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The Effects of Post-Processing and Geometric Parameters on the Compressive Strength of Additively Manufactured Resin Lattice Structures

Chance Hattrick

Abstract: Compressive strength is a crucial property in load-bearing design, yet the combined effects of post-processing and geometry on resin-based lattice structures remain underexplored. This study investigates how these parameters influence the compressive strength of SLA-printed resin lattices. Using experimental testing and Bayesian Optimization, I examined the impact of cure time, cure temperature, wash time, pre-cure time, edge length, strut diameter, and relative density on mechanical performance. Fifty octet-truss lattices were fabricated and tested under static compression to measure stress, strain, and Young's modulus. Results show that relative density is the strongest predictor of compressive strength. Longer cure times, shorter wash and pre-cure times, and smaller edge lengths significantly improve structural performance. These findings offer a holistic view of how post-processing and design choices impact mechanical behaviour, and they provide predictive models to help researchers optimize lattice structures for specific performance goals in additive manufacturing applications.

Keywords: Bayesian Optimization, Lattice Structures, Additive Manufacturing, Compressive Strength

Introduction

When maximizing the safety, stability, and longevity of a structure, understanding its compressive strength properties is essential. Compressive strength is the ability of an object to resist a force that is attempting to deform that object. (Wattoo, 2016). Compressive strength is prevalent across various fields, from civil engineering, where it is used to ensure the integrity of bridges and buildings (Ramesh, 2021), to biomedical applications such as artificial implants (Tripathi, 2023). In all these applications, compressive strength is crucial for ensuring the safety of these structures, and negligence can lead to tragedy, as seen in the 1981 incident at the Hyatt Regency Hotel, where two suspended walkways collapsed, killing 114 people. Investigations revealed that a deviation from the original design reduced the load capacity of one of the walkways to only 53% of the maximum load capacity of Kansas City Building Code standards (Wattoo 2016). To prevent such tragedies, engineers must optimize compressive strength properties.

Optimizing these properties is challenging due to an expensive and time-consuming experimentation process. The large number of variables related to design, mass, and size in typical experiments requires a large sample size. In a comparison between Grid Search and Bayesian Optimization, a Boston University group led by Dr. Keith A. Brown required 1,800 samples for Grid Search (Riley 2020). Dr. Brown's

paper demonstrated that using just 100 samples in Bayesian Optimization yielded results "superior to 1,800 experiments chosen on a grid" (Riley, 2020), demonstrating that Bayesian Optimization effectively reduces sample size while enhancing precision. To conduct many experiments, the research group used PLA (Polylactic Acid) filament to make the structures, allowing experimentation with numerous variables and designs. However, PLA, while accessible and easy to use, is brittle, which prevents the structure from exhibiting considerable compressive strength. A material that may exhibit greater compressive strength is resin printing. This resin material, while also easily attainable, is far less brittle than PLA, and its use of a UV laser allows for a greater amount of precision and detail in the complex lattice structure. Although these materials have been shown in the past to have significant tensile strength, there have been no studies on how altering the complete post-processing and geometric design of the lattice structure can impact its compressive strength. This could provide researchers with a greater understanding of the mechanical and material properties of the resin. This leads to my research question: How does post-processing and lattice geometry affect the compressive strength of the resin-printed lattice structure?

This study aims to answer this question through a quantitative correlation study. By experimenting with the curing time of roughly 50 resin prints, the displacement under compressive force was measured using a press machine. Using these measurements, a surrogate (initial model) was created to relate variables, such as curing time to ductility. After that, the Bayesian program determined the overall correlation between curing time and specific properties and suggested new experiments that it predicts will maximize the performance of the lattice (see Appendix 2).

The results of this study will broaden the applicability of autonomous 3d printing technologies in experimental applications. By using a 3d printing material closer to engineering-grade polymers, the findings will provide a more accurate depiction of how different structures perform under high compressive loads. This research aims to strengthen our understanding of how curing time affects the mechanical properties of resin-based structures. The findings could significantly improve the safety and reliability of structures across various fields.

Literature Review

Static Compression Tests

Static compression is a concern prevalent in many fields. In a study by the Central South University group led by Xibing Li (2017), researchers studied the causes of structural failures in major Chinese mines, such as the Erdaoigou gold mine and the Changba lead-zinc mine. These failures ranged from rock bursts to zonal disintegration, and future failures could pose a significant risk to any deep mining operations if the mine's construction is not structurally sound. By reproducing these events through subjecting granite and red stone to compression tests, the researchers determined that rock failure occurs when the confining pressure of the structure exceeds a certain threshold. This highlights the risks of disregarding the static compression behaviours of load-bearing structures. Due to these risks, researchers have been actively exploring methods to enhance the static compression strength of these structures. In a study at Western Sydney University led by Christophe Camille (2019), researchers examined the benefits of using fibres to reinforce concrete subjected to static and dynamic loadings. The study tested properties from compressive strength to flexural performance. While the impact of the fibres on the compressive strength was relatively insignificant, researchers found that in concrete samples with fibre, "the severity of the failure is drastically reduced" (Camille et. al., 2019). Therefore, while this does not demonstrate a significant impact on compressive strength, it does emphasize the activity in that field. However, the caveat of this study was to test these properties; the researchers utilized blocks of concrete, which both limited the number of samples they could produce and the level of detail their structures could have. These limitations point to a need for alternative methods which can offer greater flexibility and precision to the designing and testing of materials for static compression.

Additive Manufacturing

Additive Manufacturing (AM), the most common version being 3d printing, offers a new avenue for the experimentation of structures because of its ability to produce complex geometries and its reproducibility.

This capability has proven especially valuable in scientific research and engineering fields. For instance, at the University of Campania, Professor Riccio and Numan Khan studied the applicability of additive manufacturing in the design and implementation of lightweight aerospace parts (Khan & Ricio, 2024). They examined the increased interest in additive manufacturing in the aerospace field and determined that this is due to its ability to construct lattice structures. (Khan & Riccio, 2024). Lattice structures are a network-like design made up of repeating, interconnected patterns. These lattice structures provide strength through geometric arrangements that minimize the amount of material used, making lightweight, strong structures (Khan & Riccio, 2024). However, because of the complexity of the lattice structures, they are only achievable through AM. There are many versions of AM, ranging from metal additive manufacturing to fused filament fabrication. The form of additive manufacturing used in this paper was VAT polymerization. VAT polymerization is a method of creating 3d objects by curing liquid resin through UV light (Tosello, 2018). The most common type and the one used in this paper is Stereolithography (SLA), which uses a laser to cure the 3d structure. In a study by the University of Ostrava, researchers led by Marek Pagac found that VAT polymerization and SLA in particular were extremely accurate in producing detailed prints (Pagac et. al, 2021). The issue regarding additive manufacturing experiments is that the greater flexibility in design means that the experiment can consider an increased number of parameters, which in turn increases the complexity of the experimentation process. In addition, although 3d printer manufacturers do provide some data on how the post-processing of resin prints can impact their physical properties (Zguris 2025), the studies primarily focus on tensile strength and only in the context of cure time and temperature, meaning that further research must be done to create a holistic understanding of how alterations to the post-processing can impact the compressive strength of resin 3d printed lattices.

Bayesian Optimization

Bayesian optimization can be used to handle a large number of variables. According to a review of Bayesian optimization by Xilu Wang at the University of Surrey, Bayesian Optimization has "become popular for taking time-consuming and expensive problems due to its high data efficiency" (Wang, 2022). The process can be separated into two parts: the Gaussian process and the acquisition function. According to Professor Ryan P. Adams of Princeton University, the Gaussian process is a surrogate model used for estimating the true objective function in Bayesian Optimization, and the acquisition function takes this surrogate function and, based on the experimental goals, determines where the optimum next point would be (Snoek et al. 2012). Once this point is received, the researcher uses that point for the next iteration of the surrogate model (Wang, 2022). Bayesian Optimization has already been introduced to the energy absorption world with Dr. Keith Brown's paper on the use of Bayesian Optimization for dynamic impact loading. Dr. Brown's research team at the University of Boston compared results from Bayesian Optimization and Grid-Searching to find that Bayesian Optimization took fewer samples and less time. They found that five of the six optimized structures found by the experimental campaigns (Bayesian Optimization) outperformed the best structures predicted by grid searching. However, while this paper proved that it was possible to use Bayesian Optimization for energy absorption experiments, it was purely a proof of concept. The paper only used PLA, which, while easy to use, is extremely brittle, meaning its compressive properties are not similar to polymers commonly used in compressive strength scenarios. A material that may have a greater similarity to these polymers would be resin, which can print structures in greater detail and allows for varied strength depending on the curing conditions. If resin can accurately imitate these engineering-grade polymers, this approach, combined with machine learning, would open up a new avenue for experimentation with compressive loading structures. Though there have been studies on how post-processing affects the compressive strength of resin polymers, such as Professor Barne's paper from the University of Warwick, which experimented with cure temperature, none of these studies observe a cumulative effect of all aspects of the post-processing on compressive strength on the resin. Additionally, these studies do not test how the geometric properties of these resin lattice structures

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affect the performance. Therefore, the question is how do the post-processing and geometric parameters affect the compressive strength of resin-printed lattice structures?

