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Machine Learning-Based Quality Control For 3D-Printed Parts

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Abstract

Machine learning (ML) and three-dimensional (3D) printing are rapidly advancing fields that offer significant potential for modern manufacturing. ML enables computers to autonomously learn from data, while 3D printing allows for creating intricate, multi-material structures with minimal manufacturing expertise. However, determining the optimal printing parameters remains challenging, often leading to increased pre-printing time and material waste. In this study, we apply ML techniques to understand the relationship between processing parameters and mechanical properties in 3D-printed parts, aiming to optimize these parameters. Our project also focuses on involving undergraduate students in using basic ML techniques and affordable 3D printers to explore parameter settings, process control, and experimental design in Additive Manufacturing (AM). Through this approach, we extract meaningful patterns from the data, reducing the need for extensive experimentation while achieving comparable results. This educational approach seeks to standardize and generalize the learning experience in ML-based quality control of AM. We use a MakerBot Replicator+ to print a daily-use part, varying process parameters such as extruder temperature, printing speed, infill density, infill pattern, layer height, and wall layers. Our analysis identifies infill density as the most significant factor influencing tensile strength, with other parameters like printing speed, infill pattern, and wall layers also contributing. Conversely, extruder temperature and layer height have minimal impact. Our findings highlight the potential of ML to optimize 3D printing processes while providing a consistent, validated, and adaptable educational framework for students.

Keywords
Machine Learning, 3D Printing, Quality Control, Process Parameter Optimization, Engineering Education

1. Introduction
Additive Manufacturing (AM), also known as 3D printing, has become increasingly significant in both engineering and education due to its numerous advantages, such as faster prototyping, reduced manufacturing costs, enhanced product customization, and improved quality control (Attaran 2017). The process of AM involves creating objects directly from digital designs by adding material in layers through techniques like sintering, solidification, and deposition (Horn and Harrysson 2012). This approach enables the production of complex, single-piece components that traditional manufacturing methods cannot easily achieve (Adekanye et al. 2017), making it particularly useful for creating customized or otherwise challenging parts directly on-site. AM is widely utilized in industries such as medicine, automotive, and aerospace, and has expanded into areas like food production, fashion, and metalworking (Kalva 2015). Moreover, the data generated during the 3D printing process is invaluable for providing insights into product design improvements, error detection and prediction, waste minimization, and workload reduction in testing (Razvi et al. 2019). By integrating Machine Learning (ML) and Deep Learning (DL) technologies to analyze this data, AM processes can be more effectively monitored and optimized, further enhancing the design and manufacturing workflow (Qin et al. 2022).

The fused filament fabrication (FFF) process is one of the most used AM techniques due to its relatively low cost, quick prototyping, and high compatibility with many thermoplastic materials. As a result, FFF is a frequently researched and rapidly developing technique (Ford et al. 2022). However, with such rapid development, there are challenges in maintaining consistent product quality, with defects that are hard to control using the traditional methods, such as the porosity due to poor fusion between adjacent filament, the anisotropic nature of the materials, and warping as a result of the residual stress due to the fast-cooling nature of the AM processes (Goh et al. 2021). Navigating the complexities of optimizing process parameters and establishing standardized workflows for quality control, particularly in educational settings, are crucial challenges for advancing the field.

2. Literature Review
In recent years, leveraging ML techniques to improve the quality of 3D-printed parts has garnered significant attention. Researchers have applied various ML methods to optimize AM process parameters, aiming to achieve the desired quality level for 3D-printed parts. Tamir et al. (Tamir et al. 2023) integrate open-loop and closed-loop ML models to monitor the effects of process parameters on the quality of the parts. Dabbagh et al. (Dabbagh et al. 2022) introduce a user-friendly GUI to integrate ML and 3D printing and use complexity index and labeling methods to optimize printing parameters and identify the best ML model. Charalampous and coauthors (Charalampous et al. 2022) develop ML models to predict the tensile strength of 3D-printed parts and create a tool to determine the optimal printing conditions based on user-specified requirements. Nguyen et al. (Nguyen et al. 2022) propose a data-driven ML platform to optimize parameters of the 3D printing process from a model design to a complete product. Jatti et al. (Jatti et al. 2022) examine how process parameters affect PLA 3D-printed specimens, using response surface methodology and nonlinear regression to develop predictive models, with both methods showing strong agreement with experimental results and low prediction errors for tensile, impact, and flexural strength. Jayesudha et al. (Jayasudha et al. 2022) evaluate five machine learning models for predicting the tensile strength of 3D-printed objects, finding XGBoost regression to be the most effective based on various statistical metrics. Zhai et al. (Zhai and Chen 2023) review 120 papers on process optimization for additive manufacturing based on ML, summarizing the advancements, methodologies, and challenges in this field, reaching to the conclusion that "standardization, data-sharing, and collaboration between academia and industry can help establish best practices and guidelines for ML-based AM optimization."

Upon reviewing the literature, it becomes apparent that there is a notable scarcity of publications addressing the use of ML for quality control in AM within an educational framework aimed at engaging undergraduate students in research. The majority of existing studies predominantly focus on enhancing prediction accuracy rather than on designing experiments that minimize the need for extensive experimentation. Such an approach could streamline the process, thereby conserving time, reducing experimental effort, and optimizing material usage. Incorporating ML-based quality control into educational settings not only benefits research but also equips students with practical skills and insights into the experimental design process.

