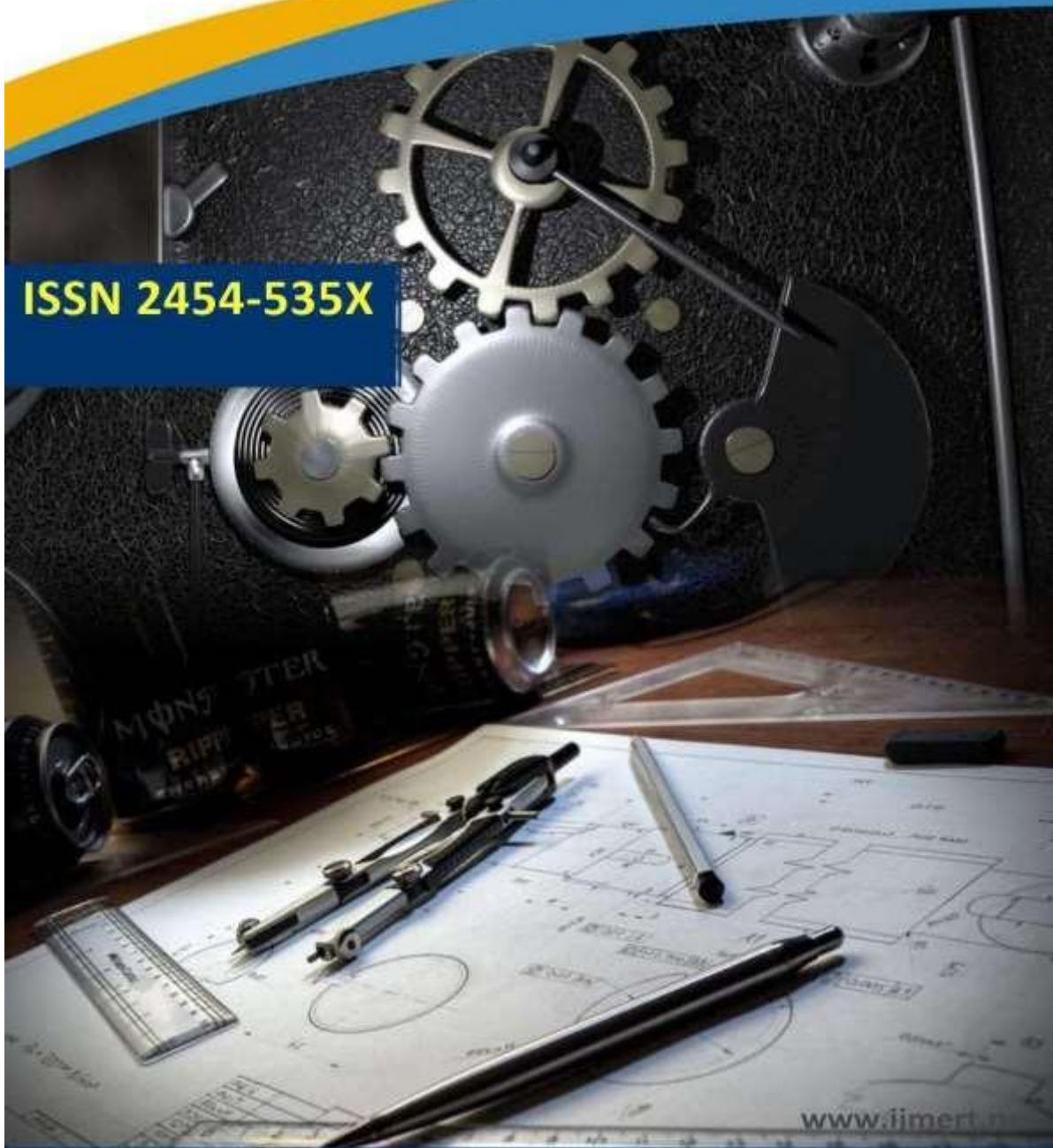




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Optimizing PEEK impact strength through multi-objective FDM 3D printing

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ABSTRACT

Because of their adaptability and low cost, thermoplastic materials including polylactic acid, nylon, polyethylene terephthalate glycol, acrylonitrile butadiene styrene, polylactic acid, and thermoplastic polyurethane are preferred in fused deposition modeling 3D printing. Unfortunately, compatibility issues with current equipment and procedures caused by high grade thermoplastic material have prevented its widespread use in FDM 3D printing. Making the necessary changes to 3D printing gear, software, and settings to accommodate new materials may be a time-consuming and costly process. The unique processing conditions and parameters required by each material make quality control and consistency maintenance a challenging task. Because of this variation, 3D printing cannot produce consistently high-quality parts. In addition, specific considerations are needed for optimizing the FDM settings for high-grade polymers (HGP)s such as polyether ether ketone (PEEK) because of the unique properties of these materials. As a result of the printing process's large temperature gradient and uneven heat distribution, residual stresses and deformations might occur, diminishing the material's quality and, more specifically, its impact strength. Using only three process parameters—build orientation, in-fill density, and chamber temperature—this paper improves a commercially available 3D printing PEEK. Additionally, the study endeavors to develop a model that can foretell the 3D printed object's Impact Strength (IS), a crucial factor to consider. In this article, we look for evidence of a relationship between the impact strength, printing time, and material use, which are all response variables or output variables. There seems to be a strong link between them, as shown by the results. The subsequent IS of 86.5 kJ/m², print time of 89 minutes, and material use of 3.26 grams are attained by using a particular parameter configuration. Setting the print density to 100% to maximize impact strength results in a notable 9.18% reduction in printing time and an 11.66% drop in material use. When a number of goals must be satisfied, this optimization method demonstrates that composite desirability is the way to go. A determination coefficient more than 50% is achieved by the suggested regression model for predicting the impact strength.

INTRODUCTION

A number of benefits, such as decreased material use, design flexibility, and near net shape production (NNSP), are offered by additive manufacturing (AM) compared to traditional manufacturing. Fused filament fabrication (FFF), often called fused deposition modeling (FDM), is one of many AM technologies that has recently gained popularity. Its simplicity, low cost, and extensive usage in engineering, education, and prototyping have all contributed to its rise in popularity [1, 2]. In comparison to other methods, FDM has lower system costs and shorter build times because to its layer-by-layer method of employing melted filament, which

allows for efficient item construction with minimum waste formation. Designers get significant insights on form, function, and fitness via the production of 3D printed products using FDM. To evaluate the mechanical behavior of 3D printed components, particularly for high-grade polymers such as Polyether ether ketone (PEEK), Polyetherketoneketone (PEKK), and Polyethylenimine (PEI), which are used as metal substitutes [3, 4], mechanical testing is essential. This has become more difficult over the years due to improvements in high-performance polymers (see Figure 1). Numerous biomedical therapies have made extensive use of PEEK and its variants.

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These include maxillofacial surgery, orthopedic surgeries, dental implants, and other similar procedures. Because of its high strength-to-weight ratio and long service life, it is widely used in many industrial applications [5]. Engineers may test a part's strength, durability, performance, and structural integrity by putting it through a series of mechanical stresses including compression, tension, bending, or torsion. By doing so, they are able to pinpoint any restrictions or shortcomings and make educated choices to enhance designs appropriately. The

optimization of FDM-AM process parameters including layer thickness, raster angle, print speed, nozzle temperature, infill patterns, and density has been the subject of several studies [6–8]. These studies aim to improve mechanical properties like tensile, compression, and flexural strengths, as well as the overall performance and durability of the parts. In order to increase the use of 3D printed components in different sectors, it is crucial to comprehend and enhance these mechanical characteristics.