Methodology

Type of Study (Quantitative, Correlation Design)

This study used a quantitative approach to investigate the relationship between the build conditions of resin prints and their static compressive behaviour. Quantitative data measured the mechanical properties of the resin prints and was then analyzed to find correlations between the different build variables and compressive performance. The experimental research method used for this study determined the correlation between certain processing conditions and the printed lattice's performance under static compression.

Tools Required

All samples were printed using the Formlabs Form 4 SLA printer, whose use of a laser to initiate the polymerization in the sample allowed for a greater amount of accuracy and complexity in the samples. Additionally, the Formlabs Form Wash and Form Cure were used in post-processing. The Form Cure is required to complete the polymerization process and ensure the sample has strong mechanical properties. This device was integral to the experimentation process as the parameters of the cure time and temperature could potentially have drastic effects on the object's mechanical strength and ability to perform in static compression. The Form Wash was the final step in the process. It was used to remove excess resin from the samples, which ensured that there were no imperfections in the structure that could interfere with the mechanical properties or the accuracy of the experimental results.

Procedure

All the samples of this study were generated using a Python program which created an STL file containing the dimensions for a 3 × 3 octet truss lattice structure (See Appendix 1), which is a lattice structure which

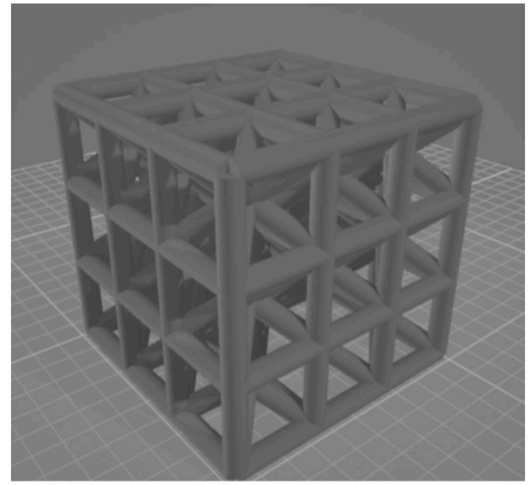

Figure 1: Octet-Truss Lattice Structure

uses 8 compressive-struts to divide the compressive force along each strut (Deshpande, 2001). To reduce variability, the geometry of the lattice was standardized across all samples. After the lattice was generated, all samples would be produced using the same Form Resin Printer. After printing the lattice and removing excess resin using the Form Wash, I waited a set amount of time before beginning the curing of the lattice through the Form Cure. This was to test whether oxidation of the resin prior to curing significantly affected its performance.

In this study, a preliminary set of 10 lattice batches was made to make the surrogate model that will be used in the experiment. Each batch contained five identical lattice structures which feature the same parameters. The surrogate model was fed into the optimization program and is also where the new experimental results were plotted. These 10 points were determined using Latin hypercube sampling (LHS). Head of Applied Research at Articul8 AI, Felipe Viana defines LHS as a statistical sampling method used to efficiently explore multidimensional parameter spaces. Essentially, it generated 10 sets of parameters with non-overlapping intervals to ensure that my initial data covers as many of the possible parameter values as possible (Viana, 2015). While this did not optimize the performance of the lattice structures, it ensured that my data is accurate for a larger scope of parameters and not a specific range.

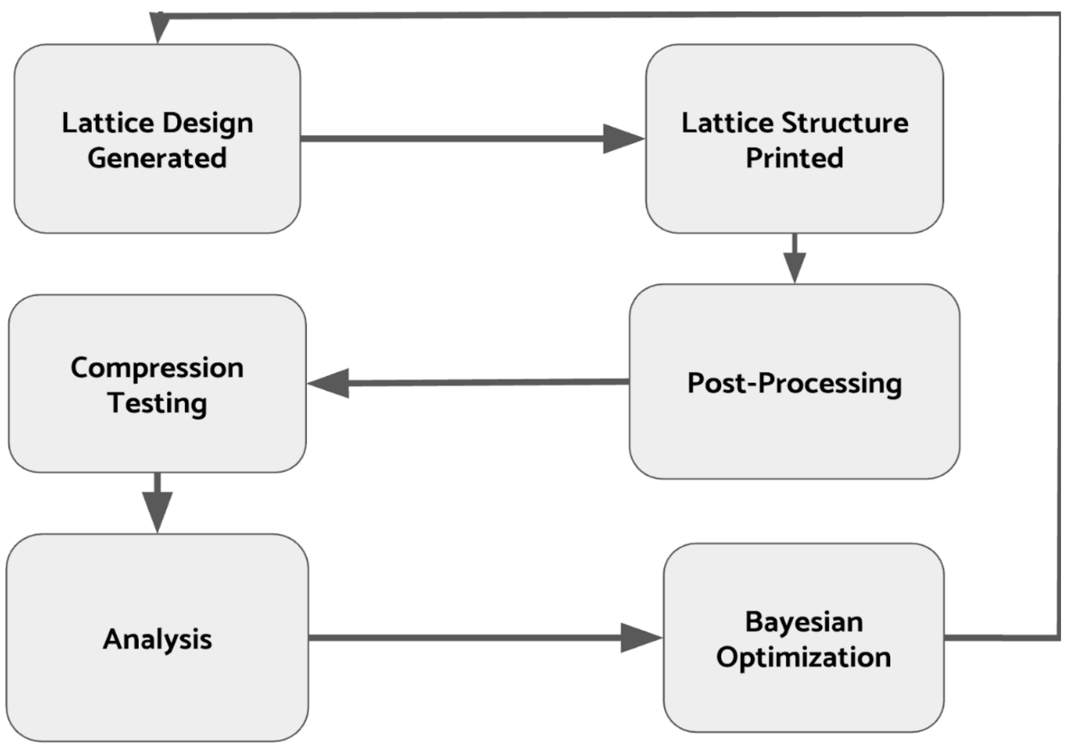

Chart 1: Flowchart of Methodology

The post-processing variables, cure time (mins), cure temperature (Celsius), pre-cure time (min), and wash time (min), were used to determine how altering the material properties of the resin could impact the compressive strength. At the same time, the geometric parameters edge length (mm), strut diameter (mm), and relative density (%) were examined to determine how altering the resin's size and density impacted its performance. The data was analyzed using correlation analysis, regression modelling (linear, polynomial, logarithmic), and machine learning-based feature importance ranking to identify which parameters most significantly influence compressive strength and how researchers could optimize these values.

For testing, the structures were placed on a universal testing machine, and the compressive force would be incrementally increased until the structure began to noticeably deform. This deformation and the force applied at that point were noted and used to calculate the compressive strength of the object in Megapascals (MPa). The performance of the lattice was then plotted on a Stress vs Strain plot, with Stress being the distribution of force on the object while Strain is the overall change in length of the object (Dong, 2015). These properties are commonly used to analyze an object's compressive or tensile strength as they accurately display the deformation of the structure. This can be seen in Professor Danial Rittel's study of the dynamic tension of ductile polymer, where stress vs. strain plots are used to effectively analyze the tension strength of the polymer structures (Tzibula et al., 2018). The details of the calculations will be explained in the Calculated Properties section; however, using the stress vs strain plots, I was able to find the compressive strength and Young's modulus of each lattice structure, creating a point for my Bayesian program (See Appendix 3).

This point was then input into the surrogate model and run through the Python Bayesian function cod-

ed in Python; this function takes the values from the surrogate model to use the acquisition function to predict the point at which the stiffness would be maximized. To limit the number of samples and time spent on this experiment, the Probability of Improvement acquisition function was used, as it provides a simple and fast way to maximize the probability of improving upon the current known objective value(Malu, 2021). Though this risks being too exploitative, meaning that the optimization focuses on making minor changes to values with good performance rather than exploring new combinations of variables, the limited time and resources of this experiment prevented me from undertaking a more exploration-focused path that would consider regions of high uncertainty in behaviour. Once the acquisition function suggested a point, this point would be tested through the same method and inputted back into the function, where the surrogate model would update itself and rerun the acquisition function.

Calculated Properties

To determine each lattice structure's performance, in addition to the compressive strength, the study also measured each lattice structure's measured stress, measured strain, Young's modulus and relative density.

The measured stress of each lattice structure was calculated using equation (1), where F is the force applied by the compression tester, and A is the cross-sectional area of the lattice structure. This calculates the distribution of force on the lattice structure, which is used to determine the compressive strength.

The measured strain of each lattice structure is calculated by equation (2), where ΔL represents the change in the length of the compressor, and L represents the original length. This is used to calculate the total displacement of the lattice structure, which was used to determine where the structure failed.

In their study of the durability of polymer composites under static loads, researchers at the Institute for Problems of Chemical and Energy Technologies defined Young's modulus as the mechanical property that measures the compressive stiffness of the structure. This modulus is defined as the ratio of stress to strain in the linear elastic region of the material. This means that when analyzing the Stress vs Strain

$$\sigma = \frac{F}{A}$$

Equation 1: Stress Definition

$$\varepsilon = \frac{\Delta L}{L_0}$$

Equation 2: Strain Definition

graph, there is an initial linear trend between stress vs strain, which is referred to as the "linear elastic region," meaning that any deformation that occurs in this region will be recovered. The maximum extent of this linear region is the yield strength of the lattice structure, and the initial linear line is used to determine the stiffness of the lattice (Fig. 1). Following the yield strength the lattice begins to experience plastic deformation where the deformations will not recover after the force is no longer applied and the final maximum force applied to the lattice before it fails is called "ultimate strength" (Startsev, 2019)

The relative density of the lattice structure is the ratio of the lattice's apparent density to the density of the solid material. This is used to compare the density of the lattice to that of a solid cube of the same material, and is calculated through equation (3), where Vsolid is the volume of the lattice, and Vtotal is the volume of the solid structure. This is also used in the Bayesian Optimization section to minimize the density of the lattice.

