



On the application of grey Taguchi method for benchmarking the dimensional accuracy of the PLA fused filament fabrication process

Kyriaki-Evangelia Aslani¹ · Konstantinos Kitsakis¹ · John D. Kechagias¹ · Nikolaos M. Vaxevanidis² · Dimitrios E. Manolakos³

Received: 22 February 2020 / Accepted: 24 April 2020 / Published online: 4 May 2020
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Abstract

The dimensional accuracy of a simple benchmark specimen fabricated with fused filament fabrication (FFF) route is discussed in the present study. FFF is a low-cost 3D-printing process that builds complicated parts by extruding molten plastic. Experimental method was designed according to Taguchi robust design based on an orthogonal array with nine experiments (L_9 orthogonal array). The printing material was the polylactic acid (PLA). First, Grey-Taguchi method was used for the identification of the optimal printing parameter levels which result in the best dimensional accuracy for the PLA FFF parts. The printing parameters selected included number of shells, printing temperature, infill rate and printing pattern; they were selected in accordance with relevant studies already published. Then, in the second phase, nine specimens were fabricated using the same optimal printing parameter values determined in the first phase. The tolerance of these specimens was characterized according to international tolerance grades (IT grades). Data analysis showed that nozzle temperature is the dominant parameter. Additionally, the parts printed using the optimized process parameter levels possess good dimensional accuracy, which is compatible with the IT grades specification.

Keywords Additive manufacturing · FFF · Grey Taguchi optimization method · Dimensional accuracy · IT grade

1 Introduction

Unlike conventional subtractive manufacturing processes, Fused Filament Fabrication (FFF) or Fused Deposition Modelling (FDM) is an Additive Manufacturing (AM) method that creates physical objects by melted material deposition layer by layer [1–5]. As a 3D printing procedure, FFF offers several advantages such as producing complex geometries with shorter cycle time and lower cost compared to other traditional manufacturing processes [6–8].

Dimensional accuracy is crucial in any manufacturing process as it is an indicator of how close a dimension of a fabricated piece to the nominal dimension of the designed

part is [9]. Tolerance is also very important for every manufactured part, because it is essential for mechanical assemblies such as shafts and holes [10]. Although FFF method has a lot potential advantages, a limiting aspect of its industrial rejection is the obtainable accuracy of the manufactured models [11]. This is the reason why dimensional accuracy of models produced by FFF technology and the factors which affect it, are major issues of examination in the literature.

Mohamed et al. [12] reviewed the literature concerning the determination and the optimization of the FDM process parameters. Notable research work has been done for improving the mechanical properties and part

✉ John D. Kechagias, jkechag@uth.gr | ¹General Department, University of Thessaly, Gaiopolis, 41500 Larissa, Greece. ²Department of Mechanical Engineering Educators, School of Pedagogical and Technological Education (ASPETE), Athens, Greece. ³School of Mechanical Engineering, National Technical University of Athens (NTUA), Athens, Greece.



quality of FDM ABS parts using statistical design optimization. It is concluded that modelling and optimization of FDM process with other significant FDM materials such as PC, PC-ABS, PPSF, etc., has not been attempted. Moreover, characterization and optimization of FDM process parameters in terms of other properties using statistical experiment design and optimization techniques do not exist in the literature. Turner and Gold [13] reviewed studies related to surface roughness and dimensional accuracy of parts fabricated with the use of FDM process. They found that dimensional accuracy and surface roughness depend on system parameters, such as the ability of control system to manage the flow rate of the material from the print nozzle. Additionally, thermal warping and shrinkage seem to play an important role. Dey and Yodo [14] reviewed a number of FDM process parameters and their impact on dimensional accuracy, surface finish and mechanical properties. They concluded that in terms of dimensional accuracy, layer thickness is one of the most examined and dominant factors. Moreover, high dimensional accuracy is achieved with low layer thickness, number of shells and extrusion temperature values. The impact of many process parameters such as infill pattern and raster width on dimensional accuracy needs further research. Valerga et al. [15] investigated the effect of process parameters and material characteristics of FDM PLA parts on dimensional accuracy, surface quality and mechanical strength. The results showed that the extrusion temperature is the most influential parameter, while the pigmentation of the material and the environmental humidity where it has been stored are also important. Moza et al. [16] studied the dimensional accuracy of FFF parts using two printing materials, PLA and ABS. The experimental results indicated that the dimensional accuracy in XY plane is mainly affected by the printing material (39.9%), followed by infill rate (23.9%), number of shells (22.5%) and layer thickness (13.7%). Additionally, PLA was found to have better dimensional accuracy than ABS. Zero values of deposition angle were used. Sudin et al. [9] investigated the dimensional accuracy of parts produced using the FDM process. They found that the machine's tolerance has a significant effect on the dimensional accuracy of the FDM parts. Moreover, the FDM machine was found to be less accurate in producing circular parts such as cylinder, sphere and hole, as the majority of them are out of the machine's tolerance. Minetola and Galati [10] investigated the dimensional accuracy and the form errors of geometrical features of four different low cost 3D printers. The benchmarking results showed that the most effective modifications of the original printer were those related to the improvement of the structure stiffness and chatter reduction.

