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Optimization of Fused Deposition Modelling Acrylonitrile-co-Butadiene-co-Styrene Parameters using ANOVA and Hybrid GRA–TOPSIS

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ABSTRACT

Traditional materials used in mechanical structures should be swapped out for less expensive alternatives that are both strong and simple to produce. ABS+, or poly (acrylonitrile-co-butadiene-co-styrene), is a substitute material used in 3D printing. The quick changes in model size and forms during the prototype stage and the comparably inexpensive cost of new parts are made possible by 3D printing technology. In the market for 3D printers, there are several suppliers of plastic materials. A combined MCDM technique and analysis of variance are used in the current work to assess the FDM process's parameters. During the experiment, three process factors—Layer height, extrusion temperature, and printing speed—are considered, and their associated response parameters, ultimate tensile strength, and surface roughness are established. The multiple-criteria decision-making strategy, which incorporates hybrid GRA-TOPSIS and ANOVA, is employed since there are two responses and two objectives. The ideal parameters determined by these statistical methods were an extrusion temperature of 2600c, layer height of 0.2 mm, and printing speed of 60 mm/s. This study concludes that the optimal parameters for the investigated experimental data are convergent regardless of the two techniques used.

1. Introduction

The additive manufacturing (AM) has emerged as one of the industry's top technologies, allowing products to be built Layer by Layer after being converted from digital format to standard triangle language (STL) [1,2]. The seven approaches include stereolithography, material jetting, material extrusion, binder jetting, powder bed fusion, sheet lamination, and direct energy deposition [3,4]. Many problems with additive manufacturing are related to product quality, mechanical properties, supply chain requirements, shrinkage, and underusing printing [5,6]. Using 3D printing technology, an object may be produced with minimal waste, reducing the raw materials needed. According to a research report [7], the application of 3D printing has increased in various fields in recent decades. Complex shapes and objects are formed easily in 3D, with possibilities for selecting modes of action in 3D printing, which is the fundamental reason [8,9]. In addition, 3D printing results in faster

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prototype creation timelines and lower production costs than CM [10]. 3D printing technology has less design flow, dependency, and features than CM [11]. Ramola *et al.,* [12] investigated 3D printing method selection in health care. It contains guidelines for using 3D printing to create personalized healthcare goods. As a result, Kokotsaki *et al.,* [13] identified a new manufacturing sector and a technique for choosing AM methods in the spare parts business. Researchers use the Taguchi method to optimize systems in a variety of applications, such as FSW operations, UWFSW and the TIG process [14,15]. Sabry *et al.,* [16,17] promoted the Taguchi process optimization methodology, a straightforward, efficient, and systematic method of enhancing procedures with favorable quality, performance, and cost [18]. In 1982, Deng suggested using the Grey-based Taguchi approach to handle multiple objective optimizations with imperfect, insufficient, and uncertain data. The welding process's error contributions in multi-objective optimization were 0.91 percent [15], 1.9 percent in the EDM process [19] and 2 % in the FDM process [20-23].

Xu and Wong investigated the Selection of a model 3D printing procedure. Process variables such as build time, build cost, surface roughness, and benchmark components were compared [24]. Masood and Soo solved 3D printing education process options using a rule-based expectation system [25]. Previous researchers have also employed the TOPSIS method to choose 3D printing techniques. The cost of the elongation prototype, the construction material, and the build time were all considered [26].

In the quantitative comparison approach, Kim and Oh [27] documented reduced material wastage in 3D printing compared to accuracy, material characteristics, speed, material cost, and roughness. Groth *et al.,* and Ramalingam, well-known for their research into orthodontist applications, have issued a paper on the capacities of 3D printing to increase accuracy and reduce material waste [28-30].