Analysis

Once all of the data was gathered, the study found the average compressive strength of each batch of lattices and plotted how the compressive strength of each batch was affected by the post-processing and geometric parameters. After reviewing, a principal parameter was chosen as the key determining factor in the performance of the lattices. Using the graph of the parameter vs the compressive strength of the batch, a trendline was generated to represent the predicted change in compressive strength with relation to the principal parameter. This predicted value was then compared to the measured average compressive strength of lattices. These values were then used to plot the effect each parameter (excluding the principal parameter) had on the "excess strength" shown by the

Figure 2: Compressive Stress vs. Strain Plot for SLA Resin Lattice

batches with respect to the predicted value. Using this method, even with the limitation of a small number of iterations, the study was still able to approximate the effect of each parameter on the lattices.

Justification

Dr. Keith Brown conducted a similar study for compressive strength testing when his group at the University of Boston was designing an autonomous experimental setup. In his study, his group found that the use of roughly 100 iterations with Bayesian optimization was more effective than the typical use of grid searching (Riley 2020). However, because I used resin rather than PLA, cost for materials was higher; therefore, I reduced the number of iterations to 50 so that I would still have a considerable sample size while conserving the material.

Findings

Table 1 displays the post-processing and geometric characteristics of each of the lattice structures; Table 2 displays the compressive strength, relative density, and Young's modulus of the respective lattice structures; and Figure 2 shows the average Stress vs Strain plot for all of the lattice structures.

Figure 2 shows the average stress vs strain plot for each of the 9 batches of lattice structures. The initial batches, such as Lattices 1 and 2, feature much longer domains than later batches, suggesting that before the optimization, the lattices were more easily deformed, which, compared to their low maximum stress, suggests that these lattice structures were compressively weak, leading to structural failure. This can be seen clearly in Lattice 2, where the jagged lines are areas where the lattice experienced buckling failure as one layer of the lattice collapsed before the force was redistributed and the structure stiffened again.

$$\rho^* = \frac{V_{\text{solid}}}{V_{\text{total}}}$$

Equation 3: Young's Modulus Definition

Analysis

Due to the limitations in the sample size, the large number of parameters examined meant that it was difficult to determine how each individual parameter affects the compressive strength. However, one parameter that showed a strong positive correlation and was relatively independent of other parameters was the relative density. When plotting the relative density of each batch vs its compressive strength, although a strong positive relationship is seen, some points show higher or lower compressive strength than the line of best fit predicts. By using the residuals of the relative density vs compressive strength plot, the study can

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Characteristics	Batch 1	Batch 2	Batch 3	Batch 4	Batch 5	Batch 6	Batch 7	Batch 8	Batch 9
Cure Time (min)	42	108	32	136	110	72	149	43	94.4
Cure Temp (Celsius)	35	78	71	36	74	53	47	35	35
Wash Time (min)	10	3	11	2	18	3	13	2	2
Pre-Cure Time (min)	225	69	29	22	39	25	21	6 mins	13
Edge-Length (mm)	4	2.21	3.16	2.21	3.09	2.7	2.11	2.40422	1.681772
Strut Diameter (mm)	0.2	0.21	0.38	0.263	0.377	0.371	0.338	0.263679	0.286151
Relative Density (%)	0.0245	0.089	0.156	0.142	0.16	0.203	0.271	0.1603	0.3044

Table 1: Compressive Strength and Parameters of Lattice Batches

Results	Young's Modulus (MPa)	Compressive Strength (MPa)	Standard Deviation	Relative Density(%)
Experiment 1	0.744016	0.2278755556	±0.0725	0.0245
Experiment 2	7.846	13.45	±3.00	0.089
Experiment 3	10.694	9.019997686	±0.706	0.156
Experiment 4	151.53	24.473	±0.272	0.142
Experiment 5	27.658	13.89796296	±7.50	0.16
Experiment 6	42.912	17.93688889	±0.590	0.203
Experiment 7	65.53	28.12555556	±3.12	0.271
Experiment 8	84.79	23.23	±0.0398	0.1603
Experiment 9	23.5	47.54	±0.0535	0.3044

Table 2: Average Compressive Strength and Young's Modulus of Lattice Batches

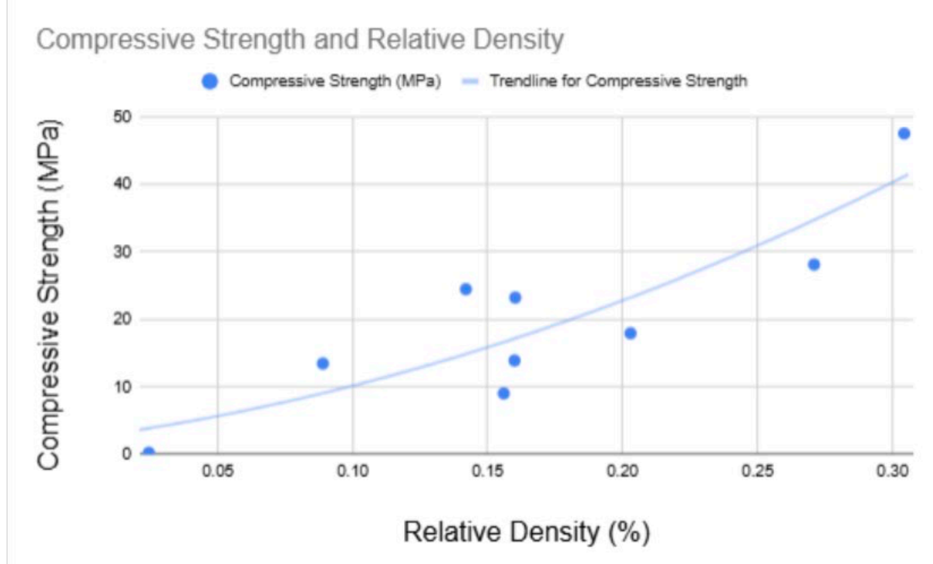

Figure 3: Compressive Strength vs Relative Density Plot for all Lattice Batches

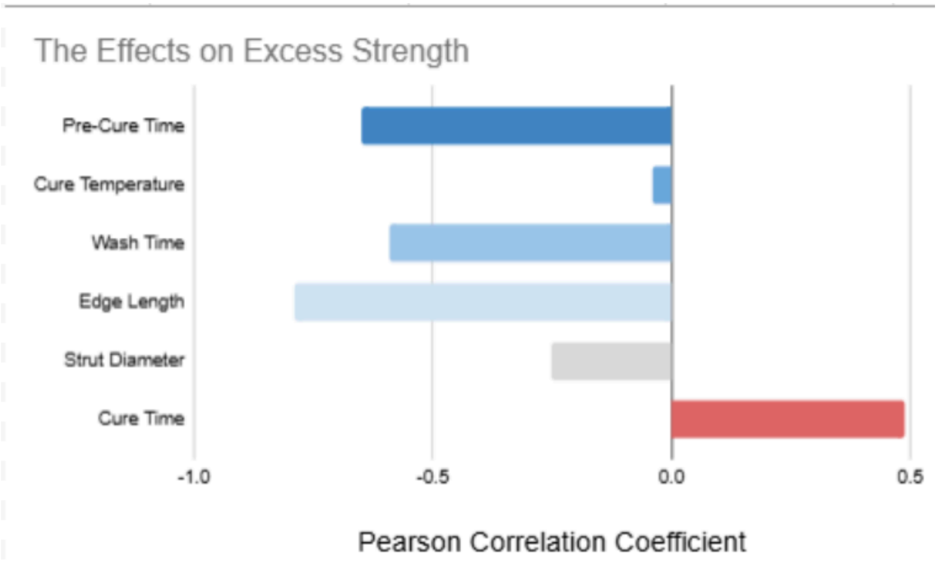

Figure 4: Pearson Coefficients of the Parameters vs Excess Strength

more clearly see how the other parameters, such as cure time and temperature, impact the excess compressive strength of the batches (See in Appendix 4).

When examining the Pearson coefficient (r-value) of the plots that compare each parameter to the excess strength of the lattice batches, it is seen that the edge length of the lattice has a strong negative correlation to the compressive strength while the wash time and pre-cure time exhibit a moderately strong negative correlation to the compressive strength. The only parameter to show a relatively strong positive correlation was the cure time.