Alafaghani et al. [17] investigated the effect of six (6) process parameters (building direction, infill percent, print speed, extrusion temperature, layer height and infill pattern) on dimensional accuracy and mechanical properties of FDM PLA parts. They used an L_{18} experimental array. They concluded that dimensional accuracy is affected more by building direction, extrusion temperature and layer height than infill percentage, infill pattern, and printing speed. Data analysis was not applied in this research; only some effect graphs. Alafaghani and Qattawi [18] used Taguchi's DOE to investigate the main effects of four processing parameters (infill percentage, infill pattern, layer thickness, and extrusion temperature) of the PLA filament FDM process. They showed that lower values of extrusion temperature, layer thickness and infill percentage along with hexagonal infill pattern are required for better dimensional accuracy. On the other hand, in order to increase the strength of FDM parts, higher extrusion temperature, optimized layer thickness, triangular infill pattern and higher infill percentage are needed. Mahmood et al. [19] investigated extensively the geometrical characteristics of ABS filament FDM printed parts. A prototype with simple geometric features was designed, which allowed measurements for both dimensional accuracy and geometric properties. Deposition angle was set at zero for all the experiments. Statistical analysis was utilized for the determination of the process parameter levels which affect most the geometrical properties of the designed prototype. They concluded that the number of shells (E), was the most important factor affecting the dimensional accuracy of the printed part. This was followed by the inset distance multiplier (G), the space between adjacent shells, chamber temperature (A), infill shell spacing multiplier (F), the amount of overlap between the innermost shell and the adjacent infill extrusion and the infill density (K). These five factors were found to be the most sensitive for the identification of the part's printing accuracy. Layer thickness proved that was not so important in this research. Vishwas et al. [20] optimized the process parameter levels for FDM printed parts in terms of dimensional accuracy and tensile strength. They utilized ABS and Nylon as printing materials and Taguchi's L_9 orthogonal array. The process parameters were orientation angle, layer thickness and shell thickness. They found that in case of ABS 0.2 mm layer thickness, 300 orientation angle and 0.8 mm shell thickness gave the best dimensional accuracy, whereas in case of Nylon, the corresponding levels were 0.3 mm layer thickness, 150 orientation angle and 0.4 mm shell thickness.

The following conclusions can be drawn from the above literature review:

- 1 Stiffness and chatter reduction of 3D printers should be improved in order to achieve better process performance [10].
- 2 Geometrical features and deposition angle (orientation of STL model) are very important for the quality performance of 3D printed parts [9, 18]. Optimization of these parameters is needed before the 3D printing process starts.
- 3 Layer thickness has small effect on XY plane dimensional accuracy, when zero values of deposition angle are used [16, 19]. When deposition angle is changed, effect of layer thickness on XY plane dimensional accuracy is observed [10, 17, 18]; in these cases smaller values of layer thickness give the best performance.
- 4 Number of shells, infill rate, and printing (infill) pattern affect significantly the process quality performance [9–12, 14, 16–20].

Based on the above conclusions, an experiment for optimizing the FFF process' dimensional accuracy was designed using four (4) process parameters (number of shells, printing nozzle temperature, infill rate and printing pattern). Deposition angle and layer thickness were held constant (zero angle and 0.2 mm, correspondingly) throughout the whole process. As it is mentioned above, when zero values of deposition angle are used, layer thickness has small effect on XY plane dimensional accuracy [16, 19]. PLA material was used as the printing material as it was found to give better dimensional accuracy performance [16].

