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Probabilistic Modeling and Mechanical Characterization of PLA Filaments in FDM-Based 3d Printing

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Abstract

Subtractive manufacturing entails subtracting material until the required shape is achieved; in contrast, additive manufacturing entails constructing objects directly from a CAD model by layering materials. One popular method of three-dimensional printing that uses melted material to create successive layers is fused deposition modeling (FDM). We tested the extruded strands, the fundamental pieces, might simplify the time-consuming and expensive process of material characterization of 3D printed structures to acquire characteristics like stiffness and strength. Towards this, single strands the axial tensile modulus, ultimate strength, and failure strain of PLA material with different gauge lengths are tested, as well as those of numerous extruded filaments with or without overlap. This is done using the 2-parameter Weibull distribution in a probabilistic strength prediction model to ascertain the likelihood of extruded strand material failure at a certain stress.

Keywords: 3D printing, FDM, thermoplastic, manufacturing

Introduction

Obtaining component characteristics and lowering print cost and time are both helped by parameter optimization. It also reduces the cost of 3D printing and allows maximum machine utilization. Moreover, it is important to comprehend how altering individual and group criteria affects part quality.

Industrial usage of rapid prototyping technologies has been on the rise for a while now. Instead of removing layers of material, rapid prototyping methods like 3D printing add them, creating three-dimensional objects. Layers of material are used in additive manufacturing to construct objects using data from 3D computer-aided design models, instead of the specialist tools required for traditional machining. The most popular additive manufacturing (AM) technology is fused deposition modeling (FDM) because to its low cost, simplicity of usage, and large variety of commercially available materials. By cutting down on material waste and making complicated forms cheaper, these solutions are great. The FDM printer uses a heated print head to extrude a semi-melted stream of thermoplastic, allowing it to build up layers of material from the bottom up. As soon as the material leaves the heated print head, it begins to solidify, producing a product in record time.

A large number of academics are interested in finding the optimal process parameters since the printed items' mechanical qualities change depending on those factors. Items made using FDM machines have recently sparked interest from academics who want to learn more about their structural performance. Recent years have seen a deluge of Studying the effects of input factors on mechanical properties, with a focus on flexural and tensile strengths. Layer thickness, orientation, raster angle, raster width, air gap, feed rate, print speed, filling ratio, extruder temperature, nozzle diameter, and shell number are some of the parameters that renowned researchers have examined. According to Dhinesh *et al*. (2011) [3], the tensile strength of PLA is greater than ABS, and it is much higher when an 80/20 mix is used. Mixed with half PLA and half ABS, it has the best flexural strength. More investigation into different percentages of PLA and ABS is now possible because to this. S. Singh *et al*. studied PLA reinforced with chitosan and found that compressive strength increased but tensile and flexural strengths dropped as the chitosan weight % raised. According to research, the most important aspect for wood PLA composites is the thickness of the layers. When it came to the mechanical characteristics of PLA+ samples, Günaya found that infilled density was the most critical element. Printing at a faster pace decreased tensile strength, but an orientation of 0 or 90 degrees increased it. As the layer height was raised, Camargo *et al*. discovered that the mechanical qualities of PLA-graphene improved. Rajpurohit and Dave and Gebisa and Lemu demonstrated both parameters are inversely related, with layer thickness being the more important. There was an effect of raster angle and raster width on FDM specimen flexural strength, which was also found. In order to maximize mechanical qualities like tensile and flexural strength, Chacón *et al*. propose orienting the edges. Using response surface analysis, Anoop Kumar Sood, Ohdar, and Mahapatra found the best combination of parameters for tensile and flexural strength.

3D Printing: Subtractive manufacturing, in which the final product is created by removing existing materials, is at the heart of traditional manufacturing processes. Because of this excessive material loss, additive manufacturing was born, a process that involves preparing the final product by adding more material. The process of 3D printing, which involves printing two-dimensional material in consecutive layers over each other to achieve the required dimension or design, is among the most prevalent forms of 3D printing. In 1986, Charles W. Hull filed for a patent on this fantastic method of making 3D items using stereolithography with little waste. There have been several advancements in the field of 3D printing and printable materials ever since. Figure 1 shows one way to classify 3D printing materials: by their state.