Discussion

Summary

Through analyzing the plots, several main themes appear for optimizing the post-processing and geometric parameters. The first is that for post-processing, time is the most important parameter to optimize. When comparing the Cure Time and Cure Temperature plots in relation to compressive strength, it becomes clear that cure time has a much greater impact on the performance of the lattice structure. This plot shows that researchers looking to maximize the compressive strength should cure their lattices for extended periods of time to ensure that the curing process is fully complete. Additionally, the Pre-Cure Time to Compressive Strength plot exhibits a negative exponential relation, meaning that researchers should avoid leaving uncured lattices in oxygen-rich environments for extended periods of time, as the resin tends to oxidize, preventing the curer from fully polymerizing the lattice. Secondly, the geometric plots show that smaller and less dense lattice structures tend to perform better than larger lattices. While this seems counterintuitive, as larger lattices should have a greater distribution of the compressive force, it is possible that for larger lattices, the force is less evenly distributed, leading to localized failures. Finally, it shows that the geometric parameters, such as the edge length of the lattice, significantly affect the compressive strength of the lattice structure and that minimizing the size of the unit cells in the lattice will positively affect the compressive strength.

Through the use of Bayesian optimization and Pearson's coefficient, this study offers a foundational understanding of how the post-processing and geo-

metric parameters of SLA resin lattices impact their compressive strength. By identifying which parameters strongly correlate with mechanical performance, such as the positive effect of cure time and the negative impact of delaying the curing of the lattices, this study allows researchers to make informed trade-offs with their parameters without compromising compressive strength. For instance, if a larger unit cell is required for functional or design restraints, the researcher can use this data to determine that they will need to increase the cure time or optimize the strut diameter to a certain amount to offset the negative effect of the larger unit cell. These insights give researchers and engineers the flexibility to fine-tune their parameters and still accurately predict the compressive strength behaviour of the lattice structure.

Interpretation

The results of this study support evidence from Dr. Brown's study on oxygen inhibition in resin printing in that a significant impact on performance was observed when the resin was left uncured for extended periods of time (Saygin 2023). Additionally, a study conducted by Professor Stuart Barnes at the University of Warwick confirms that at a certain temperature, resin compressive strength tends to decrease (Ateş 2011). However, unlike Professor Barne's experiment, this study found that cure temperature has minimal impact on the performance of the lattice and that cure time is a more important parameter to optimize. Finally, unlike studies conducted by Sholana Iffat at the Bangladesh University of Engineering (Iffat 2015), this study found that relative density does not have a positive linear relationship with compressive strength and is optimized at around 14.2% of the density of a solid cube with the same edge length.

Limitations

The accuracy of the plots is limited due to the small sample size of this study. Though this study did use Bayesian optimization to suggest optimized lattice structures to test, the small sample size means that the model's predictions may to be an accurate representation of how each parameter affects the performance of the structure. The models used in the study serve as a preliminary overview of the effects of each parameter on the lattice structure. Additionally, the mechanical limitations of the compression tester used meant that the height of the lattice structure was limited to 15 mm and had a maximum force of 1200 Newtons. This severely limited the edge-length parameter and meant that some structures could not reach failure, preventing me from measuring their actual compressive strength. Finally, due to budgetary and time constraints, this study only observed the effects of these parameters on Clear Resin; for resins with different properties, such as Rigid 10k Resin, the results may vary due to different material properties. Nonetheless, the results provide an accurate but general understanding of how post-processing and geometric properties come together to affect the compressive strength of resin lattice structures.

Recommendations

Future research studies could observe how these parameters affect the properties of the different types of resins used in additive manufacturing. Additionally, understanding how applying different methods of resin additive manufacturing changes the results could provide a greater number of researchers using different resin printers with how these parameters will affect their results. Further research could be done on how altering the post-processing of resin prints could allow researchers to mimic the compressive properties of more complex materials, such as PEEK polymers.

Conclusion

As additive manufacturing continues to progress, lattice structures will become more prevalent in day-to-day applications, from vehicles to buildings. Additionally, polymers provide a cost-effective way of producing high-performing materials for tensile and compressive applications. Thus, by assessing how post-processing and geometric parameters affect the compressive strength of resin lattice structures, this study establishes that to maximize compressive strength, researchers should aim to minimize the size of the unit cells, the wash time, and the pre-curing time, while maximizing the amount of time the lattice spends curing. Researchers can also use this data to optimize the performance of their resin lattice structures and predict how a large number of lattice samples will perform based on their post-processing and geometry. The field of compressive strength is a vital field for ensuring the safety of workers and civilians alike, and with these models, researchers will be able to more effectively test and analyze the performance of countless lattice structures in their research to advance our understanding of compressive strength.

Acknowledgements

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Appendix 1

```
#Python script for generating the Octet-Truss Lattice
import numpy as np
import trimesh
def generate_octet_truss(grid_size, unit_cell_size, strut_radius):
    """
    Generate an octet-truss lattice as a trimesh object.
    Args:
        grid_size (tuple): Number of unit cells along (x, y, z) directions.
        unit_cell_size (float): Size of each unit cell in mm.
        strut_radius (float): Radius of the struts in mm.
    Returns:
        trimesh.Trimesh: Combined mesh of the octet-truss lattice.
    """
    cylinders = []
    # Create the grid of unit cell centers
    for x in range(grid_size[0]):
        for y in range(grid_size[1]):
            for z in range(grid_size[2]):
                # Origin for the current unit cell
                origin = np.array([x, y, z]) * unit_cell_size
                # Define nodes of the unit cell relative to the origin
                nodes = [
                    origin + np.array([0, 0, 0]),
                    origin + np.array([unit_cell_size, 0, 0]),
                    origin + np.array([0, unit_cell_size, 0]),
                    origin + np.array([0, 0, unit_cell_size]),
                    origin + np.array([unit_cell_size, unit_cell_size, 0]),
                    origin + np.array([unit_cell_size, 0, unit_cell_size]),
                    origin + np.array([0, unit_cell_size, unit_cell_size]),
                    origin + np.array([unit_cell_size, unit_cell_size, unit_cell_size]),
                    origin + np.array([unit_cell_size / 2, unit_cell_size / 2, unit_cell_size / 2]),
```

```
        ]
        # Define edges (connections between nodes)
        edges = [
            (0, 1), (0, 2), (0, 3), (1, 4), (1, 5), (2, 4), (2, 6),
            (3, 5), (3, 6), (4, 7), (5, 7), (6, 7),
            (0, 8), (1, 8), (2, 8), (3, 8), (4, 8), (5, 8), (6, 8), (7, 8)
        ]

        # Create struts (cylinders) for each edge
        for start, end in edges:
            start_node = nodes[start]
            end_node = nodes[end]
            edge_vector = end_node - start_node
            length = np.linalg.norm(edge_vector)

            # Create a cylinder along the edge
            cylinder = trimesh.creation.cylinder(
                radius=strut_radius,
                height=length,
                sections=32
            )

            # Align cylinder to edge vector
            transform = trimesh.geometry.align_vectors([0, 0, 1], edge_vector)
            cylinder.apply_transform(transform)

            # Translate cylinder to the correct position
            midpoint = (start_node + end_node) / 2
            cylinder.apply_translation(midpoint)

            cylinders.append(cylinder)

    # Combine all cylinders into a single mesh
    return trimesh.util.concatenate(cylinders)

def main():
    # Define parameters
    grid_size = (2, 2, 3)       # Number of unit cells in each direction (x, y, z)
    unit_cell_size = 4       # Size of each unit cell (mm)
    strut_radius = 0.3       # Radius of the struts (mm)
    output_file = "lattice_exp14.stl"  # Output STEP file name
    material_density = 1.2       # g/cm³ (example for a plastic-like material)

    print("Generating octet-truss lattice...")
    lattice = generate_octet_truss(grid_size, unit_cell_size, strut_radius)

    # Compute Volume
    volume = lattice.volume  # mm³
    print(f"Total Lattice Volume: {volume:.2f} mm³")
```



```
    # Assign Material Density and Compute Mass
    lattice.density = material_density  # g/cm³
    mass = lattice.mass  # grams
    print(f"Total Lattice Mass: {mass:.2f} g")

    # Export as STEP
    print(f"Exporting lattice to {output_file}...")
    lattice.export(output_file, file_type='stl')
    print("Export complete. You can now import the STEP file into your CAD software.")
if __name__ == "__main__":
    main()
```

Appendix 2

```
import numpy as np
import pandas as pd
from ax.service.ax_client import AxClient, ObjectiveProperties
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
obj1_name = "compressive_strength"
obj2_name = "relative_density"
obj3_name = "y_modulus"


def measure_properties(cure_time, cure_temp, wash_time, pre_time, edge_len, strut_dia):
    #Insert matethematical model once the intial experiments are complete.
    y= 0

    #return y


# Define the training data

#training data, all of the parameters for the experiment data
X_train = pd.DataFrame(
    [
        {"cure_time": 42.0, "cure_temp": 35.0, "wash_time": 10.0, "pre_time": 225.0, "edge_len": 4,
"strut_dia": 0.2},
        {"cure_time": 42.0, "cure_temp": 35.0, "wash_time": 10.0, "pre_time": 225.0, "edge_len": 4,
"strut_dia": 0.2},
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"strut_dia": 0.2},
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"strut_dia": 0.2},
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```

