Statistical Strategies for Enhanced Quality in the 3D Printing Process

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Abstract. In today's competitive environment, achieving high levels of product quality is crucial for both manufacturing and service industries. This pursuit of quality is essential for maintaining a competitive edge in the market and ensuring customer satisfaction. The study systematically explores various statistical quality tools, and the review delves into the theoretical foundations of each tool, highlighting their specific applications and efficacy in the 3D Printing industry. By integrating the quality tools into the broader quality management framework, the study provides valuable insights by offering a strategic roadmap for optimizing quality control processes. It advocates the informed use of statistical quality tools as indispensable instruments in achieving and sustaining excellence in 3D Printing. The 3D printing process was identified as out of control from the results of various quality control tools, and optimization of process parameters was carried out to enhance the quality of the product.

Keywords: 3D printing; Taguchi method; quality control; process optimization; statistical analysis; quality tools

1 Introduction

Statistical quality control (SQC) refers to the use of statistical methods in the monitoring and maintenance of the quality of products and services. The primary objective of statistical quality tools is to provide organizations with the means to make data-driven decisions, leading to the prevention or early detection of defects, errors, or deviations in their processes. Quality control (QC) tools are often referred to as a set of techniques and methods used in quality management and process improvement. 3-D printing is an additive manufacturing technique in which an object is manufactured layer by layer. The output parameters such as surface roughness (μm), tensile strength (N/mm²), and elongation (mm) are considered for the study. The outputs are based on the layer height (mm) during the 3-D printing process. The statistical quality control helps to optimize the 3-D printing process. SQC involves inspecting a random sample of output from the process for characteristics. The 3D printing process is analyzed by the usage of seven QC tools, to obtain the optimum combination of the input parameters to attain the desired output.

2 Literature review

Raveendran et al.(2023) highlighted the role of distinguishing 'special' and 'routine' variations in patient-specific quality assurance (PSQA), advocating a two-stage approach for tailored Tolerance and Action Limits. Incorporating Shewhart's and time-weighted control charts in routine Linac Quality Assurance (QA) offers deeper insights. Moreover, leveraging statistical process control (SPC) tools in image review modules or dedicated clinical software enhances QA efficiency, emphasizing the need for prudent tool selection aligned with data and process drift [1]. Ritchie et al.(2023) introduced a novel temporal histogram model and synthesizer that accurately captures individual household electricity and hot water usage behavior. Using a substantial dataset, the model demonstrates high accuracy in characterizing usage behavior and predicting future consumption [2]. Rohani and Teng (1995) highlighted the crucial role of quality control tools, specifically the "seven basic QC tools," in enhancing both product quality and process efficiency within a competitive market. In a case study of a plastic injection molding company, the successful deployment of these tools led to a substantial reduction in monthly defect rates [3]. Rooyen

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et al. (2023) employed ANOVA-simultaneous component analysis (ASCA) to analyze the impact of roasting and wheat type on shortwave-infrared (SWIR) spectra of whole wheat and flour. Employing a full factorial design, the research examines various factors and interactions, revealing significant effects on spectral data, notably on protein structures and starch in wheat [4]. A study by Abbasi and Mahmoudi (2021) proposed a novel approach utilizing statistical control charts and transfer function indices to objectively classify faults in FRA results, specifically targeting short circuits, axial displacement, and radial deformation. Experimental findings indicate improved fault detection and classification accuracy, affirming the efficacy of this method in enhancing visual fault identification and precise determination of diverse faults within power transformers [5]. Srinivasu et al. aim to control quality aspects across methods, machinery, products, and equipment, utilizing the "seven basic QC tools" to achieve cost-effective objectives. However, the success of these tools as problem-solving assets relies significantly on robusttop-management commitment [6]. Pavol Gejdoš (2015) delves into the historical evolution of statistical tools emphasizing their role in continuous process improvement through Statistical Process Control and Process Capability Indices. It underscores the significance of these tools in enhancing processes via continuous monitoring and sample inspection, aligning with Total Quality Management principles[7]. A study by Irena Ograjensek (2016) emphasized the critical role of statistical quality control and improvement tools in enhancing the quality of services, which constitute a significant portion of developed economies' GDP. It advocates for a broad interpretation of these tools, extending beyond traditional control charts to encompass a wide array of statistical methods [8]. Cohen et al.(2023) investigated the impact of quality tools on companies' performance within French industries, focusing on Lean and Six Sigma methodologies. The findings highlight the efficacy of specific tools: One Piece Flow and GEMBA for quality improvement, Value Stream Mapping and Takt Time for cost reduction, and KANBAN for enhancing productivity [9]. Jennings and Drake (1997) introduced a novel approach by applying statistical quality control charts to monitor machine tool performance parameters. It incorporates a unique measurement normalization method, employing a "normalization chart" to compensate for parameter inter-dependence. By calculating residuals based on deviations from this chart, the study utilizes statistical control charts to monitor machine tool conditions [10]. Research on 3D printing quality control needs comprehensive studies integrating various statistical methods with specific technologies. There is a scope for improvement in real-time monitoring and control. Holistic approaches considering multiple quality dimensions are needed. Advanced statistical methodologies tailored to the unique challenges of 3D printing quality control require further exploration.

