T.R.
ONDOKUZ MAYIS UNIVERSITY
INSTITUTE OF GRADUATE STUDIES
DEPARTMENT OF NANOSCIENCE AND NANOTECHNOLOGY

OPTIMIZATION OF NANOCOMPOSITES PRODUCTİON WİTH SLA 3D PRINTER

Master's Thesis

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Supervisor
Dr. İbrahim İNANÇ

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ACCEPTANCE AND APPROVAL OF THE THESIS

The study entitled **"OPTIMIZATION OF NANOCOMPOSITES PRODUCTION WITH SLA 3D PRINTER "** prepared by **Amenah abdulrazzaq IBRAHIM**, and supervised by **Dr. İbrahim İNANÇ**, was found successful and unanimously accepted by committee members as Master thesis, following the examination on the date 9.5.2023 .

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ÖZET

SLA 3B YAZICI İLE NANOKOMPOZIT ÜRETİMİNİN OPTİMİZASYONU

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3B baskı veya eklemeli üretim, bir CAD modelinden veya dijital bir 3B modelden herhangi bir şekil veya geometride üç boyutlu katı nesneler oluşturma işlemidir. Ürün kalitesi ve performansı üzerindeki önemli etkisinden dolayı 3B yazıcılar ile üretilen parçaların yüzey pürüzlülük ve sertlik testi 3B baskı işleminde önemli faktörlerden biridir. Bu araştırmanın ana hedefi, Box-Behnken ve Taguchi Yöntemi gibi deney tasarımı yöntemlerini kullanarak yüzey pürüzlülüğünü en aza indirmek ve nesnenin sertliğini en üst düzeye çıkarmak için SLA 3B yazıcıda girdi parametrelerinin optimal yapısını bulmaktır. Kürlenme süresi, baskı hızı ve reçine ile karıştırılan nanoparçacık oranı ile üç seviyeli üç bağımsız parametre ile deney tasarımı yapılmıştır. Bir 3B yazıcı ile üretilen parçanın mekanik özelliğini geliştirmek için nanokil nanoparçacıkları reçine ile karıştırmanın amacı, birçok farklı alandaki uygulamalar için çok önemlidir. Tepki Yüzey Metodu (TYM) sonuçlarına göre, minimum pürüzlülük elde etmek için en uygun girdi parametreleri sırasıyla; kürleşme süresi 3 s, tabla hızı 50 mm/s ve nanoparçacık oranı %1'dir. Maksimum sertlik elde etmek için en uygun giriş parametreleri kürleşme süresi 5 s, table hızı 100 mm/s ve nanoparçacık oranı %1'dir. Ayrıca, iki yanıt yüzeyi için gri ilişki analizi, hangi parametrelerin optimal deney koşulları olduğunu bulmak için kullanılmıştır. Deney 2'nin en yüksek gri ilişkisel derece değerine sahip olduğu bulunmuştur. 2 numaralı deney için parametreler kürleşme süresi 5 s, table hızı 100 mm/s, ve nanoparçacık oranı %1'dir.

Anahtar Sözcükler: Katmanlı imalat, SLA, Nanokompozit, Deney tasarımı.

ABSTRACT

OPTIMIZATION OF NANOCOMPOSITES PRODUCTION WITH SLA 3D PRINTER

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3D printing is a revolutionary technology that has transformed the manufacturing industry. It is a process of creating three-dimensional objects from a CAD model or a digital 3D model using additive manufacturing technology. The surface roughness and hardness test of the parts produced using the 3D printer is one of the most important factors that greatly affect the quality of the product. The major target of this research is to find optimal values of input parameters in 3D SLA printer to minimize the surface roughness and maximize the hardness of the object using methods of experiment design such as Box-Behnken and Taguchi Method which is done with three independent parameters with three levels. The parameters are cure time, printing speed, and the weight ratio of nanoparticle mixed with the standard resin. The purpose of mixing nano clay nanoparticles with resin to improve the mechanical property of a 3D printed object is important to used in many applications. Based on the results of Response Surface Method (RSM), the optimal input parameters to obtain minimum roughness are cure time 3 s, platform speed 50 mm/s and the nanoparticle ratio %1 and the optimal input parameters to obtain maximum hardness are cure time 5 s, platform speed 100 mm/s and the nanoparticle ratio %1. In addition, the grey relation analysis for two response surface is used to find the optimal experiment conditions. It was found that the experiment 2 has the highest value of grey relational grade. The parameters of experiment number 2 is cure time is 5 s, platform speed 100 mm/s, added nanoparticle ratio % 1.

Keywords: Additive manufacturing, SLA, Nano composite, Design of experiment.

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Amenah Abdulrazzaq İBRAHİM

CONTENTS

SYMBOLS AND ABBREVIATIONS

AM	: Additive Manufacturing
SLA	: Stereo Lithography
FDM	: Fused Deposition Modeling
CAD	: Computer Aided Design
CAM	: Computer Aided Manufacturing
UV	: Ultraviolet
FFF	: Fused Filament Fabrication
SLM	: Selective Laser Melter
SLS	: Selective Laser Sintering
SLM	: Selective Laser Melting
ANOVA	: Analysis of Variance
DOE	: Design of Experiment
GRA	: Grey Relation Analysis
SNR	: Signal to Noise Ratio
RSM	: Response Surface Method

FIGURES LEGENDS

TABLES LEGENDS

1. INTRODUCTION

Three dimensional (3D) printing or Additive manufacturing (AM) is a popular printing technology which is used in different industries today. In the coming years it is expected to replace traditional manufacturing. This technology is gaining more and more attention because of its freedom design, which allows making things without the limits of imagination.

3D printing using a stereolithography (SLA) machine creates parts by curing photopolymer resin layer with layer depend on a computer aided designed (CAD) model. 3D printed objects are created using the additive processes. The additive process in which successive layers of material are applied in different shapes. Objects can have virtually any shape and geometry, and are created from models of 3D printing or other various sources of electronic data.

There are some issues with using 3D printers such as they are time consuming and printed objects need to be stronger. Improving mechanical properties of 3D printed objects is important due to their application in different fields. A promise solution is to mix liquid resins with nanoparticles. Various combinations of the printing parameters such as cure time, speed and nanoparticle are taken into consideration and are selected based on Taguchi's design of experiment (DOE) orthogonal array. Test specimens are printed using SLA technique. This is done by taking the various experimental combinations of factors obtained as the input parameters and then responses are measured. The normal probability plots of signal to noise ratio for each measured response (roughness, hardness) are plotted in order to indicate the process stability and the parametric conditions are ranked based on their individual influence. Optimization of process parameters will then be carried out to improve the responses and validate them experimentally. Then grey relation analysis for two response surface is used to find the optimal experiment conditions.

1.1. Literature Review

Additive manufacturing (AM) is used in many applications such as manufacturing, medical, aerospace, manufacturing, fashion, because of the low cost of materials and the state of material available. Although AM can bring great benefits to components, 3D printers can make many mistakes during the process of printing. Because of material characteristics or the process defects, parts will have various defects when printing, such as blistering, warping, air holes, residual stress and cracking. In recent years, there have been many studies aimed at solving problems in 3D printers.

In the research paper written by (Sager and Rosen, 2008) on surface improvement in stereolithography (SLA), the exposure on the surface of the desired SLA construct as a function of a process parameters, is formulated. The perversion of the exposure on the surface from critical exposure which defines the handling in the SLA method is minimized utilizing the least squares fittings. This is achieved by applying inverse design techniques, least squares minimization to determine the SLA process parameters. The application of the parameter estimation model to critical SLA geometries is provided, also the results which include surface finish improvements are discussed.

Nasiri and Khosravani (2021) within their review, examine the numerous ways in which mechine leaning (ML) has been applied to anticipate the mechanical behavior and breaking points of 3D printed parts. They analyze previous studies that have considered the use of ML in characterizing polymeric and metallic 3D printed parts. Alongside this, the authors outline the difficulties and hindrances that exist while trying to apply ML to AM, whilst also providing a perspective and potential for the industrial applications of ML. Ultimately, their review highlights the opportunities of ML in the field of AM, such as enhancing the prediction of mechanical performance, as well as refining the optimization of 3D printing parameters.

The study of (Guo et al., 2019) explains the three diminsion printing of composites based on graphene according to different AM techniques that include selective laser sintering (SLS), Fused Deposition Modeling (FDM), stereolithography (SLA) and Direct Ink Writing (DIW). First, various AM techniques are introduced to understand the 3D printing principles’s. The structural properties, fabrication process and the applications of various techniques of 3D printing for composites based on graphene are summarized. In addition to that, some efficient characterization methods and simulation are included. This review highlights the possibility of additive manufacturing technologies in composite materials and open new avenues for the development of novel materials.

The development of three dimensional printed thermoplastic antimicrobial nano composites by adding Metal oxide or antimicrobial metal (MO/M) nanoparticles is discussed in a study of (Abdullah et al., 2020). Medical devices and everyday objects could be made by using 3D printed thermoplastics, but microbial contamination is the major hurdle to their using (MO/M) nanoparticles must be injected prior to or during mixing, to overcome this challenge. Different MO/M nanoparticles could prevent microbial infections, which include antibiotic resistant bacteria, through differen antimicrobial mechanisms.

The review of (Kadam et al., 2021) study layer-by-layer anomaly detection methods using the Machine learning algorithms and pre-trained models. The suggested combination is trained offline and implemented online for error detection. It also examines various pre-trained models using the algorithms of machine learning for fault detection and monitoring in fused deposition modeling (FDM). The results show the SVM algorithm and Alexey groups provide a greatest accuracy. The suggested error detection process has low computational and experimental costs, and could easily achieve the error detection on the real-time.

The object surface of additively manufactured parts for predicting the surface roughness in additive manufacturing and the predictive of data driven modeling process are used in the work of (Li et al., 2019). Many sensors such as infrared temperature, accelerometers and thermocouples sensors are utilized to gather temperature and the vibration data. The surface roughness prediction model was trained by using an ensemble learning algorithm. This model was validated utilizing condition control data gathered from a series tests of AM that performed on a (FFF) Fuse Filament Fabrication device.

There is many application of using machine learning in additive manufacturing. The study of (Nasiri et al., 2021) focuses on the application of ML to fracture, optimizing 3D printing parameters and predicts the mechanical behavior and of 3D printed parts. In addition, this study provides prospects, disadvantage, challenges of using ML in the AM.

The study of (Tontowi et al., 2017) used a 3D printer with PLA filament material. Sample standards of ASTM D638 Type IV are used as tensile tests and dimensional error tests to indicate the quality of printed parts: layer thickness, temperature and angles mesh are used as parameters with Taguchi and Response surface method. A test was performed to determine lowest dimensional error and the highest tensile strength by finding the optimal parameter settings and validated both experimentally.

A state-of-the-art machine learning algorithm to indicate the porosity of 3D objects and classify the grain growth structure is used in a study of (Nasiri et al., 2021). The input parameters affecting porosity and grain growth structure are energy density, atmosphere, powder particle size and overlap ratio. In addition, various classification models such as support vector machines and meta-classifiers classify microstructures as columnar or even granular, thereby improving qualityof part.

A predictive model based on Gaussian processes has been implemented by (Tapia et al., 2016) to learn and predict porosity using selective laser melting. This model is an algorithim of machine learning and by using it the porosity of SLM 3D printer has been developed. Next, a model and emission data are used, predicting porosity rate of the part in a frame using kriging method.

The Machine learning is used to predict and improve the surface roughness in Fused Filament Fabrication (FFF) 3D printer, a data-driven predictive modeling and ensemble learning algorithm are used for this purpose. Many type of sensor are utilized such as accelerometers to collect temperature and infrared temperature sensors. The result presented by a review of (Li et al., 2019) is that the learning algorithm could predict the surface roughness with high precision.