```
"strut_dia": 0.2},
        {"cure_time": 108.0, "cure_temp": 78.0, "wash_time": 3.0, "pre_time": 69.0, "edge_len": 2.21,
"strut_dia": 0.21},
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"strut_dia": 0.380},
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"strut_dia": 0.380},
        {"cure_time": 32.0, "cure_temp": 71.0, "wash_time": 11.0, "pre_time": 29.0, "edge_len": 3.16,
"strut_dia": 0.380},
        {"cure_time": 32.0, "cure_temp": 71.0, "wash_time": 11.0, "pre_time": 29.0, "edge_len": 3.16,
"strut_dia": 0.380},
        {"cure_time": 32.0, "cure_temp": 71.0, "wash_time": 11.0, "pre_time": 29.0, "edge_len": 3.16,
"strut_dia": 0.380},
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"strut_dia": 0.263},
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"strut_dia": 0.263},
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"strut_dia": 0.377},
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"strut_dia": 0.371},
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```


COMPRESSIVE STRENGTH OF ADDITIVELY MANUFACTURED RESIN LATTICE STRUCTURES

```
"strut_dia": 0.371},
        {"cure_time": 149.0, "cure_temp": 47.0, "wash_time": 13.0, "pre_time": 21.0, "edge_len": 2.11,
"strut_dia": 0.338},
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"strut_dia": 0.338},
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"strut_dia": 0.338},
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"strut_dia": 0.338},
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"strut_dia": 0.264},
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"strut_dia": 0.264},
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"strut_dia": 0.264},
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"strut_dia": 0.264},
    ]
)

#The outputs of the experiment data
y_train = [
    {obj1_name: 3.01, obj2_name: 0.0245, obj3_name: 1.10},
    {obj1_name: 1.45, obj2_name: 0.0245, obj3_name: 0.59},
    {obj1_name: 1.44, obj2_name: 0.0245, obj3_name: 1.11},
    {obj1_name: 2.00, obj2_name: 0.0245, obj3_name:0.62},
    {obj1_name: 2.30, obj2_name: 0.0245, obj3_name:0.81 },
    {obj1_name: 90.0, obj2_name: 0.089, obj3_name:33.89},
    {obj1_name: 97.3, obj2_name: 0.089, obj3_name: 32.22},
    {obj1_name: 130.6, obj2_name: 0.089, obj3_name: 27.93},
    {obj1_name: 155.54, obj2_name: 0.089, obj3_name: 35.70},
    {obj1_name: 131.8, obj2_name: 0.089, obj3_name: 27.94},
    {obj1_name: 79.62, obj2_name: 0.156, obj3_name:22.35},
    {obj1_name: 74.11, obj2_name: 0.156, obj3_name:21.17},
    {obj1_name: 76.67, obj2_name: 0.156, obj3_name:20.31},
    {obj1_name: 88.86, obj2_name: 0.156, obj3_name:19.59},
    {obj1_name: 86.65, obj2_name: 0.156, obj3_name:21.62},
    {obj1_name: 214.5, obj2_name: 0.142, obj3_name:214.4},
    {obj1_name: 135.6, obj2_name: 0.142, obj3_name:38.93},
    {obj1_name: 230.94, obj2_name: 0.142, obj3_name:246.29},
    {obj1_name: 299.99, obj2_name: 0.142, obj3_name:106.5},
    {obj1_name: 102.09, obj2_name: 0.16, obj3_name:38.89},
    {obj1_name: 126.07, obj2_name: 0.16, obj3_name:26.10},
    {obj1_name: 126.03, obj2_name: 0.16, obj3_name:25.80},
```
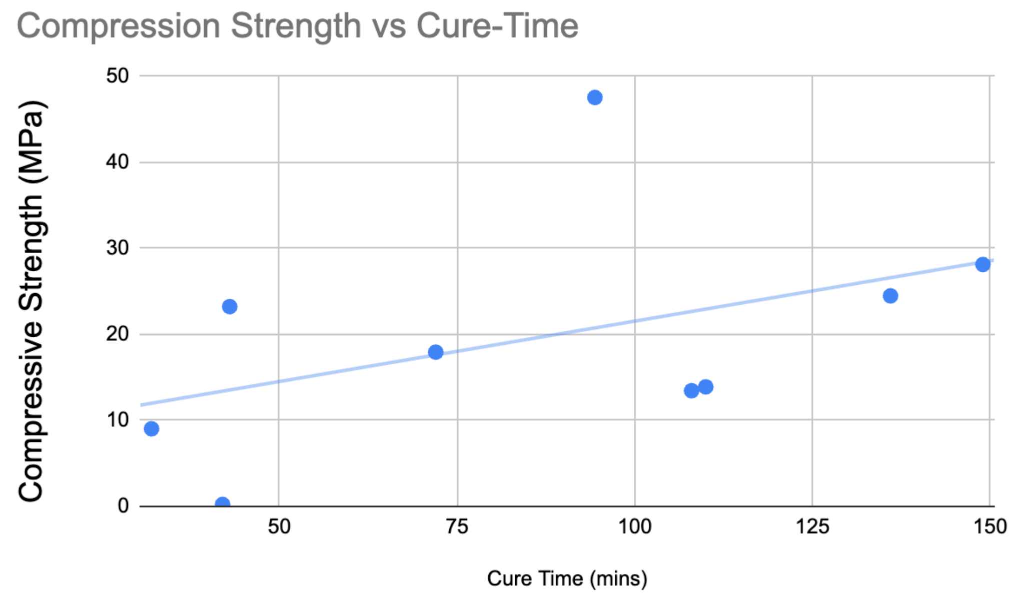

```
    {obj1_name: 126, obj2_name: 0.16, obj3_name:22.7},
    {obj1_name: 126.1, obj2_name: 0.16, obj3_name:24.8},
    {obj1_name: 126.2, obj2_name: 0.16, obj3_name:39.0},
    {obj1_name: 154.56, obj2_name: 0.203, obj3_name:43.27},
    {obj1_name: 163.93, obj2_name: 0.203, obj3_name:39.54},
    {obj1_name: 165.92, obj2_name: 0.203, obj3_name:45.40},
    {obj1_name: 156.95, obj2_name: 0.203, obj3_name:41.08},
    {obj1_name: 165.8, obj2_name: 0.203, obj3_name:45.27},
    {obj1_name: 271.42, obj2_name: 0.271, obj3_name:71.87},
    {obj1_name: 271.61, obj2_name: 0.271, obj3_name:66.71},
    {obj1_name: 271.6, obj2_name: 0.271, obj3_name:69.30},
    {obj1_name: 270.34, obj2_name: 0.271, obj3_name:63.95},
    {obj1_name: 217.52, obj2_name: 0.271, obj3_name:63.4},
    {obj1_name: 216.29, obj2_name: 0.271, obj3_name:57.95},
    {obj1_name: 208.7, obj2_name: 0.1603, obj3_name:91.3},
    {obj1_name: 208.6, obj2_name: 0.1603, obj3_name:90.6},
    {obj1_name: 209.3, obj2_name: 0.1603, obj3_name:82.9},
    {obj1_name: 209.3, obj2_name: 0.1603, obj3_name:79.1},
    {obj1_name: 209.3, obj2_name: 0.1603, obj3_name:79.9}
]

# See https://youtu.be/4tnaL9ts6CQ for simple human-in-the-loop BO instructions

# Define the number of training examples
n_train = len(X_train)

#Create the AxClient
ax_client = AxClient()

#Here I am defining the different parameters I am measuring and the outcomes that I wish to optimize
ax_client.create_experiment(
    parameters=[
        {"name": "cure_time", "type": "range", "bounds": [0.0, 300.0]},
        {"name": "cure_temp", "type": "range", "bounds": [35.0, 80.0]},
        {"name": "wash_time", "type": "range", "bounds": [2.0, 30.0]},
        {"name": "pre_time", "type": "range", "bounds": [0.0, 300.0]},
        {"name": "edge_len", "type": "range", "bounds": [1.0, 4.0]},
        {"name": "strut_dia", "type": "range", "bounds": [0.2, 0.5]},
    ],
    objectives={
        obj1_name: ObjectiveProperties(minimize=False, threshold = 200),
        obj2_name: ObjectiveProperties(minimize=True, threshold = 0.15),
        obj3_name: ObjectiveProperties(minimize=False, threshold = 50),
    },
)

# Add existing data to the AxClient
for i in range(n_train):
    #Converts each X_train entry into a dictionary
    parameterization = X_train.iloc[i].to_dict()
```