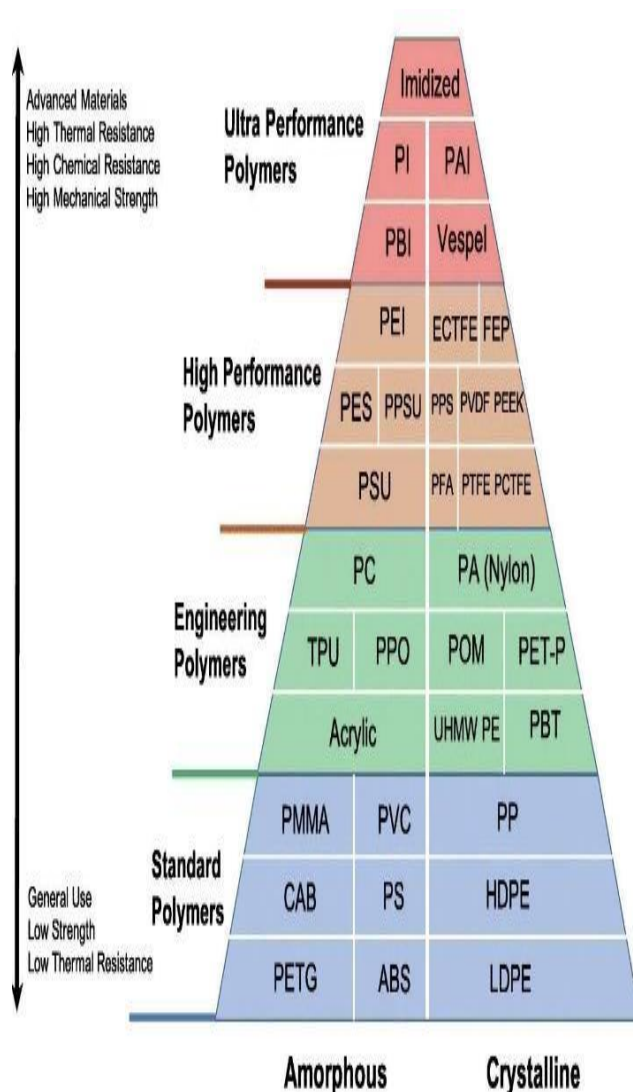


Figure 1. Classification of polymers [9]



Focusing on PEEK, a high-performance thermosetting polymer, this research aims to assess the impact behavior of 3D-printed components made from high-performance polymers. Although several studies have investigated how different process parameters affect 3D printed PEEK components, the correlation between these factors, build time, and impact strength has received comparatively less attention. To better understand how filler content affects mechanical properties and tribological properties of PEEK composites, Zhang et al. (2004) investigated this topic [10]. Wu et al. (2014) examined the effect of printing settings on thermal deformation and dimensional accuracy in 3D printed PEEK. They discovered that although the printing technique achieved excellent precision, it was susceptible to distortion when subjected to high temperatures [11]. Higher printing and chamber temperatures enhanced crystallinity and strength, but slower cooling rates improved crystallisation and mechanical performance, according to Yang et al. (2017), who studied the effects of thermal processing parameters on the mechanical characteristics and crystallinity of PEEK [12]. In their 2017 study, Berretta et al. compared FDM-fabricated CNT-PEEK composites to pure PEEK in terms of mechanical qualities and thermal behavior, and they found that the addition of carbon nano tubes (CNTs) increased mechanical capabilities but decreased thermal stability [13]. Printing parameters had a major influence on the mechanical strength of 3D printed PEEK components, as shown by Rinaldi et al. (2018). Printing temperatures had a positive effect on mechanical characteristics, whereas raster angle and layer height had a negative effect [14]. Deng et al. (2018) investigated the best temperature, speed, and infill density settings for FDM printing of PEEK in order to improve its mechanical characteristics [15]. Research on biocompatible PEEK characteristics was carried out by Arif et al. (2018). Their analysis included print orientation, layer thickness, and the impact of post-processing on mechanical behavior and surface quality [16]. Subsequently, in 2019, Saja et al. explored PEEK's mechanical characteristics in an effort to determine its suitability as a

denture material [17]. According to Wang et al. (2019), PEEK surface quality was enhanced with higher printing temperatures and lower printing rates, while flaws and degradation were produced by excessive temperatures [18]. Concurrently, Li et al. (2019) examined the effects of building orientation, fiber content, and fiber length on the flexural characteristics and fracture behavior of CF/PEEK composites [19]. The addition of multi-walled carbon nanotubes (MWCNTs) supposedly increased the impact strength of PEEK, according to Yingshuang et al. (2019) [20]. In addition, a 2019 research by Haijun et al. investigated the impact strength of 3D printed PEEK, focusing on the assessment of PEEK's resistance to impact pressures; this provided more information on the material's mechanical performance and identified practical possible uses [21]. Singh et al. (2019) investigated the potential of 3D printing to produce PEEK parts for a range of biomedical uses, yielding useful information for healthcare professionals and researchers [22]. The tensile modulus was found to be higher in PEEK/HA composite filaments manufactured by Zheng et al. (2021) than in pure PEEK, but the tensile strength was found to be lower [23]. There has been little investigation into the correlation between high-performance polymer process parameters, build time, and impact strength in the context of 3D printing, despite the abundance of literature on the subject. In order to evaluate production processes for efficiency, safety, and quality control, it is essential to understand and measure the optimal material impact strength. So, taking material utilization and production efficiency into account, this study intends to evaluate the impact behavior of 3D printed components and investigate the effect of process factors on impact strength, namely print orientation, infill density, and environmental conditions—chamber temperature. An overview of the FDM method using PEEK and pertinent studies on process parameter optimization are included in the article's organization. Next, we will go over the specifics of the experiment, the technique used, the extensive data analysis, the key conclusions, and finally, we will wrap up the study.

EXPERIMENTAL DETAILS

Figure 2 shows the schematic layout of FDM 3D PEEK printing, where CreatBot F160 PEEK-3D printer (manufacturer: Createbot Inc, China) is used to create the specimens. The 3D printer is equipped with a sizable build volume of (x:160mm, y:160mm, z:200mm) and incorporates a specialised heating system optimised for handling high- grade polymers efficiently.

Setting Parameters

Given the constraints of the research scope, the authors focused on the most critical printing

parameters that directly impact the impact strength of thermoplastic polymers. These parameters were carefully selected based on insights gleaned from various previous studies. For the investigation, the author chose to work with PEEK, a high-grade polymer featuring a filament diameter of 1.75 mm. Table 1 outlines the essential properties of PEEK. By systematically studying the influence of specific printing parameters on PEEK's mechanical properties, the aim was to gain valuable insights into enhancing the impact strength of 3D printed PEEK components.

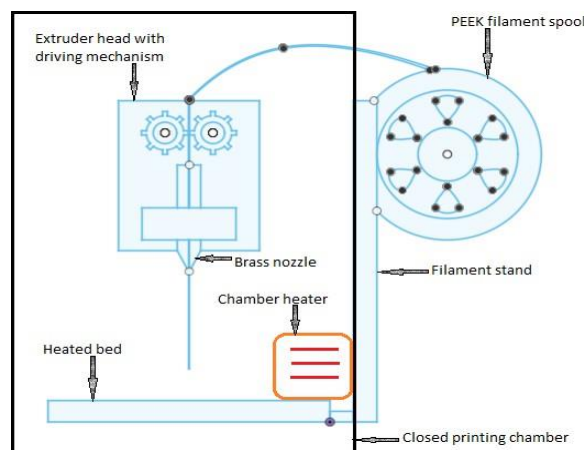


Figure 2. Schematic layout of FFF 3D PEEK printing

Sample Preparation

A nano polymer adhesive (manufacturer: Visionminer) designed for high-temperature build plate glue was initially used to address the common issue of bottom layer stick-out encountered while handling PEEK in Fused Deposition Modeling (FDM-AM). To further enhance print quality and reduce defects caused by moisture in the PEEK filament, the filament was dried in a filament drier (manufacturer: Creality Inc.) for 2 hours at 60°C, following the recommendations from Cicala et al. (2017) [24]. For the experiment, SolidWorks (2022 edition) was employed to model the printed samples according to ASTM standards (refer to Figure 3). The STL file (*.stl) of the samples was then imported into Simplify3D, a licensed 3D slicing software, to configure print parameters and generate the necessary G-Code for the 3D-printer. To optimise the impact strength (IS) of

PEEK, the study considered various print parameters, such as chamber temperature (CT) and build orientation (XY: horizontal, XZ: vertical, refer to Figure 4(a) and (b)). Specimens were printed using the optimised parameters for strength [25] which included a layer thickness of 0.01 mm, nozzle temperature of 440 °C, print direction at 0°, while printed with a speed of 15 mm/sec and 0.4 mm brass nozzle [25]. The bed temperature was maintained at 120 °C for printing all specimens used in this research. The impact of print density, along with other selected print parameters on the impact strength of PEEK was investigated through the fabrication of the specimens (refer to Figure 4(c)). Moreover, balancing the strength, weight, and print time, the optimal infill density was determined through iterative testing and adjustments.