The study of (Vaidya et al., 2018) used atomic force microscopy to establish a polymer smoothing method to enhance surface quality. This research minimize the surface roughness to a few nanometers, the smoothing method is a promising approach for using 3D printing as a flexible tool for prototyping and creating high-quality small optical parts.

A deep learning (DL) accredited framework is used in a study of (Khadilkar et al., 2019). The stress distribution of layer of a printed object that is produced by SLA 3D printer is predicted. To train the deep learning network, a 3D printer database captures a range of geometrical traits present in actual 3D parts is created first. On the test data set, DL networks were trained to predict stress using two different types. The outcomes further demonstrate that, in comparison to the FE simulation, this approach greatly cuts down on calculation time.

Two polishing techniques were predicted by (Son et al., 2020) to lessen the gloss and surface roughness of an ABS (acrylonitrile butadiene styrene) like resin used in 3D stereolithography (SLA). In experiments, the chemical mechanical polishing (CMP) was applied directly to a 3D plastic that resembled ABS (one-step polishing) as well as sequentially with sandpaper (two-step polishing). The moiré on the surface of 3D printer sample took a long time to remove using CMP, according to one-step polishing trials. In this work compared polishing using CMP and sanding, two-step polishing reduced surface roughness and raised gloss more quickly. According to the data, the two step polishing process reduced roughness more successfully than the one-step polishing technique.

Statistical regression and machine learning approaches are used in the study of (Perdomo et al., 2022) to assess the mechanical properties and estimate the effect on surface roughness of selective laser melting (SLM) 3D printer. To predict key properties of laser-printed metallic parts, Multi-layer Perceptron, Support Vector Regression, Response Surface method using Box-Behnken design of experiment (DOE), Gaussian Process, adaptive Neuron-Fuzzy and Random Forests were discussed. The input parameters for this work is hatch spacing, scanning speed, laser power and layer thickness.

The consequences of these factors are covered in a study by (Arnold et al., 2019). SLA 3D printer was utilized to carry out twelve printing procedures on solid and hollow objects that were parallel to and across from the front of the printer. In half of all operations, the models were tilted at 15 degrees and three layer thicknesses were used. Eight milled polyurethane designs and eight gypsum designs were created for comparison. By using the perthometer, the average roughness index of each model was calculated.

In a study by (Luganson, (2018)) SLA 3D printer was used to examine the relationship between additive manufacture and artificial intelligence. This printer were discovered during a visit to the Agnatic factory, where small batches of products and rapid prototypes were produced using lithography. First, the lithographic design process is described based on previous reviews of the literature and on actual experience. also the Photopolymer composites used as resins in SLA 3D printers and photopolymerization reactions have also been studied in previous reviews. Algorithms and schemes were used to find solutions to control the different steps of the SLA process.

An overview (Hassan et al., 2019) of nanostructured ceramic, metal, and carbon is given. Using several types of 3D printing, polymer materials are combined with hard and soft biopolymer shapes to create cellular and non-cellular 3D tissue structures. When these materials are combined with nanomaterials, biopolymer compounds will exhibit improved characteristics and develop novel functional features. Results from stem cell and 3D printed scaffold in vitro and in vivo studies are discussed.

The surface roughness of fused deposition modeling FDM 3D is discussed (Brien et al., 2019) which was caused by variations in printing speed, construction angle, and layer height. Scanning was used to first determine surface roughness parameters *Rq* and *Ra*. The perception of surface roughness was then evaluated by sense of touch using a specifically constructed instrument, which used only the sense of touch to determine the difference in roughness. This study's main finding is that, its goal surface roughness characteristics (*Ra, Rq*) are not enough to forecast the users tactile experiences.

The surface quality of SLA 3D printed objects is enhanced in the work of (Lu et al., 2018) using a controlled double coating at various rates, various resolution, and tilted at various angles, contact profilometer data was gathered. The outcomes show that dip-coating, is an efficient means of increasing surface quality which give surface roughness at range (0.3 to 0.5), and with resolution 0.2 mm. Printing with a resolution of 0.2 mm offered a considerable improvement in surface quality.

The technologies used in 3D printing SLA, DLP, LCD, CLIP, and MJP are explained in study by (Quan et al., 2020). The benefits and drawbacks of each were discussed, and the procedure for using the approach in the biomedical sector is also covered. Finally, the problems and disadvantages of 3D printing with photocuring are also highlighted.

Interest SLA geometries have been obtained in the work of (Stellmar et al., 2020). The effectiveness of the concept has been computationally and experimentally shown using flat surfaces. An inverse design method was accomplished to improve the sloping surfaces. Both computational and experimental evidence has been shown to support the effectiveness of this model and show how it differs from more established cure models. Based on the experimental findings, process planning using the analytical model significantly reduces the average surface roughness of SLA parts.

The goal of the research of (Shirmohamm et al., 2021) is to enhance the surface roughness of 3D printer using a hybrid artificial neural network and the particle swarm technique. The input parameter is (printing speed, nozzle diameter, layer thickness, material density) all with 3 level. A total of 43 experiment were created using a 3D printer, before using these algorithms Central Composite Design (CCD) to reduce the number of experiments.

Models for predicting the surface roughness of items printed are developed by utilizing data mining methods in this work (Molero et al., 2020). 27 horizontal (X-Y) and 27 vertical (X-Z) samples printed with varied values of the input parameters printing acceleration, layer height, printing speed, extrusion temperature served as the experimental data are used to train the models. The FDM 3D printer with polylactic acid (PLA) is used in this work.

A study of (Alsoufi et al., 2018) examines the quality of the surface, dimensional accuracy, and cost-effectiveness of 100% infill density FDM 3D printed items created from a variety of thermoplastic filament materials, consisting of PLA, PLA+, ABS, and ABS+. After the constructed parts had at least three hours to naturally cool to room temperature, many experiments were performed. The results of this research are that the thermoplastic filament material PLA+ showed excellent surface behavior and was found to be more fine while ABS shows high surface roughness, waviness and waviness. Basic behavior. Both PLA and ABS+ show good surface performance.

This study (Panda et al., 2016) uses grey relational analysis in conjunction with the Taguchi design experiment approach to demonstrate the optimization of input process parameters. It has been determined that combining ceramic inserts produces surface roughness and flank wear values that are less than the criteria limit all experimental runs, and that this technique may be successfully used to the hard turning of hardened AISI 52100 steel utilizing ceramic environment multi-criteria.

2. GENERAL INFORMATION

Based on the printing medium and printing mechanism, 3D printers can be categorized. Cost, print quality, printer capacity, print speed, user expectations, and practicality are things to think about while creating a 3D printer. Table 2.1 provides an overview of the various 3D printer models, along with their benefits and drawbacks.

Table 2.1. The various 3D printer models

Type of 3D printer	**Process**	**Advantages**	**Disadvantages**
Stereolithography (SLA)	It makes use of an ultraviolet (UV) laser to create a design on the resin surface of a bowl by emitting a laser beam. As a result, the polymer resin's atom chain bonds. The printed item is patterns, prototypes, and models	Requiring less time Cheaper Superior surface machining A uniform surface	Structural support is needed for intricate parts
Digital light processing (DLP)	Constant light sources are used to treat photosensitive polymer resin. The print items is prototypes that are not functioning, intricate artwork, and patterns	High resolution requires less resin than SLA. Fewer waste-related costs It operates more quickly than a sla Able to print items with high-performance characteristics	It requires editing after. Depending on the design, this result Costly Require Resins may be fragile.
Fused deposition modelling (FDM)	The object is constructed layer by layer when the melted thermoplastic is applied to the predetermined area. The next layer will stick when each layer solidifies. the prior one to. With this method, objects are printed bottom up.	cheaper than SLA	Processing for some geometric materials takes longer. Utilized just thermoplastic

Selective laser sintering (SLS)	The tiny particles are held together by the heat produced by the high-energy laser beam. the main material utilized in the SLS printer is Nylon polymer (PA) , which is employed in the form of granules. The print items is hearing aids, dental retainers, automotive and aerospace components, and prosthetics	Doesn't require structural support for components that are intricate. Lessen the amount of raw resources used. lower manufacturing costs. few post-treatments High detail structures is printable. Requiring less hours the Printed components are robust and reliable	Greater lead time The printed object needs to be post-treated and given a rough surface finish because the internal porosity is visible. The small holes and broad flat surfaces prevent the product from being printed accurately.
Selective laser melting SLM	The operation is a part of the melting of the powder layer. The primary sort of materials used are minerals. The print items is medical equipment, automobile, aerospace, and tooling components	Vast selection of minerals available Able to recognize intricate forms or interior details Shortened lead time because no equipment are needed. Produce several components at once.	Costly production techniques, specialized design knowledge needed a rough surface that needs post-processing
Electronic beam melting (EBM)	The components were put together in a vacuum by joining the various components with an electron beam. The print items is Custom-made skull	Rapid-fire typing The powder is not sintered and is recyclable. High density as a result of the mineral powder's total dissolution It takes little assistance.	Expensive equipment and supplies Limited options for metal materials a small print run
Laminated object manufacturing (LOM)	High pressure and temperature are used to fuse thermoplastic materials Together. Finally, the object is cut or sculpted with a laser or blade controlled by	The surplus material can be easily removed with the laser. Readily available materials Wood texture may be seen on the printed part.	Not appropriate for complex geometry or working prototypes

	computer. The print items is Models that scale up and concept prototypes	No chemical process of any kind is required. Construction of larger models is made easier by the lack of a sealed space requirement. It doesn't need any kind of chemical procedure.	
Binder jetting (BJ)	When placing the powder particles layer by layer to create a solid body, use a binder to link them. Most often, metal, and ceramic, sand are used. The print items is Large sandcasting patterns, prototypes, and molds	Compared to a MJ or SLM, produce hardware prototypes in full color for less money. Bble to create incredibly massive and intricate metallic pieces Thermal impacts do not affect printing. The ability to work with a variety of materials	Aprinted object is sculpted with rough detailing. Parts with lower mechanical qualities are the result of the high porosity. During post-processing, parts may break since they are exceedingly brittle.

Stereolithography (SLA), the most widely used 3D printing process in additive manufacturing, can produce objects with a high degree of accuracy and a flawless surface finish, making it ideal for creating prototypes. However, the substance utilized, a liquid resin, which ranges in price from $50 to $400 per kilogram, makes this type of printer exceedingly expensive. Fused deposition modeling (FDM) is a possible substitute because it is more affordable than other 3D printing technologies and suitable for domestic use, but the FDM 3D printer is limited to thermoplastics.

Selected Laser Sintering (SLS), which can create items with intricate geometries, is also a great choice. The key benefit of employing an SLS 3D printer is that, unlike other 3D printing technologies, there is no need for extra support during printing, resulting in minimal material waste and no need for post processing after the production process. And the other disadvantage of using FDM 3D printer is that the finished item might not be precisely measured, and the surface polish is a little rough.

Since paper is the primary material utilized, laminated object manufacture (LOM) is suitable for non-functional prototypes and is also a low-cost method. The biggest disadvantage is that the printed product won't be strong enough and will have low resolution because the surface isn't smooth because of the texture resembling wood. Additionally, it necessitates additional post-printing steps.

