SHRINKAGE MEASUREMENT OF NYLON AS A BUILD MATERIAL IN 3-D PRINTING BY MACHINE LEARNING

A Dissertation submitted

in partial fulfilment of requirements

for the degree of

Master of Engineering
in
Production Engineering
by

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AUGUST 2019

CERTIFICATE

I hereby declare that the dissertation entitled **"SHRINKAGE MEASUREMENT OF NYLON AS A BUILD MATERIAL IN 3-D PRINTING BY MACHINE LEARNING"** is an authentic record of my work carried out as requirements for the award of the degree of **Master of Engineering in Production Engineering** at **Thapar Institute of Engineering and Technology, Patiala** under the supervision of **Dr. Vineet Srivastava (Assistant Professor, MED) & Dr. Karun Verma (Assistant Professor, CSED).** No part of the matter embodied in this report has been submitted to any other university or institute for the award of any degree.

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Acknowledgement

I woud like to express my sincere and devoted gratitute to Assistant Proffesor, **Dr. Vineet Srivastava** and Assisstant Proffesor **Dr. Karun Verma**, for their continous encouragement, support and guidance throughout this work, without which this wouldn't have been completed. They were always been behind in every step of this work and has always stood for any problems, difficult situations whatsoever.

I am thankfull to **Mr. Shakti Singh** for assisting me in labroratory work. I am also grateful to all faculty members of the Department of Mechanical Engineering for their help and encoragement.

I would also like to thank **Dr. T.P Singh, Head & Senior Professor, Mechanical Engineering Department, Thapar University, Patiala** for providing facilities for completion of my work.

A special thanks to my friends and Phd scholar **Mr. Amrinder Singh** who helped and supported me throughout this endevour.

In the end I wish to express my deepest gratitute to my parents for their love and support. Without them, this work wouldn't never had been completed.

Sourabh

Sourabh Sharma

Dedicated to

The people whose collective guidance and knowledge, since childhood, enables me to write this piece of work; whom I owe a great debt of sincere gratitude. My teachers.

Abstract

Rapid Prototyping (RP) is a very efficient manufacturing technique which is widely used for improving the design quality of products manufactured. The surface quality and dimensional accuracy should be good for success of a RP process and these two important factors mainly depends upon the selected input variables or process parameters. In this study, the input variables are extrusion speed, layer thickness, extrusion temperature, part bed temperature and the nozzle diameter and an attempt has been made to improve the dimensional accuracy of nylon parts fabricated by 3D printing process. Experiments have been performed with respect to central composite rotatable design (CCRD). Empirical statistical model has been developed for predicting the dimensional accuracy of the fabricated parts in x direction laying. Analysis of variance (ANOVA) has been performed to test the significance of process variables on dimensional accuracy. It has been observed that nozzle diameter, layer thickness, part bed temperature and extrusion speed are most significant factors which affect shrinkage. It has been discovered that with increase in nozzle diameter, shrinkage increases, whereas increase in layer thickness, part bed temperature and extrusion speed decreases shrinkage. Verification of developed model was done by doing experiments at different settings which confirm that forecast of model is precise. Further a predictive model has been developed for forecasting shrinkage using Nylon using machine learning. The competence of machine learning based model is checked and the results show that quadric model generated for shrinkage is significant.

Keywords: 3D printing, nozzle diameter, bed temperature, extrusion speed, extrusion temperature, layer thickness, machine learning.

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Nomenclature

3D	3 Dimensional
ABS	Acrylonitrile Butadiene Styrene
ANOVA	Analysis of variance
CAD	Computer Aided Design
CCRD	Central Composite Rotatable Design
FDM	Fused Deposition Modelling
FFM	Fused Filament Modelling
LOM	Laminated Object Manufacturing
LENS	Laser Engineered Net Shaping
ND: YAG	Neodymium-Doped Yttrium Aluminium Garnet
PET	Polyethylene Terephthalate
PLA	Polylactic Acid
RP	Rapid Prototyping
RSM	Response Surface Methodology
SL	Stereolithography process
SS	Sum of Square
ND	Nozzle Diameter
PBT	Part Bed Temperature
HS	Head Speed
LT	Layer Thickness
ET	Extrusion Temperature
βi, βii & βij	Beta (constant coefficient)
Y	Response
N	Total number of experiments
A	Level of confidence interval
SLS	Selective laser sintering
SLM	Selective laser melting
STL	Stereolithography

CHAPTER 1: INTRODUCTION

The demand for manufactured products between manufacturing industries is increasing day by day which is forcing them to produce goods with good quality in lesser time and with the ease of effective cost. To make the manufacturing goods available on time, many of the processes related to the test, designing, manufacture and marketing of the product has been compressed, both in terms of time and material resources. The systematic use of such essential resources calls for developing new tools and techniques in dealing with them and many of these tools and techniques have developed. They are mainly based on computer technology. This is due to fast development and progress in such technologies over the last few years. During product making, time pressure has been a major factor in deciding the direction and success of developing new methods and advanced technologies. This directly affects the age old practice of fabrication in the product making process. One such technical development is Rapid Prototyping. [1]

1.1 <u>RAPID PROTOTYPING</u>

“Rapid Prototyping can be characterized as the production of any physical model of a part, mechanism, component or item by utilizing new technologies before the product’s modelling, with the goal of confirming all or a portion of its fundamental qualities and theoretical functions, or as an practical element that can be directly applied in a manufacturing process" [1]. Rapid Prototyping is related to new category of manufacturing machines which produces physical prototypes from 3D CAD models swiftly and is also known as Additive Manufacturing process. RP commonly lies within the range of physical prototypes, which are quite accurate and can be executed on a component or system level. The utility and range of different prototypes, from complete system to individual components, that can be made by RP at changing degrees of approximation thus makes it an important tool for part fabrication. Advantage of speed in delivery makes it an important component in the prototyping field that cannot be ignored. It offers various advantages over conventional machining procedure like manufacturing engineer can minimize design time, manufacturing time and confirmation of tooling during the manufacturing procedure.

1.2 BASIC PRINCIPLE OF RAPID PROTOTYPING:

The basic principle of Rapid Prototyping is shown in figure 1.1 and can be explained in the following steps:

1. RP process belong to the generative (or additive) production processes unlike subtractive or forming processes such as lathing, milling, grinding or coining etc. in which form is shaped by material removal or plastic deformation.
2. In all commercial RP processes, the part is fabricated by deposition of layers contoured in a (x-y) plane two dimensionally.
3. The third dimension (z) results from single layers being stacked up on top of each other, but not as a continuous z-coordinate. Therefore, the prototypes are very exact on the x-y plane but have stair-stepping effect in z-direction. If model is deposited with very fine layers, i.e., smaller z-stepping, model looks like original.
4. RP comprises of two fundamentals process steps namely generation of mathematical layer information and generation of physical layer model. [W1]

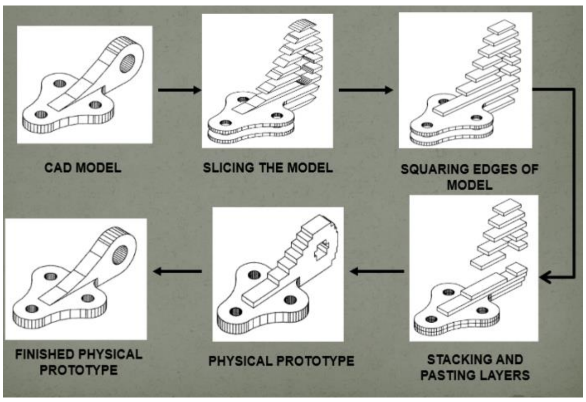

Figure 1.1: Principle of Rapid Prototyping [W1]

1.3 PROCESS CHAIN OF RAPID PROTOTYPING:

The process chain of Rapid Prototyping is shown in figure 1.2 and involves the following steps:

1. Creation of geometric model or cad model in a designing software which is then saved as STL file format (STteriLithography).
2. Tessellation is done by approximating the geometry of the surface of the solid into number of triangles.
3. Slicing of the tessellated model is done by a slicing software.

4. Then the generation of laser scanning path or material deposition path is done based on individual layer geometry by the software.
5. Part fabrication by depositing one layer atop another.
6. Final step is post processing where supports are removed.
7. Then the prototype is tested against the requirements. If passed OK, it is the final prototype otherwise the cycle is repeated with design modifications.

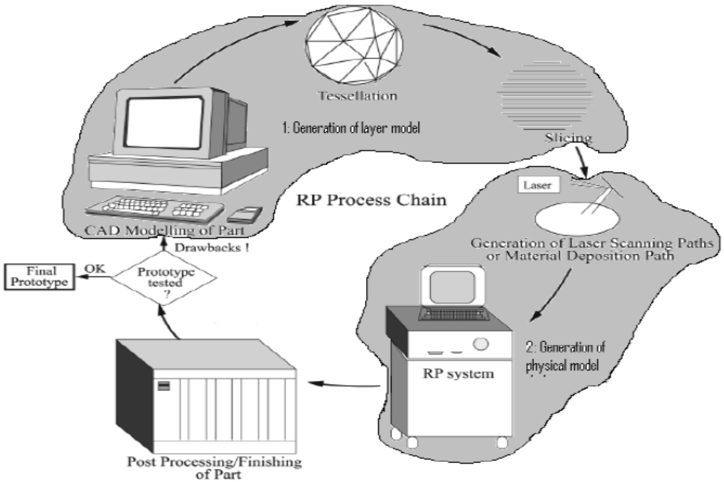

Figure 1.2: RP Process Chain [2]

1.4 TYPES OF RAPID PROTOTYPING SYSTEMS

Different types of RP processes are classified on the basics of raw material as shown in figure 1.3 which are used for fabrication of products.

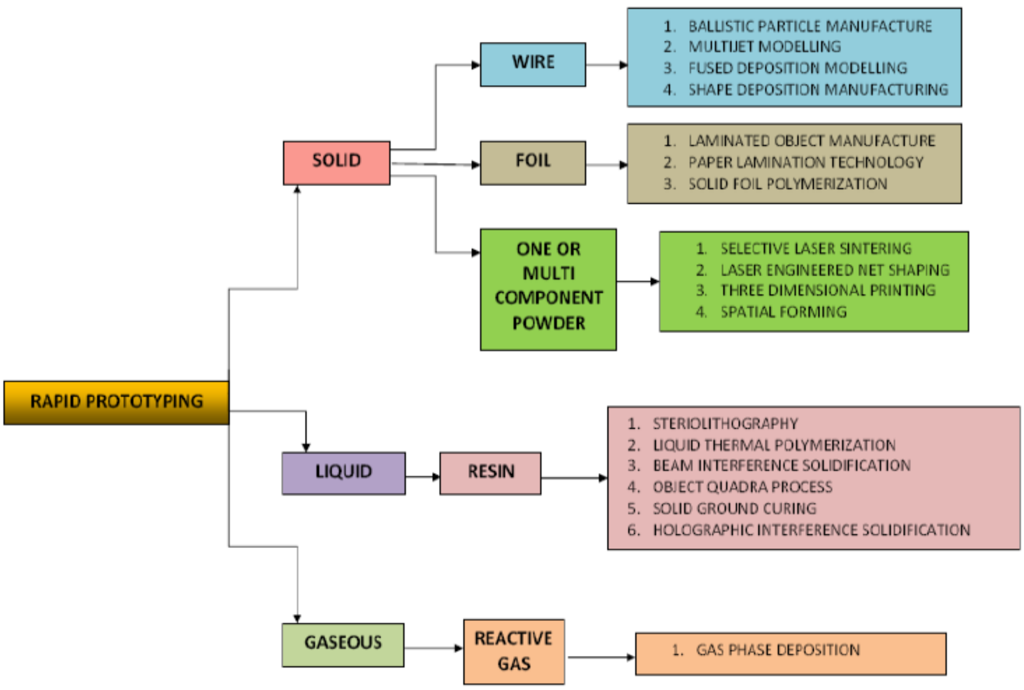

Fig 1.3: Classification of RP on the basics of raw material [3]

Commonly used RP processes:

1. Fused Deposition Modelling (FDM)
2. Steriolithography
3. Selective Laser Sintering
4. Laser Engineered Net Shaping (LENS)
5. 3D Printing
6. Laminated Object Manufacturing

FUSED DEPOSITION MODELLING: The fundamental principle of FDM is associated with surface chemistry, thermal energy and additive manufacturing technology. The material is heated and melted in specifically designed printing head which moves over the model geometry and as it is extruded, it gets cooled and thus results in formation of the part. The movement of the printing head is controlled by the machine in x and y direction. Part is deposited layer by layer. When the first layer gets deposited, the bed moves down by one layer thickness which results in the z direction. The build material commonly used in FDM is acrylonitrile butadiene styrene (ABS). The materials employed in FDM are suitable for detailed functional model, manufacturing low volume parts. This technology makes use of support materials to create supportive structures that are removed by force or solution. [4]

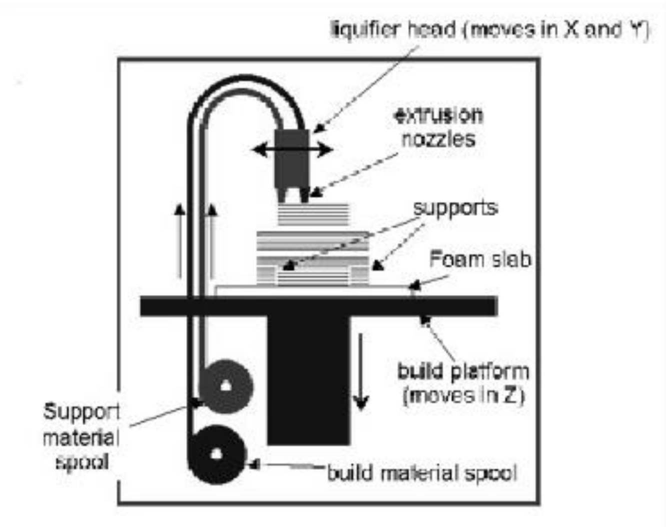

Fig 1.4: Fused Deposition Modelling [4]

ADVANTAGES-

1. Produces parts in lesser time with low manufacturing cost.
2. Contact to lasers, toxic chemicals is not an issue in FDM.

