PREDICTIVE ANALYSIS OF FUSED DEPOSITION MODELLING OF PLA MATERIAL THROUGH MACHINE LEARNING

A Thesis Submitted

In partial fulfilment for the award of the degree of

Master of technology

In

Production Engineering

SUBMITTED BY

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(2K20/PIE/04)

UNDER THE GUIDANCE OF

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CANDIDATE'S DECLARATION

I, HARDIK BISHT, hereby certify that the work which is being presented in this thesis entitled "PREDICTIVE ANALYSIS OF FUSED DEPOSITION MODELLING OF PLA MATERIAL THROUGH MACHINE LEARNING" being submitted by me is an authentic record of my own work carried out under the supervision of Prof. A. K. Madan, Department of Mechanical Engineering, Delhi Technological University, Delhi.

The matter presented in this thesis has not been submitted in any other University/Institute for the award of M.Tech Degree.

HARDIK BISHT

(2K20/PIE/04)

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It is a matter of great pleasure for me to present my dissertation report on "PREDICTIVE ANALYSIS OF FUSED DEPOSITION MODELLING OF PLA MATERIAL THROUGH MACHINE LEARNING". First and foremost, I am profoundly grateful to my guide Prof. A.K. Madan, Mechanical Engineering Department for their expert guidance and continuous encouragement during all stages of thesis. I feel lucky to get an opportunity to work with them. Not only understanding the subject, but also interpreting the results drawn thereon from the graphs was very thought provoking. I am thankful to the kindness and generosity shown by them towards me, as it helped me morally complete the project before actually starting it.

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Finally, and most important, I would like to thank my family members for their help, encouragement and prayers through all these months. I dedicate my work to them.

DATE: **HARDIK BISHT**

PLACE: **(2K20/PIE/04)**

CERTIFICATE

I, HARDIK BISHT, hereby certify that the work which is being presented in this thesis entitled "PREDICTIVE ANALYSIS OF FUSED DEPOSITION MODELLING OF PLA MATERIAL THROUGH MACHINE LEARNING" in the partial fulfilment of requirement for the award of degree of Masters of Technology in Production Engineering submitted in the Department of Mechanical Engineering, Delhi Technological University, Delhi is an authentic record of my own work carried out during a period from July 2021 to June 2022, under the supervision of Prof. A.K. Madan, Department of Mechanical Engineering, Delhi Technological University, Delhi.

The matter presented in this thesis has not been submitted in any other University/Institute for the award of M.Tech Degree.

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LIST OF ABBREVATIONS

ABBREVATIONS	DESCRIPTIONS
AM	Additive Manufacturing
CAD	Computer Aided Design
CAM	Computer Aided Manufacturing
FDM	Fused Deposition Modelling
ML	Machine Learning
STL	Stereolithography

CHAPTER 1
INTRODUCTION

1.1 ADDITIVE MANUFACTURING

ADDITIVE MANUFACTURING (AM) OR 3D Printing, the inception of the concept started very early in 1950s where material is fed and it come out through heated nozzle and solid and hardened according the need of design but in 2000s it started to rise with fast pace as the patent of FDM expire in 2009 and various technique get mature and with time the it get more affordable that now nit only it use in prototyping but also replace some part in finished product.

It is an enhanced manufacturing technology that has given the manufacturing industry a new perspective. In contrast to subtractive manufacturing methods, AM refers to a group manufacturing process that fabricates parts and products by adding layer by layer. Computer systems, 3D modelling software (Computer Aided Design), and slicing software are used in this type of manufacturing process.

New products, prototyped models, pre-surgical models, and conceptual models all benefited from AM technology. This technique is being used in a variety of technical and manufacturing areas, including aviation, fashion industry, medical implants, and automotive items. With increased global competitiveness, designers and production engineers must produce items faster than ever before to meet client demands and maintain a competitive advantage. Because no tooling is required, the AM process is a cost-effective way to manufacture complex geometries and reduce development and manufacturing cycle time.

Lot of companies now working on it to make it more cost effective either in process basis or product basis and other aspect is to use new metal in 3d printing to make it more competitive when we produce them in conventional method

1.1.1 AM PROCESS CHAIN

AM usually has 8 different type of process as you can see it in figure 1.1. Generally all type of AM follow same type of process sometime in different sequence

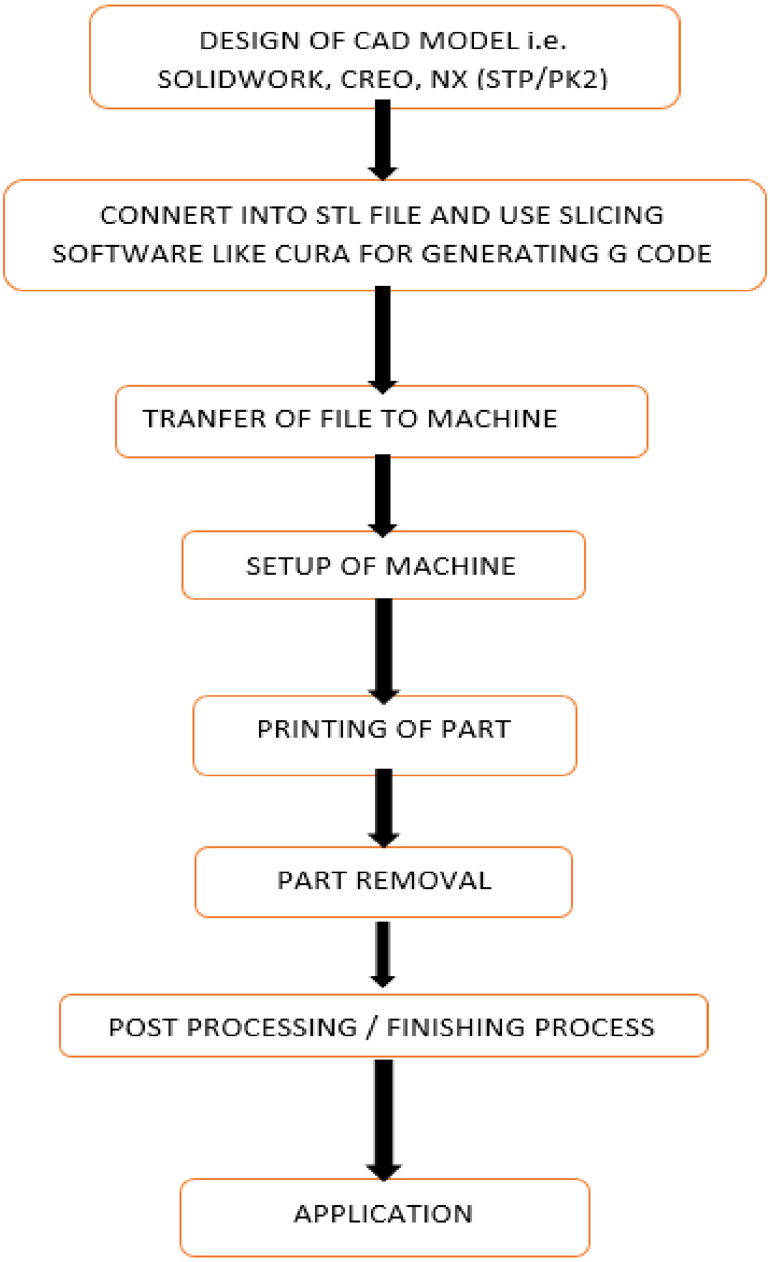


Fig. 1.1. Steps in AM process

STEP 1: CAD MODEL

The initial stage in of product development is to decide a design concept according to the need and feedback i.e how the product is going and function. A generic AM procedure must begin with 3D CAD data. Sophisticated CAD solid modelling software is required for this. This representation be done with other process like reverse engineering

STEP 2: CONVERTING TO STL FILE

This stage converts the CAD model to an AM format which the machine can understand. Almost all AM technologies now employ the STL file format, which is evolved from StereoLithograhy, 3D Systems' initial commercial AM technology from the 1990s. All building data and modelling information are removed at this point, leaving only the surfaces of the item to be modelled by a series of triangular facets.

STEP 3: TRANSFERING TO MACHINE & MANIPULATION

After generating the STL file, it is delivered directly to a specific AM machine. After part verification, AM systems normally allow the user to view and modify the part. Repositioning or changing the orientation of a part to permit it to be produced at a certain location inside the machine is a common example of manipulation.

Step 4: MACHINE SETUP (forming G-CODE)

The following phase is machine setup, which includes both software plus physical preparation. The user may need to manually set building settings like as layer thickness, speed, and material loading on occasion. When completing physical preparation, the controller must ensure that the machine has enough build material to complete the build.

STEP 5: PRINTING OF PART

The AM machine will normally complete the build automatically. The part is created layer after layer in different methods until the entire procedure is completed during this step. The AM machine's output should, in concept, be ready to use with minimal operator intervention.

STEP 6: REMOVAL OF PART

The printed material is stick in bed after printing, it has to be removed as well as in some closed chamber machine where bed temperature is controlled safety hatch has to be removed.

