Accuracy Investigation of Fused Deposition Modelling (FDM) Processed ABS and ULTRAT Parts

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ABSTRACT

This paper aims to assess the dimensional deviation of fused deposition modeling (FDM) processed ABS and ULTRAT parts using a new geometrical model that can evaluate three types of dimensional deviation: along the z-axis, along external and internal dimensions, and through diameters. The methodology involves a step-by-step procedure wherein after establishing the experimental plan and manufacturing the specimens, the measurements taken are analyzed via grey relational analysis (GRA) to find out the optimal combination of parameters leading to the minimum deviation in all dimensions of parts for both materials. Statistical techniques such as analysis of variance (ANOVA) and signal to noise (S/N) ratio were also used. Subsequently, a confirmation test was carried out to validate the results obtained. The findings of the ANOVA and the S/N ratio were in good concordance with those of GRA.

KEYWORDS

Additive Manufacturing, Dimensional Accuracy, FDM Process, Grey Relational Analysis, Taguchi

INTRODUCTION

Since the emergence of the first AM process, Stereolithography (SLA) in the late 1980s, additive manufacturing (AM) technology has been the subject of several studies with numerous patents accepted, and new processes widely commercialized (Levy & Schindel, n.d.). Hence, the AM market has grown rapidly and generated revenue of more than USD 1 billion for manufacturers of AM machines and service providers (Wohlers Associates, 2011). Guo and Leu (Guo & Leu, 2013) explained that this evolution is due to the varying opportunities offered by the AM compared to other manufacturing processes in terms of the exploitation of geometric complexity, the use of new classes of materials (e.g. functionally gradient materials), the widespread of new, open-architecture controllers for AM machines, and embedding of components during the fabrication process, etc. But

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despite these advantages, the use of AM is still limited due to defects in surface finish as well as low dimensional and geometrical accuracy which hamper their suitability for net shape manufacturing (Insaf Bahnini et al., 2020). The large divergence between design requirements and manufactured parts' specifications is on account of (i) non-consideration of the physical phenomena involved during the manufacturing process early in the design phase (Boyard, 2015), coupled with (ii) difficulties of upstream prediction of the manufactured parts' quality (Huang, 2018).

Consequently, the proposed method in this paper aims to characterize the capability of FDM process in terms of dimensional accuracy of parts manufactured using two materials; Acrylonitrile Butadiene Styrene (ABS) and ULTRAT (a specific material developed by Zortrax; the constructor of Zortrax m200 machine). The diversity in material usage will not only assist in adjusting the process parameters along with defining optimal combination resulting in high-quality end parts, but will also help in highlighting the tolerances that the machine is likely to reach. The paper is, therefore, divided as follows: Section 2 provides the concerned literature review; Section 3 discusses the materials and methods, including the step-by-step process adopted for the proposed methodology and the experimental procedure; Section 4 presents and discusses the statistical analysis and the validation of test results; and finally, Section 5 concludes the article.

LITERATURE REVIEW

Many researchers have tried to improve the characteristics of AM end parts in terms of dimensional accuracy, surface roughness, and mechanical properties. In relation to mechanical properties, the optimal combination of process parameters was obtained to maximize the compressive strength of FDM-built drilling grids by Zaman et al. (Zaman et al., 2018) using Taguchi's Design of Experiments (DOE). Domingo-Espin et al. (Domingo-Espin et al., 2014) studied the influence of number of contours, raster-to-raster air gap, and nozzle diameter on the mechanical behavior of FDM-produced Poly carbonate (PC) parts. The authors tested the samples under dynamic loading at specified conditions of amplitude, frequency and temperature. Moreover, Torres et al. (Torres et al., 2016) constructed a set of experiments to study the tensile and fracture properties of FDM-built Polylactic acid (PLA) components. With respect to surface roughness, Boschetto and Bottini (Alberto Boschetto & Bottini, 2016) developed a novel formulation to predict dimensional deviations of parts fabricated by FDM when subjected to variations in layer thickness and deposition angle. Chen and Zhao (Chen & Zhao, 2016) optimized printing saturation, layer thickness, drying time, and heater power ratio to enhance dimensional accuracy and surface quality for parts manufactured by binder jetting process. A robust model was also developed by Vahabli and Rahmati (Vahabli & Rahmati, 2017) to estimate the distribution of surface roughness in FDM parts according to the floated design criteria. Furthermore, regarding dimensional accuracy, Sood et al. (Sood et al., 2009) investigated the dimensional deviation through the length, width and height of a FDM processed prismatic part using Taguchi method combined with the GRA. The authors defined the optimal combination of the chosen process parameters levels. Górski et al. (Górski et al., 2013) also studied the effect of part orientation on the repeatability and dimensional accuracy of manufactured parts when the geometry was defined by PN-EN ISO 527 standard. The study concluded that the orientation along the x- and y-axis influenced both the accuracy and the repeatability of fabricated parts. However, it did not define a specific orientation to consider since it is not easy to meet all requirements in terms of accuracy, repeatability, strength, etc., by modifying only the orientation. The authors subsequently developed an Artificial Neural Network (ANN) model to foresee accurately the end parts' characteristics. Noriega et al. (Noriega et al., 2013) studied the influence of dimensions of CAD model on the accuracy of end-parts' dimensions by developing an ANN model to redesign a test part shaped as a regular prism having a hollow square cross-section. The distance between parallel faces was optimized in this case by treating the internal and external geometries separately. The authors realized that the error in manufacturing part was reduced by 30% for internal dimensions and 50% for external dimensions.

However, this approach, again, did not consider any of the other process/machine parameters. Also, while developing the predictive model, all the parts' geometry (external and internal) should have been taken into account for more precise results, instead of treating them separately, which is not suitable for real applications.

