Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 10, No. 9, 202-211
2026
Publisher: Learning Gate
DOI: 10.55214/2576-8484.v10i9.13594

Selection of additive manufacturing process parameters by using ANOVA and regression analysis

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Abstract: The importance of additive manufacturing is increasing in day-to-day industrial applications due to its versatile uses. Process parameter selection is a tedious trial-and-error task. Supervised machine learning helps researchers use decision models to predict process parameters based on existing process data. The dataset is prepared from the literature, and the collected data are classified into training and testing datasets before the model is developed. The dataset is analyzed for variations using ANOVA, and it is found that there is no significant variation in the data. The dataset has three process parameters: average pressure, temperature, and speed. Regression analysis is performed, regression coefficients are calculated, and the intercept is determined. This analysis is helpful for researchers and 3D printing manufacturers when selecting process parameters effectively. ANOVA isolates statistically significant factors, while regression analysis models their relationships, facilitating the prediction of optimal parameter values for improved additive manufacturing efficiency. This approach streamlines the parameter selection process, reduces trial-and-error iterations, and contributes to consistent quality in additive manufacturing.
Keywords: *ANOVA, Data analysis, Machine learning, Polycaprolactone, Regression, Stereolithography.*

1. Introduction

Additive manufacturing, also called fused filament fabrication or 3D printing, has a history spanning several decades. The development of AM involves key technological developments and milestones. In the 1950s and 1960s, the first concepts of 3D printing emerged, including stereolithography (SLA). It was not until the 1980s that the first viable technology, SLA, was developed by Hull [1], marking the birth of additive manufacturing. In 1986, selective laser sintering was industrialized by Carl Deckard and Joseph Beaman at the University of Texas at Austin. In the 1990s, additive manufacturing technologies began to be commercialized. Companies like 3D Systems, founded by Charles Hull, introduced the first commercial 3D printers. The technology gained attention in industries such as aerospace and automotive for rapid prototyping. The 2000s saw advancements in the materials used for 3D printing, expanding the range of applications. The technology became more accessible with the development of affordable desktop 3D printers. Additionally, applications extended beyond prototyping to include tooling, jigs, and fixtures. The year 2010 marked a significant period of growth for additive manufacturing, as applications expanded into various real-time applications [2, 3].

3D printing stands as a superior technology for tailored manufacturing [4, 5]. This process involves the layer-by-layer stacking of materials to create objects based on CAD design models, and it has found widespread applications in fields such as medicine [6, 7] and part manufacturing [8]. Various types of 3D printing technologies exist, including FDM [9], SLA [10], SLS [11], LOM [12], PCM [13], and more.

FDM stands out as a widely embraced 3D printing method, primarily owing to its cost-effectiveness and user-friendly procedure [14, 15]. Within the FDM process, material selection plays a crucial role in determining the quality and functionality of the resulting printed products [16-18]. This underscores

History: Received: 12 June 2026; Revised: 17 August 2026; Accepted: 20 August 2026; Published: 16 September 2026
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the dual importance, both in theory and practice, of advancing the development of high-performance materials tailored specifically for FDM.

Conventional thermoplastic materials utilized in FDM, such as polylactic acid [19], poly(acrylonitrile-co-butadiene-co-styrene) [20], and polycarbonate [21], require manufacturing temperatures above 200 °C. Nevertheless, these elevated temperatures present challenges, including increased energy consumption and safety concerns, particularly for small-scale household FDM printers. Moreover, research indicates the continuous generation of volatile organic compounds (VOC) and airborne plastic microparticles during FDM processes conducted at elevated temperatures, potentially posing health risks to users [22, 23]. Furthermore, elevated manufacturing temperatures impede the integration of bioactive components into FDM materials, limiting the possibilities for functionalizing these materials.

Stereolithography (SLA) is one of the oldest and most reliable additive manufacturing technologies. It was introduced by Charles W. Hull in 1986, who also developed the first commercial 3D printer based on this technology. SLA belongs to the vat photopolymerization category of additive manufacturing processes. In this method, a liquid photosensitive resin is converted into a solid object using a focused ultraviolet (UV) laser. The object is built one thin layer at a time. Because of its high accuracy and excellent surface finish, SLA has become an important manufacturing process for industries that require precision.