DISADVANTAGES-

1. Parts fabricated using FDM has limited accuracy because of shape of the material being used.
2. Support structures are required.
3. Longer build time

STERIOLITHOGRAPHY: The major concept of steriolithography is a photosensitive fluid which frames a strong polymer on exposure to ultravoilet beams. The process is also known as photo polymerization. Steriolithography machine composed of vat of liquid resin and a ultraviolet helium cadmium or argon- ion laser. The laser binds the first layer and platform is then lowered with the thinking that fluid polymer settles to a level and does not form bubbles. In SL a blade is used to apply liquid resin on the part for good surface finish. Once the part is being made, it is removed from the vat and then excess resin is depleted out. The green part is then post-relived in an UV stove after removing support structures. One of the greatest advantage of a steriolithography process is that a functional part can be built in shorter period of time. Steriolithography process enables one to decrease costly mistakes by detecting design flaws before the development of product. This process provides rapid building of prototypes with high level of precision and excellent surface characteristics. [5]

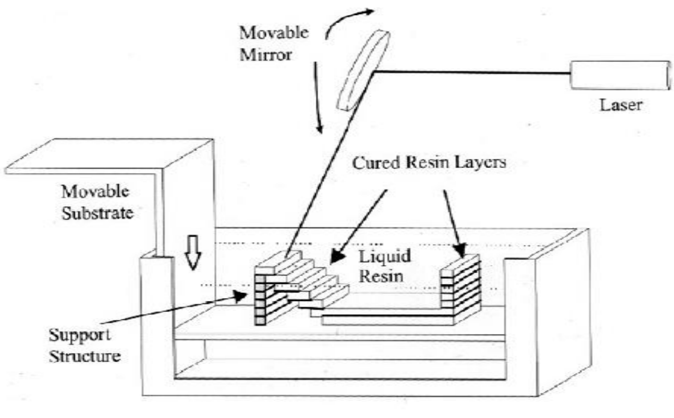

Fig 1.5: Steriolithography [5]

ADVANTAGES-

1. Capable of high detail and thin walls
2. Good surface finish.
3. Several parts may be made at once.

DISADVANTAGES-

1. Post curing required
2. Some shrinkage, curl and shrinkage due to phase change.
3. Support structures needed.

SELECTIVE LASER SINTERING: This process involves melting followed by solidification of the part. Fine polymeric powder is applied over to the substrate surface using a roller, involves polystyrene or poly carbonate. In order to minimize curling and for strong bonding between the layers, the bed is heated just below its melting point. Powder is then fused with a heat generated CO_2 laser to fabricate a part. Once the laser treats the first layer of the powder material, the bed is lowered to one slice thickness and again the steps are repeated. Its ability is to produce several pieces at a time. Parts produced by this process tends to stand up better to wear and environmental conditions. One of the major advantage of the process is that no support structures are required. Hence it imposes few limitations on manufacturing design. [6]

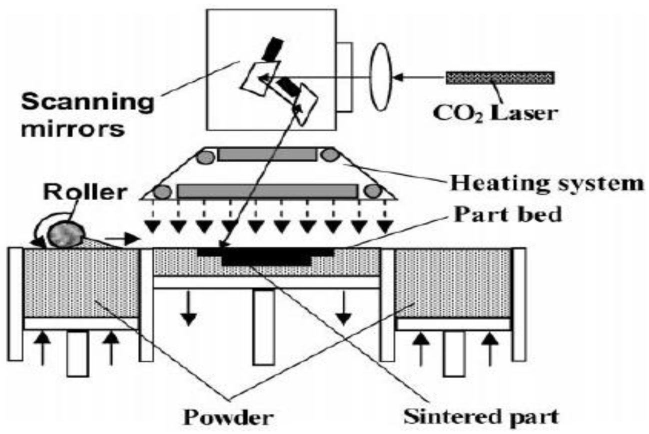

Fig 1.6: Selective Laser Sintering [6]

ADVANTAGES-

1. Good part stability
2. Wide range of processing materials
3. Support structure not required
4. High accuracy
5. No post curing required
6. Large parts can be built

DISADVANTAGES-

1. Poor surface finish
2. High power consumption
3. Large physical size of unit

LASER ENGINEERED NET SHAPING (LENS): An excessively powered ND: YAG laser (250W to 1000W) is used to form a molten pool over the substrate surface. Lens is an innovation for manufacturing metal parts legitimately from CAD model by utilizing a metal powder infused into a liquid pool made by a concentrated powerful laser beam. It is equipped for delivering essentially graded materials. Lens framework comprises of solid ND: YAG laser, a controlled air glove box and 3-axis PC controlled situating framework. This technology is extraordinary in creating completely dense metal parts directly from raw materials bypassing initial forming tasks, for example, casting and forging. Lens can manufacture near net-shaped models, excellent quality metal parts and even unique tooling for injection moulding. It has higher fixing efficiency, small heat affecting zone which results in better mechanical properties of the products after fabrication process. [7]

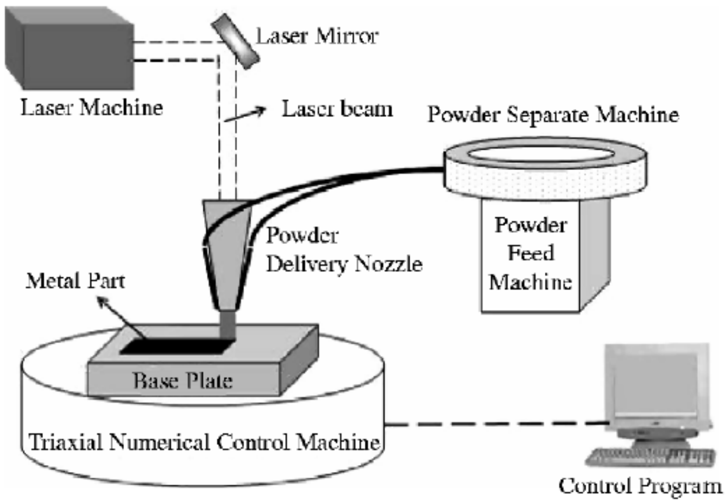

Figure 1.7: LENS [W2]

ADVANTAGES-

1. Superior material properties: The process is capable of producing fully dense metal parts and has superior material properties.
2. Embedded structures: The metal parts produced can also include embedded structures and have a relatively good microstructure.

3. Complex parts: Functional metal parts with complex features, can be produced by LENS system.

DISADVANTAGES-

1. Limited material
2. Large physical size of unit
3. High power consumption

3D PRINTING: It is a very flexible system which can produce parts of any geometry using any type of material. Commonly used materials in 3D Printing are ABS, PLA and NYLON etc. 3D printing allows easy fabrication of complicated shapes, many of which cannot be produced by any other manufacturing method. 3D printing is of three types (a) 3D printing with the binder (b) 3D printing with laser head (c) 3d printing with wire based. This process has control on microstructure, surface texture and material composition. 3D Printing utilizes ink jet printing technology. The machine spreads a layer of the powder from the feed box over to the surface of the build platform. The re-coater then moves across and spreads a uniform layer of powder. Then the binder solution is printed onto the free powder by the printer. In some cases, laser is also used to bind the free powder. Bed is lowered to one slice thickness after the completion of one layer. [W3]

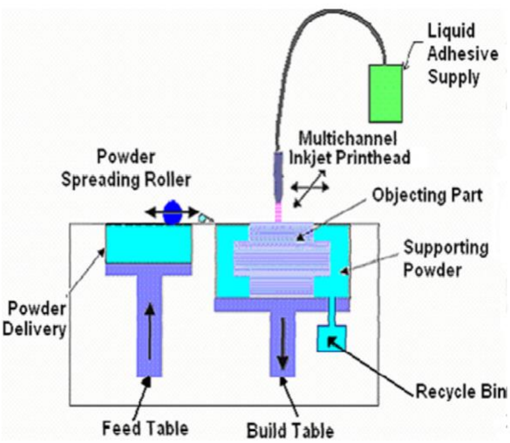

Fig 1.8: 3D printing with the binder [W3]

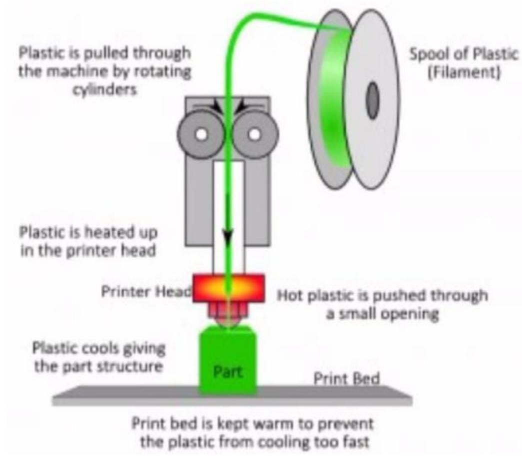

Fig 1.9: 3D printing with wire based deposition [W3]

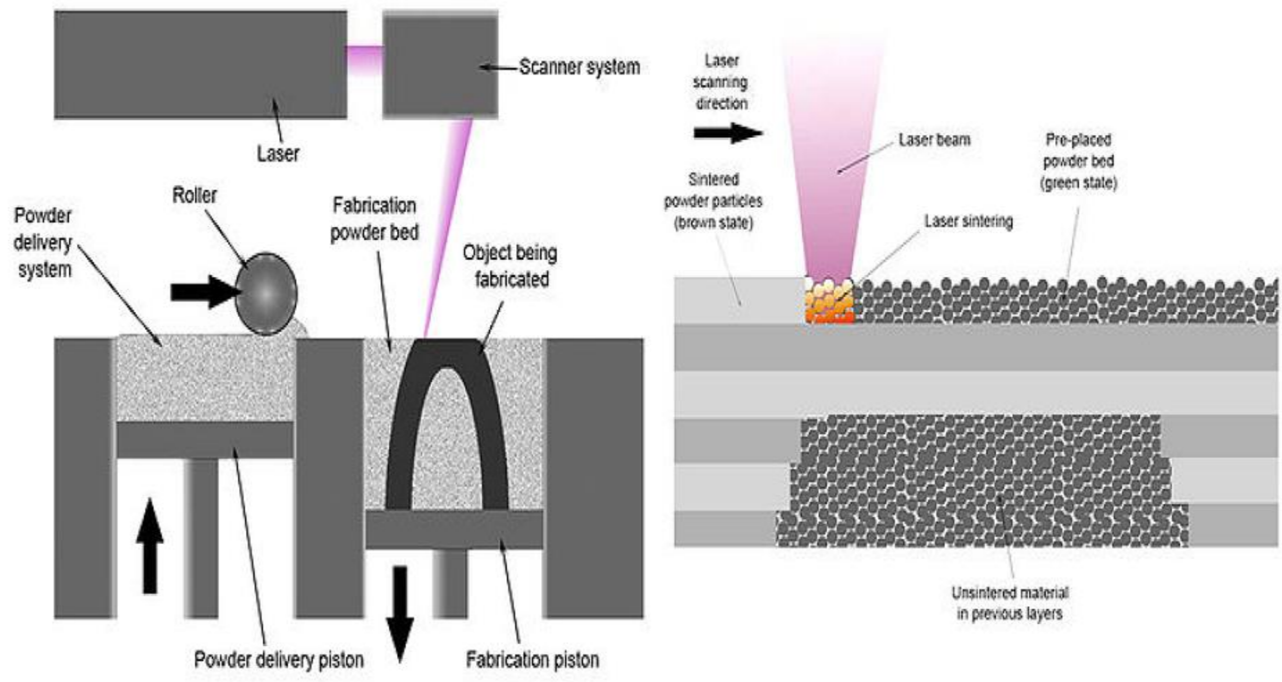

Fig 1.10: 3D printing with laser head [W3]

ADAVANTAGES-

1. High speed manufacturing system
2. No wastage of material
3. Complex colour schemes can be incorporated

DISADVANTAGES-

1. Part produced by this process have poor surface finish relatively to SLS parts
2. Part produced by this process have very dimensional tolerance
3. Post processing is frequently required

LAMINATED OBJECT MANUFACTURING: LOM process makes use of a hot roller which generates a heat sensitive adhesive in order to facilitate bonding between the layers. The shape of each layer is cut with a laser, which is balanced to enter to the precise profundity of one layer thickness. Unwanted material get cut's into rectangles to commend its removal later. But it is present during the product development phase to act as support. The platform with bonded layer moves down and a new sheet of material is rolled into its place. The steps are repeated till the part is fabricated. While LOM is not the most popular method of 3D printing used today but it still one of the fastest and most affordable ways to create 3D parts. LOM is not ideal for producing parts with complex geometries and it cannot produce hollow parts. For creating scaled models and conceptual prototypes that can be tested for form or design this process preferred. [8].