For optimization purposes, an L_9 orthogonal array (OA) was designed and nine (9) parts were built as the first run. Then, Grey Taguchi approach was used along with ANOM and ANOVA techniques to identify the process parameters which affect the dimensional accuracy and to establish an optimal selection of them. After the selection of the best printing parameter levels, nine (9) new parts (replicas) were printed as a second run, using only these particular printing parameter values. Finally, international tolerance (IT) grade was used for specifying the tolerances of these nine replicas. To the best of authors' knowledge, the tolerance characterization of FFF PLA parts printed with the use of the optimized printing parameters levels has not been addressed before.

2 Experimental procedure

2.1 Preparation of 3D printed PLA specimens

In this investigation, a 3D model was created, consisting of a square base with three orthogonal parallelepiped features. The nominal dimensions of these parallelepiped

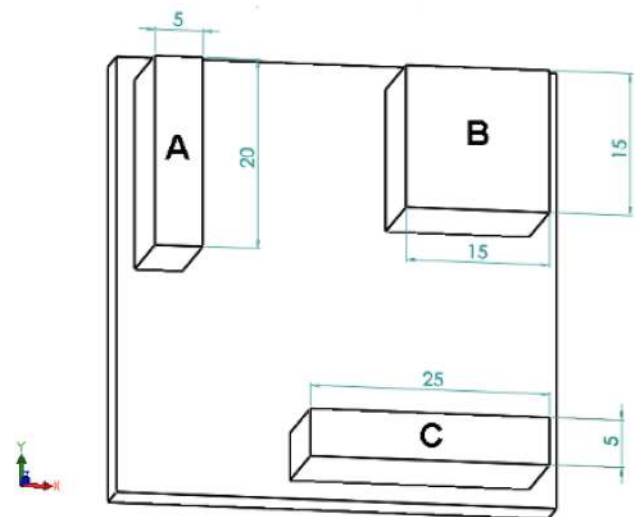


Fig. 1 Printed model and feature dimensions

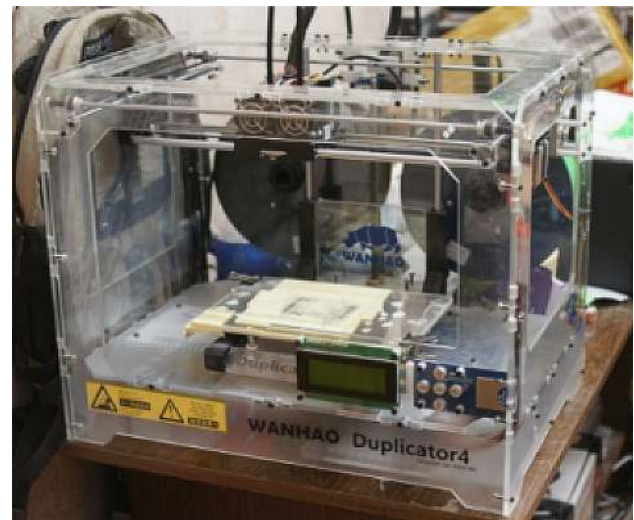


Fig. 2 Wanhao duplicator 4X 3D printer [16]

features for X and Y directions are shown in Fig. 1. The base's height is 2 mm, while feature's height is 5 mm. This 3D model was designed by Solidworks software and it was extracted in STL format. The 3D printer which was used was Wanhao Duplicator 4X (Fig. 2) [16], while the printing material was polylactic acid (PLA). PLA is a thermoplastic polyester and it is produced by renewable resources such as corn starch, tapioca roots or sugarcane [21]. MakerBot Print desktop application was also used for preparing, managing and monitoring all 3D prints. At the first attempt of this project, nine specimens were printed (Fig. 3). Different combination of process parameters' values was used each time, according to L_9 Taguchi design.