3 Methodology

The statistical analysis was performed using quality tools including control charts, histograms, scatter plots, regression analysis, analysis of variance, and a two-factor factorial experiment. While the optimization is carried out using the Taguchi method. The data obtained during the 3-D printing process was assessed with statistical quality tools. The results from each quality tool show whether the process is under control and to optimize the process. The graphs and results were obtained from Minitab statistical software and Microsoft Excel.

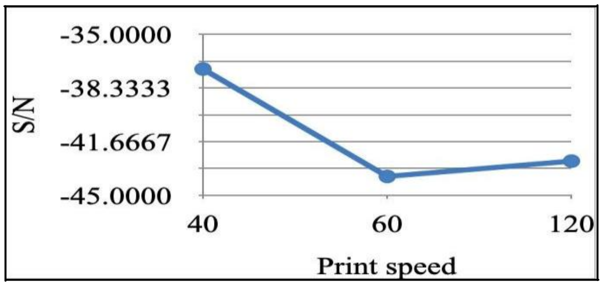
4 Results and Discussion

Taguchi Method

The obtained data was refined and organized to form the L_{30} orthogonal array shown in Table 1. Three factors - Print speed (mm/sec), Material, and Fan speed (rpm) of levels three (40, 60, and 120 mm/sec), two (PLA and ABS), and five (0, 25, 50, 75, and 100 rpm) respectively were taken into consideration. The output factor was chosen as Surface roughness (in µm) for which the process parameters are to be optimized. The Taguchi Method utilizes orthogonal arrays to conduct experiments efficiently. These arrays allow for the study of multiple factors simultaneously, reducing the number of experiments needed to identify critical parameters affecting product quality. Design of Experiments (DOE) forms the backbone of the Taguchi Method, providing a systematic approach to optimize design parameters. By planning and conducting experiments, manufacturers can comprehensively evaluate the critical factors. The Signal-to-Noise (S/N) ratio is a pivotal concept in the Taguchi Method. It assesses the quality characteristics of a product or process in the presence of variations or "noise" factors. From the response graphs, the optimal combination is A1 B2 C3, i.e. Print speed = 40 mm/sec from Figure 1, Print Material = ABS from Figure 2, and Fan speed = 50 rpm from Figure 3 respectively.

Table 1. L_{30} Taguchi orthogonal array

Print Speed (mm/sec)	Material	Fan Speed (rpm)	Surface Roughness (μm)	S/N Ratio
40	ABS	0	25	-27.9588
40	ABS	25	32	-30.1030
40	ABS	50	40	-32.0412
40	ABS	75	68	-36.6502
40	ABS	100	92	-39.2758
40	PLA	0	60	-35.5630
40	PLA	25	55	-34.8073
40	PLA	50	21	-26.4444
40	PLA	75	24	-27.6042
40	PLA	100	30	-29.5424
60	ABS	0	75	-37.5012
60	ABS	25	92	-39.2758
60	ABS	50	118	-41.4376
60	ABS	75	200	-46.0206
60	ABS	100	220	-46.8485
60	PLA	0	126	-42.0074
60	PLA	25	145	-43.2274
60	PLA	50	88	-38.8897
60	PLA	75	92	-39.2758
60	PLA	100	74	-37.3846
120	ABS	0	120	-41.5836
120	ABS	25	144	-43.1672
120	ABS	50	265	-48.4649
120	ABS	75	312	-49.8831
120	ABS	100	368	-51.3170
120	PLA	0	180	-45.1055
120	PLA	25	176	-44.9103
120	PLA	50	128	-42.1442
120	PLA	75	138	-42.7976
120	PLA	100	121	-41.6557