Step 7: POST PROCESSING/FINISHING PROCESS

Before they become ready to use, the built portion may require some more cleaning. This involves the removal of any supporting features or materials in the area. As a result, it frequently necessitates patience and skilled finishing

Step 8: PART APPLICATION

The components can be used for it function. They may, however, require further treatment before suitable for usage. They may, for example, require priming as well as painting to get a satisfactory exterior texture and finish. If the finishing standards are extremely complicated, treatment may be difficult and time-consuming. They may also need to be combined with other electronic or mechanical components to come up with desired result

1.1.2 MAJOR TYPE OF AM PROCESS

In this research we are working only with FDM process but there are lot of process in AM differentiated on basis of their working principle and process

a) **Direct Energy Deposition**:

The basic principle used in the process is welding. As raw material in powder form or in wire with the help of laser or electron beam it melt the material at the precise location ,through this line by line part is built in closed chamber. It fabricate very precise as well as tough part.

DED has the advantage of being able to do more than simply create items; it can also repair as well as add material to existing designs or preforms. It also has the capability of printing several materials in a single process.

b) **Laminated Object Manufacture (LOM)**

It fabrication is done by layer by layer as the stacking of material in form of sheet is done in first phase and after that they join together with the help of ultrasonic welding, brazing or adhesion . The part take shape as layer get added one by one. Further cutting of extra part is done with help of automated part with lamination to give final look

c) **Vat Polymerization**

It is identical to fused deposition except it use photopolymer resin that is ultraviolet rays sensitive as U.V ray impact the resin it will solidify. This principal is used to fabricate part as UV ray impact resin in shape of model layer by layer vat solidify and give finished part, the cost of resin is very high but it give very precise and smooth surface in part

d) Binder jetting:

Binder jetting, sometimes called material jetting, it most frequent techniques of AM.

This technology operates in the same way as a regular office printer, but it produces three-dimensional structures. Binder jetting blasts glue into a powder material instead of ink onto a page. With each pass, the print head turns horizontally and vertically, laying down a fresh layer of construction material.

1.2 EXTRUSION BASED PROCESS: FDM

FDM/FFF (Fused Deposition Modeling/Fused Filament Fabrication)

In this process material is received in machine in form of wire and it get heated in nozzle itself and get through it in very precise location where it get cool and fused with previous layer and by line by line it form one layer and with this whole model

FDM is the most utilized **AM** procedure .It help industry in product Conceptualize and product prototype presently it use as manufacturing for quick tooling and completed items in low and medium bunch. Because of its:

- It is simple to carry out
- It take less initial setup cost compared to other **AM**
- It required less material
- It can able to build huge part
- With this process fabrication is fast and cost effective
- It has wide reach application in aviation, biomedical, car, footwear industry and consumer industry

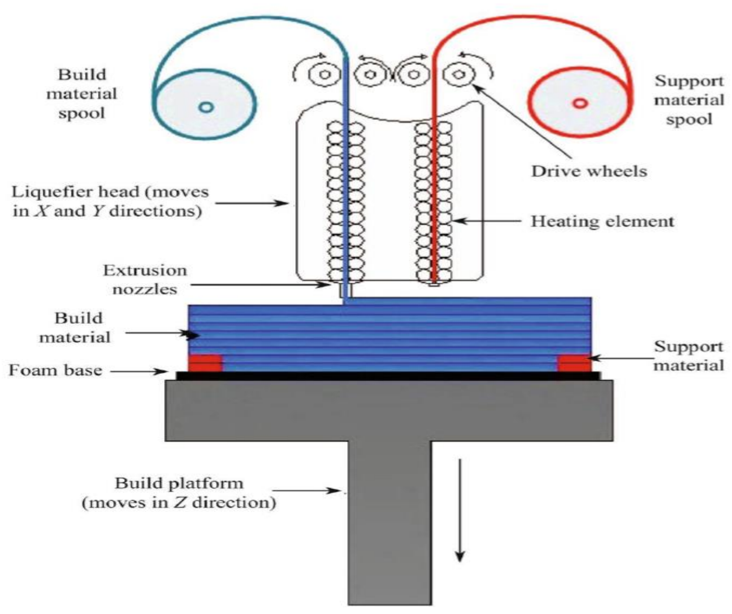


Fig. 1.2 Principal of FDM Process (Omar A Mohamed et al)

1.2.1 Parameter influencing the FDM process

The correct selection of process parameters is critical to the additive manufacturing framework's effectiveness. Process parameters are critical for ensuring product quality, improving dimensional precision, avoiding unacceptable wastes and excessive amounts of scrap, increasing productivity, and reducing manufacturing time and cost. The parameters affecting FDM manufactured pieces are shown in fig.

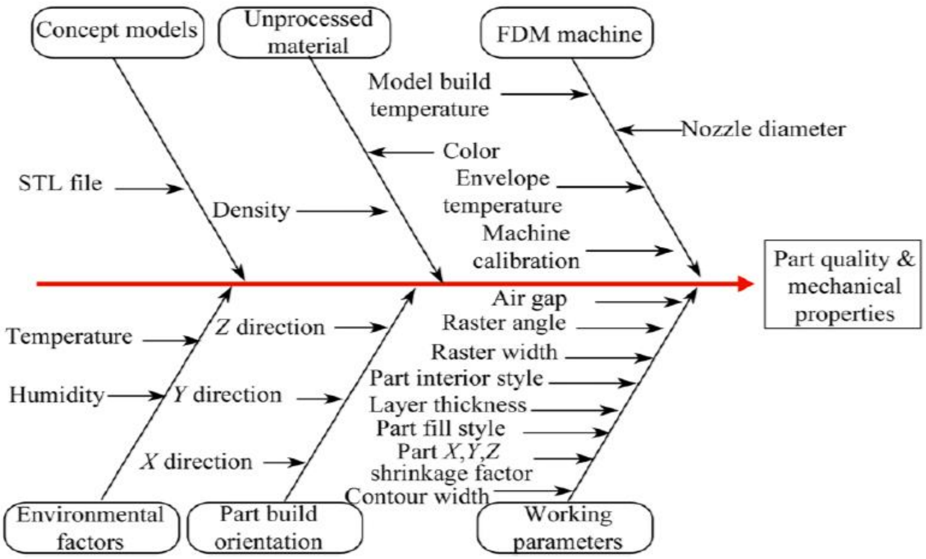


Fig. 1.3 Parameters influencing FDM process (Omar A Mohamed et al)

1.2.2 MACHINE SPECIFICATION

Fig 1.4 contain printer CADx-ARYA_UNO which is been used in our finding . it is manufactured by **CADX TOOLS AND TECHNOLOGIES Pvt. Ltd,** they are only **CE** and **ISO 9001:2015** certified manufacturer of 3D printers

Fig. 1.4 CADx-ARYA_UNO (3d printer used for research)

Table 1.1. Machine Specifications

S.No	Model specification	ARYA UNO+
1	Print Size/Build Volume	180 X 180 X 180 (mm)
2	Printing Resolution	100 microns
3	Number of Nozzles	Single (Can be extended to double)
4	Assisted Bed Levelling	-
5	Nozzle Type	Brass Material
6	Nozzle Maximum Temperature	Up to 300°C
7	Maximum Bed Temperature	100°C
8	Compatible Materials	PLA, ABS, PC- ABS, PET-G, etc.
9	Connectivity	SD-Card/ WiFi
10	Power Supply Input	Universal 100-240 VAC, 50/60 Hz, 5- 6 Amp
11	Interface	LCD Touch
12	Nozzle Diameter	0.4/0.6/0.8
13	Body material	Metal
14	Mechanics	Standard Cartesian X& Y Mechanism
15	Stepper motors	1.8-degree step angle
15	Slicing software plug and play	CURA
16	Filament diameter	1.75 mm

17	Change Filament	Yes
18	Input file	STL, .AMF

1.2.3 SLICING SOFTWARE

Cura is used for slicing 3D CAD objects. The G-codes for each layers to be printed are also generated by the cura programme. The desktop screenshot gallery of the slicing software