2.1. Additive Manufacturing Process Flow

The making of a 3-D object using CAD modeling software is the initial step in the typical AM process. The CAD model's components are then produced by converting it to an STL file format. Triangular faces can be used to simulate item shapes in STL files. The order of the additive manufacturing process, regardless of the AM method employed, is shown in Figure 2.1. Based on a specific AM system, the model is prepared for printing using slicing software. By optimizing various process parameters inside the AM system, the slicing software serves as the interface between the chosen AM system and the computer. The manufacturing equipment used in the additive manufacturing process, such as 3D printers, does not comprehend CAD files. To circumvent this, the file must be transformed into a set of instructions that additive manufacturing equipment can comprehend. The tool path or G-Code required to build the object is calculated using "slicer" software, such as Spatial's CGM Polyhedra, which transforms the 3D design into 2D layers or slices.

The "printing" phase might appear in a variety of ways depends on the technology being employed for additive manufacturing. In a traditional 3D printing technique, such as those used in widely available 3D printers, the print heads alternately print a layer of powdered material and a layer that includes a liquid binder. To create the finished result, these layers are constructed on top of one another. The more precise name for this procedure is “binder puffing”. However, other types of additive manufacturing have completely diverse aesthetics.

In the future, many AM technologies will be developed based on the most popular techniques, and the fillers that have been used to create composites particles, fibers, polymers and nanoparticles.

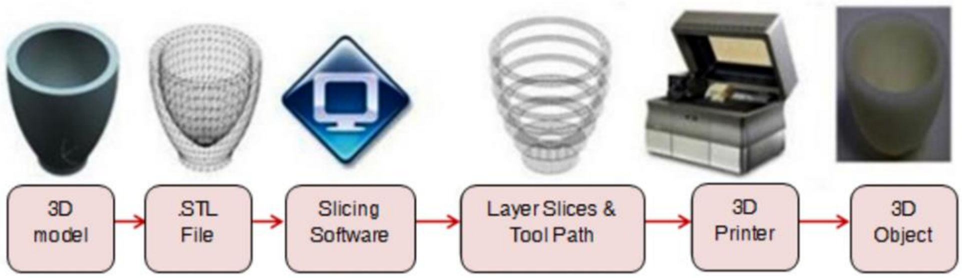


Figure 2.1. Steps of 3D printer for product the 3D object

2.2. Classification of Additive Manufacturing Technique

Because new varieties are always being generated and additive manufacturing technology is constantly improving, the association known as the American Society for Testing and Materials (ASTM) has classified different additive manufacturing techniques into seven kinds, which include:VAT photopolymerisation, Material Extrusion, Powder Bed Fusion, Material Jetting, Binder Jetting, Sheet Lamination and Directed Energy Deposition.

2.2.1. Photo Polymerization and VAT Photopolymerisation

In this type of printing, a viscous / gel substance consisting of a polymer that is sensitive to ultraviolet rays and a UV laser are used, where the surface of the polymer is illuminated by a laser beam according to a specific pattern, which is the cross-section of the layer to be printed, and after the laser beam passes over on the surface, the polymer hardens and becomes solid, so the layers are built one on top of the other, and one of the most popular techniques that use this technique is stereolithography (SLA), and the materials used in this technique are photopolymer.

2.2.2. Material Extrusion

In this technique, the materials used in printing are in the form of wires or threads, attached to a precise pointed head with a nozzle. This head is heated to melt the printing material, and when the material comes out of the head, it cools at room temperature and hardens. As it is moved horizontally and vertically, and for this it is shaped according to the required shape. One of the most famous techniques based on this experience is fused deposition modeling (FDM), which was invented by Scott Crump in the late 1980s. Thermoplastics are one of the most used materials in this technology.

2.2.3. Powder Bed Fusion

One of the technologies that makes use of this method is selective laser sintering (SLS). In this technology, the printing material is created as powder. A high energy laser beam is projected onto the powder's surface in accordance with the cross-section of the shape to be printed, and after printing the entire layer on the powder's surface, the printer descends a layer to enable the creation of a new layer of powder with a layer that matches the pattern. Thermoplastics, glass, and sand are the three most commonly utilized materials in this process.

2.2.4. Material Jetting

The procedure for jetting the material is comparable to that of a 2D inkjet printer. Multiple print heads, similar to those in an inkjet printer, disperse the material as liquid droplets. The substance is a photosensitive polymer that hardens when exposed to UV light, layer by layer piling up.

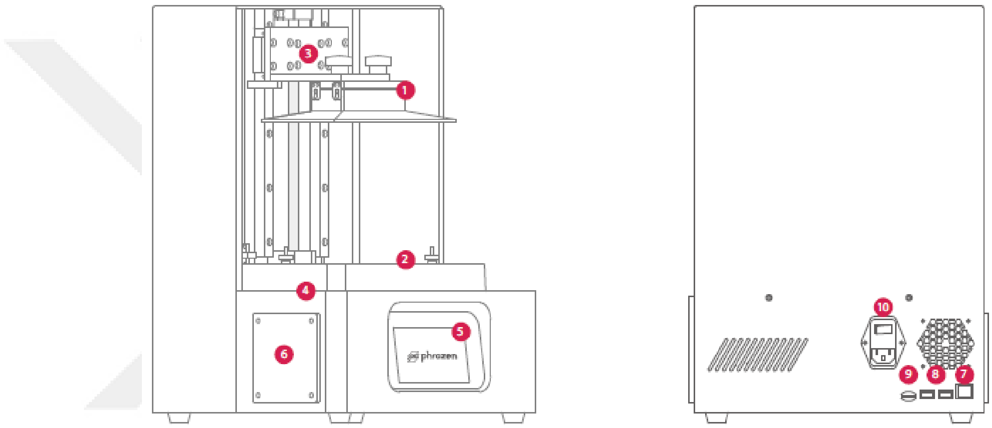
2.2.5. Binder Jetting

Although it uses two materials instead of one, the procedure is similar to material jetting. These materials consist of a binder and a powdered base ingredient. The binder, which is layered over the powder in the build chamber, serves as a glue for the different layers to adhere to one another and form the item.

2.3. Introduction to Stereolithography (SLA) 3D printer

One of the most widely used resin 3D printing techniques is 3D lithography (SLA), which produces the sharpest details, smoothest surfaces, anisotropic waterproof prototypes. The VAT polymerization process, also referred to as resin 3D printing, includes lithography. All of these devices follow the same design principles; curing liquid resin into a rigid plastic using a light source such as a laser or projector. The placement of the fundamental elements, including the light source, build platform, and resin tank, accounts for the majority of the physical variations.

SLA 3D printers employ resin, a thermoset material that responds to light. When SLA resins are exposed to particular light wavelengths, short molecular chains are formed, oligomers and polymerizing monomers into rigid or flexible geometries that are hardened. Figure 2.2 Illustrate the fundamental principles of the SLA 3D printing using a graphic.



1. Build platform   2. Resin vat   3. Z-Axis   4.LCD   5. Touch panel   6. Fan
   7 Ethernet port   8. USB port   9. SD Card   10. Power Switch

Figure 2.2. Basic mechanics of stereolithography (SLA) 3D printing

Lithography is extremely versatile, and material producers have developed SLA resin formulations with a variety of mechanical, optical, and thermal properties to match different processes, such as engineering processes, industrial thermoplastics with iterating faster and optimizing production processes. Current 3D printing methods for polymers are shown in Figure 2.3 with comparison of fused deposition modeling (FDM) and selective laser sintering (SLS) to 3D SLA printing, two alternative additive methods for creating plastic parts.

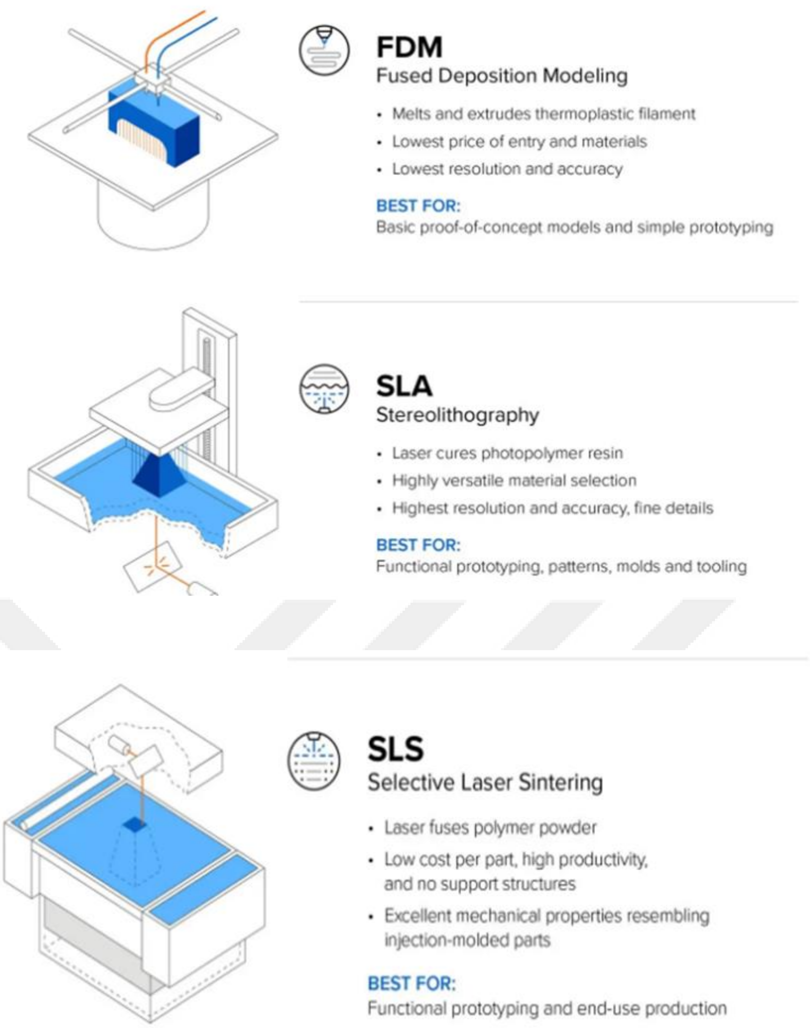


Fig 2.3. The 3D printing technologies for plastics.

2.3.1. How SLA 3D printing works?

The first step is one layer height from the liquid surface, the liquid photopolymer is originally positioned in the build platform then to generate the next layer the UV laser selectively cures and solidifies the photopolymer resin. Then the liquid resin's monomer carbon chains are activated by the UV laser light and solidify during the photo polymerization process solidification stage, forming strong, irreversible bonds with one another after that the laser beam is focused using a galvo, which is a set of mirrors, along an established path. The resulting portion is entirely solid since the entire cross-sectional area of the shape is erased at the last the object is in an incompletely cured state, after printing. More post-curing under UV light is required to obtain high structural and thermal characteristics. The finished product will burn if heated, so it cannot be changed back into a liquid. This is because, in contrast to thermoplastics, which are manufactured using fused deposition modeling (FDM), materials created using SLA are made of thermosetting polymers. Figure 2.4 shows how a SLA 3D printer works.

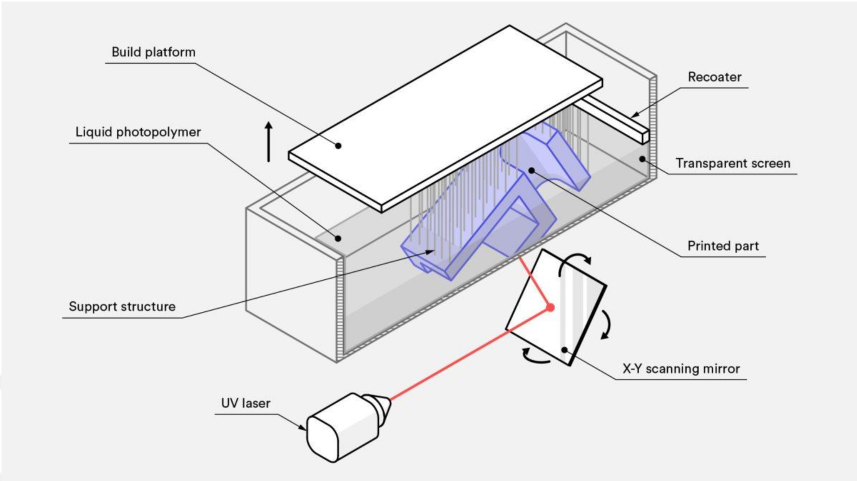


Figure 2.4. SLA 3D printer working scheme

One of the crucial equipment in many industrial sectors is the laser. Due to its accuracy and dependability, lasers have been employed in welding processes as well as the cutting industry. One of the applications for lasers that has the most potential is additive manufacturing. In photopolymers, laser technologies are employed. In the SLA 3D printing technique, the photo polymerization reaction is started at precise locations where the UV laser beam strikes (Varotsis, 2018).