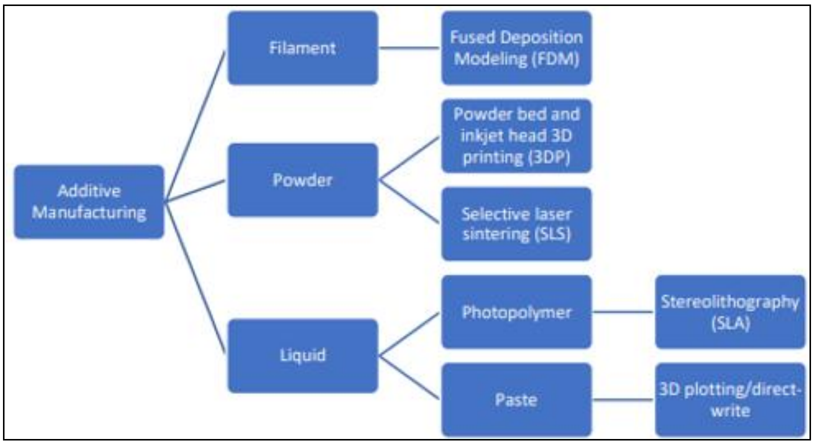

Fig 1: Adding Value: A Classification System

For the specimen preparation, we opted for an FDM-based 3D printer because of its affordability, speed, excellent strength, and compatibility with both PLA and acrylonitrile butadiene styrene (ABS). In 1989, S. Scott Crump submitted a patent application for the method. Fused deposition modelling (FDM) involves the sequential extrusion of heated filament towards the platform via a nozzle.

Literature Review

Valizadeh *et al.* (2021) [1] researched the major effect on the quality and performance of 3D printed products, including surface roughness. Locating the sweet spot for surface roughness reduction input parameters, this research used a hybrid artificial neural network in conjunction with a particle swarm approach. This was accomplished by conducting three-level tests utilising a 3D printer and layer thickness, printing speed, nozzle diameter, material density, and nozzle temperature are five separate variables. The outcome was 43 flat components printed using Central Composite Design (CCD). Next, the completed components were tested for roughness. Following training using the subjected matrix was used in conjunction with a multilayer perceptron neural network (7-4-1) that had a coefficient of 0.95 in order to find the best combination of input parameters using the particle swarm technique.

Menderes & Ahmet (2021) [2], The filament materials (ABS-Acrylonitrile Butadiene Styrene, PLA-Poly Lactic Acid, and PET-G-Polyethylene Terephthalate Glycol), raster angle (30, 45, and 60°), and layer thickness (0.15, 0.2, and 0.25 mm) were all investigated by. The Taguchi approach was used to minimize the amount of tests and determine the optimal process parameters for goods with excellent mechanical characteristics, quick printing, and low weight. Using by analyzing the Signal-to-Noise ratio, regression, and variance, we determined the extent to which 3D printing settings affected mechanical behaviour and printing time. The most effective 3D printing settings for strength were determined to be PET-G filament, A raster angle of 45 degrees and a layer thickness of 0.25 mm. The best mechanical behavior at each layer was achieved using a 45° raster angle, as opposed to the 30° and 60° angles. As a final step, we ran the numbers to see how long printing would take and how the result would act mechanically.

Saed *et al.* (2020) [5] studied A 3D printing material that is Poly-L-Lactic Acid (PLLA) was used to construct hard tissue scaffolds that are compatible with the Digital Light Processing (DLP) technique. The material PLLA was selected for the purpose of simulating biological structures because to its good biocompatibility, rapid biodegradation, relatively high strength, and suitable biocompatibility. In order to investigate how two process variables-light exposure duration and dye concentration-impacted the compressive strength and morphological characteristics of the printed samples, DLP was used to design and create porous models with a pore size of 600 microns and a notional porosity of 70%. We checked the experimental results with the generated working curves for each dye concentration to ensure that the established exposure time values were accurate. It was shown that scaffolds with complicated architectures may be created using the 3D printing process and synthetic polymer. Maximum strength was also seen in the sample that had the longest exposure duration and lowest dye concentration during the compression test of 2.2 MPa. A three-day *in vitro* cell viability test found no detectable cytotoxic effect. Overall, the depicted working curves showed that dimensions and mechanical parameters must bead just ed to their ideal levels by the use of the best possible processes.