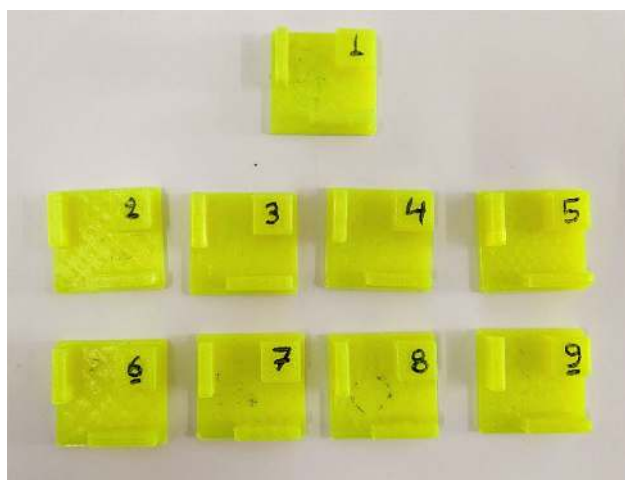


Fig. 3 Printed parts for process optimization (first run)

Table 1 Different process parameters and their levels

Process parameters	Levels		
	1	2	3
Number of shells (–)	2	3	–
Printing temperature (°C)	210	220	230
Infill rate (%)	10	15	20
Printing pattern (–)	D	E	R

These nine specimens were used for the parameters' optimization. At the second run, after the selection of the best process parameter levels according to the Grey Taguchi study that has been executed (see Sect. 3), nine new parts were printed using the same 3D model and printer.

2.2 Preparation of 3D printed PLA specimens

The dimensional accuracy of parts created using FFF technology is affected strongly by the process parameters' values that are selected during the printing process (see Sect. 1). The process parameters whose impact on the dimensional accuracy is studied here are: number of shells, printing temperature, infill rate and printing pattern. For experimentation, two or three levels have been selected for each printing parameter. Table 1 outlines the FFF printing parameters and their levels that are used in this study. The process parameters are briefly defined as follows:

- **Number of shells:** It is a key parameter which defines the outline shape and inner support structure of an object. At least one shell is needed for printing an object and additional shells add strength and weight but increase the printing time [22].

- **Printing temperature:** It is the temperature that the material is heated to during the printing process. The recommended printing temperature for PLA is 195–230 °C [23].
- **Infill rate:** It is the ratio of printed material to air volume and its value vary from 0 to 100%. It controls the final mass density of the 3D printed part. Once selected, the infill value is constant throughout the fabricated object and cannot be altered mid-print [24].
- **Printing pattern:** It is the geometric pattern that it is used in the printing process [25]. The capitals letters assigned as: D for diamond fill, E for hexagonal and R for linear.

As it is analyzed in Sect. 1, a number of process parameters such as deposition angle, layer thickness and printing speeds were held constant throughout the printing process. These parameters and their values are:

- **Deposition angle: 0°**
The value of this parameter should be chosen before the start of the printing process, according to geometrical features and shape of the model [9, 18].
- **Layer thickness: 0.2 mm**
When deposition angle is zero, layer thickness has small effect on XY plane dimensional accuracy [16, 19].
- **Printing material: PLA**
PLA material was found to give better dimensional accuracy [16].
- **Printing speeds**
 - **Travel speed: 150 mm/s**
This speed occurs when printer is not extruding material.
 - **Infill printing speed: 90 mm/s**
 - **Shell printing speed: 40 mm/s**
In general, speed and material's deposition volume are related. These parameters are very important and are associated with stiffness and printer's design [10]. They are kept constant, because when they are increased, the quality and the dimensional accuracy of the printed models become worse. Analytical and arithmetical models should be developed in order to optimize these parameters.
- **Printing table temperature: 70 °C**
- **Environment temperature: 25 °C**

2.3 Design of experiments (first run)

In this research, Taguchi's orthogonal array has been used for the design of experiments. Taguchi's design is generally adopted by a number of researchers in order to make

experiments with smaller number of trials [26–28]. This method provides an efficient and systematic approach to optimize a number experiments and the utility to study the interaction effects among parameters [29]. In Taguchi design, selection of the proper orthogonal array is a very important issue in order to obtain valid conclusions. Since there is one factor with two levels and three factors with three levels, the appropriate orthogonal array for this case is L_9 . Many researchers have utilized the L_9 orthogonal array for the optimization of various manufacturing processes. Singh et al. [30] used an L_9 array to optimize the dimensional accuracy and surface roughness of an Investment Casting (IC) printed implant. Sundaramoorthy et al. [31] investigated the optimum tool wear of CNC milling magnesium silicide alloys with the use of Taguchi's L_9 orthogonal array. Satyanarayana et al. [32] studied the optimized laser welding process parameters for P92 steel using an L_9 array and modified Taguchi design of experiments. The L_9 orthogonal array with all process parameters and their levels that has been used in this study is shown in Table 2.

