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Investigation on selected factors causing variability in additive manufactured parts

by

Anusha Velineni

A thesis submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

Major: Industrial Manufacturing and Systems Engineering

Program of Study Committee:
Gül E. Okudan Kremer, Major Professor
Michael Helwig
Leifur Thor Leifsson

The student author, whose presentation of the scholarship herein was approved by the program of study committee, is solely responsible for the content of this thesis. The Graduate College will ensure this thesis is globally accessible and will not permit alterations after a degree is conferred.

Iowa State University

Ames, Iowa

2018

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DEDICATION

I dedicate this effort to my beloved parents, Mr. Srinivas Rao Velineni, Mrs. Sunitha Rani Velineni and sister, Sirisha Velineni for making me who I am today and for the unconditional love and support. I'm very thankful to you for believing in me and letting me pursue higher studies. I couldn't have asked for more and thanks for everything.

للاستشارات
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TABLE OF CONTENTS

www.manaraa.com

www.manaraa.com

LIST OF FIGURES

www.manaraa.com

المنارة للاستشارات

www.manaraa.com

LIST OF TABLES

www.manaraa.com

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ABSTRACT

Additive Manufacturing (AM) is known for its ability to manufacture complex parts layer by layer using 3D design data. AM brings significant freedom in design, yet it can get hard to produce the same parts with identical dimensional tolerances, a.k.a. reproducibility problem. Reproducibility, the ability to produce the same part again under same conditions, is one of the major challenges in AM as it plays an important role in the replacement of worn-out/damaged parts in an assembly. Ceramics, metals, alloys, and plastics are being used for the biomedical implants in which the concept of reproducibility is crucial. To obtain quality products and maintain consistency, this study is conducted to analyze the effects of most common and critical factors – layer thickness, printing speed, orientation angle on dimensional accuracy and surface roughness of AM parts. A full-factorial Design of Experiment (DOE) involving these factors with three levels each is implemented to determine their effect on overall length, height, width, middle height, and surface roughness, which are the response parameters. A dog-bone shaped tensile testing specimen is printed with Poly Lactic Acid (PLA) polymer using Fused Filament Fabrication (FFF) technology. Dimensional features and surface roughness of parts are then measured to determine the variability in output for different levels of input. The results of ANOVA analysis are used to conclude about the significant factors and their levels. The ANOVA results show that the response parameters are affected by main effects, 2-way interactions, and 3-way interactions in different combinations. The optimal conditions obtained from ANOVA analysis are used to print some more parts to plot control charts and conduct capability analysis. Control charts are used to monitor the process variability and capability analysis is conducted to check if the

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process is in statistical control and can produce parts within specifications. The small size of the parts allows the results of this study to be applicable in biomedical and industrial sectors. This study containing three input parameters with three levels each considers main effects along with interaction effects which have not been considered previously in our literature review. Also, the combination of factors is unique and their effect combined has not been focused in previous studies.

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CHAPTER 1. INTRODUCTION

1.1 Overview

Additive manufacturing (AM), contrast to the traditional material removing/subtractive manufacturing is a process in which parts are built in layer by layer. The data for depositing the layers is obtained from the 3D CAD model, which is converted into STL (standard triangulation) file format. The 3D model is divided into a number of two-dimensional layers which form a reference for the 3D printing process. The first 3D printer which used the concept of stereo lithography was created by Charles W. Hull in the mid-1980's. Unlike conventional manufacturing, AM is known for its freedom in design, reduction in supply chain cost, support for green manufacturing initiatives etc. In AM, 3D-printing and rapid prototyping can be used interchangeably to describe the process [1].

Additive manufacturing has begun to capture its place only recently though it has been around for more than two decades. In recent years, the overall market situation for AM was characterized by significant growth rates. The financial crisis of 2007–2008, also known as the global financial crisis, is considered by many economists to have been the worst financial crisis. The 2008 global economic crisis has resulted in unprecedented declines in output and exports from both industrialized and newly-industrializing economies. After the 2008 crisis, there was significant growth from services as well as products and worldwide numbers surpassed the value of $5 billion USD in 2015 which spurred a lot of interest in AM-related activities [1]. Different AM technologies are available right now for different applications.

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In 2010, the American Society for Testing Materials (ASTM) formulated a set of standards that classify the range of AM processes into seven categories as presented in Table 1. They are vat photopolymerization, material jetting, binder jetting, material extrusion, powder bed fusion, sheet lamination and direct energy deposition. AM technologies differ in application, the initial condition of processed products, the principle of working, workable materials, processing times and many more advanced features.

Table 1: Categories of AM and their principles [1]

Categories	**Principle**
Vat Photo polymerization	Process in which liquid photopolymer is selectively cured by light-activated polymerization. 2PP(2 photon polymerization), digital light processing (DLP), and stereo lithography (SLA) come under this category.
Material Jetting	Process in which droplets of build material (such as photopolymer or thermoplastic materials) are deposited as per the geometry of the part. Inkjet-printing falls into this category.
Binder Jetting	Process in which a liquid bonding agent is deposited to fuse powder materials.
Material Extrusion	Process in which material is dispensed through a nozzle as per the geometry of the part. Fused deposition modeling (FDM), fused filament fabrication (FFF), 3D dispensing, and 3D bio plotting fall into this category.
Power bed Fusion	Process in which heat energy (from laser or electron beam) fuses regions of a powder bed. Selective laser sintering (SLS) & Electrical discharge machining (EDM) come under this category.
Sheet Lamination	Process in which sheets of material are bonded together to form an object.
Direct Energy Deposition	Process in which focused thermal energy is used to fuse materials by melting as they are being deposited. This process is currently only used for metals.

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Fused filament fabrication (FFF) technology, developed by Scott Crump in the late 1980s, is a popular rapid prototyping technology widely used in industries to build complex geometrical functional parts in a short time due to its advantages on cost, material use efficiency, and time [1]. FFF shows great potential in mold fabrication, bio-medical device design, tissue engineering, and other industrial fields. However, many problems such as reproducibility, post-processing, being limited to low-volume production are still unsolved [2]. These drawbacks decrease its comparability across traditional manufacturing processes. Reproducibility, ability to produce the replicas of the same part under same conditions with high dimensional accuracy, is one of the major challenges in AM.

AM is not widely accepted in the industrial sector yet, however their applications in different industries are continuously evolving and they will be one of the popular technologies of future production. AM at present is suitable for the manufacturing complex parts in smaller quantities as it is expensive, takes significant amount of time, and might need post-processing operations [3]. When such complex parts are damaged or worn out, they need to be replaced with newer ones. Lack of reproducibility may cause serious problems as one has to come up new tooling setup and adapt to conventional manufacturing which can be daunting for intricate parts. Since AM involves various complex factors that do not exist in conventional manufacturing, producing same parts with same dimensional tolerances strictly depends on determining the optimal setting of these factors. Some of those factors in AM are layer thickness, temperature gradient, tool

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path generation, build orientation, printing speed, etc. [2,4,5,6,7]. It is important to find the extent to which these factors affect reproducibility of AM.

FFF process applications range from prototypes to functional parts [2]. Despite AM being able to manufacture complex parts that cannot be produced by conventional manufacturing, many problems such as cost, restriction of materials, being limited to low volume productions, reproducibility, post-processing, etc. are still unsolved [2]. Due to its advantages of cost, convenience in printing and material use efficiency, FFF shows great potential in mold fabrication, bio-medical device design [8], tissue engineering [1] and other industrial fields. In efforts to increase FFF's adoption in industry, some of the major concerns like dimensional accuracy and surface quality needs improvement [9,10]. Post-processing techniques, process and fabricating parameters, virtual model processing methods are the factors affecting dimensional accuracy and surface roughness [2,4].

There are several attempts in the literature to understand the cause of variation in dimensional accuracy for AM parts printed by material extrusion approach. Dimensional accuracy is the measure of how close the dimensions of a product is to that of the ideal product dimensions. Surface roughness is a good predictor of the performance of a mechanical component, since irregularities on the surface may form nucleation sites for cracks or corrosion. On the other hand, roughness may promote adhesion as well, however high values of roughness are undesirable. From our thorough literature review, it is observed that the factors layer thickness, printing speed, orientation angle and raster width are the major cause for dimensional inaccuracy, whereas the surface roughness is

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affected by the type of equipment, the direction of build and the process parameters used [11]. Further research is needed to investigate the validity of these factors for specific technology, material and process parameters, and geometric complexity. The possible factors responsible for variation may vary depending on the material, technology, and the complexity of the part.

The objective of this thesis is to understand the effect of layer thickness, printing speed and orientation angle on dimensional accuracy and surface finish of PLA parts printed using FFF technology. The effect of these factors on dimensional accuracy and surface roughness is investigated by adopting a full-factorial design of experiment (DOE). The outcomes of this research will provide optimal levels of factors that can be used to produce more accurate products using AM. Once the optimal factor settings are determined, more parts are printed with at those levels to see if the process can produce consistent results. Capability analysis is conducted to assess if the FFF technology is statistically able to meet the production requirements under optimal level of factors.

1.2 Motivation

Reproducibility, being able to produce the same results every time under same conditions, is one of the many challenges which needs wide research and serious attention for AM to be widely accepted in the industrial sector. There are various reasons, which cause variation in the process such as the material type and AM printing technologies. Therefore, there is a need for increased research in this area for different materials and AM technologies. Additive manufactured parts should be reproducible to

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replace the worn out or broken parts. Failure to reproduce the same part causes complications in the delivery process and assembly. Thus, there is a need to assess the reasons causing variability and optimize them before manufacturing.

Most of the studies related to reproducibility of parts considers metals [11,12], however, polymers are also commonly used in AM. Polymers are interesting and attractive materials in AM because they are economical, provide a large range of properties and cooperate with low energy fabrication technologies [1]. In 2016, the revenues from material sales for AM passed the value of 900 million USD (Fig 1) of which the largest fraction were into photopolymers (350 million USD) [8]. As such there is need to understand the efficiency and properties of polymers used for AM.

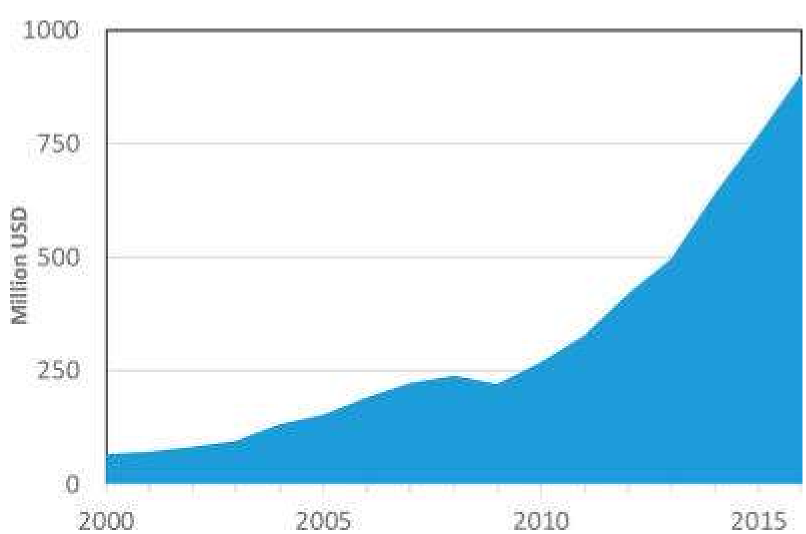

Fig 1: Worldwide revenues from AM material sales between 2000 and 2016 adopted from [13]

In this thesis, reproducibility of polymers is assessed by manufacturing polymeric parts using FFF technology. There are challenges involved with additive manufacturing

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of polymer e.g., life cycle and sustainability, printer and equipment variability, and inferiority in mechanical features when compared to conventional manufacturing [14]. All these challenges must be given significant consideration along with the present problem. The overall goal of this study is to find the factors that cause variability in production of polymer parts and thereby help produce more standardized parts each time. We performed full-factorial DOE to determine the optimal factor levels with minimum dimensional accuracy and better surface finish. With regards to the Analysis of Variance (ANOVA) results, the optimal factor levels are determined. Then, under the optimal factor settings, parts are printed for which the control charts are plotted to monitor the variability in the process. Apart from control charts, capability analysis is also conducted to check for the process capability (C_{pk}). If a process has a desirable C_{pk} value, that means it is under statistical control and can produce conforming products. If the C_{pk} values are below the specified level, then the process must be revised to improve the response quality.

1.3 Thesis Organization

Chapter 2 covers the detailed literature review on material extrusion technology, DOE, and control charts.

Chapter 3 discusses the importance of DOE, its principles and types of factorial designs that will be used in this thesis along with the specific choices of factors, levels, responses, and hypotheses for this experiment.

Chapter 4 discusses data collection, grouping and the results of the ANOVA analysis for the response parameters.

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Chapter 5 discusses conclusions for the entire thesis research, gives recommendations for future work, and shares some details of planned future work on this project.

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CHAPTER 2. LITERATURE REVIEW

This chapter includes four sections. Chapter 2.1 discusses studies that consider dimensional accuracy and surface roughness as the response parameters and studies that worked on improving these features. Chapter 2.2 focuses on DOE applications in AM. Chapter 2.3 presents the studies about control charts. Lastly, Chapter 2.4 points out the research gap and points to the potential contribution of the research.

2.1. Dimensional Accuracy and Surface finish in AM

Dimensional accuracy and resolution of finished parts made with extrusion AM processes depend on the process (e.g., layer thickness, printing speed, raster angle) and product design parameters, as well as the properties of the feedstock filament properties. Aside from aesthetic considerations, these properties of the finished part can be critical for applications where fit and form are important or when parts have very small feature sizes [15]. Fused Deposition Modeling (FDM), Fused Filament Fabrication (FFF), 3D dispensing, and 3D bio plotting are the examples of the material extrusion technology.

Gorski et al. [16] studied the effect of process parameters (e.g., layer thickness, part orientation and filling strategy) on dimensional accuracy and reported that orientation angle directly influences reproducibility of FFF technology. Tensile test specimens which contain both straight and curved profiles are used to evaluate shape accuracy. Dul et al. [17] built dumbbell and rectangular specimens along three different orientations i.e., horizontal, vertical and perpendicular. The direction of filament deposition changes with the orientation. The importance of orientation effect was highlighted by the FDM process

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while comparing 3D printed and compression molded parts. Moroni et al. [18] determined that optimal part orientation is crucial for considering functional assembly in case of a universal joint. Results show that the final recommended orientation angle is different for individual part and assembly of universal joint. Ippolito et al. [5] manufactured benchmark parts in FDM machine and showed that geometrical deviations may reach up to +0.7 mm. Poor tessellation accuracy leads to inaccuracy in parts due to errors in the data source. Hällgren et al. [19] compared the results of tessellation from six different CAD systems, which showed that tessellation effects may be visible even when dimensional requirements are fulfilled. Tessellation is the process of tiling a surface with one or more geometric shapes such that there are no overlaps or gaps. They proposed a method for 3D data exchange using traditional file format and geometric requirements. AMF (Additive Manufacturing File Format) and 3MF (3D Manufacturing Format) are still under development but can facilitate different materials and different densities in the same part.

Giovanni et al. [18] proposed a methodology to estimate dimensional and geometric deviation of features apart from its STL format by simulating the AM process incorporating confounding errors from volumetric and material-related errors, such as material flow and shrinkage. The cylindrical feature was selected in the study due to its fundamental functionality in mechanical components. The case study considers the FDM technology. The results show that it is reasonable to estimate the dimensional feature's deviation of the part from its STL file before fabrication given that the different types of STL files have different effects on the response.

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Lieneke et al. [2] developed a new method to analyze geometrical accuracies and influencing factors based on the knowledge obtained by reviewing the dimensional accuracies of FDM parts and observed the lack of geometric tolerances. This method defines relevant geometries and influencing factors for the experimental tolerance development. The derived tolerance values were also compared to values reached by conventional manufacturing technologies. It was concluded that the specifications of the key factors need to be varied to expand the methodical procedure and determine the deviations for several geometrical shapes.

Unfortunately, FDM shows its main limits when the mechanical properties must go hand in hand with surface finish [20]. Galantucci et al. [21] presented an in-depth knowledge of the process that can improve the surface finish of FDM printed parts. The author treated the FDM prototypes treated with a solution of 90% dimethyl ketone and 10% water to improve the surface finish and observed an increase in ductility and a decrease in tensile strength. It was also observed that the angle of the filaments loses its influence on the mechanical properties, probably due to an improved isotropy (uniformity in all orientations) after the treatment.

Nourghassemi [22] studied the effect of build angle and layer thickness on the surface finish of the parts to establish a relation between the factors and surface finish. An equation relating them was developed and is shown below:

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$$R_a = \begin{cases} (69.28 \sim 72.36)\frac{t}{cos\theta}, & 0° \leq \theta \leq 70° \\ \frac{1}{20}(90R_{a70°} - 70R_{a90°} + \theta(R_{a90°} - R_{a70°})), & \text{if } 70° < \theta < 90° \\ 117.6 \text{ X t}, & \text{if } \theta = 90° \\ R_{a(\theta-90)°}(1+w) & \text{if } 90° < \theta < 180° \end{cases}$$

(1)

Where θ is the build angle and t is the layer thickness, R_a is the arithmetic-mean-surface roughness in micron and w is a dimensionless adjustment parameter for supported facets and chosen to be 0.2 for FDM system. One more interesting thing is that, when parts are printed with the same specifications on a different printer, a difference was observed in the values of surface finish.

Garg et al. [23] investigated the effect of part orientation on surface finish and dimensional accuracy of FDM parts built at seven different part orientations (0^0, 15^0, 30^0, 45^0, 60^0, 75^0 & 90^0 about Y-axis) with and without post-building chemical vapor treatment. From the results, it has been observed that a reasonable low surface finish is obtained at 90^0 part build orientation for each primitive surface of the FDM part. To obtain a minimum dimensional deviation of parts, surfaces of the FDM part should be orientated either in parallel or in a perpendicular direction with respect to the axis of a part. Post-built treatment with cold vapors of acetone yielded a dramatic improvement in the surface finish due to a reduction in staircase effect present on surfaces. Surface roughness values as low as 0.02 mm can be achieved. Chemical treatment of the specimen causes a very minimal change in dimensional accuracy, and in many cases reduction in dimensional deviation is achieved. Chemical treatment also leads to rounding of the corners i.e., radius less than 1 mm is obtained. Thus, chemical treatment

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with cold vapor could be used as an excellent alternative for FDM parts to improve surface quality without much sacrifice in dimensional or geometry loss.