In addition, for the profile of the deposited filament, Boschetto and Bottini (A. Boschetto & Bottini, 2014) developed a geometrical model based on the variation of the layer thickness and deposition angle. The idea was to know upstream the manufactured parts' dimensions and to be sure of their functionality. A complex shape specimen was fabricated to perform the validation test to evaluate different deposition angles resulting in the predicted values being approximated to the experimental ones. Lieneke et al. (T. Lieneke et al., 2015) followed another approach to find out the tolerance intervals related to additively manufactured parts in normal manufacturing conditions. The authors considered geometrical, process and machine factors for the experiments and fabricated specimens. The measured deviations turned out to be not only different from one axis to another, but also the tolerances intervals established were formed by deviations derived from different axis/plans. Moreover, Galantucci et al. (Galantucci et al., 2015) compared the performances of two 3D printers; an open source and an industrial, considering dimensional accuracy. A simple prismatic specimen was fabricated by both printers to measure the deviation in length, width, and height. The authors concluded that the open-source printer demonstrated an acceptable performance. However, as same parameters were not used for both printers, the validity of this comparison can raise questions. Lieneke et al. (Tobias Lieneke et al., 2016) also conducted an experimental research to drive dimensional tolerances for four types of dimensions: internal, external, dimensions of various types, and distance dimensions. Different shapes of parts were manufactured in different positions and directions, and the deviation along each axis was defined. The authors concluded that the deviation along the z-axis was the most important, which can also be explained by the successive deposition of layers in that direction. This further approximates the nominal dimensions with the layer thickness value.

Considering the overarching aim of this research and the associated literature review, it is evident that several approaches and methodologies were established to investigate the dimensional accuracy in FDM processed parts. However, there exist research gaps which are given as follows:

1. The geometries of the parts used in the tests are generally simple, containing one type of dimensions (internal or external) leading to the investigation of only one type among other types of dimensional accuracy.
2. In all of the cited literature, the material type was fixed to only one material. It is suggested in this paper that the testing accuracy achieved using different materials could be considered as interchangeable, but, in reality, it would lead to different accuracy values as they are also influenced by the selected manufacturing parameters and their levels.

The proposed methodology is explained in the following section along with experimental procedure, and the obtained results, thereafter.

MATERIALS AND METHODS

Methodology

The aim of this paper is the investigation of the dimensional accuracy in FDM processed parts. To do so, a step-by-step procedure was adopted. Firstly, new specimen geometry was proposed to test the deviation of different types of dimensions, viz. along z-axis, external and internal dimensions, and through diameters. The specimens were then manufactured using two materials, ABS and ULTRAT, in order to conduct a comparative study of the achievable performances of the two materials. Controllable factors were then chosen, and the experimental plan was established using orthogonal arrays of Taguchi. The statistical analyses using GRA combined with S/N ratio were further used to carry out the multi-optimization to determine the optimal combination of levels that can minimize the deviation along all part's dimensions. ANOVA was also applied to determine the factors having the most/least effect on the deviation.

Equipment and Part Geometry

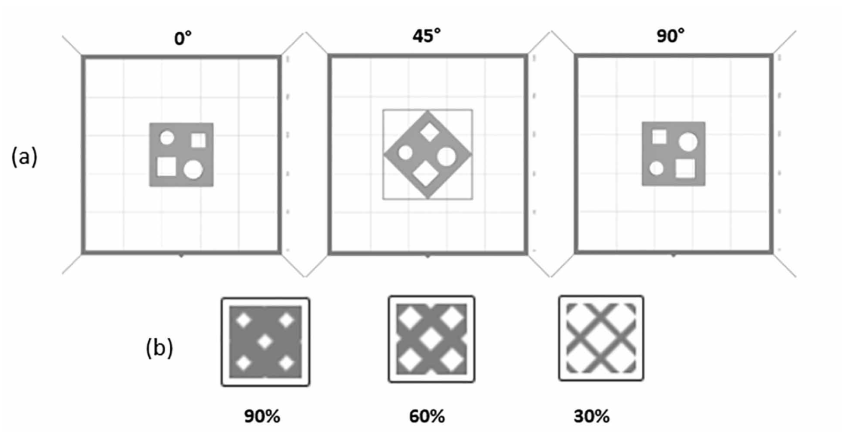
FDM process, developed by Stratasys and commercialized in 1991, is one of the most popular AM technologies (I. Bahnini et al., 2018). It follows laying of tracks of thermoplastic material in semi-molten form onto a substrate in a bottom to top manner. Moreover, FDM carries multiple advantages such as easiness of use, capability to fabricate functional parts, absence of toxic materials, supervision-less manufacturing of parts, reproducibility, and use of low temperatures (Galantucci et al., 2015). But as stated by Boschetto and Bottini (A. Boschetto & Bottini, 2014), this technology has limitations in terms of poor surface roughness and restricted accuracy.

The underlying principle of obtaining high-quality AM parts, hence, lies in the proper selection of process parameters. Villalpando et al. (Villalpando et al., 2014) explained that FDM is considered as a complex process since it includes heat gradients due to airflow, solidification, melting, orientation, and slicing. Hence, the determination of optimum parameters becomes a difficult task as multiple conflicting parameters exist which in turn affect the material properties and the part quality (Mohamed et al., 2015). Therefore, a selection must be made to select those parameters which are more likely to influence the part's quality in terms of the performance being studied. In this paper, three parameters were selected:

- **Layer thickness:** It is the thickness of each deposited layer. It refers to the step made by the platform along the z-axis once the previous layer is done and another layer starts to be deposited.
- **Part orientation:** It refers to the orientation of the part on the construction platform, relative to x-, y-, and z-axis as shown in Figure 1.
- **Infill density:** It is the density of the infill of mid-layers (Figure 1). The top and bottom layers have a solid linear infill (density of 100%) to give shape and strength to the part.