2.4 Dimensional measurement techniques (first and second run)

For all nine components, both in the case of using L_9 DOE and the best parameter levels in printing, dimensions of the three features were measured in X and Y direction (see Fig. 1). Three measurements were conducted for every direction and their average value was calculated. Next, dimensional deviation was computed, which shows the difference between the nominal and the average measured values and represents dimensional accuracy of the parts. The goal here is to find the process parameter levels that minimize dimensional deviation for both directions, then using these levels for printing new parts and study their dimensional

deviation and tolerance. A micrometre with 0–25 mm range and 0.01 mm accuracy was used for the dimensional measurements. Average dimension values, nominal dimension values and deviation of each feature for the nine DOE parts are shown in Table 3 (first run).

3 Statistical analysis of DOE parts (first run)

3.1 Grey Taguchi approach

The Taguchi method optimizes single response performance, but for multiple responses optimization gets complex [33]. In this case, grey relational analysis optimization methodology is recommended. The Grey–Taguchi approach is an advanced form of the Taguchi method. It is used for the optimization of more than one responses rather than optimizing a single response as in case of the classic Taguchi approach [34]. In this investigation, Grey–Taguchi method is employed to find the best level arrangement of both X and Y dimensional deviation of all three features.

In the grey Taguchi method, all dimensional deviation results (six in total, see Table 3) are first normalized to a range of 0–1. Then, the grey relational coefficient is calculated in order to relate the desired and actual normalized data. Next, the grey relational grade is derived, by averaging the previous calculated grey relational coefficient values. The optimization of the grey relational grade is equivalent with the optimization of the multiple process responses. The optimum printing parameter levels are computed by maximizing the grey relational grade [35, 36]. The normalized deviation values which correspond to the smaller-the-better are expressed as:

$$x_{ij} = \frac{\max y_{ij} - y_{ij}}{\max y_{ij} - \min y_{ij}} \quad (1)$$

where x_{ij} is the normalized deviation value, $\min y_{ij}$ is the lowest value of i th experiment in the j th response and $\max y_{ij}$ is the highest value of i th experiment in the j th response. Table 4 shows the normalized deviation results of all the experiments.

The grey relational coefficient γ can be calculated as:

$$\gamma_{ij} = \frac{\Delta_{\min} + \zeta \Delta_{\max}}{\Delta_{ij} + \zeta \Delta_{\max}} \quad (2)$$

where $\Delta_{ij} = |x_{0j} - x_{ij}|$, $\Delta_{\min} = \min \Delta_{ij}$ for all i and j , $\Delta_{\max} = \max \Delta_{ij}$ for all i and j while ζ is called distinguishing coefficient (0 ~ 1). The value of the distinguishing coefficient is considered as 0.5 in this research. The grey relational coefficient values are tabulated in Table 5.

Table 2 L_9 experimental design for selected process parameters and their levels

Exp. no.	Number of cells (–)	Temperature (°C)	Infill (%)	Pattern (–)
1	2	210	10	E
2	2	220	15	D
3	2	230	20	R
4	3	210	15	R
5	3	220	20	E
6	3	230	10	D
7	2	210	20	D
8	2	220	10	R
9	2	230	15	E

Table 3 Dimensional accuracy measurement results for nine printed parts (first run)

Feature	Nominal dimension (mm)		Measured dimension (mm)			
	X direction	Y direction	X direction		Y direction	
			Average	Deviation	Average	Deviation
A	5	20	5.063	0.063	19.940	0.060
			5.063	0.063	19.850	0.150
			5.040	0.040	19.890	0.110
			5.113	0.113	19.990	0.010
			4.963	0.037	19.930	0.070
			5.090	0.090	20.030	0.030
			5.070	0.070	19.920	0.080
			5.257	0.257	19.890	0.110
			5.007	0.007	19.920	0.080
B	15	15	14.855	0.145	14.905	0.095
			14.825	0.175	14.915	0.085
			14.875	0.125	15.055	0.055
			14.845	0.155	15.045	0.045
			14.785	0.215	14.895	0.105
			14.950	0.050	15.005	0.005
			14.750	0.250	14.865	0.135
			14.825	0.175	14.970	0.030
			14.750	0.250	14.975	0.025
C	25	5	24.670	0.330	5.107	0.107
			24.610	0.390	5.087	0.087
			24.800	0.200	5.100	0.100
			24.640	0.360	5.127	0.127
			24.750	0.250	5.040	0.040
			24.670	0.330	5.067	0.067
			24.650	0.350	5.113	0.113
			24.670	0.330	5.043	0.043
			24.640	0.360	5.020	0.020