Typically, laser printers are protected from oxidation and also dangerous to the user. Companies are using 3D printing to create these shields in order to create machines that are simple to operate both in industrial manufacturing settings and in normal consumers' homes (Lipson and Kurman, 2013). The SLA polymer absorption spectrum determines the laser to use. With the advancement of technology and probable replacement of outdated production methods, 3D printing has a bright future (Rogers, 2015). SLA technology has no indirect expenses, but injection molding requires advance planning and preparation delivery of molds, etc. The Service Level Agreement (SLA) is one of the greatest technologies for speedy production and a quick response to a demanding client because of these time-saving factors (Rogers, 2015).

2.3.2. A Brief History of Stereolithography

The contemporary stratified technique of UV lithography, developed by Japanese researcher Dr. Hideo Kodama to cure photosensitive polymers, was used for the first time in SLA 3D printing in the early 1970s. Charles (Chuck) W. Hull is credited with coining the phrase stereolithography. According to Hall, the process entails "printing" a material that can be cured by ultraviolet light in a series of thin layers.

SLA 3D printing did not, however, become a widely used 3D printing technology right away. Around the end of the 2000s, when patents started to run out, 3D printing entered the desktop market, broadening the use of additive manufacturing. Fused deposition modeling (FDM) also had its first uptake on desktop platforms around this time. FDM 3D printers have not completely satisfied professional needs, despite the fact that this 3D printing technology is the first to use an economical extrusion-based technique. Industrial applications demand high resolution outcomes, biocompatible materials for the dental sector, and the ability to create eye-catching embellishments for sectors like jewelry.

2.3.3. Advantages of Stereolithography

- The SLA 3D printer's capacity to create 3D models with extreme precision and exquisite detail is what sets it apart. Thanks to the gentle laser beam and the incredibly thin applied layers (0.05 to 0.10 mm), prototypes with a very realistic finish and intricate geometric shapes may be produced.
- Piece quality: Although resin was used as a substitute material, lithograph components still have good surface functionality.
- Smooth finish: This printer's body has a smooth finish, and there are many resins available for custom rendering.
- From smallest to largest: High precision can be maintained in the creation of both small parts and larger parts up to two meters in size.
- Price and turnaround time: Lithography can produce a part in a matter of minutes or two days, depending on the size of the final product, and the 3D files are sufficient to begin printing.
- Cost: Reasonable since lithography is accomplished by the addition of materials rather than by the creation of a mold.

2.3.4. Isotropy

Due to the fact that 3D printing produces parts one layer at a time, the strength of prints produced using a 3D printer varies depending on the orientation of the part throughout the printing process. By fusing the chemistry of the materials with the printing process, a number of variables that are crucial to achieving the desired characteristics may be accurately controlled. The resin's components establish covalent connections as the item is being printed, but it still has a semi-reactive "green state."

The resin still has polymerizable groups in the green state that can establish cross-layer linkages and give the part characteristics like water resistance after final curing. There is no distinction between the X, Y, or Z levels at the molecular level. As a result, parts have predictable mechanical performance, which is crucial for applications like functional prototypes, assembly, and end-use parts. Figure 2.5 illustrates the x, y, and z axes' differences between FDM and SLA.

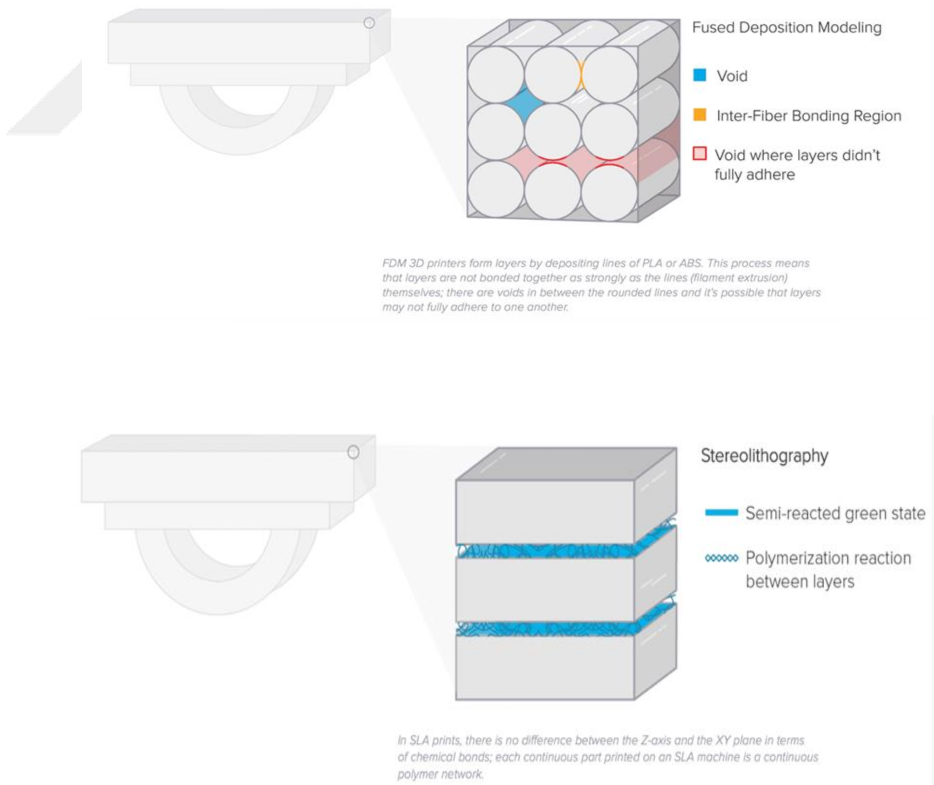


Figure 2.5. Difference between FDM, SLA in x,y,z axes

2.3.5. Limitation of Stereolithography

The 3D printers are exposed to multiple defects during printing, and for this reason, the object is printed with many defects. The product is generally fragile and unsuitable for functional prototyping. The mechanical properties and visual appearance of the printed object deteriorate over time when the parts are exposed to sunlight. Supporting structures are always required and post-treatment is necessary. Lithographic pieces are substantially more brittle than finished parts. Lithography does not allow for the production of components that can be used for mechanical testing even though it employs equivalent materials, namely resins, if the quality of the finish allows for the production of functioning prototypes.

Despite the widespread use of lithographic printers, experts ignored the equipment's high cost and challenging operation. Because it is challenging for businesses to produce their own lithographic prototypes, they frequently choose to work with specialized organizations. Since lithography can only be used for three copies of a part at a time, mass production is unnecessary.

2.3.6. Print Parameters of SLA

2.3.6.1. Layer Thicknes

One of the fundamental technological features of every 3D printer is layer thickness. In an additive manufacturing process where layers are stacked, it is a measurement of the height of the layer with each subsequent addition of material, the layer height is basically the vertical resolution of the z-axis. Layer thickness is a factor that has an impact on the printed part's printing time, cost, aesthetics, and physical characteristics. Table 2.2 show the different Printers with their range of layer thickness. The orientation that is selected for the printing items affects how the layer height of a 3D printer influences the printing results .

Table 2.2. The ranges of layer thickness of different printers

Printers	Layer Thickness (mm)
Fused Deposition Modelling (FDM)	0.17 to 0.33
Fused deposition modeling at the workplace or fab lab	0.10 to 0.33
Selective laser sintering (SLS)	0.06 to 0.15
Stereolithography, (DLP)	0.05 to 0.15

2.3.6.2. Printing Temperature

The temperature at which you print resin in a comparatively hot perimeter must be to improve resin printing; we can heat the resin in a water bath before starting the process. The temperature range of most resins is between (25-30C).

2.3.6.3. Cure Time

Curing time is the time that defines how long it takes for an SLA 3D printer to convert liquid polymer resins into solid geometries until they are fully cured using UV lasers or exposures built into the 3D printer hardware. Curing 3D prints with resin allows them to achieve their optimum mechanical properties and superior performance in terms of strength and toughness.

2.3.6.4. Speed

3D printing speed is the rate at which the print head moves along the X and Y axes as it lays a layer of material down. Fast 3D printing speed will reduce overall printing time, but "fast" prints can take a long time, when the product is relatively large. Printer speed is measured in millimeters per second (mm/s), 3D printing speed can also vary across builds: sometimes a slower speed is used for the first layer (to ensure good adhesion to the build surface) and a higher speed is used for packaging (where accuracy is less important). The quantity of layers required to create an object determines the print speed and consequently the amount of time necessary. The thinner the layer, the longer it will take to produce a 3D-printed object of a certain height. Therefore, for an object that is around 1 centimeter high, 100 layers with 100 μm would be required. This explains why 3D printing with the same technology and thinner layers costs more.

2.3.6.5. Hardness

Hardness is a material's resistance to being mechanically indented by a harder item. Heat has the ability to change hardness, so after undergoing heat treatment, a product acquires a new (higher) hardness value. The amount of time the indentation is in the object, the indenter's geometry, and work engineering can all affect the hardness value specified in a hardness test.

2.3.6.6. Surface Roughness

The relatively high-quality surface finish of SLA 3D printing has boosted its application. In comparison to polishing/finishing techniques, which typically range from 0.1 to 0.4 µm , the average surface roughness of SLA 3D printed items is in the range of 0.4 to 2 µm .

2.4. Basic Components For 3D Printing

The majority of printing materials are made from a select group of materials that are malleable or have high ductility and permeability. The most important of these is polymer, which is used in 3D printers because it is inexpensive and lightweight.

2.4.1. Polymer/Plastics

Thermoplastics are used in the production of most consumer goods. Polymers are frequently utilized in 3D printing to produce consumer goods and prototypes. The most widely utilized polymers in the past for FDM technique were Polylactic Acid (PLA) and Acrylonitrile Butadiene Styrene (ABS). Other polymers, like thermoplastic polyurethane (TPU), nylon, polycarbonate (PC), and polyethylene terephthalate (PET) have recently been employed.

2.4.2. Photopolymer

Chain creation in the photopolymerization process makes it more significant for our study than stepwise polymerization. The photopolymer typically consists of monomers, trimmers, photo inverters, and other additives. The photopolymerization reaction, which depends on the functional group in the photo monomer that needs to be activated, is accelerated by the laser beam's wavelength. Any molecule that may combine with other molecules to form a polymer is known as a monomer. Asmall number of monomers make up an oligomer. When photoinitiators are exposed to ultraviolet laser radiation, reactive species such cations, free radicals, or anions are produced.