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In this study, we address this gap by developing a workflow for utilizing ML techniques to enhance the quality of 3D-printed parts through the control of process parameters. This approach not only advances the application of ML in AM but also serves as an educational framework. By engaging in this workflow, students gain practical experience in applying ML techniques, mastering quality control methods, and balancing the efforts between data analysis and experimental procedures. Additionally, the study facilitates hands-on learning with computer-aided design, AM prototyping, and on-line quality control, thereby providing a well-rounded educational experience that integrates theoretical knowledge with practical skills.

3. Methods

Various factors influence the quality of the printed end-product, including the printing layout, material, fused deposition modeling (FDM) environment, FDM process parameters, and the machine used (see Figure 1 for more details). Our study focuses specifically on the FDM process parameters, such as extruder temperature, infill density, infill pattern, and wall layers.

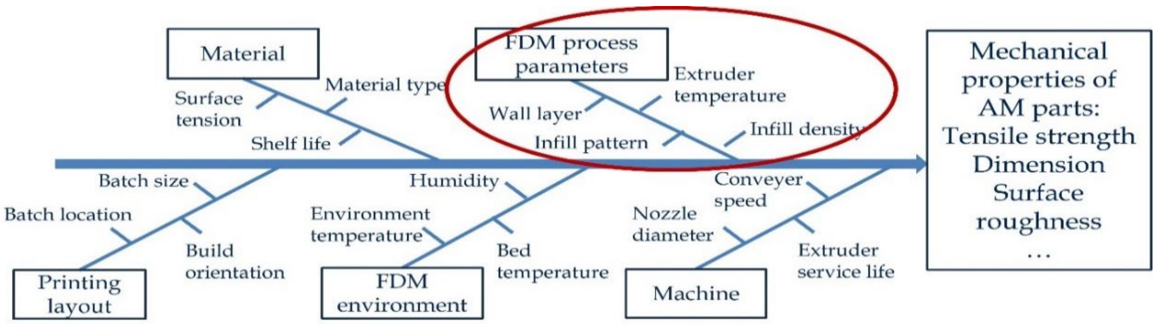
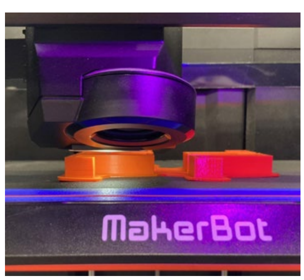
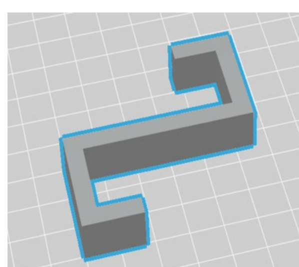


Figure 1. Cause-and-effect diagram

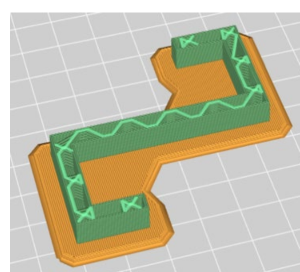
A MakerBot Replicator+ 3D printer is employed for the practical experiments. Figure 2(a) shows an image of the printing process. We use standard polylactic acid (PLA) filament, a cost-effective and eco-friendly alternative to conventional plastics, for its wide applicability.



(a) Printing using MakerBot Replicator+

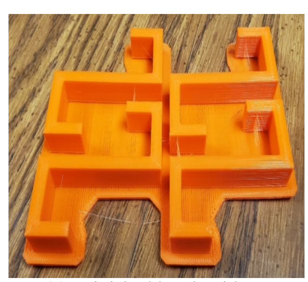


(b) 3D design of a coat hook

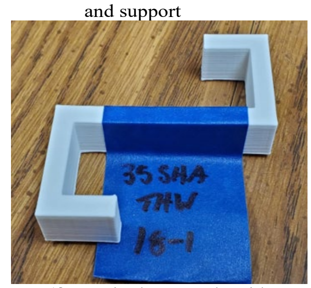


(c) Print preview with infill and support

(d) Coat hook use example



(e) Finished batch with retained support



(f) A single example with labeling

Figure 2. Coat hook design, printing, and printed product presentation, labeling

The test structure is a simple coat hook designed to be mounted on a desk or chair back for easy organization. The design, along with the preview of the infill and support structure, is illustrated in Figures 2(b) and 2(c). Figure 2(d) demonstrates the coat hook in real-life use, while Figures 2(e) and 2(f) show the printed elements both on the support structure and after detachment.