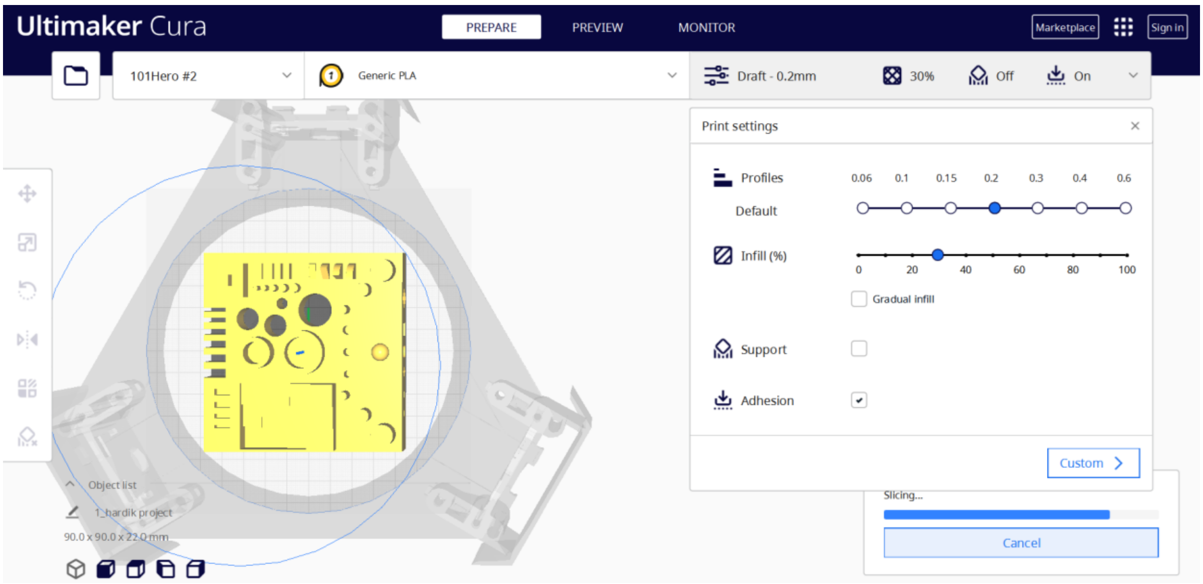


Fig. 1.5. ULTIMAKER CURA.V.5 slicing software

Table 1.2. Variable parameters options in ULTIMAKER CURA.V.5

Material	Infill percentage
Extrusion width	Shell (no of Loops)
Extrusion temperature	Bed Temperature
First layer thickness	Part Orientation
Infill style (straight, orthogonal, rounded)	Layer thickness
Infill Extrusion width	Deposition speed (perimeter, loop. Infill)

1.3 BENCHMARK COMPONENT

The benchmark geometry establishes a common ground for comparing and fine-tuning of diverse processes, and it includes certain features and dimensions that ensure that the operating capabilities are adequately assessed.

"A standard or point of reference in evaluating or judging quality, value, etc.," according to Webster's Dictionary. Benchmarking is used in additive manufacturing to compare not just the strength and weakness of parts, but also the precision, surface quality, repeatability, and resolution of the geometrical features of the parts produced. Benchmarking aids in the identification of "highest standards of excellence" for various products/processes, allowing for the subsequent modifications required to meet those levels. The three types of AM benchmarking are as follows

A part's geometric features are measured using a Geometric Benchmark (i.e. tolerances, accuracy, repeatability and surface finish).

Mechanical Benchmark is a tool for evaluating mechanical qualities (tensile strength, compressive strength, creep, etc.).

Process benchmarking is a technique for determining process-related metrics (part orientation, support structures, layer thickness, speed, etc.)

1.4 MACHIINE LEARNING (ML)

Machine learning is a branch of computer science and it come under artificial intelligence, ML is make programming system more independent as it learn and develop their own logic working on that program and making it self-sufficient come under ML domain. It contain finding the decision making pattern or attribute which ultimate help come to conclusion. To help this lot of algorithm is designed and still new are coming, with the help of logic, statistical science, probability and control theory

Typical ML program contain read part where data is interpreted and then able to find any distinct pattern, trend and their effect in outcome and after it trained, prediction on the basic of logic is done and with feedback system it get more refine iteration by iteration

The main aim is to learn or train the computer on the basis of developing logic

1.4.1 ML METHODS

The method are categorised in supervised or unsupervised

Supervised machine learning algorithms: in this the data which is feeded to the algorithm are categorised data so when algorithm find the pattern or attribute because of data is labelled it connect the pattern with it output and easily link and find relation for example if trained model contain all the gun data it can easily identify gun by it attribute like long cylinder, curve structure for holding like wise. After training it will forecast or show the dissimilarity between other data for improvement, it need lot of resources for data cleaning and labelling

Unsupervised machine learning methods: In this method, all data given to algorithm are not labelled, algorithm only classify data on basis of their similarity to each other, it able to find the hidden pattern or influence attribute to the front example of it is giving data set to algorithm of all type of object and let him differentiate on the basis of pattern, figure etc. it is used to address complicate data/big data

Semi supervised machine learning algorithm: Generally labelling of data take huge resource and it will not be economical. To overcome the problem this algorithm is used it is mixture of supervised and unsupervised, Here some data taken is supervised which help to find the critical pattern or logics and unsupervised help to find their susceptibility which help to increase overall accuracy of the system

Reinforcement machine learning algorithms: in this type of algorithm trial and error methods used many algorithm interact with its surrounding and help to make decision based on the reward system if the outcome is not correct no reward given but if its correct reward is given, it’s like a feedback system in similar way it will get better and better in every reward/feedback cycle.

In today’s world machine is collecting lot of data in form of information receiving or in form of GPS tracking or either KYC in bank. All the data if can be accessed and used to find the pattern lot of prediction in form of possibility can be done and also already it’s there in form of weather forecasting , stock market trend forecasting, robotics and pattern recognition

1.4.2 ML GENERIC STEPS

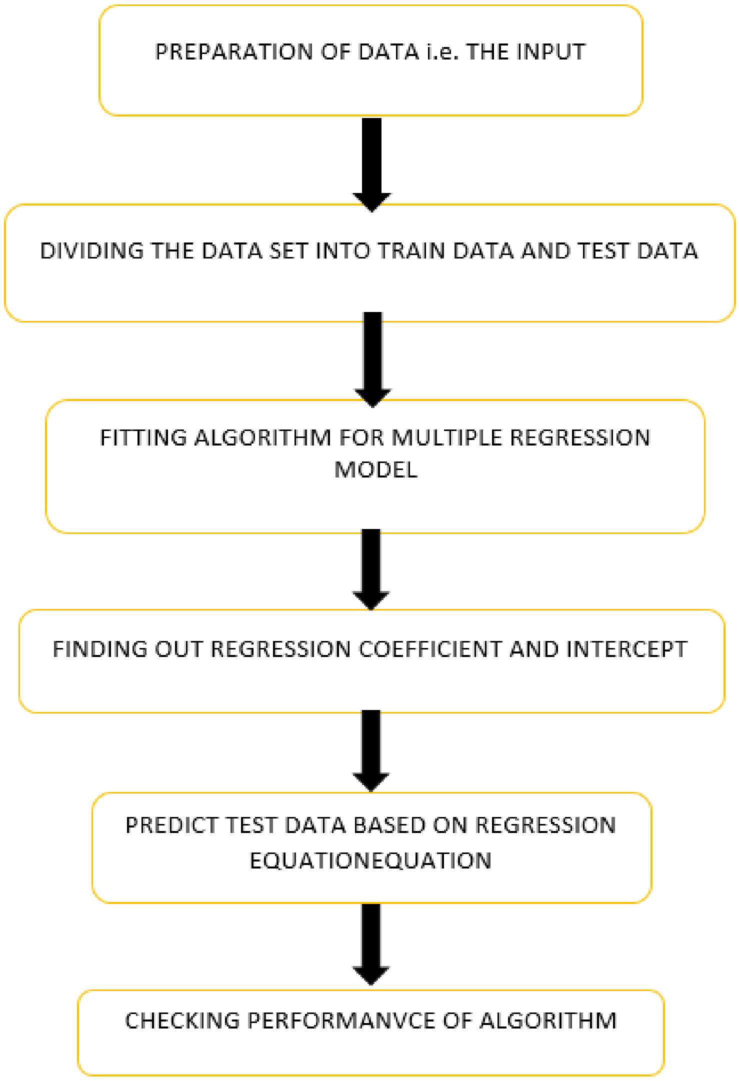


Fig. 1.6 Process Flow in ML for Analysis

1.4.3 PYTHON LANGUAGE

Python is a easy to learn as well as easily understandable language and very helpful for data analysing and data cleaning. It has lot of modules, packages, and libraries can help you to analyse lot of data easily. Although there are lot of libraries but most used libraries such as NumPy, SciPy, Scikit-Learn, and Matplotlib are used. They are vastly used in industry to produce scalable machine algorithm. Python library Sklearn has lot of machine learning techniques including classification, regression, and clustering. The basic goal of machine learning is to discover the pattern from the data it is feeded and predict the future outcome

Anaconda is a free software platform for scientific computing that uses the high-level computer languages Python and R. Python was chosen for Machine Learning (ML) technique because of its ease of learning and application. Python has modules and techniques that aid in predictive analytics.

During the coding process, the relevant Python libraries were used.

Pandas : A Python library that provides fast, simple data structures and data analysis capabilities.

Matplotlib: A plotting library python - Based.

Sklearn : Scikit-learn (previously scikits.learn) is a library of python which has inbuilt model of clustering regression technique

These libraries also have many functions that enable operations like to read a .csv file pd.read_csv (<file name>) command is used. Here Pd is an object for panda's library.