Photoinitiator and monomer need to make good contact. Monomers often need a lot more energy than functional groups in photocatalysts to activate their electrons. as a result, the monomers are stable and are unaffected by ultraviolet radiation. But long-term exposure to sunlight energizes electrons and destroys bonds that interact with oxygen in the air in items that are utilized outdoors; oxidative deterioration is the name given to this process. In order to stop oxidative breakdown, UV protection chemicals are added to the material. For the duration of the photopolymerization reaction, the electrons affected by ultraviolet radiation gain additional energy and become more active. The electrons return to their usual energy level after the process is finished (Terselius, 1998). When a substance is exposed to light, its qualities change. Only the places where the UV laser strikes are used to process the photopolymer liquid. The chains attach to one another during the curing phase in a cross-linking reaction. The material hardens and solidifies after UV light-induced polymerization (Varotsis, 2018). According to Bourell et al. (2017), the following ingredients can be used in the VAT polymerization process: epoxy, acrylics, and acrylat.

The initial material's viscosity is crucial to this process. Particulate matter shouldn't stop re-flow into the work area (Bourell et al., 2017). The only components of one of the earliest photopolymer materials employed in a photopolymerization method were acrylate monomers and photo antigens. Additionally, vinyl ether monomers have been utilized in resins, although shrinkage of between 5 and 20% is what causes the material's noticeable distortion. The advent of epoxies in the 1990s provided a remedy to the materials issue. However, the resin formulation process has grown more difficult as a result of the material's ability to solve the earlier issues (Bourell et al., 2017). The cationic polymer epoxy has been polymerized. The epoxy's rings are opened to create the chemical connections monomer. The amount and kind of chemical bonds are the same before and after the ring is opened, hence volume change is not significant in this process. Despite this, epoxies outperform acrylates because of their resilience to warping and shrinking (Bourell et al., 2017).

2.5. Development of 3D Printed Nano Composites

Nanoparticles are incorporated into a polymer matrix to reduce some limitations such as brokerage or some polymers have toxicity or they can be combined for improvement to produce a more useful product that cannot be achieved using the matrix alone. In this section, it will be discussed.

2.5.1. Nanoparticles as an Additive in the Compound

A nano-additive is an additive that has nanoparticles added to it. A nanoparticle is a very small particle with a diameter of between 1 and 100 nanometers. Materials for high-volume 3D printing frequently have voids or cracks, which render the structure brittle and unsuitable for many applications. Most of these issues can be solved by incorporating the mechanical attributes of the nanoparticles into the overall form because they can reduce wear and friction between surfaces, form an anti-corrosion film, and have a repairing effect that makes up for mass loss and smooths out rough surfaces. The several types of nanoparticles (NPs) include those made of carbon, metal, ceramic, magnetic materials, semiconductors, polymers and lipids.

2.5.2. Carbon Based Nanoparticles

Due to their outstanding mechanical, thermal, optical, and physical properties, carbon-based NPs are well-known and frequently used in many different disciplines. Carbon at the nanoscale is created by the processes of carburization, grinding, heating, and activation. The use of carbon fibers improves polycarbonate even more, enabling new 3D printing applications. To create a composite with greater mechanical strength, Espalin and his research group added carbon fibers to a PC polymer. The tensile strength was 77% higher than it would have been with just the PC polymer. The SEM result also demonstrated that as the carbon fibers were made stiffer, the porosity decreased.

2.5.3. Ceramic Based Nanoparticles

This kind of nanoparticle has strong heat resistance, low electrical conductivity, corrosion resistance, and high toughness while being chemically inert. Examples include titanium dioxide, alumina and hydroxyapatite. Tensile strength was measured by the Ahuja research team to be 44.52 MPa, when aluminum oxide was reinforced with nylon to characterize the use of ceramic based nanoparticles as additives.

2.5.4. Metal Based Nanoparticle

Although metal products are efficient heat and electrical conductors, corrosion damage can occur. However, it is possible to boost the required material's mechanical strength by adding metal-based nanoparticles to the polymer.

2.5.5. Nano Clay Nanoparticles

Nano clays are widely distributed in nature and frequently appear as a result of the chemical weathering of silicate minerals near the earth's surface. Nano clays can be separated from the clay fraction using a variety of physical separation processes. The characteristics of Nano clay/polymer composites are greatly influenced by a number of elements. The shape of the composite is affected by the dispersion of the Nano chips in the polymer matrix and chemical compatibility, which in turn affects the capabilities for elastic modulus, heat distortion temperature, strength, thermal stability, self-healing, gas barrier and shape memory. Different dispersion strategies can be used to generate a more homogeneous dispersion depending on the type of nanomaterial. The clay substance is machined on its surface, most frequently. At the temperatures above the polymer's transition temperature, the intercalated clay particles are blended with the polymer material using the molten blending technique. An inert environment is used for the mixing process. Blends that are static or dynamic in a molten state. The composites are blended in a vacuum at temperatures above the polymer transition point during static melt blending, also referred to as melt annealing.

In this work, the Nano clays and photopolymer are combined in several ratios (0.01, 0.03, and 0.05). The downward force used to guide the nano chips into a plate shape in each layer is created by the build platform's descent into the resin tank during the printing process. Upon prolonged exposure, the photopolymerization of the Nano chips will immobilize them. This new approach will open up possibilities for printing high-performance parts using lithography, increasing their functionality.

2.6. Experimental Design

Experimental design is a common and widely used research approach in which research is conducted in an objective and controlled manner such that a hypothesis statement's accuracy is maximized and precise conclusions can be made. It is meant to be used to ascertain how an independent variable or factor affects a dependent variable. Experimental design includes hypothesis statements, experimental control, identification of independent and dependent variables, sample selection and allocation, data collection, and selection of correct statistical tests through accurate and precise experimental measurement and control.

The accuracy with which the link between a variable can be examined is the most crucial consideration for researchers when choosing experimental design, as experimental design attempts to avoid ambiguity and uncertainty. Real experimental designs explore relationships between variables while controlling one of them to determine how it affects the other dependent variables. A causal link between the independent variable and the dependent variable or variables can be established if the experimental design is appropriately implemented. This article primarily focuses on developing an experimental design for a study that will test and examine the link between experimental variables.

2.6.1. The Response Surface Design

It is a set of modern Design of Experiments (DOE) techniques that are commonly used to improve models after identifying important factors using DOE as it helps to understand and optimize the response.

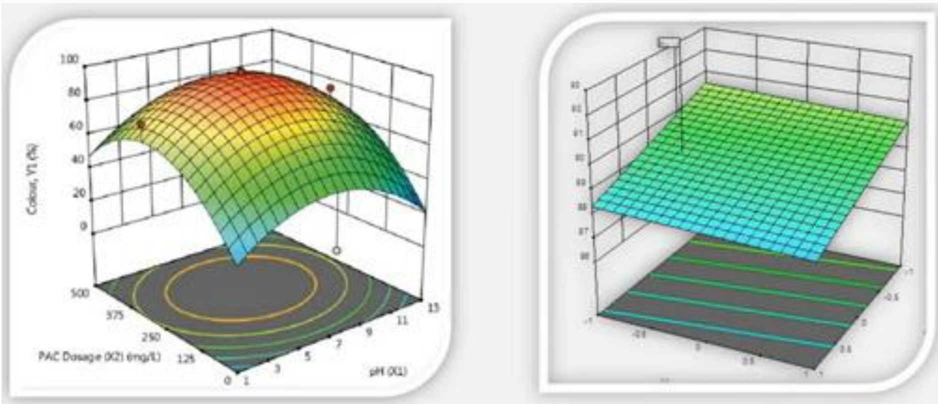


Figure 2.6. Graphs of two Response Suface Experiment Equations

$$R1 = \beta_0 + \beta_1 A + \beta_2 B + \beta_3 C + \beta_4 AB + \beta_5 AC + \beta_6 BC + \beta_7 A^2 + \beta_8 B^2 + \beta_9 \qquad \textit{Eq (2.1)}$$

$$R2 = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \qquad \textit{Eq (2.2)}$$

This equations represent a model of how variations in factors impact the interest's reaction. Thus, we can understand or identify an area of the response surface, find the levels of variables that improve the response, as well as determine the operating conditions that conform to the specifications. Figure 2.6 represent two response surfaces first with with curvature depend on Eq (1) second without curvature depend on the Eq (2). The types of response surface designs are present below.

2.6.1.1. Central Compound Designs

It is one of the main popular response surface designed experiments. It is a fractional design with central points, augmented by a set of pivot points also called star points that let you know the amount of curvature. By including central and focus points for a pre-implemented global design, a central composite design can be utilized to estimate first and second order efficiency as well as to model a response variable with curvature. A complete quadratic model can be fitted by composite center designs. Due to the fact that these designs can take into account data from an appropriately planned working experiment, they are frequently utilized when a design plan calls for serial trials. Fig 2.7 and fig 2.8 represent the design considerations for this experiment.

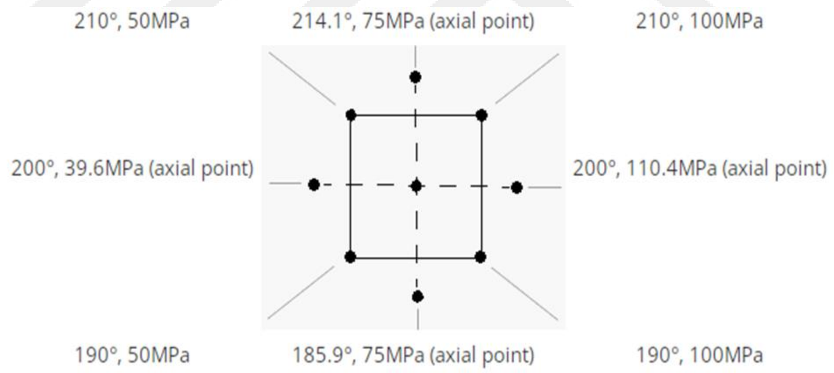


Fig 2.7. The central componant design point

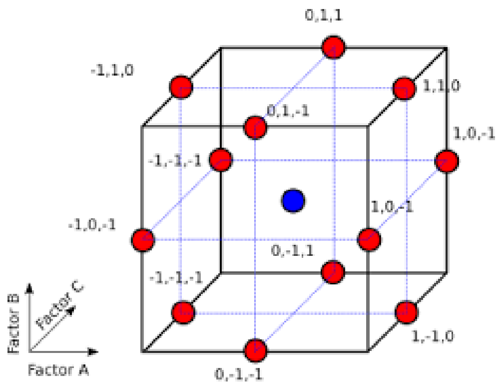


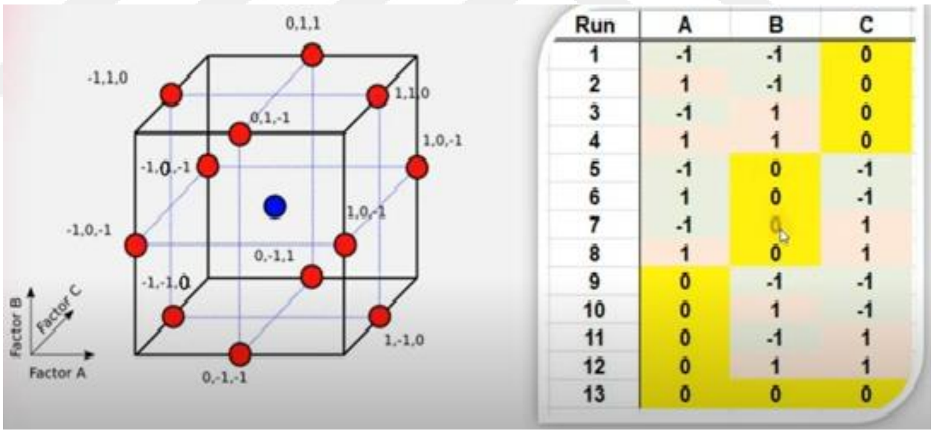
Fig 2.8. Central compound design

2.6.1.2. Face Centered Design

A sort of central composite design with an alpha of 1 is a face-centered design. Since each face of the factorial space in this design has an axial point at its center, levels = + 1. Three tiers of each element are needed for this type of design. This design can easily be created by adding the right axial points to an existing factorial or resolution V design.