We define three phases in the whole process of quality control (see Figure 3). In the first phase, we focus on identifying the controllable parameters of the FDM process. We begin by pinpointing potential parameters that could impact the product's properties. For parameters that we can directly set their values, we aim at defining their specific ranges or levels in the later phases. For uncontrollable parameters, we seek to determine the optimal range of controllable parameters that minimize the impact of these uncontrollable variations on the product's properties. In Phase 2, we use the controllable parameters that we identified from Phase 1 to create various scenarios by combining their different levels or values. For each scenario, we model the product tensile strength as a linear regression of the controllable parameters and test the sensitivity of each parameter. Sensitivity is assessed by calculating the Pearson correlation coefficient and the p-value between each parameter and the tensile strength. The correlation coefficient is calculated using the formula:

$$\boldsymbol{r} = \frac{\sum(\boldsymbol{x_i} - \overline{\boldsymbol{x}})(\boldsymbol{y_i} - \overline{\boldsymbol{y}})}{\sqrt{\sum(\boldsymbol{x_i} - \overline{\boldsymbol{x}})^2(\boldsymbol{y_i} - \overline{\boldsymbol{y}})^2}}$$

where x_i is the value of a record for each parameter, $\bar{x}$ is the mean of all records, y_i is the value of a record for tensile strength, and $\bar{y}$ is the mean. If a parameter's p-value is less than 0.05, it is considered a significant or sensitive parameter. Parameters with p-value between 0.05 and 0.5 are considered predictors with moderate influence, while those with p-values greater than 0.5 are deemed insensitive and excluded from the regression model.

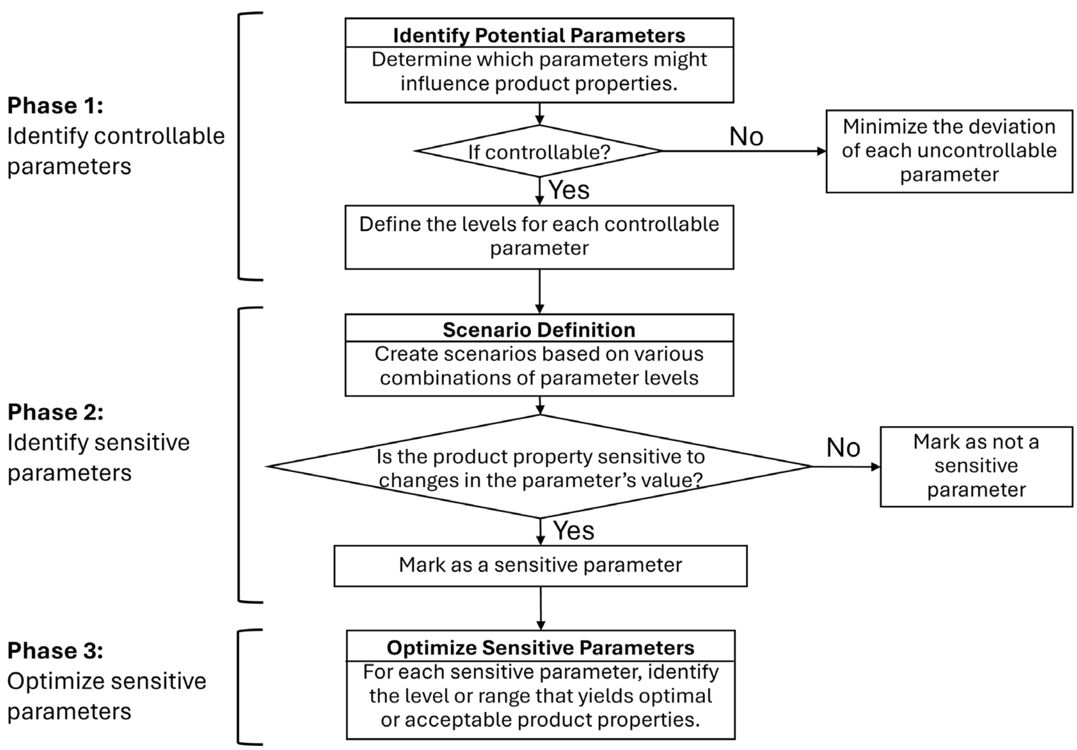
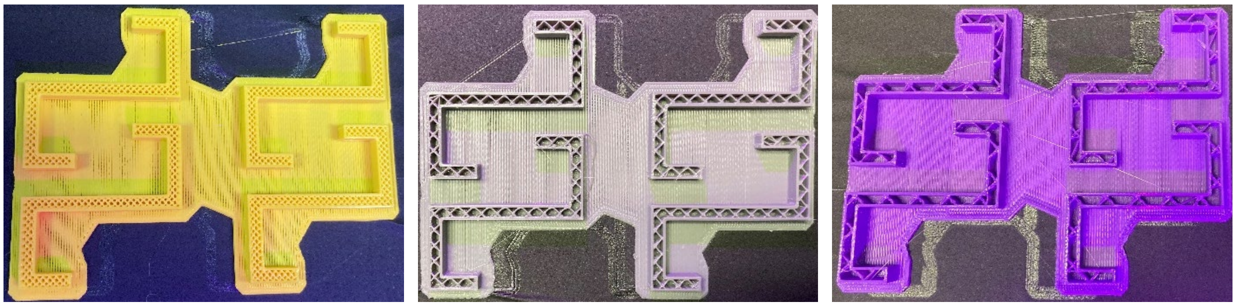


Figure 3. The flowchart of research methodology, phases 1-3

Next, we further investigate these sensitive parameters. In Phase 3, we identify the level or range of each sensitive parameter that yields optimal or acceptable product properties by conducting additional experiments. In these experiments, we keep all sensitive parameters constant except one, which we vary to observe its effect. By changing the value of this parameter, we print batches of objects and obtain the average product property for each batch. Figure

4 presents an experiment for the sensitive parameter infill density, with a constant printing speed of 80 mm/s, a diamond infill pattern, and 2 wall layers. Figure 4(a) shows the infill structure with 50% infill density, 4(b) shows the infill structure with 20% infill density, and 4(c) shows the infill structure with 10% infill density. We derive the robust range of infill density from this experiment. Similarly, we determine the robust range or level for other sensitive parameters through the same experimental approach.