The essential processes of MCDA involve choosing the optimal alternative based on the decision-criteria maker and available options [31-35]. ABS may be used in additive printing to create a prosthetic foot prototype that is both inexpensive and pleasant. Therefore, more BKA patients will be able to gain from affordable prostheses, which will ultimately enable them to live better lives [36]. Studying the rheology of composite filament before printing or manufacturing processes is important. The proper extrusion temperature, viscosity, and shear rate for various fiber fractions may be determined through rheological study. Therefore, the latest research on the rheological characteristics of fiber reinforced thermoplastic composite for FDM has been reviewed [37].

2. Material

The used 3D printer is a fused deposition modeling (FDM) printer, and printer specification is tabulated in Table 1.

Table 1
3D printer machine specification

Specification	Description
Nozzle Temperature	220 - 270 ^{0}C
Layer Resolution	20 – 180 Micron
Build Volume	180 x 180 x 280 mm
Print Speed	30 - 150 mm/s
Nozzle diameter	0.4 mm

In this investigation, the variable input factors were extrusion temperature, layer height, and printing speed. The three experimental input variables are shown in Table 2, together with their current level values. The test specimens used in this experiment, as shown in Figure 1, were built using SOLIDWORKS CAD modeling software. To study the mechanical properties of FDM-3D printed specimens, each sample was tested at room temperature during a quasi-static tensile test with a 1 mm/min loading rate. Three samples were printed for each experiment and examined. The test machine was STM-250 with a 500 kg load cell capacity. Elongation was also measured using an extensometer with a gauge length of 50 mm. Data on energy consumption and processing time are collected during the production process. The tensile strength test is performed after the product has been manufactured.

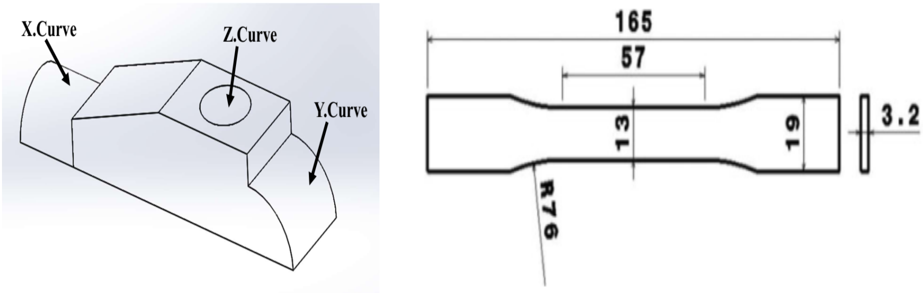

Fig. 1. (a) The geometry of the SR test content (b) TS of specimen ASTM D638

Figure 2 shows ASTM D638 specimens before and after the test.

Fig. 2. Specimen ASTM D638

Surface roughness was assessed with the Form Talysurf® i-Series device, as shown in Figure 3, with an 8 mm sampling length and a 0.75 mm/s measurement speed. This method was used to measure cylindrical samples like the ones.

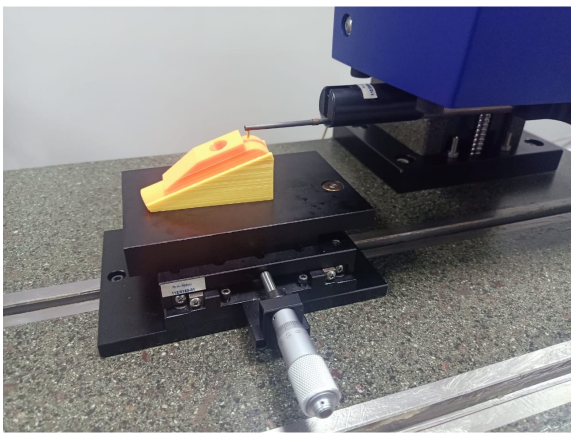

Fig. 3. Surface roughness measurement setup for printed samples

3. Research Methodology

This study paper's goal was to use the multi-criteria decision-making (MCDM) technique to make it possible to choose a particular industry's best FDM process parameters. The TOPSIS-GRA-TOPSIS and GRA MCDA approaches are used to identify the best and most appropriate option utilizing the three criteria in this study and the two suggestions made by the professionals in the field. The primary goal is to choose an optimal and acceptable FDM. Furthermore, this study aimed to identify common and crucial standards from industry professionals who supported FDMs by examining the works of previous literary scholars.

