The International Journal of Advanced Manufacturing Technology
https://doi.org/10.1007/s00170-018-2117-4

ORIGINAL ARTICLE

# Statistical analysis of dimensional accuracy in additive manufacturing considering STL model properties

**Ivanna Baturynska**[1]

Received: 19 February 2018 / Accepted: 6 May 2018



## Abstract

Additive manufacturing (AM) is a technology that produces a part layer by layer based on the computer-aided designed (CAD) model. Each AM process is defined by a set of parameters and materials. The laser power, scan spacing and speed, preheating and bed temperatures, hatch length, pulse frequency, and part placement (coordinates of a part placed in the build) are among the most studied process parameters reported in the literature. Recent attention to improving part quality is caused by the possibility of using AM for manufacturing, but the inconsistency of results' repeatability is the main challenge that is not solved yet. This work attempts to improve the dimensional accuracy by predicting dimensional features of the part, namely length, width, and thickness. Data is collected from two identical runs done on EOS P395 polymer laser sintering system. By identical runs is meant that build layout, material and process parameters were kept constant in both runs. Pearson correlation test is used to identify whether the new parameters (the number of mesh triangles, surface, and volume of CAD model) are significantly correlated to dimensional features. Based on the correlation results, linear regression models are developed to predict dimensional features (compensate shrinkage effect). The obtained results are the following: models for thickness (in *XZY* orientation), length (in *ZYX* orientation), and length and thickness (in Angle orientation) can already be used to predict dimensional features (to minimize shrinkage effect by proposing scaling ratio for each specimen in the build separately).


**Keywords** Additive manufacturing · Statistical analysis · Polymer powder bed process · Dimensional accuracy · STL model parameters · Regression modeling

## 1 Introduction

Dimensional accuracy of additively manufactured parts is already presented in different studies. Interest to this topic is motivated by importance of dimensional accuracy for automotive, aerospace, and medical applications [1, 3, 4, 14, 16]. Typically, studies are focused on the investigation of interaction of machine process parameters on shrinkage effect, while just a few made attempts to explain which building parameters should be controlled in terms of dimensional accuracy improvements.

Optimization of laser power, scan spacing, bed temperature, and hatch length of polymer powder bed fusion process (3D Systems) was performed to predict shrinkage effect [15]. Authors used analysis of variance (ANOVA) based on quadratic model for shrinkage, and their results showed that all parameters are significant but scan spacing is the most significant one.

Another example of statistical optimization of metal powder bed fusion process parameters is described by [2]. Analysis of variance with linear models was used to define interactions of laser power and scan speed considering relative density, hardness HRC, ultimate tensile strength (UTS), and surface roughness. Authors identified that scan speed and laser power are significant for all mechanical properties except surface roughness, and proposed a map for the correct combination of these two process parameters [2].

Mechanical properties are also dependent on build orientation not less than on production parameters [3]. This phenomenon was reported by [3] based on the various mechanical testing of polyamide specimens. In addition to mechanical properties of specimens, thickness, and width were also investigated in terms of their dependence on

✉ Ivanna Baturynska
ivanna.baturynska@ntnu.no

[1] Department of Manufacturing and Civil Engineering, Department of Mechanical and Industrial Engineering, Norwegian University of Science and Technology, Gjovik, Norway

Published online: 21 May 2018

energy density and build orientation. However, authors have not included length of the part and *Y* orientation that could provide more information for the better understanding of sintering process. Caulfield et al. [3] also documented that "role of the build orientation and parts dimensions may be more complicated than the influence of energy density." Therefore, more investigation of dimensional accuracy interaction with build properties is needed.

Yang et al. [17] proposed a set of models for optimization of shrinkage ratio for part placement in *X*, *Y*, or *Z* directions. Models are built based on the results from Taguchi and analysis of variance and supported their optimization with experimental testing of models.

Senthilkumaran et al. [12] investigated influence of different building strategies on shrinkage effect. Authors studied effects of beam compensation, contouring and hatching, inertia of scanning mirror, scan direction and compensation of positioning errors on shrinkage effect, and effect of part orientation on deviations per unit length [12].

Later, [13] introduced a new model for shrinkage compensation based on the results and gained knowledge from previous study. This model was developed for compensation of shrinkage "at every layer and at every hatch length, unlike a uniform compensation scheme applied to entire part" [13]. Results were compared with suggested compensation by machine manufacturer, and improvements of dimensional accuracy approximately by 55–62% were observed for newly developed compensation scheme.

Delgado et al. [5] also evaluated significance of effects of process parameters on dimensional error, surface roughness and mechanical properties for metal powder bed fusion systems. Authors also reported that research on dimensional accuracy for two metal materials is very limited comparing with surface roughness and mechanical properties. Another study on part quality of fabricated parts by Selective Laser Sintering (SLS) was statistically investigated concerning various machine parameters by [7], but dimensional accuracy was not mentioned.

To date, it is not reported what is the role of STL model properties. The number of mesh triangles, surface, and volume of CAD model will be considered as the STL model properties and are new parameters in this study. In some AM systems, a number of process parameters that can be variated is limited. For example, EOS P395 polymer laser sintering machine can be operated under one of five process parameters sets (i.e., TopQuality, Performance, Balance, Speed, TopSpeed) proposed by machine producer. However, user needs to compromise either on production speed or part quality.

Therefore, in this article, STL model properties that are open for the users at a stage of part placement were chosen to be investigated. A number of mesh triangles, surface, and volume can be variated while designing part to improve dimensional accuracy. Besides, all part placement coordinates (e.g., central, maximal, and minimal coordinates that are shown in Fig. 3) also need to be considered because number and placement of triangular facet sets influence the dimensional accuracy [8].

In this article, the role of STL model properties in combination with all part placement coordinates is investigated in the context of the only parameters influencing dimensional accuracy (process and material properties are not considered in this article, and more details on this are provided in Section 2). Specifically, the following aims were addressed:

– Tolerances for dimensional features, which are the width, thickness, and length, were compared for AM and injection molded polymers based on the [6] standard.
– A linear correlation between dimensional features and both part placement and STL model properties were studied by using Pearson correlation test.
– Linear regression models for prediction of thickness, width, and length were developed. These models can be used to calculate scaling ratio for each sample separately to minimize dimensional error.

Graphical visualization of collected data showed that it is important to analyze data separately for each parts' orientation groups (see Fig. 3). Thus, all dimensional features were predicted separately for each orientation group. Non-linear correlation and non-linear regression are outside of the scope of this study.

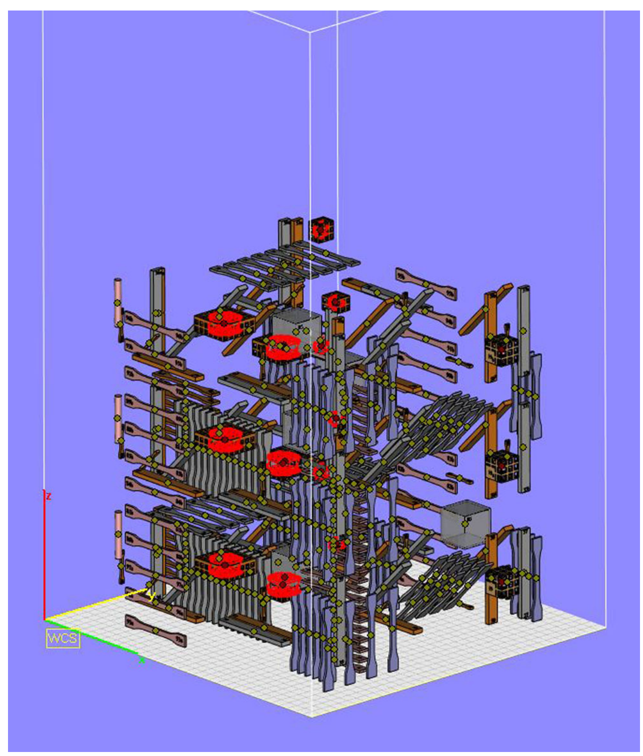


**Fig. 1** Build layout in Magics 20.0

**Table 1** Material and process parameters used in experiment

| Parameters | Value |
|---|---|
| Virgin/aged PA2200 powder ration (%) | 50/50 |
| EOS P395 system settings | Balance |
| AM system warm up time (min) | 120 |
| AM system cooling down time (min) | 240 |
| Working chamber temperature (°C) | 180.5 |
| Removal chamber temperature (°C) | 130.0 |

## 2 Experimental work

EOS P395 polymer laser sintering system from EOS Electrical Optical Systems GmbH was used in a practical experiment. The build layout illustrated in Fig. 1 was fabricated in two identical runs, where process (see Table 1) and material parameters were kept the same for both runs. The control of material properties were done based on the study of [11]. The authors introduced a procedure of artificial aging of virgin polymer powder, which allowed to control the material properties at each step of aging. The same procedure of polymer powder aging was used in this study, but the number of parts and placement strategy are different.