CHAPTER 2
LITERATURE SURVEY

S. L. Sing, C. N. Kuo, C. T. Shih, C. C. Ho & C. K. Chua (2021), explain the use of machine learning in laser powder bed fusion in metal printing due to high cost of material as well as complexity, ML can use the data at every stage of process from digital phase to manufacturing to post processing phase it can help to build better quality of product giving suggestion at every stage with the help of prior data set

The principles and numerous processes involved in the AM process were explained by K Satish Prakash et al (2018). This article provides a quick overview of all of the AM techniques that have been created over time, as well as the materials have and the fields of use. The authors also discussed the benefits, drawbacks, and potential future advances in the AM.

Shahrain Mahmood et al. (2018) used an experimental technique to evaluate the effects of changes in the FDM process parameters on the geometrical properties of the printed items. Simple geometric characteristics were included in the design of a benchmark component. However, only linear and circular features are available. The theoretical print settings were discovered after identifying the important process parameters impacting dimensional accuracy and geometrical qualities.

Experiments were conducted by Mahdi Kaveh et al. (2015) to identify the optimal amount of efficient printing parameters for HIPS materials. Extruded temperatures, feed rate, flow rate, and raster width are among the characteristics. Finally, calibrating factors of parts, slots, and thicknesses were computed using correct benchmarks and statistical formulae to reduce systematic inaccuracies between the specified and actual dimensions. This method can be used to determine the value of PPs for different substances or to optimise PPs for established materials like ABS or PLA where dimensional precision or internal cavity reduction are needed.

Alaaldin Alafaghani et al. (2017) conducted an experiment to look into the independent effects of every processing parameter just on mechanical qualities, dimensional accuracy, and repeatability of 3d printed parts. Using different processing conditions, a total of 18 test piece samples were produced. The measurements of these specimen was measured and compared to a 3D CAD model in order to study the repeatability and resulting tolerances. The mechanical properties of each generated sample are determined using a tensile test according to ASTM D638 guidelines. A Finite Element Analysis (FEA) model for AM parts is also included in the paper.

Paola Minetola et al. (2016) offered a comparative of industrial FDM and desktop FDM machines based on dimensional accuracy using a benchmarking part. The item provides a variety of basic geometries (planes, cylinders, spheres, and cones) in various sizes to cover the ISO 286 standard's basic size ranges. Furthermore, the component does not need support structures to be manufactured, allowing it to be printed on 3D printers with a unique extruder. The comparative machines produce replicas of the reference part out of ABS (acrylonitrile butadiene styrene) material with various layer thicknesses. The dimensional accuracy of the comparing FDM methods is reported through part quality after checking the replicas with a Coordinate Measuring Machine (CMM). Part quality utilising IT grades related with ISO basic sizes is used to report the dimensional correctness of the comparing FDM systems. For several of the geometric characteristics of the reference part, GD&T values are also examined.

Omar A Mohamed et al. (2015) examined the research done so far in establishing and optimising the FDM method's process parameters. A comparison is made between standard experimental design and optimization strategies. The report also identifies a number of important areas for further research in terms of optimising and characterising the FDM process and materials. Their investigation revealed that crucial process characteristics such as air gap, layer thickness, raster angle, raster width, and construction orientation must be researched and analysed in future research.

Finite Element Method (FEM) and Machine Learning (ML) approaches were used to analyse and optimise AM process parameters by Ivanna Baturynska et al (2018). ML is relies on a large amount of data, whereas FEM requires particular information. This paper presents a conceptual framework for avoiding these problems using a combination of mathematical modelling and machine learning.

Michael Sharp et al (2018) used NLP to search through a decade of manufacturing publications to estimate the application of machine learning and popular algorithms. It presented the manufacturing industry with current priority areas and gaps in machine learning applications. The research demonstrates that ML approaches have been used for a long time, but instead of using the term "machine learning," various terms were used in the research to indicate the same notion.

Using a geometrical benchmarking approach, Fabio Alberto Cruz Sanchez et al (2014) evaluated the creation, manufacture, and testing of geometrical correctness and performance of open source 3D printers (GBM). A series of nine tests was created using Taguchi's L9 orthogonal array. Layer thickness, raster width, and nozzle speed were the three control elements used to print the benchmarking model. The benchmarking features' geometrical deviations are measured and compared to the CAD model.

A study by Friendrich Bahr et al (2018) looked at the relationship between printing parameters and quality attributes for FDM printed items. This report discusses cutting-edge research on effect mechanisms during thermoplastic polymer extrusion in FDM. Mechanical attributes and geometric precision were studied in relation to machine and material factors, as well as process changes.

L M Galantucci and colleagues (2015) investigated the dimensional performance of a 3D open source printer using the FDM technology. An industrial system and an open-source system were used to evaluate and compare the benchmark, which was created using 3D FDM printers. Optimal process parameters for improving dimensional accuracy on rectangular test specimens were discovered using Design of Experiments (DOE), reducing variations in length, breadth, and height.

Dr Muhammad Fahad and Dr Neil Hopkinson (2012) investigated the various benchmarking parts and developed a new benchmarking part that not only incorporates all of the necessary features in a compact manner, but also allows for the measurement of feature repeatability by integrating the features in a symmetrical manner.

W M Johnson et al (2011) examined prior benchmarking methods and proposed a new strategy for evaluating an open - sourced AM system based on FDM. The suggested benchmarking model incorporates a number of geometric elements to assess the AM system's dimensional accuracy, thermal warpage3, staircase effect, and geometric and dimensional tolerances.

M N Islam et al. (2013) looked into the dimensional correctness of parts by looking at two types of errors: variation in linear dimension and variation in hole diameter. The results revealed that the 3D printing method has intrinsic size inaccuracies.

Nur Saaidah Abu Bakar et al. (2011) conducted experiments to determine the impact of varied FDM parameters on the test model they intended. Because the gantry system restricts the movement of the deposition head, they discovered that FDM is less accurate in producing circular holes.

A Gregorian et al (2011) used the benchmark "user part" to study the in-plane accuracy of FDM machines and demonstrated the effect of shrinkage on the accuracy of prototyped parts. The part's precision was impacted by the changing temperature and build speed during the process.

Anoop Kumar Sood et al (2010) studied the influence of five parameters on the dimensional accuracy of FDM printed parts: layer thickness, component construction orientation, raster angle, air gap, and raster width. It was discovered that shrinkage is most noticeable along the length and width of the test portion, whereas thickness is always more than the acceptable value.

A study by Lidong Wang and Cheryl Ann Alexander (2016) addressed the benefits, applications, and technological progress of additive manufacturing technology. They also discuss big data in additive technologies and big data analytics in their technical script. The report identifies domains where additive technology can be used, including aerospace, manufacturing, automotive, and medical industries. Part accuracy, surface finish, and production speed are all limits of AM. Big data analytics aids in the comprehension of additive technologies.

Lennart Bochmann and colleagues (2015) conducted research to identify the origins of imprecision in fused deposition modelling (FDM). Surface quality, accuracy, and precision process faults are found and quantified. It was discovered that in the y direction, accuracy and precision are often higher than in the x and z directions. Furthermore, if the axis position is increased, accuracy and precision tend to diminish.

According to studies by Mohammadhossein Amini and Shing I Chang (2018), 3D printing is one of the fastest developing technologies on the planet. Despite numerous advancements in technical capabilities, reliable metal printing remains a mystery. One of the challenges to the industrialization of AM technology is the monitoring of the AM process and product quality assurance.Their suggested framework attempts to prevent faults by employing data-driven methodologies and gives a blueprint for control tactics during the printing process.

According to Boschetto A and I. Bottini (2014), in order to use AM in the industrial setting, a set of theoretical and/or empirical formulations is required that allows for the prediction of attainable component quality in terms of surface roughness and accuracy. Their research focused on predicting dimensional variations of FDM-fabricated items as a function of process parameters such as layer thickness and deposition angle.

2.2 RESEARCH GAP

According to the literature, identifying important factors and determining optimum process parameters can lead to an improvement in the quality of FDM produced parts in terms of dimensional accuracy and surface roughness.

Individual optimization approaches have limitations; hence, combining optimization techniques such as statistical analysis with FEM, statistical analysis with ML, and ANN with ML can produce superior results. For example, DOE can help determine which parameters and combinations of parameters have the greatest impact on geometrical dimensions and mechanical qualities, which may then be fed into a machine learning system.

ML gives a mixture of values based on regression equations that predict the quality parameters of the part, whereas optimization techniques merely supply a set of optimum values.

2.3 OBJECTIVES OF THE PROJECT

- To choose a component for the benchmark.
- To print the benchmarking section, obtain the combination of input parameters.
- That's the input for the ML algorithm while preparing a data collection.
- To compare the algorithms' performance using anticipated and test data set values.
- To predict the unknown output, here it is dimensional accuracy when provided with the known input parameters without actually printing the components.