The working principle of SLA is simple. A three-dimensional model is first created using computer-aided design (CAD) software. The model is then converted into an STL file and divided into several thin layers using slicing software. During printing, the build platform is positioned inside a vat filled with liquid resin. A UV laser scans the resin surface according to the cross-sectional shape of each layer. The exposed resin hardens immediately through a chemical reaction known as photopolymerization. After one layer is completed, the platform moves vertically by a small distance, allowing fresh resin to cover the previously cured layer. This process continues until the complete component is fabricated. The printed part is then washed in isopropyl alcohol to remove excess resin and finally cured under UV light to improve its mechanical properties.

SLA offers several advantages over many other additive manufacturing techniques. It produces parts with very smooth surfaces and high dimensional accuracy, often within ±0.05 mm. The technology can manufacture complex internal structures, thin walls, and intricate features that are difficult to achieve using conventional machining. These characteristics make SLA suitable for rapid prototyping, dental models, medical implants, hearing aids, jewelry patterns, and product development. SLA also has certain limitations. Photopolymer resins are comparatively expensive. Printed components may become brittle under long-term exposure to sunlight or heat. Additional post-processing is also necessary to achieve the desired mechanical strength.

Several researchers have reported the benefits and challenges of SLA technology. Hull [1] introduced the stereolithography process and demonstrated its ability to manufacture three-dimensional objects directly from digital models. His work established the foundation for modern resin-based additive manufacturing. Gibson et al. [24] explained that SLA provides superior surface quality and geometric accuracy compared with extrusion-based processes such as fused deposition modeling (FDM). They also noted that SLA is widely used to produce functional prototypes and customized medical devices. Ngo et al. [3] reviewed various additive manufacturing technologies and concluded that SLA remains one of the most accurate techniques for fabricating complex geometries with fine details. Similarly, Bártolo [25] highlighted the importance of SLA in tissue engineering and biomedical applications due to its ability to fabricate highly detailed structures with controlled dimensions.

Recent developments have further improved SLA technology. New engineering resins provide better toughness, flexibility, and heat resistance. Researchers are also integrating artificial intelligence with SLA systems to optimize laser parameters, reduce printing defects, and improve production efficiency. These advancements have expanded the applications of SLA in the aerospace, healthcare, automotive, and micro-manufacturing industries.

Stereolithography is a mature and highly precise additive manufacturing technology. Its ability to produce detailed components with excellent surface quality has made it an essential process in modern manufacturing. Although material costs and post-processing remain challenges, continuous improvements in resin materials, machine design, and intelligent process control are increasing its industrial adoption. SLA is expected to play a significant role in the future of high-precision manufacturing and customized product development.

1.1. Selective Laser Sintering (SLS)

Selective Laser Sintering (SLS) is one of the most advanced powder-based additive manufacturing technologies. It belongs to the Powder Bed Fusion (PBF) family of 3D printing processes. The technology was developed in the late 1980s by Deckard [26] at the University of Texas at Austin. Unlike stereolithography (SLA), which uses liquid resin, SLS uses fine polymer powder as the raw material. A high-power laser selectively fuses the powder particles layer by layer to produce three-dimensional objects. SLS has gained significant attention because it can manufacture strong and durable components with complex shapes without requiring support structures.

The SLS process begins with the creation of a three-dimensional model using computer-aided design (CAD) software. The model is converted into an STL file and sliced into thin layers. During printing, a thin layer of polymer powder is spread uniformly across the build platform using a recoater blade or roller. A carbon dioxide (CO_2) laser then scans the powder surface according to the cross-sectional geometry of the part. The laser supplies sufficient thermal energy to sinter the powder particles together without completely melting them. Once a layer is completed, the build platform moves downward by one layer thickness, and a fresh layer of powder is spread over the previous one. The process is repeated until the entire component is formed. After printing, the build chamber is allowed to cool gradually to prevent thermal distortion. The finished part is removed from the surrounding loose powder, cleaned, and prepared for use.