Elkaseer *et al.* (2020) [4] examined how the as-built component quality and resource efficiency were affected by process parameters and how they interacted with one another in the context of fused filament fabrication 3D printing. Using a Taguchi orthogonal array (L50) type of experiment, we looked at how five process factors affected process productivity, energy consumption, surface roughness of the manufactured item, and dimensional accuracy. Those five variables were surface inclination angle, printing speed, temperature, layer thickness, and infill percentage during printing. The optimal response parameters were identified via statistical analysis and analysis of variance (ANOVA) of the experimental results. The purpose of this study was to forecast potential reactions to five process parameters using regression models. Because of the thick layers of material's tendency to spread out and the difficulty in depositing the printed material correctly at high printing speeds, dimensional precision was greatly affected. Surface inclination angle, layer thickness, and printing temperature were the variables that ultimately dictated the staircase effect's impact on surface roughness. Since printing temperature regulated the material's viscosity, it was crucial for reducing the dimensional inaccuracy brought about by thick layers printed at high rates. Energy usage and productivity were primarily affected by printing speed and layer thickness because of the significant relationship they had with build time.

Asadollabi-Yazdiet *et al.* (2018) [6] examined the important benefits and down sides of Advanced Manufacturing Techniques (AM). One common AM technique, Fused Deposition Modeling (FDM), uses a simultaneous approach to determine the optimal production conditions for AM objects, was utilized. An FDM technology analysis-based multi-optimization issue was created with this objective in mind. Layer thickness and part orientation, two crucial production characteristics, served as the problem's decision factors. Constraint functions included material mechanical behavior and surface roughness of FDM outputs, while end functions included production time and material mass. Various approaches were being developed in order to simulate the AM criterion in connection to these decision variables. The most effective manufacturing solutions were discovered using the An algorithm for non-dominated sorting genetic algorithms, NSGA-II. Lastly, the reliability of the proposed method was shown by a case study.

Materials and Methods

Fused deposition modeling among different 3-DP techniques extends greater prevalence to explain its capacity to deliver prototypes or products with complex parts geometry with better quality with diverse ratings of manufacturing materials (Chen, Yang *et al.* 2016) [7]. Therefore, the requirement of FDM is growing in different engineering industries like aerospace, automotive, biomedical implants, telecommunication, electronics (Im, Cho *et al.* 2007, Lohfeld, McHugh *et al.* 2007) [8, 9].

Fused deposition modeling (FDM) uses a mechanically modified material extrusion method to deposit layers sequentially throughout the manufacturing process (Yan, Lin *et al.* 2018) [10]. Thermal bonding, a diffusion welding process, holds the adjacent deposited layers together. Ohdar, Sood *et al.* (2010) [11]. Some problems, such as low mechanical strength and poor quality of FDM to make end-use items for any manufacturing business, have limited the precise usage of the predetermined performance. (Ippolito, Iuliano *et al.* 1995, Kim and Oh 2008) [12, 13].