This selection was made based on the recommendation of experts in the Renault Technologies, Romania who also helped in manufacturing specimens.

Figure 1. (a) part orientaion on the platform, (b) infill density



Concerning the considered geometry, a new prismatic part (65 × 65 × 10) mm was suggested. The part contained different geometries with different sizes, as shown in Figure 2, to assess the ability of the machine to fabricate accurately different geometries and allow the investigation of three types of dimensional accuracies, viz. z-axis, diameters, and XY plane.

The experiments were carried out using a Zortrax m200 machine (Figure 3). It is a 3D printer that consists of a vertically translating construction platform along the z-axis (with a maximum height

Figure 2. (a) Technical drawing of the proposed part, (b) Designation of nominal dimensions

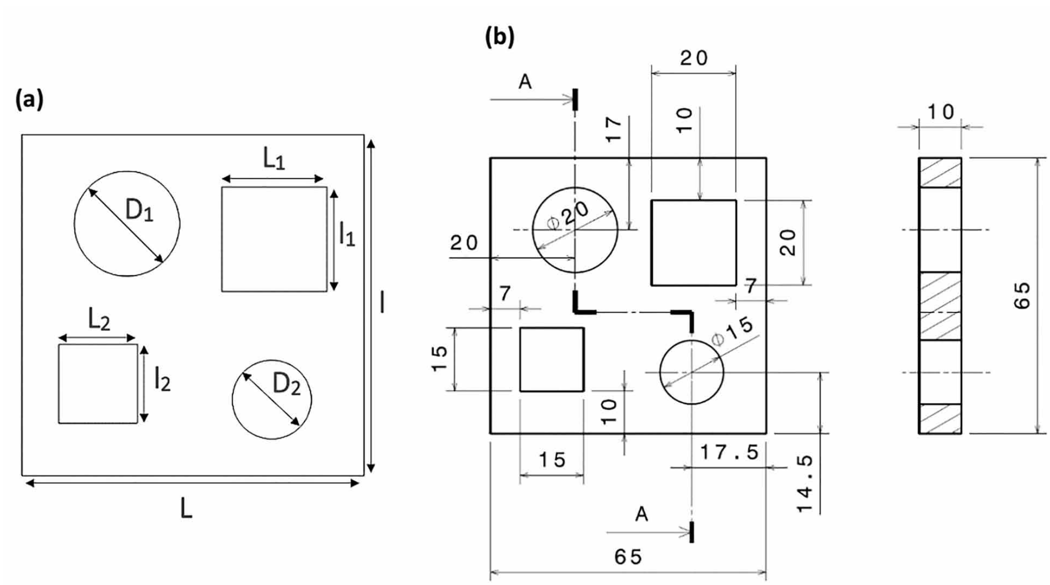
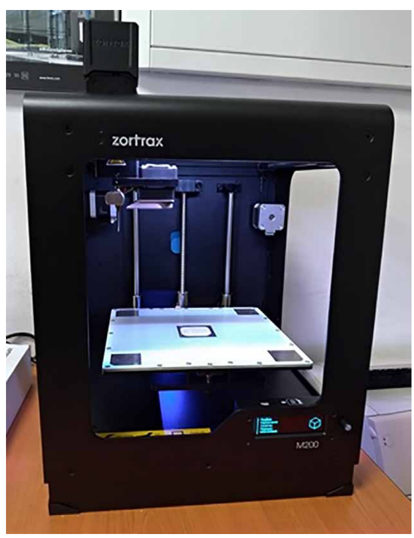


Figure 3. The Zortrax m200 3D printer



of 180 mm), a build area of (200 × 200) mm, and an extruder nozzle with translation along x- and y-axis. The x- and y-axis movement was achieved by a belt-driven pulley system with stepper motors, while the vertical translation along the z-axis was driven by a trapezoidal screw. For the extrusion system, a 1.75 mm diameter of filament was fed into a nozzle of 0.4 mm diameter by the help of a stepper motor. The control of the printer was assured through USB connection to PC or with SD card with the part's G-code in it. The part's CAD was modeled in CATIA V5, exported as STL file, and was then sent to Z-Suite software, where the manufacturing parameters and their levels were chosen.

Design of Experiments and Preliminary Statistical Analysis

An important step in the establishment of the experimental plan is to select the controllable factors for the experiments. As mentioned earlier in this article, three controllable factors, namely layer thickness (A), part orientation (B), and infill density (C), each at the levels (Table 1), were selected. Other process parameters of the Z-Suite software were fixed as shown also in Table 1.

To establish the experimental plan, orthogonal arrays (OAs) established by Taguchi were chosen for the simple reason of reducing the number of trials, which lead to reduced material cost and time. According to the given number of parameters and their levels, the L_9 array was chosen (Table 2). Hence, 9 trials were considered (Figure 4).