2.6.1.3. Box Behnken Design

Inline factorial design and fractional factorial design are not included in the form of response surface design known as Box-Behnken design. Treatment groups in Box-Behnken designs must be situated in the center of the edges of the experimental area and must include at least three continuous elements. The three-factor Box-Behnken design can be seen in the following illustration. Fig 2.3 show the experiment operations are represented by the points on the diagram.



Run	A	B	C
1	-1	-1	0
2	1	-1	0
3	-1	1	0
4	1	1	0
5	-1	0	-1
6	1	0	-1
7	-1	0	1
8	1	0	1
9	0	-1	-1
10	0	1	-1
11	0	-1	1
12	0	1	1
13	0	0	0

Figure 2.9. Box-Behnken design

$$R1 = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \qquad Eq\ (2.3)$$

Box-Behnken designs are less expensive since they have fewer design points than center-combined designs with the same number of factors, but they cannot be used for sequential trials because they lack built-in factorial design.

The "cube" is rarely the only focal point in composite central designs. It's possible that these points are not in the desired area or that they cannot be performed because they exceed safe operating limitations. You may be confident that every design element is within its safe operating range. This design make sure that all factors are not set to their high levels simultaneously because they do not have pivot points.

2.6.1.4. The Taguchi Method

This method created by Dr. Genichi Taguchi from Japan. Producing a high-quality product at a reasonable price for the manufacturer was his goal. The Taguchi approach focuses on minimizing process variance through robust experiment design. The Taguchi-type experimental design method focuses on a process performance characteristic's variance and mean to assess how well a process functions under the impact of various parameters. To arrange the variables that affect the process and the levels at which they must be altered, in Taguchi's experiment, orthogonal matrices are used. Like a factorial design, the method tests pairs of possibilities rather than needing to test every conceivable combination. This reduces the amount of trial required to get the data needed to determine the variables that most affect product quality, saving resources and time. When there are minimal interactions between variables, few substantial contributors, and a modest number of variables (3 to 50), the Taguchi approach is chosen. The Taguchi Method involves the following basic stages:

a) Set the process goal value for the process's performance metric.This could be hardness, speed, etc. The goal may be need to be minimum or maximum, the loss function of the process is established using the performance property's departure from the target value.

b) Define the input parameters affecting the goal, and others that have an impact on performance measurement. Every parameter have levels at which the parameters should change. As more tests need to be run, the level might be adjusted to a low and high value, respectively.

c) Construct orthogonal arrays to be used in the parameter design. To do this the number of parameters must be fixed and the degrees of change for every input must be determined.

d) Running the tests outlined in the finished matrix and gathering information on how they affect the performance metric.

e) Complete the data analysis to ascertain how various elements would affect the performance metric.

One of the main advantages of this method is the improvement of product quality because it emphasizes the value of intermediate performance characteristics close to the target value. The Taguchi technique is a powerful yet simple tool since it is clear-cut and simple to use in many technical settings. It can be used to swiftly focus a research study or find issues with a manufacturing process using data that is already available. Also, the Taguchi method allows many different parameters to be analyzed. That is, in the event that there have 8 variables, each of which has 3 cases, it may require conducting 6561 (38) experiments to test all the variables. But using Taguchi's orthogonal matrices, these parameters and the factors with little impact may be omitted, one establishes the key parameters that have the biggest influence on the performance characteristics value. So that if we have 8 variable, only 18 experiments are conducted (less than 0.3% of the original number).

The main limitation of this approach is that it only yields relative results, not precise indications of which variable most significantly affects the performance characteristic value. Furthermore, because orthogonal matrices do not test all possible combinations of variables, this approach should not be used with all correlations between all relevant variables. The offline nature of the methods is another drawback; as a result, they are unsuited for a process that is changing dynamically. Furthermore, the methodologies work best when used in the early stages of process development since they focus on excellent design instead of the correction of quality. Using an experimental design might not be as cost-effective, once the design variables have been established.

2.7. Optimization Methodology Using Grey Relational Analysis (GRA)

Relational grayscale analysis (Panda and Round, 2016) with multiple responses is used to optimize control parameters through relational grayscale in order to provide a single value that can be used as a single property in optimization problems. Gray relational analysis is used to aggregate all examined performance aspects. GRA have five steps to be processed.

Step 1. Normalization of response values

By this step, GRA can be classified into three types depending to the desired nature of the response values. The first normalization is ‘higher the better’ where highest values of the result are the desired , second ‘ smaller the better' where the lowest values is the goal function are desired, the third is the 'nominal the better' where the goal function has average values. The values for hardness are expected to be high in this research, hence, 'higher the better' normalization criteria is considered for hardness. The equations for 'higher the better' normalization criteria considered is as follows:

$$z\ (k)= \frac{yi(k)-minyi(k)}{maxyi(k)-minyi(k)} \qquad \text{Eq (2.4)}$$

where, *z (k)* = value after the grey relational generation, max *yi(k)* = largest value of the *yi(k)* for the kth response, min *yi(k)* = smallest value of *yi(k)* for the *kth* response,

And the value of roughness test is decreased. Therefore, the better normalizing requirements for roughness are lower values. The following is the analytical formula for the "lower the better" criteria taken into account:

$$zi\ (k)= \frac{maxyi(k)-yi(k)}{maxyi(k)-minyi(k)} \qquad \text{Eq(2.5)}$$

where, *z(k)* = value after the grey relational generation, max *yi(k)* = largest value of the *yi(k)* for the *kth* response,min *yi(k)* = smallest value of *yi(k)* for the k_{th} response.

Step 2. determining the deviation sequence by using the formula below

Deviation sequence = *max-xi* *Eq(2.6)*

Step 3. new have to calculate grey relation coefficient, *ε(k)* from the normalized values by the following equation:

$$\varepsilon_i = \frac{\Delta_{min}+\varepsilon\Delta_{max}}{\Delta_{oi}(k)+\varepsilon\Delta_{max}} \qquad \text{Eq(2.7)}$$

Where *min*= 0 *max*= 1

ε_i is an identifying coefficient, and its range is 0 to 1. Typically, 0.5 is used as the value of ζ. .

Step 4. finding out the grey relational grade (GRG):

$$\gamma_i = \frac{1}{n} \sum_{k=1}^{n} \varepsilon_i\ (k) \qquad \text{Eq(2.8)}$$

Where, γ_i, *n* is the number of response characteristics, it is the necessary grey relational grade for the experiment. The degree of correlation between the reference sequence and the comparability sequence is represented by the grey relational grade, which is the overall representation of all the quality criteria (Noorul Haq et al., 2008). Thus, using grey relational analysis and the Taguchi technique, the multi-response optimization problem is reduced to a single response optimization problem.

Step 5. Ranking alternatives:

After we get the grey relational grede value; an optimal level of process parameters is determined which are the higher grey relational grade that refers to the better product quality to obtain this, the rank equation will be used, which returns the rank of a number in a list of numbers. The rank of a number represents its size relative to the sizes of other values in the list. Number 1 in rank represent the higher grey relational grade. Figure 2.10 presents the details of GRA method in an algorithm.

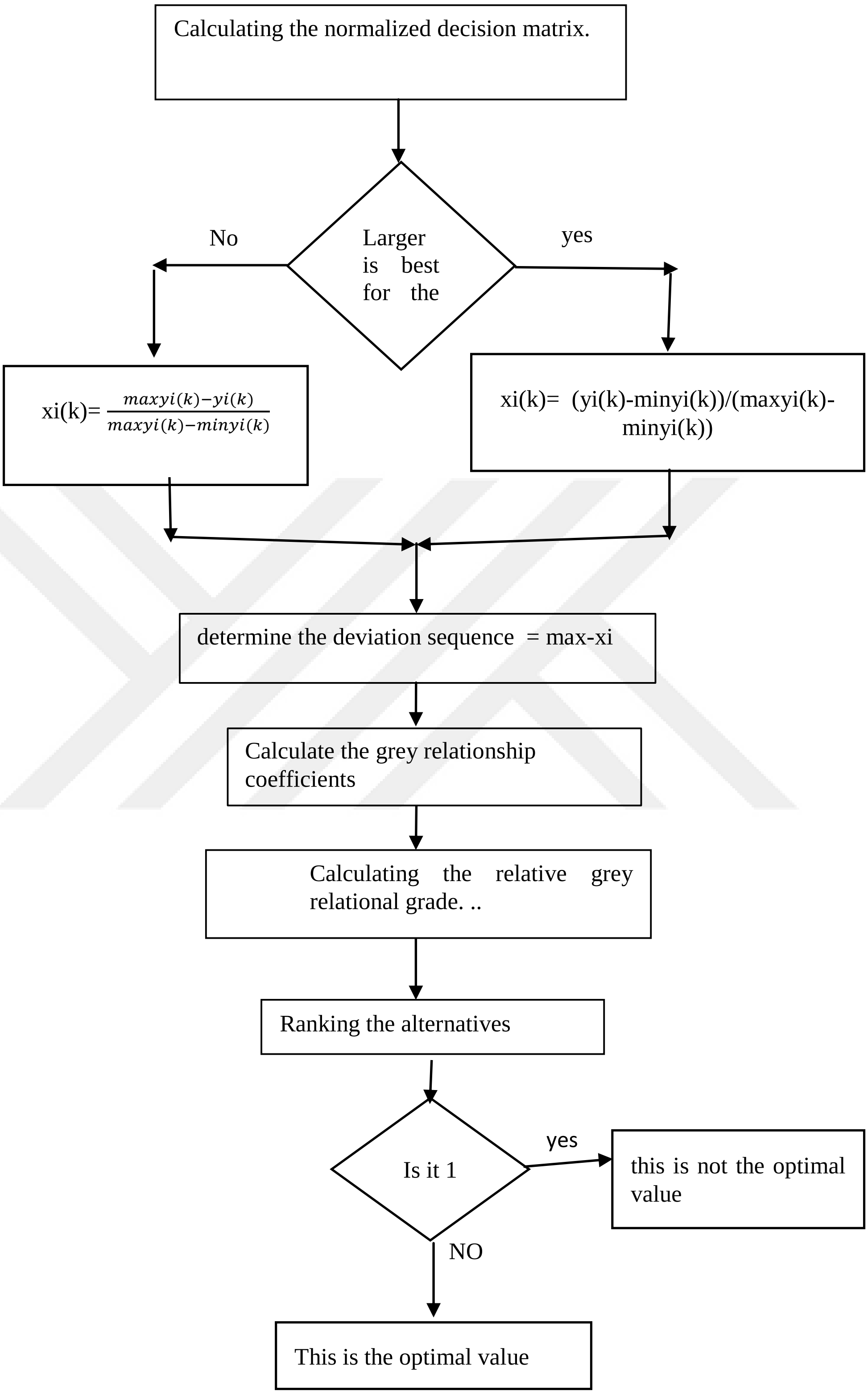


Figure 2.10. The algorithm of Grey Relation Method

3. MATERIAL AND METHOD

3.1. Software Requirements

3.1.1. Minitab Program

Minitab, an analysis software program used by businesses for process improvement, statistical analysis and data analysis. This program used different tools such as Six quality engineers and Sigma experts. The users of Mintab can access many tool for statistical analysis such as regression analysis, ANOVA, creating graph and charts, etc... This program using using in many different field include education, solving many mathematical, healthcare, and manufacturing applications. Users of Minitab can access to tools for statistical analysis, experiment design, Six Sigma and quality enhancement.