Table 1. Properties of PEEK [3]

Properties	Values	Properties	Values
Specific gravity	1.3 gm/cc	Flexural strength	125-128 MPa
Glass transition temperature	143 °C	Young's modulus	3.7 GPa
Melting point	340 °C	Operating temperature	250 °C

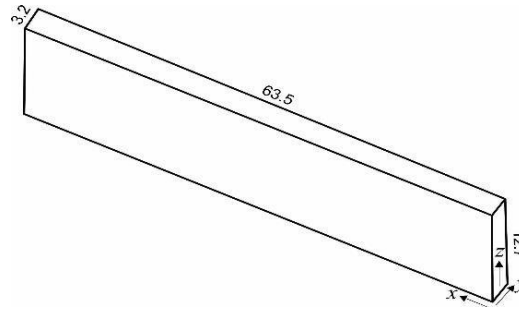


Figure 3. CAD model of the specimen (all dimensions are in mm)

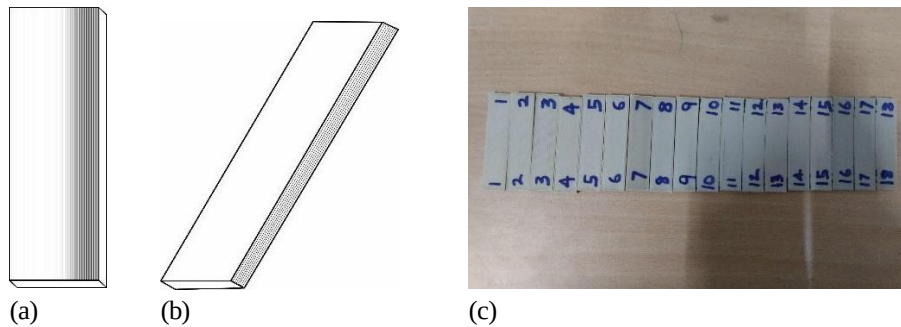


Figure 4. Representation of: (a) XY-build orientation, (b) XZ-build orientation and (c) Printed impact test specimens

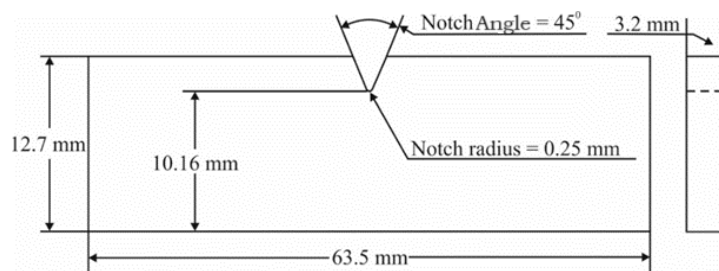


Figure 5. Specification of notched ASTM D256 specimen

Sample Testing

Subsequently, the printed specimens were notched in accordance with the ASTM standard (see Figure 5) and prepared for the mechanical Izod impact test (see Figure 6). The Izod impact test was conducted using an Izod impact tester (manufacturer: Deepak Polyplast, Unique ID No.: KL/ICT/01, Sl. No.: 2K103074) equipped with a digital impact indicator and a hammer mass of 4260 gms (see Figure 7).

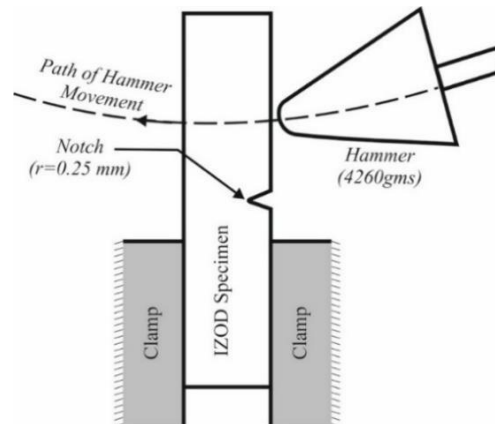


Figure 6. Impact test of ASTM D256 specimen



Figure 7. Izod impact test equipment

METHODOLOGY

In order to maximize or reduce a desired response variable or performance parameter, 3D printing process optimization entails methodically choosing the right values for process parameters. Finding the optimal combination of parameters to produce the target result in the 3D printed product is, to put it more simply, what it's all about. Print orientation (PO), print density (PDN), and chamber temperature (CT) [in 0C] are the process factors that are taken into account in this PEEK material based printing. As indicated in the introduction, the process parameters for extrusion-based 3D printing have been extensively covered in previous publications. Currently, this article takes into account three performance characteristics, or response variables: print time

(PT) [in minutes], impact strength (IS) [in kJ/m²], and material utilized (MU) [in gms]. Production time is an important metric for evaluating manufacturing efficiency and product quality in the manufacturing industry. A key metric for evaluating the quality of a 3D printed object is its impact strength, however. One of the major response variables is the material usage indicator, which is connected to printing cost, along with these response parameters. In order to determine the effect of each process parameter on the dependent variable, this study first employs the analysis of variance (ANOVA) technique. The next step was to determine the relationship between the process parameters and the response variables by using correlation analysis. An appropriate explanation of their link may be found in the ANOVA and correlation analyses.



After that, a regression equation is derived to estimate the impact strength of printed objects for PEEK based on two modified Taguchi methods: Taguchi and Composite Desirability Taguchi (TOPSIS). The final results are compared with those of the mix Taguchi method.

Data Generation

The initial data generation has been done through

2. Also the parameters, which are kept constant during the printing process, are provided in the same Table 2.

conducting lab experiments. In this article the data for the analysis has been generated based on the orthogonal array L18, which is a schema for performing experiments [26]. Here the L18 orthogonal array is selected as the number of process parameters are three with a mixed number of levels. The detailed level information for various input parameters including output parameters used in this article has been provided in Table

Table 2. Details of printing parameters

Input Parameter(s)				Output Parameter(s)
Level (s)	Level 1	Level 2	Level 3	
Print Orientation (PO)	XY	XZ	-	Impact Strength (IS)
Print Density (PDN)	High (100%)	Medium (90%)	Low (80%)	Print Time (PT)
Chamber Temperature (CT)	70° C	60° C	50° C	Material Utilization (MU)
Other setting print parameters, which are kept constant				
Nozzle temperature	440 °C	Print speed	15 mm/sec	
Layer height	0.01 mm	Print direction	0°	

The orthogonal array with the response values is provided in Table 3. In this table aforementioned three process parameters levels along with the response values, which are obtained through lab testing are provided. This data set is further used for all kind of data analysis process for performing correlation analysis, analysis of variance, process optimization and regression analysis.

Table 3. L18 OA data for analysis

TN	PO	PDN (%)	CT (°C)	PT (mins)	IS (kJ/m ²)	MU (gms)
1	XY	80	50	84	74.03	3.08
2	XY	80	60	84	75.51	3.08
3	XY	80	70	84	75.88	3.08
4	XY	90	50	89	117.59	3.27
5	XY	90	60	89	91.33	3.27
6	XY	90	70	89	100.51	3.27
7	XY	100	50	98	112.48	3.64
8	XY	100	60	98	81.61	3.64
9	XY	100	70	98	96.53	3.64
10	XZ	80	50	84	65.25	3.08
11	XZ	80	60	84	71.79	3.08
12	XZ	80	70	84	55.98	3.08

Table 3. (cont.)

TN	PO	PDN (%)	CT (°C)	PT (mins)	IS (kJ/m ²)	MU (gms)
13	XZ	90	50	89	86.98	3.27
14	XZ	90	60	89	72.63	3.27
15	XZ	90	70	89	99.78	3.27
16	XZ	100	50	98	230.4	3.64
17	XZ	100	60	98	224.13	3.64
18	XZ	100	70	98	225.49	3.64

*TN=Treatment No.



Analysis of variance (ANOVA)

Analysis of variance is a process where the variances in response variables are analyzed to understand the contribution of each process parameter. The ANOVA has been conducted for each response variable and tabulated the summary of the analysis in Tables 4 through 6 [26]. The important statistics can be found in the table which are useful for describing the phenomenon.