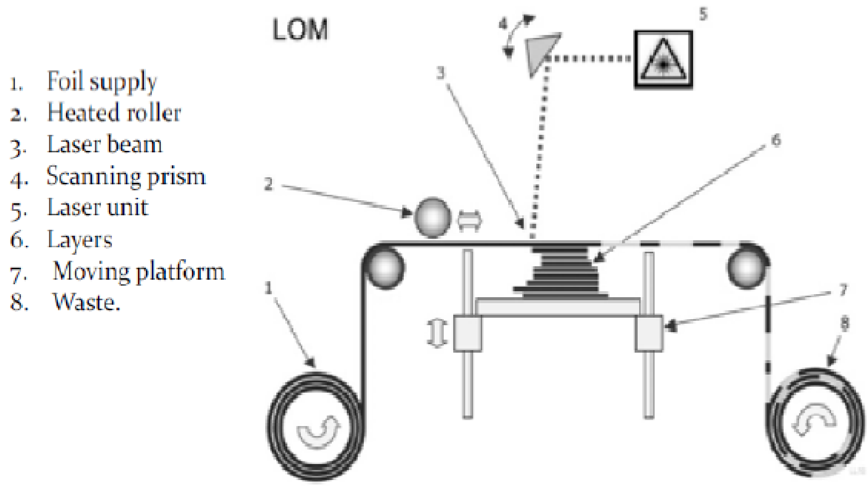

Fig 1.11: Laminated Object Manufacturing (LOM) [W2]

ADVANTAGES-

1. Speed of processing is fast in LOM, it 5 to 10 times higher than any other process.
2. Parts produced appear to be as wooden pieces.

DISADVANTAGES-

1. Large amount of scrap produced.
2. There may be fire hazard because of the use of laser and adhesives.
3. It is hard to make hollow parts due to difficulty in removing core.

1.4 PROBLEM AREA OF RP

RP is a fast and effective process for producing 3D part in lesser time in comparison of other manufacturing processes but it lacks in some fields due to the internal mechanical properties of raw materials used. Below are the problem areas of RP process.

- **SHRINKAGE-** Dimensional accuracy gets affected due to the shrinkage or warping which is very common phenomenon in parts fabricated by any RP process due to material phase change.

- **STRENGTH-** Parts produced by RP have low strength in comparison to conventional machining processes. It depend upon the type of material being used.

- **HIGH PRICES OF THE EQUIPMENT-** Machines employed in RP are not cost effective.

- **PART ACCURACY-** Curling of a part is linked with the deformation of the base section of part due to various reasons like temperature, humidity, material, process parameters etc.

- **SINGLE FEATURE-** Rapid Prototyping manufacturing system can be a single moulding process at a time.

- **SURFACE QUALITY-** Parts produced in Rapid Prototyping faces surface quality issues which depends upon the build time of the printing machine.

1.5 MOTIVATION

It has been observed that the parts fabricated by Rapid Prototyping processes offers limited dimensional accuracy. Most of the parts undergoes shrinkage due to temperature difference from molten to semi- molten state and secondly when it changes to solid state. This leads to deflection from the original dimensions of the CAD model. Hence, shrinkage of parts fabricated by RP processes should be seriously observed which can give rise to problems where any work is required with precision, affecting the dimensional accuracy of the parts. So, it is necessary to try and understand the factors that affects the dimensional accuracy of the parts so that parts produced by RP should be more accurate for success of RP.

1.6 THESIS ORGANIZATION

This thesis is divided into 6 chapters as follows:

Chapter 1 introduces the concept of Rapid Prototyping, explains the fundamental principles behind major RP processes and finally the motivation behind the present work.

Chapter 2 describes various efforts undertaken by various researchers till date aimed at investigating and understanding the factors affecting the dimensional accuracy of the build parts.

Chapter 3 further the properties of the selected material, selection of process parameters with their ranges and material fabrication has been explained.

Chapter 4 describes the statistical modelling of shrinkage and discusses the various inferences drawn from the developed models that help in understanding the effect of various parameters.

Chapter 5 describes the modelling of shrinkage using machine learning techniques with its validation.

Chapter 6 describes the conclusions of the work and future scope of this effort.

CHAPTER 2:
LITERATURE REVIEW

In RP techniques, shrinkage of the parts made-up through 3D printing processes is the major factor which requires serious observation to enhance the use of RP products. Shrinkage of the parts is mainly influenced by the selected process parameters. The basic process parameters observed during the study are hatch spacing, laser power, bed temperature, extrusion temperature, layer thickness, head speed and angle of orientation etc. In order to understand how shrinkage varies for different RP processes considering different input parameters, a exercise was done to understand the different input variables affecting the shrinkage of workpiece developed by different rapid prototyping processes.

2.1 LITERATURE REVIEW FOR SHRINKAGE

Forderhase et al. (1994) concluded that in order to compress the development of unbalanced stresses and shrinkage in nylon parts fabricated in SLS process, it is necessary to set the rate of cooling from the bed temperature to room temperature. Normal cooling rates for SLS nylon build parts was achieved by controlling the piston temperature.

Wang et al. (1996) developed a relationship between post cure shrinkage and various process parameters in an SL machine. To find major factors affecting shrinkage, method of least squares have been used. Regression showed that there is much correlations between shrinkage and process parameters. Major finding is that post curing degree affects the final dimensional accuracy of the parts.

Anitha et al. (2001) determined the influence of various process parameters on the quality characteristics of the prototypes by the help of Taguchi technique. Process used for fabrication is FDM. They worked to improve the design, quality of the manufactured parts. They found that the layer thickness was a major factor affecting the surface roughness or dimensional quality of the parts.

Gregorian et al. (2001) made an attempt towards finding the shrinkage compensation factor for FDM-1650 and producing accurate parts. Data was being evaluated by co-ordinate measuring machine and then analysed for precision. They found the shrinkage compensation factor of 1.007 for FDM-1650 machine using ABS as the work material.

Raghunath and Pandey (2006) developed a model for shrinkage by using Grey Taguchi method in a SLS process. They established a relationship between the shrinkage and various process parameters namely laser power, beam power, hatch spacing, part bed temperature and scan length in SLS parts. Regression have been performed for developing an empirical model for finding shrinkage along X, Y and Z direction. Dominating factors for shrinkage in X-axis were laser power and scan length, while in Y-axis were laser power and beam speed; and in the Z-axis were beam speed, hatch spacing and part bed temperature. Case study has been done which presents the validation of developed models for improving the dimensional accuracy of SLS parts.

Senthikumaran et al. (2008) developed an empirical relationship between shrinkage and the dexel length. Their work is concentrated towards improving the accuracy of the parts fabricated by SLS process. New shrinkage compensation factor have been evolved by compensating the geometry along single direction dexel space. Proposed model has the ability of improving the accuracy of laser sintered parts.

Sood et al. (2009) used artificial neural network for predicting the overall dimensional accuracy of the FDM parts. They studied the influence of parameters namely layer thickness, part orientation, raster angle, air gap and raster width on shrinkage. Grey Taguchi method has been used to obtain optimum level of process parameters in order to minimize shrinkage along length, width and height of the part. His major finding was that shrinkage is dominant along length and width but it is always more than the desired value for thickness.

Sukhdeep et al. (2016) presented a mathematical model between shrinkage and process parameters namely layer thickness, head speed and length of the part. Their major finding includes that a shrinkage has a direct relation with length of the part and varies indirectly with the layer thickness. Length of the part majorly affects the shrinkage.

Wang et al. (2017) developed a mathematical model for shrinkage and sintering parameters such as sintering temperature, heating rate and sintering time in an binder jetting additive manufacturing process. Taguchi method have been employed for designing the test data. ANOVA have been performed based on S/N ratio for analysing the experimental results. They found sintering temperature as the most important factor that affects the dimensional accuracies of each axis.

Tran et al. (2017) analysed the factors influencing the part quality of the material printed in a FDM process. They derived optimal values of process parameters. Further these optimal values were used in printing the gears and shaft with both ABS and PLA as a build material. On evaluation, it was observed that the gears and shaft were made successfully within the allowable limit of their dimensional accuracies.

These works point toward understanding the effects of various process parameters on the Shrinkage of RP products. Many of the different types of study have been done in order to develop models attaining reduced shrinkage. Shrinkage varies according to the input variables.

2.4 MACHINE LEARNING

"Machine learning is an efficient investigation of algorithms and architecture that improve their performance or knowledge based upon experience"[9]. Machine learning is all about using right features to build the right models that can achieve the right task. Machine learning is about training computers to modify or adapt their actions in order obtain more precise actions, where accuracy is measured by how accurate the selected actions reflect the correct ones. It is based on ideas from neuroscience, biology, statistics, mathematics and physics. An overview of implementing machine learning is provided in figure 2.1.

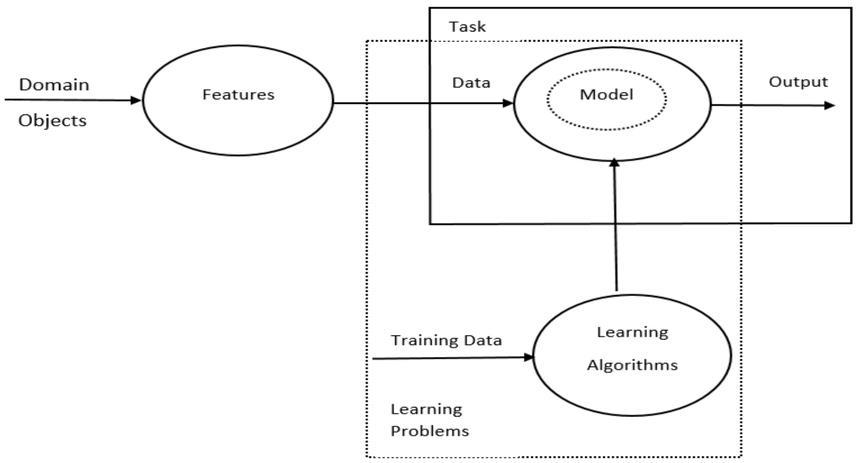

Fig 2.1: An overview of how machine learning is used to address a given task [9]

2.2 LITERATURE REVIEW OF MACHINE LEARNING APPLIED IN RP

Shushmit et al. (2016) used a feed-forward ANN model to present thermal deformations in AM parts. The purposed geometry served as an efficient tool to present FEM based thermal deformations. The purposed framework was then used on STL file of the part CAD model to produce the required geometrical compensation to the part design.

Yao et al. (2017) developed a hybrid machine learning algorithm to make change recommendations during design phase. The purposed geometry serves an efficient tool for providing optimal design solutions for un-experienced designers and by the help of this model one can make full use of AM design knowledge.

Ugandhar et al. (2018) presented an approach that automatically controlled the quality of 3D printed parts by the use of camera, image processor and Supervised Machine Learning techniques. Semi-finished images have been taken considering critical stages of the part geometry. They made use of Support Vector Machine method of machine learning for detecting good or defective parts. The purposed framework worked successfully in detection of defective parts made. Major findings were that that the method is capable of real time examining of a 3D printing process.

Munteanu et al. (2018) presented applications of Artificial Neural Network for improving the knowledge of FDM process, process controlling and detecting trend. Taguchi technique was employed in reducing the input parameters. Their major findings was that they found layer thickness as the most influencing parameter whereas temperature and deposition speed played significant but smaller roles.

Ye et al. (2018) presented an innovative approach for controlling and recognition of defects in Selective Laser Melting by SVM technique utilizing extracted features from acoustic signals. Features were extracted through principle component analysis (PCA) and fisher discriminant analysis (FDA). The purposed framework can be directly applied for defect diagnosis in SLM process.

Panda et al. (2018) presented an approach for performance modelling of parts fabricated in FDM process by a general regression neural network and studied the effect of three input process parameters namely layer thickness, orientation and raster angle. Study was carried out using multi-gene genetic programming and general regression neural network and it was seen that performance of GP lacks in comparison to GRNN.

Kim et al. (2018) developed a controlling and detection system for FDM process based on Support Vector Machine algorithm. An accelerometer and acoustic emission sensor were employed for analysing the data. The final accuracy was 87.5% and the working ability of the developed model was verified. The purposed model serves as an effective tool for preventing faults in advance. Hence, wastage of energy and material can be minimized.

Alabi et al. (2018) applied machine learning along with the applications of big data in the field of Additive Manufacturing. Their work involves detection of any type of defect during product development in Additive Manufacturing process.

The literature presented above shows that many of the machine learning techniques have been successfully applied in RP processes. Further machine learning has become a significant research area for solving problems using small and large data (historical or real-time data) from sensors or through other medium of collecting data. The main motive of applying machine learning in RP is two fold, i.e. firstly to identify the significant process parameters and secondly to verify and validate the developed model.

2.3 RESEARCH GAP

It is clearly evident from the review of literature that most of the past work is limited towards FDM, SLS and SLA processes and PLA, ABS, Polyamides as raw material. There is no literature available on shrinkage of NYLON. As NYLON parts have high strength, elasticity, durability and is unlikely to deform, therefore it has been considered for work material. Further machine learning has developed into a very effective tool in analysing the data and verifying and validating the developed model, therefore it has been chosen as the preferred tool.