3.1 Design of Experiments

Layer height (L), extrusion temperatures (T), and printing speed (N) were discovered to be independent process variables influencing ultimate tensile strength (UTS) and surface roughness (SR) based on preliminary testing and earlier investigations (S). Table 2 shows the parameters of the FDM process. Trial runs were undertaken by altering one parameter at a time to determine the maximum and lower limits of process parameters for FDM.

$$X_i = 2X - \frac{X_{max}+X_{min}}{X_{max}-X_{min}} \tag{1}$$

Where X_i, X, X_{max} and X_{min} Are the necessary coded value, the variable value, the lower limit of the variable, and the higher limit accordingly DOE. Table 2 provides the process parameters' ranges, units, and notations.

Table 2
Levels of process parameters in FDM

Process Parameters	Unit	Symbol	Levels		
			-1	0	1
Printing speed	mm/s	N	40	60	80
Temperature	°C	T	220	240	260
Layer height	mm	L	0.1	0.15	0.2

The layer height, printing speed, and Temperature affect the FDM's ultimate tensile strength and Surface roughness. As a result, it may be written as Eq. (2).

$$Y = f(N, L, T) \tag{2}$$

Where Y is the response; N is the Printing speed ; L is the Layer height, and T is the Temperature. The chosen polynomial might be represented as Eq. (3) for the three factors.

$$\beta_0 + \beta_1 N + \beta_2 T + \beta_3 L + \beta_{11} N^2 + \beta_{22} T^2 + \beta_{33} L^2 + \beta_{12} NL + \beta_{13} NT + \beta_{23} TL \tag{3}$$

Where β_0 is the free term of the regression equation; the coefficients β_1, β_2 and β_3 are linear terms; the coefficients β_{11}, β_{22} and β_{33} are quadratic terms;, the coefficients, β_{12}, β_{13} and β_{23} are interaction terms. The following equations are used in regression analysis to determine the polynomial coefficient values:

$$\beta_0 = 0.1663 \sum(Y) - 0.0568 \sum\sum(X_{ii}Y) \tag{4}$$

$$\beta_j = 0.0732\ (X_i Y) \tag{5}$$

$$\beta_j = 0.0625 \sum(X_{ii}Y) + 0.00689 \sum\sum(X_{ii}Y) - 0.0568 \sum(Y) \tag{6}$$

$$\beta_{ij} = 0.1250 \sum(X_{ij}Y) \tag{7}$$

Where i; j = 1, 2, 3 and i < j

3.2 MCDM Approach: Grey–TOPSIS Study

Combining different multi-criteria optimization approaches simplifies data processing and saves time, allowing decision-makers to choose the proper criteria more quickly.

The TOPSIS is examined for optimal parametric combinations, and the decision-making model is built to identify the FDM process parameter and the performance criterion. The TOPSIS and Analytic Hierarchy Process (TOPSIS–GRA) hybrid MCDM technique simplifies calculations and reduces processing effort compared to other standard optimization approaches. As a result, this optimization method can be used to resolve conflicts in machining settings. This study utilized the hybrid technique (Entropy-TOPSIS-GRA) to calculate FDM process parameters. Figure 4 depicts the computational procedure. The TOPSIS approach is designed to handle problems requiring simultaneous optimization of a single portion or feature. It divides the output reactions into two categories: benefit and cost.