The schematic representation of the design of our experiment is shown in Fig. 2. The PA2200 powder was self-aged through 3 cycles of running EOS P395 without laser deposition. The aged PA2200 was mixed with virgin powder with a mixing ratio of 50/50% respectively. In each run, 358 different types of specimens were produced, but 217 standardized specimens type ISO 527-2 1BA are investigated in this article.

Each specimen has a label (on the top and bottom areas) to be able to follow part placement that is defined by the coordinates (*X*, *Y*, *Z* axes). A strategy for placement of the specimens was set to be close to real manufacturing conditions. It means that parts are placed as close to each other as possible, and the minimum distance between the specimens is set to 5 mm based on the recommendations from Magics 20.0 software. Additional attention was paid to the specimens, which are placed in the same orientation for the verification and validation of the results. In other words, more than five specimens in the same orientation were placed as close to each other as possible for better control of potential coordinate variations.

### 2.1 Part orientations

All investigated parts were placed in four different orientations (see Fig. 3), and names of the orientations were defined according to the [9] standard:

- Group 1. *XYZ* (*XY* in Fig. 3)-oriented parts
- Group 2. *XZY* (*XZ* in Fig. 3)-oriented parts
- Group 3. *ZYX* (*Z* in Fig. 3)-oriented parts
- Group 4. Angle-oriented parts

By the Angle-oriented parts, the author means parts oriented at 45° between *X* and *Z* axes.

Since the design of the experiment defined the requirement to fit as many specimens as possible, the number of specimens (the word “parts” is used as a synonym) in each orientation differ. Thus, 65 parts are placed in *XY* orientation, 24 parts in *XZ* orientation, 84 parts in *Z* orientation, and 44 in Angle orientation.

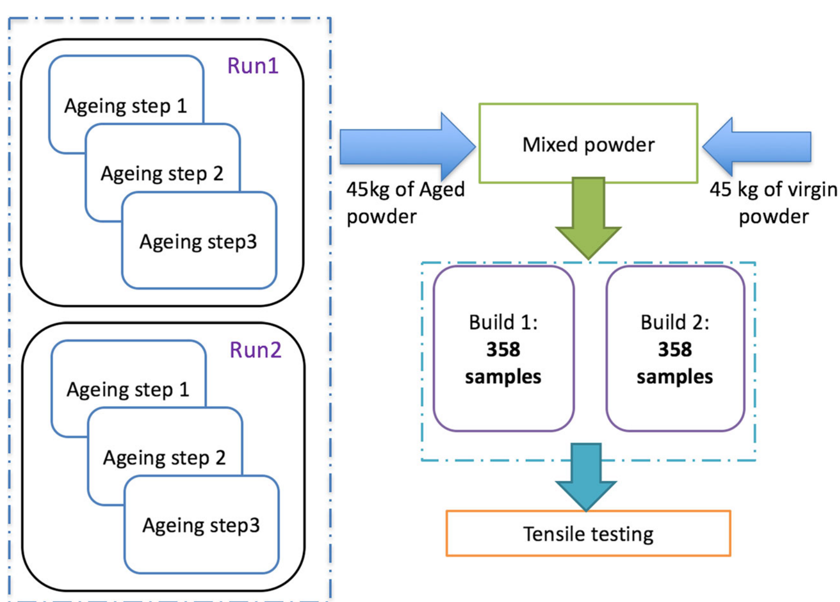


**Fig. 2** Visualization of design of experiment: from powder preparation to mechanical testing

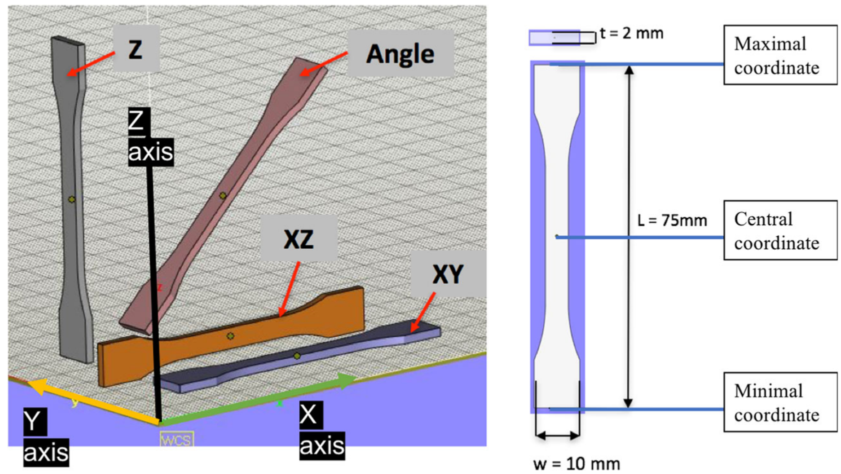


**Fig. 3** Schematic visualization of parts' orientation and dimensional features (where $t$ – thickness, $w$ – width, and $L$ – length )

Besides, to identify parts and be able to connect results of testing and measurements by part placement, every part has its label, which is placed on two sides of the part. This led to variations in the number of mesh triangles, surface and volume values for each part. Therefore, it is critical to evaluate whether these variations can influence the quality of the parts, and if yes, how we can control them.

## 2.2 The process of data collection

The data is collected from two identical runs and is used to evaluate the dimensional accuracy of produced specimens. Length value was measured using Digital ABS Caliper CoolantProof IP67 with accuracy ± 0.02 mm. Width and thickness were measured using Digital Micrometer QuantuMike IP65 with accuracy $\pm\ 1\mu m$. In addition, to minimize measurement error, the final value of each dimensional feature (see Fig. 3) was calculated as a mean of three repeated measurements, and mathematically described as follows:

$$y_1 = \frac{\sum_{n=1}^{3} y_1(n)}{n} \tag{1}$$

$$y_2 = \frac{\sum_{n=1}^{3} y_2(n)}{n} \tag{2}$$

$$y_3 = \frac{\sum_{n=1}^{3} y_3(n)}{n} \tag{3}$$

where $y_{1...3}$ represent measured thickness, length, and width respectively, and $n \in \{1, 2, 3\}$ is a number of repeated measurement.

## 3 Analysis and evaluation of the results for polymer laser sintering AM process

Since this experiment was based on the referencing work of [11] and their main goal was repeatability of the results, an evaluation of repeatability of the results for two identical runs should also be mentioned in this article. To evaluate the repeatability of results for polymer powder-based laser sintering AM process, visualization of values of dimensional features for different part orientations is used and presented in Figs. 4, 5, 6, 7, and 8.

For example, Fig. 4 illustrates the distribution of dimensional error for the thickness of all specimens obtained from two identical runs. The distribution of values for run 1 is identical to the distribution of the results for run 2. This means that distribution of obtained values are repeatable, and it is similar to the results from [11]. However, instead of normal distribution, a multimodal distribution is present. This can be explained by the presence of different placement orientations (see Fig. 4).