3.2. Hardware Requirements

3.2.1. Stereolithography (SLA) 3D Printer

Stereolithography (SLA) uses UV lasers as a light source to selectively cure a polymer resin. Figure 3.1 shows the type of SLA printer used in the laboratory which is Sonic XL 4K Phrozen.

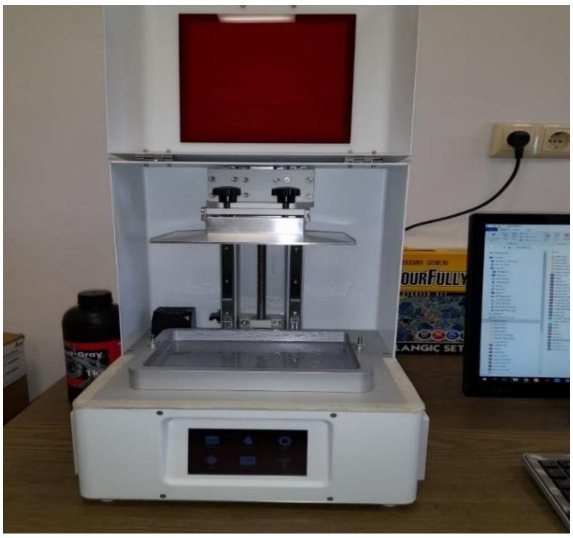


Figure 3.1. SLA 3D printer photo

There are the general specifications of Sonic XL 4K Phrozen printer:

1. Operation: The System used in SLA 3D printer is Phrozen Os, for the operation is 5 inch touch panel, slicer software is phrozen 3D powered by firmware, and for connectivity to send the model from CAD program there are USB, Ethernet, and WIFI.

2. Printing specification: The used technology is resin 3D printer- LCD type, for user light source is 405nm paraLED 3.0 Module, layer thickness is 0.01 – 0.03 mm .

3. Printing speed: is 90mm /hr, power requirement: is AC 100- 240 ~ 50/60HZ.

4.Hardware specification: Printer size of SLA is L11.4×W13×H 18.5 in ches, Printing volume of 3D printer is L4.7 ×W7.5×H7.9in ches and printer weight of SLA is 19.5 kg.

3.3. Proposed System

The primary goal of this project is to enhance the mechanical property of a 3D printed parts. This is done first by add Nanoparticles to the liquid resin of SLA printer second by looking of combined and individual effects of SLA printing parameters:

- Cure time
- Speed
- The added nanoparticle ratio.

On the mechanical characteristics of these printed parts which include: hardness and surface roughness.

Various combinations of the printing parameters (cure time, speed and added nanoparticle ratio) are taken into consideration and are selected based on Taguchi's DOE L9 orthogonal array. This is done by taking the various experimental combinations of factors obtained as the input and then responses are measured. The normal probability plots of signal to noise ratio for each measured response are plotted in order to indicate the process stability and the parametric conditions are ranked based on their individual influence. The optimization of the process parameters will then be done to improve the responses and validate them experimentaly.

3.3.1. Design and Implementation

In this project, the liquid resin of SLA printer is mixed with nanoclay. The figure 3.2 represent the photopolymer resin used in experiment and the nanoclay.

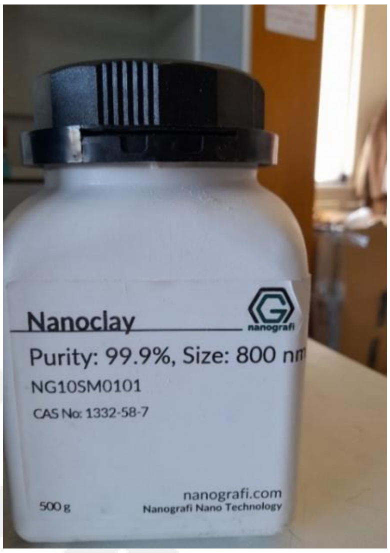


Figure 3.2. The resin and nanoclay used in the experiments

The experimental methodology adopted in this project included the identification of various factors and levels to obtain a layout for the Design of Experiments (DOE).

Table 3.1. Factors and levels selected for analysis

Factor	Unit	Level 1	Level 2	Level 3
Cure time	s	1	3	5
Speed	mm/s	50	100	200
Nanoparticles ratio		0.01	0.03	0.05

Based on the previous table we need to make 3^3 =27 experiments, in this study in order to reduce the number of experiment the Box Behnken method is used, which is a type of design of experiment.

Table 3.2. Box -Behnken experiment design parameters.

Run	Cure time (s)	Speed (mm/s)	Nano particle ratio
1	3	50	0.05
2	3	200	0.01
3	5	200	0.03
4	5	125	0.05
5	3	50	0.01
6	3	200	0.05
7	5	125	0.01
8	1	125	0.05
9	5	50	0.03
10	1	50	0.03
11	1	200	0.03
12	1	125	0.01

As shown above we have to do 12 experiment and this take time and cost. To reduce the number of experiment, Taguchi's Design was used that is an optimization technique which can be used as an effective tool to obtain the desired results efficiently with minimum prescribed number of trials. This facilitates in determining the best possible combinations of parameters so as to produce the desired characteristics in the response. DOE helps to identify the effect of Multiple factors for a single response. Taguchi design implemented using Minitab program that it needs 9 exponents (3 factor * 3 level).

Table 3.3. Taguchi experiment design parameters.

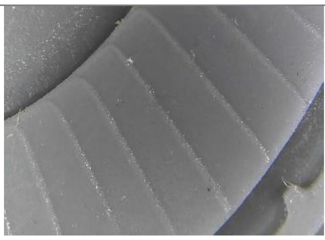
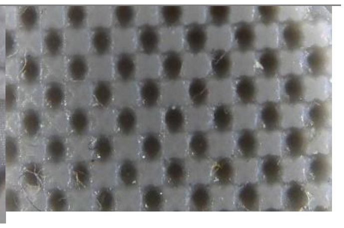
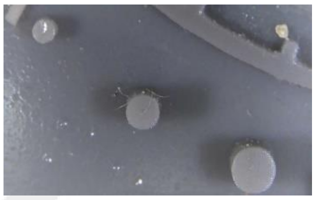
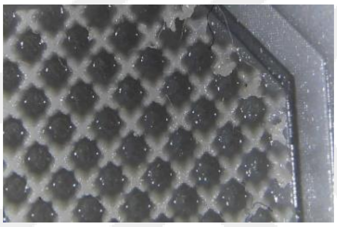
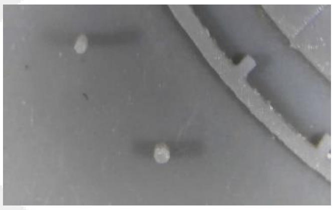
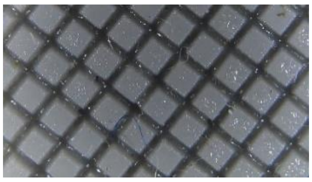
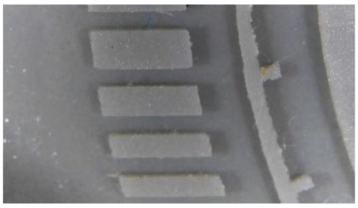
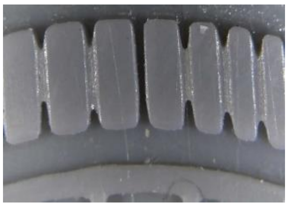
Exp #	**Cure time (s)**	**Speed (mm/s)**	**N/P ratio**
1	1	50	0.01
2	5	100	0.01
3	3	200	0.01
4	5	50	0.05
5	3	50	0.03
6	1	100	0.03
7	3	100	0.05
8	1	200	0.05
9	5	200	0.03

The samples are printed depending on the Table 3.3 using 3D SLA printer. The samples are shown in Figure 3.3

Figure 3.3. Photos of printed parts

And Table 3.4 show some samples of printed part that enlarged by optical micro scope to see the accuracy and quality of the printed part in various experiments.

Table 3.4. Some optical images of printed parts (scale: 50x)

Exp	Part 1	Part2	Part3
4			
5			
6			
7			
8			
9			

4. RESULTS AND DISCUSSION

4.1. Measurement of Responses

Two main response factors are measured by using a handheld surface roughness tester PCE-RT 1200 that shown in Figure 4.1a and hardness that is measured by using a digital manual hardness tester shown in Figure 4.1b.

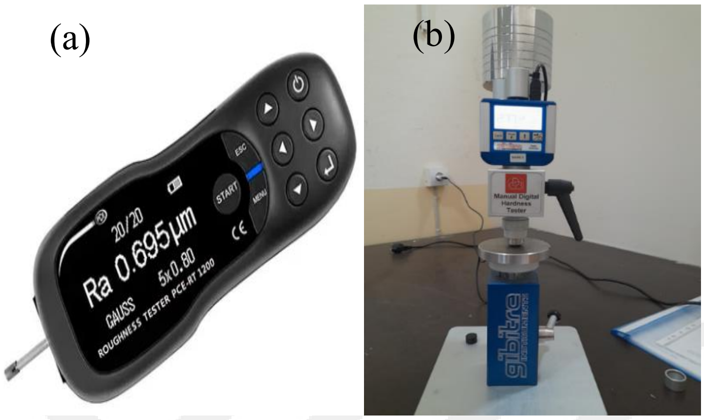


Fig 4.1. a) Surface Roughness Tester (PCE-RT 1200),
b) Digital manual Shore hardness tester (Gebitre Inst- Shore D)

The hardness and roughness test of each experiment are measured and tabulated in Table 4.1.

Table 4.1. The response measurements

Exp #	Cure time (s)	Speed (mm/s)	N/P ratio	Hardness (shore D)	Surface roughness (µm)
1	1	50	0.01	62.486	0.719
2	5	100	0.01	72.861	0.323
3	3	200	0.01	60.735	0.375
4	5	50	0.05	66.707	0.257
5	3	50	0.03	62.960	0.278
6	1	100	0.03	57.776	0.698
7	3	100	0.05	61.157	1.012
8	1	200	0.05	55.627	2.803
9	5	200	0.03	62.356	0.291

4.2. Analysis Of Variance in Minitab

The Analysis of variance (ANOVA) which help the user to find which factors have an important effect on each response, where analysis of variance shows the effect of different factors individually and the associated statistical model. It also depicts differences around the mean of the ANOVA results for each response. The main use of ANOVA is to control and eliminate variance in a process; then, steps can be taken regarding the parameters that most affect the process capacity. Through ANOVA, parameters can be classified based on important process parameters. In this project ANOVA analysis is performed in Minitab software. Table 4.2 represents ANOVA for hardness test and Table 4.3 represents ANOVA for roughness test.

Table 4.2. ANOVA for hardness test

Source	DF	Seq SS	Adj SS	Adj MS	F	P
cure time(s)	2	2.1776	2.1776	1.08879	20.85	0.046
Speed(mm/s)	2	0.7448	0.7448	0.37238	7.13	0.123
N/P ratio	2	0.6561	0.6561	0.32807	6.28	0.137
Residual Error	2	0.1044	0.1044	0.05222		

The ANOVA table contains degree of freedom (DF), sum of squares (SS) significance factor ratio (F-Ratio), probability (P) and mean of squares (MS) the value of P depends on the value of F. Based on the value of F (the value of significance factor) parameters that have significance can be determined. The value of F represents the ratio of the means variance to the summed ratio within the group variance. The higher the F value, the greater the relative variance between groups means.

The number of independent pieces of information that can be gleaned from a particular set of data is measured in degrees of freedom, or DF. The number of levels is one more than the DF of the relevant factor. The variation in the data that a component provides is measured by the modulated sum of squares (Adj SS) of that factor. The single factor Adj SS and the error SS are added to create the total SS. The parameters can be divided into significant and non-significant printing parameters using ANOVA. Roughness test ANOVA data is provided in Table 4.3. These data allow us to draw the conclusion that the most significant element influencing the hardness and roughness result is the cure time.