CHAPTER 3
METHODOLOGY

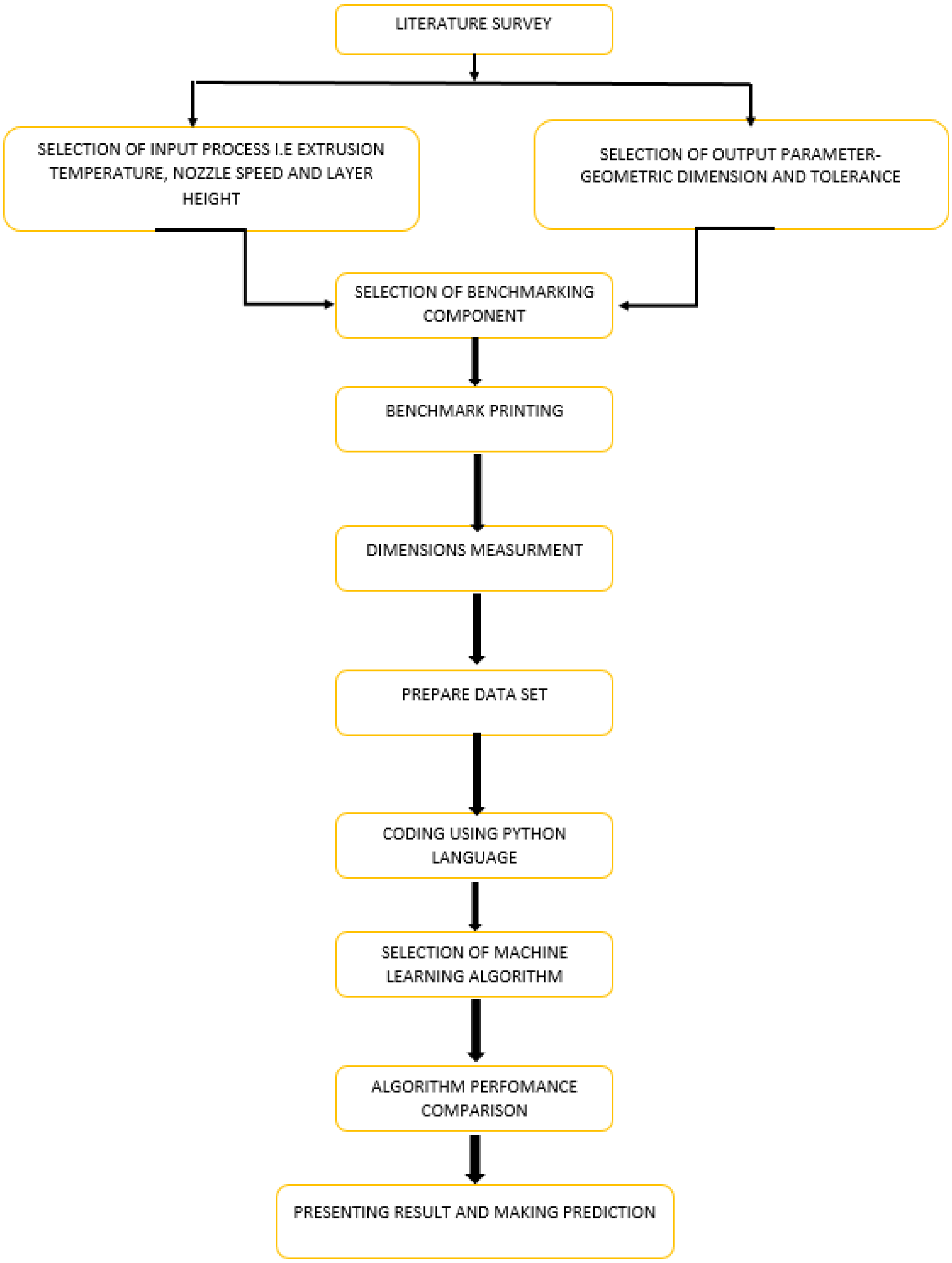


Fig. 3.1 Methodology Flow chart

CHAPTER 4

EXPERIMENTATION AND OBSERVATIONS

4.1 BENCHMARK COMPONENT

A benchmarking component was selected, fig. 4.1 [5] and CAD model was made using SOLIDWORKS, a 3D modelling software. Fig. 4.2 depicts the benchmarking CAD model

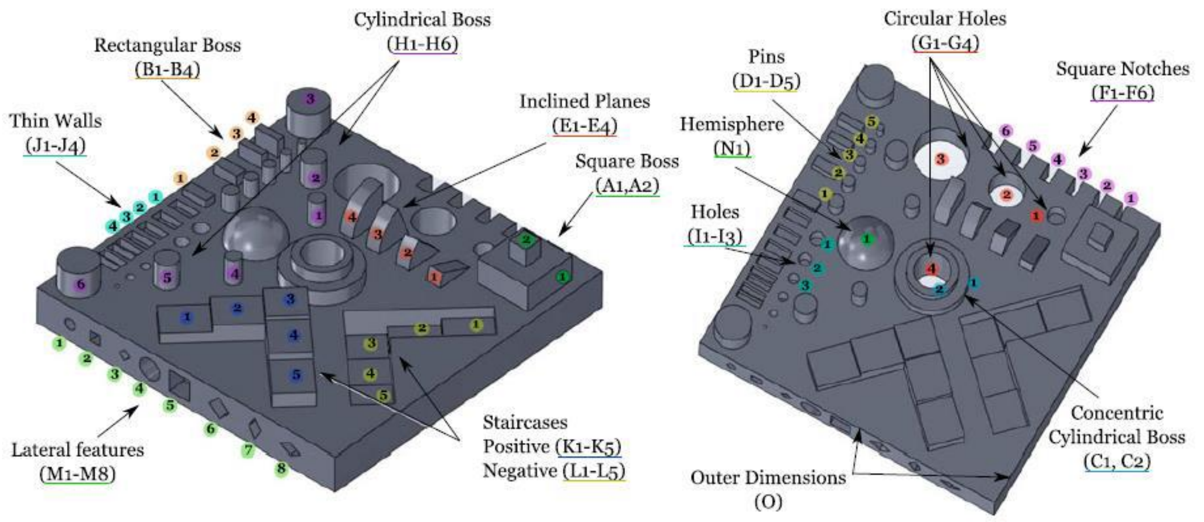
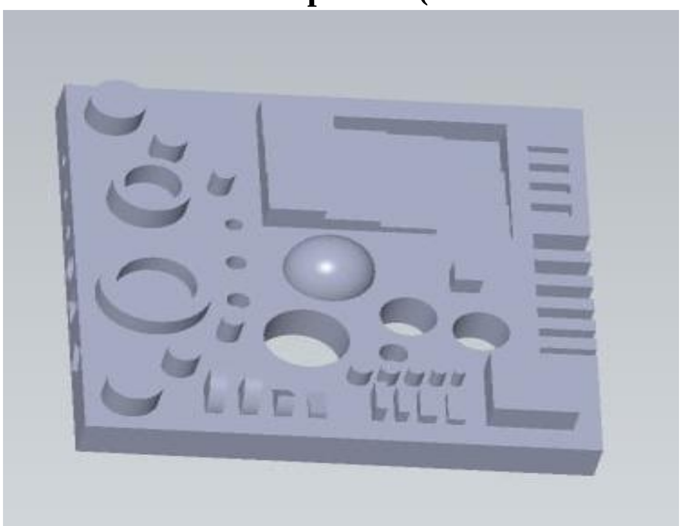


Fig. 4.1. Benchmark component (Fabio Alberto Cruz et al)



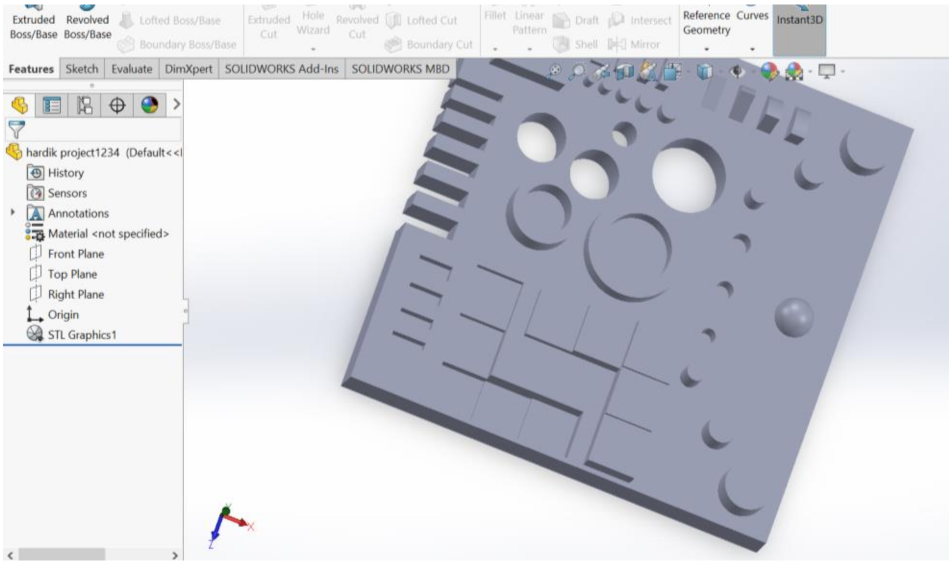


Fig. 4.2. Benchmark component designed in Solidwork

Table 4.1. Benchmark model features description

ID	Family of features	Features	Description (All dimensions in mm)
1	Boss(Square)	a1,a2	a1 = 15 x 15 x 7, a2 = 5 x 5 x 5
2	Boss(Rectangular)	b1,b2, b3, b4	b1 = 7 x 3 x 2, b2 = 7 x 3 x 3, b3 = 7 x 2 x 4, b4 = 7 x 2 x 5
3	Boss(Cylindrical)	c1,c2	c1 od = 20, id = 14, h = 5; c2 od = 14, id = 10, h = 7
4	Pins	d1,d2, d3,d4, d5	d1 = 4, d2 = 3.5, d3 = 3, d4 = 2.5, d5 = 2, h = 5