(a) 50% infill density (b) 20% infill density (c) 10% infill density

Figure 4. Infill structure with different density but same printing speed 80mm/s, diamond pattern and 2 wall layers

The proposed methodology identifies the robust levels or ranges of sensitive parameters that yield optimal or acceptable product properties, making it both time-saving and cost-efficient for product design and quality control. By streamlining the process of parameter selection, we enhance efficiency and reduce the need for extensive trial-and-error testing. Furthermore, in our experiment, we focus exclusively on tensile strength as the target property of the end product. This targeted approach allows for a precise evaluation of how each parameter influences this critical aspect, though the methodology can be adapted to consider other properties as needed.

4. Data Collection

As stated in methodology section, in phase 1, we proposed potential parameters and identified controllable parameters. There are various FDM process parameters such as extruder temperature, infill density, infill pattern, wall layer, etc. We identified six controllable parameters that will influence the property of the end-product: extruder temperature, printing speed, infill density, infill pattern, layer height, and wall layer. Furthermore, we need to define the range or level of these parameters.

Table 1 presents the levels of each controllable parameter. The extruder temperature, which determines how hot the extruder gets to melt the material during the printing process, typically ranges from 215 to 250°C for PLA. For our experiment, we set the extruder temperature at three levels – 215, 220, and 225°C. Printing speed, the rate at which the 3D printer extrudes and lays down material to build the object, is usually measured in millimeters per second. We tested speeds within the set {75, 80, 90, 100, 120, 125, 150} mm/s. Infill density refers to the percentage of material used to fill the interior of each layer in the 3D-printed object. We explored densities from {5, 10, 15, 20, 25, 30, 35, 40, 45, 50}%. The infill pattern is the internal structure at each layer of the printed object. With a variety of patterns available, we focused on testing several in our study, including diamond, donut, and shark, as well as a few others such as hexagonal, cat, linear, Hilbert, and Moroccan star, which we categorized as "other." Layer height, the vertical measurement of each layer deposited during printing, was considered at 0.15, 0.2, and 0.25 mm in Phase 1 of our study. Lastly, the wall layer, or the thickness of the printed product's walls, was tested at 2, 3, 4, and 5 layers in our experiments.

Table 1. FDM processing parameters and range/level values

Parameter	Value
Extruder temperature (ºC)	215, 220, 225
Printing speed (mm/s)	75, 80, 90, 100, 120, 125, 150
Infill density (%)	5, 10, 15, 20, 25, 30, 35, 40, 45
Infill pattern	Diamond, Donut, Shark, Other
Layer height (mm)	0.15, 0.2, 0.25
Wall layer	2, 3, 4, 5

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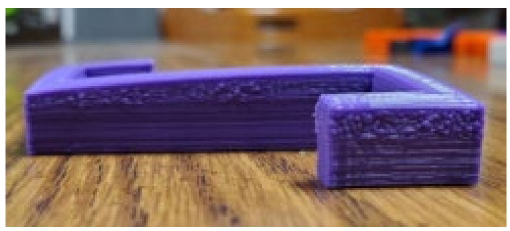
During our experiment, we occasionally produce products with defects such as warping, often caused by high printing speeds or printing too many items in one batch. Figure 5 illustrates an extreme case of warping, with two different views provided in Figures 5(a) and 5(b). The hook's shape is imperfect compared to the non-warped hook shown in Figure 5(c), though the tensile strength remains unaffected. Figure 5(d) highlights a case of breakage due to poor tensile strength. We exclude any printed products with obvious defects from our dataset.

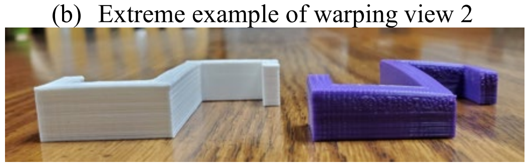
For each print, we select a set of parameters by combining any value of each parameter within the specified range. In each batch, we print four identical parts simultaneously (see Figure 2(e)). We then measure the tensile strength of the four parts and calculate their average, which we record as the average tensile strength for that batch. Since infill pattern and wall layer are categorical variables in this experiment, we use the One Hot Encoding method to convert them into dummy numerical variables (3 for infill pattern and 3 for wall layer).

To model the tensile strength as a function of FDM processing parameters, we train the model data to derive the appropriate coefficients. We choose to represent tensile strength as a linear regression of the parameters. The data are split into training and testing sets with an 80/20 ratio. After training, we test the model using the testing data. To evaluate the performance of the regression model, we measure the mean squared error (MSE), mean absolute error (MAE), and regression score R^2.