2.4 RESEARCH OBJECTIVE

1. To build up a statistical model of shrinkage dependent on various input variables for parts fabricated by 3d printing process.
2. To study the effect of various process parameters on shrinkage of parts.
3. To validate the developed shrinkage model by Machine Learning Techniques.

2.5 PLANNED METHODOLOGY

1. The first step is to select the process parameters and their levels according to the ranges available on the machine.
2. A Solid model of the proposed work piece is to be created with the help of CAD software.
3. Use the design of experiments (DOE) methodology to create an experimental plan.

4. Fabricate the work pieces according to the experimental plan designed using DOE.
5. The shrinkage is measured using Vernier calliper along the direction of laying.
6. Perform analysis of variance to determine significant parameters and develop a statistical model to predict shrinkage.
7. Estimate the error of the developed model and validate the model.
8. Develop a model of shrinkage using machine learning.
9. Determine significant parameters; develop a statistical model to predict shrinkage, estimate the error of the developed model and validate the model.

CHAPTER 3:
DESIGN OF EXPERIMENTS

3.1 <u>RESPONSE SURFACE METHODOLOGY</u>

- "Response Surface Methodology (RSM) is a combination of logical and factual framework helpful for showing and investigating issues in which a response of interest is affected by several variables and the goal is to optimise this response" [10]

In our study, the aim was to develop an empirical correlation between contributing parameters and shrinkage along the direction of laying. Therefore, it was required to settle on a set of parameters which realizes particularly equally spaced numbers for the experiments. As it was seen that the factors affecting the response are quite large, therefore it was quite difficult to assume response as of first degree. If assumed so, it will not consider the interrelationship of the various parameters and thus would not be able to explore the curvatures in the response, if any. Hence, the best realistic approach was to assume the response as minimum second degree polynomial. Even though this might may not be the best approximation of the response function over the entire space of the parameters, but it would be precise enough for a relatively smaller area. A second degree response model is defined as follows [11]:

$$Y = ß_0 + \sum_{i=1}^{k} ß_i\, x_i + \sum\sum_{j<i} ß_{ij}\, x_i x_j + \sum_{i=1}^{k} ß_i\, x_i^2 + \varepsilon \tag{3.1}$$

Where,

Y = response,

x = input variable,

ß = constant coefficients, and

ε = random error

The equation 3.1 contains quadratic terms which shows the parabolic curvature of the response surface. Since the input variables and the response is known and the constant coefficients of the polynomial equation are unknown. Hence, method of least squares is used for their evaluation. In this method, those coefficients which offer the least value of the sum of squares of the errors are chosen to fit the response. In order to evaluate this, the above polynomial equation is first reduced to a linear equation of the form:

$$[Y] = [ß]\,[X] + [\varepsilon] \tag{3.2}$$

Y= n×1 matrix containing the response values

X= n×s matrix containing the various levels of process parameters and their interaction

Ɛ= n×1 matrix containing random experimental errors

ß= s×1 matrix containing constant coefficients

Now we have to find those values of β which reduces the error. This least square estimator of ß is given by the following equation:

$$ß= (X^T \times X)^{-1} X^T Y \tag{3.3}$$

Where, X^T = Transponse of matrix X.

Execution of correct experimental plan is required in getting response surfaces. The best way is to use a full factorial design in which the experiments lie at every point of interaction of the parameters over the entire area of interest in order to fit this second order model. Number of experiments in full factorial design is n^k, where *k* represents the parameters that affect the response and *n* represents the number of levels of process parameters. But in our study, there were countless parameters and furthermore trials that had been performed at more subsequent levels in order to better optimise the response. Considering the workability of number of experiments, CCRD (Central Composite Rotatable Design) is being used which is mostly preferred for second order responses. CCRD for 3 factors or parameters is shown in figure 3.1.

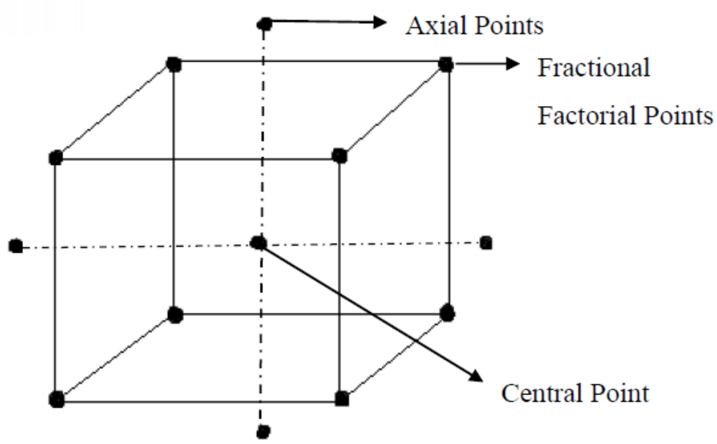

Figure 3.1: Experimental points in CCRD [11]

One has to decide different variables that affects the response before design of experimental plan, in this technique. This depends upon the process selected for fabrication. In this approach process selected for fabrication is 3D printing. Along with selected process parameters is discussed in next section.

3.2 3D PRINTING PROCESS

3D Printing process used in this work is a wire based manufacturing technique used to produce 3 dimensional parts by depositing the part in layer by layer manner utilizing a wire as material. In this process, the molten material is forced out by the help of rollers from the nozzle tip. This technique allows direct printing of products with very complex geometry. It makes production of parts suitable on any level. Figure 3.2 shows Flash Forge Creator Pro 3D printer which has been used in this study. This printer can be associated with different materials like Acrylonitrile Butadiene Styrene (ABS), Poly-lactic Acid (PLA), Nylon, HIPS etc. It has a software named 'Simplify 3d' which is required for setting process parameters or input variables which are necessary for fabrication.

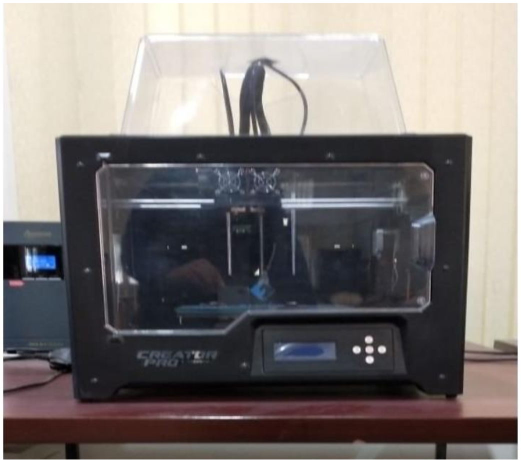

Figure 3.2: Wire based 3D printer

3.3 MATERIAL CHARACTERIZATION AND SELECTED PROCESS PARAMETERS

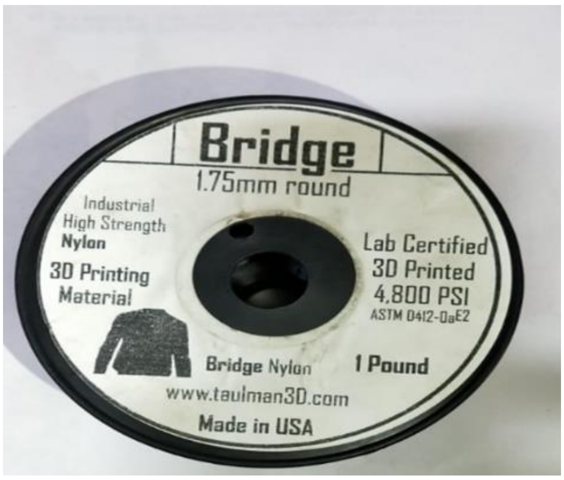

Figure 3.3: Nylon Material

Nylon is an engineered thermoplastic linear polyamide material having glass transition temperature of 52°C. Nylon is better known for its sticking capacity with the printing platform and diminished water up take from the environment. Nylon has high strength, highly elastic and is less likely to shrink. Selected material is bridge Nylon (figure 3.3) because it bridges the strength of Nylon. Table 3.1 shows the properties of Bridge Nylon. [W4]

Table 3.1: Properties of bridge nylon [W4]

SPECIFICATIONS	BRIDGE NYLON
THERMAL	
1. Printing temperature	250-255℃
2. Melting temperature	217℃
3. Glass transition temperature	52℃
4. Part bed temperature	30℃-65℃
PHYSICAL	
1. Nominal diameter	1.75 mm / 2.85mm
2. Weight/spool	1 lb
3. Shrinkage in/in	0.0061
MECHANICAL	
1. Tensile stress “PSI” when 3D printed	4800 psi
2. Ultimate elongation when 3D printed	248.20%

3.4 PLANNING OF EXPERIMENTS

3.4.1 FOR SHRINKAGE

During the survey of the literature, it was found that nozzle diameter, layer thickness, extrusion speed, part bed temperature and extrusion temperature majorly affects the shrinkage. According to the limitations and permissible ranges available in the machine, the range and levels of different process parameters were defined and are presented in table 3.2.

1. **Layer Thickness**: This is the thickness at which the STL file is sliced for part fabrication. It is also the distance by which the part bed moves down in the Z direction after completion of a layer. The layer thickness directly affects the build time and the surface quality. **(100/175/250/325/400 microns).**

2. **Extrusion Speed**: It is the rate at which material is deposited on the part bed. It is usually measured as the distance covered in one second. **(2000/2375/2750/3125/3500 mm/min)**

3. **Part Bed Temperature**: It is the temperature of the part bed on which the part is being built. The part bed is preheated to control the curling or warping of the part. **(53/56/59/62/65**℃)
4. **Nozzle Diameter**: It is the diameter of a nozzle used to control the rate of flow, speed, direction, mass, shape of the material that emerges from it. **(.2/.3/.4/.5/.6 mm)**

5. **Extrusion temperature:** It is basically the temperature of the nozzle by the help of which the melted material comes out. **(230/235/240/245/250**℃)

Table 3.2 Process parameters with their levels

LEVELS / PROCESS PARAMETERS	-2	-1	0	1	2
Nozzle Diameter	0.2 mm	0.3 mm	0.4 mm	0.5 mm	0.6 mm
Layer Thickness	100 microns	175 microns	250 microns	325 microns	400 microns
Part Bed Temp.	53°C	56°C	59°C	62°C	65°C
Extrusion Speed	2000 mm/min	2375 mm/min	2750 mm/min	3125 mm/min	3500 mm/min
Extrusion Temp.	230°C	235°C	240°C	245°C	250°C

A total of 32 experiments have been carried out and studied based on these process parameters.

3.4.2 <u>EXPERIMENTAL PLAN</u>:

The experimental plan used for the determination of shrinkage is presented in Table 3.3:

Table 3.3 Experimental Plan

S. No.	**ND**	**LT**	**PBT**	**ES**	**ET**
1	0.4	250	59	2750	240
2	0.4	250	59	2750	240
3	0.5	175	62	3125	235
4	0.5	325	62	3125	245
5	0.3	175	56	3125	235
6	0.2	250	59	2750	240
7	0.5	325	56	3125	235
8	0.5	175	56	2375	235
9	0.4	250	59	2750	240
10	0.4	250	59	3500	240
11	0.6	250	59	2750	240
12	0.4	250	65	2750	240

13	0.3	175	62	2375	235
14	0.3	325	62	2375	245
15	0.3	325	62	3125	235
16	0.3	175	56	2375	245
17	0.4	250	53	2750	240
18	0.5	325	56	2375	245
19	0.4	250	59	2750	250
20	0.4	400	59	2750	240
21	0.4	250	59	2750	230
22	0.5	175	62	2375	245
23	0.3	325	56	3125	245
24	0.3	325	56	2375	235
25	0.4	250	59	2000	240
26	0.4	250	59	2750	240
27	0.4	250	59	2750	240
28	0.4	250	59	2750	240
29	0.4	100	59	2750	240
30	0.3	175	62	3125	245
31	0.5	175	56	3125	245
32	0.5	325	62	2375	235

3.5 SPECIMEN'S FABRICATION

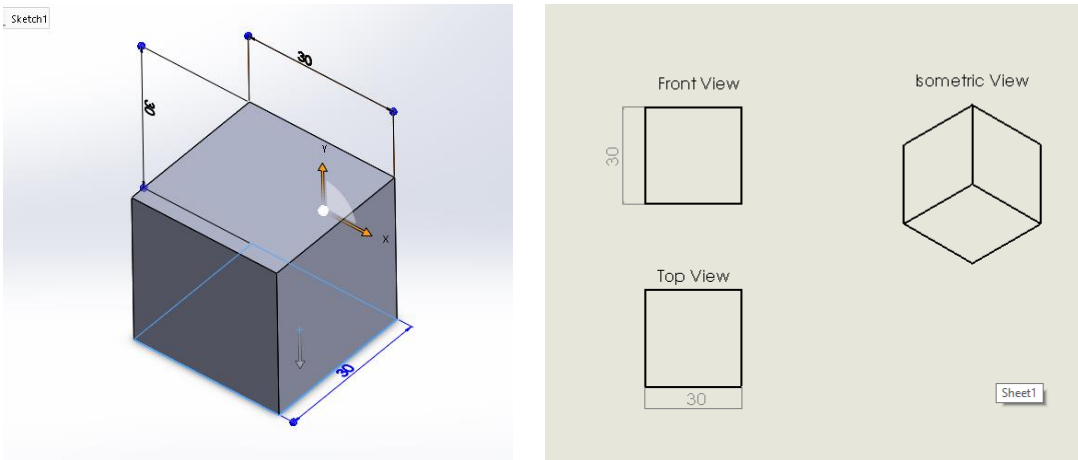

Figure 3.4: CAD model of the specimen developed on ProE software

- A cube of 30×30×30 mm was designed as shown in figure 3.4 as the specimens for this work. In total 32 cubes were designed in the ProE designing software and saved as .STL file format.