Several works among those presented in the literature review suggested the fabrication of more than one part for each set of parameters and then calculation of the average of the measures taken to assess the repeatability of the machine. However, this approach has a lot of drawbacks. Firstly, each

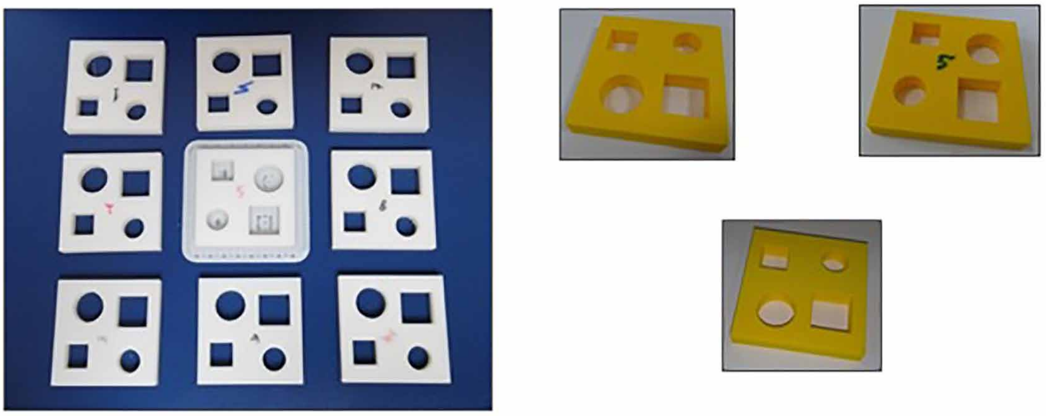
Table 1. Manufacturing factors and their values

Factors	Units	Level 1	Level 2	Level 3	Fixed Factors	Values	Fixed factors	Values
A: Layer thickness	(mm)	0,09	0,19	0,29	Nozzle temperature	280°C /ABS 265°C/ULTRAT	Infill pattern	Hexagonal
B: Density infill	(%)	90	60	30	Bed temperature	105þ C	Top/bottom fill pattern	Rectilinear
C: Part orientation	(°)	0	45	90	Nozzle diameter	0,4 mm	Infill speed	100 mm/s
					Number of perimeters	3	Solid infill speed	100 mm/s

Table 2. L_9 array

N° of trial	A	B	C
1	0,09	90	0°
2	0,09	60	45°
3	0,09	30	90°
4	0,19	90	45°
5	0,19	60	90°
6	0,19	30	0°
7	0,29	90	90°
8	0,29	60	0°
9	0,29	30	45°

Figure 4. The specimens fabricated in ULTRAT (in white) and some of the specimens fabricated in ABS (in yellow)



fabricated part will have some defects evidently, which involve errors in measurement, as well as errors related to the measuring device, the operator, etc. Secondly, the repetition of this operation with other parts and then calculating the average will increase the error margin which will lead to large deviation. The suggestion, therefore, in this paper is to fabricate one part for each set of parameters, and then perform several measures for each dimension.

The measurements of the different dimensions of the fabricated parts (Figure 2) were taken using a digital caliper with an accuracy of 0.001 mm. Then the percentage change in length was calculated for each dimension using Equation 1:

$$\%\Delta L = \frac{\left|L - L_{CAD}\right|}{L_{CAD}} \times 100 \tag{1}$$

where L is the measured value of length, LCAD is the nominal length, and %ΔL is the percentage change in L.

The percentage change values were calculated for each type of the dimensional accuracy investigated: z-axis, external & internal dimensions (XY plan), and diameters. These values will constitute the input of the Grey Relational Analysis (GRA) method as explained below.

Grey Relational Analysis (GRA)

The GRA, as explained by Pan et al. (Pan et al., 2007), is a method that aims to study systems with insufficient, incomplete, or uncertain information. This is a statistical method and an efficient tool for multi-optimization problems and experimental results analysis. Its aim is the conversion of multiple optimized responses into a single one, giving at the same time a ranking of the performed experimental sets, to find out the optimal combination of the controllable factors. The first step in performing GRA is the data pre-processing, which consists of a conversion of all the obtained measurements to a set of normalized values in a range of 0–1, called Grey relational coefficient, using one of the following equations (see Equation 2) according to the type of performance characteristic. $x_i^{(0)}\left(k\right)$ is the measured value of the kth characteristic for the ith experiment and for $i = 1,2,..,n \in N$ and $k = 1,2,..,m \in N$, the measurements taken from all the experiments could be represented by the following sequences:

$$\begin{array}{cccccc} x_1^{(0)}(1) & x_1^{(0)}(2) & \ldots & x_1^{(0)}(k) & \ldots & x_1^{(0)}(m) \\ \vdots & \vdots & \ldots & \vdots & \ldots & \vdots \\ x_i^{(0)}(1) & x_i^{(0)}(2) & \ldots & x_i^{(0)}(k) & \ldots & x_i^{(0)}(m) \\ \vdots & \vdots & & \vdots & & \vdots \\ x_n^{(0)}(1) & x_n^{(0)}(2) & \ldots & x_n^{(0)}(k) & \ldots & x_n^{(0)}(m) \end{array} \tag{2}$$

In case where minimizing a performance characteristic is required (as we aim in this paper for dimensional deviation), then the lower-the better equation is used:

$$x_i^* \tag{3}$$

Following the calculation of the Grey relational coefficient, a weighting adjustment is required which is defined by Equation 4:

$$x_{iwi}^*(k) = x_i^*(k) \times w_i, \quad \sum_{i=1}^{n} w_i = 1 \tag{4}$$

The weights could be assigned equally in case there is no information on the contribution of each performance characteristic to the final response. However, a subjective factor of decision maker will be then introduced. In this context, the entropy weighting has the advantage of calculating the relative weighting factors in a well-defined, objective way. The entropy weighting method computations were fulfilled based on procedure outlined by (Chung Wang et al., 2007).

The last step in the Grey procedure is the calculation of the Grey relational grade (GRG) related to each trial as given by Equation 5:

$$\Gamma_i = \frac{\Delta_{\min} + \Delta_{\max}}{\Delta_{0i}^* + \Delta_{\max}}, \qquad 0 < \Gamma_i \le 1 \tag{5}$$

where:

$$\Delta_{0i}^* = \frac{1}{n}\sum_{i=1}^{n} \Delta_{0i}(k), \quad \Delta_{0i}(k) = \left| x_0^*(k) - x_{iwi}^*(k) \right|$$
$$\Delta_{\max} = \max \left| x_0^*(k) - x_{iwi}^*(k) \right|$$
$$\Delta_{\min} = \min \left| x_0^*(k) - x_{iwi}^*(k) \right|$$

Here, $x_0^*(k)$ and $x_{iwi}^*(k)$ are respectively, the reference sequence and the specific relative (comparability) sequence. Based on the value of the GRG, Γ_i, the sequence with the greatest effect, is noted. The higher value of the Γ_i stands for the trial fulfilled with the optimal combination of parameters.