(a) Extreme example of warping view 1



(b) Extreme example of warping view 2



(c) Warped hook side-by-side with non-warped hook

(d) Break due to poor tensile strength

Figure 5. Examples of defects

5. Results and Discussion

5.1 Numerical Results

In phase 2, we develop a formula to model the relationship between tensile strength and various controllable parameters. The formula is as follows:

$$\boldsymbol{Tensile\ strength = 0.095 * extruder\ temperature + 0.060 * printing\ speed + 0.726 * infill\ density - 1.059 * layer\ height + 5.033 * Donut\ infill\ pattern - 7.862 * Other\ infill\ pattern + 2.073 * Shark\ infill\ pattern + 1.997 * three\ wall\ layer + 2.566 * four\ wall\ layer + 3.206 * five\ wall\ layer}.$$

The model's coefficient of determination ($\boldsymbol{R^2}$) is 0.8363, indicating a good fit. Further evaluation of the model's performance is shown in Table 2, where we report the MSE, MAE, and MAPE for both training and test datasets. For the training data, the MSE, MAE, and MAPE are 11.573, 2.623, and 0.126, respectively. For the test data, the MSE, MAE, and MAPE are 24.716, 3.673, and 0.232, respectively, demonstrating good predictive performance.

To identify the most influential parameters, we calculate the Pearson correlation coefficient and p-values, which are detailed in Table 3. Parameters such as printing speed, infill density, and wall layer have p-values less than 0.05

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indicating that they are significant and sensitive variables. The infill pattern, with a p-value of 0.366, is a predictor with moderate influence as it falls between 0.05 and 0.5. Both extruder temperature and layer height have p-values greater than 0.5, classifying them as insensitive. Consequently, the key sensitive parameters identified are printing speed, infill density, infill pattern, and wall layer.

Table 2. Performance metrics for a model with all parameters

Metrics	Train Data	Test Data
MSE	11.573	**24.716**
MAE	2.623	**3.673**
MAPE	0.126	***0.232***

Table 3. Pearson correlation coefficient between parameter and tensile strength and p-value

Parameter	Pearson Correlation Coefficient	P-value
Extruder temperature (ºC)	0.035	0.740
Printing speed (mm/s)	0.310	0.003
Infill density (%)	0.771	3.98e-19
Infill pattern	0.096	0.366
Layer height (mm)	0.033	0.753
Wall layer	0.252	0.016

Using the identified sensitive parameters, we formulate the tensile strength as a linear regression model. The updated formula is as follows:

$$Tensile\ strength = 0.058 * printing\ speed + 0.724 * infill\ density + 5.196 * Donut\ infill\ pattern - 7.848 * Other\ infill\ pattern + 2.593 * Shark\ infill\ pattern + 2.051 * three\ wall\ layer + 2.604 * four\ wall\ layer + 4.099 * five\ wall\ layer.$$

The model's coefficient of determination (R^2) is 0.8357, again, indicating a good fit. Further performance evaluation, detailed in Table 4, includes the MSE, MAE, and MAPE for both training and test datasets. For the training data, the MSE, MAE, and MAPE are 11.619, 2.662, and 0.128, respectively. For the test data, the MSE, MAE, and MAPE are 24.343, 3.655, and 0.235, respectively, demonstrating strong predictive performance. Compared to the previous model, the refined model exhibits lower MSE and MAE on the test data, indicating improved performance. This improvement suggests that excluding insensitive parameters enhances the model's predictive accuracy.

Table 4. Performance metrics for model with sensitive parameters

Metrics	Train Data	Test Data
MSE	11.619	**24.343**
MAE	2.662	**3.655**
MAPE	0.128	***0.235***

Furthermore, after conducting the experiments illustrated in phase 3 in the methodology part, we derive the optimal or acceptable range/level values for the sensitive parameters presented in Table 5. As illustrated in Table 5, optimal range for printing speed is less than or equal to 125mm/s, optimal range for infill density is greater than or equal to 20%, optimal levels for infill pattern are diamond, donut, and shark, optimal wall layer levels are 3, 4, and 5.

Table 5. Range and level values for sensitive parameters yield optimal or acceptable tensile strength

Parameter	Optimal/Acceptable Value
Printing speed (mm/s)	75, 80, 90, 100, 120, 125
Infill density (%)	20, 25, 30, 35, 40, 45
Infill pattern	Diamond, Donut, Shark

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Wall layer	3, 4, 5

5.2 Graphical Results

Figure 6 illustrates the correlation degree between each pair of parameters in the dataset. To further validate the robust range and levels of the sensitive parameters, we compare control charts across three scenarios: all records, records that satisfy each sensitive parameter's condition individually, and records that satisfy the combination of all sensitive parameters' conditions. For consistent comparison, Figures 7 and 8 use the same upper control limit (UCL) and lower control limit (LCL) derived from the dataset of all records. The UCL and LCL are calculated as the mean $\pm$ 3 times the standard deviation of the tensile strength.