Sheydaeian et al. [24] manufactured Titanium structures for orthopedic applications using the principle of Binder jet 3D printing multi-scale 3D printer by varying layer thickness during the process. The specimens are cylindrical samples, designed with 5 mm diameter and 8 mm height and are grouped in to four categories. The first two categories were printed with a single layer thickness of 20 μm throughout and in the second two categories, the layer thickness was varied from high to low and then to high (150 μm/80 μm/150 μm) (Category A) and from low to high (80 μm/150 μm/80 μm) (Category B) in each batch, respectively. The latter two were designed with a symmetrical distribution of layer thickness with similar weight (0.5) to investigate the effect of layer thickness arrangement on mechanical properties of the specimens. Height and diameter of each sample were measured three times with digital caliper before and after sintering. ANOVA analysis revealed that there is a significant difference in both height and diameter shrinkage among the categories. The first two categories showed a lot more height difference compared to the next two categories.

A summary of all relevant studies is presented below in Table 2 from which we can conclude that the layer thickness, orientation angle, printing speed, fill angle, shell thickness, raster angle and power level did have significant effect on the response parameters. Main effects and interaction effects of printing speed and layer thickness have significant effect on overall length and height which were published in ISERC conference paper [63].

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Table2: Summary of relevant studies

Author	Material	Technology	Factors	Responses	Significant factors
Galantucci e t al. 2010	ABS	FFF	Chemical treatment	Surface finish	-
Ranga et al. 2010	ABSP400	FDM	layer thickness, orientation, raster angle & width	Dimensional accuracy	Thickness and raster angle
Chang et al. 2011	ABS	FDM	Layer thickness, fill angle, orientation	Manufacturing time, surface finish and tensile strength	Layer thickness, fill angle
Nourghasem mi et al. 2011	PLA	FDM	Build orientation and layer thickness	Relation betwee n factors and surface finish	Orientation angle, thick ness
Singh 2014	ABS	FDM	Orientation	Length, height	Orientation angle
Nidagundi et al. 2015	ABS-PA-747	FDM	Layer thickness fill angle	Dimensional accuracy, Surface roughness	Layer thickness
Tateno et al. 2015	PLA	FDM	Thickness	Cylindricity, Squareness	Thickness
Garg et al. 2016	ABS (P430)	FDM	Orientation	Surface finish and dimensional accuracy	Orientation
Fahad et al. 2017	Duraform pol yamide (Nyl on 12)	High-speed sintering (HSS)/Selectiv e laser sintering (SLS)	Layer thickness, printing speed, power level	Flatness, Squareness	Layer thickness, printing speed
Sheydaeian et al. 2017	Titanium	Binder jet	Layer thickness	Dimensional accuracy & tensile strength tensile strength	Thickness
Vishwas et al. 2017	ABS	FDM	Shell thickness, layer thickness	Dimensional accuracy, Time took	Layer and shell thickness
Velineni et al. 2018	PLA	FDM	Layer thickness, printing speed, orientation angl e	Dimensional features, surface roughness	Different combination s of factors for different responses

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Different parameters effect differently in the presence of other factors and at different levels. Therefore, the combination of layer thickness, printing speed and orientation angle which has not been studied is considered to determine the effect on dimensional accuracy and surface finish.

2.2 Design of Experiments and applications

Before setting up a new manufacturing process to produce parts, it is necessary to study the effect of process variables on the output. When a process involves multiple factors, there is more chance for the output to be inconsistent as there is no fixed trend for variability. It is necessary to consider the effect of both individual effects and interaction effects and the latter is believed to have a significant influence on the response parameters yet are often ignored. DOE is an efficient procedure to investigate the effect of process parameters on the output so that the obtained results can be analyzed to yield valid conclusions. It is used to determine the factors that causes the variation in response and find the optimal conditions under which desirable response (minimum or maximum) is achieved [25].

Several DOE studies focus on determining the optimal factor levels for the AM process parameters in order to print the parts in desired quality. Albert [26] adopted 2^5 full factorial experiment with 5 factors being laser power, laser spot diameter, laser scan speed, feature thickness and support structure. Melt pool stress and center feature stress are the response parameters. There was a total of 64 runs including a complete set of cases for each of two materials. Vishwas et al. [7] used Taguchi approach for design

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optimization method as it provides a systematic and efficient procedure within a reduced number of runs. As this approach involves a reduced number of experiments, cost and time will be relatively less compared to a full-factorial design. With layer thickness, orientation, and shell thickness as the three factors and with three levels each, Taguchi orthogonal array with 9 runs (27 runs in case of full factorial) is used. ANOVA analysis was used for Signal-to-Noise ratios to interpret the results. The results showed that the best results were obtained with 0.3mm layer thickness, 30^0 orientation angle and 0.8 mm shell thickness. Nidagundi et al. [8] adopted the same Taguchi approach for a 3-level 3 factor experiment. Three factors being layer thickness, orientation angle, and fill angle with three levels each used the L9 orthogonal array. The advantages of this approach include simplification of the experimental plan and feasibility of a study of the interaction between various process parameters. The response parameters are surface roughness, ultimate tensile strength, and dimensional features [5]. It is observed that higher ultimate strength and optimal dimensional accuracy were observed at 0.1mm layer thickness, 0 ° orientation angle and 0° fill angle. Minimum surface roughness was observed at 0.3 mm layer thickness, 15^0 orientation angle and 0^0 fill angle.

There are studies that considered the effect of layer thickness, part build orientation angle, raster angle, raster to raster gap, and raster width on the dimensional accuracy of FDM printed parts [27]. Raster angle is measured from x-axis on the bottom layer of the part to the angle at which the layer is deposited. Both main effects and interaction effects are considered to comment on the significance of factors. Process parameters were optimized by using Taguchi's L9 orthogonal array on the tensile testing specimen. Significant process parameters were identified using ANOVA. The main effect plots for

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signal-to-nose ratios for dimensional accuracy and manufacturing time are plotted. By observing the experimental results, dimensional accuracy is maximum at 0.3 mm layer thickness, 30° orientation angle, and 0.8 mm shell thickness. It is concluded that the thinner layer thickness gives better bonding strength and gives good axial loading capability. Upon varying layer thickness and orientation angle, the bonding strength changes between the layers. Chang and Huang [28] considered layer thickness, fill angle, orientation angle with three levels each to print specimens with ABS material using FDM technology. They used the Taguchi method to select a specific set of runs instead of selecting all 27. The response parameters were an ultimate tensile strength, surface finish and manufacturing time. One of the limitations with this study is that authors did not incorporate interaction effects between factors on each response since they implemented the Taguchi method.

2.3 Control charts and capability studies

Control charts, a crucial tool in statistical quality control, can be classified as control charts for variables and control charts for attributes [29]. The first category contains control charts for individual measurements that are common in 3D printing. However, such control charts are designed for identical products, which seldom happen in 3D printing. The second category contains control charts for attributes that have great potential to be applied to 3D printing. For example, the number of defects on a 3D-printed object is a critical problem. Under the assumption that the number of defects on a unit of surface follows a Poisson distribution, control charts for nonconformities (defects) can be constructed to minimize the number of defects [29]. They also check the

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sample to sample variation to determine the variation is within the established stable range.

X-R charts are ideal for smaller sample sizes and S charts are typically used for larger sample sizes. The "chart" consists of a pair of charts: One to monitor the process standard deviation and another to monitor the process mean. The Xand R chart plots the mean value for the quality characteristic across all units in the sample X_i plus the range of the quality characteristic in the sample as $R=X_{max}-X_{min}$, where X_{max} shows the maximum value of the quality characteristic while X_{min} shows the minimum.

Process capability analysis entails comparing the performance of a process against its specifications. It is a statistical measurement of a process's ability to produce parts within specified limits on a consistent basis. C_p (Process Capability), C_{pk} (Process Capability Index), or P_p (Preliminary Process Capability) and P_{pk} (Preliminary Process Capability Index) can be calculated to monitor how the processes are operating. The C_p and C_{pk} calculations use sample deviation or deviation mean within rational subgroups. C_p tells if your process is capable of making parts within specifications and C_{pk} shows if your process is centered between the specification limits. They can be calculated using the following formula [30]:

$$C_p = \frac{USL - LSL}{6\sigma}$$

$$C_{pk} = \text{Min}\left(\frac{USL - \mu}{3\sigma}, \frac{\mu - LSL}{3\sigma}\right)$$

Where USL and LSL are the upper and lower specification limits, μ is mean of the process, σ is the standard deviation of the process.

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Rupender Singh [6] plotted X and R charts for the feature groove width (10mm) of parts produced by FDM, a highly capable process which helps us determine if a process is stable and predictable. The X-bar chart shows how the mean or average changes over time and the R chart shows how the range of the subgroup's changes over time. Graphically, we assess process capability by plotting the process specification limits on a histogram of the observations. If the histogram falls within the specification limits, then the process is capable. It is observed that the C_{pk} value of 1.33 or greater is considered to be the industry benchmarks. The response parameters being hardness, surface finish and nominal dimensions had C_{pk} value greater than 1.33, so this process will produce conforming products if it remains in statistical control. Also, the control chart of these features had response values within the upper and lower control limits.

2.4 Research gap and contribution of the study

From the review of past potential studies, various studies considering different factorial designs, factors, and responses are compared and it is observed that most of the studies either considered one or two factors at a time and only very few studies considered three factors at a time. We set up a full factorial design of experiment with three factors layer thickness, printing speed and orientation angle and considered interaction effects along with main effects. Our goal is to determine if the significant factors still remain the same when both main effects and interaction effects are considered. Once the significant factors are determined, a capability analysis is conducted to test if the FFF process can produce PLA parts within specifications. Not only factors but changing the 3D printer also affects the dimensional features. From literature review on dimensional accuracy and surface finish studies, there is a need to examine the effect

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of multiple factors on the response parameters. Different combination of factors has a different effect on the output parameters of parts. This thesis is an effort made to understand the effect of the three mentioned factors on dimensional accuracy and surface finish. In this thesis, the full factorial design is used to avoid data loss about output variability. As the specimens are smaller in size, the cost factor didn't play a major role in our study. Since the FFF process is one of the most important and widely used technologies, it has been closely studied regarding the relationship between mechanical properties, dimensional features, surface finish and process parameters [31].

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CHAPTER 3. METHODOLOGY

In a production environment, it is important to manage the variation in the process in order to maintain a specified level of quality. There are many reasons of variation due to controllable factors and uncontrollable factors. Controllable factors are the ones which we may set their levels during the process; however, the levels of uncontrollable factors cannot be set. The general view of a process showing the cause of variations is presented in Fig 2.

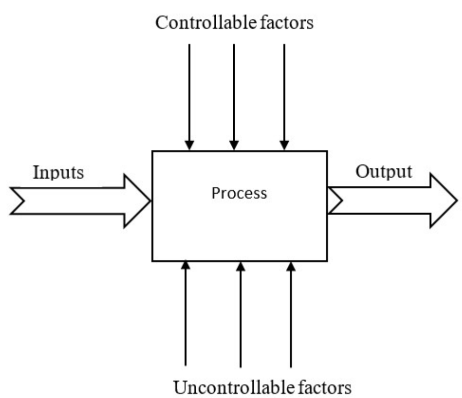

Fig 2: General model of a process [32]

Different applications of additive manufacturing may require different levels of input variables/process parameters. It is necessary to study the effect of various levels of factors on the output parameters to improve productivity and quality. All engineering processes in a manufacturing organization are subject to variation, sources of which may be combinations of materials, equipment, method or environmental conditions [33]. Because of the limited resources available, experimentation is the best choice to [34]

- reduce time to design/develop new products & processes
- improve the performance of existing processes

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- improve reliability and performance of products
- achieve product & process robustness
- perform an evaluation of materials, design alternatives, setting component & system tolerances, etc.

It is beneficial to work beforehand in selecting the suitable levels of controllable factors rather than working for a solution after sensing the problem. To finalize optimal conditions for a process, the factors are varied within a reasonable range and the response parameters are measured and analyzed to conclude the effect of different levels of factors. Response parameters are the output of the process which shows the quality level of interest. When two or more variables are involved in an experimental study, there is more to consider than simply the main effect. The effect of one independent variable may depend on the level of the other independent variables [35]. Often interaction effects are ignored to avoid the complexity which shouldn't be the practice.

- **Main effect** - the effect of a single independent variable on the response ignoring all other process variables.
- **Interaction effect** – When the effect of a factor on the product or process is altered due to the presence of one or more other factors, that relationship is called an interaction effect.

DOE plays an important role in Design for Reliability (DFR) programs, allowing the simultaneous investigation of the effects of various factors and thereby facilitating design optimization.

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3.1 Design of Experiments (DOE)

DOE is one such methodology that can involve multiple factors in a process. It is defined as a series of tests in which purposeful changes are made to the input variables of a system or process to observe and identify the reasons for changes in responses [36]. The response values are analyzed by ANOVA using statistical packages like Minitab, JMP, Stat graphics, R, SPC XL, etc. DOE can also be understood as a crucial technique that is used to find if the key inputs are related to key outputs based on statistical analysis [37]. DOE can accommodate experiments where multiple factors can be varied at once. DOE is more beneficial and convenient because it involves fewer runs, less time, and less material usage, it includes the effect of interactions, estimated effects of variables are more precise, and it maximizes the amount of information gained while minimizing the amount of data to be collected [38].

3.2 Important Principles of DOE

3.2.1 Randomization

An essential component of every experiment that needs to be validated. Generally, it is extremely difficult for researchers to eliminate unknown potential bias using only their expert judgment or literature review, so a deliberate process which randomizes the experiment to eliminate these biases from the conclusions is required. In a randomized experimental design, objects or individuals are randomly assigned to an experimental group [39,40]. Using randomization is the most reliable method of creating homogeneous treatment groups, without involving any potential biases or judgments. From various types of randomizations available, two types of it are discussed below:

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a) Completely randomized design

In a completely randomized design, objects or subjects are assigned to groups completely at random. One standard method for assigning subjects to treatment groups is to label each subject, then use a table of random numbers to select from the labeled subjects. This may also be accomplished using a computer [41]. In MINITAB, the "SAMPLE" command will select a random sample of a specified size from a list of objects or numbers.

b) Randomized block design

If an experimenter is aware of specific differences among groups of subjects or objects within an experimental group, the experimenter may prefer a randomized block design to a completely randomized design. In a block design, experimental subjects are first divided into homogeneous blocks before they are randomly assigned to a treatment group [42]. For easy understanding, let us assume that an experimenter had reason to believe that a factor in an experiment might have a significant effect on the response, he might choose to first divide the experimental subjects into groups based on the levels of factors considered. Then, the segregated groups would be assigned to treatment groups using a completely randomized design [43]. In a block design, both control and randomization are considered. In our present study, we used the completely randomized experiments using MINITAB to randomize the experiment runs as there was no potential grouping of factors was seen.

3.2.2 Replication

To understand the concept of replication, let's revise the definition of the standard error of the mean. It is the square root of the estimate of the variance of the sample mean.

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The width of the confidence interval is determined by this statistic. The estimates of the mean become less variable as the sample size increases. Replication is the basic issue behind every method used to estimate or control the uncertainty in our results [44]. But it is important to note the difference between replicated runs and repeated runs, although the multiple response readings are taken at the same factor levels for both. However, repeated runs are response observations taken at the same time or in succession whereas replicated runs are response observations recorded in a random order. Therefore, replicated runs include more variation than repeated runs [45].

3.3 Factorial Designs

A factorial design is one of the important principles examining several factors simultaneously. The factorial experiments, where all combinations of the levels of the factors are run, are usually referred to as full factorial experiments.

3.3.1 Two-level factorial design

Full factorial two-level experiments are also referred to as 2^K designs where K denotes the number of factors in the experiment. A full factorial two-level design with K factors requires 2^K runs for a single replicate [46]. For example, a two-level experiment with three factors will require $2^3 = 8$ runs. The first level, i.e. lower level, of the factors are usually represented as -1, while the second level, i.e. higher level, is presented as +1.

3.3.2 Three-level factorial design

Similar to two-level, three-level factorial designs are referred to as 3^K designs, where K shows the number of factors. For instance, a three-level experiment with three-factor

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requires 3^3=27 runs. The runs are usually represented as in the table below. In our study, we have three factors which are layer thickness, printing speed, and orientation angle. The notations A, B, and C represent these factors respectively. The experimental set is tabulated in Table 3, where 1, 2, and 3 show the levels of each factor. For instance, "111" shows that all the factors should be set at "Level 1" and "211" shows that Factor A should be set at "Level 2" while both Factor B and C are set at "Level 1".

Table 3: Possible combination of runs with three factors and three levels [47]

Factor A	Factor B	Factor C		
		1	2	3
1	1	111	211	311
1	2	112	212	312
1	3	113	213	313
2	1	121	221	321
2	2	122	222	322
2	3	123	223	323
3	1	131	231	331
3	2	132	232	332
3	3	133	233	333

3.3.3 Taguchi factorial design

Taguchi envisaged a new method of conducting the design of experiments which are based on well-defined guidelines. Taguchi approach uses a special set of arrays called orthogonal arrays. These arrays stipulate the way of conducting a minimal number of experiments which could give almost the full information of all the factors affecting the response parameter. To make the best of this approach, the experimenter should be careful in selecting the factors and response parameters. Steps involved are the same as that of DOE except for the selection of orthogonal arrays [48].