Table 4 Normalized deviation values x_{ij}

Feature A		Feature B		Feature C	
X direction	Y direction	X direction	Y direction	X direction	Y direction
0.7733	0.6429	0.5250	0.3077	0.3150	0.1875
0.7733	0.0000	0.3750	0.3846	0.0000	0.3750
0.8667	0.2857	0.6250	0.6154	1.0000	0.2500
0.5733	1.0000	0.4750	0.6923	0.1579	0.0000
0.8800	0.5714	0.1750	0.2308	0.7368	0.8125
0.6667	0.8571	1.0000	1.0000	0.3158	0.5625
0.7467	0.5000	0.0000	0.0000	0.2105	0.1250
0.0000	0.2857	0.3750	0.8077	0.3158	0.7813
1.0000	0.5000	0.0000	0.8462	0.1579	1.0000

The grey relational grade can be derived as:

$$\alpha_i = \sum_{j=1}^n \gamma_{ij} \quad (3)$$

Table 6 shows the grey relational grade calculation results of each L_9 orthogonal array's experiment and their optimization order.

Table 5 Grey relational coefficient γ results

Feature A		Feature B		Feature C	
X direction	Y direction	X direction	Y direction	X direction	Y direction
0.6881	0.5833	0.5128	0.4194	0.4222	0.3809
0.6881	0.3333	0.4444	0.4483	0.3333	0.4444
0.7895	0.4118	0.5714	0.5652	1.0000	0.4000
0.5396	1.0000	0.4878	0.6190	0.3725	0.3333
0.8065	0.5385	0.3774	0.3939	0.6552	0.7272
0.6000	0.7778	1.0000	1.0000	0.4222	0.5333
0.6637	0.5000	0.3333	0.3333	0.3878	0.3636
0.3333	0.4118	0.4444	0.7222	0.4222	0.6957
1.0000	0.5000	0.3333	0.7647	0.3725	1.0000

Table 6 Grey relational grade calculation results

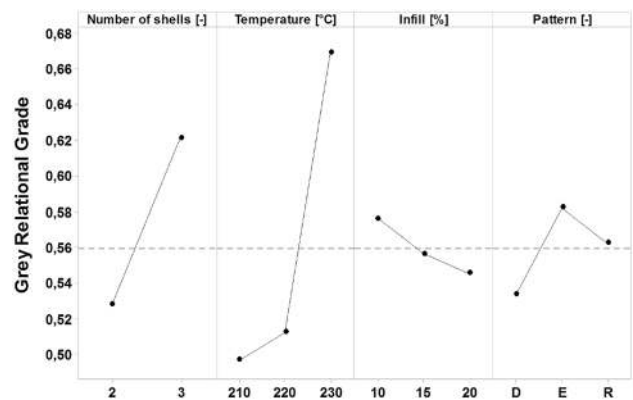
Exp. no.	Number of cells (-)	Temperature (°C)	Infill (%)	Pattern (-)	Grey relational grade	Order
1	2	210	10	E	0.5011	7
2	2	220	15	D	0.4487	8
3	2	230	20	R	0.6230	3
4	3	210	15	R	0.5587	5
5	3	220	20	E	0.5831	4
6	3	230	10	D	0.7222	1
7	2	210	20	D	0.4303	9
8	2	220	10	R	0.5049	6
9	2	230	15	E	0.6618	2

Table 7 Response table for the mean (ANOM) values of the grey relational grade

Level	Number of cells	Temperature (°C)	Infill (%)	Pattern
1	0.5283	0.4967	0.5761	0.5337
2	0.6213	0.5122	0.5564	0.5820
3	–	0.6690	0.5455	0.5622
Delta	0.0931	0.1723	0.0306	0.0483
Rank	2	1	4	3

3.2 ANOM and ANOVA for grey relational grade results

In this study, the statistical analysis and the plots were conducted with the use of Minitab 17 Statistical Software. Table 7 outlines the mean grey relational grade values calculated with the Analysis of Means (ANOM). It has been revealed that temperature is the most influential printing parameter followed by number of cells, pattern and infill. The optimal parameter levels are those that have the highest grey relational grade value as it is shown in the plot of means (Fig. 4). These levels are: (a) Number of cells: 3, (b) Temperature: 230 °C, (c) Infill: 10%, (d) Pattern: E.