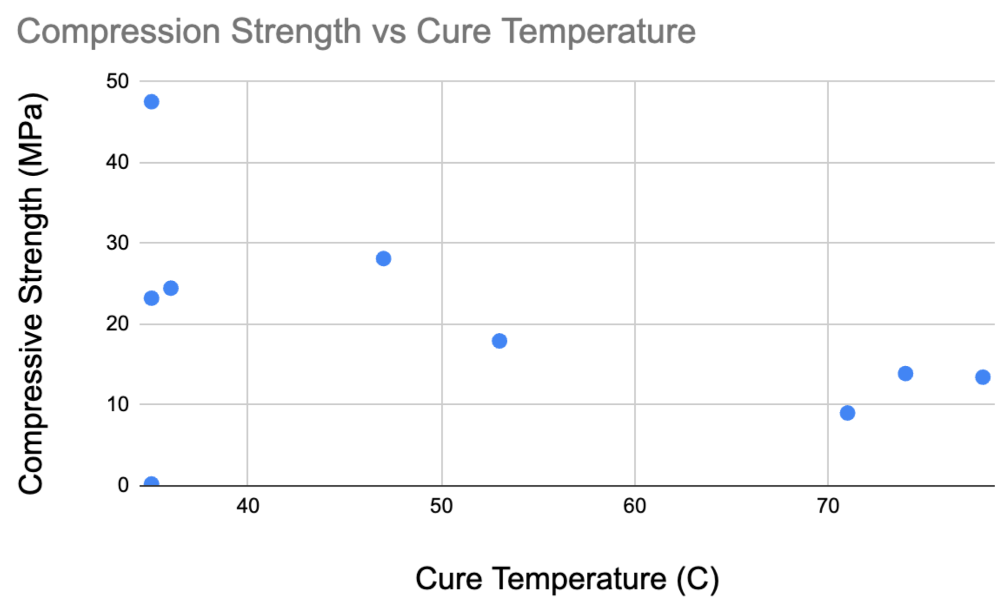


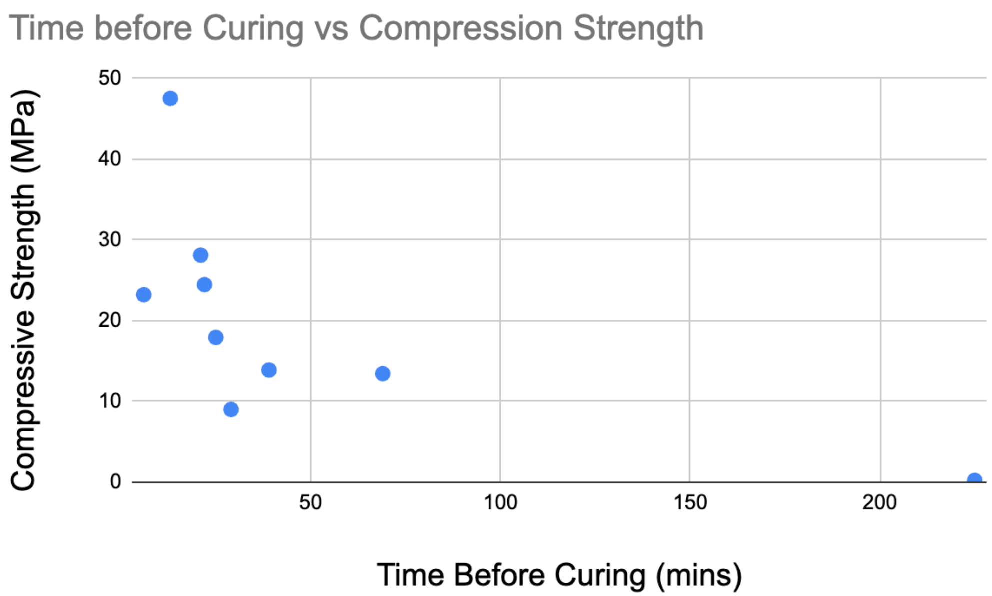
```
    #Adds the Trial to the AxClient
    ax_client.attach_trial(parameterization)
    #Links the output data to the X_Train parameters
    ax_client.complete_trial(trial_index=i, raw_data=y_train[i])

#Number of suggestions per iteration
batch_size = 3
trial_counter = 0


for i in range(19):

    parameterizations, optimization_complete = ax_client.get_next_trials(batch_size)
    for trial_index, parameterization in list(parameterizations.items()):
        # extract parameters
        x1 = parameterization["cure_time"]
        x2 = parameterization["cure_temp"]
        x3 = parameterization["wash_time"]
        x4 = parameterization["pre_time"]
        x5 = parameterization["edge_len"]
        x6 = parameterization["strut_dia"]
        if trial_counter < len(y_train):
            results = y_train[trial_counter]
            ax_client.complete_trial(trial_index=trial_index, raw_data=results)
            trial_counter += 1
# Extract observed trials (including missing values to retain all data)
df_all = ax_client.get_trials_data_frame()

# Ensure that at least one objective value is available
df_all = df_all.dropna(subset=[obj1_name, obj2_name, obj3_name], how='all')

# Debugging: Check if trials contain valid data
print("All Trials DataFrame shape:", df_all.shape)
print("All Trials DataFrame head:\n", df_all.head())

# Get Pareto-optimal points
pareto_results = ax_client.get_pareto_optimal_parameters(use_model_predictions=False)

# Debugging: Check if Pareto results are empty
if not pareto_results:
    print("⚠ Warning: No Pareto-optimal solutions found.")
else:
    print(f"Found {len(pareto_results)} Pareto-optimal points.")

# Convert Pareto results into a DataFrame
pareto_data = [p[1][0] for _, p in pareto_results.items()]  # Extract only objective dictionary
pareto_df = pd.DataFrame(pareto_data)
print("pareto_df:", pareto_df)
# Debugging: Check Pareto DataFrame
print("Columns in pareto_df:", pareto_df.columns)
```

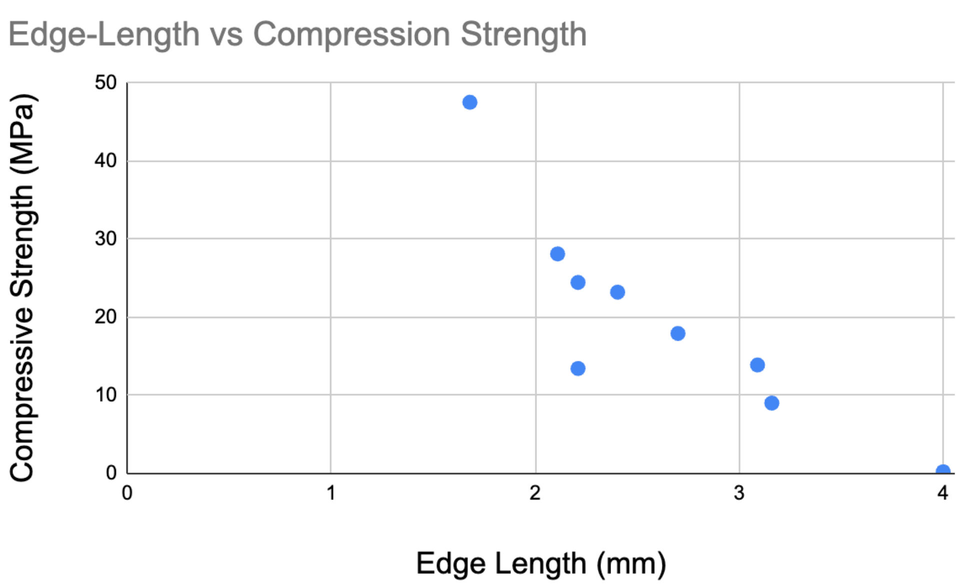
```
print("Pareto DataFrame shape:", pareto_df.shape)

# If Pareto results are empty, stop execution
if pareto_df.empty:
  print("⚠ No Pareto front to plot.")
else:
  # Ensure Pareto DataFrame is sorted for better plotting
  pareto_df = pareto_df.sort_values(by=obj1_name)

  # Extract values for plotting
  jitter = 0.05  # Adjust this value if necessary
  x_all = df_all[obj1_name] + np.random.uniform(-jitter, jitter, size=len(df_all))
  y_all = df_all[obj2_name] + np.random.uniform(-jitter, jitter, size=len(df_all))
  z_all = df_all[obj3_name] + np.random.uniform(-jitter, jitter, size=len(df_all))
  x_pareto = pareto_df[obj1_name]
  y_pareto = pareto_df[obj2_name]
  z_pareto = pareto_df[obj3_name]

  # Create a 3D scatter plot
  fig = plt.figure(figsize=(8, 6))
  ax = fig.add_subplot(111, projection='3d')

  # Plot all observed points
  ax.scatter(x_all, y_all, z_all,
        color="blue", alpha=0.4, label="All Observed Data", marker="o")

  # Plot Pareto-optimal points
  ax.scatter(x_pareto, y_pareto, z_pareto,
        color="red", s=80, label="Pareto-optimal Points", marker="^")

  # Labels and title
  ax.set_xlabel("Compressive Strength")
  ax.set_ylabel("Relative Density")
  ax.set_zlabel("Young's Modulus")
  ax.set_title("3D Scatter of All Trials and Pareto Front")

  ax.legend()
  plt.show()

  plt.scatter(df_all[obj1_name], df_all[obj2_name], alpha=0.5)
  plt.xlabel("Compressive Strength")
  plt.ylabel("Relative Density")
  plt.title("2D Projection: Compressive Strength vs Relative Density")
  plt.show()
```