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To determine the effect each variable has on the output, the signal-to-noise ratio needs to be calculated for each experiment conducted. Taguchi's method for experimental design is straightforward and easy to apply to many engineering situations, making it a powerful yet simple tool. It can be used to quickly narrow down the scope of a research project or to identify problems in a manufacturing process from data already in existence. Also, the Taguchi method allows for the analysis of many different parameters without a prohibitively high amount of experimentation [49]. One of the disadvantages is that the results obtained do not exactly indicate which parameter has a highest significant effect on output. Also, since orthogonal arrays do not test all variable combinations, this method should not be used if there’s no room for risk of losing data. Another limitation is that the Taguchi methods are offline, and therefore inappropriate for a dynamically changing process such as a simulation study [49].

Some uncontrollable noise factors cause the quality characteristics to deviate from the target values. The factors can be classified into three categories: 1) external factors, 2) manufacturing imperfections, and 3) product deterioration. The unstable environment conditions, such as power supply, temperature, humidity and vibrations of nearby machinery, are the external factors. The Orthogonal Array (OA) is used as part of the Taguchi Method to design the experiments. OA is a systematic, statistical way of testing pair-wise interactions. It provides representative (uniformly distributed) coverage of all variable pair combinations.

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a) Signal-to-Noise Ratio and Analysis of Variance

The sample signal to noise ratio is defined as the ratio of the mean to the standard deviation. It shows the variability as defined by the standard deviation relative to the mean. This definition of the signal to noise ratio should typically only be used for data measured on a ratio scale. That is, the data should be continuous and have a meaningful zero. Typically, there are three S/N ratios: the lower-the-better (people desire the quality characteristic value to be small, such as surface roughness), the higher-the-better (such as mechanical strength), and the nominal-the-better (such as the dimension). The unit of S/N is dB, the lower-the-better S/N calculation [50] is presented in Equation (1).

$$\frac{S}{N} = -10 \text{ x } \log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} Y_i^2\right) \quad (2)$$

where n is the number of measurements and Yi is the observed performance characteristic value. After the S/N value is calculated, a statistical method called analysis of variance (ANOVA) will be performed. ANOVA is used to evaluate the influence of the control factors on the experimental results and to determine which control factors are statistically significant [51].

3.4. Development of the Experiment

Having understood the importance of main effects and interaction effects, we can determine significant factors by running a full complement of all factor combinations, i.e., a full factorial design. We have adopted a full factorial design in our study to avoid missing any information about output variability, main effects, and interaction effects. Research is conducted in order to determine the factors that are responsible for

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dimensional accuracy and surface finish for material extrusion technology when polymers are used.

Even though studies exist tackling the effect of printing speed on surface finish [17, 52, 53,54], there is a need to investigate its effect on dimensional accuracy. Moreover, the interaction effect of build orientation between factors layer thickness and printing speed has not been investigated for FFF technology and polymers. In order to address these gaps in the literature, we investigate the main and interaction effects of printing speed, layer thickness, and build orientation for FFF technology and PLA material. The levels of these three factors are presented in Table 4,

Table 4: Three factors with three different levels each

Factor	**Factor labels**	**Level 1**	**Level 2**	**Level 3**
Layer thickness(mm)	A	0.1	0.2	0.3
Printing Speed(mm/s)	B	60	80	100
Orientation angle	C	0^0	45^0	90^0

With regards to the findings of the literature review, the goal of this study is to investigate the effect of layer thickness, printing speed, and orientation angle on dimensional accuracy and surface roughness. Therefore, our hypothesis is that the part's dimensional accuracy for overall length, height, width, middle height, and surface roughness might be affected by all the three factors. We consider three factors: layer thickness, printing speed and orientation angle with three levels constituting 27 different experiments. All the experiments were replicated thrice, summing to a total of 81 runs.

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The full factorial method was used to investigate the main effects of factors, and interaction effects between the factors.

We ran all 81 experiments randomly without following any order so that the machine can be set to different process parameters rather than replicating the same parts thrice in a row. All experiments are run under the same conditions; all other factors except layer thickness, printing speed, and orientation angle were kept constant for all experiments. We used PLA polymer to build the parts on the FFF machine. The FFF 3D printer that we used is Monoprice Maker Select V2 (Fig 3) with build volume 8"x8"x7", 100-micron resolution, 1.75mm filament diameter, 100mm/sec print speed and max temperature of 260^0C. The price of PLA coil 1.75mm thickness, 1kg spool was 15$. As PLA material is relatively cheap compared to other polymers, full factorial DOE is considered instead of reduced factorial methods. The price of the 3D printer, Monoprice maker select V2 was 200$.

Fig 3: Monoprice maker select V2 3D printer

Monoprice maker in Fig 3 is the 3D printer used to print PLA parts. A memory card is used to load the STL file to the printer. The building part in Fig 5(a) is a dog bone shaped

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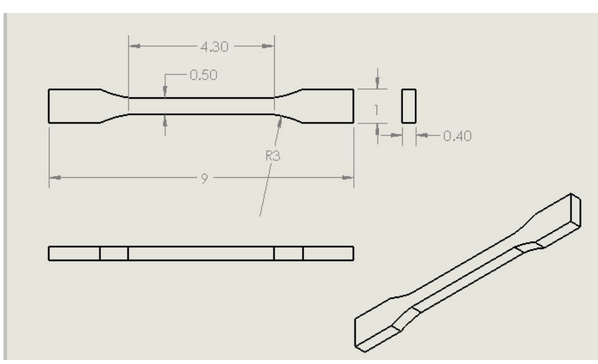
tensile testing specimen (9.00X1.00X0.4cm) taken from the literature [45, 59, 60]. The CAD model of the part Fig.5(b) was created using SOLIDWORKS which is then converted into STL file in Fig.6(a, b, c) using CURA 15.04 software. With CURA, we could vary the levels of factors such as layer thickness and shell thickness, traction, density, bed temperature, support structure and many more advanced features. Fig 4 shows the picture of a build platform of the printer with manual leveling mechanism. The circular discs underneath the platform are screws used to adjust the level and tightness of the platform.

Fig 4: Build platform with a manual levelling mechanism



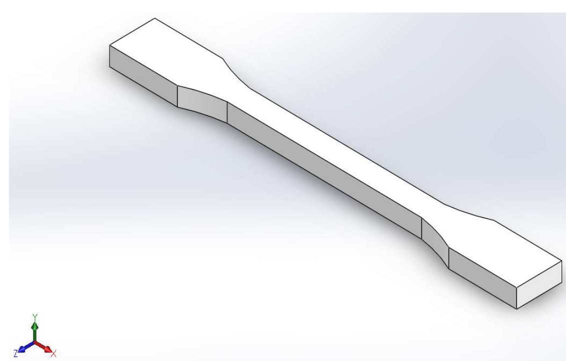


Fig 5(a): 2D and Isometric sketch of the part

Fig 5(b): 3D model of the part

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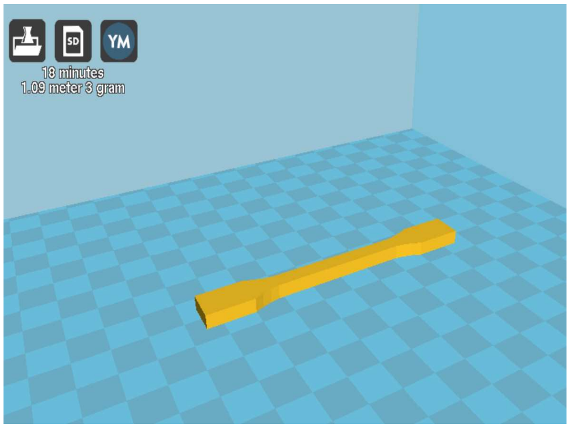

Fig 6(a): Part Orientation in CURA15.04 software with 0^0

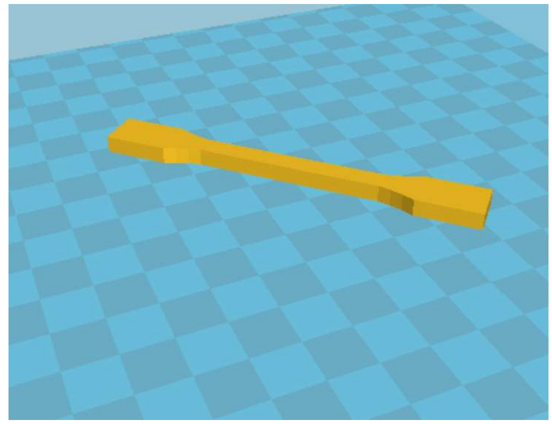

Fig 6(b): Part Orientation in CURA15.04 software with 45^0

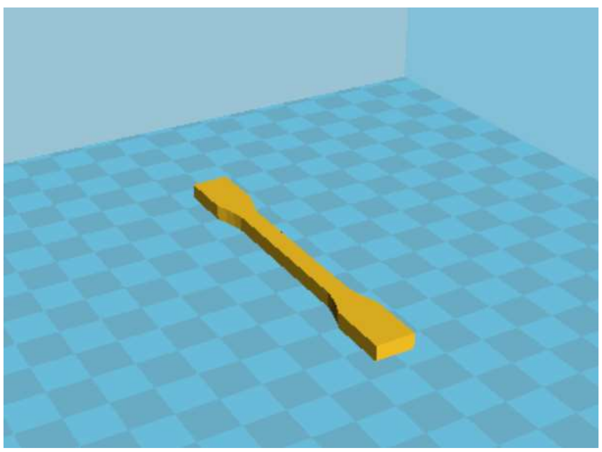

Fig 6(c): Part Orientation in CURA15.04 software with 90^0

The printing duration for building each part varies with the levels of factors. Though the factors layer thickness and printing speed are kept constant, the building time of each part varies when the build orientation is changed. The depositing direction, i.e build orientation, changes to horizontal, inclined or vertical depending on the angle. The setup of Factor A in Level 3, Factor B in Level 3 and Factor C in Level 2 took the least time of 5 min per part. The set up with Factor A in Level 1, Factor B in Level 1 and Factor C in Level 1 took the longest printing time of 18 min per part. Table 5 shows the time taken to

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print each part at different levels of factors. In Table 5, 1, 2, 3 refer to the levels of each factor.

Table 5: Manufacturing time required for each run

Factor Levels			
A	B	C	Time (Min)
1	1	1	18
		2	17
		3	18
	2	1	16
		2	15
		3	16
	3	1	14
		2	13
		3	14
2	1	1	10
		2	10
		3	10
	2	1	9
		2	8
		3	9
	3	1	8
		2	7
		3	8
3	1	1	7
		2	7
		3	7
	2	1	6
		2	6
		3	6
	3	1	6
		2	5
		3	6

The methodology, experimental set up, and equipment are clearly discussed in this chapter. The results and the effects of input on output parameters will be explained in chapter 4

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CHAPTER 4. RESULTS & DISCUSSIONS

All the parts with different levels of factors are printed according to the DOE plan and procedures discussed in Chapter 3. A full factorial design of experiment is performed for each level of layer thickness, printing speed, and orientation angle. Layer thickness is the thickness of the material being deposited on the build platform from the nozzle of a 3D printer. Printing speed is the speed at which the nozzle moves with respect to the stationary bar of the 3D printer. Orientation angle is the angle which can be set through CURA software so that the part will be printed in that angle on the build platform, i.e. the angle at which the layers are deposited will change for different orientations.

After experiments, the end products are measured. Overall length is the horizontal length of the part from extreme right to extreme left point of the part. Height is the vertical distance from top most point to lowest point of the part when its placed as the top part as shown in the Fig 5(a). Width is the thickness of the part and middle height is the vertical distance of the part in the middle section. Instead of considering the actual measured dimensional values for analysis, the values are subtracted from the nominal dimensions of the part to provide a direction and aim to the analysis. The aim is to minimize the deviation of the response values from target values. All four dimensions are measured at the same location on each part using digital Vernier calipers with an accuracy of 0.001mm. Table 6 shows the actual measured values whereas Table 7 shows the absolute value of difference of measured response parameters from nominal values. The percentage change in each dimension i, i=length, width, height, is calculated based on Eq. (2), where X_i shows the measured value for dimension i, and X_{iCAD} shows the respective CAD dimension of the part. The term $\%\Delta X_i$, stands for the percentage change

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according to the CAD value for each dimension i. It should be noted that the higher percentage deviations refer to lower dimensional accuracy. R1, R2, and R3 presents to 1st, 2nd, and 3rd replicas of the experiment.

$$\%\Delta X_i = \frac{|X_i - X_{iCAD}|}{X_{iCAD}} \times 100 \qquad (3)$$

A, B, C columns in Table 6 and Table 7 are used to represent the factors and corresponding levels. Since the full-factorial design was repeated thrice, R1, R2, and R3 represent each replication for all the responses. The surface finish of all parts is measured using Profilometer at the same location. Fowler surface roughness gage Ra; Rz with stylus tip (Universal product code - 646795168008). Fig 7 shows the picture of equipment used to measure the surface roughness.

Fig 7: Fowler surface roughness

Table 8 shows the surface finish values of all parts. In this study, a design which consists of three factors with three levels each can be expressed as 3 x 3 x 3 = 27 runs and its model can be represented as

$$Y_{ijk} = \mu + A_i + B_j + C_k + AB_{ij} + AC_{ik} + BC_{jk} + ABC_{ijk} + \varepsilon_{ijk}$$

Where Y_{ijk} shows the predicted response, A, B, and C are the factors labelled for layer thickness, printing speed and orientation angle for easy representation in equation. i, j, k

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are the levels of factors respectively and ε shows the error term. These terms are used for all regression equations in this study. In this case, main effects have 2 degrees of freedom, two-factor interactions have 4 degrees of freedom and similarly, k-factor interactions have 2^K degrees of freedom. This model contains a total of 26 degrees of freedom.

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Table 6: Measured values of dimensional response parameters in mm.

				Overall Length (mm)			Height (mm)			Width (mm)			Middle height (mm)		
Run	LT	PS	OA	R1	R2	R3	R1	R2	R3	R1	R2	R3	R1	R2	R3
1		60	0	8.960	8.983	8.970	1.006	1.010	1.004	0.382	0.389	0.389	0.512	0.516	0.514
2		60	45	8.950	8.950	8.959	1.005	1.000	1.003	0.378	0.385	0.370	0.507	0.509	0.506
3		60	90	8.981	8.967	8.960	1.000	1.000	1.003	0.374	0.391	0.354	0.505	0.505	0.503
4		80	0	8.980	8.971	8.980	1.000	1.000	0.994	0.372	0.362	0.360	0.508	0.511	0.515
5	0.1	80	45	8.976	8.985	8.974	1.002	1.003	1.004	0.372	0.387	0.335	0.510	0.503	0.505
6		80	90	8.970	8.960	8.975	1.010	1.000	1.005	0.388	0.392	0.389	0.512	0.511	0.512
7		100	0	8.970	8.968	8.967	0.993	0.996	0.994	0.399	0.395	0.395	0.507	0.503	0.503
8		100	45	9.000	8.976	8.997	0.990	1.000	0.989	0.394	0.373	0.404	0.496	0.501	0.499
9		100	90	8.986	8.984	8.950	0.990	0.998	0.998	0.391	0.368	0.368	0.504	0.507	0.506
10		60	0	8.980	8.966	8.970	0.995	0.995	1.000	0.398	0.396	0.400	0.509	0.504	0.509
11		60	45	8.990	8.982	8.976	1.000	0.993	0.992	0.408	0.404	0.408	0.497	0.499	0.494
12		60	90	8.970	8.973	8.966	0.997	0.992	0.993	0.409	0.406	0.408	0.499	0.499	0.497
13		80	0	8.960	8.980	8.983	0.992	0.980	0.984	0.361	0.385	0.322	0.488	0.499	0.496
14	0.2	80	45	8.983	8.925	8.980	0.993	0.990	0.994	0.397	0.385	0.397	0.495	0.484	0.493
15		80	90	8.979	8.971	8.980	0.996	0.992	0.993	0.400	0.378	0.371	0.487	0.494	0.492
16		100	0	8.958	8.959	8.962	0.989	0.973	0.987	0.404	0.406	0.409	0.485	0.485	0.490
17		100	45	8.954	8.954	8.946	0.976	0.975	0.984	0.410	0.370	0.367	0.476	0.479	0.480
18		100	90	8.952	8.973	8.969	0.995	0.979	0.984	0.374	0.377	0.384	0.488	0.486	0.483
19		60	0	8.960	8.960	8.938	0.980	0.980	0.989	0.377	0.381	0.375	0.494	0.486	0.494
20		60	45	8.988	8.997	9.000	0.979	0.984	0.992	0.400	0.410	0.411	0.483	0.494	0.498
21		60	90	8.965	8.960	8.960	0.976	0.978	0.981	0.392	0.390	0.392	0.483	0.486	0.486
22		80	0	8.966	8.967	8.970	0.988	0.984	0.988	0.389	0.389	0.388	0.498	0.496	0.500
23	0.3	80	45	8.961	8.937	8.992	0.977	0.981	0.979	0.369	0.388	0.385	0.478	0.481	0.483
24		80	90	8.969	8.971	8.965	0.986	0.984	0.988	0.339	0.340	0.386	0.490	0.479	0.483
25		100	0	8.977	8.980	8.978	0.980	0.990	0.998	0.381	0.336	0.334	0.517	0.506	0.507
26		100	45	8.981	8.970	8.994	0.993	0.990	0.976	0.388	0.352	0.391	0.484	0.485	0.491
27		100	90	8.960	8.942	8.940	0.976	0.992	1.000	0.368	0.363	0.360	0.560	0.522	0.520

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Table 7: Absolute deviation values of dimensional features in mm