**Fig. 4** Plot of means for grey relational grade**Table 8** Response table for ANOVA of grey relational grade

Source	df	Adj. SS	Adj. MS	F value	P value
Number of cells	1	0.017319	0.017319	176.81	0.048
Temperature (°C)	2	0.054492	0.027246	278.16	0.042
Infill (%)	2	0.001446	0.000723	7.38	0.252
Pattern	2	0.003534	0.001767	18.04	0.164
Error	1	0.000098	0.000098	–	–
Total	8	0.076890	–	–	–

The purpose of the Analysis of Variance (ANOVA) is to investigate which process parameters affect significantly the dimensional accuracy. Two values, the F and P value are computed for this reason. High F values imply that a parameter is important; so do small P values ($P < 0.05$). The ANOVA results for grey relational grade are tabulated in Table 8. It is appeared that the temperature is the most influential parameter ($F = 278.16$, $P = 0.042 < 0.05$), followed by number of cells ($F = 176.81$, $P = 0.048 < 0.05$). The other two process parameters are not so important. It should be noted that the ANOM gave the same results as ANOVA in terms of process parameter significance.

4 Tolerance grade study of optimized parts (second run)

In this research, a multi-response optimization was executed regarding dimensional deviations for two dimensions, using Grey Taguchi approach and statistical analysis. The whole study showed that the optimal printing parameters which result in best dimensional accuracy are: (a) Number of cells: 3, (b) Temperature: 230 °C, (c) Infill: 10%, (d) Pattern: E (see Sect. 3.2). Nine parts were printed using only these particular process parameter levels with the same design and 3D printer as the ones used in DOE parts (see Sect. 2.1). Features A, B and C of the new parts were measured in X and Y direction. Three measurements were taken for every direction again. Table 9 shows the highest and lowest measured dimensional values and their deviation for the three features in X and Y direction.

Table 9 Highest, lowest and deviation values of the measured dimensions of the optimized parts

Feature	Nominal dimension (mm)		Measured dimension (mm)					
	X direction	Y direction	X direction			Y direction		
			Min	Max	Deviation	Min	Max	Deviation
A	5	20	5.02	5.03	0.01	19.96	19.99	0.03
			5.01	5.02	0.01	19.96	19.98	0.02
			5.00	5.03	0.03	19.98	19.99	0.01
			5.00	5.01	0.01	19.98	19.99	0.01
			5.03	5.05	0.02	20.00	20.01	0.01
			5.01	5.01	0.00	19.99	20.01	0.02
			5.02	5.05	0.03	20.00	20.02	0.02
			5.01	5.03	0.02	19.98	19.99	0.01
			5.01	5.02	0.01	20.00	20.01	0.01
			5.01	5.02	0.01	20.00	20.01	0.01
B	15	15	15.01	15.02	0.01	15.02	15.04	0.02
			15.01	15.02	0.01	15.04	15.04	0.00
			15.03	15.05	0.02	15.02	15.03	0.01
			14.98	14.99	0.01	14.99	15.01	0.02
			14.99	14.99	0.00	15.00	15.01	0.01
			15.03	15.06	0.03	14.99	15.00	0.01
			15.01	15.02	0.01	15.02	15.03	0.01
			15.02	15.03	0.01	15.01	15.03	0.02
			14.99	15.02	0.03	14.98	14.99	0.01
			14.99	15.02	0.03	14.98	14.99	0.01
C	25	5	24.82	24.85	0.03	5.06	5.08	0.02
			24.83	24.85	0.02	5.06	5.09	0.03
			24.85	24.86	0.01	5.05	5.06	0.01
			24.83	24.84	0.01	5.01	5.04	0.03
			24.85	24.85	0.00	5.06	5.07	0.01
			24.85	24.86	0.01	5.06	5.06	0.00
			24.85	24.87	0.02	5.07	5.08	0.01
			24.88	24.88	0.00	5.04	5.07	0.03
			24.86	24.88	0.02	5.08	5.09	0.01