Materials

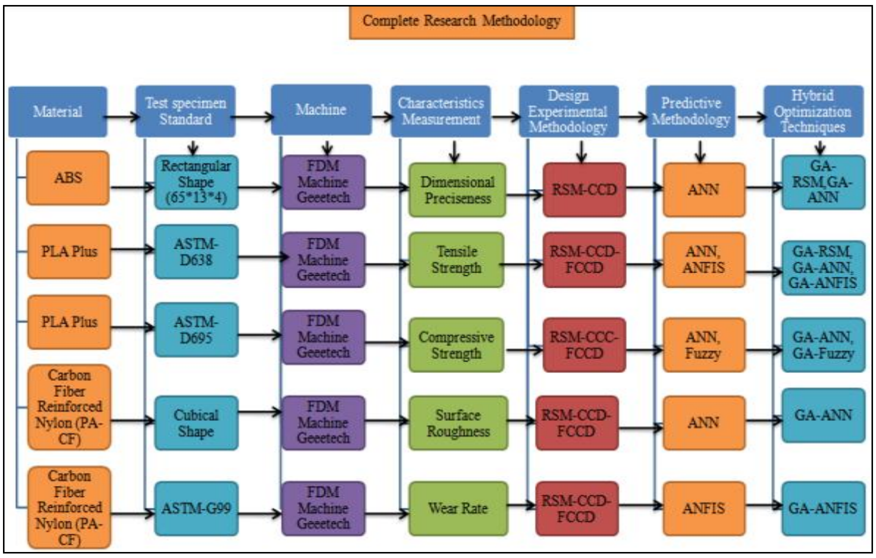

Fig 2: The complete research methodology flow process chart

Thermoplastic lactic acid (PLA), which is made up of the monomer's lactic acid and lactide, and composite materials such as carbon fiber nylon (PA-CF), are used to examine the various properties of produced components. Most PLA polymers are made from renewable materials. It makes it more environmentally friendly than alternative fibers that are created from non-renewable sources.

Regardless, PLA has an enhanced variety known as PLA+, which is marketed as having superior properties over standard PLA. PLA + is often a mix of other polymers, additional compounds, or colors that assist improve the faults of normal PLA, such as moisture absorption and fragility. PLA + is harder and less brittle than standard PLA. PLA Plus is also widely used in engineering applications that need strong dampening and low breakage rates.

ABS is a stretched carbon string structure that is very rigid and shock-resistant. ABS, a terpolymer, is produced by the polymerization process by combining styrene, acrylonitrile, and polybutadiene. Possible elemental proportions are 15%-35% acrylonitrile, 40%-60% styrene, and 5%-30% butadiene. The nitrile group makes ABS more grounded than pure polystyrene and helps connect the chains together. Styrene gives the plastic its glossy, impermeable surface. Even at low temperatures, the polybutadiene toughens the ABS material. ABS is lightweight and has the ability to be evacuated, making it useful for speedily fabricating things using FDM. For most purposes, ABS's mechanical properties alter according to temperature, therefore it may be utilized anywhere from -20 °C to 80 °C.

Test Pieces Fabrication

Figure 3 depicts the FDM machine (Geeetech) used to create all test specimens. Shenzhen Reality 3D Technology Co., Ltd. created this FDM machine. Geeetech is an all-new 3D printer featuring a bigger print area, a user-friendly interface, and two extra features: Unlike previous CR series printers, this one has a filament detector and a resume printer. Even if the power goes off by mistake, the resume printing facility will keep printing. This won't stop the component production process. The filament detector facilitates the printer's automated shutdown when filament runs out.

The excellent print resolution of the Geotech FDM 3D printer, at +/-0.1mm, and the big printing size of 300*300*400mm make it ideal for producing any planned object. A broad variety of thermoplastic and composite materials filaments, including PLA, ABS, PETG, TPU, PA6, polycarbonate, polycarbonate, and many more, are compatible with this printer. By delivering a considerable extrusion force, the extrusion mechanism (double-gear) guarantees that the filament is fed smoothly.

The process began with creating a CAD model in the appropriate software, saving it as a printable STL (Stereolithography) file format (.stl), and then converting it to G code using the Cura 3.4.1 slicer. Afterwards, the experimental design matrix was used to transmit the generated G codes to the FDM machine. This machine then guided the tool and, during component manufacture, suitably adjusted all process parameters. Starting with computer-aided design (CAD), the process moves on to cutting, outer contour creation, and finally, the FDM component.