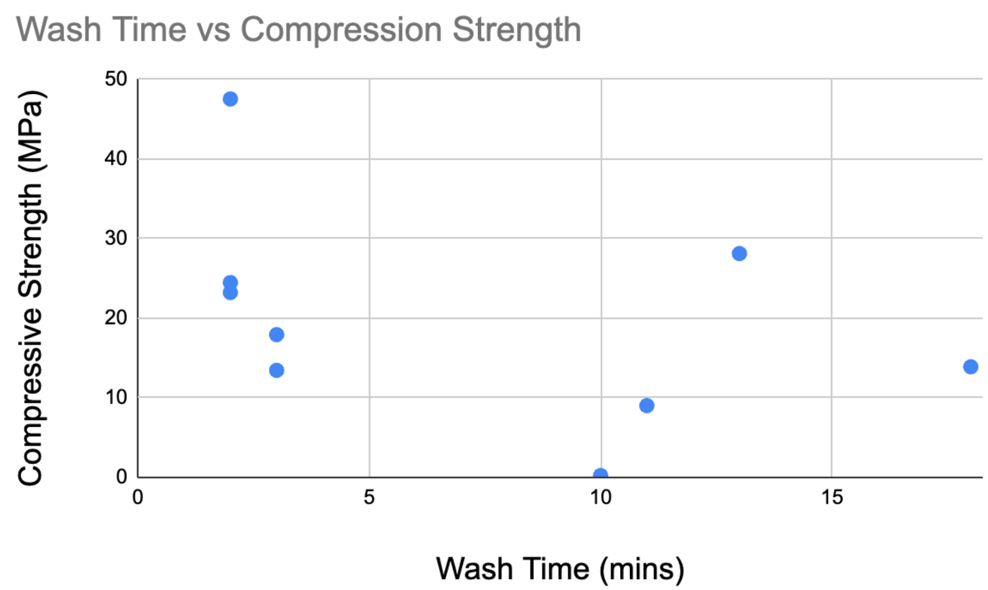

Appendix 3

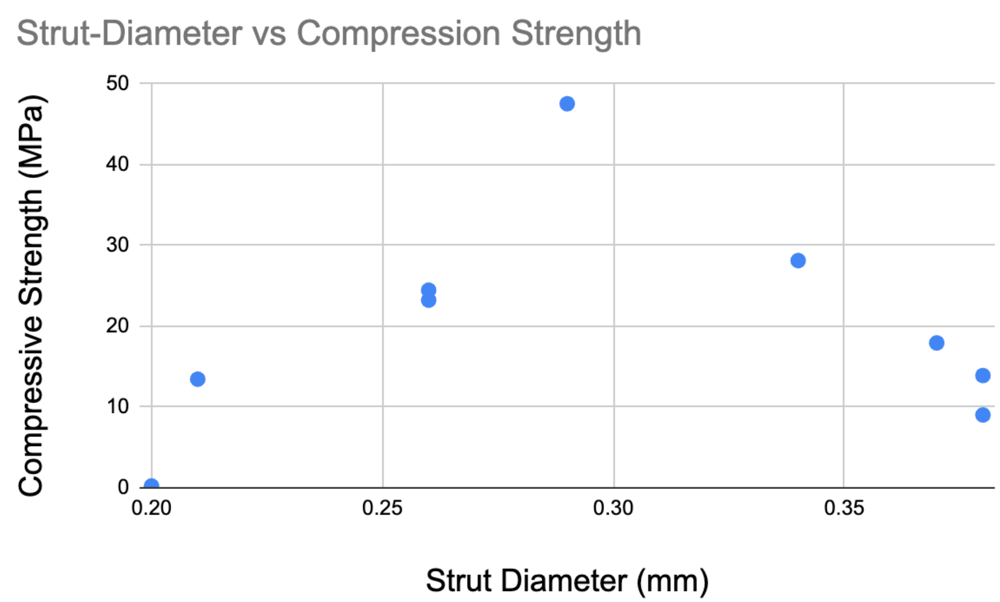


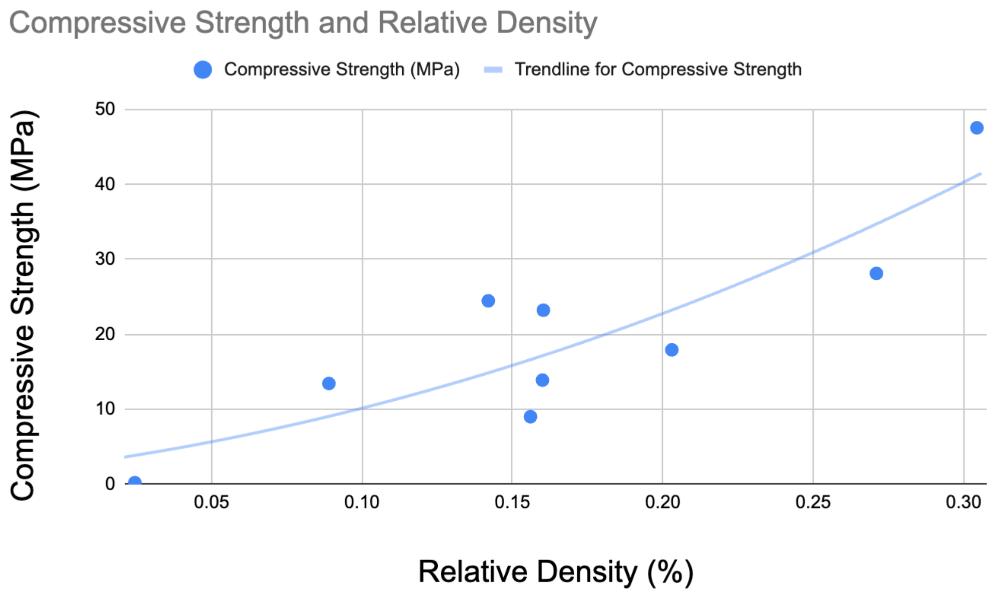



Time before Curing vs Compression Strength
Compressive Strength (MPa)
0
10
20
30
40
50
50
100
150
200
Time Before Curing (mins)

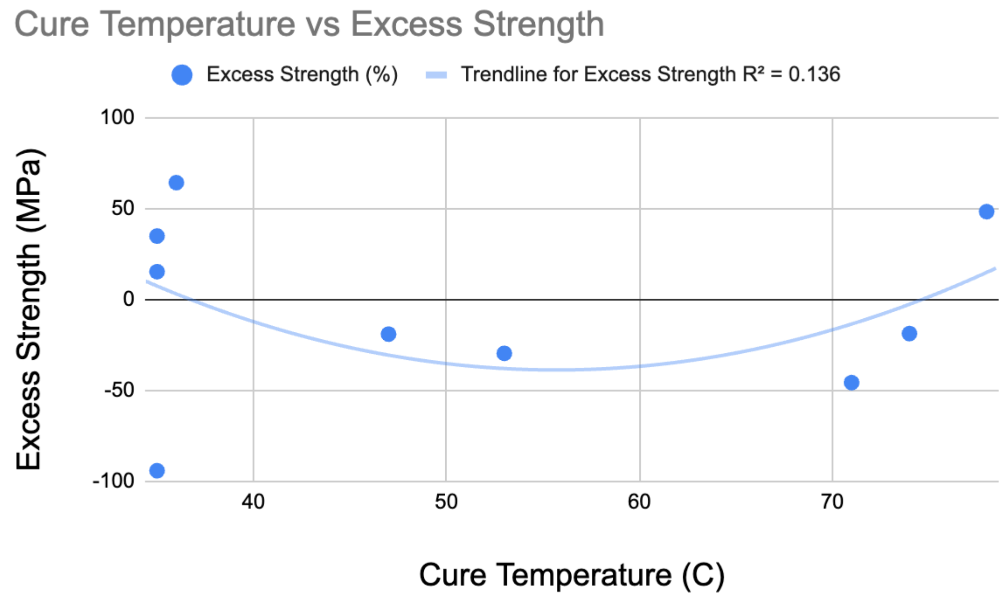

Edge-Length vs Compression Strength
Compressive Strength (MPa)
0
10
20
30
40
50
0
1
2
3
4
Edge Length (mm)

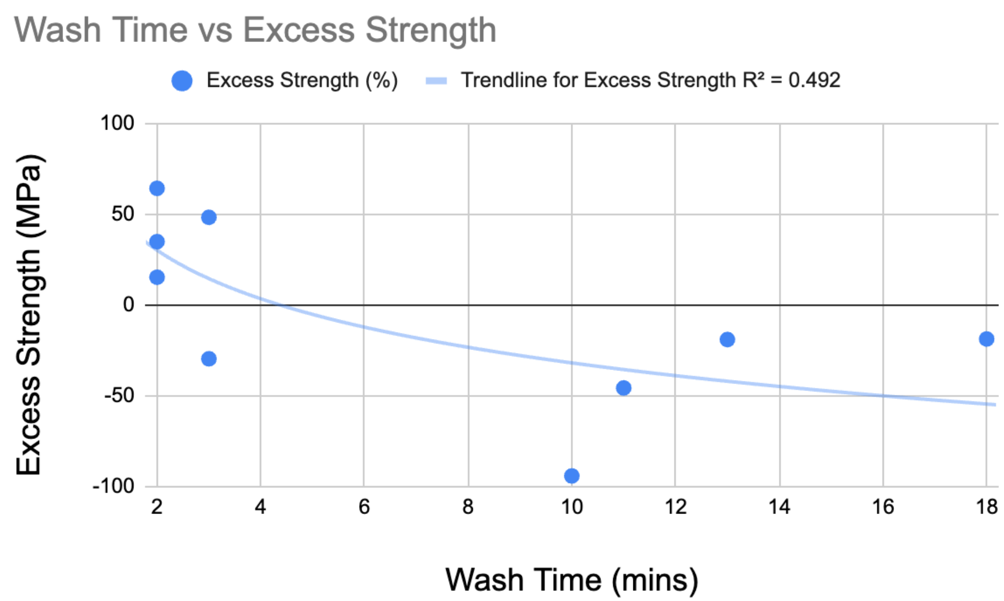

Wash Time vs Compression Strength
Compressive Strength (MPa)
0
10
20
30
40
50
0
5
10
15
Wash Time (mins)