Table 4.3. Test of ANOVA for roughness test

Source	DF	Seq SS	Adj SS	Adj MS	F	P
cure time(s)	2	212.75	212.75	106.37	8.25	0.108
Speed(mm/s)	2	45.96	45.96	22.98	1.78	0.359
NP ratio	2	94.10	94.10	47.05	3.65	0.215
Residual Error	2	25.78	25.78	12.89		

4.3. Determination of Signal to Noise Ratio (SNR)

In the Taguchi method, it is the ratio of signal to noise where noise denotes the unwanted value (deviation from the mean) and signal (mean) denotes the desired value for the output characteristics. The amount of variation that is present in a specific data is reflected by the united value of SNR, so the SNR is the ratio of the mean to the deviation. It is indicated by η and is measured in unit *db*. This experiment enables one to optimize the parameters and also determine the effect of each variable on the output. For this reason, SNR needs to be set for each of the tests contained by the analysis depending on the type of characteristic.

SNR shows the advantage of selection of optimum parameter levels with significant variation in levels so that different SNR are obtained such as smaller-the-better, larger-the-better, and nominal-the-best.

In the present work for this project, the following SNR quality characteristics are used:

1. Hardness test – Larger is better
2. Surface Roughness – Smaller is better

The major effect is obtained by graphing the characteristic average for each level of the component and is when the different levels of the factor affect the desired result in distinct ways, a straight line connected the response mean for each level of the primary effect that was displayed.

Figure 4.2 with using MINITAB 18, the main effects plot of SNR was respectively prepared. The highest SNR is shown at a cure time of 5 s (level 3), but we can select 3 to spend the least amount of time, 50 mm/s for print speed (level 1), and 0.03 for NP ratio(level 2), though we can choose 0.01 to spend a little less nanoparticle because it is expensive.

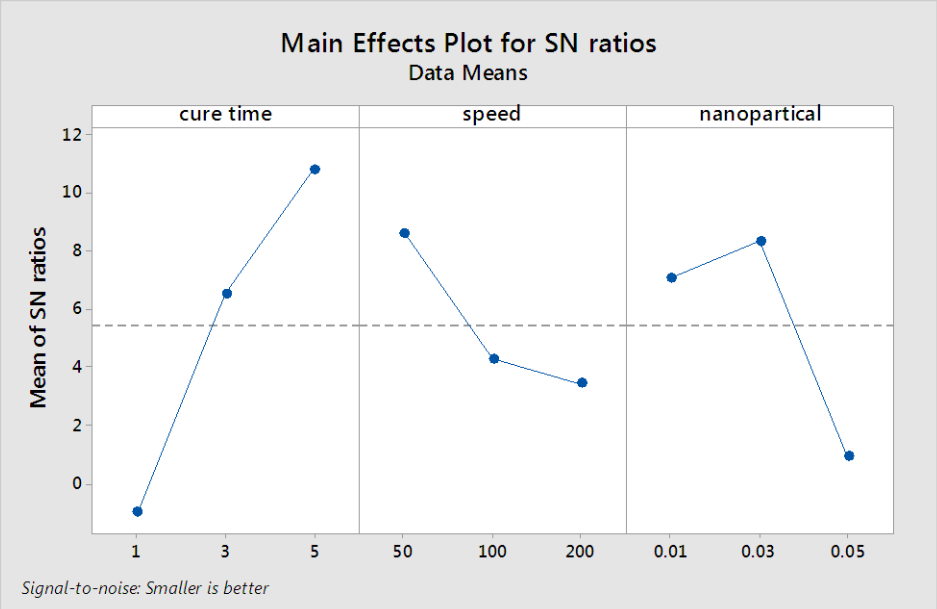


Figure 4.2. SNR graph for surface roughness test

Table 4.4. Response Table for SNR

Level	**Cure time(s)**	**Speed(mm/s)**	**NP ratio**
1	0.9908	8.5846	7.0618
2	6.4995	4.2756	8.3084
3	10.7727	3.4212	0.9113
Delta	11.7636	5.1634	7.3970
Rank	1	3	2

Table 4.4 represents SNR of Response Table for roughness and Figure 4.3 represents SNR for hardness test. The maximum value of SNR is observed at cure time 5s (level 3), print speed of 50 mm/s (level 1) and NP ratio at 0.01 (level1). These levels of factor present optimal setting for maximizing hardness test, the optimal setting for different noise factors are different. To select the optimum parameter levels we must choose largest is better to obtain SNR of the hardness test, Figure 4.3 show the SNR of the hardness test where the largest value is required.

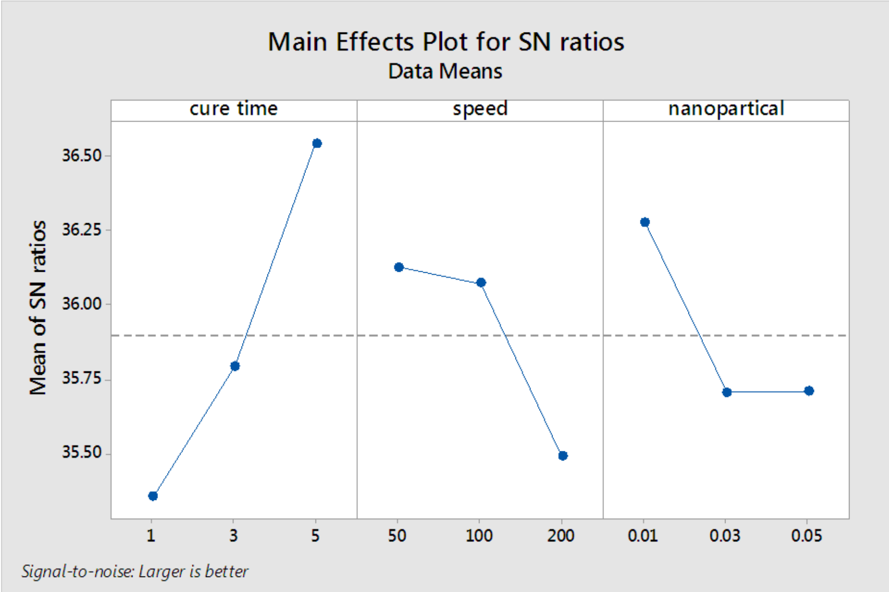


Figure 4.3. SNR graph for hardness test

Table 4.5. Response for SNR for hardness

Level	**Cure time(s)**	**Speed(mm/s)**	**NP ratio**
1	35.35	36.13	36.28
2	35.79	36.07	35.70
3	36.54	35.49	35.71
Delta	1.19	0.64	0.57
Rank	1	2	3

4.4. Implementation of Grey Relation Analysis

Grey relation analysis is used to drive optimum condition for multi-output by providing weightages to individual responses. There is four steps: normalization, deviation sequence, grey relation coefficient, and the last step is grey relation grade.

Step 1:

The hardness and surface roughness data have been normalized using *Eq (2.4)* for hardness (larger is better):

$$z\,(k)=\frac{yi(k)-minyi(k)}{maxyi(k)-minyi(k)} \qquad Eq\ (2.4)$$

And Eq (2.5) for roughness (smaller is better)

$$zi\ (k)= \frac{maxyi(k)-yi(k)}{maxyi(k)-minyi(k)} \qquad Eq(2.5)$$

Table 4.6. The response measurement

Exp #	**Hardness (psi)**	**Surface roughness (µm)**
1	62.4862	0.719000
2	72.8612	0.323000
3	60.7350	0.375667
4	66.7075	0.257333
5	62.9600	0.278667
6	57.7762	0.698667
7	61.1575	1.012000
8	55.6275	2.803000
9	62.3563	0.291333
min	**55.6275**	**0.257333**
max	72.8612	2.803000

Table 4.7. Grey relational generations table

Exp	**Hardness (psi)**	**Surface roughness (µm)**
1	0.397982	0.818646
2	1	0.974204
3	0.296367	0.953516
4	0.642926	1
5	0.425475	0.991619
6	0.12468	0.826633
7	0.320883	0.703548
8	0	0
9	0.390444	0.986644
min	0	0
max	1	1

Step 2:

From the normaliztion Table, deviation sequence have been obtain for hardness test and roughness test.

Deviation sequence = *max-xi* *Eq (2.6)*

Table 4.8. The results of deviation sequence

	deviation sequence	
Exp #	Hardness (psi)	Surface roughness (μm)
1	0.602018	0.181354
2	0	0.025796
3	0.703633	0.046484
4	0.357074	0
5	0.574525	0.008381
6	0.875320	0.173367
7	0.679117	0.296452
8	1	1
9	0.609556	0.013356
min	**0**	**0**
max	1	1

Step 3:

Eq (2.7) was used to compute the grey relationship coefficients. Given that both quality characteristics have received equal weight, the distinguishing coefficient is judged to be 0.5 in Table 4.8 .

$$\varepsilon_i = \frac{\Delta_{min}+\varepsilon\Delta_{max}}{\Delta_{oi}(k)+\varepsilon\Delta_{max}} \qquad \textit{Eq (2.7)}$$

where *max*=1 *and min* =0.

Table 4.9. Grey relation coefficient results

Exp #	**Hardness (psi)**	**Surface roughness (µm)**
1	0.312	0.423
2	0.500	0.487
3	0.293	0.470
4	0.368	0.500
5	0.317	0.495
6	0.266	0.426
7	0.297	0.385
8	0.250	0.250
9	0.310	0.493
min	**0.25**	**0.25**
max	0.50	0.50

Step 4:

Next, based on the findings of grey relational coefficients, the grey relational grade (GRG) has been determined using Exp #3. In Table 4.9, the GRG findings are displayed. This result shown that Exp #2 has the biggest value in the multi-responses when it is reduced to a single grade, indicating that it has the best input parameter.

Table 4.10. The ranking results

Exp #	**grey relation grede**	**rank**
1	0.367	6
2	0.493	1
3	0.385	5
4	0.434	2
5	0.406	3
6	0.346	7
7	0.341	8
8	0.250	9
9	0.402	4

Conclusion

The stereolithography (SLA) 3D printer creates parts by curing photopolymer resin layer with layer depend on CAD model. Various printing parameters which include cure time, speed and the ratio of nanoparticle added to the resin are obtained as the input parameters and selected based on Taguchi's design of experiment (DOE) orthogonal array with using MINITAB software. The normal probability plots of SNR for each measured response (roughness, hardness) are plotted in order to indicate the process stability and the parametric conditions are ranked based on their individual influence.

This included three parametric factors for the purpose of optimization along with three different levels for each factor. Based on the experimental results, the following conclusions were arrived at. According to the results of SNR plots it was shown that for hardness we obtained maximum value for hardness in cure time 5s, speed 50 mm/s and nanoparticle ratio 0.01, but we can take cure time 3s for reducing the time required to produce the product. For roughness to get minimum value the input parameters must be cure time 5s, speed 50mm/s, the nanoparticle ratio is 0.03. Also we can take cure time as 3s and for the added nanoparticle ratio we can take as 0.01 to reduce the cost.

Grey relational analysis has been used to maximize the input parameters with multiple responses. All the performance characteristics that are taken into consideration are compiled by using the Grey relational analysis into a single value that may be used as the sole characteristic in optimization tasks. The experiment #2 was determined to have the greatest value of the grey relational grade and was given the rank one designation. The criteria for experiment #2 setup are cure time of 5s, speed of 100 mm/s, and additional nanoparticle ratio of 0.01. In order to create a competent manufacturing process that also satisfies industry standards, it's critical to design a reliable evaluation technique.

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Publications:

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