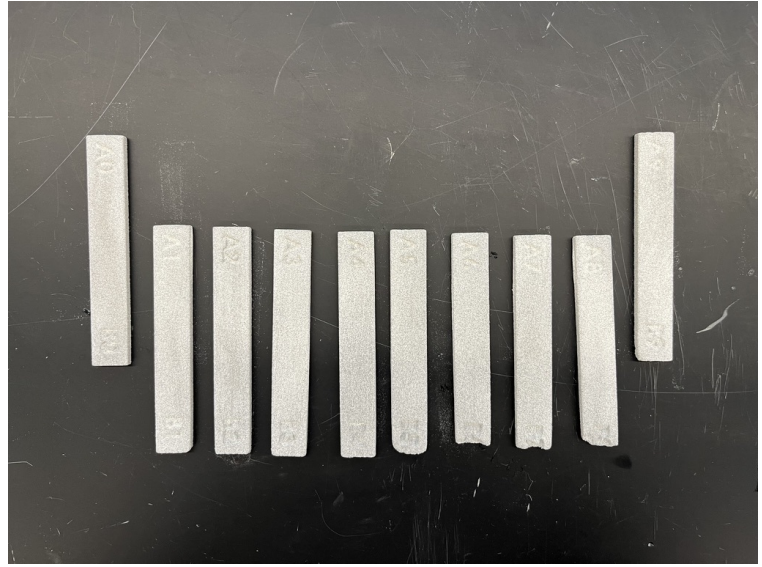
Figure 10: Agentically optimized PA12 Blend tensile and flexural samples adjusted to print with an elevated fill energy density for Batch T. Portions of samples towards the bottom right of the print surface displayed poor sintering, as seen with brittle ends in both flexural and tensile samples around this area.

MPa for the flexural modulus and 60.6 MPa for the flexural strength.

Reference samples and properties advertised in TDS for Formlabs PA12 White and PA12 Glass Fiber achieve higher tensile modulus values (TDS 1950 MPa and TDS 2800 MPa respectively) compared to that of PA12 Blend (1678 MPa). However, the ultimate tensile strength of PA12 Blend (44.4 MPa) is greater than that of PA12 GF (TDS 38.0 MPa and REF 26.5 MPa) but less than that of PA12 White (TDS 47.0 MPa), though greater than that of PA12 White REF at 40.0 MPa (Figure 12a). Flexural modulus from PA12 Blend (1830 MPa) is greater than that of both the REF and TDS of PA12 White (1519 MPa and 1500 MPa respectively), but less than that of PA12 GF (TDS 2400.0 MPa and REF 2251.0 MPa). The flexural strength however, is greater than both PA12 White (TDS 56.0 MPa and REF 58.0 MPa) and PA12 GF (TDS 56.0 MPa and REF 50.9 MPa) at 60.6 MPa for PA12 Blend (Figure 12b). This aligns with initial expectations that PA12 Blend would exhibit a mixture of mechanical properties between PA12 White and PA12 Glass Fiber, sometimes exceeded reference and TDS properties of both materials in the case of flexural strength.

