Research on the study of the dimensional precision of the parts obtained by Additive Manufacturing

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Abstract. This article presents research concerning the dimensional accuracy of parts obtained by additive manufacturing, 3D printing. The challenges of additive technology are exposed and also the need to have a vision on the influence of certain technological and geometric parameters on the precision of geometric surfaces. First, a virtual prototype was produced with Catia V5. Then, the virtual prototype was imported by the 3D machine software to obtain the prototyping codes for nine prototypes. The parameters of these prototypes were chosen with the Taguchi method. On the basis of the code obtained with the printer software, the parts have been prototyped, using the Z-ULTRAT material with a ZORTRAX M200 printer. All parts were measured and a database was created. The results were interpreted in order to establish the influence on the dimensional precision for the parts obtained by Additive Manufacturing.

1. Introduction

Today, the products have become more and more personalized, due to the high demands of the users. Additive Manufacturing is a new technology that allows the production of the parts with complex shapes and structures. Additive Manufacturing is defined as a process of joining materials to realize objects based on 3D model data, usually layer upon layer, as opposed to sub-tractive manufacturing methodologies, ISO/ASTM 52915 [1].

The development of the low-cost 3D printers was opened new perspectives for the designers and for the students at the engineering’s faculty. Thus, they can design and prototype structures at low costs, rapidly, in their laboratory and the interaction with a real prototype being much more accessible than in previous years.

Most of the low-cost printer’s make the pieces from ABS (acrylonitrile butadiene styrene) or PLA (polylactic acid). There are, of course, some materials developed by the printer manufacturers. This article presents a study performed on parts obtained from the Z-ULTRAT material developed by the printer manufacturer ZORTRAX. The parts obtained by Additive Manufacturing have a resistance of 80% of that of the original material.

This technology is a very complex one, based on thermomechanical processes, on high speed and precise displacements [2, 3, 4, 6]. Because of this complexity of technology an important number of problems that are still vague, like: clogged extruder, grinding filament, material stringing, overheating, layer shifting, weak infill, inconsistent extrusion and so on. This technological issues causes some inconvenient for the parts realized: dimensional instability, structural anisotropy, inhomogeneous roughness and so on [8, 10].
In order to be able to use the prototypes made for the applications they develop, the specialists need to know the influences of the technological parameters for a certain category of printers and for a certain material, on the dimensional precision of the parts obtained in the laboratory [9, 11].

An experiment was made at University of Pitești, in the laboratory of Product design and development, in order to determine the dimensional accuracy of the pieces with the thin walls obtained by Additive Manufacturing process.

2. Material, samples and measuring equipment
The material used for this experiment is Z-ULTRAT. This material is a thermoplastic one, characterized by good impact resistance, which gives a uniform texture to the surface of the parts. By this material we can print high durability parts, also finished parts, which can retain their original shape after a long use. With Z-ULTRAT, it is possible to produce pieces with the properties comparable to those manufactured by conventional technologies (for example the injection moulding), including functional prototypes and some mechanical parts.

![Figure 1](image1.png)

**Figure 1.** Geometry of specimen and measurement scheme.

The 3D model of the specimen is realized with Catia V5 software. The 3D model is imported in Z-Suite software in order to generate the code for the 3D Printer ZORTRAX M200, figure 2.
Figure 2. The specimen imported in Z-Suite software.

For measuring the dimensions on the samples, we used a caliper with a range of measurement between 0 to 150 mm and an accuracy of 0,01 mm.

The Minitab software was used to create a Taguchi plan for experimentation. We chose a plan with 3 factors and 3 levels for each factor. A number of 9 specimens was realized. The following parameters were chosen as inputs: layer thickness, infill density and orientation of the specimen on the table of the printer (0° - parallel with X axis, 90° - perpendicular on X axis of the printer table). The output parameters are: HR – height right and HL – height left, table 1.

Table 1. The dataset for the experiment.

| Exp. no. | Layer thickness (mm) | Infill density (%) | Orientation (degrees) | HR1 | HR2 | HR3 | HR4 | HR5 | HL1 | HL2 | HL3 | HL4 | HL5 |
|----------|----------------------|--------------------|-----------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 1        | 0,14                 | 10                 | 0                     | 22,05 | 22,20 | 22,24 | 22,18 | 21,95 | 22,05 | 22,14 | 22,24 | 22,16 | 21,94 |
| 2        | 0,14                 | 50                 | 45                    | 22,03 | 22,20 | 22,26 | 22,17 | 22,03 | 22,01 | 22,19 | 22,23 | 22,14 | 22,04 |
| 3        | 0,14                 | 90                 | 90                    | 21,98 | 22,22 | 22,23 | 22,22 | 21,98 | 21,96 | 22,16 | 22,23 | 22,14 | 21,95 |
| 4        | 0,19                 | 10                 | 45                    | 22,05 | 22,15 | 22,17 | 22,18 | 22,10 | 21,95 | 22,15 | 22,16 | 22,15 | 22,04 |
| 5        | 0,19                 | 50                 | 90                    | 21,99 | 22,15 | 22,15 | 22,14 | 21,99 | 21,85 | 22,05 | 22,15 | 22,16 | 21,91 |
| 6        | 0,19                 | 90                 | 0                     | 22,06 | 22,21 | 22,26 | 22,19 | 22,11 | 21,90 | 22,18 | 22,25 | 22,18 | 21,97 |
| 7        | 0,29                 | 10                 | 90                    | 21,76 | 22,00 | 22,03 | 21,95 | 21,83 | 21,78 | 21,94 | 21,95 | 21,92 | 21,90 |
| 8        | 0,29                 | 50                 | 0                     | 21,92 | 21,97 | 22,06 | 21,98 | 21,92 | 21,76 | 21,96 | 22,00 | 21,94 | 21,87 |
| 9        | 0,29                 | 90                 | 45                    | 21,83 | 21,89 | 22,00 | 21,98 | 21,85 | 21,76 | 21,94 | 22,03 | 22,01 | 21,84 |