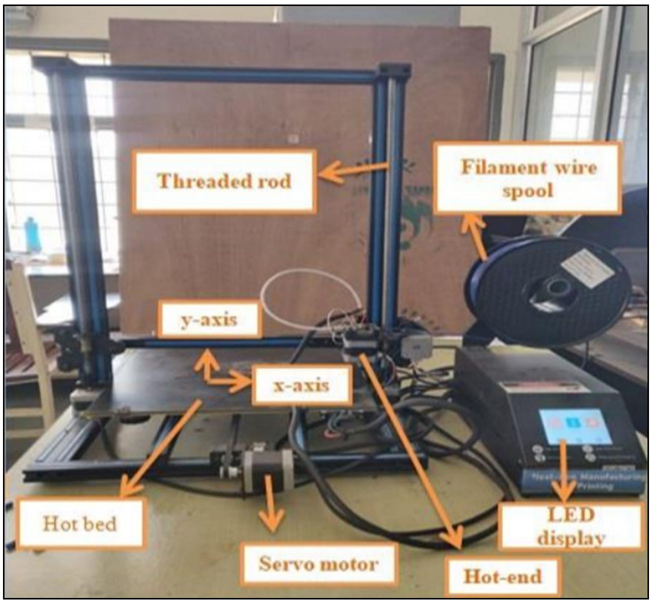

Fig 3: FDM technique machine

Hybrid evolution ARY algorithms

In order to effectively model A GA-integrated hybrid technique using GA-ANN, GA-Fuzzy, GA-ANFIS, and GA-RSM is suggested for the purpose of combining FDM parameters with response values for output. Researchers have used a variety of sophisticated optimization approaches to find the best combinations of process parameters for improving the mechanical characteristics of FDM components. These methods include Taguchi, RSM, GA, Factorial design, ANN, and ANFIS, among others. Equbal *et al*. (2011) [14] used mathematical models including Taguchi, ANN, and FLM to examine five process factors that impacted the dimensional accuracy of FDM components. In their 2014 study, Peng, Xiao *et al*. used an RSM, ANN, and FIS approach to provide a framework for FDM construction time, deformation, and dimensional accuracy.

To identify optimal parameter combinations, we also used GA. Increased component tensile strength was achieved in 2020 by Yadav, Chhabra *et al*. with the application of GA-ANN, an ANN with GA that improved FDM process parameters. Values predicted by the model were supported by the experimental data. Yadav, Chhabra, and colleagues modeled and analyzed FDM process features using the ANFIS technique in their 2020 research. They found that the numerically generated model might be better estimated using the ANFIS technique. To optimize the output response value and examine the influence of various process factors, many research has employed soft computing methodologies as ANN, ANFIS, and GA.

The capacity to print better-characterized prototypes or finished goods is driving demand for FDM in various production areas. (Rayegani and Onwubolu 2014) [15]. However, dimensional accuracy, quality, and other physical and mechanical features Fused deposition modeling (FDM) components are affected by a number of intricate process parameters that are chosen (Sood, Ohdar *et al*. 2010, Rayegani and Onwubolu 2014, Nidagundi, Keshavamurthy *et al*. 2015) [11, 15, 16].

In addition, a number of hybrid statistical approaches, such as GA-RSM and GA-ANN, are used in the optimization of process parameters in order to achieve better magnitude precision. Using the following factors as inputs: build orientation, infill density, layer thickness, and the number of contours, this research offers a thorough examination of the FDM machine.

Parameter Optimization by GA-RSM

A genetic algorithm's (GA) efficiency is proportional to the epoch count; a measure of cycle count it processes. Based on the population size of 50 generations and the generational value of 200, this study determines the optimal number of spirits to achieve the objective value. Images 4.7, 4.8, and 4.9 showcase the many functions used to converge the GA-RSM plot in this study. Among these operations are mutation and constraint dependent crossover. With all other GA and process parameters within the required range, we set the crossover % to 0.8 and the elite count to 0.05 for the population size.