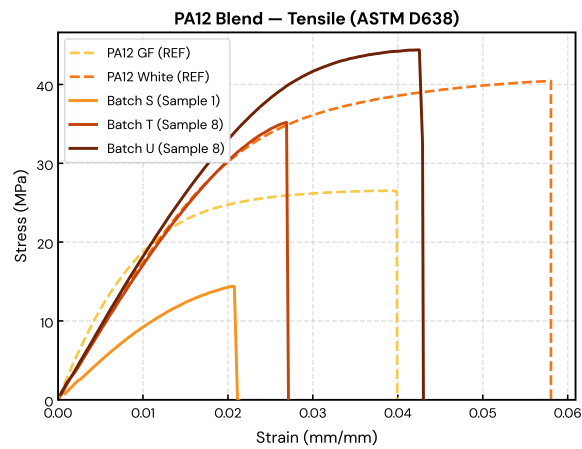


(a) Batch U Tensile

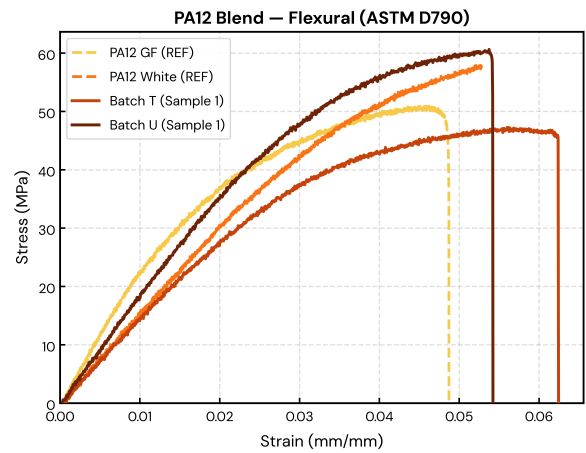


(b) Batch U Flexural

Figure 11: Batch U printed with agentic system recommended surface temperature adjustment to 172 °C resulted in optimal sintering throughout all samples with minor brittleness towards the bottom right of the print surface.



(a) PA12 Blend Tensile Samples



(b) PA12 Blend Flexural Samples

Figure 12: PA 12 Blend tensile and flexural properties show gradual improvement with each subsequent batch. Best sample from Batch U exhibits greater ultimate tensile strength and flexural strength than reference materials.

Table 4: Baseline tensile and flexural properties obtained from Technical Data Sheet (TDS) and manufacturer printed Reference (REF) samples. Reference samples printed with Fuse series printers from Formlabs Formnow manufacturing service.

Material	Tensile		Flexural	
	E_t^* (MPa)	UTS* (MPa)	E_f^* (MPa)	σ_f^* (MPa)
Formlabs PA12 White (TDS)	1950.0	47.0	1500.0	56.0
Formlabs PA12 White (REF)	1920.0	40.0	1519.0	58.0
Formlabs PA12 Glass Fiber (TDS)	2800.0	38.0	2400.0	56.0
Formlabs PA12 Glass Fiber (REF)	2577.0	26.5	2251.0	50.9
Sinterit PA11 Onyx (TDS)	1680.0	55.0	1290.0	54.2

*Best-specimen value of five tested per ASTM D638 (E_t , UTS) and D790 (E_f , σ_f)

5 Discussion

5.1 Baseline Mechanical Properties

Table 4 provides a listing of the baseline mechanical properties used for the optimization of materials 1, 2, and 3. Powders manufactured from Formlabs include Reference (REF) samples printed by Formlabs Formnow service through their Fuse series of printers along with their respective properties listed in the Technical Data Sheet (TDS). In both PA12 White and PA12 Glass Fiber (GF) it is observed that the TDS exhibits greater values than that obtained through testing via reference samples. These deviations are rather minor for Formlabs PA12 White but are significantly greater for PA12 GF, exhibiting deviations of up to 30% from that of the manufacturer’s specification. One potential explanation for this could be the print orientation of the reference sample as visible layer lines on the PA12 GF D638 sample indicate that the manufacturer printed this sample vertically.

5.2 Build Layout

For Material 2 of PA11 Onyx, Batch Q and Batch R achieve tensile modulus values close to that of the manufacturer published specification, however these mechanical properties

were not observed uniformly across the print bed. This was reflected in the two stacks of ASTM D638 tensile samples which were printed where a trend of decreasing mechanical properties were observed from the recoater side to the overflow side in both stacks. In Batch Q (Figure 16), the samples with the highest tensile modulus were found to be closest to the recoater side of the print chamber where samples closer to the overflow showcased insufficient sintering, even breaking before testing such is with the case on sample A7 of Batch Q. Batch R displays the same trend as samples with the highest tensile modulus are positioned closer to the recoater side of the print chamber (Figure 13). This may be due to uneven heating of the print chamber surface where temperatures are higher towards the recoater and along the Y direction.