Results of GRA

The GRA approach was applied in this paper to determine the optimal combination of the levels of the factors that allowed the reduction of the dimensional deviation of ABS and ULTRAT parts. Since the aim was to minimize the dimensional deviation, i.e., the percentage change, $\%\Delta L$, in each dimension of the specimens, the lower-the-better was the type of the performance characteristic used. 9 trials were run to identify the three input controllable factors, and 9 quality characteristics were optimized, viz. the percentage in change in height (z), in diameters (D1 and D2), in external dimensions (L and l), and in internal dimensions (L1, l1, L2, and l2). This multi-optimization method transformed the nine quality characteristics into a single response, i.e., the GRG. The highest value of the GRG denoted the optimal combination of parameters. Table 3 shows the calculation of the GRG for ABS and ULTRAT parts.

According to the GRG results, the fourth and the first experiment have the highest values of GRG for ULTRAT and ABS parts, respectively, which denote the optimal combination of parameter levels. Therefore, the combination of fabrication parameters leading to minimizing the dimensional deviation in all parts' dimensions stands for 'A2B1C2 for ULTRAT parts', i.e., a layer thickness of 0.19 mm, an infill density of 90%, and an orientation of 45°. For the ABS parts, 'A1B1C1' constitute the optimal combination, i.e., the layer thickness is 0.09 mm, the density infill of 90%, and the part orientation of 0°.

After calculating the GRG values for each material, the GRG for each factor level could be calculated from Table 3 as the mean of the GRG values related to each parameter level. As an example, the GRG for the parameter (A) at the first level for ULTRAT parts is shown below:

GRG (A1) = (0.9710 + 0.96910 + 0.97060) / 3

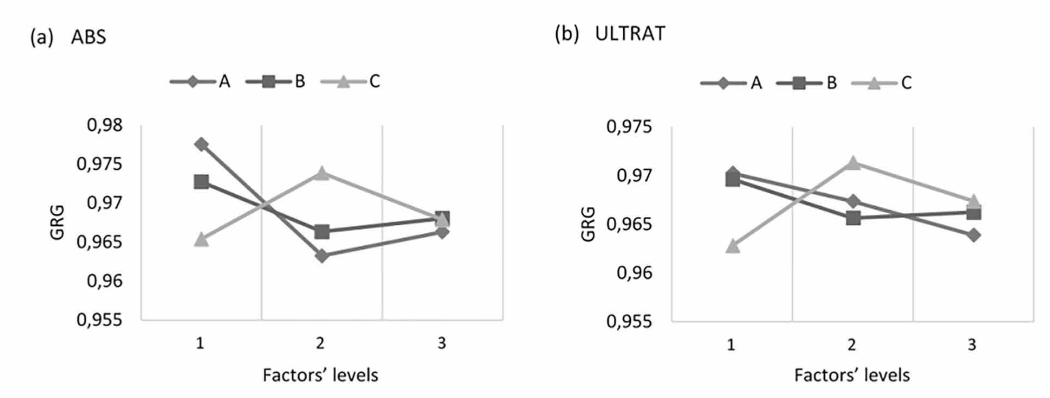
For each parameter, the difference between the minimum and the maximum value of the averages of GRG was calculated. This difference symbolizes the effect of each controllable factor on the response. The higher is this difference, the higher is the effect of the parameter on the quality characteristic.

To better visualize these values and the interrelations between them, the average of the GRG values related to each parameter level, were represented in Figure 5. This could assist in figuring out the levels giving rise to the highest mean. These levels comprise of the optimal combination. From Figure 5, the first level of A, the first level for B, and the second level for C, are the levels with the

Table 3. The Grey Relational Grade (GRG) calculated for ABS and ULTRAT Parts

N° of trial	ABS parts		ULTRAT parts	
	GRG	Order	GRG	Order
1	0,98206	1	0,97107	2
2	0,97768	2	0,96910	5
3	0,97294	4	0,97060	3
4	0,96931	5	0,97505	1
5	0,96381	6	0,96877	6
6	0,95665	9	0,95827	9
7	0,96684	8	0,96280	7
8	0,95752	7	0,95907	8
9	0,97460	3	0,96985	4