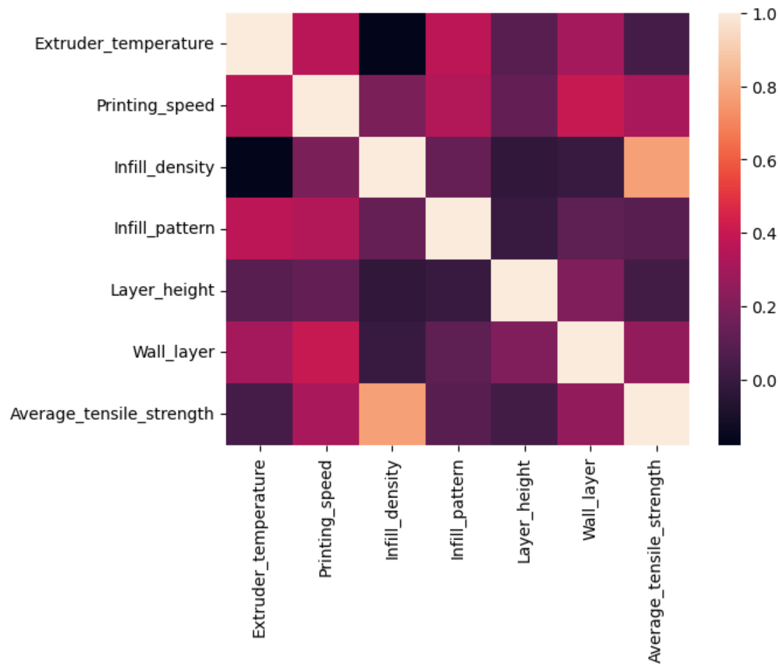
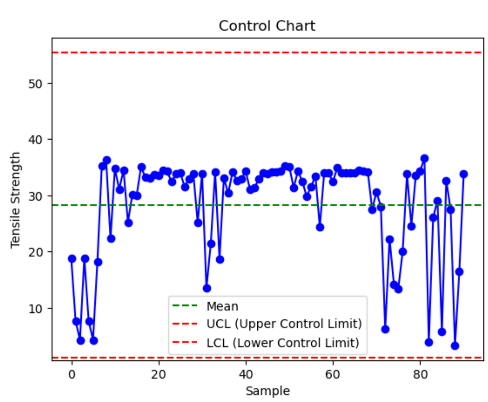
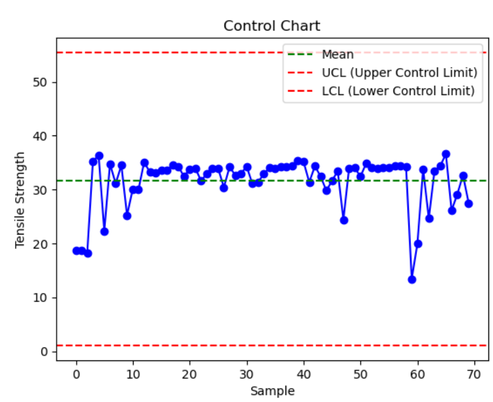


Figure 6. Heatmap for the dataset

Figure 7(a) displays the control chart of all records, revealing several outliers. Figure 8 presents control charts for records that meet the conditions of each single sensitive parameter. Compared to Figure 7(a), when excluding the records from robust setting of infill density, infill pattern, and wall layer, the number of outliers decreases (see Figures 8(a) – (c) for more details). However, excluding records from the printing speed > 125 mm/s does not show a clear reduction in outliers, as printed products with warping defects caused by high printing speed were already excluded.



(a) All records



(b) Records satisfying combination conditions

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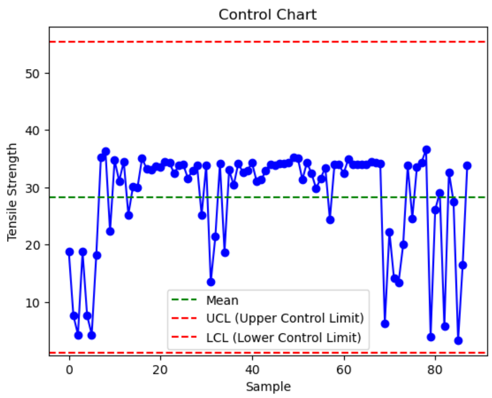
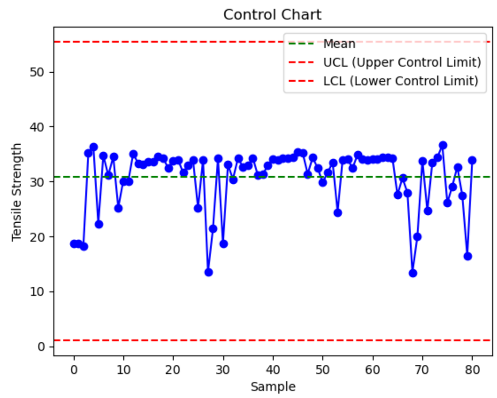
Figure 7. Control chart of all records, only records satisfying all the sensitive parameter conditions

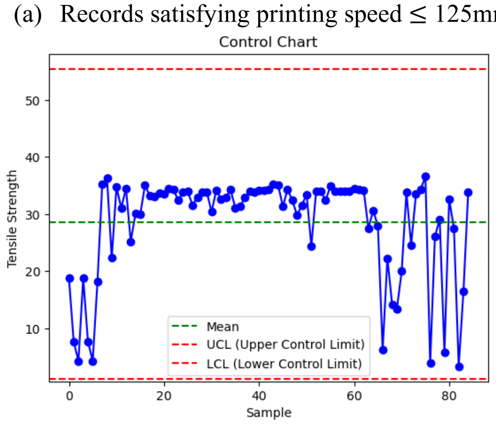
Finally, when we remove records that do not satisfy all four sensitive parameters' conditions, all outliers are removed from the control chart (see Figure 7(b)). This outcome validates that the robust range and level values of the sensitive parameters can indeed yield an optimal or acceptable tensile strength.