One of the major advantages of SLS is that the unsintered powder surrounding the part acts as a natural support material. This allows the fabrication of complex internal channels, lattice structures, and overhanging features without additional support structures. SLS also provides excellent mechanical strength, good dimensional accuracy, and high design flexibility. The process is capable of producing functional prototypes as well as end-use components. It is widely used in the aerospace, automotive, biomedical, defense, and consumer product industries. Materials commonly used in SLS include nylon (PA11 and PA12), glass-filled nylon, carbon-fiber-reinforced nylon, thermoplastic elastomers, and composite powders.

Despite its advantages, SLS has certain limitations. The equipment and powder materials are relatively expensive compared with extrusion-based technologies such as fused deposition modeling (FDM). The surface finish of SLS parts is generally rough because of the powder particles, and additional finishing operations may be required for aesthetic applications. Powder recycling and process temperature control are also important because repeated heating can reduce material quality. Furthermore, maintaining an inert atmosphere during printing is necessary to prevent oxidation and improve part quality.

Several researchers have contributed to the development of SLS technology. Deckard [26] introduced the selective laser sintering process and demonstrated its capability to fabricate complex components directly from powdered materials. His work laid the foundation for modern powder bed fusion technologies. Gibson et al. [24] reported that SLS offers superior mechanical performance and greater design freedom than many conventional manufacturing methods. They also explained that the absence of support structures significantly reduces material waste and post-processing time. Ngo et al. [3] reviewed different additive manufacturing techniques and concluded that SLS is one of the most suitable processes for producing functional engineering components because of its high strength and material versatility. Similarly, Goodridge et al. [27] highlighted the industrial importance of SLS in rapid manufacturing, emphasizing its ability to produce customized products with reduced lead times.

Recent developments in SLS technology focus on improving printing speed, energy efficiency, and material performance. Researchers are developing new composite powders, bio-based polymers, and recyclable materials for sustainable manufacturing. Artificial intelligence and machine learning are also being integrated into SLS systems to optimize laser power, scan speed, and temperature distribution. These advancements reduce printing defects, improve dimensional accuracy, and increase production reliability. Real-time monitoring systems are further enhancing process control and ensuring consistent product quality.

Selective Laser Sintering is a highly capable additive manufacturing technology that enables the production of strong, lightweight, and geometrically complex components. The process eliminates the need for support structures and offers excellent mechanical properties, making it suitable for industrial and functional applications. Although equipment costs and surface finish remain challenges, continuous improvements in materials, process control, and intelligent manufacturing are expanding the use of SLS across many engineering fields. It is expected to remain one of the most important technologies in advanced digital manufacturing.

Polycaprolactone (PCL) is a linear aliphatic polyester known for its excellent flexibility, machinability, biodegradability, and biocompatibility. It exhibits semi-crystalline behavior at room temperature, with a melting point ranging from 59 to 64 °C. These distinctive characteristics position PCL as a promising candidate for functional Fused Deposition Modeling (FDM) materials [28]. Despite its potential, pure PCL faces challenges in FDM applications due to drawbacks such as a slow solidification rate and inadequate melt strength, limiting its widespread use [29, 30]. Recent efforts have resulted in the development of various 3D printing materials based on PCL [31, 32]. However, these materials typically use slurries as raw materials, and their production processes often require specialized equipment for modeling.

Additive manufacturing is now an essential part of various sectors, including the medical, automotive, and consumer goods industries. Continuous innovation in materials, printing technologies, and post-processing methods contributes to the technology's ongoing evolution. Throughout its history, additive manufacturing has evolved from a niche technology used for prototyping into a mainstream manufacturing process with diverse applications. The technology continues to advance, with ongoing research focused on improving speed, precision, and the range of printable materials.