Table 10 D and T values with international tolerance (IT) grade

Feature	X direction			Y direction		
	D value	T value	IT grade	D value	T value	IT grade
A	4.2426	68.2376	IT11	23.2379	45.8935	IT9
B	13.4164	73.8896	IT11	13.4164	55.4172	IT10
C	23.2379	45.8935	IT9	4.2426	109.1801	IT12

In all manufacturing processes, especially additive manufacturing, deviations from the nominal dimensions cannot be avoided due to number of reasons. These deviations from the nominal should not exceed a specific limit, in order that the manufactured component is able to fit. International tolerance (IT) grade numbers, according to ISO 286 -1:2010, define whether a manufactured part lies within the desired tolerance or not [37]. For sizes up to 3150 mm there are twenty IT values, IT01, IT0, IT1, ..., IT18; the lower the IT grade is, the higher is the precision of a machining process [38]. In this section, the tolerance grade calculations for the parts that were printed with the optimized parameter levels is presented. The process tolerance (T) was calculated as follows:

$$T = \frac{n}{0.45 \sqrt[3]{D} + 0.001D} \quad (4)$$

where D is the geometrical mean dimension in mm and is calculated by the function:

$$D = \sqrt{D_{min} D_{max}} \quad (5)$$

where D_{min} and D_{max} are the limits of the dimension range. The n value is calculated as:

$$n = 1000(D_{msmax} - D_{msmin}) \quad (6)$$

where D_{msmax} is the highest measured dimensional value of all nine parts and D_{msmin} is the lowest measured dimensional value of all nine parts (see Table 9).

All values of n were calculated and the corresponding IT grades have been obtained for all the items printed with the optimal parameter levels. The results are shown in Table 10. It has been observed that IT grades for X direction range between IT9 and IT11. In case of Y direction, IT grades are between IT 9 and IT12. The IT grades of the components printed with the optimal printing parameter levels are consistent with the permissible range of tolerance grades as per ISO standard UNI EN 20286-I (1995).

5 Conclusions

In the present study, the effect of four process parameters namely number of shells, printing temperature, infill rate and printing pattern on the dimensional accuracy of

FFF build parts was studied. Two levels were specified for number of shells, while printing temperature, infill rate and printing pattern had three levels. Taguchi's L_9 design of experiment was used along with grey Taguchi approach in order to find the optimum factor levels (first phase). Important process parameters, such as deposition angle and layer thickness were hold constant, due to their predictable effect on dimensional accuracy according to previous studies. After the selection of the parameter levels which gave the best dimensional accuracy, in a second phase, nine parts were printed using only these optimum levels. The tolerance of these nine parts was analyzed using the international tolerance grade. Summarizing the present research, the following conclusions may be drawn:

- 1 Analysis of Means showed that the levels which minimize dimensional deviation are: (a) Number of cells: 3, (b) Printing temperature: 230 °C, (c) Infill rate: 10%, (d) Printing pattern: E.
- 2 The Analysis of Variance indicated that the factor which affects most dimensional accuracy is temperature, followed by number of cells, printing pattern and infill rate.
- 3 The new nine parts printed using the optimal printing parameter levels (second phase of experiments) possess better dimensional accuracy compared to the parts printed using Taguchi's L_9 design of experiment (first phase). This is evident from the values tabulated in Tables 3 and 9; dimensional deviation reaches the value of 0.1 mm in the case of Taguchi's L_9 DOE, whereas in the case of the optimal printing parameter levels, the deviation values range between 0.00 mm and 0.03 mm.
- 4 In the case of international grade study, it was revealed that the nine parts printed with the optimum process parameter levels possess IT grades between IT9 and IT12. This finding implies that these parts are consistent with the permissible range of standard tolerance grade as per ISO standard UNI EN 20286-I (1995).

As future perspectives, the optimization of surface roughness of the L_9 DOE parts and the optimization of both dimensional accuracy and surface roughness for the same parts may be mentioned. Grey Taguchi approach can be used for both cases.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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