For better understanding of why multimodal distribution was observed and how different orientations contribute to it, visualization of the results for different part orientations separately is shown in Figs. 5, 6, 7, and 8. The first peak (to the left) in Fig. 4 is similar to the results in Fig. 7, but results in Fig. 6 has also values in the range of the first peak. The second peak can be defined by contributions of Angle orientation (the highest frequency—number of specimens with same value—of the values clothest to the peak range),

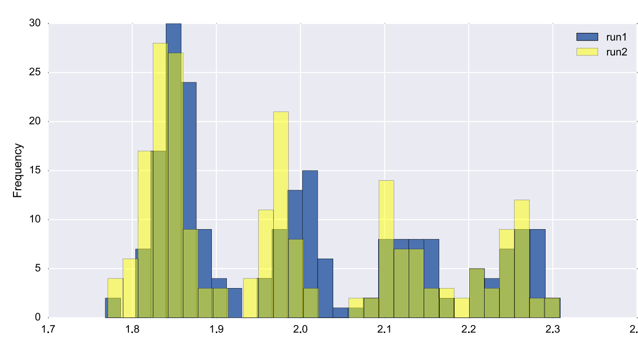


**Fig. 4** Dimensional error for thickness in all orientations

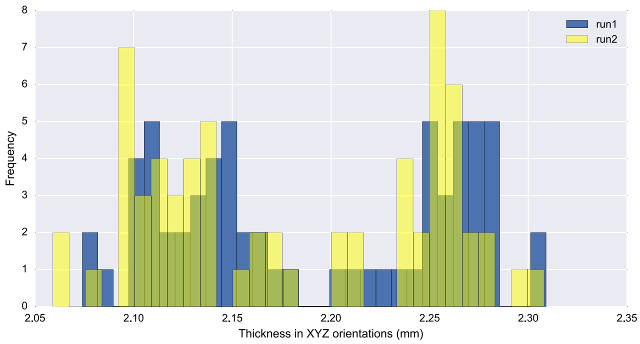


**Fig. 5** Dimensional error for thickness in *XYZ* orientation

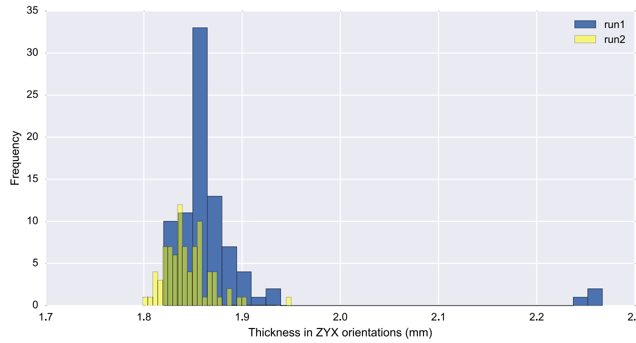


**Fig. 7** Dimensional error for thickness in *ZYX* orientation

then *XYZ* and *XZY* orientations. For the third peak in Fig. 4, the dominant orientations are *XYZ* and *XZY* following by the Angle orientation. The last peak can be described as a combination of *XYZ* (Fig. 5), *ZYX* (Fig. 6), and Angle (Fig. 8) orientations.

Since peaks cannot be described by one placement orientation, more detailed analysis should be performed to explain the observed variations for each dimensional feature. In addition, to identify the factors that have impact on the observed deviation, the correlation between dimensional features and both part placement (x, y, z coordinates) and STL model properties (number of mesh triangles, volume and surface of CAD model) is studied by using Pearson correlation test.

### 3.1 Comparison of tolerances for dimensional features for AM and injection molded polymers

According to DIN 16742:3013 standard [6], dimensional tolerances for objects with different sizes must differ. Even though this standard is used for injection molding, it can be considered for dimensional accuracy for polymer powder bed fusion AM process. The standard differentiates tolerance classes on fine, medium, coarse, and very coarse. In this article, the medium tolerance class is used as a reference class. For 2 mm object the dimensional tolerance is $\pm$ 0.1 mm, for 10 mm, it is $\pm$ 0.2mm, and for 75 mm $\pm$ 0.3 mm. These values are recalculated in percentage for easier comparison of the results, and are presented in Table 2 as DIN 16742 Medium tolerance class. Percent dimensional feature's deviation for the collected data is also shown in Table 2 and was calculated as follows:

$$D_a = D_o / D_t \times 100\% \tag{4}$$

where $D_a$ represents a percent dimensional feature's deviation, $D_o$ is a value of one of observed dimensional features, and $D_t$ is a theoretical/given (taken from CAD model) dimensional feature.

The average percent for dimensional feature's deviation was calculated using Eq. 4, and for example, for width, deviation is satisfactory in regard to medium tolerance class, except one value in Angle orientation for second run. However, tolerances for thickness and length are out of range (italic scripts in Table 2), especially for thickness values in *ZYX* and *XYZ* orientations [6].

For the better understanding of reasons why tolerances for dimensional feature's deviation are out of range defined by the standard, further analysis of data is required. Additionally, from Table 2 can also be seen that results for the first run are almost the same as for the second run, which supports previous statement about repeatability of the results for two identical runs.

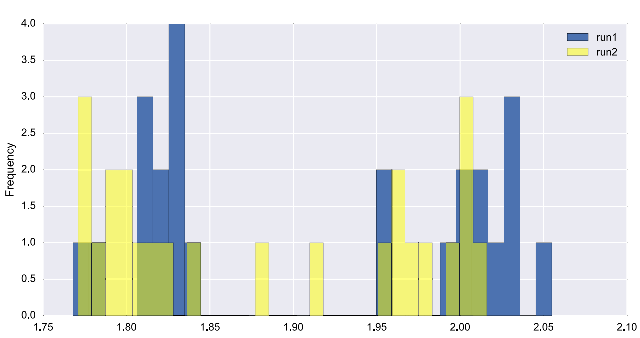


**Fig. 6** Dimensional error for thickness in *XZY* orientation

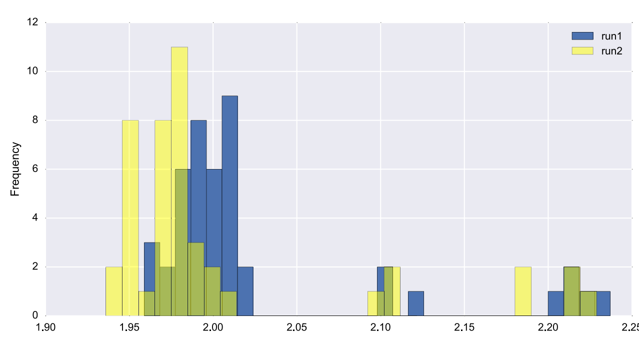


**Fig. 8** Dimensional error for thickness in Angle orientation

**Table 2** Average percent for dimensional feature's deviation for all specimens together and based on their orientations

| Orientation | Run | Thickness (%) | Width (%) | Length (%) |
|---|---|---|---|---|
| DIN 16742 Medium tolerance class | | 95–105 | 98–102 | 99.96–100.04 |
| *XYZ* | 1 | *109.586* | 98.619 | *99.764* |
| | 2 | *109.084* | 98.426 | *99.697* |
| *XZY* | 1 | 95.573 | 101.779 | *99.682* |
| | 2 | *94.248* | 101.598 | *99.684* |
| *ZYX* | 1 | *93.016* | 98.108 | *100.161* |
| | 2 | *92.219* | 98.159 | *100.189* |
| Angle | 1 | 101.387 | 98.095 | *100.088* |
| | 2 | 100.4 | *97.843* | *100.096* |
| All together | 1 | 99.959 | 98.665 | 99.974 |
| | 2 | 99.154 | 98.555 | 99.967 |

### 3.2 Study of linear correlation between dimensional features and both part placement and STL model properties by using Pearson correlation test

To study the linear correlation between thickness, width, length, and both part placement and STL model properties, Pearson correlation test is used. The correlation test was performed in the IBM SPSS Statistics software.

In addition, for better understanding of correlation test results, STL file data is presented for each orientation separately and compared with specimens in all orientations together. Thus, STL file data description for *XYZ* orientation is shown in Table 3, for *XZY* Table 5, for *ZYX* orientation Table 7 and Angle orientation is described in Table 9.