- Then these .STL files were transported to Simplify3D software for generating slices of the sample into layers. Further other noteworthy variables like part bed temperature, layer thickness, extrusion speed, extrusion speed and nozzle diameter etc. are defined. The modified files are then transferred to RP system using a memory card. The specimens are fabricated using wire based 3D work station. Figure 3.5 illustrates the developed workpiece.

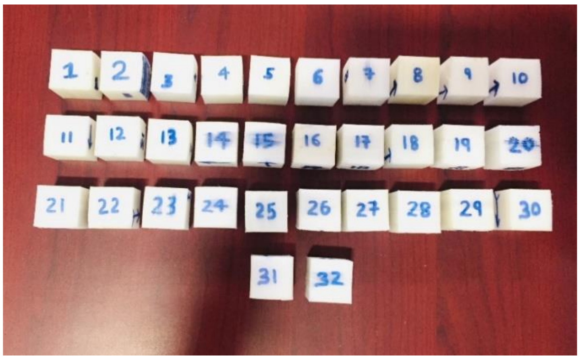

Figure 3.5: Nylon parts fabricated by 3d printer (30×30×30mm)

3.6 MEASUREMENT OF SHRINKAGE

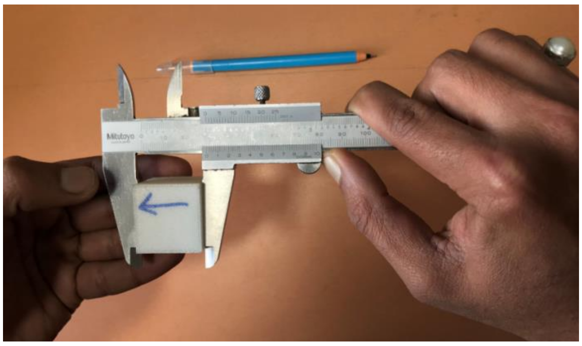

Fig 3.6: Vernier caliper (mitutoyo) least count: 0.02 mm

After using the designed experiments to fabricate specimens, the next step was to measure the response. A Vernier caliper with least count of 0.02 mm is used to quantify shrinkage along length of the parts as shown in figure 3.6. Ten readings for each sample was taken and average of that has been considered as response of each specimen. The difference of the actual dimension and response is recorded as the shrinkage of the specimen and taken as the observation for the model. The final readings are given in the table 3.4.

Table 3.4: Measurement of shrinkage

S. No.	ND	LT	PBT	ES	ET	Sh
1	0.4	250	59	2750	240	0.30
2	0.4	250	59	2750	240	0.30
3	0.5	175	62	3125	235	0.36
4	0.5	325	62	3125	245	0.28
5	0.3	175	56	3125	235	0.30
6	0.2	250	59	2750	240	0.20
7	0.5	325	56	3125	235	0.30
8	0.5	175	56	2375	235	0.36
9	0.4	250	59	2750	240	0.30
10	0.4	250	59	3500	240	0.26
11	0.6	250	59	2750	240	0.36
12	0.4	250	65	2750	240	0.24
13	0.3	175	62	2375	235	0.26
14	0.3	325	62	2375	245	0.20
15	0.3	325	62	3125	235	0.14
16	0.3	175	56	2375	245	0.30
17	0.4	250	53	2750	240	0.32
18	0.5	325	56	2375	245	0.34
19	0.4	250	59	2750	250	0.28
20	0.4	400	59	2750	240	0.22
21	0.4	250	59	2750	230	0.30
22	0.5	175	62	2375	245	0.34
23	0.3	325	56	3125	245	0.20
24	0.3	325	56	2375	235	0.28
25	0.4	250	59	2000	240	0.32
26	0.4	250	59	2750	240	0.32
27	0.4	250	59	2750	240	0.30
28	0.4	250	59	2750	240	0.30
29	0.4	100	59	2750	240	0.34
30	0.3	175	62	3125	245	0.28
31	0.5	175	56	3125	245	0.34
32	0.5	325	62	2375	235	0.30

CHAPTER 4:
STATISTICAL MODELLING OF SHRINKAGE

4.1 <u>STATISTICAL MODELLING</u>

A predictive model for shrinkage along direction of laying has been developed, after removing all the parameters which were unimportant. This model is based on the investigation of the data presented in table 3.4, and is given below as equation (4.1):

$$Sh = 5.74 - (1.27 \times ND) + (0.00314 \times LT) - (0.0676 \times PBT) - (0.000239 \times ES) - (0.0251 \times ET) - (0.423 \times ND^2) - (0.000001 \times LT^2) - (0.00047 \times PBT^2) + (0.00117 \times ND \times LT) + (0.0292 \times ND \times PBT) - (0.000039 \times LT \times PBT) - (0.000001 \times LT \times ES) + (0.000006 \times PBT \times ES) + (0.000417 \times PBT \times ET) \cdots\cdots\cdots\cdots\cdots (4.1)$$

Table 4.1 ANOVA Table for Shrinkage Model

Source	DF	SS	MS	F value	P value	R	Remarks
Regression	20	0.083956	0.004198	58.16	0	0.974	Model is Adequate 58.16>4.10
Linear	5	0.074083	0.000113	1.56			
Square	5	0.001623	0.000325	4.50			
Interaction	10	0.008250	0.000825	11.43			
Residual Error	11	0.000794	0.000720				
Lack-of-Fit	6	0.000461	0.000077	1.15	0.448		1.15< 5.07 Lack of fit is insignificant
Pure Error	5	0.000333	0.000067				
Total	31	0.084750					

The fitness of model has to be evaluated for the importance of regression and the lack of fit. Table 4.1 shows the analysis of variance. The value of R^2 is 97.4% which establishes a well-built connection between the selected process variables and the shrinkage. The frequency assessment of the regression is 58.16. In the analysis, $F_{0.01, 20, 11}$ is 4.10 for a significance level of α = 0.01. As this assessment is lesser than the frequency value of regression, the model is significant at 99% confidence level. Further the F value of lack of fit is 1.15. The value of $F_{0.01,}$

$_{6, 11}$ is 5.07 for a significance level of $\alpha = 0.01$. As this value is greater than the frequency value of lack of fit, so the lack of fit is insignificant.

The individual contributions of all the significant variables of predicted model are described in figure 4.1. Nozzle diameter, layer thickness, part bed temperature and extrusion speed is the most major variables which influences the shrinkage of the workpiece. The nozzle diameter is highest noteworthy with a contribution of 47%. The layer thickness has a contribution of 27%. Part bed temperature has a contribution of 9% followed by Extrusion speed with 4%. Extrusion temperature has minimal effect on the shrinkage.

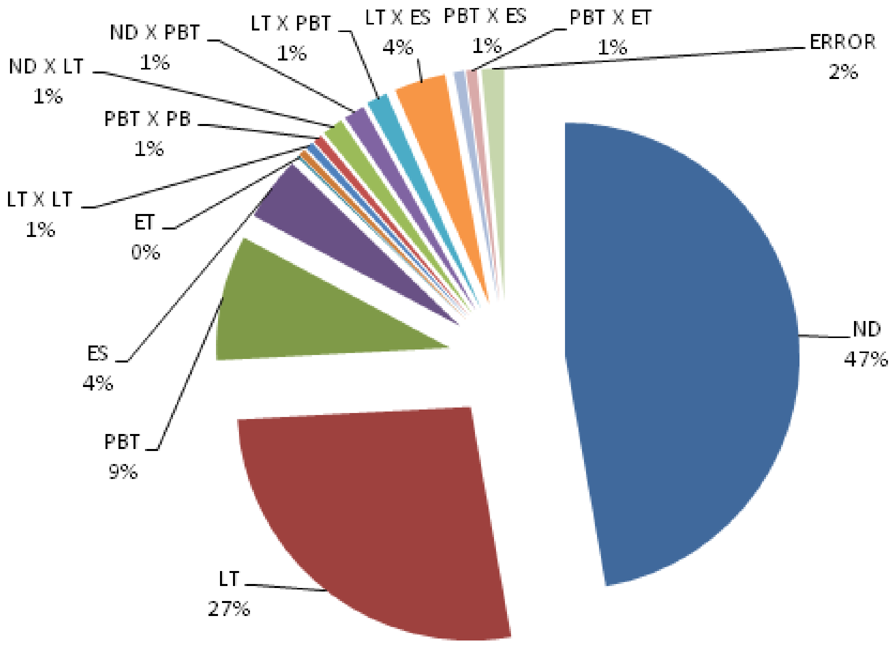

Figure 4.1 Contribution of Factors on Shrinkage of Upward Face

4.2 <u>RESULT AND DISCUSSION</u>

Figure 4.2 shows the main effect plot of shrinkage. Increase in nozzle diameter causes the shrinkage to increase. Shrinkage reduces with amplification in layer thickness, part bed temperature and extrusion speed. It is observed from figure 4.1 and figure 4.2 that the extrusion temperature do not sway the shrinkage.

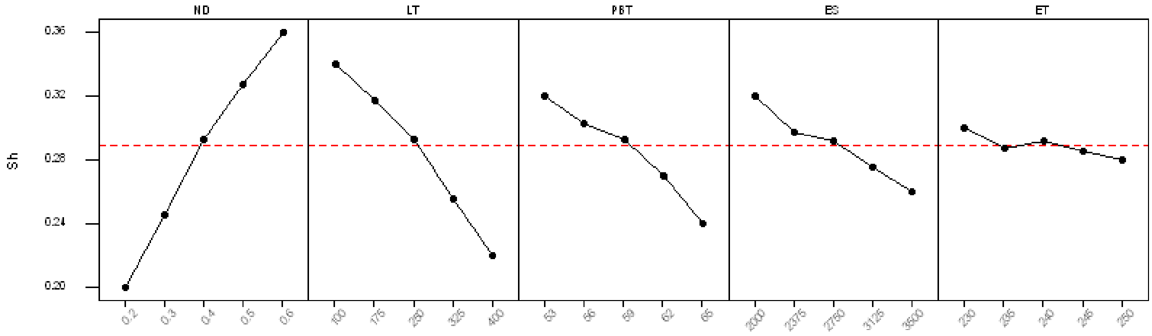

Figure 4.2 Main Effect Plot of Shrinkage

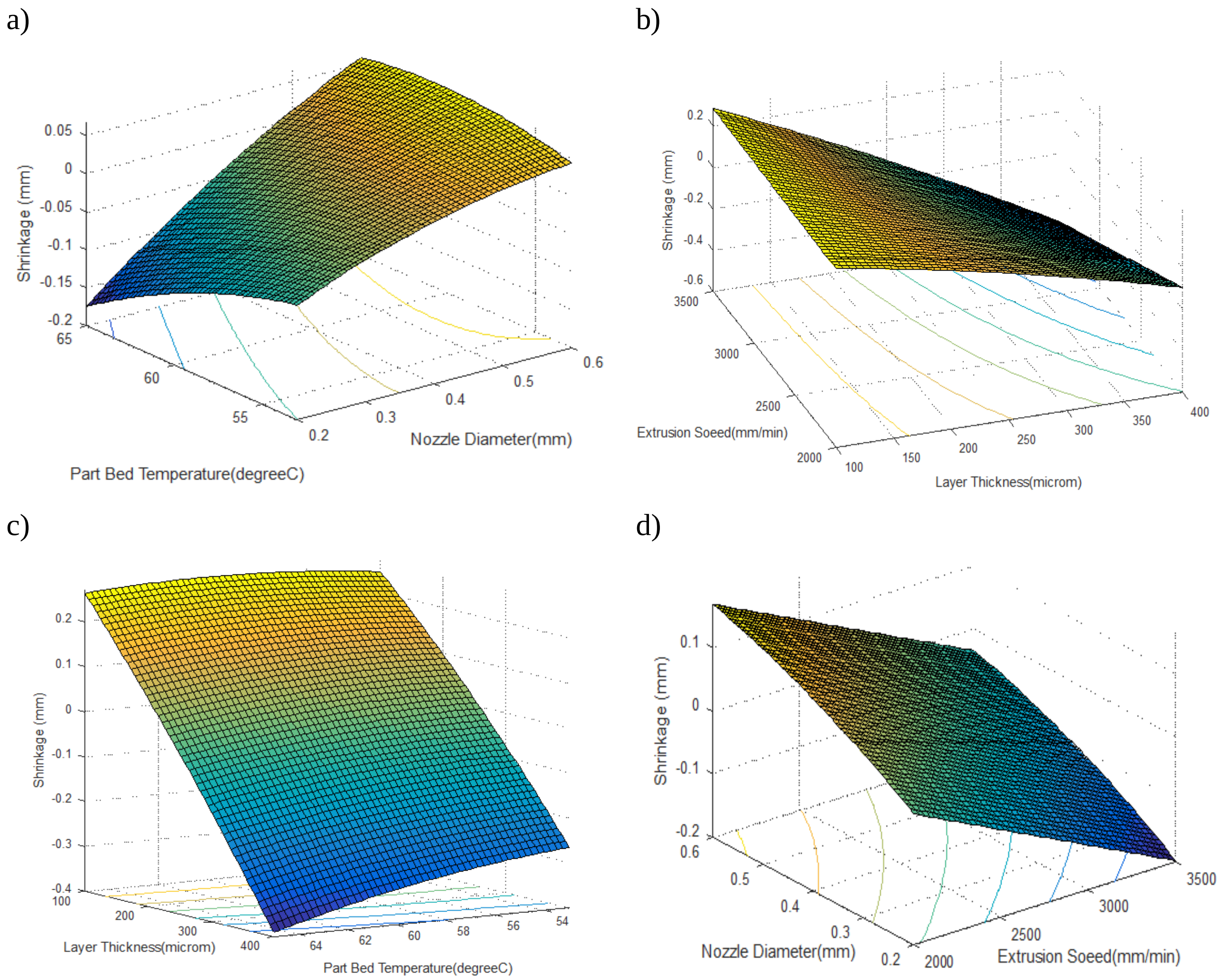

Figure 4.3 Response Surfaces of Shrinkage

Figure 4.3 illustrates the contour plots for the shrinkage. The contour plots helps to understand and interpret the surface design. The deviation of shrinkage in relation to nozzle diameter is presented in figure 4.3 (*a*). The graph discloses that shrinkage enhances with addition in nozzle diameter. Due to increase in nozzle diameter, there is more volume of molten material ejecting from the nozzle tip. This results in substantial increase in internal stresses because more material results in greater time for heat dissipation. This increase in volume of molten material and thermal stresses lead to more contraction and shrinkage.