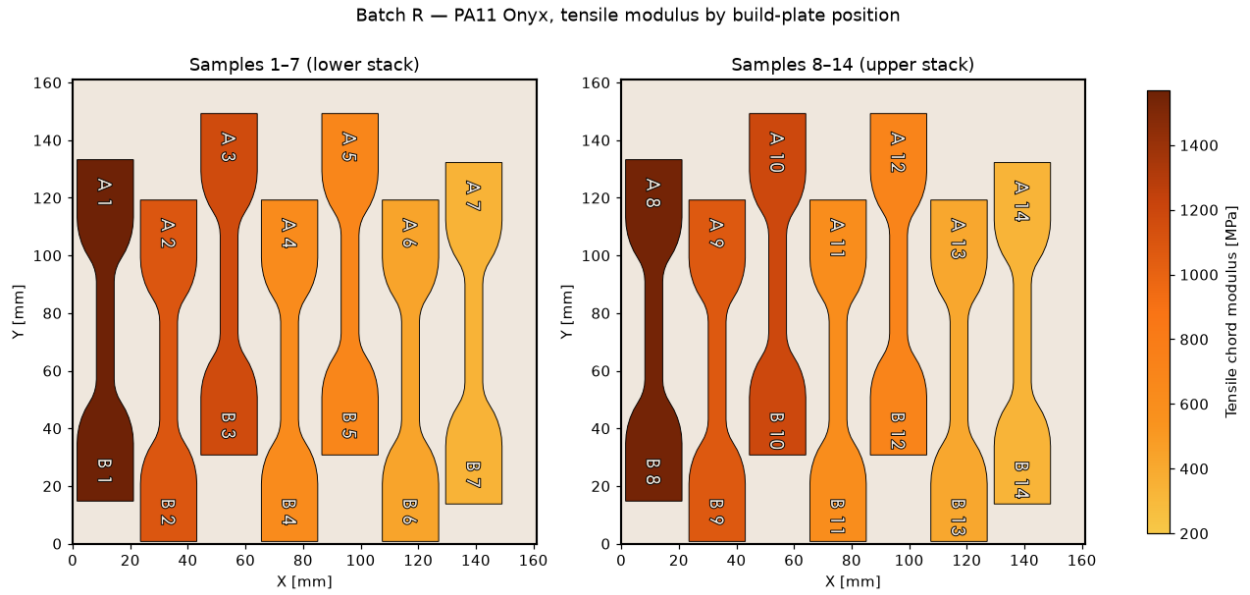


Figure 13: Samples 1 and 8 showcase the highest tensile modulus values and are closest to the recoater.

Material 3 confirms this trend with Batch S, T, and U for Nylon 12 Blend. Batch S (Figure 17) and Batch T (Figure 18) show a similar trend in mechanical properties with placement along the print surface. Batch U produced the best results and does show a more even distribution of tensile modulus however a gradient of properties is still visible (Figure 14).

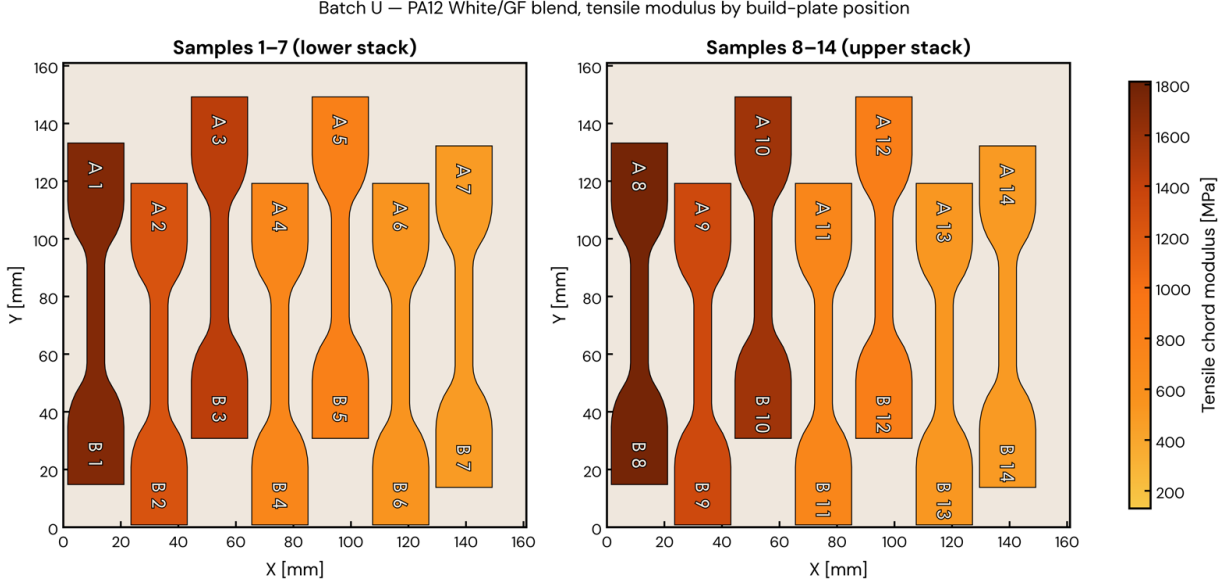


Figure 14: Samples 1 and 8 showcase the highest tensile modulus values and are closest to the recoater.