				Overall Length (mm)			Height (mm)			Width (mm)			Middle height (mm)		
Run	LT	PS	OA	R1	R2	R3	R1	R2	R3	R1	R2	R3	R1	R2	R3
1	0.1	60	0°	0.040	0.017	0.030	0.006	0.010	0.004	0.018	0.011	0.011	0.012	0.016	0.014
2		60	45°	0.050	0.050	0.041	0.005	0.000	0.003	0.022	0.015	0.030	0.007	0.009	0.006
3		60	90°	0.019	0.033	0.040	0.000	0.000	0.003	0.026	0.009	0.046	0.005	0.005	0.003
4		80	0°	0.020	0.029	0.020	0.000	0.000	0.006	0.028	0.038	0.040	0.008	0.011	0.015
5		80	45°	0.024	0.015	0.026	0.002	0.003	0.004	0.028	0.013	0.065	0.010	0.003	0.005
6		80	90°	0.030	0.040	0.025	0.010	0.000	0.005	0.012	0.008	0.011	0.012	0.011	0.012
7		100	0°	0.030	0.032	0.033	0.007	0.004	0.006	0.001	0.005	0.005	0.007	0.003	0.003
8		100	45°	0.000	0.024	0.003	0.010	0.000	0.011	0.006	0.027	0.004	0.004	0.001	0.001
9		100	90°	0.014	0.016	0.050	0.010	0.002	0.002	0.009	0.032	0.032	0.004	0.007	0.006
10	0.2	60	0°	0.020	0.034	0.030	0.005	0.005	0.000	0.002	0.004	0.000	0.009	0.004	0.009
11		60	45°	0.010	0.018	0.024	0.000	0.007	0.008	0.008	0.004	0.008	0.003	0.001	0.006
12		60	90°	0.030	0.027	0.034	0.003	0.008	0.007	0.009	0.006	0.008	0.001	0.001	0.003
13		80	0°	0.040	0.020	0.017	0.008	0.020	0.016	0.039	0.015	0.078	0.012	0.001	0.004
14		80	45°	0.017	0.075	0.020	0.007	0.010	0.006	0.003	0.015	0.003	0.005	0.016	0.007
15		80	90°	0.021	0.029	0.020	0.004	0.008	0.007	0.000	0.022	0.029	0.013	0.006	0.008
16		100	0°	0.042	0.041	0.038	0.011	0.027	0.013	0.004	0.006	0.009	0.015	0.015	0.010
17		100	45°	0.046	0.046	0.054	0.024	0.025	0.016	0.010	0.030	0.033	0.024	0.021	0.020
18		100	90°	0.048	0.027	0.031	0.005	0.021	0.016	0.026	0.023	0.016	0.012	0.014	0.017
19	0.3	60	0°	0.040	0.040	0.062	0.020	0.020	0.011	0.023	0.019	0.025	0.006	0.014	0.006
20		60	45°	0.012	0.003	0.000	0.021	0.016	0.008	0.000	0.010	0.011	0.017	0.006	0.002
21		60	90°	0.035	0.040	0.040	0.024	0.022	0.019	0.008	0.010	0.008	0.017	0.014	0.014
22		80	0°	0.034	0.033	0.030	0.012	0.016	0.012	0.011	0.011	0.012	0.002	0.004	0.000
23		80	45°	0.039	0.063	0.008	0.023	0.019	0.021	0.031	0.012	0.015	0.022	0.019	0.017
24		80	90°	0.031	0.029	0.035	0.014	0.016	0.012	0.061	0.060	0.014	0.010	0.021	0.017
25		100	0°	0.023	0.020	0.022	0.020	0.010	0.002	0.019	0.064	0.066	0.017	0.006	0.007
26		100	45°	0.019	0.030	0.006	0.007	0.010	0.024	0.012	0.048	0.009	0.016	0.015	0.009
27		100	90°	0.040	0.058	0.060	0.024	0.008	0.000	0.032	0.037	0.040	0.060	0.022	0.020

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Table 8: Measured values of surface roughness

				R1	R2	R3
Run	LT	PS	OA	Ra	Ra	Ra
1		60	0	2.90	4.10	7.90
2		60	45	11.21	1.41	1.76
3		60	90	7.14	5.92	7.02
4		80	0	6.12	12.01	7.22
5	0.1	80	45	12.08	15.21	9.11
6		80	90	1.58	3.97	5.13
7		100	0	13.35	16.78	15.09
8		100	45	1.56	3.12	1.76
9		100	90	9.36	10.00	10.30
10		60	0	9.37	8.07	11.89
11		60	45	3.71	21.53	1.46
12		60	90	5.13	8.23	5.10
13		80	0	15.18	17.41	5.56
14	0.2	80	45	19.78	2.63	13.12
15		80	90	21.22	14.25	21.22
16		100	0	7.00	12.11	24.17
17		100	45	34.27	39.01	45.26
18		100	90	24.76	19.81	21.08
19		60	0	36.12	7.41	15.11
20		60	45	3.01	1.18	2.09
21		60	90	21.52	8.22	10.55
22		80	0	45.28	21.22	15.55
23	0.3	80	45	-	12.58	27.61
24		80	90	37.81	49.44	-
25		100	0	-	-	51.16
26		100	45	56.01	61.01	39.03
27		100	90	-	40.36	-

'-'Device gave no reading at those level of factors

Table 8 lists the values of surface finish of eighty-one parts measured using profilometer at same location. Ra is the arithmetic average of the absolute values of the profile height deviations from the mean line, recorded within the evaluation length. Table

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8 has some cells with '-', which means the profilometer couldn't give a reading at those factor levels because of too large values. Simply put, Ra is the average of a set of individual measurements of a surface's peaks and valleys [56].

The Figures 8 (a) and 8 (b) show the resolution obtained at different factor levels. Clearly, the Fig 8(a) is much finer when compared to 8(b).

Fig 8(a): Specimen with 0.1mm layer thickness, 60mm/s printing speed & 0^0

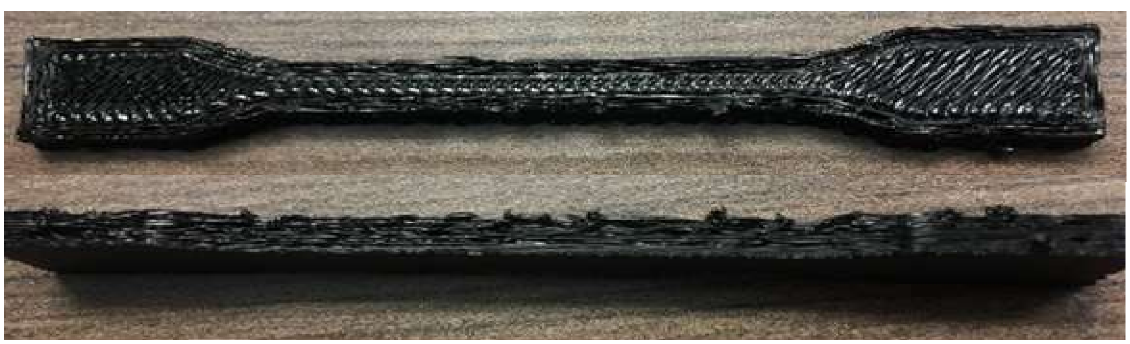

Fig 8(b): Specimen with 0.3mm layer thickness,100mm/s printing speed & 0^0

Full factorial design of experiment is beneficial when considering multiple factors and interaction effects between them. To examine the statistical significance of factors on each response, we performed analysis of variance (ANOVA) method using Minitab 18 statistical software. Our hypothesis in this study is that the layer thickness, printing speed, orientation angle and their interactions might have a significant effect on the deviation

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from nominal dimensions. A brief explanation of ANOVA interpretation is discussed followed by the ANOVA results for deviation of all the responses.

4.1 Interpretation of ANOVA

Significant factors are those which cause a change on the output not due to chance. Statistical evidence is used to comment on significance level of factors. ANOVA analysis is used to determine the p-values which are used to assess the null hypothesis by comparing them with the significance level. A significance level indicates the probability of rejecting the null hypothesis given that it is true [57]. In our current example, we have:

Null Hypothesis (H_0) – Response parameters are not affected by the input variables.

Alternative Hypothesis (H_1) – Response parameters are affected by the input variables.

Small p-values (<=0.05) are counted as evidence against H_0 and in favor of H_1 in 95% confidence. However, a p-value may not be interpreted as a "probability that H_0 is true," a quantity that is simply without a rational definition. So, even if we fail to reject the null hypothesis, it does not mean the null hypothesis is true [58]. That's because a hypothesis test does not determine which hypothesis is true, or even which is most likely, it only assesses whether available evidence exists to reject the null hypothesis.

The following sections discuss about the results from the 81 experiments in Table 7 and Table 8. The basic summary statistics were calculated, an Analysis of Variance (ANOVA) was performed, and model validation is done for each of the five responses. A multivariate analysis of variance (MANOVA), is an analysis of variance except that there are more responses involved. This is used in studies where more than one dependent variables are affected by one or more factors. Various methods related to analysis of variance like hypothesis testing, partitioning of sum of squares, additive models and

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experimental techniques have been around the since the beginning of the 19th century. ANOVA tests the differences between three or more groups means and it can assess only one dependent variable at a time. ANOVA analysis is adopted in this study to test the effects of dependent variables at a time and then study the effects of multiple factors from interaction effects. ANOVA analysis for each response parameter is conducted separately and is discussed simultaneously with main effect and interaction plots.

4.2. Optimal factor determination for overall length

The first step in the ANOVA process is to identify the potentially significant factors and interactions. Factors/combinations affecting overall length will be discussed in this section as each response parameter is analyzed separately. Before proceeding with the ANOVA analysis, data must be checked for normality, because like other parametric tests, ANOVA assumes that the data fits the normal distribution. If the measurement variable (response parameter) is not normally distributed, there may be an increase in the chance of a false positive result if analyzed with an ANOVA or another test that assumes normality. If data is not normally distributed, many practitioners suggest that a non-parametric version of the test which does not assume normality should be conducted.

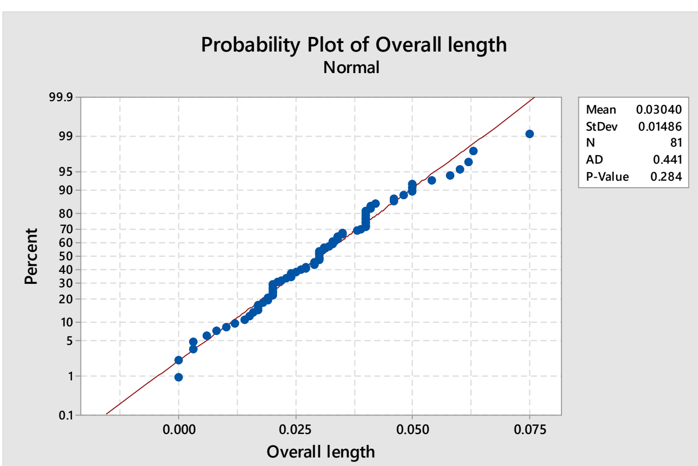

Fig 9: Normality test for overall length

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Anderson-Darling test is used to test the normality of the data. In this test, null hypothesis is H_0: Data follows normal distribution and alternative hypothesis is H_1: Data does not follow normal distribution. In Fig 9, the p-value for Anderson-Darling test is 0.284. Thus, the decision is not to reject the null hypothesis in 90% confidence level. We cannot conclude that the data is not normally distributed.

Our hypothesis is that all the factors and their interactions do not have significant effects on the deviation in overall length. The ANOVA results are presented in Table 9.

Table 9: ANOVA results for deviation in overall length

Source	DF	SS	MS	F-Value	P-Value
LT	2	0.000003	0.000002	0.98	0.383
PS	2	0.000001	0.000000	0.27	0.767
OA	2	0.000008	0.000004	2.2	0.121
LT X PS	4	0.000026	0.000007	3.87	0.008
LT X OA	4	0.000020	0.000005	2.88	0.031
PS x OA	4	0.000012	0.000003	1.75	0.153
LTX PS X OA	8	0.000056	0.000007	4.09	0.001
Error	54	0.000092	0.000002		
Total	80	0.000218			

According to the ANOVA results in Table 9, we observe that the interaction effect of LT X PS, layer thickness and printing speed (p-value = 0.008), interaction effect of LT X OA, layer thickness and orientation angle (p-value = 0.031) and interaction effect of all three factors LT X PS X OA, (p-value = 0.001) have significant effects on the overall length. The rest of the factors do not have significant effects on the response based on the statistical evidence.

The Pareto chart is used to determine the magnitude and the importance of the effects. On the Pareto chart, bars that cross the reference line are statistically significant [62]. With regards to the Pareto chart in Fig 10, the bars that represent factors LT X PS, LT X

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OA and LT X PS X OA cross the reference line that is 2.005. These factors are statistically significant at the 0.05 level with the current model terms.

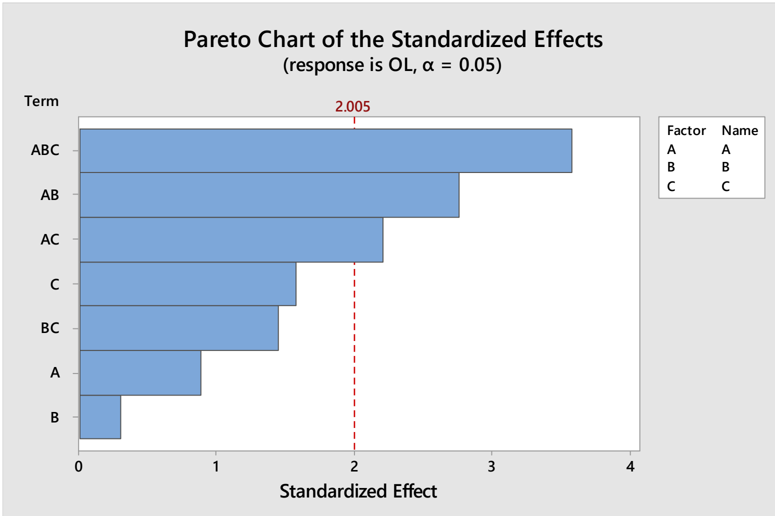

Fig 10: Pareto chart of standardized effects for overall length

4.2.1 Accuracy of the model

A very important part of an analysis is to test model validity, as an invalid model produces invalid conclusions. Model adequacy is tested by examining the validity of three assumptions for the residuals using a 4-in-1 residual plot: normality, equal variances, and data independence [59]. A residual plot is a graph that is used to examine the goodness of fit in regression and ANOVA. First, the normality of the residuals was tested using a normal probability plot (please see Fig 11). This plot shows no outliers, significant gaps or clear tails. Similarly, the histogram at the bottom left of Fig 11 clearly displays a bell-shaped distribution indicating that the normality assumption of residuals is satisfied.

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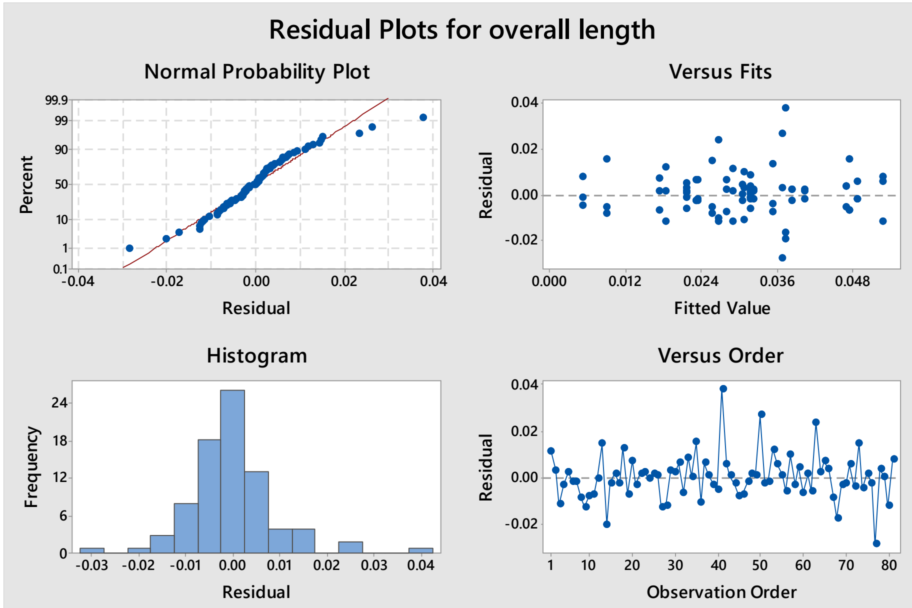

Fig 11: Residual plots of overall length

The versus-fits plot in Fig 11 indicates the validity of the constant variance assumption. In this case, the assumption is satisfied because the residual data had a nice random spread, except for a couple of outliers right to the center but they don't seem to follow a specific pattern, so the independence assumption cannot be rejected. The versus order plot (bottom right of Fig 11, "Versus Order") is used to validate the independence assumption. This plot is appropriate if you know the order in which the data is collected. There is nothing extremely different about the plot except few points shooting long from the center. In order to check the equal variance assumption, we plot variation in residuals at different levels of treatment in Fig 12. The distribution of residual is very similar at all three levels, so we can assume equality of variance between the levels. After all the assumptions for the residuals are met, we identify the optimal factor settings in Section 4.2.2.

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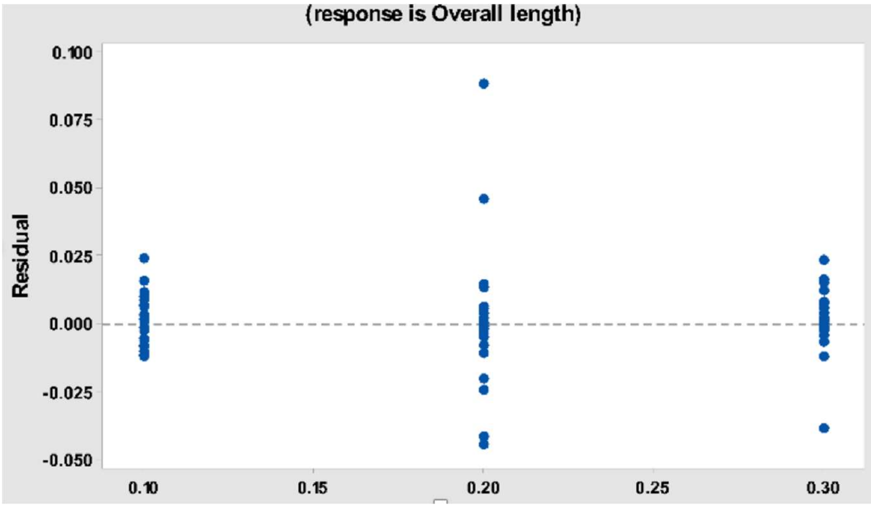

Fig 12: Residual versus layer thickness

4.2.2 Main effect and interaction plots

Main effects and interaction plots will assist us in finding the optimal level of significant factors on the mean response, i.e., deviation in the overall length. Fig 13 illustrates the main effect plots of all the three factors on the mean response of overall length. Since the individual main effects do not have significant impacts to explain the variation in the length, we only focus on the two-way interaction plot in Fig 14. The lowest point on the graph indicates the factor levels that has minimum deviation in the response.