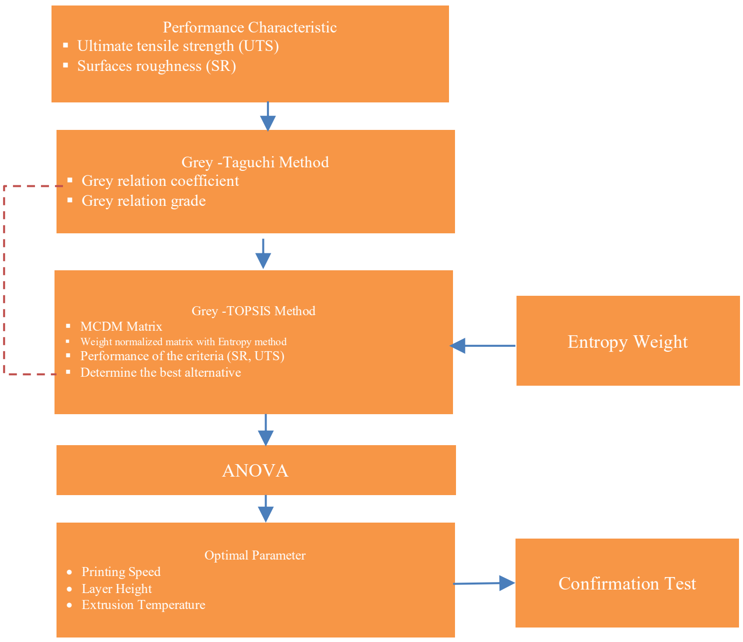

Fig. 4. Flowchart of the optimization and evaluation process

Consequently, the optimal solution is achieved by maximizing the beneficial feature and minimizing the cost attribute. TOPSIS calculates the positive and negative best alternatives, and benchmarks for determining the optimum solution. The surface roughness and UTS were regarded as positive features in this circumstance, with the highest values preferred.

4. Results and Discussions

4.1 Analysis of Variance (ANOVA)

The Design of experiments was used to carry out the entire factorial analysis. Figure 5 demonstrates the main effect graphs and interaction graphs of parameters to the tensile strength test. The magnitude of tensile strength changed significantly from one level to the next for each parameter. Based on the probability value (p-value) for the response-tensile strength-Table 3illustrates the importance of the main effects and interactions

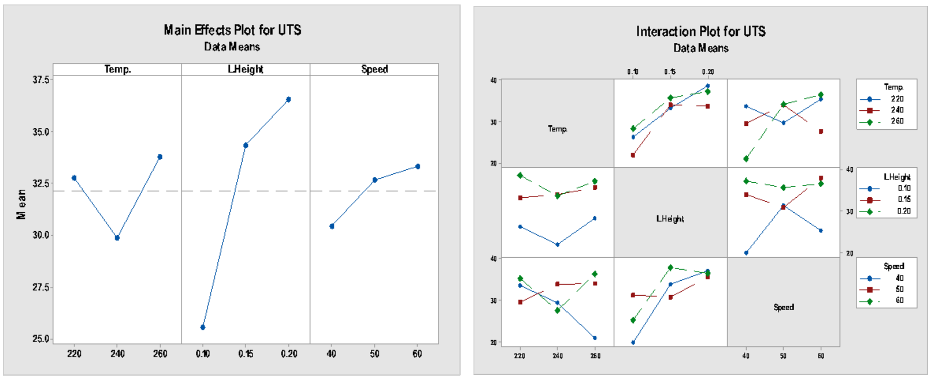

Fig. 5. For Tensile strength (a) Main effect graphs (b) Interaction effect plots

. The findings demonstrate that each of the three parameters is significant, with p-values with a 95% confidence interval less than 0.05.

Table 3
Tensile strength main effect and interaction effect statistics

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	736.42	9	81.82	3.14	0.0202	Significant

Statistical examination of three parameters and three levels revealed that, since all primary parameter influences and their interactions have p-values more than 0.05 in the 95% confidence interval, they are not all statistically significant for surface roughness. The small variation in surface roughness for each characteristic from one level to the next is what causes the insignificance. Similar results were obtained from the interaction plots (Figures 6, 7 and 8), (Table 4), where the interactions were shown to be minimal due to a minor change in the roughness of the surface. In a 95% confidence interval, the p-values for all interactions, such as layer height-extrusion temperature, Layer height-printing speed, and extrusion temperature-printing speed, were greater than 0.05.