6 Conclusion

With initial calibration on Material 1 (PA12 GF) and further tuning with Material 2 (PA11 Onyx), the agentic system is able to tune selective laser sintering process parameters, optimizing for tensile and flexural properties, achieving mechanical properties that exceed that of the reference samples on Material 3 (PA12 Blend). Using knowledge from previous builds and their respective mechanical properties and minimal guidance from the user, the agentic system was able to optimize process parameters over a small number of iterations to achieve comparable TDS specified mechanical properties for various materials. This work showcases the ability for an agentic system to continually learn from updated data, enabling the intelligent automation of complex tasks such as process parameter optimization for selective laser sintering.

Appendix A Manufactured Samples



Figure 15: Initial set of tensile samples (Batch S) printed with Nylon 12 Blend (25% PA12 GF and 75% PA12 White by volume) exhibits a relatively lighter color than Material 1 or Material 2.

Appendix B Layout Dependent Tensile Properties

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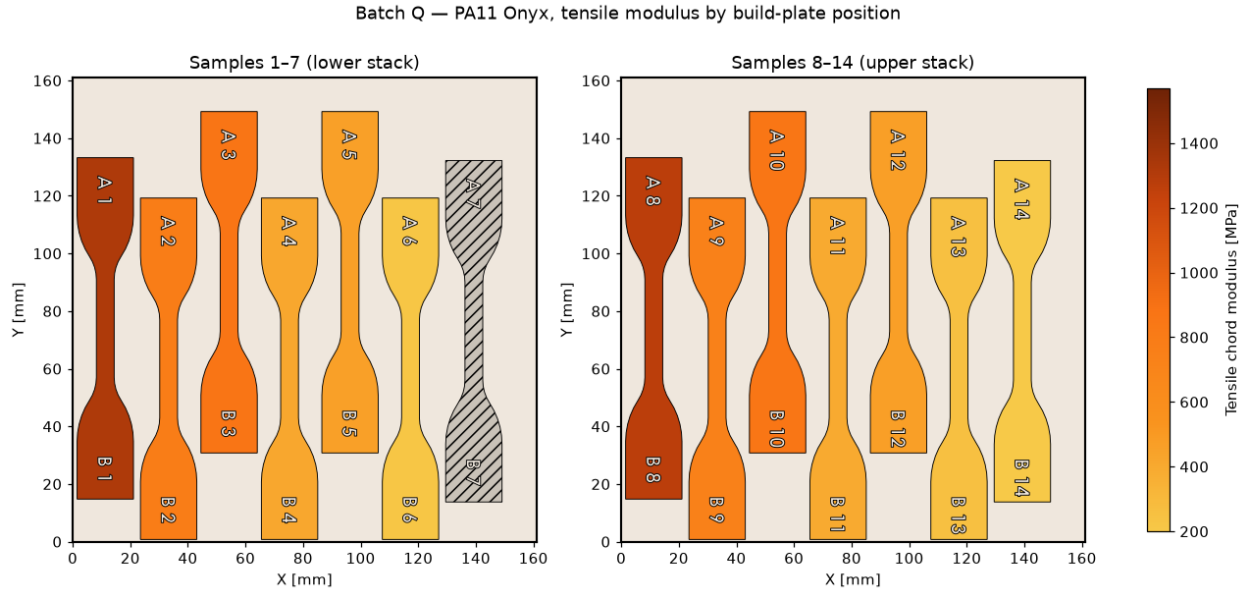


Figure 16: Batch Q Samples printed with PA11 Onyx showcased a trend of weaker mechanical properties with increasing x and decreasing y positioning on the print chamber. Sample 7 displayed low stiffness and fractured before tensile load values recorded.