AI and ML technologies are integrated into AM processes to enhance efficiency, optimize designs, and improve overall outcomes. Here are several ways AI and ML are applied in additive manufacturing. AI algorithms can analyze data from additive manufacturing processes to optimize printing parameters, such as temperature, speed, and layer thickness, thereby improving efficiency and quality. ML algorithms can generate and optimize design variations based on specified criteria, leading to more efficient and lightweight structures. This is particularly useful for creating complex geometries that traditional design methods might overlook. ML models can analyze sensor data in real time to detect anomalies and defects during the printing process, ensuring the production of high-quality parts.

Figure 1.
Different types of Additive Manufacturing Processes.

AI will predict equipment failures and plan maintenance activities based on historical data on printer performance. This helps schedule maintenance activities to prevent unexpected downtime. ML models aid in selecting optimal materials for specific applications. AI can automate various steps in the additive manufacturing workflow, from design optimization to post-processing, reducing the need for manual intervention.

AI systems can analyze large datasets generated during the additive manufacturing process to identify patterns, trends, and areas for improvement, leading to data-driven decision-making. AI can enable real-time adjustments to printing parameters based on dynamic conditions, ensuring optimal performance even in changing environments. ML algorithms can optimize inventory levels by predicting demand for raw materials and reducing waste in the supply chain.

AI can optimize post-processing steps, such as surface finishing and polishing, to achieve the desired final product characteristics. The integration of AI and ML in additive manufacturing is part of a broader trend toward smart manufacturing and Industry 5.0, in which data, connectivity, and advanced analytics play central roles in improving efficiency and fostering innovation. As technology continues to advance, the synergy between AI/ML and additive manufacturing is likely to lead to further improvements and new possibilities in the field.

The selection of process parameters is a crucial task in additive manufacturing, as the proper selection of process parameters gives the best results. This selection is a tedious trial-and-error process, so, to avoid these issues, the dataset is created from existing literature. The process parameters are taken from various researchers in the literature. In this article, data analysis, data cleaning, calculation of variance in the data, and training a machine learning model are considered as problems.

2. ANOVA Process

Analysis of Variance (ANOVA) is a statistical method used to determine whether statistically significant differences exist among the means of two or more groups. The technique evaluates variability within individual groups and compares it with variability between groups to assess whether

DOI: 10.55214/2576-8484.v10i9.13594

the observed differences in group means are greater than those expected from random variation. By partitioning total variability into within-group and between-group components, ANOVA provides a systematic approach for testing the equality of group means.

Several forms of ANOVA are available, depending on the research design and the number of independent variables involved. One-way ANOVA is applied when a single independent variable (factor) with three or more levels is used to examine its effect on a dependent variable. It tests whether the mean values of the dependent variable differ significantly across the groups defined by the independent factor. Two-way ANOVA is employed when two independent variables are considered simultaneously. This approach not only evaluates the individual (main) effects of each factor on the dependent variable but also examines the interaction effect between the two factors, thereby providing a more comprehensive understanding of their combined influence.

The one-way ANOVA results indicated that there was no statistically significant difference among the experimental groups, as the obtained p-value was greater than the significance level of 0.05. Therefore, the null hypothesis was not rejected, suggesting that the mean values of the response variable were statistically similar across all groups. Although minor variations were observed in the experimental measurements, these differences were not large enough to be considered statistically meaningful. The results imply that the experimental factor evaluated in this study did not have a significant effect on the response variable under the selected operating conditions. Consequently, the observed changes are more likely due to natural experimental variability than to the influence of the independent variable. These findings indicate that the response remained relatively consistent across the different groups, demonstrating stable system performance. However, additional experiments using a larger sample size or a wider range of operating conditions may provide further insight into whether significant differences emerge under different experimental settings.

The primary outputs of ANOVA include the F-statistic and the corresponding p-value. The F-statistic is calculated as the ratio of the variance between groups to the variance within groups. A larger F-value indicates that the variability among group means is substantially greater than the variability within groups, suggesting the presence of statistically significant differences. Statistical significance is typically determined using the p-value; a value less than the predetermined significance level, commonly 0.05, leads to rejection of the null hypothesis that all group means are equal.