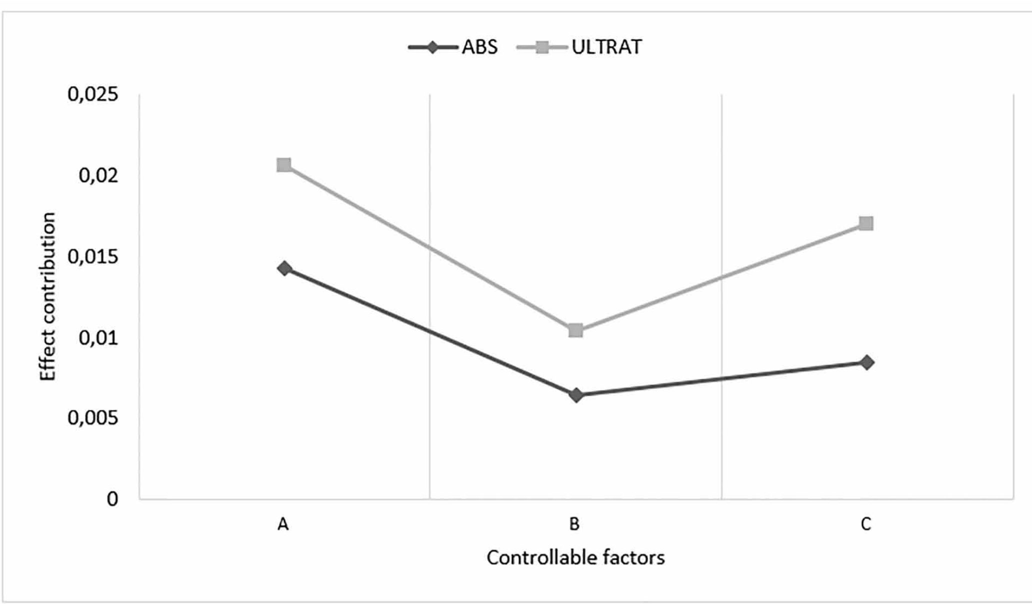
Figure 5. Average grey relational grade (GRG) for each factor level – (a) ABS parts, (b) ULTRAT parts



highest mean for both materials, ABS and ULTRAT. Thus, a layer thickness of 0.09 mm, a filling density of 90%, and a part orientation of 45°, constitute the optimal combination of controllable factors for minimizing the dimensional deviation in all of the part's dimensions.

Furthermore, Figure 6 depicts the effect contribution of layer thickness, filling density, and part orientation on multiple performance characteristics for ABS and ULTRAT. The highest effect contribution for the ABS parts stands for the layer thickness with a difference value of 0.01430. At the second place is the part orientation with a value of 0.0084, while the density of the infill has the least effect on the multi-quality characteristic, with a 0.0063 of the difference of the GRG means. For ULTRAT parts, the highest value of the difference between the means was recorded for the part orientation with a value of 0.0085, the layer thickness came at the second place with a value of 0.0063, and the lowest effect contribution was registered for the filling density with a difference value of 0.0039.

Figure 6. Effect contribution of controllable factors on the performance characteristics



These results highlight the importance of selecting materials in the design phase. Indeed, the material selection could be influenced by the selection of the manufacturing parameters, which implies the need to choose carefully how to set up the manufacturing parameters and to take them into account when choosing the appropriate material for a specific application.

VERIFICATION AND DISCUSSION

Analysis of Variance (ANOVA)

The purpose of ANOVA is to determine the manufacturing parameters that significantly affect the performance characteristic. In this section, the GRG values (Table 3) are considered as the performance characteristic on which the ANOVA is applied. The aim is then to investigate which controllable factors affect the multiple-performance characteristics, i.e., which factors are more likely to reduce the dimensional deviation for all the investigated dimensions. To run the ANOVA calculations, the procedure described by (Condra, 1995) is used. The results obtained are shown in Table 4 for data of GRG related to the ABS parts, and in Table 5 for those related to the ULTRAT parts.

As it could be seen from Tables 4 and 5, the infill density (B) has the lowest percentage contribution (10.81% and 10.46% for ABS and ULTRAT, respectively) which means that it has low effect on the GRG for both materials. For ABS parts, the layer thickness (A) has the highest percentage contribution (55.90%) which indicates that it has the most effect on the deviation of part dimensions compared to the part orientation (C) that has a contribution percentage of 18.64%. This is in contrary to the ULTRAT parts, where the layer thickness has a low percentage contribution 22.76%, while the part orientation (C) has the highest value (41.04%), implying that it is more likely to affect the dimensional deviation of parts. These results are in good concordance with those found through GRA method and confirm the inference stated regarding the influence of choice of values of parameters on the material selection.

Table 4. ANOVA applied for GRG of ABS parts

Parameters	DF	Sum of squares (SS)	Mean squares (MS)	F-value	Percentage contribution
A	2	0,000340	0,000170	3,81	55,90%
B	2	0,000066	0,000033	0,74	10,81%
C	2	0,000113	0,000057	1,27	18,64%
Error	2	0,000089	0,000045	-	14,65%
Total	8	0,000609	0,000305	-	100,00%

Table 5. ANOVA applied for GRG of ULTRAT parts

Parameters	DF	Sum of squares (SS)	Mean squares (MS)	F-value	Percentage contribution
A	2	0,000061	0,000030	0,88	22,76%
B	2	0,000028	0,000014	0,41	10,46%
C	2	0,000109	0,000055	1,59	41,04%
Error	2	0,000069	0,000034	-	25,75%
Total	8	0,000266	0,000133	-	100,00%

Integration of Taguchi Method With the GRA

The application of GRA method facilitated through a multi-objective optimization, was used to find the optimal combination allowing the reduction of the dimensional deviation in all dimensions of a part. From the obtained values of the GRG, the experiment with the highest GRG value is nominated as the optimal combination of the levels of parameters. It has been found that 'A1B1C2' is the optimal combination for the ABS and the ULTRAT processed parts.

