Prediction of Dimensional Changes of Low-cost Metal Material Extrusion Fabricated Parts Using Machine Learning Techniques

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Introduction

Additive manufacturing (AM) is a widely used layer-by-layer manufacturing process [1]. However, it is limited by material options, different fabrication defects, and inconsistent part quality. Material extrusion (ME) is one of the most widely used AM technologies [2]. Thus, it is adopted in this research. Low-cost metal ME is a new AM technology used to fabricate metal composite parts using sintering metal infused filament material. Since the materials and the process are relatively new, there is a need to investigate the dimensional accuracy of low-cost metal ME fabricated parts for real-world applications. Each step of the manufacturing process such as 3D printing of the samples and the sintering will affect the dimensional accuracy significantly. By using several machine learning (ML) algorithms, a comprehensive analysis of dimensional changes of metal samples fabricated by low-cost metal ME process is developed in this research. ML methods can assist researchers in sophisticated pre-manufacturing planning and product quality assessment and control. The findings of this study can help researchers and engineers to predict the dimensional variations and optimize the printing and sintering process parameters to obtain high quality metal parts fabricated by the low-cost ME process.

Process

The schematic of this research is shown in Figure 1. There are three main sections in the research. The first section is the data collection. The g-code was generated from a CAD model in the slicing software, which then is used to fabricate the non-sintered parts in the 3D printer. After measuring the non-sintered dimensions, the non-sintered parts were sintered in the muffle furnace. After sintering, the sintered parts were polished and then measured. The second section is prediction. Prediction algorithms were trained, tested, and evaluated using the collected data. The third section is verification, where the performance of the prediction algorithm is validated via experimental results.

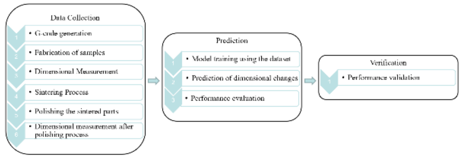


Figure 1 Research Process

Material & Equipment

In this research, the bronze-PLA filament made by The Virtual Foundry was used to print the non-sintered parts and fabricated in an Ultimaker S5 3D printer. The sintering process was performed with the use of a KSL-1100X muffle furnace. A 35-025 electronic micrometer was used to take the measurement of the dimensions before and after the sintering process. The material and equipment are shown in Figure 2. Also, the CAD, non-sintered and sintered parts are shown in Figure 3.

Figure 2 Material & Equipment

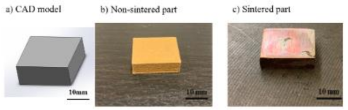


Figure 3 Samples in Three Different Stages

Parameters

From the printing process, layer thickness, nozzle temperature, and printing speed were chosen as explanatory variables. For the sintering process, sintering temperature, and temperature increasing ratio were chosen as the explanatory variables. Table 1 shows the values of each parameter.

Table 1 Research Parameters

<table>
<tr><th>Printing parameters</th><th colspan="3">Values</th><th>Sintering parameters</th><th colspan="7">Values</th></tr>
<tr><td>Layer thickness (mm)</td><td>0.1</td><td>0.2</td><td>0.3</td><td>Layer thickness (mm)</td><td colspan="2">0.1</td><td colspan="3">0.2</td><td colspan="2">0.3</td></tr>
<tr><td>Nozzle temperature (°C)</td><td>220</td><td>230</td><td>240</td><td>Sintering temperature (°C)</td><td>870</td><td>875</td><td>880</td><td>885</td><td>890</td><td>895</td><td>900</td></tr>
<tr><td>Printing speed (mm/s)</td><td>10</td><td>15</td><td>20</td><td>Temperature increasing ratio (°C/min)</td><td colspan="2">2</td><td colspan="3">3</td><td colspan="2">4</td></tr>
</table>

Machine Learning Algorithms

The three types of algorithms used in this research were single Linear Regression (LR), Linear Regression with Interactions (LRI) and Neural Networks (NN). In this research, the CAD dimension is the response variable. The 8 independent variables are Layer thickness (LT), Sintering temperature (ST), Temperature increasing ratio (TR), Nozzle temperature (NT), Printing speed (PS) and the final length (L), width (W), and height (H).

LR is a type of supervised ML algorithm that is used to predict continuous outcomes using a constant slope [3].

LRI is a kind of unique linear regression method. Among the independent variables, there might be some interactions. LRI will involve these interactions during the analysis process.

NN is a kind of ML algorithm which uses a set of network layers to translate an input data into an output [4]. NN uses multiple layers of linear processing units for feature extraction and transformation. Each layer uses the output from the previous layer as input, learning in supervised or unsupervised manners. The schematic of NN is shown in Figure 4.

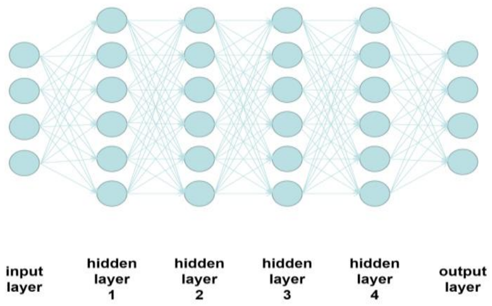


Figure 4 Schematic of the NN [1]

Discussion

Figures 5, 6, and 7 show the predicted results of different ML algorithms.

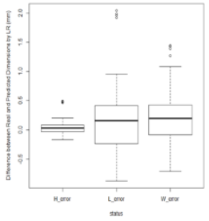
The boxplots are the difference between the predicting CAD dimensions and real dimensions. It is easy to get the point that, closer to zero the difference is, more accurate the algorithm is.

The medians of all three algorithms are closer to zero, but the max errors are different. The LR prediction has the largest error 2mm, LRI has the largest error 1mm and the largest error for NN is 0.8mm.

Also, different ML algorithms have different variance. From the boxplots, the variance of NN is much smaller than LR and LRI.

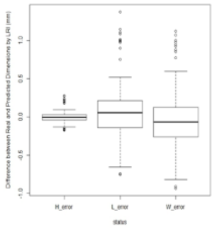
The medians are close and the variance is small, from the boxplot, the NN is the most reliable ML algorithm to use in this research.

Table 2 shows the Mean Square Error of these three ML algorithms, and NN has the smallest MSE.



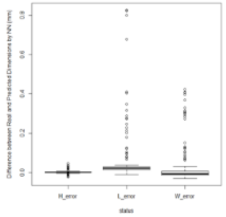
Difference between Real and Predicted CAD dimensions by LR.

Figure 5 Results of LR.



Difference between Real and Predicted CAD dimensions by LRI.

Figure 6 Results of LRI



Difference between Real and Predicted CAD dimensions by NN.

Figure 7 Results of NN

Table 2 MSE of Different ML Algorithms

Method	Mean Square Error		
	Length (mm)	Width(mm)	Height (mm)
LR	0.269	0.183	0.0119
LRI	0.118	0.121	0.00532
NN	0.00228	0.0117	0.0000878

Conclusion

In this research, the dimensional changes of low-cost metal ME fabricated parts are analyzed by different ML algorithms and these three types of algorithms behave differently in predicting CAD dimensions. The medians of them are all close to zero, but NN has smallest variation. Besides, NN has the smallest MSE and, hence, will be the best algorithm to predict the initial CAD dimensions.

Acknowledgement

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References

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