3. Findings
The values obtained in all of the 5 measuring zones, for both parts of the specimens (on the side with holes - HR and on the side without holes - HL) have approximately the same tendency of variation, figure 3.
Figure 3. The variation of the HR (a) and HD (b) for each specimen, for all of the 5 measuring points.

For data processing with regression analysis and with Artificial Neural Networks, the mean values for each side of the specimens (HR and HL) and the overall mean H, between HR and HL, were calculated, table 2 and figure 4.

Table 2. The average values of the datasets.

| Exp. no. | Layer thickness (mm) | Infill density (%) | Orientation (degrees) | HR  | HL  | H   |
|---------|----------------------|--------------------|----------------------|-----|-----|-----|
| 1       | 0.14                 | 10                 | 0                    | 22.12 | 22.11 | 22.115 |
| 2       | 0.14                 | 50                 | 45                   | 22.14 | 22.12 | 22.130 |
| 3       | 0.14                 | 90                 | 90                   | 22.13 | 22.09 | 22.107 |
| 4       | 0.19                 | 10                 | 45                   | 22.13 | 22.09 | 22.110 |
| 5       | 0.19                 | 50                 | 90                   | 22.08 | 22.02 | 22.054 |
| 6       | 0.19                 | 90                 | 0                    | 22.17 | 22.10 | 22.131 |
| 7       | 0.29                 | 10                 | 90                   | 21.91 | 21.90 | 21.906 |
| 8       | 0.29                 | 50                 | 0                    | 21.97 | 21.91 | 21.938 |
| 9       | 0.29                 | 90                 | 45                   | 21.91 | 21.92 | 21.913 |

Figure 4. The averages values for HR and HL on each specimen and H (the average value between HR and HL).
With the Minitab software, a regression analysis was realized: H versus Layer thickness, Infill density and Orientation of the specimen, figure 5.

![Regression equation and analysis](image)

**Figure 5.** Regression rapport made by Minitab software.

### Analysis with Artificial Neural Network

In order to realize this kind of analyze, the data was imported into the MATLAB Artificial Neural Network Toolbox and The Neural Fitting application was chosen. The Neural Fitting application gives us the opportunity to select the data, to create and train a network, and to evaluate its performance using mean square error and regression analysis. Also, this tool has the possibility to randomly distribute the data sets in the three categories.
For the inputs of the network we created a matrix of 3x18 (Layer thickness, Infill density, Orientation), and for the output of the network a matrix (vector) of 1x18 (Height of the wall) were created.

All of the 18 datasets was divided into 3 categories: 70% for training, 15% for testing and 15% for validation.

![Neural Network Training](image)

**Figure 6.** The training process of the neural network.
Using the “Bayesian-Regularization” backpropagation algorithm, the network was trained [5, 7], figure 6. The training process is an iterative one. For this case, to train the network a number of 824 iterations was needed.

When the training process is considered done, the results are displayed in the Train Network window. The values for R and the mean square error are displayed too.

![Train Network](image)

**Figure 7.** The results of network training, testing and validation.

After the training process, the network can be used to predict the value of the output parameter in function of the new values of the input parameters.

In table 3 an example of simulation by the trained network is presented.

**Table 3.** New parameters simulated with RNA.

| INPUT                      | OUTPUT       |
|----------------------------|--------------|
| Layer thickness (mm) 0.14  | H (mm) 22.1315 |
| Infill density (%) 10      |              |
| Orientation (degrees) 0    |              |

5. Conclusions

The height of the thin walls obtained by Additive Manufacturing process has a strong dependency of the layer thickness and a weak dependency of infill density and orientation of the specimen on the printing table.

A regression equation was established after regression analysis: Height = f (parameters).

Artificial Neural Network Toolbox from MATLAB was used to realize an analyze for small datasets.

The network was trained, tested and validated using the results of measurements.

After the training, the network was able to "simulate" new parameters. Thus, we will introduce a new set of input data, corresponding to a new situation and thus we will be able to find the answer given by the network.
The research presented in this paper can give useful additional scientific data to understand how to improve the quality of the parts obtained by Additive Manufacturing.

In the future, it is desired to perform a series of tests on several specimens, in order to ensure a better assessment of dimensional variations. Thus, the designers can find important information regarding the influence of technological and design parameters on the dimensional accuracy of the parts obtained by Additive Manufacturing.

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