Herein, Taguchi method is integrated with the analysis to increase the scope of the application of GRA method. The key tool in Taguchi's algorithm is the calculation of the S/N ratio, which reveals the fluctuation of the tested quality characteristic. The highest S/N ratio value corresponds to the best quality characteristic index. In the analysis in this paper, the calculated GRG for both materials, ABS and ULTRAT, was the quality characteristic on which the S/N ratio calculation was applied. There are three types of S/N ratio calculations according to the type of the performance characteristic to be inspected; the-higher-the-better, the-lower-the-better, and the-nominal-the-better. For the case registered in this paper, the aim is to find the highest GRG value. So, the S/N ratio values are calculated as shown in Equation 6 and as suggested by (Markopoulos et al., 2016):

$$\eta = -10\log\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right) \tag{6}$$

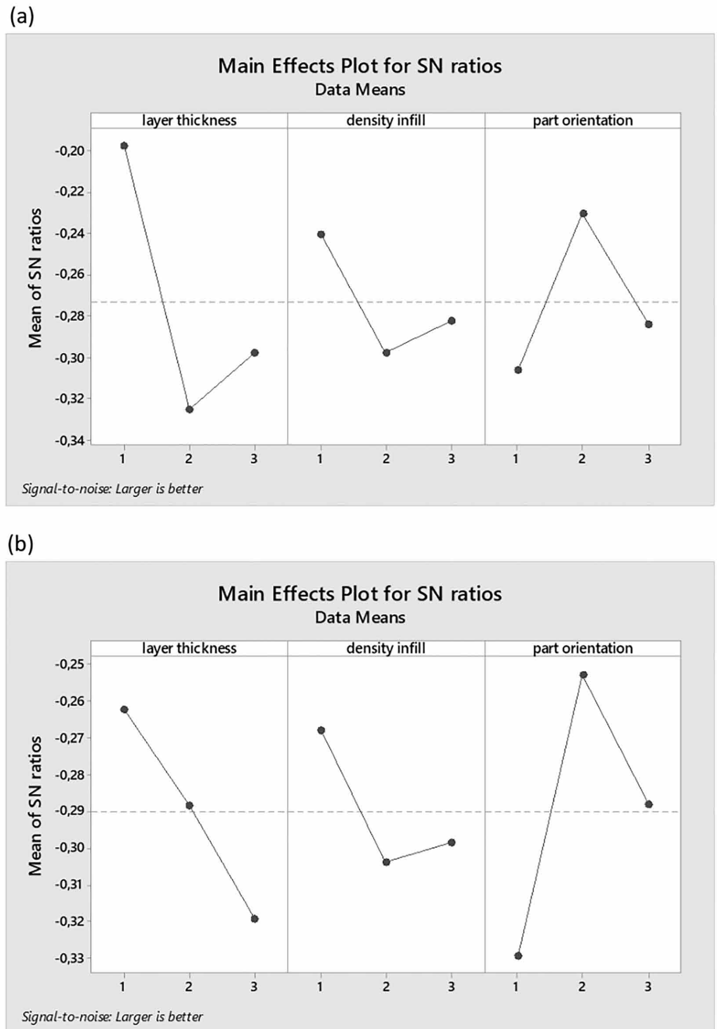
where y_i represents the measured data, which is the GRG values for both materials, and n is the number of the performed trials.

Table 6 shows the calculated S/N ratio values for GRG for ABS and ULTRAT parts. Figure 7 shows the main effects plot for the S/N ratio calculated for the GRG values for all the levels of the parameters for ABS and ULTRAT parts. The optimal level of each parameter stands for the highest value of the mean of S/N ratio values calculated for each level of the controllable factors. Thus, A1B1C2 constitutes the optimal combination of parameters' levels, i.e., 0.09 mm for layer thickness (A), 90% for the filling density (B), and 45° for part orientation (C). This result matches the results revealed by the ANOVA analysis as well as the calculations of effect contribution of each factor level determined from the GRG values which prove that the results generated from Taguchi method are in a good agreement with the other methods used.

Table 6. S/N ratio calculation performed on the GRG values of ABS and ULTRAT parts

Trials	S/N ratio for ABS parts	S/N ratio for ULTRAT parts
1	-0,157240	-0,254989
2	-0,196065	-0,272628
3	-0,238279	-0,259194
4	-0,270746	-0,219462
5	-0,320171	-0,275586
6	-0,384938	-0,370242
7	-0,292908	-0,329278
8	-0,377043	-0,362994
9	-0,223472	-0,265909

Figure 7. Main effects plot for S/N ratio applied for GRG values. (a) ABS parts, (b) ULTRAT parts.



Verification Test

The multi-objective analysis GRA defined the optimal combination as 0.09 mm for layer thickness, 90% for the filling density, and 45° for part orientation, allowing minimizing the deviation for all dimensions of the part for both materials; ABS and ULTRAT. The ANOVA analysis and the Taguchi method found the same combination of parameters and confirmed the results given by GRA. However, to be able to validate the attained optimal combination, a confirmation test is necessary. This was accomplished by means of manufacturing two parts, each with each material (a part with ABS and another with the ULTRAT) using the same fixed factors as set before (Table 1) as well as the controllable factors set at the optimal levels (A1B1C2). Once the fabrication was finished, the measurements of the different dimensions of the parts were taken. The aim was to compare these results with the predicted ones for optimal levels. The predicted values (noted P) for each response and characterized as the quality characteristic, were calculated as follows:

P = mean of response for A1 + mean of response for B1 + mean of response for C2 – 2 x Mean of response.

Figures 8 and 9 shows the deviation values of the manufactured parts using the optimal combination and the predicted values from the previous nine experiments.

It is evident from Figure 8 that for the deviation values of the ABS parts, some values of dimensions taken from the confirmation test are higher than those predicted, which reflect an improvement in minimizing the deviation using the optimal combination. This is true for the two circles, D1 and D2, and for the dimensions measured along the width, i.e., l, l1, and l2. The other values differ by 0.073 mm for the measurement along the z-axis, by 0.015 mm for L1, by 0.025 mm for L2, and by 0.171 mm for the outer dimension, L. For the ULTRAT part (Figure 9), all the values from the confirmation test are higher than those predicted. It follows from the foregoing comparison that there is a notable improvement in values of dimensions recorded from parts fabricated using the optimal combination of parameters A1B1C2, especially the part manufactured using the ULTRAT. This further confirms the method used and permits to declare that a layer thickness of 0.09 mm, an infill density of 90% and a part orientation of 45° is the optimal combination of parameters leading to the minimum deviation along all the part's dimensions. Our methodology, therefore is validated and confirmed.