Table 4. Analysis of variance for impact strength

Source	df	Adj SS	Adj MS	F Value	P Value	VIF
Regression	3	30733.4	10244.5	6.06	0.007	
PDN	1	25410.4	25410.4	15.04	0.002	1
CT	1	88.3	88.3	0.05	0.822	1
PO	1	5234.7	5234.7	3.10	0.100	1
Error	14	23648.2	1689.2			
Total	17	54381.6				

Table 5. Analysis of variance for print time

Source	df	Adj SS	Adj MS	F	p	VIF
Regression	3	588.0	196.000	171.50	0.00	
PDN	1	588.0	588.000	514.50	0.00	1
CT	1	0.0	0.000	0.00	1.00	1
PO	1	0.0	0.000	0.00	1.00	1
Error	14	16.0	1.143			
Total	17	604.0				

Table 6. Analysis of variance for material used

Source	df	Adj SS	Adj MS	F	p	VIF
Regression	3	0.9408	0.3136	135.51	0.00	
PDN	1	0.9408	0.9408	406.52	0.00	1
CT	1	0.000	0.0000	0.00	1.00	1
PO	1	0.000	0.0000	0.00	1.00	1
Error	14	0.0324	0.002314			
Total	17	0.9732				

Tables 4–6 show that PDN accounts for the largest percentage of variation across all response variables. Among the factors influencing impact strength, print orientation (PO) ranks second in terms of variation. Similarly, the (PDN) significantly affects the response variables according to the F and p values. Newton's

Correlation (3.3)

Prior to optimizing the process, a correlation study was carried out to determine the link between various kinds of factors. The statistical relationship between two variables may be discovered using the Pearson correlation. The fundamental formula for this is the product of the standard deviation and the ratio of the covariance. Based on the data that was obtained, the correlation coefficient gives important information about the behavior of the two variables in relation to each other. Eq. (1) [27] gives the formula for determining the Pearson correlation coefficient (rp). Table 7 displays the computed correlation coefficients.



Table 7. Correlation analysis summary

	PDN	CT	PT	IS	MU
PDN	1.000				
CT	0.000	1.000			
PT	0.987**	0.000	1.000		
IS	0.684**	-0.040	0.704**	1.000	
MU	0.983**	0.000	1.000**	0.705**	1.000

** indicates the 95% confidence interval

According to the data, material utilization (MU) and print time (PT) has full positive significant correlation. Similarly, impact strength (IS) and MU have high significant positive correlation (0.705**). The impact strength is high positively correlated to print time (0.704**). As per the correlation values, if only material utilization is considered in analysis then the print time will be automatically taken care off. So, accordingly further in the optimization of process only MU and IS are considered. The correlation analysis also indicates that which process parameters out of the selected three process parameter need to be given importance while optimizing the process. The correlation analysis indicates the print density have high positive correlation on the IS, MU and PT. So, for the two cases are represented with Eqs. (2) and (3) [26].

$$SNR_s = -10 \log \log \left(\frac{1}{n} \sum_{i=1}^n y^2 \right) \quad (2)$$

$$SNR_L = -10 \log \log \left(\frac{1}{n} \sum_{i=1}^n \bar{y}^2 \right) \quad (3)$$

The Taguchi method is applied to optimize individual response variables. The main effect and signal to noise effect has been observed and the effects are provided in Tables 8 through 10.

Table 8. Main effect of signal to noise ratio and mean value for impact strength

Levels	Signal to noise ratio			Mean		
	PO	PDN	CT	PO	PDN	CT
1	39.13	36.82	40.36	91.72	69.74	114.46
2	40.63	39.44	39.39	125.83	94.80	102.83
3		43.38	39.89		161.77	109.03
Delta	1.50	6.56	0.96	34.11	92.03	11.62
Rank	2	1	3	2	1	3



Table 9. Main effect of signal to noise ratio and mean value for print time

Levels	Signal to noise ratio			Mean		
	PO	PDN	CT	PO	PDN	CT
1	-39.10	-38.49	-39.10	90.33	84.00	90.33
2	-39.10	-38.99	-39.10	90.33	89.00	90.33
3		-39.82	-39.10		98.00	90.33
Delta	0.00	1.34	0.000	0.000	14.00	0.000
Rank	2.5	1	2.5	2.5	1	2.5

Table 10. Main effect of signal to noise ratio and mean value material used

Levels	Signal to noise (S/N) ratio			Mean		
	PO	PDN	CT	PO	PDN	CT
1	-10.428	-9.771	-10.428	3.330	3.080	3.330
2	-10.428	-10.291	-10.428	3.330	3.270	3.330
3		-11.222	-10.428		3.640	3.330
Delta	0.000	1.451	0.000	0.000	0.560	0.000
Rank	2.5	1	2.5	2.5	1	2.5

The data is analysed using the Taguchi DOE for the objective of smaller the better. Here for the three response parameters data analysis has been presented in Tables 6 through 8. In Table 6, 7, and 8 the main effect of signal to noise ratio (S/N) and mean can be observed where the PDN got the highest rank of 1. On the other hand, PO and CT have an equal rank of 2.5 for PT and MU. While, in case of IS, the PO has got rank 2 and CT ranked as 3.

Technique for Order Preference by TOPSIS based Taguchi

Technique for TOPSIS is a method for selecting the best alternative based on the criteria values [28]. The technique is a well-known multicriteria decision making method and this method is utilized for combining the three response variables into a single variable for applying the Taguchi based response optimization.

Step 1: Prepare the table containing the alternatives and criteria values (x_i). Fix the weight values (w_i) for the criterias. Step 2: Normalise the criteria values for particular alternatives using Eq. (4).



$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{k=1}^m x_{kj}^2}} \quad i = 1, 2, 3, \dots, n; j = 1, 2, 3 \dots m \quad (4)$$

where n is the number of alternatives and m is the number of criteria.

Step 3: Calculate the weighted normalised values (v_i) for criteria for alternatives based on the Eq. (5).

$$v_{ij} = r_{ij} \times w_{ij} \quad (5)$$

Step 4: Identify the positive ideal solution (A^+) and negative ideal solution (A^-) which are represented with Eqs. (6) and (7).

$$A^+ = \{v_1^+, v_2^+, \dots, v_m^+\} \quad (6)$$

$$A^- = \{v_1^-, v_2^-, \dots, v_m^-\} \quad (7)$$

Step 5: Calculate the distance (d_{pi}) between every alternative and positive ideal solution using Eq. (8). Similarly, calculate the distance (d_{ni}) between every alternative and negative ideal solution using Eq. (9).

$$d_{pi} = \sqrt{\sum_{j=1}^m (v_{ij} - v_j^+)^2} \quad (8)$$

$$d_{ni} = \sqrt{\sum_{j=1}^m (v_{ij} - v_j^-)^2} \quad (9)$$

Step 6: Now calculate (C^*) using Eq. (10). The range of value for $0 \leq C^* \leq 1$

$$C^* = \frac{d_{pi}}{d_{pi} + d_{ni}} \quad (10)$$

the lower value of C^* is desired as it indicates a solution nearer to the positive ideal solution. In the proposed methodology this C^* is used as the response variable for Taguchi's design for experiment based optimization. Such an approach of hybridization, where a multicriteria decision making approach is combined with design of experiment can be found in recent literature [29, 30] for combining several objectives.

The 18-treatment condition can be considered as alternatives for the process of the TOPSIS method. The three response variables can be considered as the criteria for the best alternative selection. Two different sets of weight values are considered (0.4,0.3,0.3) and (0.5,0.25,0.25) for IS, PT and MU. The main reason for assigning same weight values to PT and MU is because of the full correlation between them ($r_p = 1.00^{**}$). The TOPSIS scores C^* for these two cases are

provided in Figure 8. The intermediate calculation of weighted normalised matrix, distance from positive ideal solution (d_{pi}), distance from negative idle solution (d_{ni}) and TOPSIS score C^* for each alternative has been provided for the two cases with different criteria weights in Table 11 and Table 13 given below. The ANOVA for the two TOPSIS scores are also provided in Table 12 and Table 14. This selection of best alternative using TOPSIS has been conducted for weight values of IS, keeping the other two responses with equal weightage indicates no change in best alternative selection.



Table 11. Weighted normalized alternatives for TOPSIS case 1

Alternatives	W_{IS}	W_{PT}	W_{MU}	d_{pi}	d_{ni}	C^*
	0.4	0.3	0.3			
	nIS^*w	nPT^*w	nMU^*w			
1	0.057270408	0.065618325	0.065243	0.12096952	0.021338	0.850057801
2	0.058415352	0.065618325	0.065243	0.11982458	0.022104	0.844259063
3	0.058701588	0.065618325	0.065243	0.11953834	0.022301	0.842774403
4	0.090968894	0.069524178	0.069268	0.08745106	0.048811	0.641784616
5	0.070653874	0.069524178	0.069268	0.10773214	0.029304	0.786158688
6	0.077755622	0.069524178	0.069268	0.1006407	0.036022	0.736416829
7	0.087015743	0.076554713	0.077106	0.09264002	0.043709	0.67943292
8	0.063134377	0.076554713	0.077106	0.11623084	0.019828	0.854271166
9	0.074676651	0.076554713	0.077106	0.10481256	0.03137	0.769647921
10	0.050478105	0.065618325	0.065243	0.12776182	0.017656	0.878581716
11	0.055537519	0.065618325	0.065243	0.12270241	0.020246	0.85836659
12	0.043306733	0.065618325	0.065243	0.1349332	0.016134	0.893197063
13	0.067288667	0.069524178	0.069268	0.11109292	0.026191	0.809217711
14	0.056187352	0.069524178	0.069268	0.12218136	0.016636	0.880156954
15	0.077190886	0.069524178	0.069268	0.10120456	0.035482	0.74041181
16	0.178239928	0.076554713	0.077106	0.01613447	0.134933	0.106802937
17	0.173389389	0.076554713	0.077106	0.01684782	0.130083	0.114665222
18	0.174441499	0.076554713	0.077106	0.01657556	0.131135	0.112216665

**Note: PIS: [0.065618325,0.178239928,0.065243]; NIS: [0.076554713,0.043306733,0.077106]

W indicates the weight value for particular response variable, n indicates the normalized value.