5	Notch	f1,f2,f3,f4,f5, f6	width, f1 = 1.5, f2 = 2, f3 = 2.5, f4 = 3, f5 = 3.5, f6 = 4
6	Cylindrical Holes	g1,g2, g3,g4	diameter, g1 = 5, g2 = 10, g3 = 15, g4 = 10
7	Cylindrical Boss	h1,h2,g3,g4,g5,h6	diameter, h1, h4 = 4; h2, h5 = 6; h3, h6 = 10; h = 7
8	Holes	i1,i2,i3	diameter, i1 = 4, i2 = 3.5, i3 = 3, depth = 5

ID	**Family of features**	**Features**	**Description (All dimensions in mm)**
9	Thin slot	J1,j2,j3, j4	wall thickness, j1 = 3, j2 = 2.5, j3 = 2, j4 = 1.5
10	Positive Staircase	k1,k2,k3,k4,k5	height, k1 = 2, k2 = 4, k3 = 5, k4 = 6, k5 = 7, l = 10, w = 10
11	Negative Staircase	l1,l2,l3, l4, l5	depth, l1 = 2, l2 = 4, l3 = 5, l4 = 6, l5 = 7, l = 10, w = 10
12	Lateral Feature	m1,m2, m3,m4, m5, m6	m1 = 3, m2 = 3 x 3, m3 = 3 x 3, m4 = 6, m5 = 6 x 6, m6 = 6 x 6, depth = 5
13	Hemisphere	n1	r = 8 mm
14	Overall dimension	o1	90 x 90 x 10

4.2 3D PRINTING OF BENCHMARK COMPONENT (Preliminary Experiment)

After studying all the factor effect, the following step was to put the benchmark design for 3d printing for preliminary in fig4.3

Fig. 4.3 printing part at preliminary stage

The process parameter are between the acceptable ranges of material, machine:

Based on material capability: Extrusion temperature (190-210) ^{0}C

Based on machine capability: Layer thickness (0.15-0.25) mm

: Nozzle speed (30-40) mm/s

While printing the part as trial version in extreme parameter. Lot of defected part are printed as shown in fig as first time while in printing it was seen that top layer thickness is 0.8 mm as well as fill density is 10% due to which there are lot of hole at top layer because top layer not able to sustain itself so infill density change to 20% and top layer change to .12 mm thickness , In other iteration the part is printed small cube is above the big cube due to placement of cube at corner side it not able to print so some modification is done in design and small cube is placed in middle of part and in third iteration extrusion temperature is 190 due to which PLA material not able to melt properly due to which it clogging the nozzle and the part is not print as machine able to move but not able to release material and after this it will be difficult start it with the same position

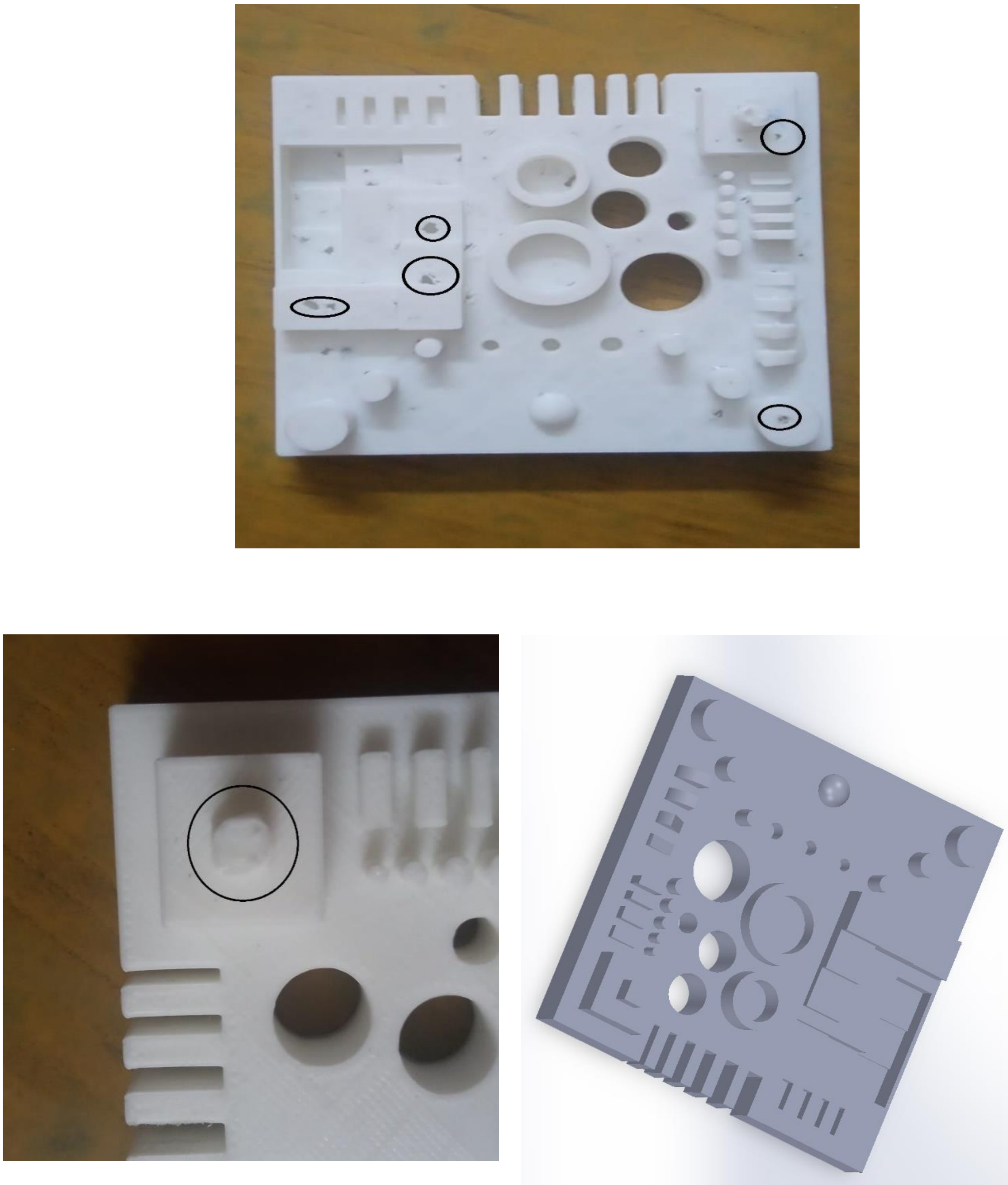


Fig 4.4 Failed printed and design components

4.3 Revised control and fixed Parameter

Table 4.2. Revised Control parameters

Control Factor	ID	LEVELS		
		1	2	3
Extrusion temperature (^oC)	A	195	200	205
Nozzle speed(mm/s)	B	30	35	40
Layer thickness(mm)	C	0.15	0.2	0.25

Table 4.3. Revised Fixed parameters

Parameter	Value	Parameter	value
Material	PLA(poly lactic acid)	Filament diameter	1.75mm
Infill	30%	Nozzle size	0.4mm
Support structure	NA	Flow %	100
First layer temperature	Same as printing temperature	Top/bottom layer thickness	0.12mm
Bed temp	50ºC		
Infill style	straight		

After setting the control & fixed parameters, L9 orthogonal array was selected to get a non-redundant combination of process parameter levels to study the printing of the geometric benchmarking component

Table 4.4. L9 Orthogonal Array, 3^3 (Non-redundant combination)

Part no.	A	B	C
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	2
5	2	2	3
6	2	3	1
7	3	1	3
8	3	2	2
9	3	3	1

Part no.	Layer height(mm)	Nozzle temp(^oC)	Nozzle Speed(mm/s)
1	0.15	195	30
2	0.15	200	35
3	0.15	205	40
4	0.2	195	35
5	0.2	200	40
6	0.2	205	30
7	0.25	195	40
8	0.25	200	30
9	0.25	205	35