From Fig 14, for LT X PS, lowest point of deviation is found at 0.1mm of layer thickness and 100mm/s of printing speed. For LT X OA, lowest point of deviation is found at 0.3mm of layer thickness and 45 deg of orientation angle.

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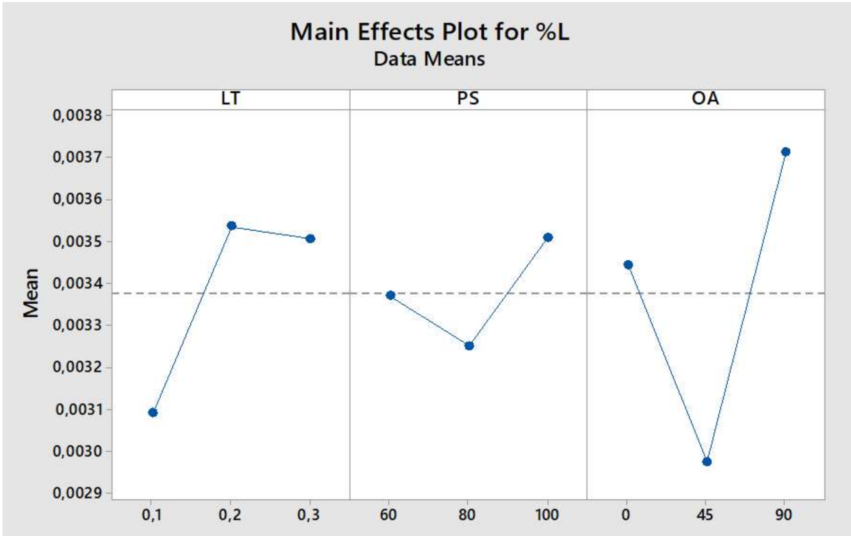

Fig 13: Main effects plot of factors for deviation in overall length(%L)

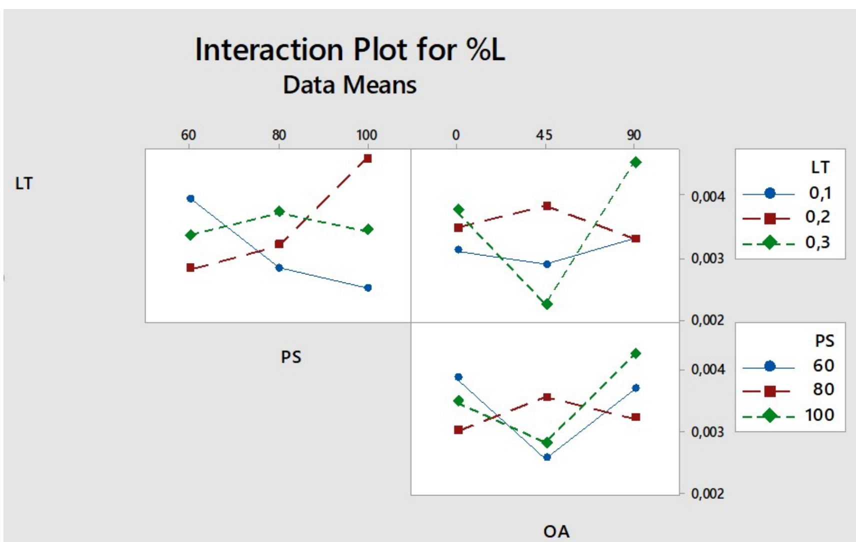

Fig 14: Interaction plot of factors for deviation in overall length

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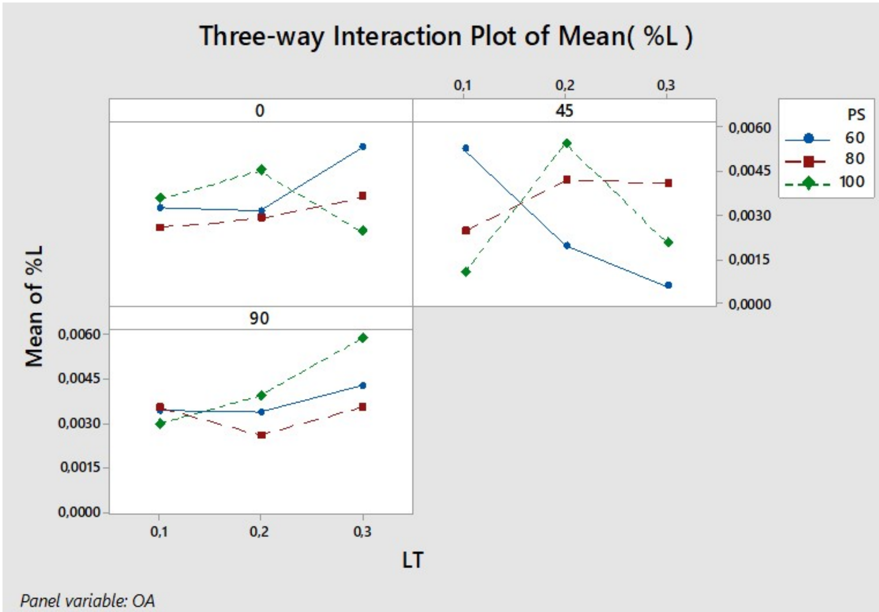

Fig 15: Three-way interaction plot for deviation in overall length

Since there is also three-way interaction, optimal factor levels cannot be determined only considering main effects and two-way interaction plots. From the three-way interaction plots in Fig 15, AXB vs C and AXC vs B, 0.3mm of layer thickness, 60mm/s of printing speed and 45^0 of orientation angle are found to be the optimal levels. The desired value is the smallest mean value of deviation in responses. The final optimal levels of significant factors for overall length are 0.3mm, 60mm/sec and 45^0.

Regression model for the predicted mean response at the optimal condition is estimated only from the significant main or interaction effects. The selection of factor levels to be used in the prediction equation is dependent on the nature of chosen quality characteristic for the experiment. General form of regression model for 3 factor and 3 levels is:

$$Y_{ijk} = \mu + A_i + B_j + C_k + AB_{ij} + AC_{ik} + BC_{jk} + ABC_{ijk} + \varepsilon_{ijk}$$

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For deviation from overall length LT X PS, LT X OA, and LT X PS X OA are the significant factors, thus the regression equation reduces to:

Deviation from overall length = 0.03040 - 0.00657 A_1B_3- 0.00794 A_3C_2 -0.01006 $A_3B_1C_2$

4.3 Optimal factor determination for height

In this section, only factors affecting height will be discussed. Before ANOVA test, the data should be checked against normality. Normality test for deviation in height data is presented in Fig 16. In Fig 16, the p-value (0.067) is greater than 0.05. Thus, the decision is not to reject the null hypothesis for 95% confidence level. We cannot conclude that the data is not normally distributed.

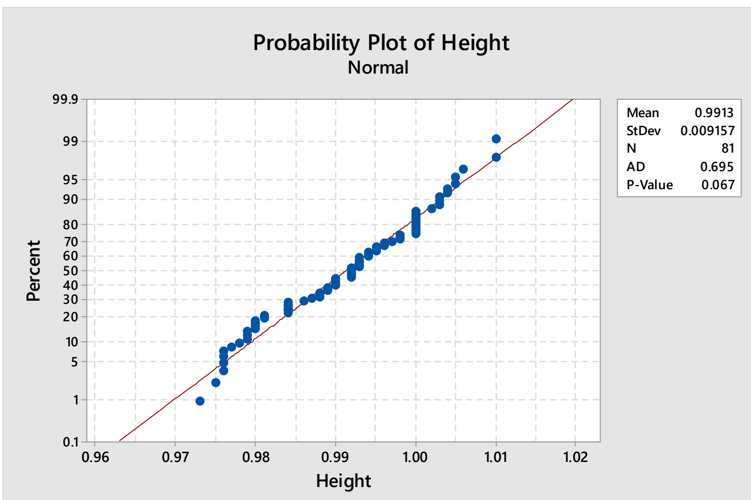

Fig 16: Normality test for height

The ANOVA results are represented in Table 10. Our hypothesis is that all the factors and their interactions might have significant effects on deviation in height. In Table 10, we observe that the main effect LT (p-value = 0.00), interaction effect LT X PS (p-value = 0.00) have significant effects on the response parameter, deviation in height. The rest of the factors do not have significant effects on the response.

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Table 10: ANOVA results for deviation in Height

Source	DF	SS	MS	F-Value	P-Value
LT	2	0.010375	0.005187	29.19	0.000
PS	2	0.000771	0.000385	2.17	0.124
OA	2	0.000185	0.000093	0.52	0.597
LTXPS	4	0.005288	0.001322	7.44	0.000
LTXOA	4	0.000386	0.000097	0.54	0.704
PSXOA	4	0.000623	0.000156	0.88	0.484
LTXPSXOA	8	0.001869	0.000234	1.31	0.256
Error	54	0.009596	0.000178		
Total	80	0,029094			

4.3.1 Accuracy of the model

Model adequacy is tested by examining the validity of three assumptions using a 4-in-1 residual plot in Fig 17, normality, equal variances, and data independence. First, the normality of the data was tested using a normal probability plot of Fig 17. The data points could be covered by a pencil lying on top of the fitted red line; thus, the residuals could be considered as normally distributed. Moreover, the histogram at the bottom left displays a bell-shape like distribution. Therefore, we can conclude that the response is not non-normal.

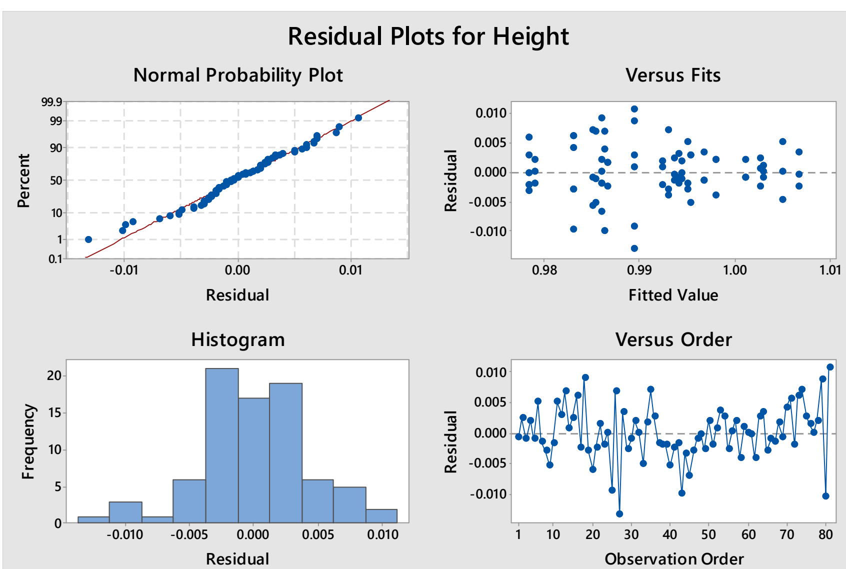

Fig 17: Residual plots of height

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The plot in Fig 17 is appropriate if you know the order in which the data is collected. Except few residuals, we could conclude that data meets independence assumption. From the versus-fits plot, the assumption is satisfied since the residual data had a random spread, except for a couple of outliers left to the center but they don't seem to follow a specific pattern, so the independence assumption cannot be rejected.

4.3.2 Main effect and interaction plots

Having identified the significant factors, the next step is to determine optimal setting of the factors. Main effects and interaction plots will assist us in finding the optimal level of significant factors on the mean response, i.e., deviation in height. Fig 18 illustrates the main effect plots of all the three factors on the mean response of height. From ANOVA table, we observed that the factor LT has significant effect on height. We need points closer to zero on the graph indicating the minimum deviation from target value.

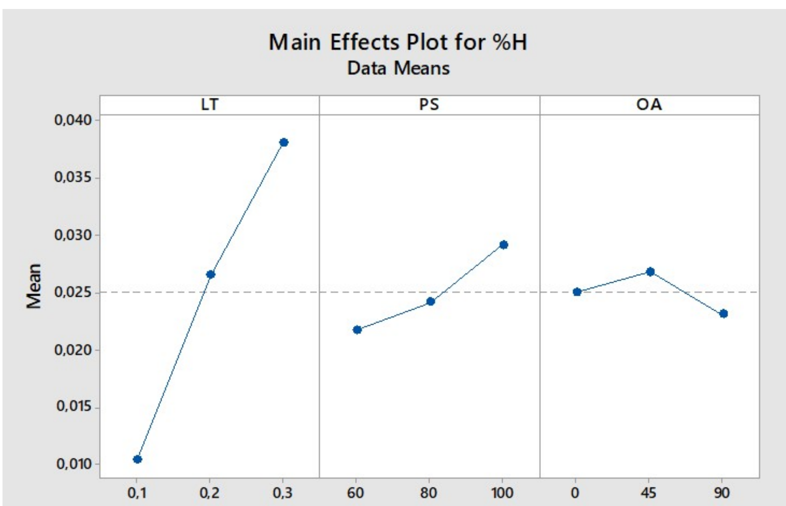

Fig 18: Main effects plot of factors for deviation in height (%H)

Looking at main effects in Fig 18, we see that the least deviation in height is observed at 0.1mm of layer thickness.

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Fig 19: Interaction plot of factors for deviation in height

Fig 19 shows the two-way interaction plot of the factors for the height. The interaction LT X PS is presented at the top right part of Fig 19. The lowest deviation occurs at 0.1mm of layer thickness and 80mm/sec of printing speed. As orientation angle alone has no significant effect, any level can be used with above optimal levels. Final optimal levels of significant factors for height are 0.1mm, 80mm/sec, any level of OA.

The optimal levels of LT and PS from main effect plots are 0.1mm and 60mm/sec respectively, similarly interaction effect LT X PS has 0.1mmx80mm/sec as the optimal level. With LT, and LT X PS as the significant factors, the regression equation reduces to:

$$\text{Deviation from height} = 0.008654 - 0.008543\ A_1 - 0.00135\ A_1B_2$$

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4.4. Optimal factor determination for width

Factors effecting width will only be discussed this section. Before ANOVA test, normality check of the data is performed by Anderson-Darling test in Fig 20. With regards to the p-value (p-value=0. 689) in Fig 20, we cannot conclude that the data is not normally distributed in 95% confidence level.

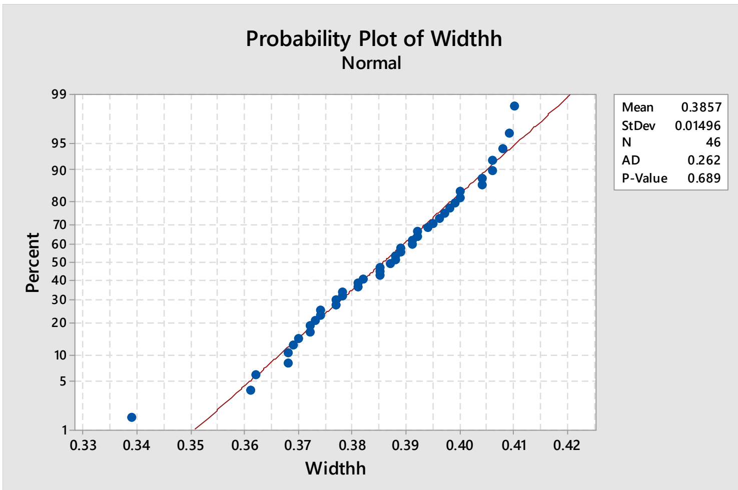

Fig 20: Normality test for width

Our null hypothesis is that all the factors and their interactions do not have significant effects on deviation in width. The ANOVA results are represented in the Table 11.

Table 11: ANOVA results for deviation in Width

Source	DF	SS	MS	F-Value	P-Value
LT	2	0.001237	0.000618	3.29	0.045
PS	2	0.002143	0.001072	5.70	0.006
OA	2	0.000299	0.000150	0.80	0.456
LTXPS	4	0.002614	0.000653	3.47	0.013
LTXOA	4	0.000912	0.000228	1.21	0.316
PSXOA	4	0.000503	0.000126	0.67	0.617
LTXPSXOA	8	0.006638	0.000830	4.41	0.000
Error	54	0.010155	0.000188		
Total	80	0.024501			

From Table 11, we observe that the main effect A (p-value = 0.045), B (p-value = 0.006), interaction effect AXB (p-value = 0.013) and three-way interaction effect

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AXBXC (p-value = 0.00) have significant effects on the deviation in width. The rest of the factors do not have significant effects on the response based on the statistical evidence.

4.4.1. Accuracy of the model

The model accuracy is evaluated in terms of normality, equal variance, and independence assumption of the residuals. In Fig 21, normal probability plot (at the top left of the graph) shows a smooth curve but no outliers, significant gaps or clear tails. Additionally, the histogram, at the bottom left displays a bell-shaped distribution. Thus, the normality assumption for the residuals is satisfied.