In order to minimize the dimensional precision and get the optimal value input parameter combination set, The GA-RSM hybrid evolutionary method was used, which entails defining the GA's lower and upper limits for factors. The lowest variance for length utilizing GA-RSM at optimized input settings (layer thickness = 0.19mm, construction) is 0.17919 percent. Our parameters were orientation = 22,500, infill-density = 75%, and number of contours = 8. The experimental validation also indicated that a construction orientation of 22.50 degrees, an infill density of 25%, a number of contours of 4, and a layer thickness of 0.33 mm were optimal for minimizing a thickness variance of 0.87418% and a minimal width variation of 0.05342%.

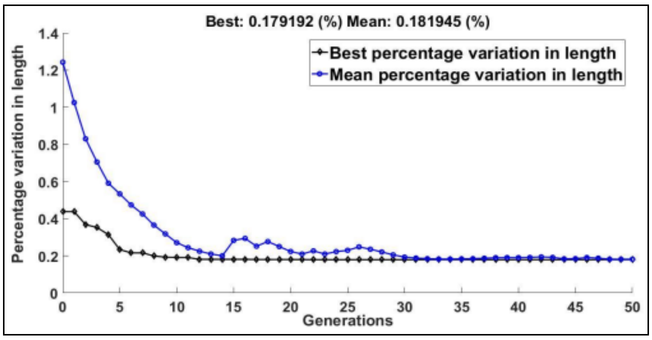

Fig 4: GA-RSM plot for percentage variation in length

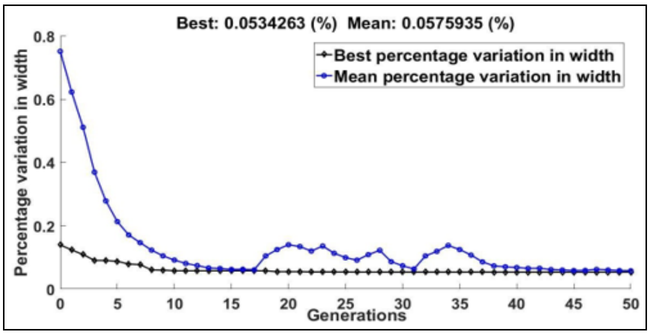

Fig 5: GA-RSM plot for percentage variation in width

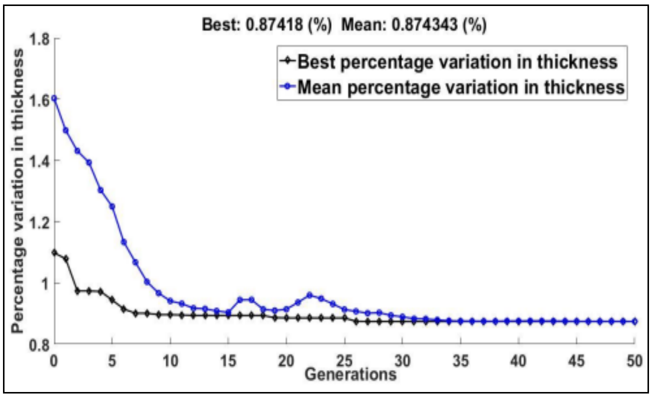

Fig 6: GA-RSM plot for percentage variation in thickness

Experimental and Optimization study on Tensile Strength

There is no industrial sector that can make use of FDM technology due to the created components' low strength. To that end, knowing the strength of components created using this process is very crucial. The brittle behaviour and layer distortion inherent to FDM-fabricated components need careful investigation of the many process factors that influence strength.

The research in this study used an FDM machine to make test specimens that met the requirements of ASTM-D638-V. A variety of evolutionary algorithms, including RSM, ANN, ANFIS, and GA, were used to optimize the tensile strength, and the FCCD was employed to conduct the tests necessary to determine the optimal process parameters. Each material's tensile strength was evaluated using the UNITEK-94100 UTM machine manufactured component. To begin, the RSM-derived regression model was used to forecast the process factors impacting the components' tensile strength. The next step is to find the optimal combination of process parameters that maximizes tensile strength by using GA after ANN and ANFIS have proposed a fitness function for the best correlation coefficient (R).