Table 12. Analysis of variance for first case 1

Source	df	Adj SS	Adj MS	F	p	VIF
(TS1)						
Regression	3	1.03829	0.346096	6.59	0.005	
PDN	1	0.87513	0.875135	16.67	0.001	1.00
CT	1	0.00267	0.002668	0.05	0.825	1.00
PO	1	0.16048	0.160484	3.06	0.102	1.00
Error	14	0.73500	0.052500			
Total	17	1.77328				



Table 13. Weighted normalised alternatives for TOPSIS case 2

Alternatives	W_{IS}	W_{PT}	W_{MU}	d_{pi}	d_{ni}	C^*
	0.5	0.25	0.25			
	nIS*w	nPT*w	nMU*w			
1	0.071588009	0.054681938	0.054369	0.15199633	0.036056	0.808267094
2	0.073019189	0.054681938	0.054369	0.15057261	0.03677	0.803728824
3	0.073376984	0.054681938	0.054369	0.1502167	0.036955	0.802561012
4	0.113711117	0.057936815	0.057723	0.10961715	0.065359	0.626468983
5	0.088317343	0.057936815	0.057723	0.13491151	0.043484	0.756250303
6	0.097194527	0.057936815	0.057723	0.12606454	0.05076	0.71293648
7	0.108769679	0.063795594	0.064255	0.11404908	0.057559	0.664589572
8	0.078917972	0.063795594	0.064255	0.14389688	0.030696	0.824187466
9	0.093345813	0.063795594	0.064255	0.1294707	0.043192	0.749847293
10	0.063097631	0.054681938	0.054369	0.1604452	0.032798	0.83027575
11	0.069421899	0.054681938	0.054369	0.15415142	0.035058	0.814711362
12	0.054133416	0.054681938	0.054369	0.1693701	0.031549	0.842975485
13	0.084110834	0.057936815	0.057723	0.13910505	0.040261	0.775537348
14	0.070234191	0.057936815	0.057723	0.15294396	0.031329	0.829983818
15	0.096488607	0.057936815	0.057723	0.1267679	0.050162	0.716485118
16	0.22279991	0.063795594	0.064255	0.00207354	0.169636	0.012075839
17	0.216736736	0.063795594	0.064255	0.00640794	0.163609	0.037690066
18	0.218051874	0.063795594	0.064255	0.00518106	0.164916	0.030459486

**Note PIS: [0.054681938, 0.22279991, 0.054369]; NIS: [0.063795594, 0.054133416, 0.064255],
W indicates the weight value for particular response variable, n indicates the normalized value.

Table 14. Analysis of variance for case 2

Source (TS2)	df	Adj SS	Adj MS	F	p	VIF
Regression	3	0.471945	0.157315	6.69	0.005	
PDN	1	0.436419	0.436419	18.55	0.001	1.00
CT	1	0.002183	0.002183	0.09	0.765	1.00
PO	1	0.033344	0.033344	1.42	0.254	1.00
Error	14	0.329298	0.023521			
Total	17	0.801243				

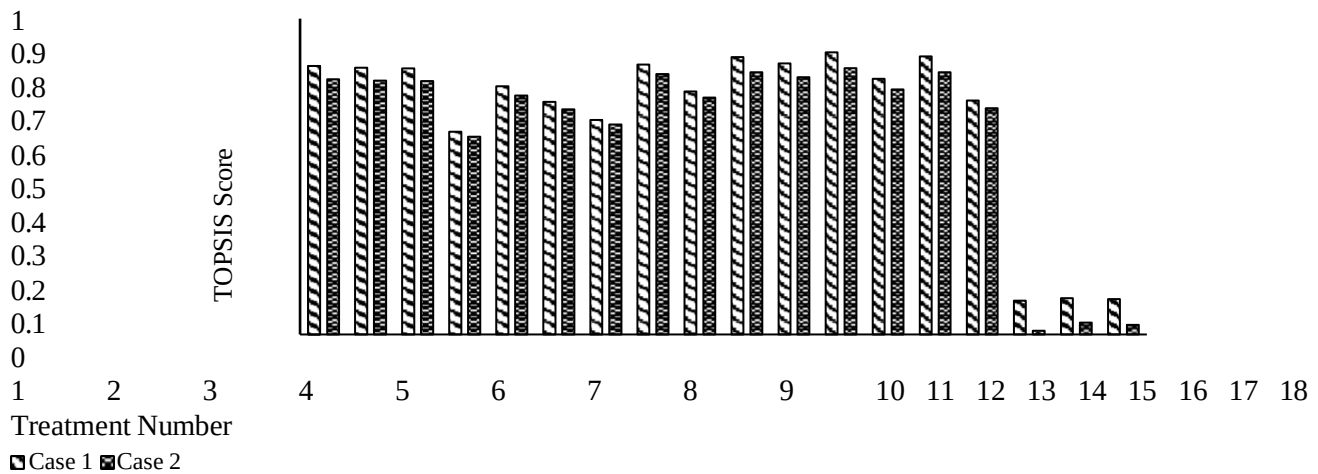


Figure 8. Weighted normalised alternatives for TOPSIS score for two cases

The application of the Taguchi based method on the TOPSIS scores for two cases indicates that the importance of PDN is highest followed by PO and CT. The main effects of signal to noise ratio and mean for both cases are provided in Table 15 and Table 16. The delta values and rank for all process parameters are provided in same tables. The score of C^* is used as the response variable for Taguchi design experiment with smaller-the-better approaches. The calculated levels for the three process parameters are PDN=100%, PO=XZ and CT=50°C. The details for the results has been provided in results discussion. So further, the same problem has been solved using composite desirability.

Table 15. Main effect of signal to noise ratios and mean for case 1

Levels	Signal to Noise ratio			Mean		
	PO	PDN	CT	PO	PDN	CT
1	2.218	1.300	5.169	0.7783	0.8612	0.6610
2	7.359	2.360	4.363	0.5993	0.7657	0.7230
3		10.706	4.835		0.4395	0.6824
Delta	5.140	9.406	0.806	0.18885	0.4217	0.0620
Rank	2	1	3	PO	PDN	CT

Table 16. Main effect of signal to noise ratios and mean for case 2 (Smaller is the better)

Levels	Signal to Noise ratio			Mean		
	PO	PDN	CT	PO	PDN	CT
1	2.132	1.047	5.602	0.7867	0.8867	0.6655
2	8.229	2.291	4.720	0.6009	0.7720	0.7284
3		12.203	5.220		0.4228	0.6875
Delta	6.098	11.155	0.883	0.1858	0.4639	0.0629
Rank	2	1	3	2	1	3

Composite Desirability Based Optimization

The traditional Taguchi analysis can provide the optimal process parameter value for a specific objective, but it has limitation in tackling multiple objectives. Now here two objectives, namely, maximum impact strength and minimum material utilization is considered as there two parameters for optimization problem. The composite



desirability, D is calculated based on the Eqs. (11) through (13) [31], whereas desirability function $d_j(Y_j)$ is used to convert the response values $Y_j(x)$, between 0 and 1. The individual desirability values are combined using Eq. (11), which gives the composite desirability, D .

$$D = (d_1(Y_1) \times d_1(Y_1) \times \dots \times d_k(Y_k))^k \quad (11)$$

where, 'k' is the number of responses. The desirability for maximization is presented in Eq. (12).

$$d_j(Y_j) = \begin{cases} 0 & \text{if } Y_j < L_j \\ \frac{Y_j - L_j}{T_j - L_j} & \text{if } L_j \leq Y_j \leq T_j \\ 1 & \text{if } Y_j > T_j \end{cases} \quad (12)$$

Desirability function for Y_j response minimization

$$d_j(Y_j) = \begin{cases} 1 & \text{if } Y_j < T_j \\ \frac{Y_j - U_j}{T_j - U_j} & \text{if } T_j \leq Y_j \leq U_j \\ 0 & \text{if } Y_j > U_j \end{cases} \quad (13)$$

where, $s = t = 1$, the desirability function increases linearity towards T_j , for $s < 1$, $t < 1$ function is convex; $s > 1$, $t > 1$ concave.