Comparing STL model data from different orientation groups and results from Pearson correlation test, a few observations can be evoked: if mean of STL model parameter within one orientation group is lower than its mean for all together, then in Pearson correlation test this parameter does not have linear correlation with dimensional features or has correlation but weak one. Another observation is that with higher STL model parameter value, linear correlation is also stronger.

STL data for both runs are the same because build layout were kept constant. This means that build layout was designed before fabricating specimens and used in both runs. However, variations between orientation groups and within orientation groups were observed due to different labels on each specimens (more details are described in Section 2.1).

#### 3.2.1 Data analysis of *XYZ*-oriented specimens

The results of Pearson correlation test are illustrated in Table 4 for the *XYZ*-oriented parts. These results show that the surface parameter has a significant negative linear correlation with width feature. It means that as the value of surface parameter increases, the width value decreases or opposite way. Along with this, volume value also has a significant positive linear correlation with width feature.

**Table 3** Comparison of STL model data in *XYZ* orientation and all specimens together

| Orientation | Run | Number of mesh triangles ($N$) | Volume ($m^3$) | Surface ($m^2$) |
|---|---|---|---|---|
| Mean value—*XYZ* | 1 | 3641.107 | 1034.347 | 1407.658 |
| | 2 | 3641.107 | 1034.347 | 1407.658 |
| Min value—*XYZ* | 1 | 1996.0 | 1030.372 | 1392.44 |
| | 2 | 1996.0 | 1030.372 | 1392.44 |
| Max value—*XYZ* | 1 | 6390.0 | 1036.854 | 1434.472 |
| | 2 | 6390.0 | 1036.854 | 1434.472 |
| Mean value—all together | 1 | 4130.359 | 1032.625 | 1417.69 |
| | 2 | 4130.359 | 1032.6259 | 1417.69 |
| Min value—all together | 1 | 1700.0 | 1028.445 | 1381.555 |
| | 2 | 1700.0 | 1028.445 | 1381.555 |
| Max value—all together | 1 | 6752.0 | 1038.801 | 1441.187 |
| | 2 | 6752.0 | 1038.801 | 1441.187 |

**Table 4** Pearson correlation test for combined results of run 1 and run 2 in *XYZ* orientation

| Feature | Pearson test | Width | Thickness | Length |
|---|---|---|---|---|
| Surface | Pearson correlation | −0.21** | 0.145 | −0.138 |
| | Sig. (2-tailed) | 0.016 | 0.099 | 0.119 |
| | *N* | 130 | 130 | 130 |
| Volume | Pearson correlation | 0.206* | −0.15 | 0.157 |
| | Sig. (2-tailed) | 0.018 | 0.087 | 0.075 |
| | *N* | 130 | 130 | 130 |
| Number of mesh triangles | Pearson correlation | −0.135 | 0.059 | −0.04 |
| | Sig. (2-tailed) | 0.127 | 0.505 | 0.649 |
| | *N* | 130 | 130 | 130 |
| Central, minimal, maximal coordinates X | Pearson correlation | −0.385** | −0.471** | −0.425** |
| | Sig. (2-tailed) | 0.000 | 0.000 | 0.000 |
| | *N* | 130 | 130 | 130 |
| Central, minimal, maximal coordinates Y | Pearson correlation | *0.614*** | 0.111 | *0.656*** |
| | Sig. (2-tailed) | 0.000 | 0.208 | 0.000 |
| | *N* | 130 | 130 | 130 |
| Central, minimal, maximal coordinates Z | Pearson correlation | 0.323** | 0.701** | 0.263** |
| | Sig. (2-tailed) | 0.000 | 0.000 | 0.003 |
| | *N* | 130 | 130 | 130 |

*Correlation is significant at the 0.05 level (2-tailed)

**Correlation is significant at the 0.01 level (2-tailed)

The number of mesh triangles in *XYZ* orientation (Table 3) does not have an impact on the variations of dimensional features.

Besides, some of the parts' placement characteristics, which are minimal, maximal, and central coordinates (see Fig. 3), have a large significant correlation with dimensional features (see Table 4). Thus, if to move a part in the build towards the positive direction of $y$ coordinates, the part will be thicker and longer than it was designed.

However, if to move a part towards a positive direction of $x$ coordinates, the part could be shorter, thinner or narrower than it was desired. Although, if to move a part higher in the build, the dimensional features of the part will increase. Besides, $z$ coordinates have the largest correlation coefficient with thickness feature, while $x$ coordinates dominate for width and length.

The results of correlation test are used to develop linear regression models for prediction of dimensional features. Therefore, the results presented in Table 4 are described in a matrix form as follows:

$$Y = XA \tag{5}$$

where, $Y$ is a set of dimensional features, $X$ is a set of all investigated parameters (coordinates and STL model properties), and $A$ is a coefficient matrix.

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} \tag{6}$$

where where $y_1$ is width parameter, $y_2$ thickness, and $y_3$ length.

$$X = \begin{bmatrix} x_1 & x_2 & x_3 & x_4 & x_5 & x_6 & x_7 & x_8 & x_9 & x_{10} & x_{11} & x_{12} \end{bmatrix} \tag{7}$$

where $x_1$ is surface, $x_2$ volume, $x_3$ number of mesh triangles, $x_4$ central $x$ coordinate, $x_5$ maximal $x$ coordinate, $x_6$ minimal $x$ coordinate, $x_7$ central $y$ coordinate, $x_8$ maximal $y$ coordinate, $x_9$ minimal $y$ coordinate, $x_{10}$ central $z$ coordinate, , $x_{11}$ maximal $z$ coordinate, and $x_{12}$ minimal $z$ coordinate.

$$A_{XYZ} = \begin{bmatrix} -a_{1,1} & 0 & 0 \\ a_{1,2} & 0 & 0 \\ 0 & 0 & 0 \\ -a_{1,4} & -a_{2,4} & -a_{3,4} \\ -a_{1,5} & -a_{2,5} & -a_{3,5} \\ -a_{1,6} & -a_{2,6} & -a_{3,6} \\ a_{1,7} & 0 & a_{3,7} \\ a_{1,8} & 0 & a_{3,8} \\ a_{1,9} & 0 & a_{3,9} \\ a_{1,10} & a_{2,10} & a_{3,10} \\ a_{1,11} & a_{2,11} & a_{3,11} \\ a_{1,12} & a_{2,12} & a_{3,12} \end{bmatrix} \tag{8}$$

where $A_{XYZ}$ is a coefficient matrix for *XYZ* orientation, $a_{i,j}$ (where $i \in \{1, 2, 3\}$ – width, thickness, and length respectively, and $j \in \{1..12\}$ number of investigated parameters) are unknown coefficients, which shows the

**Table 5** Comparison of STL model data in *XZY* orientation and all specimens together

| Orientation | Run | Number of mesh triangles ($N$) | Volume ($m^3$) | Surface ($m^2$) |
|---|---|---|---|---|
| Mean value—*XZY* | 1 | 5076.25 | 1029.512 | 1434.408 |
| | 2 | 5076.25 | 1029.512 | 1434.408 |
| Min value—*XZY* | 1 | 4158.0 | 1028.445 | 1428.687 |
| | 2 | 4158.0 | 1028.445 | 1428.687 |
| Max value—*XZY* | 1 | 6030.0 | 1030.963 | 1441.187 |
| | 2 | 6030.0 | 1030.963 | 1441.187 |
| Mean value—all together | 1 | 4130.359 | 1032.625 | 1417.69 |
| | 2 | 4130.359 | 1032.6259 | 1417.69 |
| Min value—all together | 1 | 1700.0 | 1028.445 | 1381.555 |
| | 2 | 1700.0 | 1028.445 | 1381.555 |
| Max value—all together | 1 | 6752.0 | 1038.801 | 1441.187 |
| | 2 | 6752.0 | 1038.801 | 1441.187 |

type of correlation between parameters. In addition, it is important to mention that in the coefficient matrix A, “0” means that linear significant correlation was, whereas “+ 1” or “− 1” indicate positive or negative significant correlation, respectively.