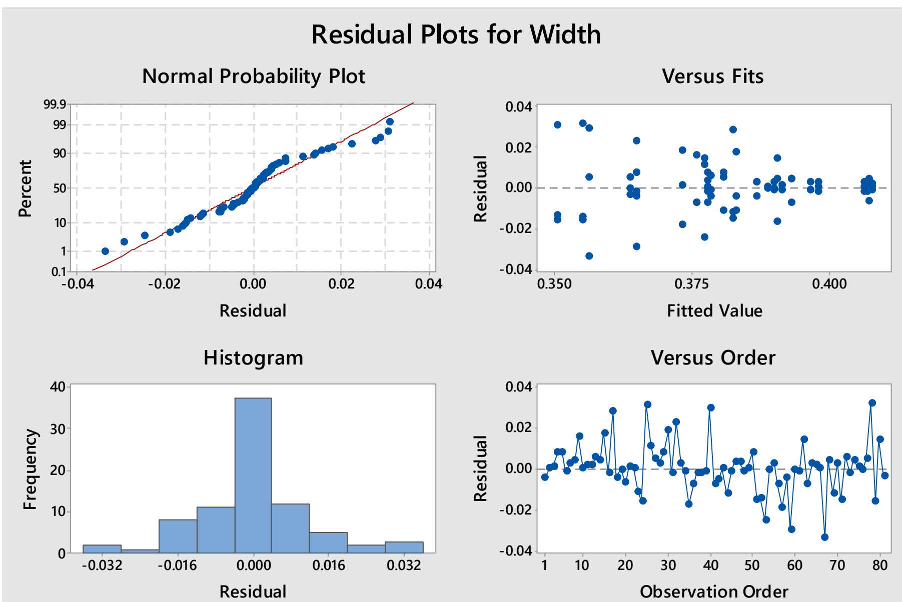

Fig 21: Residual plots for width

Like previous cases, the assumption in this case is satisfied since the residual data had a random spread, except for a couple of minor outliers. In residual vs order graph, the data on left side of the graph is above the center line whereas the data on the right side is mostly below the center line but no regular trend.

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4.4.2 Main effect and interaction plots

Having identified the significant factors, the next step is to determine optimal setting of the factors. Main effects and interaction plots will assist us in finding the optimal level of significant factors on the mean response, i.e., deviation in width. Fig 22 illustrates the main effect plots of all three factors on the mean response of width. Factor A and Factor B have significant main effects on the response. The lowest point on the graph indicates less deviation from the response; therefore, the factor levels are determined by considering the minimum deviation point.

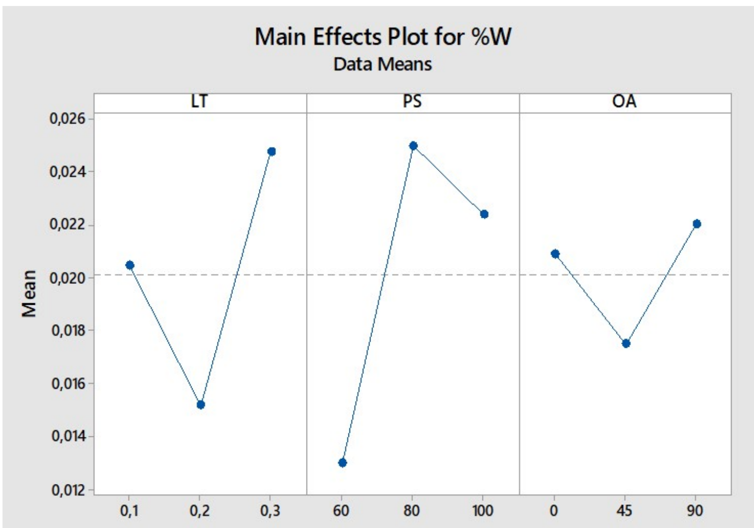

Fig 22: Main effects plot of factors for deviation in width(%W)

Looking at main effect plots Fig 22, we see that the lowest point of deviation is found at 0.2mm of layer thickness and 60mm/s of printing speed.

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Fig 23: Two-way interaction plot of factors for deviation in width

According to the two-way interaction plot of LTXPS in Figure 23, i.e., top right part of the above graph, the lowest deviation occurs at 0.2 mm of layer thickness and 60mm/sec of printing speed.

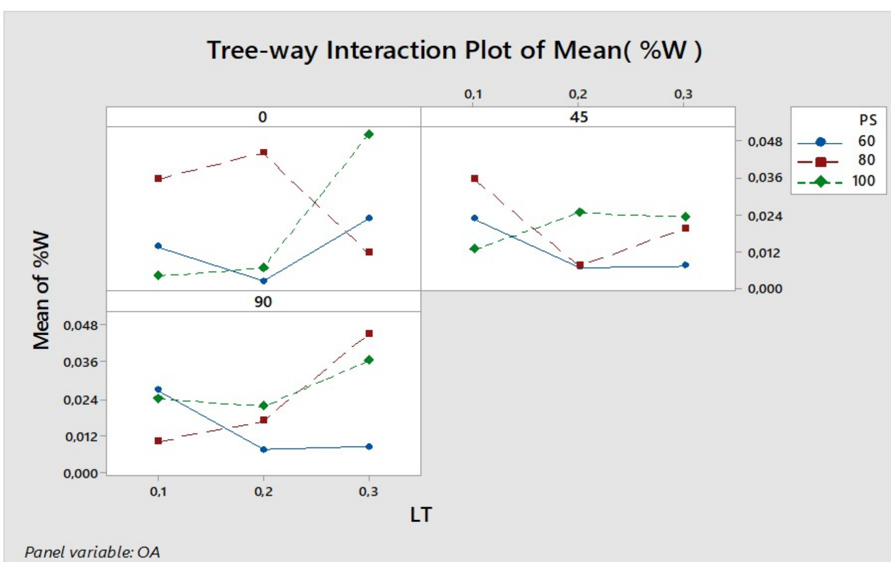

Fig 24: Three-way interaction plot for deviation in width

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Since there is a three-way interaction, the optimal factor levels could not be decided by main effects and two-way interaction plots, three-way interaction plot should also be considered. In Fig 24, the optimal factor levels that satisfy minimum deviation for width are 0.2mm layer thickness, 60mm/sec printing speed, and 0^0 orientation angle.

The predicted mean response at the optimal condition is estimated only from the significant main or interaction effects. The selection of factor levels to be used in the prediction equation is dependent on the nature of chosen quality characteristic for the experiment. The design model equation for this study reduces to:

$$Y_{ijk} = \mu + A_j + B_i + AB_{ik} + ABC_{ijk} + \varepsilon_{ijk}.$$

With LT, PS, LT XPS and LT X PS X OA as the significant factors, the regression equation reduces to:

$$\text{Deviation from width} = 0.01773 - 0.00947A_2 - 0.00804B_1 - 0.00709\, A_2B_1 - 0.00254A_2B_1C_1$$

4.5 Optimal factor determination for middle height

Factors/combinations affecting middle height will only be discussed in this section. First, we perform a normality test to check if the normality assumption of the data is satisfied. With p-value of 0.07, we can conclude that data is normal at 0.1 significance level. Our hypothesis is that all the factors and their interactions might have significant effects on the deviation in middle height. In 95% confidence, any factor with p-value less than or equal to 0.05 is considered to have a significant effect on the output. The ANOVA results are represented in Table 12.

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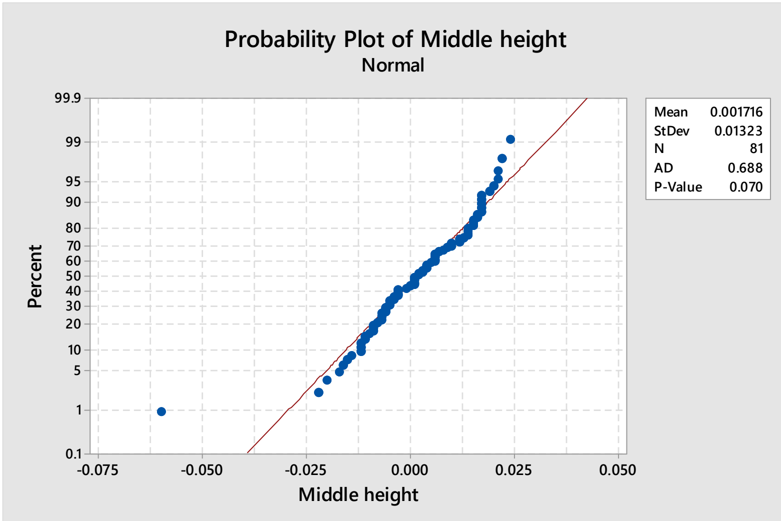

Fig 25: Normality test for middle height

In Table 12, we observe that the main effect A (p-value = 0.00), main effect C (p-value = 0.000), interaction effect AXB (p-value = 0.00), interaction effect AXC (p-value = 0.018), interaction effect BXC (p-value = 0.000) and three-way interaction AXBXC (p-value = 0.00) have significant effects on the deviation in the middle height. The rest of the factors do not have significant effects on the response based on the statistical evidence.

Table 12: ANOVA results for deviation in middle height

Source	DF	Adj SS	Adj MS	F-Value	P-Value
A	2	0.003277	0.001639	52.21	0.000
B	2	0.000149	0.000074	2.37	0.103
C	2	0.001199	0.000599	19.10	0.000
AXB	4	0.004284	0.001071	34.13	0.000
AXC	4	0.000409	0.000102	3.26	0.018
BXC	4	0.001413	0.000353	11.26	0.000
AXBXC	8	0.001568	0.000196	6.25	0.000

S	R-sq	R-sq(adj)	R-sq(pred)
0.0056	87.89%	82.06%	72.75%

DF: Degrees of freedom; SS: Sum of squares; MS: mean square of error

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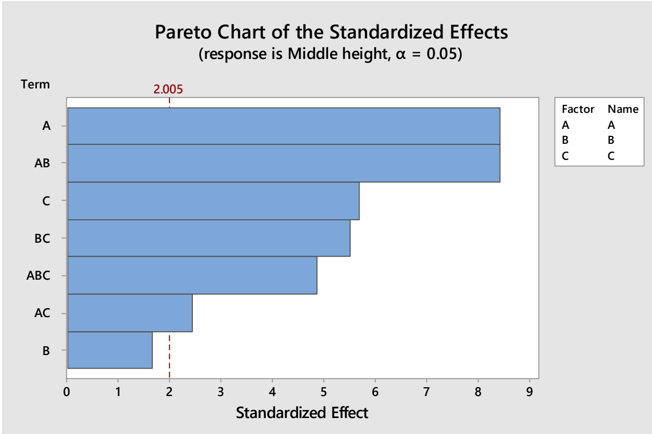

Fig 26: Pareto chart of standardized effects for middle height

On the Pareto chart in Fig 26, bars that cross the reference line are statistically significant. In the above Pareto chart, the bars that represent factors A, C, AB, AC, BC & ABC cross the reference line that is at 2.005. These factors are statistically significant at the 0.05 level with the current model terms.

4.5.1. Accuracy of the model

The normality of the data was tested using a normal probability plot (bottom left of Fig 27) and the Anderson-Darling test. This plot shows no outliers, significant gaps or clear tails, thus the normality assumption is satisfied.

In this case, the assumption of constant variance is obviously good because the residual data had a nice random spread, except few outliers on the left side of the plot. From the versus order plot (Fig 27), we can say that there are three points that have extended a little far when compared to other residuals, thus independence assumption is satisfied as most of the points remain intact with respect to center line. After checking the normality, constant variance, and independence of the errors, it has been concluded that the model is adequate.

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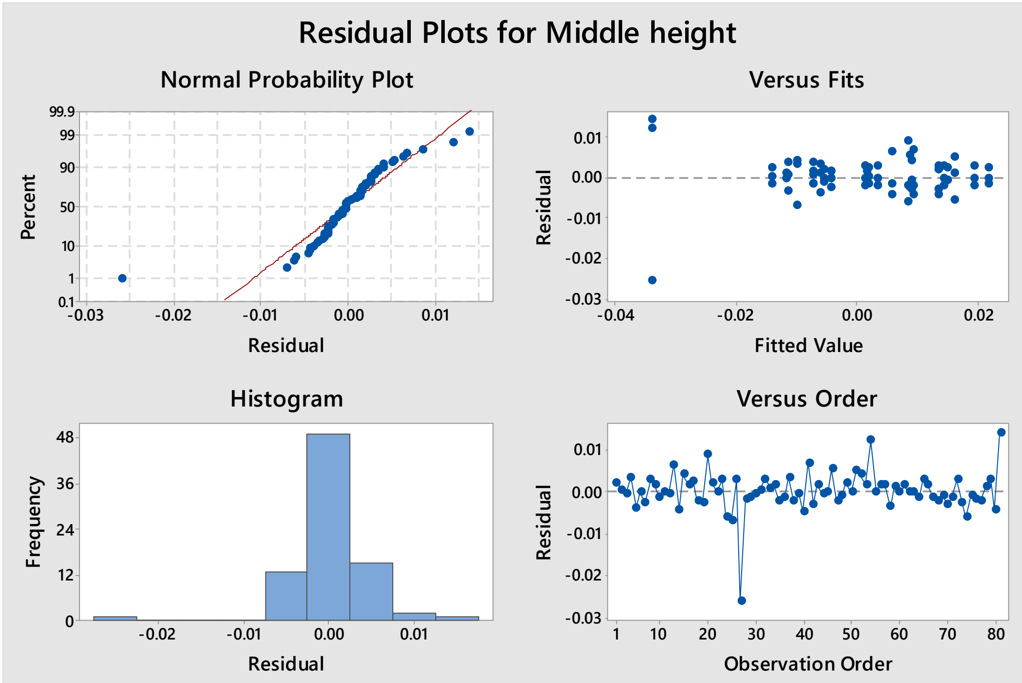

Fig 27: Residual plots for middle height

4.5.2 Main effect and interaction plots

Having identified the significant factors, the next step is to determine the optimal setting of the factors. Main effects and interaction plots will assist us in finding the optimal level of significant factors on the mean response, i.e., deviation in middle height. Fig 28 illustrates the main effect plots of all the three factors on the mean response of middle height. Main effects LT and OA have significant effect on the response. The lowest point that is close to zero on the graph indicates less deviation of the response. In Fig 28, the factor levels that achieves minimum deviation from the middle height according to the main effect plots are circled.

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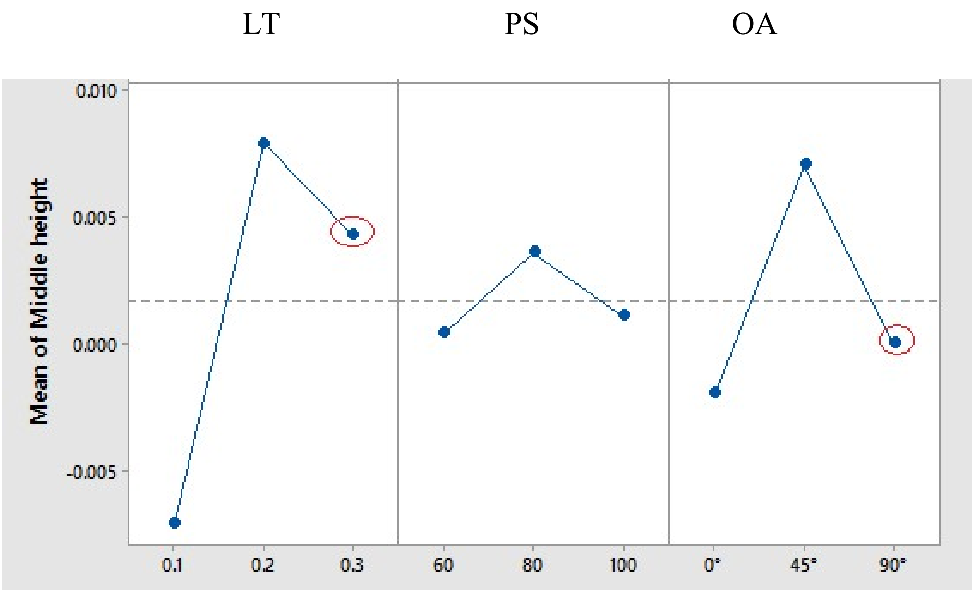

Fig 28: Main effects plot of factors for middle height

In Fig 28, we see that the minimum deviation in middle height is observed at level 3 of layer thickness i.e., 0.3mm and for factor C, lowest point at observed at an orientation angle of 90^0. The point is circled for easy observation. Factor B does not have any significant effect on the deviation from middle height.

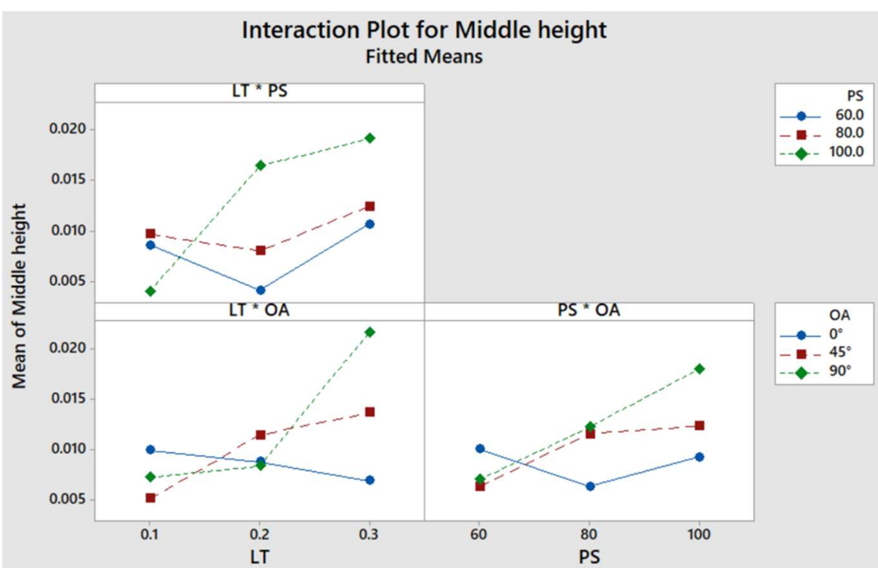

Fig 29: Two-way interaction plot of factors for middle height

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In Fig 29, for the two-way interaction LTXPS, the lowest deviation occurs at 0.1 mm of layer thickness and 100mm/sec of printing speed. For two-way interaction of PSXOA, the lowest deviation occurs at 80 mm/sec of printing speed and 0^0 of orientation angle. For two-way interaction of LTXOA, a lowest deviation occurs at the 0.1 mm of layer thickness and 45^0 of orientation angle. The lowest deviation points of all interactions are circled for easy observation in Fig 30.