The use of several evolutionary algorithms for data learning and training has allowed for the correct optimisation of targets; these methods, examples of such models are GA-ANN, GA-RSM, and GA-ANFIS, which show how the parameters input affect the output of FDM. At last, the projected model was validated by conducting tests at the optimised values. Therefore, when dealing with FDM process parameters, optimisation, and nonlinear relationships in complex manufacturing procedures, hybrid evolutionary algorithms like this one are quite useful. This sort of study could help build a reliable model for FDM technique replication projects.

Part Fabrication using Fused Deposition Modeling for the ASTM-D638-V Dogbone

Using the FDM 3D printer shown in Figure 7, create 195 test specimens, with a total of 39×5=195, in accordance with ASTM-D638-V requirements. All five specimens out of 195 were made using the identical input settings on the FDM 3D printer: infill density, temperature, and speed.

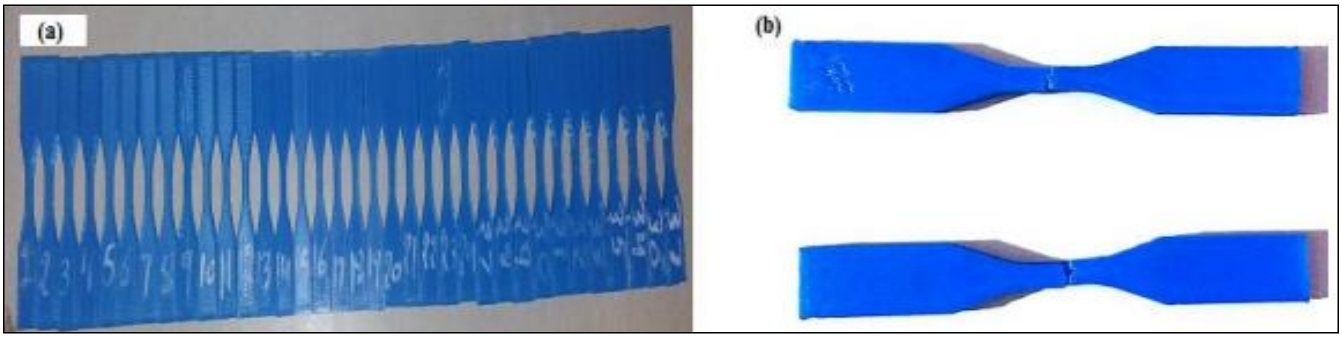

Fig 7: (a) Standards for use in fabricating test specimens according to ASTM-D638-V (b) Specimens were examined for tensile strength using a universal testing machine (UTM).

Conclusion

The present state of the worldwide market necessitates manufacturing technologies that can produce components quickly and exhibit qualities such as minimal weight, attractive appearance, few assembly parts, high precision and strength, and direct final products. A manufacturing method based on additive Three-dimensional printing (3DP) is a fabrication method with the potential to radically alter the industrial sector. To create a final product, all three-dimensional printing methods use an additive deposition process that builds up consecutive layers. The items are created by layering the necessary material in a computer-aided design (CAD) program, which is used to create a virtual three-dimensional (3D) print file.

FDM is a three-dimensional printing method that uses an additive nature process to create models, prototypes, or finished products by depositing extruded thermoplastic. A heated bed is fed layers of material via the hot end. There are several benefits of fused deposition modelling (FDM), including a shorter production cycle, higher speed, lower cost, elimination of scrap, and minimal space utilisation without the need for expensive specialised equipment and tools. The aerospace, automotive, tool and die, construction, and medical industries are just a few that make extensive use of this cutting-edge, potentially game-changing method for the safe and rapid fabrication of complicated geometric components.

Conflicting machine input process parameters and the performance of manufactured components provide the greatest challenge to the researcher in creating this approach. The quality of the produced components could be enhanced by modifying the FDM machine's parameters.

There is no better way to build, establish, or forecast the link between the features of FDM components and the input parameters using different conventional modeling and optimization approaches like as GRA and Taguchi. To address this, the present work optimises the input process parameters using both conventional and novel evolutionary modeling and optimization techniques; the focus is on FDM components made of polymers and composites for end use.

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