### 3.2.2 Data analysis of *XZY*-oriented specimens

In contrast to *XYZ* orientation, if the number of mesh triangles (in *XZY* orientation (Table 5)) decreases, according to the results in Table 6, width and thickness dimensional parameters will increase. In case number of mesh triangles increases, a part will be thinner or narrower. Besides, width is the most correlated to the number of mesh triangles among all STL model properties. Although, the surface is the only one parameter that is significantly correlated to length based on the results of Pearson correlation test.

However, both $x$ and $y$ coordinates (including minimal, maximal, and central) are significantly correlated with thickness parameter. The Pearson correlation coefficient in all cases is equal to 0.946, which is very close to the highest possible value for Pearson correlation coefficient (+ 1). Along with that, width will increase, if $z$ coordinates increase (positive correlation).

**Table 6** Pearson correlation test for combined results of run 1 and run 2 in *XZY* orientation

| Feature | Pearson test | Width | Thickness | Length |
|---|---|---|---|---|
| Surface | Pearson correlation | −0.040 | −0.177 | −0.296* |
| | Sig. (2-tailed) | 0.79 | 0.228 | 0.041 |
| | *N* | 48 | 48 | 48 |
| Volume | Pearson correlation | −0.097 | 0.149 | 0.270 |
| | Sig. (2-tailed) | 0.514 | 0.311 | 0.064 |
| | *N* | 48 | 48 | 48 |
| Number of mesh triangles | Pearson correlation | −0.522** | −0.327* | −0.189 |
| | Sig. (2-tailed) | 0.127 | 0.505 | 0.649 |
| | N | 48 | 48 | 48 |
| Central, minimal, maximal coordinates $X$ and $Y$ | Pearson correlation | −0.007 | *0.946*** | 0.129 |
| | Sig. (2-tailed) | 0.962 | 0.000 | 0.382 |
| | *N* | 48 | 48 | 48 |
| Central, minimal, maximal coordinates $Z$ | Pearson correlation | *0.618*** | 0.101 | 0.232 |
| | Sig. (2-tailed) | 0.000 | 0.493 | 0.112 |
| | *N* | 48 | 48 | 48 |

*Correlation is significant at the 0.05 level (2-tailed)

**Correlation is significant at the 0.01 level (2-tailed)

The coefficient matrix for *XZY* orientation (Eq. 9) should be used as a part of Eq. 5.

$$A_{XZY} = \begin{bmatrix} 0 & 0 & -a_{3,1} \\ 0 & 0 & 0 \\ -a_{1,3} & -a_{2,3} & 0 \\ 0 & a_{2,4} & 0 \\ 0 & a_{2,5} & 0 \\ 0 & a_{2,6} & 0 \\ 0 & a_{2,7} & 0 \\ 0 & a_{2,8} & 0 \\ 0 & a_{2,9} & 0 \\ a_{1,10} & 0 & 0 \\ a_{1,11} & 0 & 0 \\ a_{1,12} & 0 & 0 \end{bmatrix} \quad (9)$$

where $A_{XZY}$ is a coefficient matrix for *XZY* orientation, $a_{i,j}$ (where $i \in \{1, 2, 3\}$ – width, thickness and length respectively, and $j \in \{1..12\}$– number of invistigated parameters).

#### 3.2.3 Data analysis of *ZYX*-oriented specimens

In *ZYX* orientation, all STL model properties (Table 7) have significant correlation with dimensional parameters. For example, as number of mesh triangles increases, the part is longer (length value increases). On the one hand, the surface parameter is positively correlated to length. On the other hand, if volume value decreases, the length will increase, or if volume characteristic increases, length is expected to decrease—negative correlation.

Additionally, negative significant correlation was also observed for all $y$ coordinates and length, and negative for all $x$ coordinates and width feature. However, the only $y$ coordinates are significantly correlated to thickness dimension.

According to the results depicted in Table 8, the strongest positive correlation is between all $z$ coordinates and length characteristic (Pearson coefficient is greater than 0.8). It means the higher in build part is placed, the longer part will be in the result.

The coefficient matrix for *ZYX* orientation is the following:

$$A_{ZYX} = \begin{bmatrix} 0 & 0 & a_{3,1} \\ 0 & 0 & -a_{3,2} \\ 0 & 0 & a_{3,3} \\ -a_{1,4} & 0 & a_{3,4} \\ -a_{1,5} & 0 & a_{3,5} \\ -a_{1,6} & 0 & a_{3,6} \\ a_{1,7} & a_{2,7} & -a_{3,7} \\ a_{1,8} & a_{2,8} & -a_{3,8} \\ a_{1,9} & a_{2,9} & -a_{3,9} \\ 0 & 0 & a_{3,10} \\ 0 & 0 & a_{3,11} \\ 0 & 0 & a_{3,12} \end{bmatrix} \quad (10)$$

where $A_{ZYX}$ is a coefficient matrix for *ZYX* orientation, $a_{i,j}$ (where $i \in \{1, 2, 3\}$ width, thickness, and length respectively, and $j \in \{1..12\}$ number of investigated parameters).

#### 3.2.4 Data analysis of Angle-oriented specimens

In *Angle orientation*, the largest significant correlation for STL model properties (Table 9) is between number of mesh triangles and length parameter. Pearson correlation coefficient is greater than 0.5 and this value is higher even comparing to other parameters in any other build orientations. In addition, length parameter is also positively correlated to surface parameter, but negatively with volume.

**Table 7** Comparison of STL model data in *ZYX* orientation and all specimens together

| Orientation | Run | Number of mesh triangles ($N$) | Volume ($m^3$) | Surface ($m^2$) |
|---|---|---|---|---|
| Mean value—*ZYX* | 1 | 4305.404 | 1031.943 | 1422.024 |
| | 2 | 4305.404 | 1031.943 | 1422.024 |
| Min value—*ZYX* | 1 | 1700.0 | 1029.291 | 1381.555 |
| | 2 | 1700.0 | 1029.291 | 1381.555 |
| Max value—*ZYX* | 1 | 6232.0 | 1038.801 | 1438.168 |
| | 2 | 6232.0 | 1038.801 | 1438.168 |
| Mean value—all together | 1 | 4130.359 | 1032.625 | 1417.69 |
| | 2 | 4130.359 | 1032.6259 | 1417.69 |
| Min value—all together | 1 | 1700.0 | 1028.445 | 1381.555 |
| | 2 | 1700.0 | 1028.445 | 1381.555 |
| Max value—all together | 1 | 6752.0 | 1038.801 | 1441.187 |
| | 2 | 6752.0 | 1038.801 | 1441.187 |

**Table 8** Pearson correlation test for combined results of run 1 and run 2 in *ZYX* orientation

| Feature | Pearson test | Width | Thickness | Length |
|---|---|---|---|---|
| | Pearson correlation | −0.01 | 0.136 | 0.414** |
| Surface | Sig. (2-tailed) | 0.893 | 0.0.078 | 0.000 |
| | *N* | 168 | 168 | 168 |
| Volume | Pearson correlation | 0.016 | −0.143 | −0.422** |
| | Sig. (2-tailed) | 0.841 | 0.065 | 0.000 |
| | *N* | 168 | 168 | 168 |
| Number of mesh triangles | Pearson correlation | −0.041 | 0.082 | 0.420** |
| | Sig. (2-tailed) | 0.596 | 0.293 | 0.000 |
| | *N* | 168 | 168 | 168 |
| Central coordinate *X* | Pearson correlation | −0.252** | 0.113 | 0.398** |
| | Sig. (2-tailed) | 0.001 | 0.146 | 0.000 |
| | *N* | 168 | 168 | 168 |
| Minimal and maximal coordinates *X* | Pearson correlation | −0.252** | 0.112 | 0.398** |
| | Sig. (2-tailed) | 0.001 | 0.147 | 0.000 |
| | *N* | 168 | 168 | 168 |
| Central, minimal, maximal coordinates *Y* | Pearson correlation | *0.413*** | *0.419*** | −0.222** |
| | Sig. (2-tailed) | 0.000 | 0.000 | 0.004 |
| | *N* | 168 | 168 | 168 |
| Central, minimal, maximal coordinates *Z* | Pearson correlation | −0.14 | 0.142 | *0.919*** |
| | Sig. (2-tailed) | 0.069 | 0.066 | 0.000 |
| | *N* | 168 | 168 | 168 |

*Correlation is significant at the 0.05 level (2-tailed)

**Correlation is significant at the 0.01 level (2-tailed)

However, behavior of correlation between dimensional features and parameters are different than for all other orientation groups. On the one hand, strong correlation between coordinates and dimensional features is observed. On the other hand, results of Pearson correlation test for central, maximal, and minimal $z$ coordinates differ significantly. As it can be seen in Table 10, minimal $z$ coordinates does not lineary correlate to any of the dimensional features, whereas central and maximal $z$ coordinates have strong positive correlation.