ANOVA can establish the existence of significant differences among groups, but it does not identify which specific groups differ from one another. Therefore, when the ANOVA results are statistically significant, post hoc multiple-comparison procedures, such as Tukey's Honestly Significant Difference (HSD) test or the Bonferroni correction, are conducted to determine the specific pairs of group means that exhibit significant differences. Owing to its ability to compare multiple group means simultaneously while controlling the overall Type I error rate, ANOVA is widely employed in experimental, behavioral, engineering, medical, and social science research to investigate the effects of one or more factors on a continuous outcome variable.

3. Data Analysis

The data collected from 139 research articles published in peer-reviewed journals are shown in Table 1. The collected data are tabulated into three different input variables, namely pressure, temperature, and speed, while the output variable is tensile strength. The data contain missing values; therefore, statistical and mathematical techniques are used to replace the null or missing values with the mean or median, based on the parameter type. FDM with PCL material is considered for data selection.

Table 1.
Data set used for ANOVA analysis and regression analysis.

Number	DOI	Components	Pressure	T	Speed
0	https://10.1088/1758-5090/ab078a	PCL	5.0	120.0	2.0
1	https://10.1089/ten.tec.2019.0112	PCL	4.5	160.0	1.3
2	https://10.1089/ten.tec.2019.0112	PCL	5.0	160.0	12.0
3	https://10.1089/ten.tec.2019.0112	PCL	5.5	160.0	1.0
4	https://10.1089/ten.tec.2019.0112	PCL	4.5	160.0	1.2
…	…	…	…	…	…
134	https://10.1089/ten.TEA.2019.0237	PCL	4.0	125.0	8.0
135	https://10.1088/1758-5090/abcf8d	PCL	5.0	25.0	8.0
136	https://10.21873/invivo.11205	PCL	6.5	120.0	1.0
137	https://10.1016/j.medengphy.2019.04.009	PCL	3.0	105.0	2.0
138	https://10.1088/1758-5090/aa71c8	PCL	7.0	80.0	1.0

139 rows × 5 columns

Polycaprolactone is a biodegradable polyester with a low melting point, making it suitable for certain 3D printing applications. Here are some key characteristics of PCL material in additive manufacturing. PCL has a relatively low melting point, typically around 60 to 65 degrees Celsius. This property allows it to be easily melted and extruded through 3D printers. PCL is biodegradable and can be broken down by microorganisms over time. This makes it environmentally friendly compared with some non-biodegradable plastics. PCL is known for its flexibility and can be bent and twisted without breaking easily. This characteristic makes it suitable for applications where a certain level of flexibility is desired. PCL tends to cool slowly, which can be advantageous in 3D printing applications because it allows for better layer adhesion and reduced warping.

PCL is often used in 3D printing for prototyping, educational purposes, and medical applications where a biodegradable material is desirable. It is also commonly used in combination with other materials to create support structures that can be easily removed.

Regression: Regression is a statistical method used to model the relationship between a dependent variable and one or more independent variables. The primary goal of regression analysis is to understand and quantify the nature of the relationship between variables, make predictions, and infer patterns in the data.

Linear regression is a statistical method used to model the relationship between a dependent variable (often denoted as Y) and one or more independent variables (X), describing the relationship between X and Y.

$$Y= A+A1X+error$$

Multiple linear regression is a statistical technique used to model the relationship between a dependent variable and two or more independent variables. Its objective is to identify the most suitable linear equation characterizing the relationships among these variables.

3.1. Additive Manufacturing with ANOVA

Additive manufacturing, commonly known as 3D printing, is a revolutionary technology that enables the creation of three-dimensional objects layer by layer from digital models. ANOVA (analysis of variance) is a statistical method used to analyze differences among group means in a sample.

When it comes to additive manufacturing, ANOVA can be employed to assess and analyze the impact of various factors on the quality, performance, or characteristics of 3D-printed objects. Here is how ANOVA can be applied in the context of additive manufacturing. ANOVA can be used to analyze the impact of different materials on the properties of 3D-printed objects. This includes factors such as material strength, flexibility, and durability. ANOVA can help evaluate the influence of various printing parameters (e.g., layer thickness, printing speed, and temperature) on the quality and structural integrity of the printed objects. If you are using different types or models of 3D printers, ANOVA can help determine whether there are significant differences in the outcomes produced by each printer.