After calculating the composite desirability, the multivariate gradient decent algorithm has been deployed for optimizing the process [32]. The expression for calculation has been provided in Eq. (14). Repeat the process until it converges, where J is the cost function (here the composite desirability), θ_m is the m^{th} decision variable or here it is the process parameter, N is number of process parameters and α is learning rate.

$$\theta_m = \theta_m - \alpha \sum_{m=0}^N \frac{\partial}{\partial \theta} J(\theta_0, \theta_1, \dots, \theta_N) \quad (14)$$

The composite desirability change with individual objectives is provided in Figure 9. This indicates for satisfying the objectives the print density should be 87.68%, chamber temperature of 50°C and orientation of XZ.

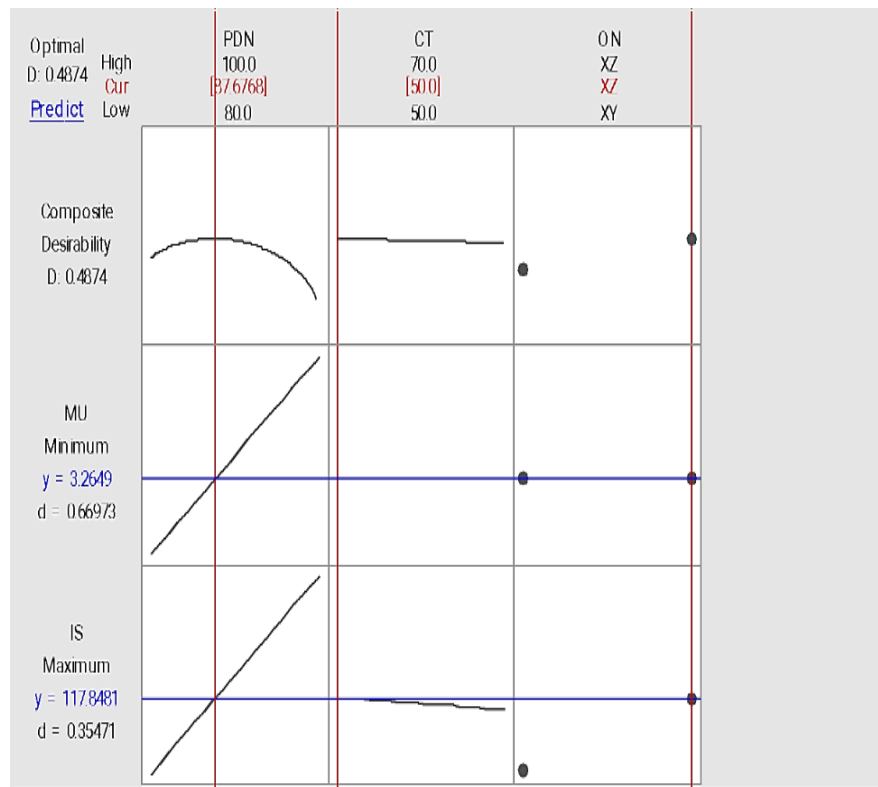


Figure 9. Desirability analysis summary

Regression Analysis

The Impact Strength estimation model is tried to derive with multiple combinations of process parameters. Regression method is deployed to establish the relationship between the impact strength and process parameters [33]. Here multiple regression models are created and then based on the Akaike Information Criterion (AIC) value [34], tries to find the best fit with minimum number fewest possible independent variable. The multiple fitted models are compared then based on minimum AIC best model is selected. The independent variable here is here impact strength and for improving the model multiple variables are created based on the concept of feature engineering. The variables are ON, PDN, CT, PDN x CT, PDN², CT². The tested models along with AIC values are provided in Table 17 and a model summary has been provided in Table 18.

Table 17. Model selection for estimating the impact strength

Model	Variable set	AIC
1	ON; PDN; CT; PDN x CT; PDN ² ; CT ²	141.58
2	ON; PDN; CT; PDN ² ; CT ²	139.60
3	ON; PDN; CT; PDN ²	137.86
4	ON; PDN; PDN ²	135.94
5	ON; PDN ²	135.01

Table 18. The summary of selected impact strength estimation model

Coefficient	P value	Adjusted R ²
-------------	---------	-------------------------



Intercept	-118.6045	0.0418	51.37%
ON: XZ	34.1067	0.0865	
PDN ²	0.0258	0.0010	

The selected predictive model has adjusted R^2 of 51.37%. It is indicating that the model parameters ON and PDN² can explain the 51.37% variability within the impact strength. The P value indicates that the PDN² have a significant impact on the Impact strength value. Thus, the regression model has been provided as Eq. (15).

$$\text{Impact Strength}_{XZ=1} = -118.6045 + 34.1067XZ + 0.0258PDN^2 \quad (15)$$

RESULTS AND DISCUSSION

The correlation coefficient values, and ANOVA indicates that the PDN has highest significance on the three response variables namely, Impact strength, Print time and Material utilization. Print density refers to the level of material filling within a 3D printed object [35]. Higher print density generally leads to increased material content and a more solid internal structure. As a result, higher PDN values can lead to improved impact strength of the printed parts. This is because a denser and more solid structure is less likely to crack or break upon impact compared to a part with lower print density, which may have voids or weaker regions [36]. However, it is important to note down that though the Print density affects the amount of material that needs to be deposited and solidified during the 3D printing process, higher PDN values often require more material to be printed, leading to longer print times. Conversely, lower print density can result in faster printing times as less material needs to be deposited. However, it's worth noting that the impact on print time may depend on other factors such as the printing technology, layer height, and complexity of the design etc. Material utilization refers to how efficiently the 3D printing process uses the input material to create the desired object. Higher print density implies more material is used, which may result in lower material utilization efficiency [36]. Conversely, lower PDN values may lead to better material utilization as less material is required to achieve the desired part geometry. Efficient material utilization is essential in reducing costs and minimizing waste in additive manufacturing [37-39]. Thus, it is important to note that the obtained relationship (refer to Eq. (15)) between PDN and the three response variables (impact strength, print time, and material utilization) may not be linear and also can vary further depending on the specific 3D printing technology and complexity of the object.

Though the Print time and Material utilization have perfect significant positive correlation and as per the observation from previous literatures the material used is directly related to print time [38, 39]. In case of three variables there is no as such any significant impact of independent variables chamber temperature

and print orientation. It is important to note that Chamber temperature can play a crucial role in certain 3D printing processes, particularly in FDM when using temperature-sensitive materials like PEEK or when attempting to control the cooling rate of the printed parts [40, 41]. However, the controlled melting and solidification of the PEEK filament occurred through the careful consideration of nozzle temperature to ensure proper melting of the filament during extrusion [10,13,16]. The extruded material then quickly solidifies and fuses with the previously deposited layer. Since the melting and solidification occur in close succession, the chamber temperature might not have a substantial impact on the bonding process. Also, in addition to that the extruder head often follows overlapping paths during the printing process, resulting in the fusion of material between adjacent passes more frequently. This overlapping pattern promotes good bonding between layers, contributing to the overall strength of the 3D printed part and hence strength. Similarly, Print orientation refers to the way a 3D model is positioned on the build platform during printing. Different orientations can result in variations in mechanical properties, printing time, and material utilization [42, 43]. However, in some cases, the effect of print orientation on the response variables might not be significant, especially when other parameters like print density and layer height are well-optimized. The layer height and extrusion settings, such as nozzle temperature and extrusion rate, have a more significant influence on material bonding in FDM [41]. Properly optimizing these parameters can lead to strong interlayer adhesion and bonding, reducing the relative impact of chamber temperature and print orientation on material bonding [44].