This result can be explained by two possible reasons. First of all, a small number of samples for this orientation

**Table 9** Comparison of STL model data in Angle orientation and all specimens together

| Orientation | Run | Number of mesh triangles (*N*) | Volume ($m^3$) | Surface ($m^2$) |
|---|---|---|---|---|
| Mean value—Angle | 1 | 4003.0 | 1033.08 | 1415.116 |
| | 2 | 4003.0 | 1033.08 | 1415.116 |
| Min value—Angle | 1 | 2468.0 | 1029.925 | 1401.787 |
| | 2 | 2468.0 | 1029.925 | 1401.787 |
| Max value—Angle | 1 | 6752.0 | 1035.427 | 1432.56 |
| | 2 | 6752.0 | 1035.427 | 1432.56 |
| Mean value—all together | 1 | 4130.359 | 1032.625 | 1417.69 |
| | 2 | 4130.359 | 1032.6259 | 1417.69 |
| Min value—all together | 1 | 1700.0 | 1028.445 | 1381.555 |
| | 2 | 1700.0 | 1028.445 | 1381.555 |
| Max value—all together | 1 | 6752.0 | 1038.801 | 1441.187 |
| | 2 | 6752.0 | 1038.801 | 1441.187 |

were produced, and this could influence the correlation test. Second of all, a layer thickness parameter of polymer powder bed fusion machine could also lead to this result. The layer thickness depends on $Z$ axis and characterizes how much powder will be distributed on the bed of AM machine. This means that before 3D printing is started, all parts in the build are sliced into layers based on the value of this parameter. Since many parts have the same Z coordinates in the build, there is a possibility that the bottom and top sides of specimens have different number of millimeters in one layer. However, more attention should be paid to this issue in the future experiments.

The correlation matrix for Angle orientation is the following:

$$A_{\text{Angle}} = \begin{bmatrix} 0 & 0 & a_{3,1} \\ 0 & 0 & -a_{3,2} \\ 0 & 0 & a_{3,3} \\ 0 & -a_{2,4} & a_{3,4} \\ 0 & -a_{2,5} & a_{3,5} \\ 0 & -a_{2,6} & a_{3,6} \\ a_{1,7} & -a_{2,7} & a_{3,7} \\ a_{1,8} & -a_{2,8} & a_{3,8} \\ a_{1,9} & -a_{2,9} & a_{3,9} \\ a_{1,10} & -a_{2,10} & a_{3,10} \\ 0 & 0 & 0 \\ a_{1,12} & -a_{2,12} & a_{3,12} \end{bmatrix} \tag{11}$$

where $A_{\text{Angle}}$ is a coefficient matrix for Angle orientation, $a_{i,j}$ (where $i \in \{1, 2, 3\}$ – width, thickness, and length respectively, and $j \in \{1..12\}$ number of investigated parameters).

### 3.2.5 Summary of the results from Pearson correlation test

Summary of the results of Pearson correlation test is illustrated in Figs. 9, 10, and 11, where 100% is equal to the sum of Pearson correlation coefficients for all investigated parameters. Then, Pearson correlation coefficient was recalculated considering this sum for easier comparison of the importance of the studied parameters in regard to each other. For example, results in Fig. 9 show the relative contribution of such parameters as $x$, $y$, and $z$ coordinates, amount of mesh triangles, volume and surface to a thickness dimensional feature. In the same way, contribution of named characteristics to width and length are illustrated in Figs. 10 and 11 respectively.

**Recommendations for *XYZ* orientation** In case when tolerance range for thickness is tight, part should be first placed close to center (height) of the build. Then, $x$ coordinate should be adjusted—to place part in the area with the lowest $x$ coordinate values. The $y$ coordinates do not influence the quality of thickness, and thus any placement for this axis can be used. For width and length dimensional features, results are different. First of all, $y$ coordinates need to be adjusted by moving part towards positive value of $y$ coordinates. The next axis is $x$, which should be chosen in the same way as for thickness. Then, $z$ coordinates will be the last to adjust, and the higher value of this coordinate the better accuracy of width and length should be achieved.

**Recommendations for *XZY* orientation** To achieve the best accuracy for thickness, $x$ and $y$ coordinates should be adjusted together by moving part in positive direction for both axes. However, number of mesh triangles in the CAD model needs to decreased.

For width dimensional feature, recommendation regarding number of mesh triangles is exactly the same as for thickness. Although, instead of considering $x$ and $y$ coordinates, part should be first placed as close to the center (height) of the build as possible to achieve better accuracy for width dimensional feature.

In order to minimize dimensional error for length, adjustments in CAD model should be done first (decrease a surface value), and then placement in the build should be adjusted considering $z$ coordinate (higher in a build—wider part will be printed). Since $x$ and $y$ coordinates do not influence quality of a part, it is not possible to give recommendations on which one should be adjusted first, or in which direction part should be moved in the build.

**Recommendations for *ZYX* orientation** Thickness dimensional feature depends the most on $y$ coordinates. This means that part should be first moved towards the positive direction of $y$ axis. For width, $y$ coordinates should also be adjusted first in the same way as for thickness. Then, $x$ coordinates should be chosen, and part needs to be moved to the area with the lowest $x$ coordinates. As a result, the height should be the last to choose, but how height in the build the part should be placed is not possible to say.

**Recommendations for Angle orientation** Improving the accuracy of thickness requires placing a part in the build by choosing $y$ coordinate first (towards the lowest values); then, the $x$ coordinate should be chosen in the same way as the latter one. Finally, $z$ coordinates can be adjusted by moving part lower in the build.

For width dimensional feature, $y$ coordinate should also be chosen first, but towards the positive directions of $y$ axis. After this, the part should be placed in the build as closed to the center as possible.

**Table 10** Pearson correlation test for combined results of run 1 and run 2 in Angle orientation

| Feature | Pearson test | Width | Thickness | Length |
|---|---|---|---|---|
| Surface | Pearson correlation | 0.002 | 0.176 | 0.295** |
| | Sig. (2-tailed) | 0.989 | 0.100 | 0.005 |
| | *N* | 88 | 88 | 88 |
| Volume | Pearson correlation | −0.002 | −0.151 | −0.305** |
| | Sig. (2-tailed) | 0.984 | 0.159 | 0.004 |
| | *N* | 88 | 88 | 88 |
| Number of mesh triangles | Pearson correlation | 0.073 | −0.037 | 0.511** |
| | Sig. (2-tailed) | 0.497 | 0.733 | 0.000 |
| | *N* | 88 | 88 | 88 |
| Central coordinate *X* | Pearson correlation | −0.033 | −0.666** | *0.604*** |
| | Sig. (2-tailed) | 0.759 | 0.000 | 0.000 |
| | *N* | 88 | 88 | 88 |
| Minimal coordinate *X* | Pearson correlation | −0.014 | −0.686** | *0.619*** |
| | Sig. (2-tailed) | 0.894 | 0.000 | 0.000 |
| | *N* | 88 | 88 | 88 |
| Maximal coordinate *X* | Pearson correlation | −0.053 | −0.646** | *0.588*** |
| | Sig. (2-tailed) | 0.625 | 0.000 | 0.000 |
| | *N* | 88 | 88 | 88 |
| Central, minimal, maximal coordinates *Y* | Pearson correlation | *0.610*** | −0.731** | 0.580** |
| | Sig. (2-tailed) | 0.000 | 0.000 | 0.000 |
| | *N* | 88 | 88 | 88 |
| Central coordinate *Z* | Pearson correlation | 0.217* | −0.260** | *0.800*** |
| | Sig. (2-tailed) | 0.043 | 0.001 | 0.000 |
| | *N* | 88 | 88 | 88 |
| Minimal coordinate *Z* | Pearson correlation | 0.148 | −0.031 | 0.061 |
| | Sig. (2-tailed) | 0.169 | 0.778 | 0.572 |
| | *N* | 88 | 88 | 88 |
| Maximal coordinate *Z* | Pearson correlation | 0.271* | −0.473** | *0.862*** |
| | Sig. (2-tailed) | 0.011 | 0.000 | 0.000 |
| | *N* | 88 | 88 | 88 |