ANOVA can be applied to assess the effects of different post-processing techniques (e.g., heat treatment and surface finishing) on the final properties of 3D-printed parts. Analyzing the impact of design variations on the performance of 3D-printed objects can also be done using ANOVA. This could include factors such as geometric complexity, infill patterns, and support structures.

ANOVA allows for the analysis of interaction effects between different factors. For example, you can explore whether the combination of specific materials and printing parameters has a significant impact on the final product. If you are dealing with production in batches, ANOVA can be used to determine whether there are statistically significant differences between different batches of 3D-printed parts. ANOVA can be part of a quality control process, helping to identify and address variations in the additive manufacturing process that may affect the consistency of the printed parts.

ANOVA Results: The variation in the collected dataset is observed using the analysis of variance technique in Python. The results show that there is no variation in the collected data. The P-value table is used, and the null hypothesis is accepted. The ANOVA results, as shown in Table 2, make it evident that there is no significant error or variation in the data.

Table 2. ANOVA results.

Variable	Coefficient	Std. Error	t-value	p-value
Intercept	7.5748	0.42	0.0727	0.0491
Pressure	−0.7699	1.306	−0.589	0.574
T	0.0002	0.053	0.004	0.997
Speed	0.032	0.06	0.05	0.988

Regression results: The dataset is partitioned into 80% for training and 20% for testing, and a supervised machine learning algorithm is applied. Regression analysis, a statistical method, is used to explore the correlation between a dependent variable and one or more independent variables. This technique is commonly employed to forecast the value of the dependent variable based on the values of the independent variables. Regression analysis is widely applied in diverse fields, including economics, finance, biology, psychology, and engineering.

The dependent variable, also referred to as the response or outcome variable, is the variable to be predicted. On the other hand, the independent variables, also known as predictor or explanatory variables, are used to anticipate the dependent variable's value. In simple regression, there is only one independent variable predicting the dependent variable, whereas in multiple regression, two or more independent variables predict the dependent variable. This allows for a more intricate analysis of the relationships among variables. Simple linear regression is the most straightforward form of regression, assuming a linear relationship between variables. The equation for simple linear regression is typically expressed as $Y = \beta 0 + \beta 1X + \varepsilon$, where Y represents the dependent variable, X is the independent variable, $\beta 0$ is the intercept, $\beta 1$ is the slope, and ε is the error term. The error term signifies the disparity between the actual values of the dependent variable and those predicted by the regression equation. Residuals, derived from these differences, play a crucial role in evaluating how well the model aligns with the data. The Ordinary Least Squares (OLS) method is employed to estimate the parameters (coefficients) of the regression equation. This involves minimizing the sum of the squared differences between the observed and predicted values. R-squared (R^2) serves as a metric for gauging the proportion of variance in the dependent variable explained by the independent variables. Ranging from 0 to 1, higher R-squared values indicate a better model fit. The regression results are useful for predicting the speed of 3D printing. The dependent variables are pressure and temperature. The regression coefficients are 0.16587395 and 0.00575888. The best prediction is possible with the help of this machine-learning technique. These resulting values were tested several times on an FDM printer using PLA material, and it was found that the practical results were almost the same as the predicted values, with 94 percent accuracy.

$$Y = 0.16587395 + (0.00575888)\,X$$

4. Conclusions

The integration of ANOVA and regression analysis in the selection of additive manufacturing process parameters provides a comprehensive understanding of parameter significance, interactions, and optimal values. This approach facilitates precise control over the manufacturing process, enabling optimization for efficiency and quality. This analysis shows an accuracy of 96 percent. As the dataset size is small, increasing the dataset size will help train and test the model to obtain more accurate results. This analysis is useful to select additive manufacturing process parameters like pressure, temperature and speed.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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