The divergence of shrinkage with layer thickness is presented in figure 4.3 (*b*). As the layer thickness amplifies, shrinkage comes down. In wire based 3D printers, the major modes of dissipation of heat are conduction and forced convection. These processes diminish the temperature, forcing the material to coagulate in less time. The bonding between the two successive layers occur due to re-melting and diffusion of previous layer. Further, when thicker layers are employed, it results in application of fewer layers. This reduces the quantity of re-heating and re-cooling cycles. Shrinkage is further minimized.

The outcome of part bed temperature on shrinkage is shown in figure 4.3 (*c*). It shows that with an increase of the part bed temperature, shrinkage is decreased. At low part bed temperature, gap with respect to the softening temperature of nylon (90°C) is more. As a result, inter layer adhesion is hindered. As the layers were separated from one another, shape errors due to the heat shrinkage increases. As the part bed temperature increases, it starts to come close to the softening temperature required for Nylon during fabrication process. The inter-layer adhesion improves the material is subjected to a slow phase transformation from the liquid phase to solid phase, and thus it hardens slowly. This results is lesser shrinkage.

The consequence of extrusion speed on shrinkage is presented in figure 4.3 (*d*). It shows that with an increase of the extrusion speed, shrinkage is decreased. At low speeds, when the material is deposited, it has more time to dissipate the heat and undergo thermally induced shrinkage. However, as the speed increases, the rate of deposition also increases. As a result, even before the bottom layer has stabilized and solidified, new layer has been deposited. As a result, there is more heat in the system which requires lesser heat dissipation for thermal equilibrium. This effect reduces the deformation in the body and reduces shrinkage.

4.3 CONFIRMATION OF EXPERIMENTS

It is often observed that there is experimental error in mechanical equipment's. Due to this, fairly accurate parameters give approximate answers which are subjected to ambiguity. The accuracy of responses is brought closer by computing error. The array of the present output is Sh ± ΔSh, where ΔSh is premeditated by the relation given below:

$$\Delta Ra = t_{\alpha/2,\ DF}\sqrt{(Ve)} \tag{4.2}$$

Here, Sh denotes shrinkage, *t* is the value of t-distribution at the described degree of freedom (DF) with their significance interval level on the horizontal coordinate and Ve is the mean square of residual error of the predicted statistical model. The value of α is taken as 0.01. The value of ΔSh is 0.03 mm. It is observed from the confirmation experiments (Table 4.2) that the accuracy of the generated model for shrinkage is adequate.

Table 4.2 Confirmation Experiments (Machining Parameters Selected from Outside the DOE Table)

	Machining Parameters					Shrinkage	
Exp No.	Nozzle Diameter	Layer Thickness	Part Bed Temperature	Extrusion Speed	Extrusion Temperature	Experimental (mm)	Predicted (mm)
1	0.2	250	59	2600	240	0.54	0.56 ± 0.03
2	0.3	175	55	3125	235	0.64	0.66 ± 0.03
3	0.3	300	56	2375	245	0.66	0.64 ± 0.03
4	0.4	400	59	2700	240	0.78	0.78 ± 0.03
5	0.5	325	62	3125	242	0.82	0.80 ± 0.03
6	0.6	250	59	2700	238	0.72	0.74 ± 0.03

4.4 CONCLUSIONS

A predictive model has been developed for forecasting shrinkage using Nylon as work material. Competence of the model is evaluated by ANOVA and most affecting variables have been identified. The results show that quadric model developed for shrinkage is statistically significant. It has been observed that nozzle diameter, layer thickness, part bed temperature and extrusion speed are most significant factors which affect shrinkage. It has been discovered that with increase in nozzle diameter, shrinkage increases, whereas increase in layer thickness, part bed temperature and extrusion speed decreases shrinkage. Verification of developed model was done by doing experiments at different settings which confirm that forecast of model is precise.

CHAPTER 5:
MODELLING OF SHRINKAGE USING MACHINE LEARNING

5.1 MACHINE LEARNING

"Machine learning is an efficient investigation of algorithms and architecture that improve their performance or knowledge based upon experience"[9]. Machine learning is about training computers to modify or adapt their actions in order obtain more precise actions, where accuracy is measured by how accurate the selected actions reflect the correct ones. It is only over the past few years that machine learning has been recognized because of its intrinsic multi-disciplinarily approach. It is based on ideas from neuroscience, biology, statistics, mathematics and physics. The amount of computing resources needed for particular type of task in machine learning methods is also of our interest since what we are producing is algorithms. The complexity in the size of dataset is broken into two parts: the complexity of the training and running the trained algorithms. Machine learning also has great societal influence across a wide range of research, industry and business applications, for examples, big data, Internet of Things (IOT), cloud computing, healthcare, etc.

APPLICATIONS OF MACHINE LEARNING:

Advances in machine learning and big data have become a broad research area for solving problems using historical or real time data from sensors. Machine learning techniques are being used in different real-world applications listed below:-

1. Manufacturing, aerospace and automotive
2. Health care and computational biology
3. Image processing and computer vision
4. Face and speech recognition
5. Natural language processing
6. Sales forecasting

5.2 TYPES OF MACHINE LEARNING TECHNIQUES

SUPERVISED LEARNING: Supervised learning allows the computer program to "learn" from a set of labelled data in the training set which permits machine learning algorithm to identify unlabelled data from the data set. [12] In supervised learning, the learning data comes with descriptions, labels, targets and the main objective is to establish a general rule that maps inputs to outputs. It is commonly used for real world applications such as face and speech recognition, sales forecasting. Supervised learning associated with learning a function from the available training data. Here, algorithm is used to analyse the training data and derives a function that can be used to map new examples. Common examples of supervised learning are voice recognition, speech recognition, classifying emails into spams and to label the web pages.

UNSUPERVISED LEARNING: On the other hand, unsupervised learning works with unlabelled data so there is no test data as such. [12] In unsupervised learning the learning data contains only few indications without any description of it, then structure of the underlying data is made by the coder to discover hidden patterns or to find how to describe the data. This kind of data is called unlabelled data. Unsupervised learning is associated with powerful tools for analysing the data and finding pattern of the data. Unsupervised learning algorithms includes hierarchical clustering, random forests, *k* means etc.

REINFORCEMENT LEARNING: Reinforcement learning lies somewhere between supervised and unsupervised learning.[13] The middle ground is where information is provided where whether or not the answer is correct but don't know how to improve it. It is basically the interaction between some agent and its environment. Where agent is the thing which is learning and environment is where it is learning. The objective function of reinforcement learning is that the algorithm gets feedback in the form of reward about how well is it doing.

5.3 MACHINE LEARNING TOOLS

- **WEKA:** Weka (Waikato environment for knowledge analysis) is an inclusive study of java class libraries that implement many advanced artificial intelligence and data mining algorithms. Weka is easily available on the web and conveys a new text on data mining which stores and fully explains all algorithm it contains. Weka can be run on any computer having browsing capability, and allows users to apply machine learning techniques to their own data without depending on the computer program. Tools are provided for data processing, analysing classifiers in terms of their performance and variety of learning schemes. [14]

- **PYTHON LIBRARIES FOR MACHINE LEARNING:**
  - **PANDAS:** Pandas is an open source information library for capturing data into good and clean structures which provides instinctive and pleasant analysis. Pandas is considered as the best libraries of python. Pandas consists of two objects – data frame (2d spreadsheet with row and column) and series (one column) and many methods for shaping, scaling and filtration of data. Pandas comes with variety of input data like Excel, SQL, HML, CSV etc. It was specially used for data preparation, extraction along with the extensive documentation of data. It comes with high level data and variety of tools for analysing the data. [W5]
  - **NUMPY:** Numpy is used for performing advanced mathematical functions and allows working with matrices and multi-dimensional arrays. It is very useful for performing fundamental scientific calculations such as mean, median, range etc. It is especially convenient for linear algebra, fourier series and random number abilities. It provides variety of useful features for performing calculations on arrays and matrices in python library. [W5]
  - **SCIKIT LEARN:** Scikit - learn is an easy to use interface which combines the range of supervised and unsupervised learning methods. Focuses mainly on performance, documentation, API consistency and allows easy comparison of methods. Scikit - learn is different from other machine learning tool in the way that (1) it was passed under the BSD licence (2) it consolidates the compiled code for performance (3) depends only upon numpy and scipy for easy distribution. It is said to be the most important tool for statistical data analysis. It is associated with various categorised models like Support Vector Machines (SVM), Regression Analysis, Data analysis, data adjustments. [W6]

5.4 MODELLING USING MACHINE LEARNING

A machine learning model for the shrinkage along direction of laying was developed, by correlating the input parameters namely nozzle diameter, layer thickness, part bed temperature, extrusion speed and extrusion temperature and statistical model developed and explained in previous chapter. Random permissible values of the five different parameters were considered within the domain defined in table 3.2 and its shrinkage is calculated using the statistical model developed. A data set of 248 such samples was developed using the above method and are depicted in table 5.1.

Table 5.1 Data set for Machine learning model

S. No.	ND	LT	PBT	ES	ET	Sh		S. No.	ND	LT	PBT	ES	ET	Sh
1	0.4	250	59	2750	240	0.68		**125**	0.3	325	62	2375	242	0.60
2	0.4	250	59	2750	240	0.68		**126**	0.3	325	62	3125	232	0.70
3	0.5	175	62	3125	235	0.70		**127**	0.3	175	56	2375	242	0.56
4	0.5	325	62	3125	245	0.82		**128**	0.4	250	53	2750	237	0.70
5	0.3	175	56	3125	235	0.64		**129**	0.5	325	56	2375	242	0.76
6	0.2	250	59	2750	240	0.58		**130**	0.4	250	59	2750	250	0.68
7	0.5	325	56	3125	235	0.84		**131**	0.4	400	59	2750	237	0.78
8	0.5	175	56	2375	235	0.62		**132**	0.4	250	59	2750	230	0.68
9	0.4	250	59	2750	240	0.68		**133**	0.5	175	62	2375	242	0.60
10	0.4	250	59	3500	240	0.78		**134**	0.3	325	56	3125	242	0.76
11	0.6	250	59	2750	240	0.74		**135**	0.3	325	56	2375	232	0.70
12	0.4	250	65	2750	240	0.64		**136**	0.4	250	59	2000	237	0.60
13	0.3	175	62	2375	235	0.52		**137**	0.4	100	59	2750	237	0.54
14	0.3	325	62	2375	245	0.60		**138**	0.3	175	62	3125	242	0.62
15	0.3	325	62	3125	235	0.70		**139**	0.5	175	56	3125	242	0.68
16	0.3	175	56	2375	245	0.56		**140**	0.5	325	62	2375	232	0.72
17	0.4	250	53	2750	240	0.70		**141**	0.5	175	60	3125	235	0.70
18	0.5	325	56	2375	245	0.76		**142**	0.5	325	60	3125	245	0.84
19	0.4	250	59	2750	250	0.68		**143**	0.3	175	54	3125	235	0.64
20	0.4	400	59	2750	240	0.78		**144**	0.2	250	57	2750	240	0.60
21	0.4	250	59	2750	230	0.68		**145**	0.5	325	54	3125	235	0.84
22	0.5	175	62	2375	245	0.60		**146**	0.5	175	54	2375	235	0.61
23	0.3	325	56	3125	245	0.74		**147**	0.4	250	57	2750	240	0.70
24	0.3	325	56	2375	235	0.68		**148**	0.4	250	57	3500	240	0.78
25	0.4	250	59	2000	240	0.60		**149**	0.6	250	57	2750	240	0.74
26	0.4	250	59	2750	240	0.68		**150**	0.4	250	65	2750	240	0.64
27	0.4	250	59	2750	240	0.68		**151**	0.3	175	60	2375	235	0.54
28	0.4	250	59	2750	240	0.68		**152**	0.3	325	60	2375	245	0.64
29	0.4	100	59	2750	240	0.54		**153**	0.3	325	60	3125	235	0.72
30	0.3	175	62	3125	245	0.62		**154**	0.3	175	54	2375	245	0.56
31	0.5	175	56	3125	245	0.68		**155**	0.4	250	53	2750	240	0.70
32	0.5	325	62	2375	235	0.72		**156**	0.5	325	54	2375	245	0.76
33	0.5	125	62	3125	235	0.64		**157**	0.4	250	57	2750	250	0.68
34	0.5	275	62	3125	245	0.78		**158**	0.4	400	57	2750	240	0.80
35	0.3	125	56	3125	235	0.60		**159**	0.4	250	57	2750	230	0.70
36	0.2	200	59	2750	240	0.54		**160**	0.5	175	60	2375	245	0.60
37	0.5	275	56	3125	235	0.80		**161**	0.3	325	54	3125	245	0.76
38	0.5	125	56	2375	235	0.56		**162**	0.3	325	54	2375	235	0.72
39	0.4	200	59	2750	240	0.64		**163**	0.4	250	57	2000	240	0.62
40	0.4	200	59	3500	240	0.74		**164**	0.4	100	57	2750	240	0.54
41	0.6	200	59	2750	240	0.68		**165**	0.3	175	60	3125	245	0.62
42	0.4	200	65	2750	240	0.60		**166**	0.5	175	54	3125	245	0.66

