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Article

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

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Abstract: Additive manufacturing (AM) is an emerged layer-by-layer manufacturing process. However, its broad adoption is still hindered by limited material options, different fabrication defects, and inconsistent part quality. Material extrusion (ME) is one of the most widely used AM technologies, and, hence, is adopted in this research. Low-cost metal ME is a new and AM technology used to fabricate metal composite parts using sintered metal infused filament material. Since the involved materials and process are relatively new, there is a need to investigate the dimensional accuracy of ME fabricated metal parts for real-world applications. Each step of the manufacturing process, from the material extrusion to sintering, might significantly affect the dimensional accuracy. This research provides a comprehensive analysis of dimensional changes of metal samples fabricated by the ME and sintering process, using statistical and machine learning algorithms. Machine learning (ML) methods can be used to assist researchers in sophisticated pre-manufacturing planning and product quality assessment and control. This study compares linear regression to neural networks in assessing and predicting the dimensional changes of ME made components after 3D printing and sintering process. The prediction outcomes using a neural network performed the best with the highest accuracy as compared to regression. 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.

Keywords: Low-cost Metal Material Extrusion, Additive Manufacturing, Machine Learning, Dimensional Accuracy, Sintering.

1. Introduction

Additive manufacturing (AM), also known as 3D printing (3DP) [1], is a set of technologies that are used to produce objects layer-by-layer from computer-aided design (CAD) models [2]. There are various types of AM processes including material extrusion (ME), selective laser sintering (SLS), selective laser melting (SLM), powder bed fusion (PBF), and stereolithography (STL) [3]. Among these techniques, ME is well-known and the most widely used process [4]. ME has plenty of advantages over traditional manufacturing methods such as the production of highly complex parts with less weight, time, and material cost [5]. The utilization of the ME process is growing sharply in plenty of areas, such as medicine [6], construction [7], machinery manufacturing [8], and the food industry [9]. Recently, ME has been used in the manufacturing of metal components [10]. However, the materials cannot be pure metal since the printing temperature of most 3D printers are lower than the melting temperatures of most metals since the process uses thermoplastic materials. In recent years, new metal-infused polymer filaments have been developed as a feedstock material for ME process and can be used to fabricate metal components using this new, low-cost manufacturing processes [11].

Sintering is a process that forms a solid mass of metal by heating the composite material of metal powder and a binding agent to just below the melting point of the metal [12]. The metal-polymer composite filament is melted and extruded in the 3D printer then sintered to change the metal-polymer composite parts to pure metal [13]. 3D printed metal-composite parts need to be sintered in order to melt the polymer and diffuse the metal particles inside the polymer matrix material. Moreover, the sintering process is crucial, because the mechanical properties of metal-polymer composite parts are much lower than pure metal [14]. In this context, by heating the metal-polymer composite parts to just below the melting temperature of the metal, the polymer will melt and evaporate slowly, which eventually will lead to having a pure metal component [15]. It has been shown by the Gong's group and the Burkhardt's group that after the sintering process, the dimensions of the samples will change [11, 16]. Thus, an accurate method is required to predict the CAD dimension.

The dimensional accuracy of AM has been studied by plenty of research groups. Yasa et. al studied the dimensional accuracy and mechanical properties of chopped carbon-fiber-reinforced, tough nylon productions, which were made by the ME method [24]. Osman et. al investigated the dimensional errors of AM fabricated samples by laser sintering [25]. The authors concluded that the precision of both selective laser sintering and 3DP models are acceptable. Ibrahim et. al analyzed the dimensional error in some AM methods [26]. They reported different dimensional errors and chose the most accurate one. In the research by Wang's group, they investigated the shrinkage caused by sintering process in the binder jetting AM technique [27]. Three sets of recommended sintering parameters were analyzed to achieve the best dimensional accuracy for each axis and one parameter in all three axes by Wang's group. Four sets of optimal sintering parameters were found by this research group to improve the dimensional accuracy.

Machine Learning (ML) can perform modeling and analysis on big data [17] to assist humans in various areas of technology such as language detection and translation [18], facial expression and motion analysis [19], medicine [20], etc. In recent years, ML has gained increasing attention in the AM field due to the application of regression, classification, and clustering. ML has numerous applications such as the prediction of tensile strength of Polylactic acid (PLA) objects fabricated by ME [21], design of AM [22], improvement of the geometrical accuracy fabricated by ME [23], etc. Although the dimensional accuracy of AM has been studied in plenty of works [24, 25, 26, 27], ML was not used in these works, since their datasets are not large enough. For example, Gong's group used only 11 samples to get their results. Thus, there is a need for a large dataset to predict the dimensional accuracy in the low-cost metal ME process using ML techniques.