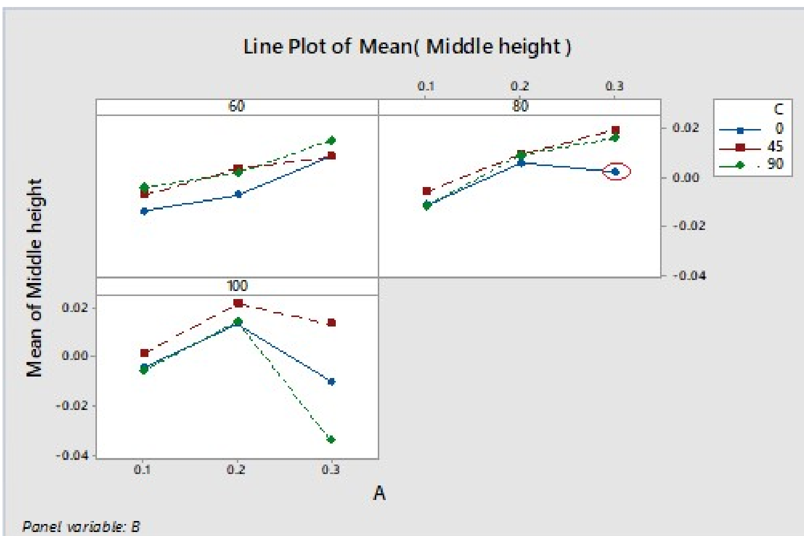

Fig 30: Three-way interaction plot of middle height

Three-way interaction plot in Fig 30 is also checked in order to determine the optimal factor levels. In review of the results of the three-way interaction, the least deviation is obtained at 0.3mm, 80mm/sec, 0^0.

The predicted mean response at the optimal condition is estimated only from the significant main or interaction effects. With LT, OA, LTXPS, LTXOA, PSXOA and LTXPSXOA as the significant factors, the regression equation reduces to:

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Deviation from middle height = 0.02763 - $0.00947A_3$ – $0.00267C_3$

- $0.00426A_2B_1$- $0.00709A_3C_3$ - $0.00105B_2C_1$ - $0.00436A_3B_2C_1$

4.6 Surface roughness

Factors/combinations affecting surface finish will only be discussed in this section. Our hypothesis is that all the factors and their interactions might have significant effects on the deviation in surface finish. Any factor with p-value less than or equal to 0.05 is considered to have a significant effect on the output in 95% confidence. The ANOVA results are represented in Table 13. With regards to adjusted R^2 , 76.45% of variation on the response, i.e., the deviation in surface finish can be explained by our model.

Table 13: ANOVA results for deviation in surface roughness

Source	DF	Adj SS	Adj MS	F-Value	P-Value
LT	2	5321.9	2660.94	54.03	0.000
PS	2	3977.7	1988.85	40.38	0.000
OA	2	21.7	10.85	0.22	0.803
LTXPS	4	1917.4	479.35	9.73	0.000
LTXOA	4	594.9	148.73	3.02	0.027
PSXOA	4	558.1	139.53	2.83	0.034
LTXPSXOA	8	1528.9	191.11	3.88	0.001

S	R-sq	R-sq(adj)
7.01789	84.73%	76.45%

DF: Degrees of freedom; SS: Sum of squares; MS: a mean square of the error

In Table 13, we observe that all the combinations of factors have significant effects on the surface finish except for the main effect of the orientation angle.

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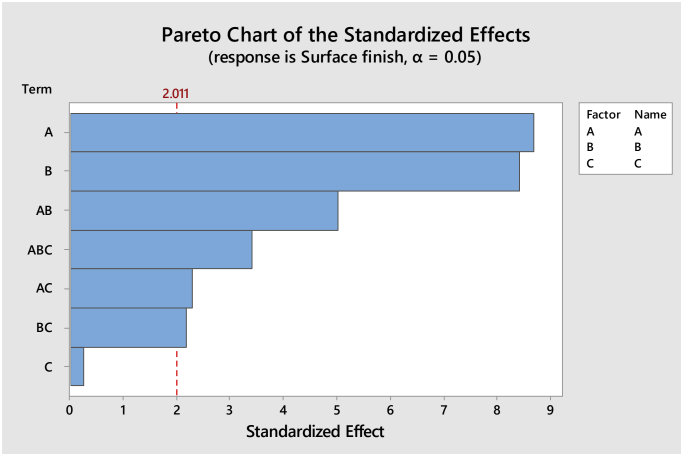

Fig 31: Pareto chart of Standardized effects for surface finish

Fig 31 shows the normal effect plot of standardized effects that help us examine the magnitude and direction of effects as Pareto chart displays only the absolute value of the effects. On the Pareto chart in Fig 31, bars that cross the reference line are statistically significant. In the above Pareto chart, the bars cross the reference line that is at 2.011ARE significant. These factors are statistically significant at the 0.05 significance level with the current model terms.

4.6.1. Main effect and interaction plots

Having identified the significant factors, the next step is to determine the optimal settings of the factors. Main effects and interaction plots will assist us in finding the optimal level of significant factors on the mean response, i.e., surface finish. Fig 32 illustrates the main effect plots of all the three factors on the mean response of surface finish. Only factors A and B have significant main effects on the response. The output values of surface roughness are not deviated values as dimensional features. The desired surface roughness value of the part depends on the application. As this is a study to investigate how varying parameters affect the surface roughness, the lesser the surface

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roughness values the better is the finish on the parts. In Fig 32, we see that 0.1mm of layer thickness alone and 60mm/s of printing speed seem to have produced parts with lesser surface roughness.

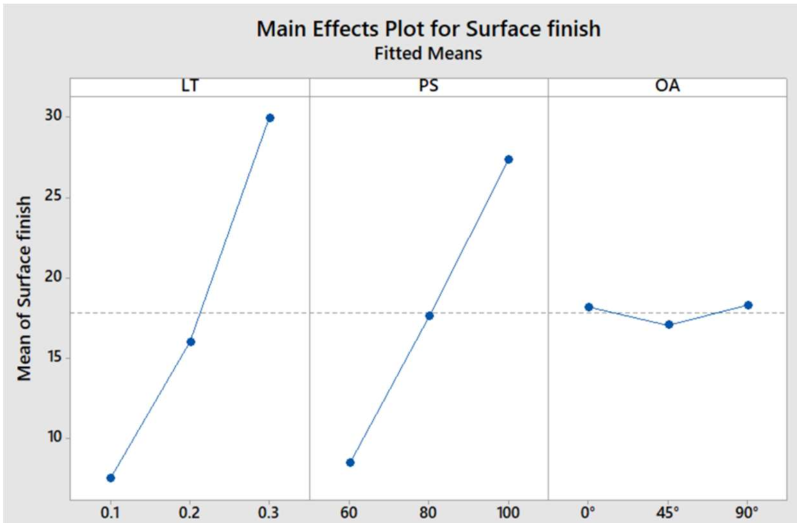

Fig 32: Main effect plots of factors for surface finish

Two-way interaction of factors has a significant effect on the surface finish. In Fig 33, for LTXPS, 0.1 mm of layer thickness and 60mm/s of printing speed, for LTXOA, 0.1mm of layer thickness and 45 deg of orientation angle, for PSXOA, 60mm/s of printing speed and 45 deg of orientation angle achieve minimum surface roughness.

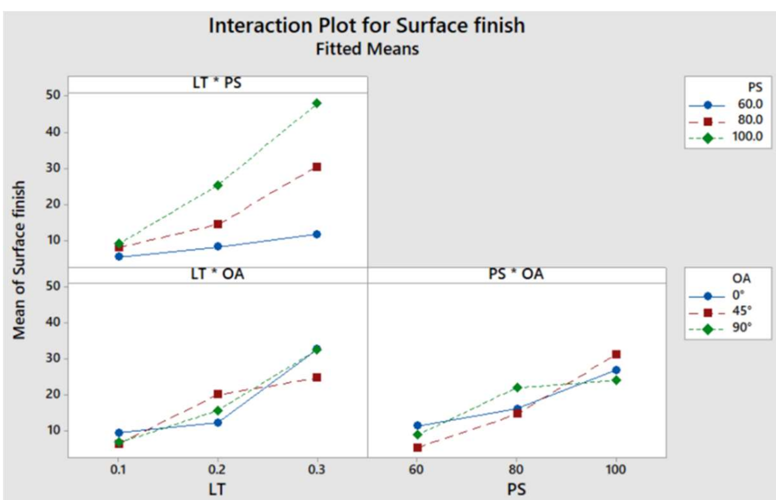

Fig 33: Two-way interaction plot of factors for surface finish

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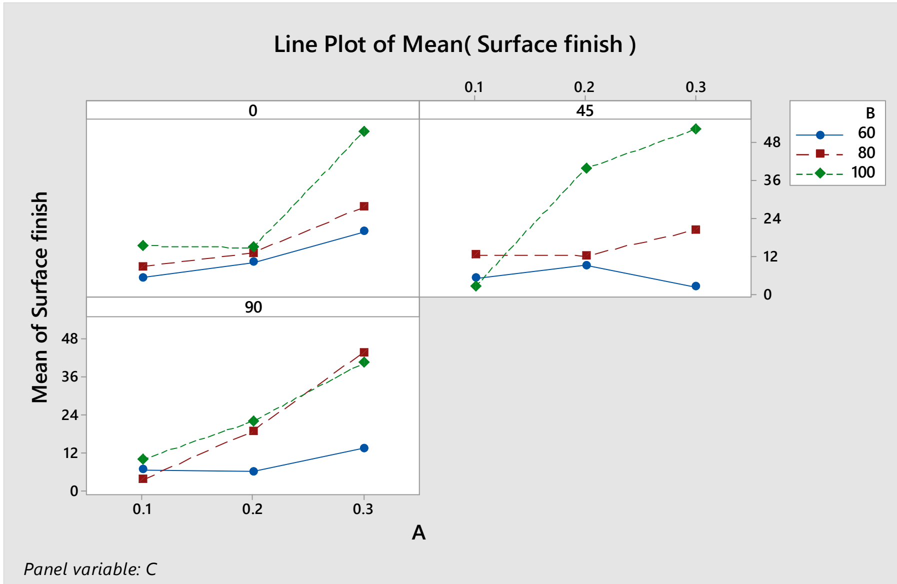

Fig 34: Three-way interaction for surface finish

The lowest values of surface finish are usually desirable; the points located closer to the 0 are considered. From Fig 34, the optimal factor levels are 0.1 mm layer thickness, 100mm/s printing speed and 45^0 orientation angle. As only the factor C doesn't have any effect on surface finish, the model design equation reduces to:

$$Y_{ijk} = \mu + A_i \text{ s } B_k + AB_{ij} + AC_{ik} + BC_{jk} + ABC_{ijk} + \varepsilon_{ijk}$$

Surface finish = 0.001716+ 0.002580 A_1 - 0.000605 B_1- 0.01391 A_1B_1 - 0.00362 A_1C_2 + 0.00568 B_1C_2 - 0.00738 $A_1B_2C_3$

4.7 Control charts

Control charts are plotted from the data of 30 parts to study how a process changes over time as the data will be plotted in a timely manner. The optimal level of factors obtained from ANOVA analysis are used to print another 30 parts to test if the process is in statistical control. Table 14 shows the measured height values of 30 parts. A control

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chart always has a central line for the average, an upper line for the upper control limit (UCL) and a lower line for the lower control limit (LCL) [60]. $\bar{X}$chart is one of the most common chart to monitor the change on the average of the process and the central tendency. If the process is under control, which means that the process is capable of producing an acceptable quality of interest, we expect the mean of the process to range between upper control limit (UCL) and lower control limit (LCL) of the $\bar{X}$ chart. If the sample mean $\bar{X}$ will fell beyond the control limits, the process average for the specified dimension is changed, and the process is incapable of printing the parts under desired tolerances. UCL and LCL of the $\bar{X}$ chart can be calculated as $UCL = \mu + k\frac{\sigma}{\sqrt{n}}$ and $LCL = \mu - k\frac{\sigma}{\sqrt{n}}$, where μ is the process mean, σ is the process standard deviation, *n* is the size of the sample which is taken to monitor if the process is in control, and *k* is the control limits distance from the process mean. A common choice for *k* is 3. The difference between a run chart and a control chart is that the run chart can help you spot upward and downward trends but lack the benefit of statistical control limits. However, a control chart plots a single line of data over time and it includes upper and lower control limit lines with a centerline.

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Table 14: Height measurement of 30 parts

Sample no	Height (mm)
1	0.998
2	0.999
3	0.998
4	0.996
5	0.997
6	1.000
7	1.001
8	1.006
9	1.002
10	1.000
11	1.003
12	1.000
13	1.001
14	1.009
15	1.000
16	0.998
17	1.002
18	0.992
19	0.998
20	1.000
21	0.999
22	1.000
23	1.000
24	1.007
25	1.002
26	1.000
27	1.003
28	0.998
29	1.003
30	0.999

Fig 35 shows the control chart of height measurement for 30 parts.

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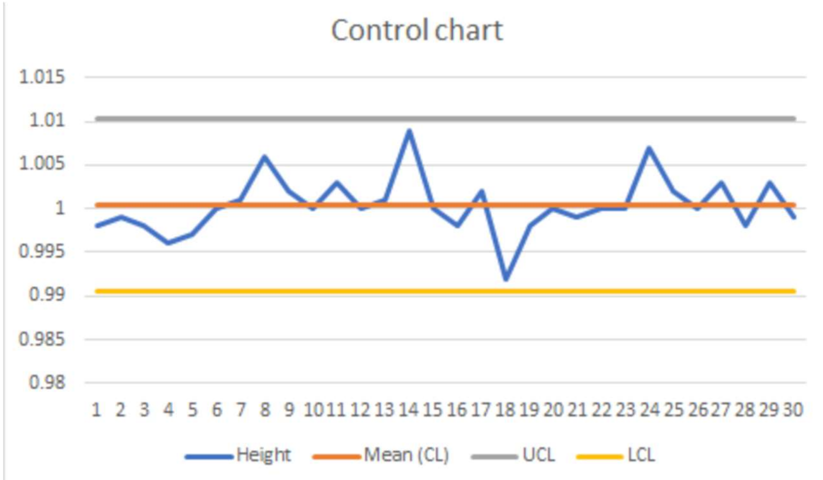

Fig 35: Control chart for the height measurements of 30 parts (UCL – 1.0101, LCL – 0.9904)

The purpose of a control chart is to monitor a process for the special causes of variation and to remove them when they occur. From Fig 34, the green line shows the average of the process. The process is under control because the sample averages lay between UCL and LCL and also they are equally distributed between UCL and average and the LCL and the average.

4.8 Process Capability Analysis

We have observed the factors/combination of factors that have significant effects on the response parameters based on ANOVA and main effects/interaction plots. In this section, we finalize the optimal levels of factors to print more parts to conduct capability analysis. The purpose of capability analysis is to check if the process is within the statistical control and the process is capable of meeting production specifications. Of all

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the response parameters available, optimal levels of factors having significant effects on height are considered to print 30 parts.

Recalling the analysis discussion of height, the optimal levels of factors from the main effect and interaction plots are 0.1mm of layer thickness, 80mm/s of printing speed. As the orientation angle doesn't have a significant effect on the height, any level of orientation angle can be used. Therefore, horizontal orientation i.e., 0^0 has been the chosen level.

4.8.1 Capability Studies

No two products are alike as the processes have many sources of variability. Different sources cause different changes - some cause short term, piece-to-piece and some cause changes over a long period. There are two types of causes responsible for variation, common causes, and special causes. Common causes produce a stable distribution in the system due to which the process is said to be in a state of statistical control. It affects the process output in predictable ways. Special causes refer to factors causing variation that affect only some of the process output in an intermittent and unpredictable way. Capability must be less than the tolerance to be acceptable for the production. If no special cause variation is found to be present, statistical process control (SPC) helps define the capability of the stable process to judge whether it is operating at an acceptable level. A process will produce conforming products as long as it remains in statistical control.

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The first step was to find the optimal level of factors capable of giving accurate results which are discussed in chapters 1 and 2. We printed 30 parts at optimal level of factors-0.1mm layer thickness, 80mm/s printing speed, and 0^0 orientation angle. Ppk (potential process capability) accounts for the overall variation of all measurements taken and it includes both the variation within subgroups and also the shift and drift between them. Capability analysis was conducted to determine the values of C_{pk} and P_{pk}, which are desired to be 1.33 or higher. C_{pk} is an index (a simple number) that measures how close a process is running to its specification limits, relative to the natural variability of the process. C_{pk} measures how close you are to your target and how consistent you are to around your average performance [60]. P_{pk} basically tries to verify the sample we generated from the process is capable to meet customer requirements. A capability analysis is conducted using the MINITAB software to find if the process is in statistical control. Fig 36 shows the capability analysis of height measurement of 30 PLA parts.

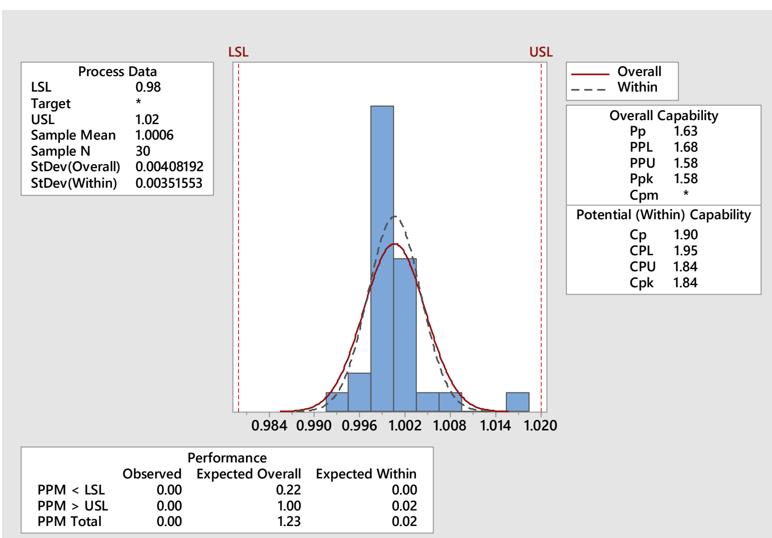

Fig 36: Capability histogram of 30 parts for height

C_{pk} values of 1.33 or greater are considered to be industry benchmarks [60]. By observing the Fig 35, C_{pk} and P_{pk} values are greater than 1.33, this process will produce

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conforming products as long as it remains in statistical control. When a process is in statistical control, it means that the adopted procedure is better for prototyping and also for the new product development, for which the cost of production for dies and other tooling is more expensive (like for biomedical applications) [61]. In the context of quality control, PPM stands for the number of parts per million that lie outside the tolerance limits. C_{pk} 1.00 means that 2700 PPM (0.27%) of the manufactured parts are out of tolerance, while C_{pk} 1.33 means that 63 PPM (0.0063%) are rejected.