In case of optimization three methods have been implemented for its analysis e.g., traditional Taguchi method, TOPSIS based Taguchi method and Composite desirability enabled gradient decent method. The optimization result indicates Taguchi based method fails to produce result out of the orthogonal array. But this method again indicates which

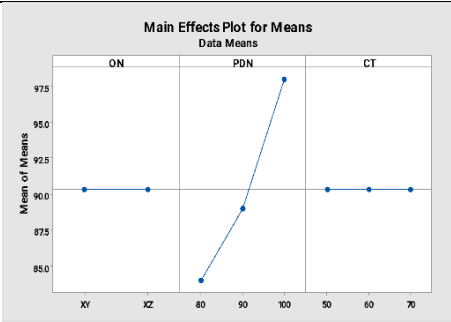
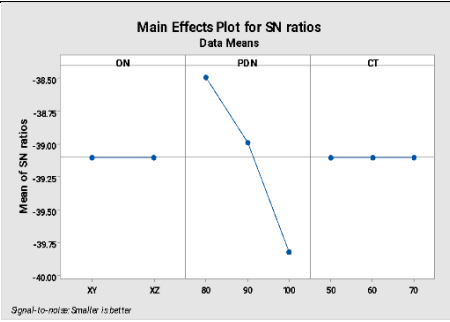
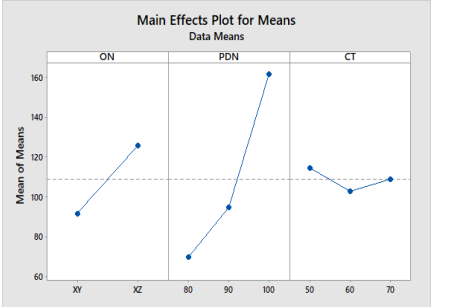
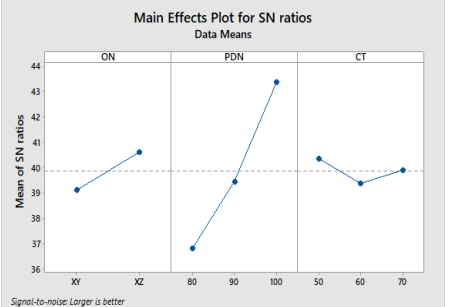
parameters are more influencing while going for optimization. It indicates print density with 100%, chamber temperature of 50°C and print orientation of XZ produces the highest impact strength but it requires higher print time of 98 min. Similar result also found in case of Taguchi based optimization where the target is maximization of impact strength. As the problem is a multi-objective problem, in that context the composite desirability produces moderate results. It selects the print density as 87.70%, chamber temperature of 50°C and print orientation of XZ. The solution indicates an impact strength value of 86.5

kJ/m², print time of 89 min and material utilization of 3.26 gm. The results from different methods are provided in Table 19. The reader can also refer to Table 20 for the main effect plot and signal to noise(S/N) ratio plot. Finally, the regression model proposed in Table 18 can be represented using Eq. (15), which can be used for estimating the impact strength of a 3D printed object printed with PEEK. The proposed predictive model is nonlinear or quadratic in nature and such model is very rare in the published domain.

Table 19. Objective wise selected process parameter value for optimal performance of the process

Method	Objective	PO	PDN (%)	CT (°C)	IS (kJ/m ²)	PT (min)	MU (gm)
Taguchi	Min PT	-	80	-	-	-	-
Taguchi	Max IS	XZ	100	50	230.4	98	3.64
Taguchi	Min MU	-	80	-	-	-	-
TOPSIS Taguchi	All Three	XZ	100	50	230.4	98	3.64
Composite Desirability with gradient decent method	All Three	XZ	87.70	50	86.5	89	3.26

Table 20. Main plot and S/N plot

Method	Objective	Main Effects Plot for Means	Main Effects Plot for SN ratios
Taguchi	Min PT		
Taguchi	Max IS		



Taguchi Min MU

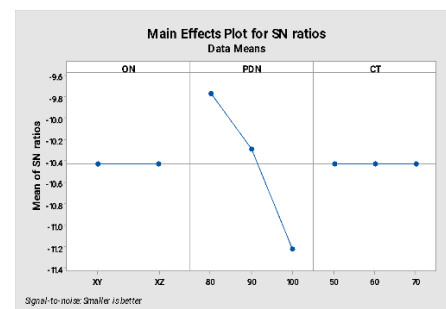


Table 20. (cont.)

Method	Objective	Main Effects Plot for Means	Main Effects Plot for SN ratios
TOPSIS Taguchi	All Three		

CONCLUSIONS

The research found that the impact strength of 3D printed objects was improved with increasing print or infill density. The downside is that this speeds up the printing process and uses more materials, which in turn raises production costs and times. Considering material utilization in process optimization brought another level to the challenge, since PEEK is a pricey printing medium. As with the other two response variables in the same procedure, printing time is also taken into account. Final considerations for process optimization include maximizing impact strength while minimizing material use and printing time. In order to optimize a process, it is necessary to first understand the relationship between its parameters and the response variables. To do this, many methodologies are used. Results from the analysis of variance and correlation show that print density significantly affects all three response variables. Full positive significant correlation between print time and material use implies a proportional connection. Conversely, there is a positive and statistically significant relationship between impact strength, print time, and material consumption; this means that as impact strength increases, printing time and material usage likewise rise. Taguchi, TOPSIS Taguchi, and gradient decent based on composite desirability are the three approaches that are used for process optimization. Although the Taguchi approach does not succeed in determining the values of the

process parameters necessary to minimize print time and material use, it does manage to choose a maximum print density of 100%, an XZ print orientation, and a chamber temperature of 500C. The TOPSIS-based Taguchi approach is used to pick the same values for the process parameters. With 98 minutes of printing time and 3.64 gram of material used, the impact strength achieved is 230.4 kJ/m². The print density is set to 87.70%, the print orientation is XZ, and the chamber temperature is 500C using the suggested desirability combined with gradient descent approach. A print time of 89 minutes and an impact strength of 86.5 kJ/m² are the results of this parameter configuration, which is comparable to treatment no. 13 from L18 OA (see Table 3), while using 3.26 gram of material. The printed product has the same level of reduced impact strength as the original, but it takes 9.18% less time to print and 11.66% less material. For the composite desirability linked gradient descent technique to work as intended, it is possible to specify a minimum and maximum value range for the impact strength, as well as an acceptable range for the other response variables. When it comes down to it, we have a regression equation that can be used to estimate the impact strength value for printed materials in the XZ plane.

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REFERENCES

"Fused deposition modeling: A review" by S. Vyavahare, S. Teraiya, D. Panghal, and S. Kumar was published in the Rapid Prototyping Journal in 2020 (vol. 26, no. 1, pp.176-201).
 [2] "A comprehensive review on fused deposition modeling of polylactic acid" (Progress in Additive Manufacturing, vol. 8, pp. 775-799, 2023), by L. Sandanamsamy, W. S. W. Harun, I. Ishak, F. R. M. Romlay, K. Kadirgama, D. Ramasamy, S. R. A. Idris, and F. Tsumori.
 [3] "3D printing of polyether-ether-ketone for biomedical applications" (European Polymer Journal, vol. 114, pp. 234-248, 2019), by S. Sunpreet, P. Chander, and R. Seeram. In their 2020 article "Current understanding and challenges in high temperature additive manufacturing of engineering thermoplastic polymers," D. Arit et al. surveyed the state of knowledge and discussed the obstacles to overcome in this field. The authors were published in Additive Manufacturing, volume 34, page 101218.
 "Mechanical impact behavior of polyether-ether-ketone (PEEK)" was published in Composite Structures in 2015 and was co-authored by D. Garcia-Gonzalez, A. Rusinek, T. Jankowiak, and A. Arias.

The article "Fused deposition modeling: Process, materials, parameters, properties, and applications" was published in the International Journal of Advanced Manufacturing Technology in 2022 and was written by K. Rajan, M. Samykano, K. Kadirgama, W. S. W. Harun, and M. M. Rahman.

The following study was published in 2022 in the International Journal of Advanced Manufacturing Technology: "Investigation of the effect of raster angle, build orientation, and infill

density on the elastic response of 3D printed parts using finite element microstructural modeling and homogenization techniques." The authors are H. Gonabadi, Y. Chen, A. Yadav, and S.

Bull. Journal of Material Engineering and Performance, vol. 32, pp. 1089-1102, 2023, "Investigating the effect of processing parameters on mechanical behavior of 3D fused deposition modeling printed polylactic acid," A. Murali, M. A. Vakkattil and R. Parameswaran. This sentence is paraphrased from an article published in 2021 in the journal Reactive and Functional Polymers, which is titled "High performance polymers for oil and gas applications" and was written by A. C. Christopher, Í. G. da Silva, K. D. Pangilinan, Q. Chen, E. B. Caldon, and R. C. Advincula. The article "Wear of PEEK composites related to their mechanical performances" was published in 2004 in Tribology International and was written by Z. Zhang, C. Breidt, L. Chang, and K. Friedrich.