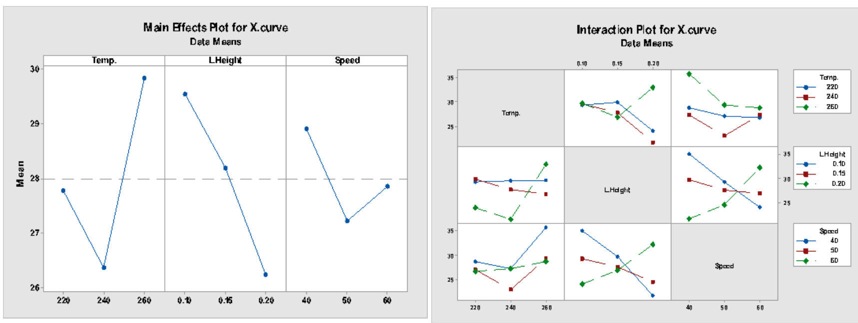

Fig. 6. For X.axis surfaces roughness (a) Main effect plots (b) Interaction effect plots

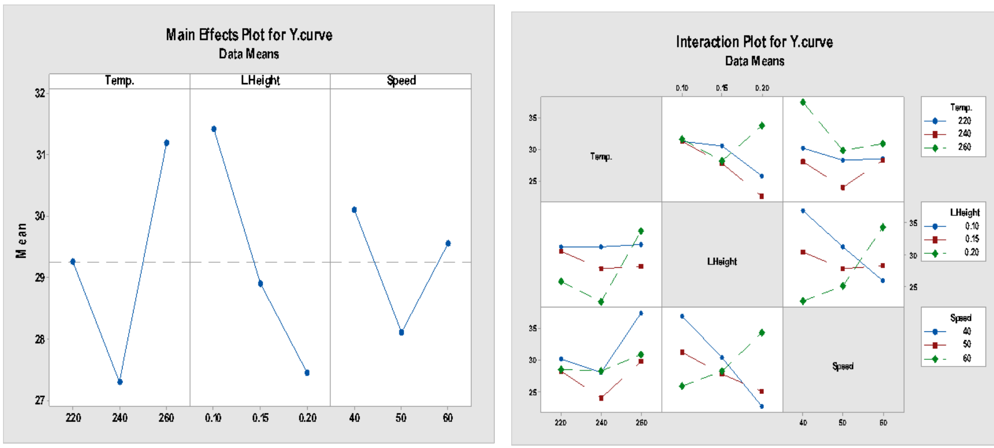

Fig. 7. For Y.axis surfaces roughness (a) Main effect plots (b) Interaction effect plots