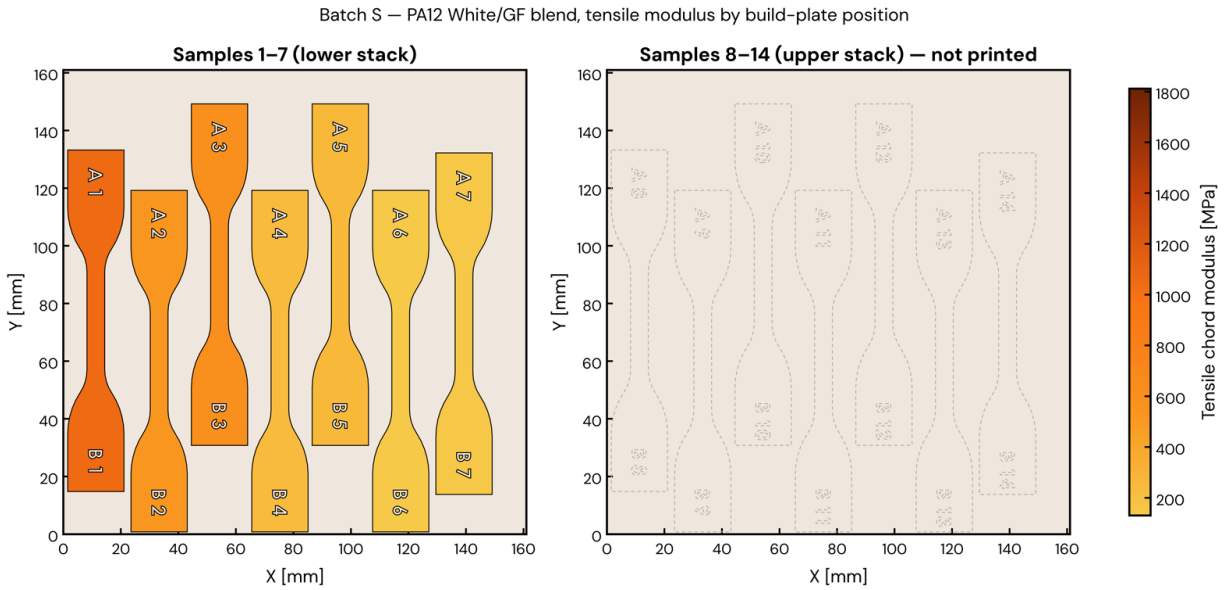


Figure 17: Batch S Samples printed with PA12 Blend displays similar trend of varying mechanical properties with respect to placement along the print surface. Lower stack was only printed due to run out of powder during print.

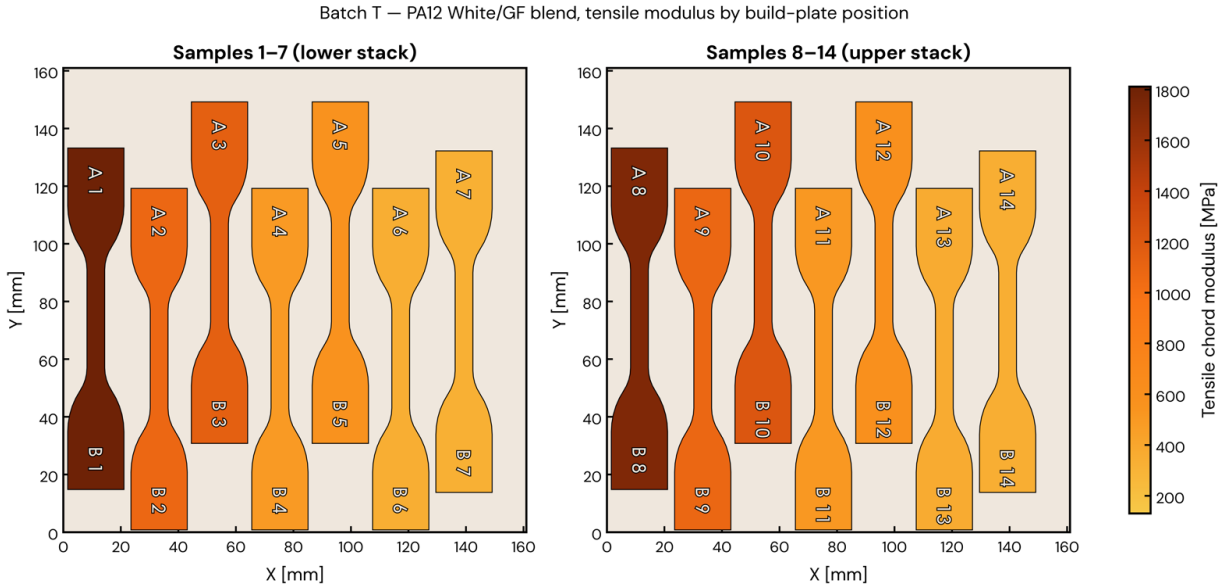


Figure 18: Batch T Samples printed with PA12 Blend exhibit greater tensile properties with the similar dependence on location within the print surface.

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