[11] "Manufacture and thermal deformation analysis of semicrystalline polymer polyether ether ketone by 3D printing," published in Materials Research Innovations, volume 18, issue 5, pages 12-16, 2014, by W. Z. Wu, P. Geng, J. Zhao, Y. Zhang, D. W. Rosen, and B. H. Zhang.

Article cited as "Influence of thermal processing conditions in 3D printing on the crystallinity and mechanical properties of PEEK material" was published in 2017 in the Journal of Materials Processing Technology and authored by C. Yang, X. Tian, D. Li, Y. Cao, F. Zhao, and C. Shi.

[13] In a 2017 article published in Polymer Testing, S. Berretta, R. Davies, Y.T. Shyng, Y. Wang, and O. Ghita investigated CNT PEEK composites using fused deposition modeling of high temperature polymers (vol. 63, pp. 251-262).

The authors of the 2018 article "Additive layer manufacturing of poly (ether ether ketone) via FDM" (M. Rinaldi, T. Ghidini, F. Cecchini, A. Brandao and F. Nanni) published in Composites Part B, were cited as follows: [14].

[15] "Mechanical properties optimization of



poly-ether-ether-ketone via fused deposition modeling," *Materials*, vol. 11, no. 2, pp. 216, 2018, X. Deng, Z. Zeng, B. Peng, S. Yan, and W. Ke.

The performance of biocompatible PEEK produced by fused deposition additive manufacturing was examined in a 2018 study by M. F. Arif, S. Kumar, K. M. Varadarajan, and W. J. Cantwell. The study was published in *Materials & Design*, volume 146, pages 249-259.

[17] "Determination of Polyetheretherketone (PEEK) mechanical properties as a denture material," *The Saudi Dental Journal*, vol. 31, no. 3, pp. 382-391, 2019, S. A. Muhsin, P. V. Hatton, A. Johnson, N. Sereno, and D. J. Wood. In their 2019 study published in the *Journal of Materials Processing Technology*, P. Wang, B. Zou, H. Xiao, S. Ding, and C. Huang examined the impact of printing settings on mechanical characteristics, surface quality, and microstructure of PEEK. The findings were published in volume 271, pages 62–74. The microstructure and mechanism of CF/PEEK's flexural characteristics and fracture behavior in an orthogonal construction orientation when reinforced by FDM was the subject of a 2019 study by Q. Li, W. Zhao, Y. Li, W. Yang, and G. Wang in the journal *Polymers*. This is a reference to an article published in 2019 in *High Performance Polymers* titled "Preparation of PEEK/MWCNTs composites with excellent mechanical and tribological properties" written by S. Yingshuang, W. Xian, L. Yifan, J. Zilong, W. Zhaoyang, J. Zhenhua, and Z. Haibo.

In the 2019 30th Annual International Solid Freeform Fabrication Symposium—An Additive Manufacturing Conference, held in Austin, Texas, USA, G. Haijun, X. Xiaodong, and N. Jan presented their research on the "impact strength of 3D printed polyether-ether-ketone (PEEK)" on pages 12–14.

[22] "3D printing of polyether-ether-ketone for biomedical applications," published in the *European Polymer Journal* in 2019, by S. Singh, C. Prakash, and S. Ramakrishna.

[23] This article was published in the *Journal of the Mechanical Behavior of Biomedical Materials* in 2021 and is titled "Effects of printing path and material components on mechanical properties of 3D-

printed polyether-ether-ketone/hydroxyapatite composites." The authors are J. Zheng, J. Kang, C. Sun, C. Yang, L. Wang, and D. Li. Engineering thermoplastics for additive manufacturing: A critical perspective with experimental evidence to support functional applications, by G. Cicala, A. Latteri, B. Del Curto, A. L. Russo, G. Recca, and S. Farè, published in 2017 in the *Journal of Applied Biomaterials & Functional Materials*, volume 15, pages 10–18. [25] "Parametric analysis of 3D printing (FDM) process parameters on mechanical behaviour of PEEK—A high-grade polymer" (NIT-Puducherry, India, February 2-4, 2023), presented by C. Padhy, S. Suryakumar, D. Bhattacharjee, and R. Reddy at the International Interdisciplinary Conference on Energy, Nanotechnology and the Internet of Things (ENT-2023).

(26) D. C. Montgomery, *Experimental Design and Analysis*, 10th Edition, John Wiley & Sons, Inc., 2019.

[27] John Wiley & Sons, Inc., 1941. *Methods of Correlation Analysis*, Second Edition, by M. Ezekiel.

[28] "A TOPSIS based Taguchi application for multi-response optimization of polymer blended concrete" by B. Şimşek and T. Uygunoğlu. The 2016 edition of *Construction & Building Materials*, volume 117, pages 251-262.

[29] In the 2022 Proceedings of the Institution of Mechanical Engineers, Part D: *Journal of Automobile Engineering*, D. Bhattacharjee, T. Ghosh, P. Bhola, K. Martinsen, and P. Dan published an article titled "Ecodesigning and improving performance of plugin hybrid electric vehicle in rolling terrain through multi-criteria optimization of powertrain." The article can be found on pages 1019–1039.

[30] A TOPSIS-based Taguchi design was used to study the optimal combination proportions of graphene oxide powder generated using the Hummers technique in an article published in the *Arabian Journal for Science and Engineering* in 2018. The authors are H. Korucu, B. Şimşek, and A. Yartaşı. An article titled "Desirability function approach: A review and performance evaluation in adverse conditions" was published in 2011 in the journal *Chemometrics and Intelligent Laboratory Systems*. The authors are N. R. Costa, J. Lourenço, and Z. L. Pereira.

33. S. Ruder, "An overview of gradient descent optimization algorithms," *ArXiv*, vol., abs/1609.04747, 2016.

Reference: *Regression Analysis*, Second Edition, by R. J. Freund, W. J. Wilson, and P. Sa., Academic Press, 2006.



"New AIC corrected variants for multivariate linear regression model selection," published in 2011 by IEEE Transactions on Aerospace and Electronic Systems, volume 47, issue 2, pages 1154-1165, is referenced as [34]. The "Glossary of 3D Printing Terms" maintained by NWA3D (35). Link: <https://www.nwa3d.com/education/glossary-of-3d-printing-terms/>, last updated: August 20, 2023. "Effect of infill density and pattern on the specific load capacity of FDM 3D-printed PLA multi-layer sandwich," published in the Journal of Polymer Engineering in 2022, was written by J. Dobos, M. M. Hanon, and I. Oldal. P. W. Simpson and I. J. Petrick [37] Researchers in the field of technology management published an article titled "3D printing disrupts manufacturing: how economies of one create new rules of competition" in 2013 in volume 56, issue 6, pages 12-16. In their 2014 article "Making sense of 3-D printing: Creating a map of additive manufacturing products and services," B. P. Conner, G. P. Manogharan, A. N. Martof, L. M. Rodomsky, C. M. Rodomsky, D. C. Jordan, and J. W. Limperos discuss additive manufacturing and its related fields. The impact of infill print design on the manufacturing cost-time of 3D printed ABS components was examined in a 2015 article by B. Liseli, M. Guha, and M. Hazel published in the International Journal of Rapid Manufacturing, volume 5, issue 3/4, pages 308-319. Materials & Design, vol. 211, p. 110163, 2021, discusses "High-temperature 3D printing of polyetheretherketone products: Perspective on industrial manufacturing applications of super engineering plastics." The authors include S. J. Park, J. E. Lee, J. Park, N. K. Lee, Y. Son, and S. H. Park. In the 2020 Proceedings of the ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, R. Kumrai-Woodruff and Q. Wang discuss the use of temperature control to enhance the bonding strength between layers in fused deposition modeling. The paper is located on page V006T06A002 and was published in 2020. [42] "Investigating the effect of orientation, infill density with Triple raster pattern on the tensile

properties for 3D Printed samples," edited by S. Kannan, R. Vezhavendhan, S. Kishore, and K. V. Kanumuru, published in 2020 in the International Journal of Physics: Scientific Notes, volume 1, page 024405. The following research was published in 2020 in the journal Additive Manufacturing: "Influence of orientation on mechanical properties for high-performance fused filament fabricated ultem 9085 and electro-statically dissipative polyetherketoneketone." The authors of the study were B. W. Kaplun, R. Zhou, K. W. Jones, M. L. Dunn, and C. M. Yakacki. [44] "Optimization of fused deposition modeling process parameters: A review of current research and future prospects," Advances in Manufacturing, vol. 3, pp. 42-53, 2015, by O. A. Mohamed, S. H. Masood, and J. L. Bhowmik. It is published in that volume.