*Correlation is significant at the 0.05 level (2-tailed)

**Correlation is significant at the 0.01 level (2-tailed)

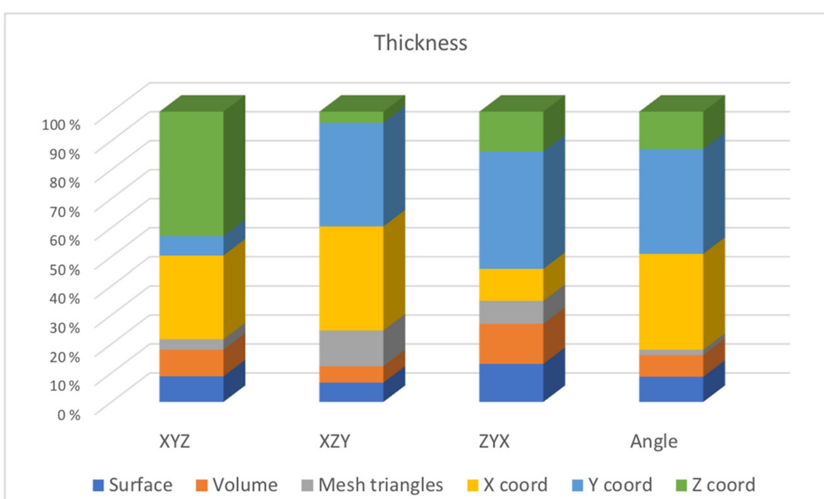


**Fig. 9** Relative contribution of investigated parameters to thickness

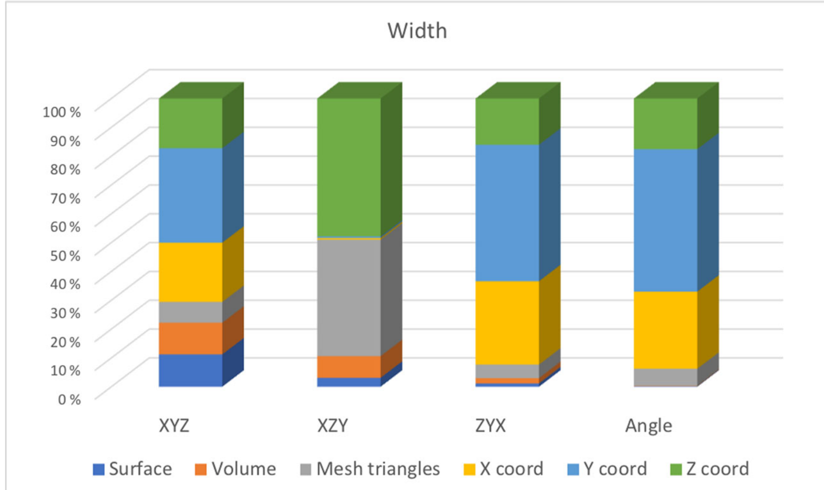


**Fig. 10** Relative contribution of investigated parameters to width

However, for the length, $z$ coordinates should be depicted first, then following by $x$ and $y$ coordinates (towards the positive direction of these values). In addition, number of mesh triangles needs to be increased, and control of surface and volume parameters should be done in CAD model of the part.

These recommendations are valid for the parts that will be 3D printed with dimensional features close to the required ones or bigger. In this case, to fix the dimensional features is possible with post-processing (CNC machining). However, this solution still requires additional cost and more time to produce the part with desired dimensional characteristics. Therefore, adjusting thickness, width, and length based on part placement and STL model properties will be a better solution. Since scaling ratio can be calculated by using predicted values of dimensional features, provided recommendations are considered for developing linear regression models.

### 3.3 Linear regression models for prediction of dimensional features

Linear regression modeling is done by using linear model module with function linear regression in Python programming language (i.e., Scikit-Learn libraries [10]). This function implements ordinary least squares linear regression including data normalization. Besides, collected data should be divided into training and testing sets. The former set is used to train a linear model and the latter set is used to make a prediction. The coefficient of determination is used as a performance metric to evaluate developed regression models. Typically, this coefficient lies in the range from 0 to 1, where 0 means that model does not predict expected value and 1 when it perfectly fits expected value. However, negative value of the coefficient of determination is presented in Table 11. This means that this model strongly does not predict an expected value.

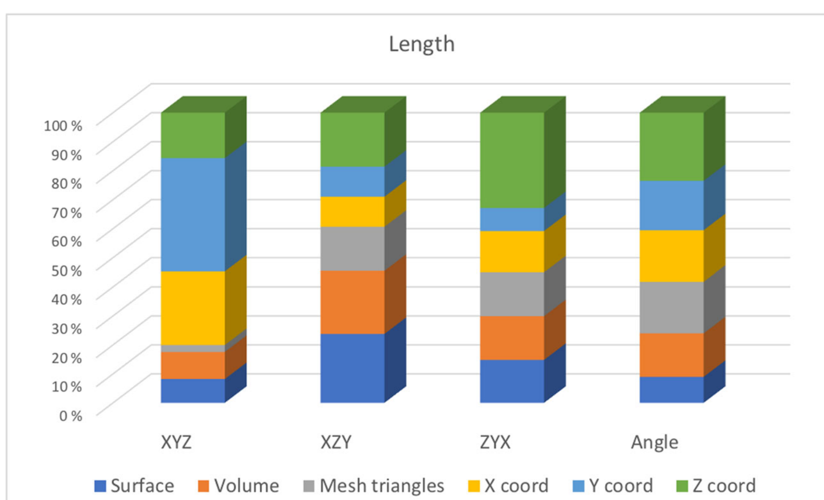


**Fig. 11** Relative contribution of investigated parameters to length

**Table 11** Regression models to predict dimensional parameters of the parts ($x_1$—surface, $x_2$—volume, $x_3$—number of mesh triangles, $x_4$—central $x$ coordinate, $x_5$—maximal $x$ coordinate, $x_6$—minimal $x$ coordinate, $x_7$—central $y$ coordinate, $x_8$—maximal $y$ coordinate, $x_9$—minimal $y$ coordinate, $x_{10}$—central $z$ coordinate, , $x_{11}$—maximal $z$ coordinate, and $x_{12}$—minimal $z$ coordinate)

| Orientation | Model | $R^2$ |
|---|---|---|
| *XYZ* | width $= -135.44 - 3.86695x_4 + 3.86685x_5 + 0.00191x_7 + 2274469275x_{10} - 113723463x_{11} - 11372346x_{12}$ | 0.096 |
| | thickness $= 11.56 - 0.009037x_2 - 0.0000177x_3 - 0.0002463x_4 + 0.0005833x_{10}$ | 0.580 |
| | length $= 74.682 - 0.000272x_4 + 0.00122x_7$ | 0.306 |
| *XZY* | width $= 10.378 - 0.000054x_3 + 0.000426x_{10}$ | 0.550 |
| | thickness $= 1.604 - 0.0000129x_3 + 0.000236x_4 + 0.000126x_{10}$ | *0.906* |
| | length $= 80.961 - 0.00435x_1 + 0.000013x_4 + 0.000181x_{10}$ | 0.084 |
| *ZYX* | width $= 9.792 + 0.000001x_3 + 0.000132x_7 - 0.000026x_{10}$ | 0.073 |
| | thickness $= 6.734 - 0.00136x_1 - 0.00288x_2 - 0.0000067x_3 + 0.00024x_7 + 0.00019x_{10}$ | −0.508 |
| | length $= 198.205 - 0.0167x_1 - 0.0966x_2 - 0.00099x_7 + 0.4715x_{10} - 0.234x_{11} - 0.234x_{12}$ | *0.935* |
| Angle | width $= 0.9799 + 0.005148x_1 + 0.00237x_2 + 0.000016x_3 + 0.000775x_7 - 0.000115x_{10}$ | 0.440 |
| | thickness $= 2.236 + 0.000025x_3 - 0.000532x_4 - 0.000837x_7 - 0.000355x_{10}$ | *0.745* |
| | length $= 181.75 - 0.0195x_1 - 0.0805x_2 + 0.000029x_3 + 0.0916x_4 - 0.0917x_6 - 0.000395x_7 -$ $-0.0453x_{10} + 0.0476x_{11}$ | *0.887* |