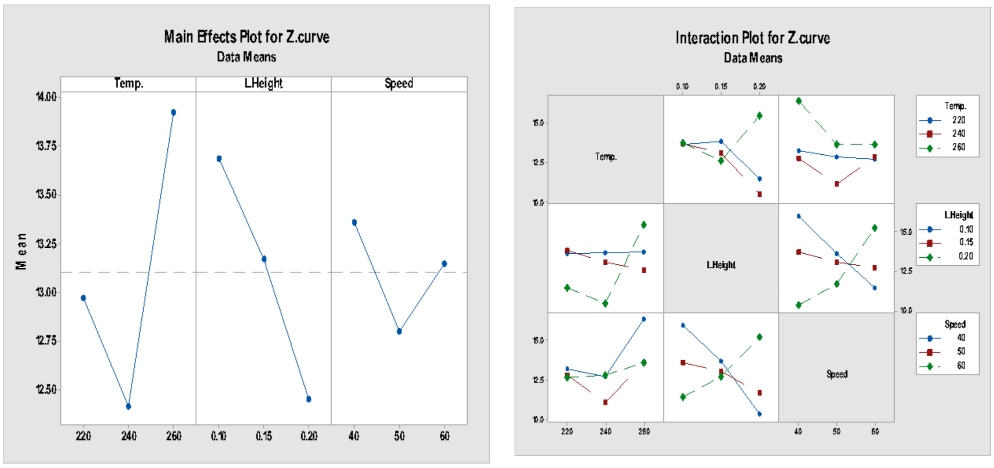

Fig. 8. For Z.axis surfaces roughness (a) Main effect plots (b) Interaction effect plots

Additionally, F-values were small, illustrating the negligibility of the interaction effect of variables on SR. This demonstrated that the FDM process parameters do not affect the surface roughness. However, to improve the parameters, tensile strength, and surface roughness are explored in this study.

Table 4
Statistics of the main effect and interaction effect on surfaces roughness

Response a: SR X-axis						
Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	834.59	9	92.73	2.78	0.0331	significant
Response b: SR Y-axis						
Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	842.30	9	93.59	2.57	0.0447	significant
Response c: SR Z-axis						
Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	149.05	9	16.56	2.62	0.0415	significant

Figure 9 depicts the response optimizer's optimal parameters (layer height, extrusion temperature, and printing speed) and the related response values (tensile strength and surface roughness). The response optimizer can decide which parameter combination is ideal for a particular answer or a collection of responses. In this case, an optimization plot was produced after optimizing a number of responses for the model input variables. Extrusion temperature, Layer height, and printing speed were optimized to 260 ^{0}C, 0.2 mm, and 60 mm/s.

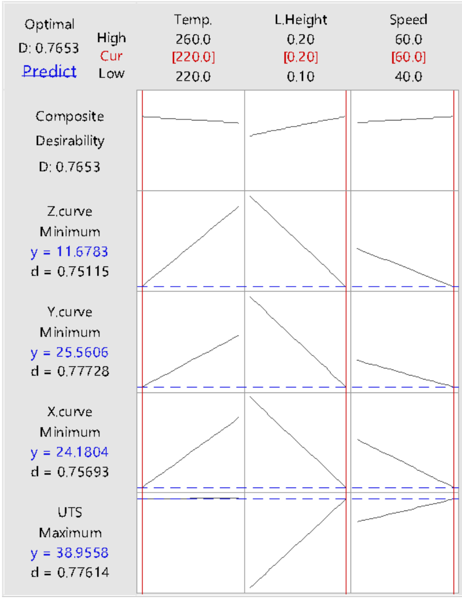

Fig. 9. Utilizing the response optimizer in ANOVA, optimize the variables and responses

4.2 Hybrid GRA- TOPSIS

One of the statistical techniques used in this study to optimize the process parameters is hybrid Grey-TOPSIS. The grey relational analysis follows the same procedure as ANOVA: layer height, extrusion temperature, and printing speed as parameters, and tensile strength and surface roughness as responses. Because tensile strength must be increased and surface roughness must be minimized, the hybrid Grey-TOPSIS is appropriate for multi-objective criterion analysis. The output responses were normalized using an equation, with higher values indicating stronger tensile strength and lower values indicating better surface roughness. Tables 4 show the normalized value of the experimental result, the GRA-TOPSIS coefficient, and the grey relational grade calculated using references. The distinguishing coefficient was set at 0.5. For each parameter, tensile strength, surface roughness, normalization, division square, and grey coefficient were determined.

The GRA-TOPSIS grade was determined by averaging the coefficients obtained for tensile strength and surface roughness. The RI was used to determine the ranking. In this situation, the greatest RI was discovered to be 0.812243, so rank one was assigned. The optimal parameters, according to GRA-TOPSIS, correspond to rank 1. In this scenario, the best parameters are an extrusion temperature of 240 ^{0}C, layer height of 0.2 mm, and printing speed of 60 mm/s. Tensile strength was 45 MPa for these values, and surface roughness was (Z-axis 8.597, Y-axis 20.562, X-axis 16.8).