4.4. Printing of Geometric Benchmark component

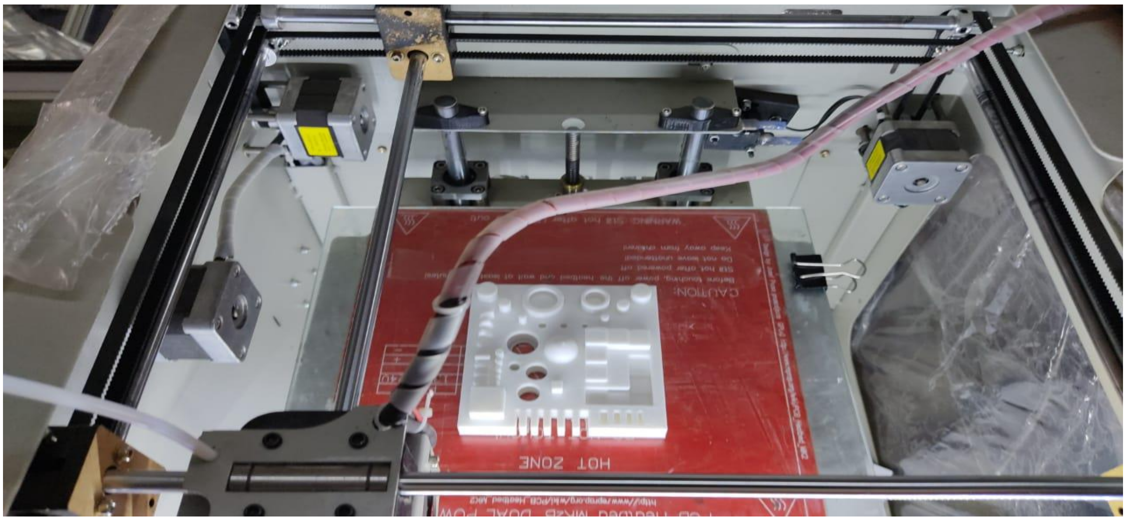


Fig. 4.5 Benchmark component after Printing

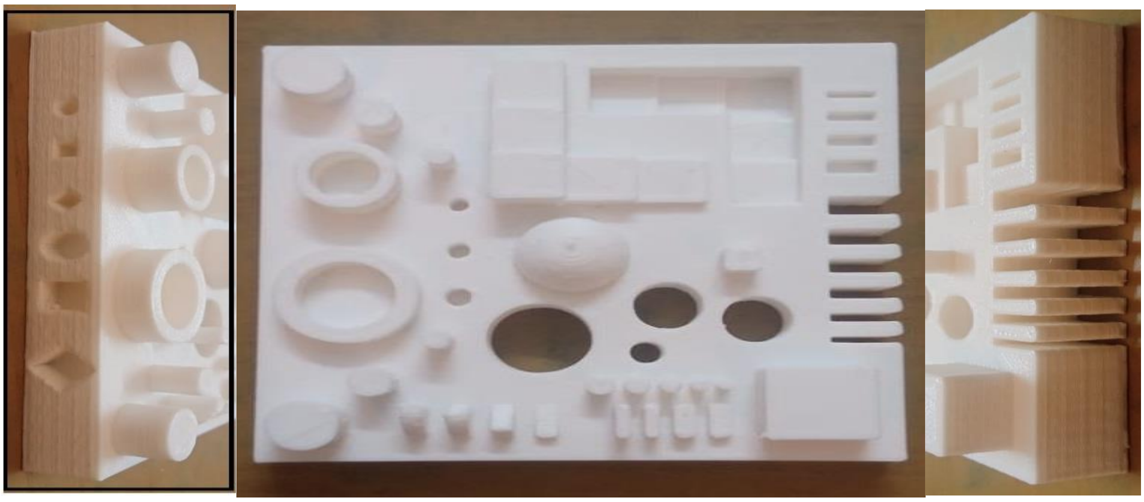


Fig. 4.6 Benchmark component top and side view

Table 4.5 Time of Printing Components & Material Used

Part no.	Printing time(h)	Material used (m)	Material used (gram)
1	7H 56mins	17.169	51.0g
2	7H 19mins	17.169	51.0
3	6H 50mins	17.169	51.0
4	5H 30mins	16.35	48.0
5	5H 10mins	16.35	48.0
6	5H 57min	16.35	48.0
7	4H 22min	17.46	50.0
8	5H 2mins	17.04	50.0
9	4H 40mins	17.046	50

The part no. 1 take the most time to print whereas part no.7 take the least time

4.5 MEASURING FEATURES OF BENCHMARK COMPONENT

Arranging all the dimension in their group for easy identification and tracking. Following table show grouped dimension based on type of dimensional accuracy

Table 4.6. Dimensional Accuracy of Features – Feature ID

Dimensional Accuracy	Feature IDs
Length	a1,a2
	b1,b2.b3,b4
	m1, m2, m3, m5

Dimensional Accuracy	Feature IDs
height	a1, a2
	b1,b2,b3, b4
	c1, c2

	o
width	
	b1,b2,b3,b4
	o
diameter	c1- c2
	d1,d2,d3,d4,d5
	g1,g2, g3,g4,g5
	h1-h6
	i1-i3

	k1,k2,k3, k4,k5
	l1,l2,l3,l4,l5
	m2, m3, m4, m5
	n1
	o
thin walls/ slots	f1,f2,f3,f4,f5f6
	j1,j2,j3,j4

Table 4.7. Summarised data sheet of value measured by digital vernier calliper

Feature	Actual value	Average value	Range(maximum-minimum)	Deviation
Length(X)	3	2.927	3.120-2.757	0.073
	4.24	4.173	4.320-4.113	0.067
	5	5.001	5.133 -4.883	0.133
	6	5.841	5.963-5.630	0.159
	7	6.899	7.147-6.77	0.101
	8.48	8.245	8.413-8.067	0.185
	15	14.950	15.047-14.830	0.050
	90	89.944	90.107-89.620	0.056
Width(Y)	2	2.020	2.330-1.880	0.020
	3	2.970	3.050-2.843	0.030
	5	5.021	5.177-4.883	0.021
	15	15.010	15.087-14.920	0.010
	90	90.020	90.167-89.933	0.020
Height(H)	2	2.010	2.170-1.840	0.010
	3	2.919	3.093-2.597	0.081
	4	3.931	4.187-3.740	0.069
	4.24	4.138	4.230-4.033	0.102
	5	4.910	5.197-3.253	0.090
	6	5.885	6.223-5.257	0.115

	7`	6.932	7.153-6.737	0.068
	8	7.800	7.977-7.560	0.200
	8.48	8.262	8.427-8.133	0.168
	10	9.935	10.227-9.750	0.065
Diameter(D)	2	1.925	2.100-1.840	0.075
	2.5	2.423	2.510-2.240	0.077
	3	2.888	2.987-2.760	0.112
	3.5	3.398	3.460-3.307	0.102
	4	3.891	4.170-3.723	0.109
	5	4.832	4.910-4.720	0.169
	6	5.915	6.037-5.780	0.085
	10	9.360	10.110-9.667	0.164
	14	13.834	14.023-13.637	0.166
	15	14.826	15.020-14.560	0.174
	20	19.885	20.097-19.663	0.115
Thin Wall(T)	1.5	1.45	1.570-1.407	0.045
	2	1.902	2.027-1.840	0.098
	2.5	2.397	2.460-2.310	0.103
	3	2.907	2.980-2.830	0.093
	3.5	3.395	3.483-3.283	0.105
	4	3.887	4.050-3.757	0.113

4.6 PROGRAMMING USING PYTHON LANGUAGE

The raw measurement of the component features was prepared as the data set and fed into the regression algorithm. Since there is very little deviation in the dimensions of the features, as shown in the deviation column in Table 4.12, linear regression algorithm is selected. Linear regression algorithm also has better interpretability than other algorithms used for predictive analytics or simply for making predictions

This code is used to fetch data and train according to multiple linear regression and some portion left for testing the pattern and boxplot function used to plot the variation of similar dimension

```
Import pandas as qw
Import seaborn as ert
Import NumPy as yu

Dat= qw.read_csv ("C:\\Users\\hardik\\Desktop\\project data sheet\\boxplot lengthxxx.csv")

Dat. Tail ()
Dat. Head ()
Dat. Shape

Dat. Describe ()
Dat

From sklearn.linear_model import (LinearRegression)
From sklearn.madel_selection import (train_test_split)


(X_train, X_test, )Y_train, Y_test= train_test_split ((train, test, test_size=0.1),(random_state=2))

sns.boxplot(x='Real value', y='Value', data=dat)

Rego=LinearRegressian ()

Rego. Fit (X_train, Y_train)

Pred=rego.predict (X_test)

Pred

Len (X_train)

rego.coef_

rego.intercept_

rego.score (X_test, Y_test)
```