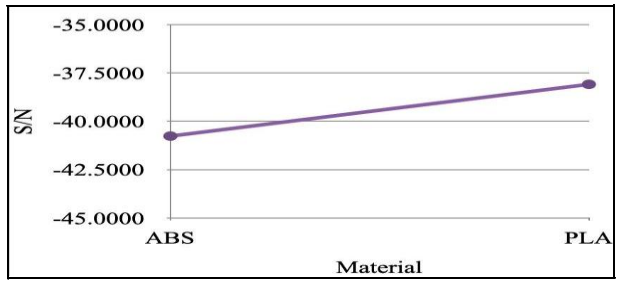


Fig. 1. Response graph for print speed (mm/sec).

Fig. 2. Response graph for material

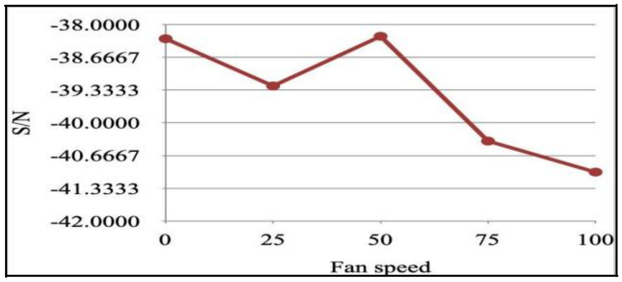


Fig. 3. Response graph for fan speed (rpm).

Individual Moving Range Chart

The tensile strength readings are taken based on the layer height during the 3-D printing process. An I-MR chart provides process variation over time in a graphical method. The data is then fed into Minitab software and the obtained I-MR chart helps to identify when the process goes out of control and indicates where to focus on the source of the assignable cause. For individual chart UCL = 42.17, LCL = 2.01, CL = 20.08 as well as for moving range chart UCL = 27.14, LCL = 0, CL = 8.31 respectively (in N/mm²). It monitors any points that are moving out of control, identifies the special cause for variation, and tries to eliminate those causes to keep the process under control. The Individual chart implies that 4 out of 5 points have more than one standard deviation from the center line (on one side of CL). The test failed at 7, 26, 27, 44, and 46 reading points. The moving range chart implies that one point is more than the standard deviation of 3.00 from the center line. The test failed at the 41st reading point. Further, this result is used to optimize the process by identifying the special causes of variation and eliminating those to keep the process under control. The process under the I-MR chart is out of control for the data sets taken.

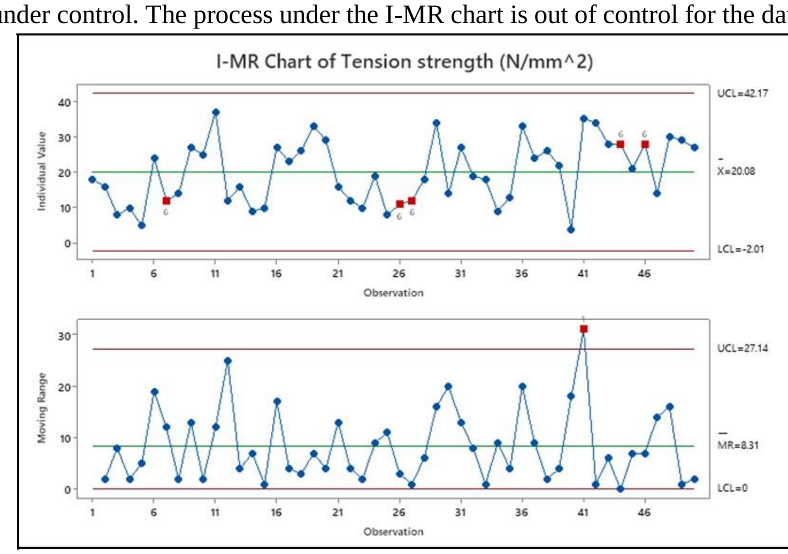


Fig 4. Individual moving range chart for tensile strength (N/mm²)