The findings of this study also highlight the importance of selecting materials in the design phase and the preparation of parts for fabrication. For applications with polymers, ABS and ULTRAT can be considered as a suitable option and are interchangeable. However, the selection can further be influenced by the selected manufacturing parameters and their levels, which implies the need to consider the manufacturing parameters as well as their values when choosing the appropriate material for a specific application. This is truly justified when other specifications are considered such as mechanical properties, when selecting the appropriate material is crucial. Furthermore, the multi-optimization procedure followed in this paper can be extended to optimize other specifications rather than dimensional accuracy, or several materials to choose from, which will help to define more

Figure 8. Predicted deviation values (without optimal combination) and confirmation test deviation values for all dimensions – ABS parts

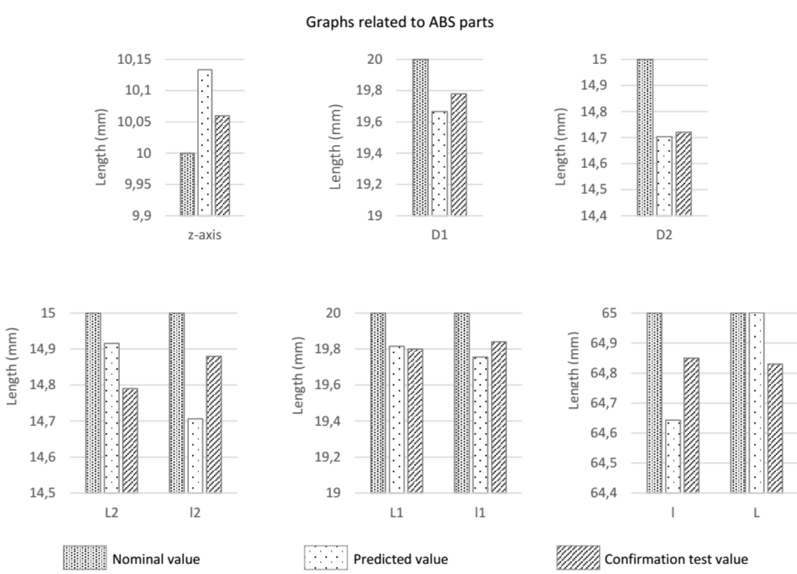
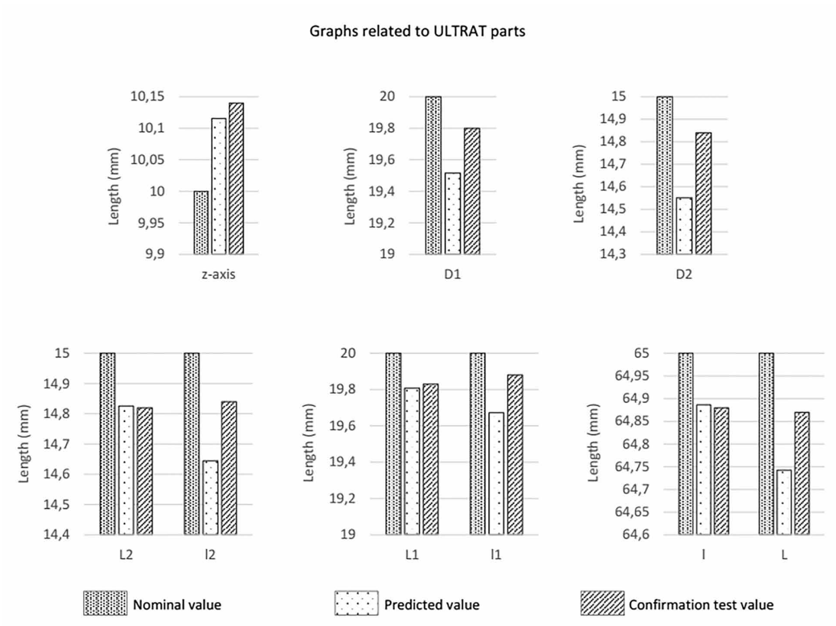


Figure 9. Predicted deviation values (without optimal combination) and confirmation test deviation values for all dimensions – ABS ULTRAT parts



accurately the optimal combination of parameters and their levels to guarantee the best material choice, the minimal dimensional deviation, the prescribed mechanical properties, and the desired surface roughness.

Moreover, for every application, although the appropriate material and the levels of the manufacturing parameters are well-chosen, the deviation will take place certainly. To predict and minimize it, a mathematical modeling of the occurred deviation can be done in order to determine the compensation values with which the CAD file would be modified before the manufacturing of the part. This was the core concept of Insaf Bahnini et al. (2020) wherein the development of this model and its application were outlined and verified.

CONCLUSION

In this paper, the dimensional deviation of parts manufactured with ABS and ULTRAT, was investigated. New part geometry was proposed to assess three types of dimensional deviations: along z-axis, in external and internal dimensions, and through diameters. According to the recommendations of experts, the controllable factors were chosen along with their levels. In order to establish the experimental plan, the orthogonal arrays of Taguchi were used. A multi-optimization using the GRA method combined with the S/N ratio and the ANOVA methods were performed to identify the optimal set of parameters and to depict the most/least influencing factors on the deviation. The optimal combination of parameters was: a layer thickness of 0.09 mm, a filling density of 90%, and a part orientation of 45° for both ABS and ULTRAT processed parts. Carrying a verification test remains important to confirm the findings and hence, a test was performed using the parameters' optimal set found previously. An improvement was evident in minimizing the deviation between the nominal and the manufactured parts' dimensions, which subsequently confirmed the proposed methodology and validation of the carried experiments.

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