CHAPTER 5
RESULTS AND DISCUSSIONS

The code which is written in section 4.6 fetch the data from the excel file which maintained all the measurement of benchmark geometry and it put the data into algorithm to solve and find the relation between output dimension(Y) and all other four parameter like Input dimension(X) , nozzle temperature(T), layer thickness(L) , nozzle speed(S) and one intercept value . it give relation in form of equation

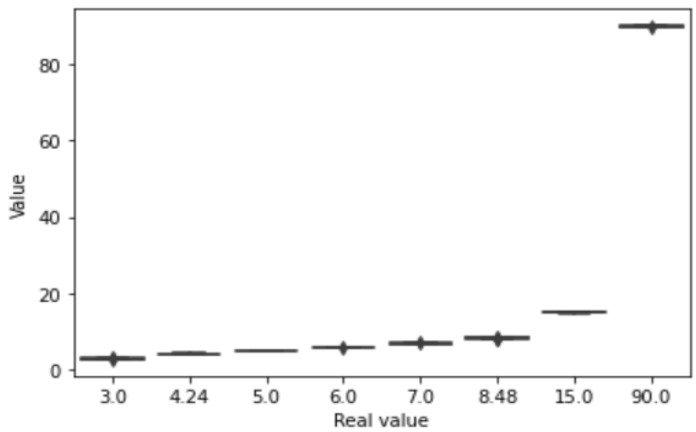
The following equation gives an overall view of how a function relates the input parameters with the output parameters

$$\mathbf{Y = a_1 X + a_2 T + a_3 L + a_4 S + b}$$

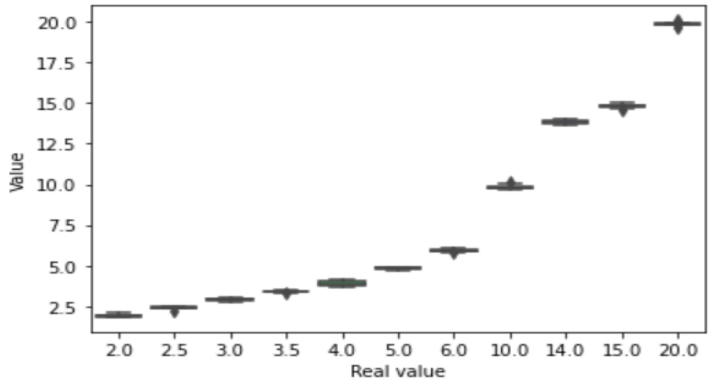
Where,

a_1, a_2, a_3, and a_4 are the regression coefficients and b is the intercept.
The data set is divided into two parts. One part is the training data set for the algorithm and other being the testing data set. By convention, the ratio of training to testing data set is 9:1 i.e. 90% of the data is used just to train the algorithm. Once the regression equation is fit into the training data, the values rest of the data set are predicted using this equation.

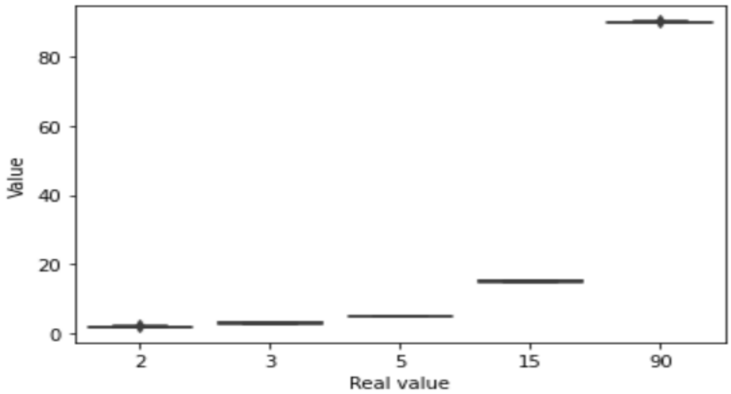
The following figures show the boxplot and outliers for the corresponding features on the benchmarking components. It help in visualize data so we can do operation according to it



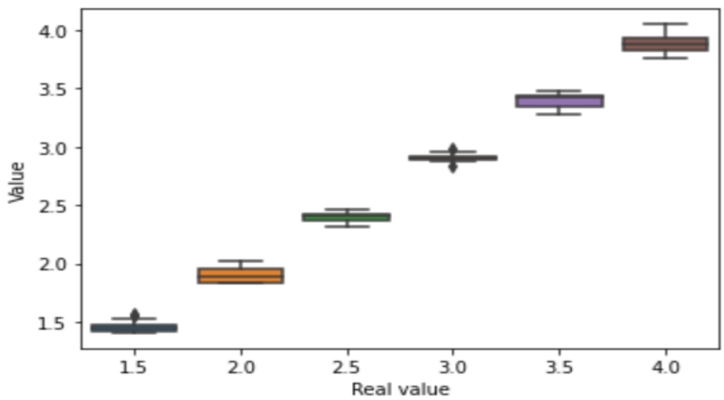
(a) Length (along X-axis)



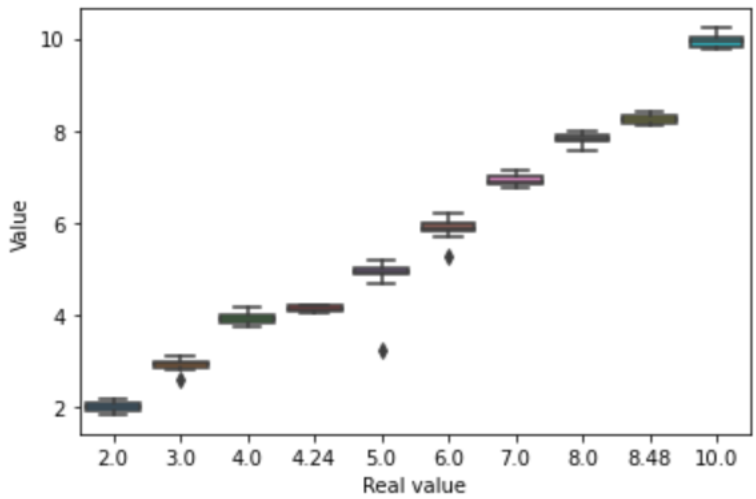
(b) Diameter



(c) Width



(d) thin wall



(e) Height

Fig. 5.1 Error Percentage – Boxplots

The above boxplot data give us a better idea of how measurement of different sizes is distributed.it can be shown that dimension with higher value show more diversion from true value, it show how minuscule variation can add up when we go for large dimension. Also it depends on the capability of the machine to print the smallest sized features with greater accuracy. There is some outlier in height boxplot. The outliers represent the odd man out readings for which there were larger variations in the dimensions of the printed features.

The coding after execution gives the regression coefficients and the intercepts for predicting the dimensions of features based on the input parameters. The code was executed separately for each of the dimensional accuracy and the regression equations are taken as shown in the following tabulation.

.

Table 5.1 – Regression equations Tabulation

S.NO	PREDICTION PARAMETER	REGRESSION EQUATION	SCORE FUNCTION()
1	Length	**Y**= 1.000287 **X** - 0.0009775 **T** + 0.155367 **L** + 0.00156152 **S** + 0.00715	0.999
2	width	**Y** = 1.0002057 **X** + 0.00041131 **T**-0.4113144 **L** + 0.0059751 **S** - 0.19052	0.999
3	Diameter	**Y** = 0.99544 **X** - 0.0018036 **T** -0.0285374 **L** + 0.00411655 **S** + 0.12542	0.999
4	Height	**Y** = 0.98395 **X** - 0.002040 **T** - 0.4123521 **L** + 0.00538366 **S** + 0.304229	0.996
5	Thin slot	**Y** = 0.977343 **X** + 0.00118207 **T** - 0.194576 **L** + 0.00134743 **S** - 0.27739	0.994

X: Input Dimension

Y: Output Dimension

T: Extrusion Temperature

L: layer thickness

S: Nozzle speed

To check the authenticity of test data score () function is use, It check closeness of test data and predicted data and it was shown in table 5.1 that all score value is coming higher than 0.94 which is satisfactory outcome

With the above equations, output dimensions can be predicted without actually printing the components which is based on the experience of the past data collected

CHAPTER 6
CONCLUSION

The FDM printed parts and components shows deviation in the dimensions of the geometric features and tolerance based on the factors involved in the printing process. The famous FDM technology faces this challenge and hence to commercially accept and implement this process there is a need to quantify these deviations in the real time printing and set the parameters to get a required output without wasting the material and manufacturing time.

Implementation of machine learning techniques is based on the experience, here experience is the past data collected during the manufacturing process. The past data enable us to form a kind of relationship between the input parameters controlled during actual manufacturing to the interested output parameters. Once the relation is known, a prediction is done to save time and money without doing trails and errors.

6.1 FUTURE SCOPE OF THE PROJECT

The future scope of this project is to extent the study of additive manufacturing with more number of influencing parameters. Increasing the number of input parameters leads to more no of iteration of experiments to have a better knowledge of how each parameter influences the output when correlated with other influencing parameters. Since machine learning and data analytics is a more powerful tool, it can have any number of input parameters to predict well the output parameters.

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