Two-factor factorial experiment

A two-factor experiment, also known as a two-way experiment, is a type of experimental design used in scientific research and statistics. In a two-factor experiment, researchers investigate the effects of two independent variables (factors) on a single dependent variable. It is affected by the level of the two factors. The bed temperature (℃) & print speed (mm/sec) were chosen as independent variables and the impact of the independent variables on tension strength (dependent variable) was assessed using a two-factor factorial experiment. ANOVA table is generated and the F value for bed temperature, print speed, and the combined effects of both were calculated. The inferences that are derived from a two-factor experiment are the percentage contribution shown in Table 2, the optimum contribution shown in Table 3, and the interaction plot which is shown in Figure 5. The percentage contribution of each source of variation is determined to understand the significance of the independent variable over the dependent variable (output parameter: tension strength (N/mm^2)). The observation shows that the bed temperature (℃) has the highest significant effect.

Table 2. Percentage Contribution

Bed temperature (℃)	17%
Print speed (mm/sec)	13%
Temperature & speed	15%

Table 3. Optimum Combination

Bed temperature (℃)	22.1	14.5	15.33	22	15.16
Print speed (mm/sec)	26.5	37	25		

The observation shows that level 1 of bed temperature (℃) is 60℃ and level 2 of print speed (mm/sec) which is 60 mm/sec is the optimum combination. An interaction plot is a graphical tool for checking potential interactions.

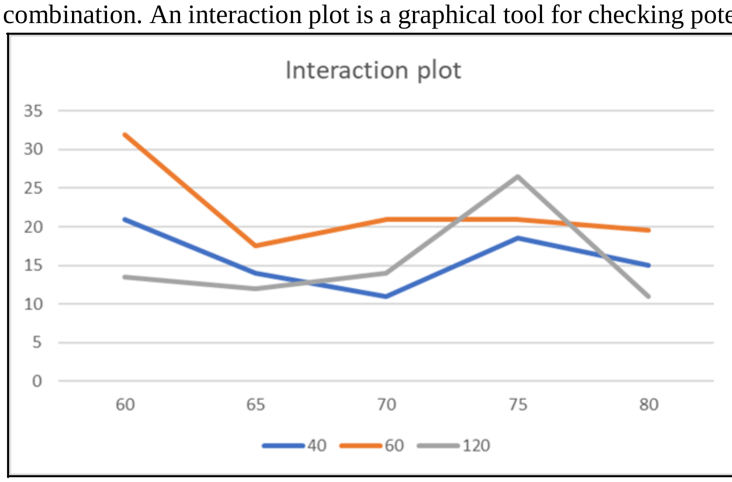


Fig 5. Interaction plot between bed temperature (℃) and print speed (mm/sec)

Parallel lines indicate that there is no significant interaction. A severe lack of parallelism indicates a significant interaction. Moderate lack of parallelism suggests a possible significant interaction may exist.

Correlation

Correlation is a statistical measure that quantifies the degree and direction of the relationship between two or more variables. The correlation coefficient (r) indicates the extent to which the pairs of numbers for these two variables lie in a straight line. In this study, the considered r values above 0.4 is to be relatively strong. The focus was on identifying input factors that demonstrated a correlation strength above a moderate level. This threshold is essential to pinpoint the most influential factors. For each combination, the correlation coefficient r is determined to quantify the strength and direction of the relationship. The input factors were selected to exhibit correlation where the values are above the predefined threshold for each of the three output factors.

Results for roughness (μm)

Layer Height (r = 0.8) indicates a strong positive correlation, meaning higher layer heights are associated with rougher surface finishes. Nozzle Temperature (r = 0.349) suggests a moderate positive correlation.