42 MPa came close to the greatest tensile strength (45 MPa) and surface roughness among the experimental experiments (Z-axis 8.76, Y-axis 19.97, X-axis 18.003). MPY had the smoothest surfaces. The least RI received a ranking of 27. (0.390044). The parameters were 220^{0}C, 0.1 mm, and 60 mm/s, and the tensile strength and surface roughness were 19 MPa and surface roughness, respectively (Z-axis 16.007, Y-axis 36.918, X-axis135.264). The ideal parameters reported by ANOVA and GRA-TOPSIS are the same (260 ^{0}C, 0.2 mm, and 60 mm/s). Figure 10 show the mean coefficient of RI at each level of the single parameter with a combination of the remaining two parameters. For each parameter—

extrusion temperature, layer height, and printing speed—the maximum RI was found for the relevant values (260 ^{0}C, 0.2 mm, and 60 mm/s)—the printing speed changes just slightly when the ideal parameters are used. As a result, it is determined that parameter interaction has an effect on RI rather than the main effect of each parameter.

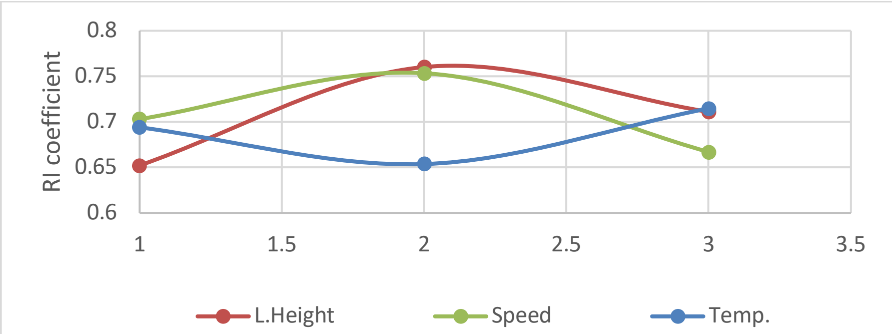

Fig. 10. The influence of process parameters on the RI coefficient

5. Conclusion

ABS was successfully manufactured using the FDM process. The process parameters were discovered to be important elements influencing tensile strength. As a result, parameter optimization is critical for achieving a stronger joint. The results of the ANOVA and hybrid GRA-TOPSIS analyses are shown below:

i. The p-values for extrusion temperature-layer height interaction, extrusion temperature-printing speed interaction, and layer height-printing speed interaction are 0.3782, 0.4081, 0.3230, 0.0030, 0.6580, 0.0050, 0.0065, 0.8014, 0.0049, 0.0041, 0.7239, and 0.0047, respectively. In a 95% confidence interval, all p values are greater than 0.05. As a result, the factors' primary effects and interactions do not affect the surface roughness (x-axis, y-axis, z-axis).
ii. A systematic to perform a hybrid GRA-TOPSIS, a systematic technique was used. The experimental runs were ranked using hybrid GRA-TOPSIS. Rank 1 was assigned to the highest RI, with 260 ^{0}C, 0.2 mm, and 60 mm/s parameters. Collecting characteristics corresponding to rank one is ideal since higher tensile strength and reduced surface roughness are crucial objective attributes.
iii. The hybrid GRA-TOPSIS and ANOVA optimum parameters are 260 ^{0}C, 0.2 mm, and 60 mm/s. No matter whether the statistical technique was performed, the outcomes of both of these studies agreed on a single set of ideal parameters.
iv. A multi-criteria decision-making approach based on hybrid GRA-TOPSIS and ANOVA is helpful for parameter optimization. To choose the appropriate parameters, both statistical techniques may be easily controlled by 3D printing from the first FDM experiments.

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