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CHAPTER 5. CONCLUSION

The main objective of this thesis is to investigate the effect of factors on the dimensional features and surface finish of PLA parts printed using FFF technology. Literature review was done on studies that focused on factors affecting the dimensional accuracy and surface roughness of 3D printed parts. The review included different AM technologies, materials, part geometry, process parameters and different experiment set up. We chose FFF technology to print PLA parts (dog bone shaped specimen) with layer thickness, printing speed and orientation angle as the process parameters with three levels each. The optimal level of factors obtained from the experiment are used to print some more parts to check whether the process is in control. Then capability analysis is conducted to determine if the process can produce consistent conforming results. As a part of the literature review, extensive research was done before setting up an experiment. Various studies considering variability in dimensional accuracy, surface finish, mechanical properties, DOE's, and different experiment strategies were thoroughly reviewed. A literature review of different AM technologies and workable materials were very useful in setting up the experiment.

After an intensive literature review, we could conclude that layer thickness, fill angle, shell thickness, printing speed, orientation angle, AM technology, type of response parameters, type of material influenced the output parameters of printed parts such as dimensional accuracy. We attempted to combine most common factors from above which have not been done before to see if one factor might effect other factors i.e., to see if they are dependent on each other. Layer thickness, printing speed, and orientation angle are

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the factors that have been considered with three levels each in this study and are replicated thrice to study the consistency of the results. A full factorial DOE experiment was set up to investigate the effects of process parameters individually and in combination with rest of the factors. The output of this experiment considered the effect of these factors on dimensional accuracy and surface finish of parts built with PLA material(polymer) using FFF technology. Each set of experiments was replicated thrice, yielding 81 runs/prints.

As we focus on dimensional accuracy, measured values were subtracted from the desired nominal values and presented in Table 7. Considering "smaller the better" quality characteristics, the deviation is minimized to be able to comment on the effectiveness of the process parameters. We conclude that the 0.3mm layer thickness, 60mm/sec printing speed, and 45^0 orientation angle are the optimal levels for overall length. For height, 0.1mm layer thickness, 80mm/sec printing speed, and any level of orientation angle are found to be the optimal levels. For width, 0.2mm layer thickness, 60mm/sec printing speed and 0^0 orientation angle and for middle height, 0.3mm layer thickness, 80 mm/sec printing speed and 0^0 orientation angle are the optimal levels at which least deviation from the targeted values is observed.

Apart from the dimensional accuracy, the surface finish of the parts is measured and almost all the factors and their combinations have significant effects on the response parameter. An in-depth study and understanding are required to decide the levels of factors to achieve the desired accuracy in surface finish. For this particular response

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parameter, the values are not subtracted from any nominal value, because the parts are tensile testing specimens and they do not have a standard finish specification to get the deviated values. As such we just calculated how the values are affected by different levels of factors. From the response values of surface finish, we desired the least surface roughness values to determine the significant factors. The ideal factors in this study to achieve better surface finish is 0.1 mm layer thickness, 100 mm/s printing speed and 45^0 orientation angle.

After finding the significant factors and their levels for each response parameter, we printed 30 more parts to conduct capability studies and plot control charts to see the if the process with our concluded optimal levels will be in statistical control and capable of producing parts within specifications. We worked on parts focusing on height as the response parameter with optimal levels as 0.1mm layer thickness, 80mm/s of printing speed and 0^0 orientation angle. MINITAB software was used to conduct the process capability studies and we were able to achieve C_{pk} and P_{pk} values higher than 1.33 implying that the optimal levels we found were responsible for the process to be stable and acceptable. The control chart shows that the measured height values are within the upper control and lower control limits.

PLA parts are not just limited to prototypes, they have wide range of applications. Some of them include plastic films, bottles and biodegradable medical devices like screws, pins, rods. Also, PLA contracts under heat, so it can be used as shrink material. Therefore, experimental studies on PLA will provide better understanding of various design applications. Design of experiments are used to design an experiment with

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different variables to study their effect on the desirable output parameters. Once you understand the effect of factors, you optimize the experiment to prevent the variability caused by those factors. Process capability studies are conducted to check the consistency in bulk productions. The samples considered in this study may be different from actual requirement of samples in an industry. To test for accuracy and consistency of the results, capability analysis is conducted on the parts produced with optimal levels of factors from DOE. Work done as a part of this thesis is useful and can be applicable in different industrial sectors. The fact that it considers multiple factors and studies their effect on the output makes it applicable in real life complex manufacturing problems.

To optimize all the response parameters at once, one can extend this study by generating and minimizing the mathematical equations that incorporate the absolute deviated values of all the response parameters. Also, one can choose complex part geometry e.g., holes, threads, curvy surfaces etc., that might vary with different levels of factors and investigate how different the effects when compared to linear parts.

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References

1. Ligon, S. C., Liska, R., Stampfl, J., Gurr, M., & Mülhaupt, R. (2017). Polymers for 3D printing and customized additive manufacturing.

2. Lieneke, T., Denzer, V., Adam, G. A., & Zimmer, D. (2016). Dimensional tolerances for additive manufacturing: Experimental investigation for Fused Deposition Modeling. Procedia CIRP, 43, 286-291.

3. Gu, P., & Li, L. (2002). Fabrication of biomedical prototypes with locally controlled properties using FDM. CIRP Annals-Manufacturing Technology, 51(1), 181-184.

4. Fahad, M., & Hopkinson, N. (2017). Evaluation and comparison of the geometrical accuracy of parts produced by sintering-based additive manufacturing processes. *The International Journal of Advanced Manufacturing Technology*, *88*(9-12), 3389-3394.

5. Ippolito, R., Iuliano, L., & Gatto, A. (1995). Benchmarking of rapid prototyping techniques in terms of dimensional accuracy and surface finish. *CIRP Annals-Manufacturing Technology*, *44*(1), 157-160

6. Singh, R. (2014). Process capability analysis of fused deposition modeling for plastic components. *Rapid Prototyping Journal*, *20*(1), 69-76 Das, P., Chandran, R., Samant, R., & Anand, S. (2015). Optimum part build orientation in additive manufacturing for minimizing part errors and support structures. *Procedia Manufacturing*, *1*, 343-354.

7. Nidagundi, V. B., Keshavamurthy, R., & Prakash, C. P. S. (2015). Studies on parametric optimization for fused deposition modeling process. *Materials Today: Proceedings*, *2*(4-5), 1691-1699.

8. Vishwas, M., & Basavaraj, C. K. (2017). Studies on Optimizing Process Parameters of Fused Deposition Modelling Technology for ABS. *Materials Today: Proceedings*, *4*(10), 10994-11003.

9. Anitha, R., Arunachalam, S., & Radhakrishnan, P. (2001). Critical parameters influencing the quality of prototypes in fused deposition modeling. *Journal of Materials Processing Technology*, *118*(1-3), 385-388.

10. Bakar, N. S. A., Alkahari, M. R., & Boejang, H. (2010). Analysis of fused deposition modeling performance. *Journal of Zhejiang University-Science A*, *11*(12), 972-977.

11. Frazier, W. E. (2014). Metal additive manufacturing: a review. *Journal of Materials Engineering and Performance*, *23*(6), 1917-1928.

12. Murr, L. E., Gaytan, S. M., Ramirez, D. A., Martinez, E., Hernandez, J., Amato, K. N., & Wicker, R. B. (2012). Metal fabrication by additive manufacturing using

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laser and electron beam melting technologies. *Journal of Materials Science & Technology*, *28*(1), 1-14.

13. B. Valentan et al (2013) Processing poly (ether ether ketone) on a 3d printer for thermoplastic modeling Materiali Technologies, 47 (6), pp. 715-721

14. Stansbury, J. W., & Idacavage, M. J. (2016). 3D printing with polymers: Challenges among expanding options and opportunities. *Dental Materials*, *32*(1), 54-64.

15. Dawoud, M., Taha, I., & Ebeid, S. J. (2016). Mechanical behavior of ABS: An experimental study using FDM and injection molding techniques. *Journal of Manufacturing Processes*, *21*, 39-45.

16. Górski, F., Kuczko, W., & Wichniarek, R. (2013). Influence of process parameters on the dimensional accuracy of parts manufactured using Fused Deposition Modelling technology. *Advances in Science and Technology Research Journal*, *7*(19), 27-35.

17. Dul, S., Fambri, L., & Pegoretti, A. (2016). Fused deposition modeling with ABS–graphene nanocomposites. *Composites Part A: Applied Science and Manufacturing*, *85*, 181-191.

18. Moroni, G., Syam, W. P., & Petro, S. (2014). Towards early estimation of part accuracy in additive manufacturing. *Procedia CIRP*, *21*, 300-305.

19. Hällgren, S., Pejryd, L., & Ekengren, J. (2016). 3D data export for Additive Manufacturing-improving geometric accuracy. *Procedia CIRP*, *50*, 518-523.

20. Žarko, J., Vladić, G., Pál, M., & Dedijer, S. (2017). Influence of printing speed on the production of embossing tools using FDM 3d printing technology. *Journal of Graphic Engineering and Design*, *8*(1), 19.

21. Galantucci, L. M., Lavecchia, F., & Percoco, G. (2009). An experimental study aiming to enhance the surface finish of fused deposition modeled parts. *CIRP Annals*, *58*(1), 189-192.

22. Surface roughness estimation for FDM systems - Behnam Nourghassemi – Master's thesis, A thesis presented to Ryerson university.

23. Garg, A., Bhattacharya, A., & Batish, A. (2016). On surface finish and dimensional accuracy of FDM parts after cold vapor treatment. *Materials and Manufacturing Processes*, *31*(4), 522-529.

24. Sheydaeian, E., Fishman, Z., Vlasea, M., & Toyserkani, E. (2017). On the effect of throughout layer thickness variation on properties of additively manufactured cellular titanium structures. *Additive Manufacturing*, *18*, 40-47.

المنارة للاستشارات
www.manaraa.com

25. B.Sagomonyants, K. B., Jarman-Smith, M. L., Devine, J. N., Aronow, M. S., & Gronowicz, G. A. (2008). The in vitro response of human osteoblasts to polyetheretherketone (PEEK) substrates compared to commercially pure titanium. *Biomaterials*, *29*(11), 1563-1572.

26. Das, P., Chandran, R., Samant, R., & Anand, S. (2015). Optimum part build orientation in additive manufacturing for minimizing part errors and support structures. *Procedia Manufacturing*, *1*, 343-354.

27. Kurtz, S. M., & Devine, J. N. (2007). PEEK biomaterials in trauma, orthopedic, and spinal implants. *Biomaterials*, *28*(32), 4845-4869.

28. Huang, S. H., Liu, P., Mokasdar, A., & Hou, L. (2013). Additive manufacturing and its societal impact: a literature review. *The International Journal of Advanced Manufacturing Technology*, *67*(5-8), 1191-1203.

29. Vaezi, M., & Yang, S. (2015). Extrusion-based additive manufacturing of PEEK for biomedical applications. *Virtual and Physical Prototyping*, *10*(3), 123-135.

30. A Quick history of Design of Experiments (DOE) – https://newonline courses.science.psu.edu/stat503/node/6

31. Huang, S. H., Liu, P., Mokasdar, A., & Hou, L. (2013). Additive manufacturing and its societal impact: a literature review. *The International Journal of Advanced Manufacturing Technology*, *67*(5-8), 1191-1203.

32. Maghsoodloo, S., Ozdemir, G., Jordan, V., & Huang, C. H. (2004). Strengths and limitations of Taguchi's contributions to quality, manufacturing, and process engineering. *Journal of Manufacturing Systems*, *23*(2), 73-126.

33. Dilberoglu, U. M., Gharehpapagh, B., Yaman, U., & Dolen, M. (2017). The Role of Additive Manufacturing in the Era of Industry 4.0. *Procedia Manufacturing*, *11*, 545-554.

34. Masood, S. H., Mau, K., & Song, W. Q. (2010). Tensile properties of processed FDM polycarbonate material. In *Materials Science Forum* (Vol. 654, pp. 2556-2559). Trans Tech Publications.

35. Griffiths, C. A., Howarth, J., De Almeida-Rowbotham, G.Rees, A., & Kerton, R. (2016). A design of experiments approaches for the optimization of energy and waste during the production of parts. *Journal of cleaner production*, *139*, 74-85.

36. Kumar, S., Kannan, V. N., & Sankaranarayanan, G. (2014). Parameter optimization of ABS-M30i Parts produced by fused deposition modeling for minimum surface roughness. *International Journal of Current Engineering and Technology*, *3*, 93-97.

المنارة للاستشارات

www.manaraa.com

37. Chang, D. Y., & Huang, B. H. (2011). Studies on profile error and extruding aperture for the RP parts using the fused deposition modeling process. *The International Journal of Advanced Manufacturing Technology*, *53*(9-12), 1027-1037.

38. Sood, A. K., Ohdar, R. K., & Mahapatra, S. S. (2010). Grey Taguchi method for improving the dimensional accuracy of FDM process. AIMS International Conference on Value-based Management, August 11-13, 2010

39. Melenka, G. W., Schofield, J. S., Dawson, M. R., & Carey, J. P. (2015). Evaluation of dimensional accuracy and material properties of the MakerBot 3D desktop printer. *Rapid Prototyping Journal*, *21*(5), 618-627.

40. Lee, P. H., Chung, H., Lee, S. W., Yoo, J., & Ko, J. (2014, June). Dimensional accuracy in additive manufacturing processes. In *ASME 2014 International Manufacturing Science and Engineering Conference collocated with the JSME 2014 International Conference on Materials and Processing and the 42nd North American Manufacturing Research Conference* (pp. V001T04A045-V001T04A045). American Society of Mechanical Engineers.

41. Antony, J., Hughes, M., & Kaye, M. (1999). Reducing manufacturing process variability using experimental design technique: a case study. *Integrated manufacturing systems*, *10*(3), 162-170.

42. Turner, B. N., & Gold, S. A. (2015). A review of melt extrusion additive manufacturing processes: II. Materials, dimensional accuracy, and surface roughness. *Rapid Prototyping Journal*, *21*(3), 250-261.

43. Montgomery, D.C. (2009). Design and Analysis of Experiments (7th ed.). Hoboken, NJ: John Wiley and Sons Publishers. ISBN: 9780470128664.

44. Kirk, R. E. (1982). *Experimental design*. John Wiley & Sons, Ltd.

45. Lochner, R. H., & Matar, J. E. (1990). *Designing for quality: an introduction to the best of Taguchi and western methods of statistical experimental design*. Springer.

46. Giesbrecht, F. G., & Gumpertz, M. L. (2004). Completely randomized design. *Planning, Construction, and Statistical Analysis of Comparative Experiments*, 13-27.

47. Huynh, H., & Feldt, L. S. (1976). Estimation of the Box correction for degrees of freedom from sample data in the randomized block and split-plot designs. *Journal of educational statistics*, *1*(1), 69-82.

48. Fraley, S., Oom, M., Terrien, B., & Date, J. Z. (2006). Design of experiments via Taguchi methods: orthogonal arrays. *The Michigan chemical process dynamic and controls open text book, USA*, *2*(3), 4.

المنارة للاستشارات

www.manaraa.com

49. Wilk, M. B. (1955). The randomization analysis of a generalized randomized block design. *Biometrika*, *42*(1/2), 70-79.

50. Tanco, M., Viles, E., Ilzarbe, L., & Álvarez, M. J. (2007, July). Manufacturing industries need Design of Experiments (DoE). In *World Congress on Engineering* (pp. 1108-1112).

51. Emerson, R. M. (1954). Deviation and rejection: An experimental replication. *American Sociological Review*, *19*(6), 688-693.

52. Barlow, D. H., Andrasik, F., & Hersen, M. (2007). *Single case experimental designs*. London: Allyn and Bacon.

53. Chen, J., Sun, D. X., & Wu, C. F. J. (1993). A catalog of two-level and three-level fractional factorial designs with small runs. *International Statistical Review/Revue Internationale de Statistique*, 131-145.

54. Ahn, S. H., Montero, M., Odell, D., Roundy, S., & Wright, P. K. (2002). Anisotropic material properties of fused deposition modeling ABS. *Rapid prototyping journal*, *8*(4), 248-257.

55. https://www.itl.nist.gov/div898/handbook/pri/section3/pri339.html

56. http://www.harrisonep.com/electropolishing-ra.html

57. Design of an experiment to analyze the effect of input parameters on thermal stress and deformation in overhanging part features created with SLM Additive manufacturing process by Albert E Patterson V.

58. Wu, H. C., & Chen, T. C. T. (2018). Quality control issues in 3D-printing manufacturing: a review. *Rapid Prototyping Journal*, *24*(3), 607-614.

59. Han Chen (2015). A Process modeling and parameters optimization and recommendation system for Binder Jetting Additive Manufacturing Process. A thesis submitted to McGill University.

60. Wachs, S., & Wachs, A. (2011). Process Capability Indices: Common Misapplications. *Manufacturing Engineering*, *147*(2), 10-10.

61. Barclift, M. W., & Williams, C. B. (2012, August). Examining variability in the mechanical properties of parts manufactured via polyjet direct 3D printing. In *International Solid Freeform Fabrication Symposium* (pp. 6-8). Austin, Texas: the University of Texas at Austin.

62. Lužanin, O., Movrin, D., & Plančak, M. (2014). Effect of layer thickness, deposition angle, and infill on maximum flexural force in FDM-built specimens. *Journal for Technology of Plasticity*, *39*(1), 49-58.

المنارة للاستشارات
www.manaraa.com

63. Velineni, Anusha & Gunay, Elcin & Park, Kijung & Kremer, Gül & Schnieders, Thomas & Stone, Richard. (2018). *An Investigation on Selected Factors that Cause Variability in Additive Manufacturing*.

www.manaraa.com