43	0.3	125	62	2375	235	0.48		**167**	0.5	325	60	2375	235	0.74
44	0.3	275	62	2375	245	0.58		**168**	0.5	175	61	3125	235	0.70
45	0.3	275	62	3125	235	0.68		**169**	0.5	325	61	3125	245	0.82
46	0.3	125	56	2375	245	0.50		**170**	0.3	175	55	3125	235	0.64
47	0.4	200	53	2750	240	0.64		**171**	0.2	250	58	2750	240	0.60
48	0.5	275	56	2375	245	0.72		**172**	0.5	325	55	3125	235	0.84
49	0.4	200	59	2750	250	0.64		**173**	0.5	175	55	2375	235	0.62
50	0.4	400	59	2750	240	0.78		**174**	0.4	250	58	2750	240	0.68
51	0.4	200	59	2750	230	0.66		**175**	0.4	250	58	3500	240	0.78
52	0.5	125	62	2375	245	0.56		**176**	0.6	250	58	2750	240	0.74
53	0.3	275	56	3125	245	0.70		**177**	0.4	250	65	2750	240	0.64
54	0.3	275	56	2375	235	0.66		**178**	0.3	175	61	2375	235	0.52
55	0.4	200	59	2000	240	0.56		**179**	0.3	325	61	2375	245	0.62
56	0.4	100	59	2750	240	0.54		**180**	0.3	325	61	3125	235	0.72
57	0.3	125	62	3125	245	0.58		**181**	0.3	175	55	2375	245	0.56
58	0.5	125	56	3125	245	0.62		**182**	0.4	250	53	2750	240	0.70
59	0.5	275	62	2375	235	0.68		**183**	0.5	325	55	2375	245	0.76
60	0.5	150	62	3125	235	0.68		**184**	0.4	250	58	2750	250	0.68
61	0.5	300	62	3125	245	0.80		**185**	0.4	400	58	2750	240	0.80
62	0.3	150	56	3125	235	0.62		**186**	0.4	250	58	2750	230	0.70
63	0.2	225	59	2750	240	0.58		**187**	0.5	175	61	2375	245	0.60
64	0.5	300	56	3125	235	0.82		**188**	0.3	325	55	3125	245	0.74
65	0.5	150	56	2375	235	0.60		**189**	0.3	325	55	2375	235	0.70
66	0.4	225	59	2750	240	0.66		**190**	0.4	250	58	2000	240	0.62
67	0.4	225	59	3500	240	0.76		**191**	0.4	100	58	2750	240	0.54
68	0.6	225	59	2750	240	0.72		**192**	0.3	175	61	3125	245	0.62
69	0.4	225	65	2750	240	0.62		**193**	0.5	175	55	3125	245	0.66
70	0.3	150	62	2375	235	0.50		**194**	0.5	325	61	2375	235	0.72
71	0.3	300	62	2375	245	0.60		**195**	0.5	175	62	2925	235	0.66
72	0.3	300	62	3125	235	0.68		**196**	0.5	325	62	2925	245	0.80
73	0.3	150	56	2375	245	0.54		**197**	0.3	175	56	2925	235	0.62
74	0.4	225	53	2750	240	0.66		**198**	0.2	250	59	2500	240	0.56
75	0.5	300	56	2375	245	0.74		**199**	0.5	325	56	2925	235	0.82
76	0.4	225	59	2750	250	0.66		**200**	0.5	175	56	2175	235	0.60
77	0.4	400	59	2750	240	0.78		**201**	0.4	250	59	2500	240	0.66
78	0.4	225	59	2750	230	0.68		**202**	0.4	250	59	3500	240	0.78
79	0.5	150	62	2375	245	0.58		**203**	0.6	250	59	2500	240	0.72
80	0.3	300	56	3125	245	0.72		**204**	0.4	250	65	2500	240	0.60
81	0.3	300	56	2375	235	0.68		**205**	0.3	175	62	2175	235	0.48
82	0.4	225	59	2000	240	0.58		**206**	0.3	325	62	2175	245	0.58
83	0.4	100	59	2750	240	0.54		**207**	0.3	325	62	2925	235	0.68
84	0.3	150	62	3125	245	0.60		**208**	0.3	175	56	2175	245	0.54
85	0.5	150	56	3125	245	0.64		**209**	0.4	250	53	2500	240	0.68
86	0.5	300	62	2375	235	0.70		**210**	0.5	325	56	2175	245	0.74

87	0.5	175	62	3125	233	0.70		**211**	0.4	250	59	2500	250	0.66
88	0.5	325	62	3125	243	0.82		**212**	0.4	400	59	2500	240	0.76
89	0.3	175	56	3125	233	0.64		**213**	0.4	250	59	2500	230	0.66
90	0.2	250	59	2750	238	0.58		**214**	0.5	175	62	2175	245	0.58
91	0.5	325	56	3125	233	0.84		**215**	0.3	325	56	2925	245	0.72
92	0.5	175	56	2375	233	0.62		**216**	0.3	325	56	2175	235	0.68
93	0.4	250	59	2750	238	0.68		**217**	0.4	250	59	2000	240	0.60
94	0.4	250	59	3500	238	0.78		**218**	0.4	100	59	2500	240	0.52
95	0.6	250	59	2750	238	0.74		**219**	0.3	175	62	2925	245	0.60
96	0.4	250	65	2750	238	0.64		**220**	0.5	175	56	2925	245	0.66
97	0.3	175	62	2375	233	0.52		**221**	0.5	325	62	2175	235	0.70
98	0.3	325	62	2375	243	0.62		**222**	0.5	175	62	3025	235	0.68
99	0.3	325	62	3125	233	0.70		**223**	0.5	325	62	3025	245	0.82
100	0.3	175	56	2375	243	0.56		**224**	0.3	175	56	3025	235	0.64
101	0.4	250	53	2750	238	0.70		**225**	0.2	250	59	2600	240	0.58
102	0.5	325	56	2375	243	0.76		**226**	0.5	325	56	3025	235	0.84
103	0.4	250	59	2750	250	0.68		**227**	0.5	175	56	2275	235	0.60
104	0.4	400	59	2750	238	0.78		**228**	0.4	250	59	2600	240	0.68
105	0.4	250	59	2750	230	0.70		**229**	0.4	250	59	3500	240	0.78
106	0.5	175	62	2375	243	0.60		**230**	0.6	250	59	2600	240	0.74
107	0.3	325	56	3125	243	0.74		**231**	0.4	250	65	2600	240	0.62
108	0.3	325	56	2375	233	0.70		**232**	0.3	175	62	2275	235	0.50
109	0.4	250	59	2000	238	0.60		**233**	0.3	325	62	2275	245	0.60
110	0.4	100	59	2750	238	0.54		**234**	0.3	325	62	3025	235	0.68
111	0.3	175	62	3125	243	0.62		**235**	0.3	175	56	2275	245	0.54
112	0.5	175	56	3125	243	0.66		**236**	0.4	250	53	2600	240	0.68
113	0.5	325	62	2375	233	0.72		**237**	0.5	325	56	2275	245	0.74
114	0.5	175	62	3125	232	0.70		**238**	0.4	250	59	2600	250	0.66
115	0.5	325	62	3125	242	0.82		**239**	0.4	400	59	2600	240	0.78
116	0.3	175	56	3125	232	0.64		**240**	0.4	250	59	2600	230	0.68
117	0.2	250	59	2750	237	0.58		**241**	0.5	175	62	2275	245	0.60
118	0.5	325	56	3125	232	0.86		**242**	0.3	325	56	3025	245	0.74
119	0.5	175	56	2375	232	0.62		**243**	0.3	325	56	2275	235	0.68
120	0.4	250	59	2750	237	0.68		**244**	0.4	250	59	2000	240	0.60
121	0.4	250	59	3500	237	0.78		**245**	0.4	100	59	2600	240	0.52
122	0.6	250	59	2750	237	0.76		**246**	0.3	175	62	3025	245	0.62
123	0.4	250	65	2750	237	0.64		**247**	0.5	175	56	3025	245	0.66
124	0.3	175	62	2375	232	0.52		**248**	0.5	325	62	2275	235	0.70

In order to train the machine learning model, we have derived quadratic features out of the five process parameters (table 3.2), which will generate a 20-tuple input vector for training. The 20-tuple vector consists of five process parameters, their square terms and the interaction of different process parameters with each other. The coefficients obtained for input variables are presented in table 5.2. The value of intercept (constant) was found to be 0.23.

Table 5.2 Coefficients of variables

Variable	Coefficient	Variable	Coefficient	Variable	Coefficient	Variable	Coefficient
ND	-1.313138	ND×ND	-0.471143	LT×LT	-0.000001	PBT×ES	0.000006
LT	0.003346	ND×LT	0.001149	LT×PBT	-0.000038	PBT×ET	0.000082
PBT	0.003686	ND×PBT	0.028623	LT×ES	0.000000	ES×ES	0.000000
ES	-0.000087	ND×ES	0.000013	LT×ET	-0.000001	ES×ET	-0.000001
ET	0.003664	ND×ET	0.000352	PBT×PBT	-0.000391	ET×ET	-0.000015

In order to determine the significance of various input vectors with respect to shrinkage, a heat map has been developed to determine the relevance. The heat map is showing the various interactions of the input vectors with respect to shrinkage. The heat map is presented in figure 5.1

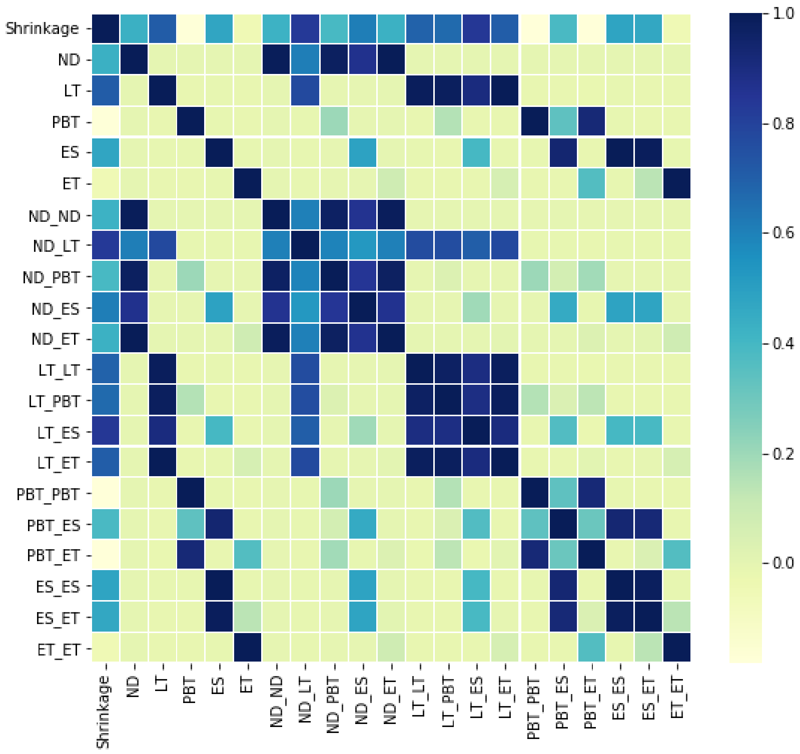

Figure 5.1 Heat map of various process parameters with respect to Shrinkage

On evaluating the heat map, it was found that $ND, LT, PBT, ES, ET, ND^2, ND \times LT, ND \times PBT, ND \times ES, ND \times ET, LT^2, LT \times PBT, LT \times ES, LT \times ET, PBT \times ES, ES^2, ES \times ET, ET^2$ are significant and influence the shrinkage. It was observed that the root mean square error for the machine learning model is 0.006756502. This means that the coefficient of correlation is 0.999932. The table highlighting the coefficients, probability and accuracy is given in table 5.3.