The first version of regression models was developed based on the results of Pearson correlation test, and by this reason, every model is developed for each type of orientation separately. After this, different sets of the parameters were tested based on the results of correlation test. Models with the highest value of coefficient of determination were chosen as the final and are shown in Table 11.

As it can be seen in Table 11, regression model for length in *ZYX* orientation shows the best fit among all developed linear models. Besides, regression model for prediction of length in Angle orientation also shows relatively good fit. In addition, regression models for prediction of thickness in *XZY* and Angle orientation have a determination coefficient higher than 0.745 (relatively good fit). These can be explained by the existence of a strong linear correlation between some of the dimensional features and investigated parameters. However, models, which do not predict expected value of dimensional feature, could have a non-linear correlation between parameters and dimensional features.

Regression models that showed a good fit may already be used to adjust scaling ratio for each specimen individually. Scaling ratio can be calculated by using predicted values versus desired ones. In this way, it will be possible to make changes in the CAD models before they will be fabricated. These changes could contribute to sustainability concept by reducing material usage (less parts with wrong dimensions or avoid post-processing) and reduce energy consumption (additional runs for parts that are not within the tolerance range, and using CNC machines for post-processing).

However, proposed models needs to be used for similar shape and size parts, or they should be modified for another cases. Therefore, more experimental work is required to collect data for different parameters, part sizes, and shapes. In addition, more complex methods for non-linear modeling should be investigated in the future for addressing issues with models' generalization.

## 4 Conclusion

Statistical analysis of dimensional accuracy in additive manufacturing considering STL model properties was done. The EOS P395 polymer powder bed fusion system was used to produce two identical runs with 358 specimens in each build, but 217 standardized specimens type ISO 527-2 1BA were investigated. The collected data from experimental work was divided into four groups (i.e., *XYZ*-oriented, *XZY*-oriented, *ZYX*-oriented, and Angle-oriented) based on the specimens' orientation.

Influence of part placement parameters ($x$, $y$, and $z$ coordinates including maximal, central, and minimal values) and STL model properties (number of mesh triangles, surface, and volume of CAD model) on thickness, width, and length of the specimens were statistically analyzed. The Pearson correlation test was used to study correlation between dimensional features and investigated parameters.

The results show that STL model properties influence some of the dimensional features depending on their orientation. For example, width (in *XYZ* orientation) and length (in *ZYX* and Angle orientation) are affected by surface and volume parameters in addition to part placement parameters. The number of mesh triangles has an impact on width and thickness (in *XZY* orientation), and length (in *ZYX* and Angle orientations).

Using results of correlation test, recommendations for part placement strategy were proposed for each orientation group separately. However, these recommendations do not provide information for all investigated parameters and are hard to follow in real-time manufacturing. Therefore, minimizing shrinkage effect with a help of predicted scaling ratio would be a better choice.

Based on these results, linear regression models were developed to predict value of thickness, width, and length. In other words, regression models can be used to minimize shrinkage effect by proposing scaling ratio for each specimen in the build separately. However, models for thickness (in *XZY* orientation), length (in *ZYX* orientation), and length and thickness (in Angle orientation) can already be used for this purpose but for the same size and shape parts like the investigated ones. All other models need to be improved in the future because their determination coefficients are low. This means that models do not approximate well values of the dimensional features.

Therefore, to improve developed models, more experiments should be done in the future. Since in this article data was collected from two identical runs, different combinations of parts' shape/size, process or material parameters will be investigated. For example, instead of self-aged used powder to use regular used powder. In process parameters, layer thickness or scan strategy could be changed in order to collect more data. In addition, more advanced regression techniques should be used to determine non-linear correlations between dimensional features and parameters related to AM process.

**Funding information** This research is funded by Norwegian Research Council as a part of MKRAM project.



## References

1. Baturynska I, Semeniuta O, Martinsen K (2018) Optimization of process parameters for powder bed fusion additive manufacturing by combination of machine learning and finite element method: a conceptual framework. Procedia CIRP 67C:227–232
2. Casalino G, Campanelli S, Contuzzi N, Ludovico A (2015) Experimental investigation and statistical optimisation of the selective laser melting process of a maraging steel. Opt Laser Technol 65:151–158
3. Caulfield B, McHugh P, Lohfeld S (2007) Dependence of mechanical properties of polyamide components on build parameters in the sls process. J Mater Process Technol 182(1):477–488
4. De Ciurana J, Serenóa L, Vallès È (2013) Selecting process parameters in reprap additive manufacturing system for pla scaffolds manufacture. Procedia CIRP 5:152–157
5. Delgado J, Ciurana J, Rodríguez CA (2012) Influence of process parameters on part quality and mechanical properties for dmls and slm with iron-based materials. Int J Adv Manuf Technol 60(5–8):601–610
6. DIN 16742:2013 (2013) Plastics mouldings: tolerances and acceptance conditions. Standard, German Institute for Standardization
7. Dingal S, Pradhan T, Sundar JS, Choudhury AR, Roy S (2008) The application of taguchi's method in the experimental investigation of the laser sintering process. Int J Adv Manuf Technol 38(9-10):904–914
8. Hur SM, Choi KH, Lee SH, Chang PK (2001) Determination of fabricating orientation and packing in sls process. J Mater Process Technol 112(2):236–243
9. ISO/ASTM 52921:2013(E) (2013) Standard terminology for additive manufacturing: coordinate systems and test methodologies. Standard, ISO/ASTM International
10. Pedregosa F, Varoquaux G, Gramfort A, Michel V, Thirion B, Grisel O, Blondel M, Prettenhofer P, Weiss R, Dubourg V, Vanderplas J, Passos A, Cournapeau D, Brucher M, Perrot M, Duchesnay E (2011) Scikit-learn: machine learning in Python. J Mach Learn Res 12:2825–2830
11. Rüsenberg S, Josupeit S, Schmid HJ (2014) A method to characterize the quality of a polymer laser sintering process. Adv Mech Eng 6:185,374
12. Senthilkumaran K, Pandey PM, Rao P (2009) Influence of building strategies on the accuracy of parts in selective laser sintering. Mater Des 30(8):2946–2954
13. Senthilkumaran K, Pandey PM, Rao P (2009) New model for shrinkage compensation in selective laser sintering. Virtual and Physical Prototyping 4(2):49–62
14. Shah P, Racasan R, Bills P (2016) Comparison of different additive manufacturing methods using computed tomography. Case Studies in Nondestructive Testing and Evaluation 6:69–78. https://doi.org/10.1016/j.csndt.2016.05.008, special Issue: Industrial computed tomography
15. Singh S, Sharma VS, Sachdeva A (2012) Optimization and analysis of shrinkage in selective laser sintered polyamide parts. Mater Manuf Process 27(6):707–714
16. Wohlers T (2016) Wohlers report 2016. Wohlers Associates, Inc
17. Yang HJ, Hwang PJ, Lee SH (2002) A study on shrinkage compensation of the sls process by using the taguchi method. Int J Mach Tools Manuf 42(11):1203–1212