Results for tensile strength (N/mm^2)

Layer Height (r = 0.388) indicates a moderate positive correlation. Wall Thickness (r = 0.4) suggests a moderate positive correlation. Infill Density (r = 0.358) This means that denser infill patterns contribute to slightly stronger tensile properties. Nozzle Temperature (r = -0.406) implies a moderate negative correlation.

Results for elongation (mm)

Nozzle Temperature (r = -0.527) indicates a strong negative correlation. In other words, higher nozzle temperatures are associated with reduced elongation properties. Layer Height (r = 0.508) Higher layer heights result in significantly greater elongation properties.

Multiple linear regression

It is a powerful statistical method used to explore and model the complex relationships between multiple independent variables (also known as input or predictor variables) and a single dependent variable (the output or response variable).

Results for roughness (μm)

Roughness = -476 + 1232 layer height + 2.330 nozzle temperature. (1)

Equation (1) represents a mathematical model that expresses roughness as a function of layer height (mm) and nozzle temperature (℃). The coefficient for layer height (1232) is positive, indicating that an increase in layer height is associated with a substantial increase in roughness. The probability value generated is 0 for the equation indicating that the model is highly statistically significant. A low p-value in the ANOVA table suggests that the model provides a good fit for the data. The overall fit of the model using metrics like R-squared (R^2) or adjusted R-squared is also assessed. The R square value generated is 76.37%, a higher R^2 value indicates a better fit of the model to the data.

Results for tensile strength (N/mm^2)

Tensile Strength = 61.7 + 56.8 layer height - 0.2789 nozzle temperature + 1.160 wall thickness + 0.1508 infill density. (2)

Equation (2) represents a mathematical model that predicts tension strength based on the combination of the four input factors. A one-unit increase in layer height is associated with an increase in tension strength of 56.8 units, while a one-unit increase in nozzle temperature is associated with a decrease in tension strength of 0.2789 units.

Results for elongation (mm)

Elongation = 7.23 + 6.21 layer height - 0.02805 nozzle temperature . (3)

The coefficients in equation (3) indicate the impact of each input factor on elongation while holding the other factor constant.

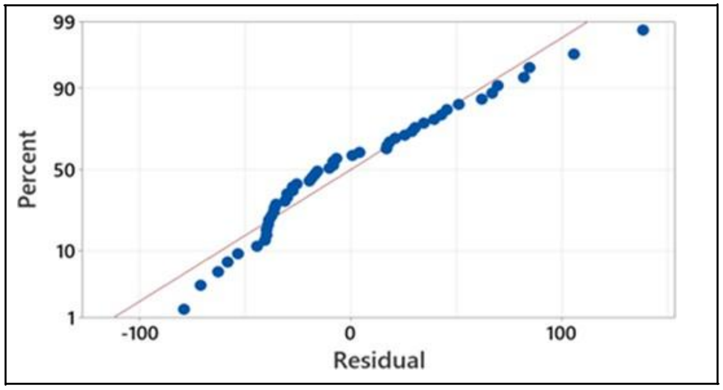


Fig 6. Normal probability plot

The normal probability plot in Figure 6 is a graphical representation to assess whether the residuals (the differences between the actual and predicted values) of your model follow a normal distribution. A probability plot shows residuals closely following a straight line suggesting the model fits the data well. For tension strength, it is found that the combination of layer height, wall thickness, nozzle temperature, and infill density significantly affects this key mechanical property. For elongation, it is identified that the combination of layer height and nozzle temperature plays a vital role in determining this property.

One-way analysis of variance

The comparison of test results between bed temperature and roughness strength revealed a noteworthy outcome based on the F table analysis. The statistical assessment indicates a significant variance among the treatment means, specifically at a 5% significance level. This substantiates that manipulating bed temperature yields discernible effects on the roughness parameter. The tabulated F value of 3.9381111, being lower than the calculated F value of 51.30623, confirms the statistical significance, underlining the impactful relationship between bed temperature and the resultant roughness strength. Table 5 gives the levels of the factors that should be maintained to attain highly confirming output which is determined by considering the mean value of observations at each level of the independent variables.