Table 5.3 Coefficients, Probability and Accuracy

	Coef	Std. Err	t	P>|t|	[0.005]	[0.995]
ND	-1.3131000	0.2830000	-4.6470000	0.0000000	-2.0470000	-0.5790000
LT	0.0033000	0.0000000	8.2660000	0.0000000	0.0020000	0.0040000
PBT	0.0037000	0.0070000	0.5580000	0.5780000	-0.0130000	0.0210000
ES	-0.0000868	0.0000708	-1.2250000	0.2220000	0.0000000	0.0000972
ET	0.0037000	0.0020000	1.9040000	0.0580000	-0.0010000	0.0090000
ND^2	-0.4711000	0.0490000	-9.5520000	0.0000000	-0.5990000	-0.3430000
NDxLT	0.0011000	0.0000767	14.9770000	0.0000000	0.0010000	0.0010000
NDxPBT	0.0286000	0.0020000	14.7290000	0.0000000	0.0240000	0.0340000
NDxES	0.0000130	0.0000162	0.8000000	0.4240000	-0.0000292	0.0000551
NDxET	0.0004000	0.0010000	0.3350000	0.7380000	-0.0020000	0.0030000
LT^2	-0.0000010	0.0000001	-11.9420000	0.0000000	-0.0000012	-0.0000008
LTxPBT	-0.0000381	0.0000025	-15.1830000	0.0000000	-0.0000446	-0.0000315
LTxET	-0.0000009	0.0000015	-0.5970000	0.5510000	-0.0000049	0.0000031
PBTxES	0.0000057	0.0000005	12.3870000	0.0000000	0.0000045	0.0000069
ESxET	-0.0000006	0.0000003	-2.1740000	0.0310000	-0.0000013	0.0000001
ET^2	-0.0000155	0.0000060	-2.6040000	0.0100000	-0.0000309	0.0000000

Based on the data obtained in table 5.3 and the heat map obtained (figure 5.1), important process variables have been determined and a model for shrinkage has been developed by correlating all the significant parameters, along with the intercept, for prediction. The model is given as:

$$\begin{aligned} Sh = 0.23 &- (1.3131 \times ND) + (0.0033 \times LT) + (0.0037 \times PBT) - (0.0000868 \times ES) \\ &+ (0.0037 \times ET) - (0.4711 \times ND^2) - (0.000001 \times LT^2) \\ &- (0.0004 \times PBT^2) - (0.0000155 \times ET^2) + (0.0011 \times ND \times LT) \\ &+ (0.0286 \times ND \times PBT) - (0.0000381 \times LT \times PBT) \\ &+ (0.0000057 \times PBT \times ES) + (0.0000818 \times PBT \times ET) \\ &- (0.0000006 \times ES \times ET) \cdots\cdots\cdots\cdots (5.1) \end{aligned}$$

The variation of shrinkage with respect to the input variables namely layer thickness, nozzle diameter, part bed temperature, extrusion speed and extrusion temperature has been shown in figure 5.2. It is seen that shrinkage increases as layer thickness and nozzle diameter increases, whereas increment in part bed temperature, extrusion speed and extrusion temperature results in decrease of shrinkage. As the mean does not variate significantly therefore the effect of extrusion temperature is very minimal or insignificant.

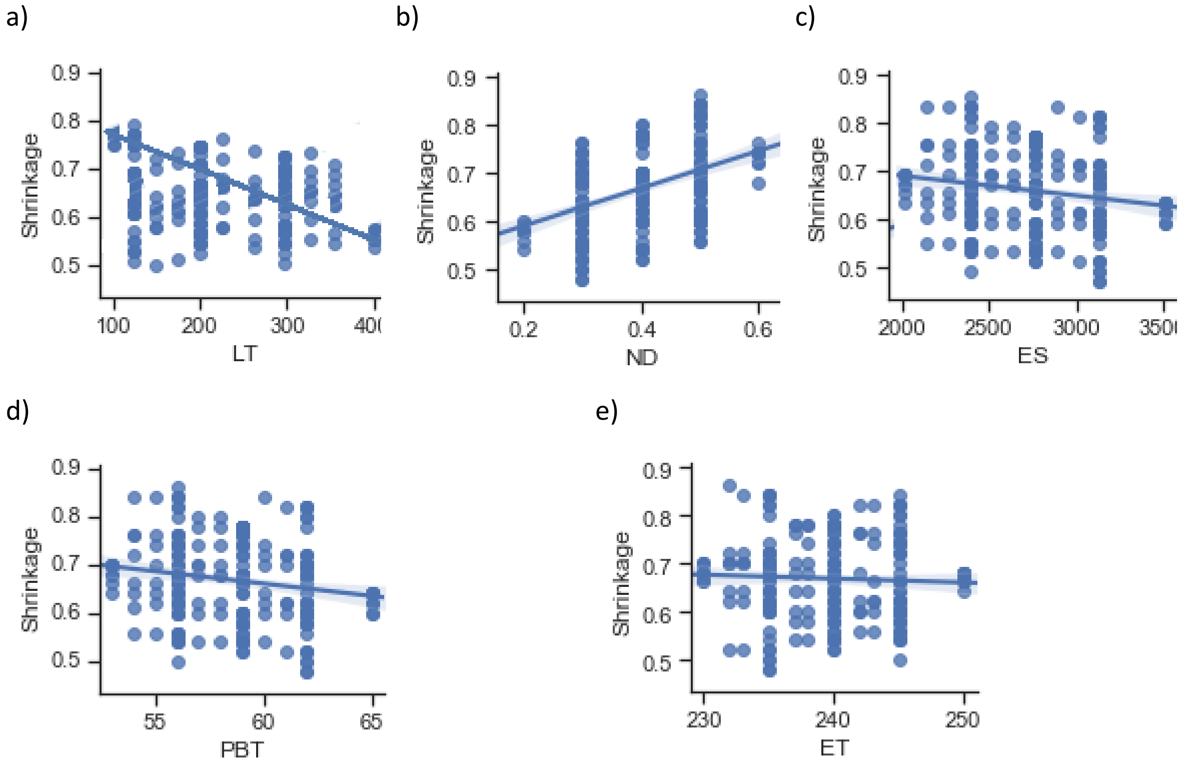

Figure 5.2 Variation of Shrinkage with respect to five process parameters

As layer thickness amplifies, shrinkage is decreased. In wire based 3D printers, the major modes of dissipation of heat are conduction and forced convection. They diminish the temperature, resulting in coagulation of the material in lesser time. The bondings between the two successive layers occur due to re-melting and diffusion of previous layer. Further, when thicker layers are employed, it results in application of fewer layers. This reduces the quantity of reheating and recooling cycles. Shrinkage is further minimized.

The graph reveals that shrinkage augments with raise in nozzle diameter. Increase in nozzle diameter results in more volume of molten material ejecting from the nozzle tip. This results in substantial increase in internal stresses because more material results in greater time for heat dissipation. This increase in volume of molten material and thermal stresses leads to more contraction and shrinkage.

Figure shows that with an increase of the extrusion speed, shrinkage is decreased. At low speeds, when the material is deposited, it has more time to dissipate the heat and undergo thermally induced shrinkage. However as the speed increases, the rate of deposition also increases. As a result, even before the bottom layer has stabilized and solidified, new layer has been deposited. As a result, there is more heat in the system which requires lesser heat dissipation for thermal equilibrium. This effect reduces the deformation in the body and reduces shrinkage.

It can be observed that the increase of the part bed temperature causes the shrinkage to decrease. At low part bed temperature, gap with respect to the softening temperature of nylon (90°C) is more. As a result, inter layer adhesion is hindered. As the layers were separated from one another, shape errors due to the heat shrinkage increases. As the part bed temperature increases, it starts to come close to the softening temperature required for Nylon during fabrication process. The inter-layer adhesion improves the material is subjected to a slow phase transformation from the liquid phase to solid phase, and thus it hardens slowly. This results is lesser shrinkage.

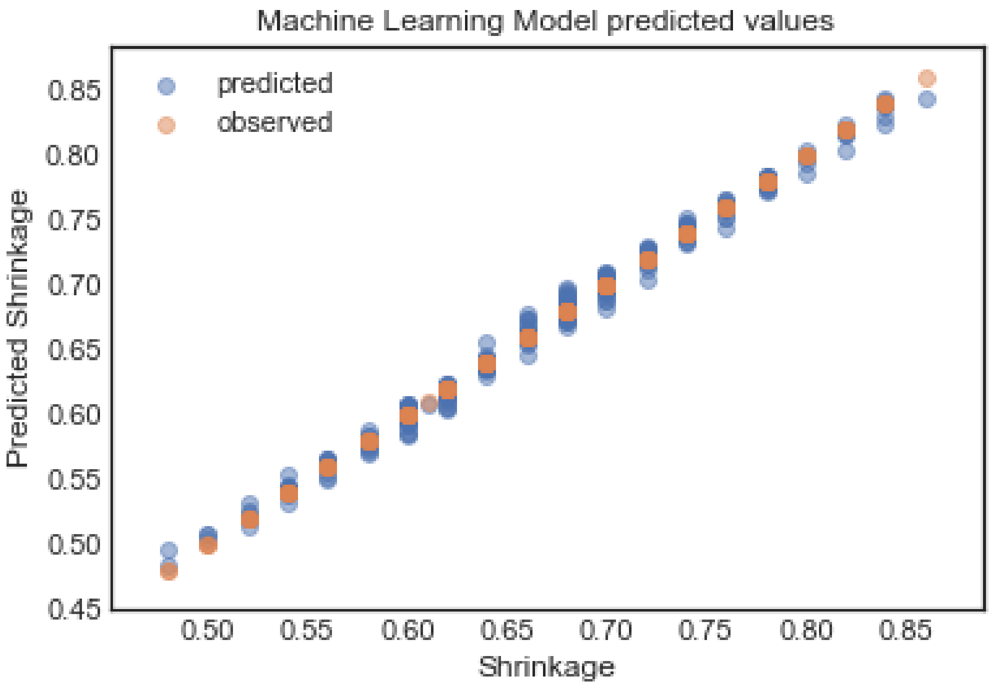

Figure 5.3 Performance of Machine Learning model

The performance of the machine learning model was predicted taking into consideration the root means square value. This value helps to define the upper and the lower boundary of acceptable range. It can be seen from the figure 5.3 that values obtained during experimentation satisfy the upper and the lower boundaries. Hence, the model developed is able to predict the shrinkage appropriately. The developed model was evaluated for accuracy and different process parameters randomly selected were tried. It can be seen from table 5.4 that the model is able to predict the shrinkage with acceptable accuracy.

Table 5.4 Confirmation Experiments

Exp. No.	Machining Parameters					Shrinkage	
	Nozzle Diameter	Layer Thickness	Part Bed Temperature	Extrusion Speed	Extrusion Temperature	Experimental (mm)	Predicted (mm)
1	0.2	100	54	2200	235	0.66	0.655±0.007
2	0.3	200	57	2900	241	0.84	0.842±0.007
3	0.4	300	59	2600	233	0.92	0.918 ± 0.007
4	0.5	400	63	2800	239	0.98	0.985 ± 0.007
5	0.6	175	53	3200	245	0.82	0.820 ± 0.007

5.5 CONCLUSIONS

A predictive model has been developed for forecasting shrinkage using Nylon. The competence of the model is checked and most affecting variables recognized. The results show that quadric model generated for shrinkage is significant. It has been observed that nozzle diameter, layer thickness, part bed temperature and extrusion speed are most significant factors. It has been discovered that with increase in nozzle diameter, shrinkage increases, whereas increase in layer thickness, part bed temperature and extrusion speed decreases shrinkage. Verification of developed model was done by doing experiments at different settings which confirm that forecast of model is precise.

CHAPTER 6:
CONCLUSIONS AND SCOPE FOR FUTURE WORK

6.1 CONCLUSIONS

In this work, shrinkage of the parts made-up by 3D printing process has been investigated. Fused Filament Modelling process has been used to fabricate the parts based on design of experiments using CCRD technique. Different process parameters related to FFM process were selected for shrinkage. For shrinkage, the process parameters were nozzle diameter, layer thickness, part bed temperature, extrusion speed and extrusion temperature. Two different models have been developed using statistical modelling and machine learning. Major conclusions drawn from the undertaken work is summarised in the following section.

- A model using statistical method has been generated for calculating the shrinkage in 3D Printing process using Nylon as work material. Quadric model developed for shrinkage is statistically considerable. It has been discovered that with increase in nozzle diameter, shrinkage increases, whereas increase in layer thickness, part bed temperature and extrusion speed decreases shrinkage.
- It is found that nozzle diameter, layer Accuracy of the created model was confirmed by validation experiments. thickness, part bed temperature and extrusion speed were the most important variables which affect the shrinkage of the parts. The nozzle diameter is highest noteworthy with a contribution of 47%. The layer thickness has a contribution of 27%. Part bed temperature has a contribution of 9% followed by Extrusion speed with 4%. Extrusion temperature has minimal effect on the shrinkage.
- It has been discovered that with increase in nozzle diameter, shrinkage increases, whereas increase in layer thickness, part bed temperature and extrusion speed decreases shrinkage.
- A model using machine learning was built up for calculating shrinkage in 3D Printing process using Nylon. The results demonstrate that quadric model generated for shrinkage is statistically considerable. It was discovered that with increase in nozzle diameter, shrinkage increases, whereas increase in layer thickness, part bed temperature and extrusion speed decreases shrinkage. Accuracy of the created model was confirmed by validation experiments.

- It has been discovered that with increase in nozzle diameter, shrinkage increases, whereas increase in layer thickness, part bed temperature and extrusion speed decreases shrinkage.

6.2 SCOPE FOR FUTURE WORK

- Experiments with larger domain of parameters can performed to better ascertain the effect of part bed temperature on dimensional accuracy.
- The procedure could be repeated on other polymers like ABS, PET, Polycarbonate, etc.

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