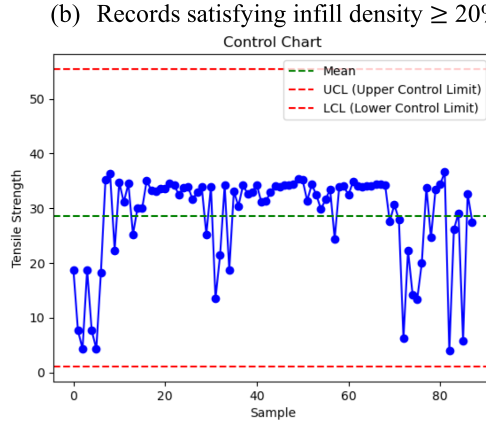
(a) Records satisfying printing speed ≤ 125mm/s



(b) Records satisfying infill density ≥ 20%



(c) Records satisfying infill pattern not Other



(d) Records satisfying wall layer ≥ 3

Figure 8. Control chart of only records satisfying each sensitive parameter condition

Using the new dataset with records that meet all four sensitive parameter conditions, we create a control chart for continuous improvement – Figure 9, showing that the LCL of tensile strength is significantly higher than the LCL in the full dataset, confirming the effectiveness of our criteria for sensitive parameters. However, there are still four outliers, all of which correspond to the infill density of 20% (highlighted by circle). This suggests that to further improve tensile strength, increasing the infill density to 25% or more would be a better approach.

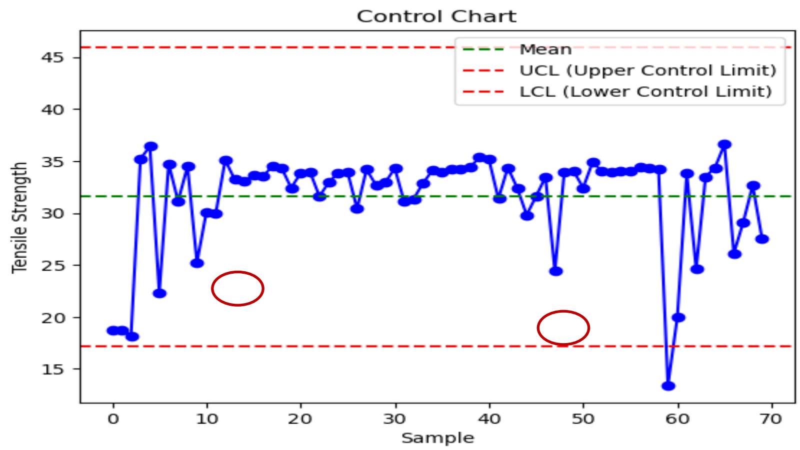


Figure 9. Control chart of only records satisfying all the sensitive parameter conditions with its own UCL, LCL

5.3 Way Forward

Our analysis is conducted after the printing process is completed. However, implementing in-situ parameter control could save more energy and materials. In-situ parameter control involves analyzing product properties during the printing process and adjusting the parameters in real time to enhance the final product's properties. We plan to investigate this methodology in our future work, alongside gathering more data to support this approach.

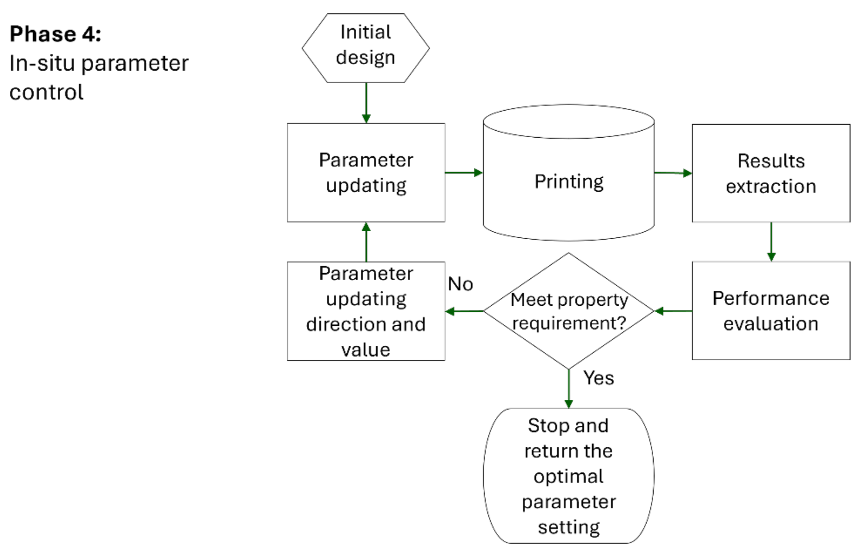


Figure 10. The flow chart of in-situ parameter control

6. Conclusion

In this paper, we propose a four-phase framework to determine the robust range and level of sensitive FDM process parameters for achieving the desired tensile strength. We implement and validate the first three phases, demonstrating the framework's effectiveness. Our approach is structured as follows:

First, we identify potential parameters and determine which are controllable based on our resources and expertise. Second, we model tensile strength as a linear regression of these controllable parameters, categorizing them using the Pearson correlation coefficient and p-value: parameters with p-values less than 0.05 are considered sensitive, those between 0.05 and 0.5 are classified as predictors with moderate influence, and those greater than 0.5 are deemed insensitive. Third, we refine the model by focusing on sensitive parameters and predictors with moderate influence, deriving robust ranges or levels that yield optimal or acceptable tensile strength. Finally, we validate these ranges or levels by analyzing outliers across control charts for records that meet various conditions. Experimental results demonstrate that the proposed framework effectively identifies sensitive parameters and determines the appropriate range or level values for achieving optimal or acceptable tensile strength. By framing this workflow into four distinct phases, we contribute to engineering education by providing a structured approach for using ML techniques to enhance the quality of 3D-printed parts.

However, we recognize several limitations in this study: (1) we only use linear regression based on our experience rather than exploring and selecting the best-fit model from various options, (2) we focus solely on tensile strength, neglecting other important properties such as stiffness, dimensional accuracy, and surface quality, and (3) the design of our experiment could be further improved to print fewer samples, making the overall process more efficient. Looking ahead, there are other factors in the cause-and-effect diagram that we can explore in future work, such as alternative materials, printing layout, supporting structures, extruder service time, and environmental settings. These aspects could provide further insights into optimizing the 3D printing process and educational experience.

References

Adekanye, A., Mahamood, R. M., Akinlabi, E. T., and Owolabi, M. G., Additive manufacturing: the future of manufacturing, *Additive Manufacturing*, pp. 709-715, 2017.

Attaran, M., The rise of 3-D printing: The advantages of additive manufacturing over traditional manufacturing, *Business horizons*, vol. 60, no. 5, pp. 677-688, 2017.

Charalampous, P., Kladovasilakis, N., Kostavelis, I., Tsongas, K., Tzetzis, D. and Tzovaras, D., Machine learning-based mechanical behavior optimization of 3D print constructs manufactured via the FFF process, *Journal of Materials Engineering and Performance*, vol. 31, no. 6, pp. 4697-4706, 2022.

Dabbagh, S.R., Ozcan, O. and Tasoglu, S., Machine learning-enabled optimization of extrusion-based 3D printing, *Methods*, vol. 206, pp. 27-40, 2022.

Ford, M.J., Loeb, C.K., Pérez, L.X.P., Gammon, S., Guzorek, S., Gemeda, H.B., Golobic, A.M., Honnell, A., Erspamer, J., Duoss, E.B. and Wilson, T.S., 3D printing of transparent silicone elastomers, *Advanced Materials Technologies*, vol. 7, no. 5, pp. 2100974, 2022.

Goh, G.D., Sing, S.L. and Yeong, W.Y., A review on machine learning in 3D printing: applications, potential, and challenges, *Artificial Intelligence Review*, vol. 54, no. 1, pp. 63-94, 2021.

Horn, T.J. and Harrysson, O.L., Overview of current additive manufacturing technologies and selected applications, *Science progress*, vol. 95, no. 3, pp. 255-282, 2012.

Jatti, V.S., Sapre, M.S., Jatti, A.V., Khedkar, N.K. and Jatti, V.S., Mechanical properties of 3D-printed components using fused deposition modeling: optimization using the desirability approach and machine learning regressor, *Applied System Innovation*, vol. 5, no. 6, pp. 112, 2022.

Jayasudha, M., Elangovan, M., Mahdal, M. and Priyadarshini, J., Accurate estimation of tensile strength of 3D printed parts using machine learning algorithms, *Processes*, vol. 10, no. 6, pp. 1158, 2022.

Kalva, R. S., 3D printing–the future of manufacturing (The next industrial revolution), *International Journal of Innovations in Engineering and Technology*, vol. 5, no. 1, pp. 184-190, 2015.

Nguyen, P.D., Nguyen, T.Q., Tao, Q.B., Vogel, F. and Nguyen-Xuan, H., A data-driven machine learning approach for the 3D printing process optimization, *Virtual and Physical Prototyping*, vol. 17, no. 4, pp. 768-786, 2022.

Qin, J., Hu, F., Liu, Y., Witherell, P., Wang, C.C., Rosen, D.W., Simpson, T.W., Lu, Y. and Tang, Q., Research and application of machine learning for additive manufacturing., *Additive Manufacturing*, vol. 52, pp. 102691, 2022.

Razvi, S.S., Feng, S., Narayanan, A., Lee, Y.T.T. and Witherell, P., A review of machine learning applications in additive manufacturing, *International design engineering technical conferences and computers and information in engineering conference, American Society of Mechanical Engineers*, vol. 59179, pp. V001T02A040, 2019.

Tamir, T.S., Xiong, G., Fang, Q., Yang, Y., Shen, Z., Zhou, M. and Jiang, J., Machine-learning-based monitoring and optimization of processing parameters in 3D printing, *International Journal of Computer Integrated Manufacturing*, vol. 36, no. 9, pp. 1362-1378, 2023.

Zhai, X. and Chen, F., A review of process optimization for additive manufacturing based on machine learning, *Annals of Applied Mathematics*, vol. 39, no. 4, pp. 493-543, 2023.

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