Table 4. Summary Table

Groups	Count	Sum	Average	Variance
Bed temperature (℃)	50	3500	70	51.02041
Roughness (µm)	50	8529	170.58	9807.759

Table 5. ANOVA table

Sources of variation	Sum of squares	Degree of freedom	Mean squares	F(Calculated)	P-value	F(Tabulated)
Between groups	252908.4	1	252908.4	51.30	1.4774E-10	3.93
Within groups	483080.2	98	4929.39			
Total	735988.6	99				

Histogram

The histogram is plotted for three different parameters which include roughness, tensile strength, and elongation and the results are discussed below.

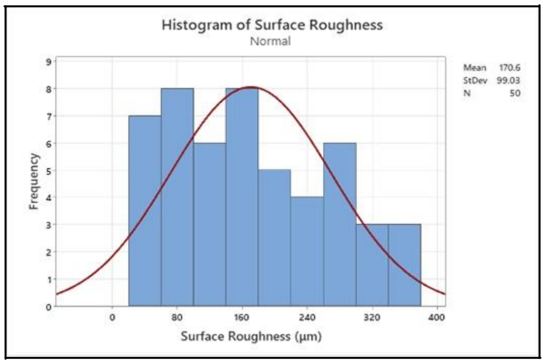


Fig 7. The histogram for Surface Roughness (μm)

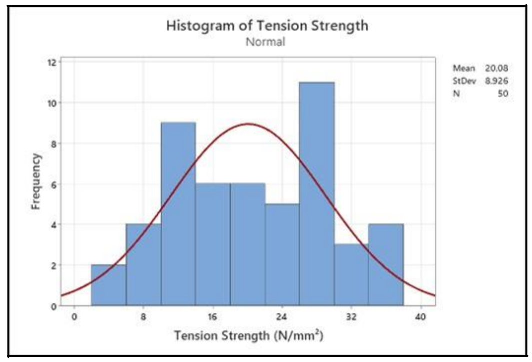


Fig 8. The histogram for Tensile Strength (N/mm^2)

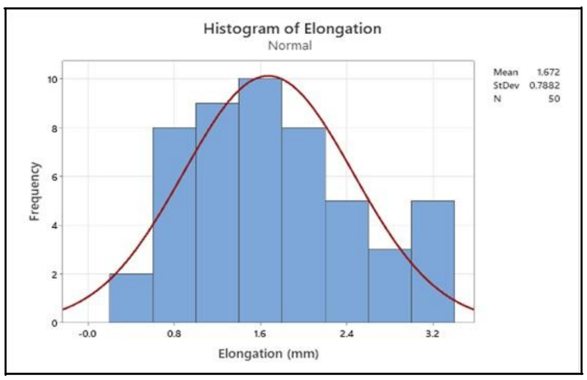


Fig 9. The histogram for Elongation (mm)

The Figure 7 histogram plot QC tool shows that the average surface roughness of the dataset is 170.6 µm, with a standard deviation of 99.03 µm. The majority of the data points fall between 160 µm and 240 µm, with a few outliers below 160 µm and above 320 µm. The Figure 8 histogram plot QC tool in the image shows the frequency distribution of tension strength in a normal population. The mean tension strength is 20.08 N/mm^2, with a standard deviation of 8.926 N/mm^2. The majority of the data points fall between 10 N/mm^2 and 30 N/mm^2, with a few outliers below 10 N/mm^2 and above 40 N/mm^2. The Figure 9 histogram plot QC tool in the image shows the frequency distribution of elongation in a normal population. The frequency distribution is approximately normally distributed, with a mean elongation of 1.672 mm and a standard deviation of 0.7882 mm. The majority of the data points fall between 0.8 mm and 2.4 mm, with a few outliers below 0.8 mm and above 3.2 mm.

5 Conclusion

The findings of this study serve as a critical assessment of the control status of the 3D printing process based on the parameters investigated. This evaluation is essential in determining the stability and reliability of the 3D printing operations under scrutiny. This paper emphasizes the pivotal role of implementing quality tools within the 3D printing process, as this significantly contributes to the assurance and enhancement of overall product quality. The adoption of these tools facilitates manufacturers in proactively identifying and addressing potential issues at the early stages of the production cycle, resulting in a notable reduction in defects and a simultaneous increase in operational efficiency. This research underscores the strategic importance of quality tools for optimizing 3D printing outcomes and ensuring the production of high-quality products.

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