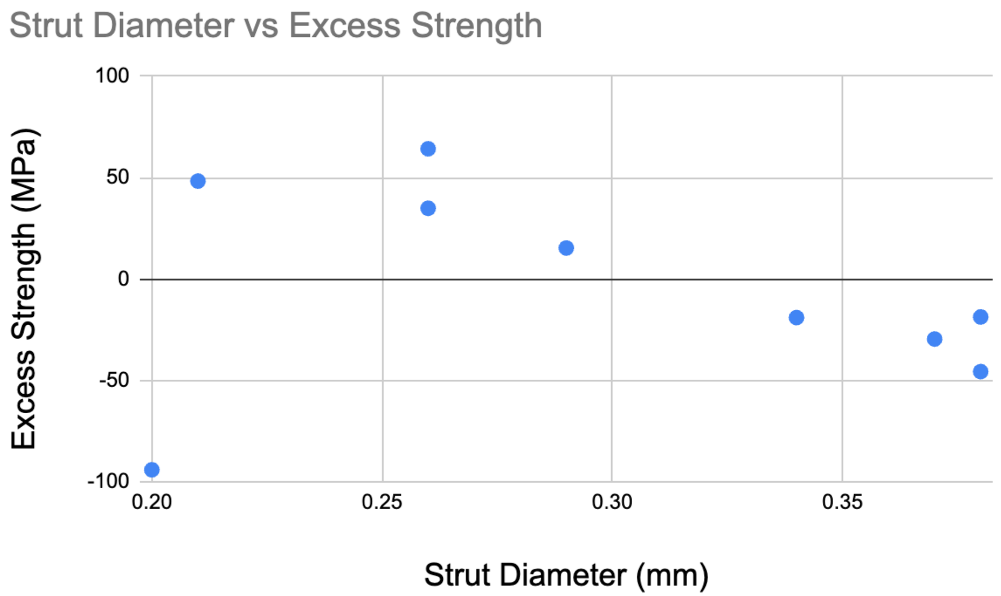

Strut-Diameter vs Compression Strength
Compressive Strength (MPa)
0
10
20
30
40
50
0.20
0.25
0.30
0.35
Strut Diameter (mm)

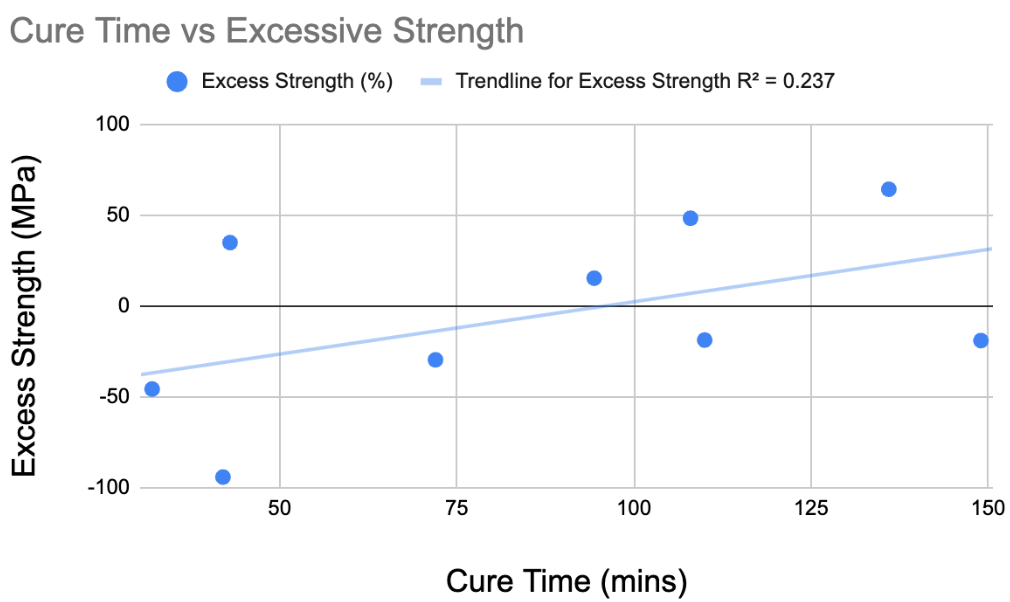

Compressive Strength and Relative Density
Compressive Strength (MPa)
Trendline for Compressive Strength
50
40
30
20
10
0
0.05
0.10
0.15
0.20
0.25
0.30
Compressive Strength (MPa)
Relative Density (%)

Appendix 4

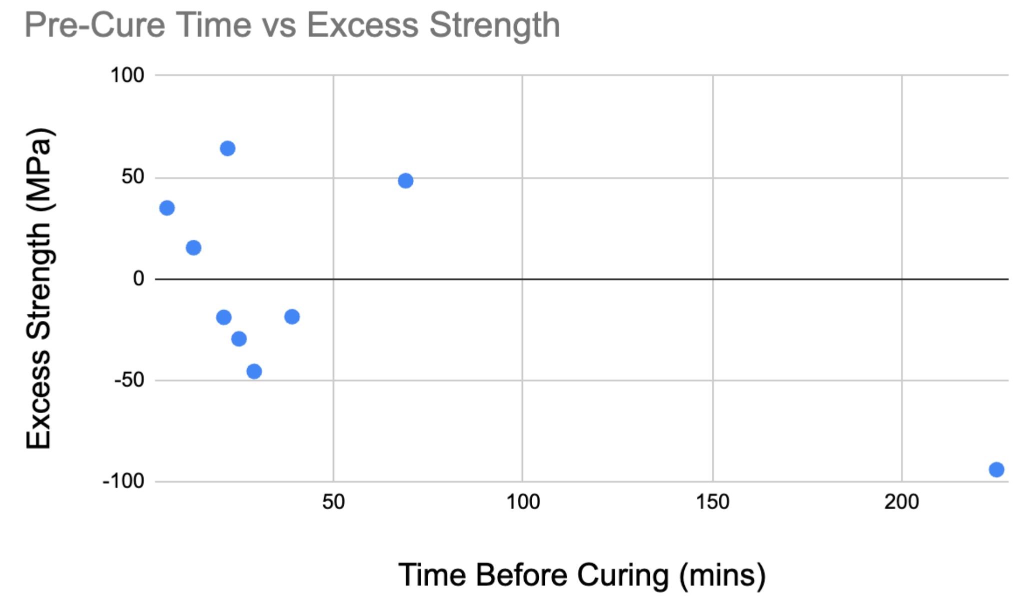

Cure Temperature vs Excess Strength
Excess Strength (%)
Trendline for Excess Strength R² = 0.136
100
50
0
-50
-100
40
50
60
70
Excess Strength (MPa)
Cure Temperature (C)

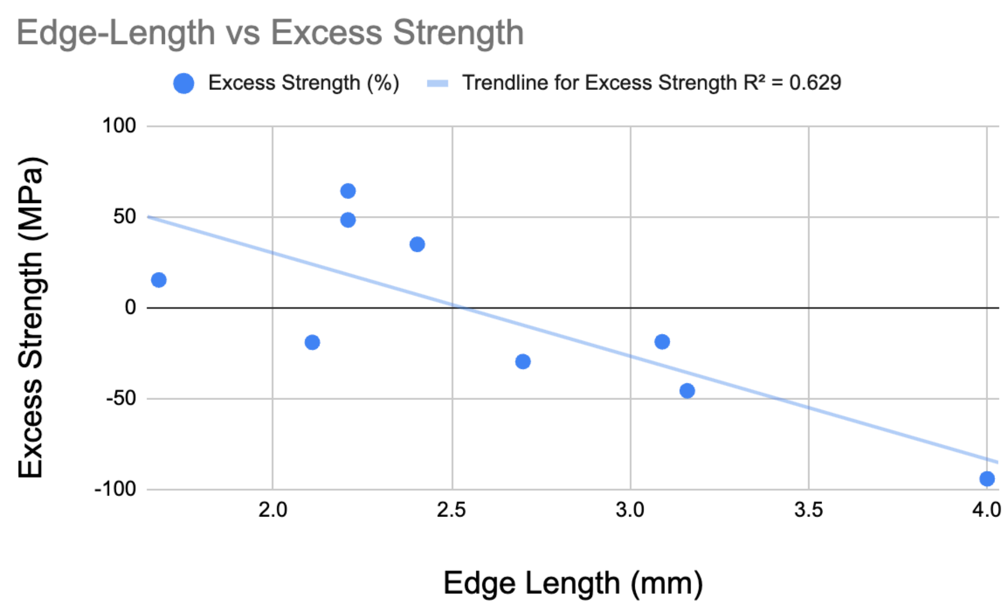

Wash Time vs Excess Strength
Excess Strength (%)
Trendline for Excess Strength R² = 0.492
100
50
0
-50
-100
2
4
6
8
10
12
14
16
18
Excess Strength (MPa)
Wash Time (mins)





COMPRESSIVE STRENGTH OF ADDITIVELY MANUFACTURED RESIN LATTICE STRUCTURES





References

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