In this study, cuboid samples were fabricated by ME and the dimensions before and after sintering of the samples were collected. This study compares linear regression to neural networks in assessing and predicting the dimensional changes of ME made components after 3D printing and sintering. These algorithms were used to predict the CAD dimensions of the samples based on the final sintered dimensions.

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2. Materials and Methods

2.1 Materials and equipment

In this research, the bronze-PLA filament made by The Virtual Foundry [28] was used to print the non-sintered parts and fabricated in an Ultimaker S5 3D printer [29]. The sintering process was performed with the use of a KSL-1100X muffle furnace [30]. A 35-025 electronic micrometer [31] was used to take the measurement of the dimensions before and after the sintering process. The materials and equipment used in this research are shown in Figure 1. Figure 2 shows the metal-composite part as a CAD model, 3D printed and, after sintering.

Figure 1. Material and equipment used in this research.

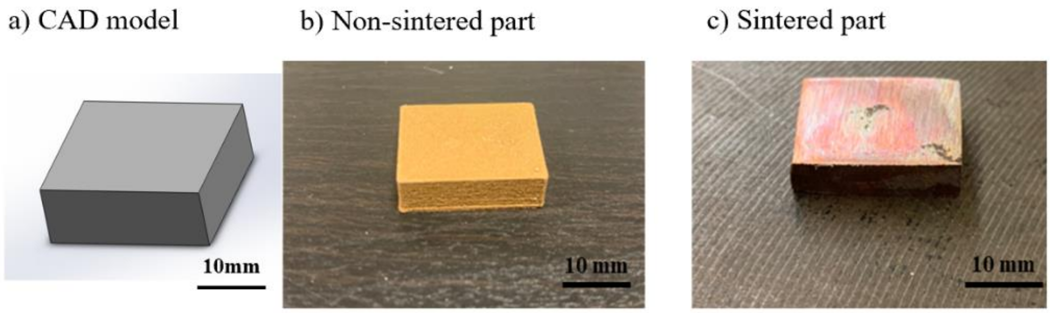

Figure 2. Samples in different status a) CAD model b) Bronze-PLA sample c) sample after sintering and polishing

2.2 Process workflow

The schematic of this research is shown in Figure 3. 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.

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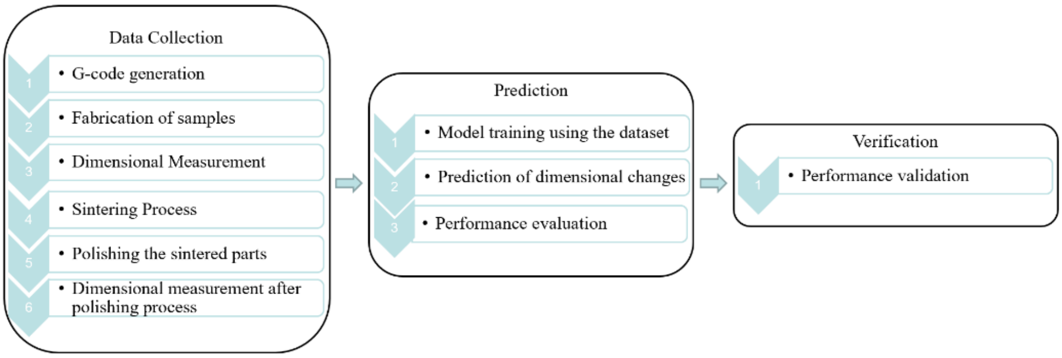

Figure 3. Process workflow of the research study

2.3 Dataset preparation

In this research, there are three different types of data, dimensions obtained from the CAD model, the non-sintered part, and the sintered and polished part. Since the dimensions of the final part are what is wanted, the regression and ML algorithms were developed to use the sintered dimensions with the various printing and sintering parameters to predict the starting CAD dimensions. Figure 4 shows an orthographic view of the CAD model and Table 1 illustrates one example of the collected data. The non-sintered and sintered dimensions were measured by an iGaging micrometer.

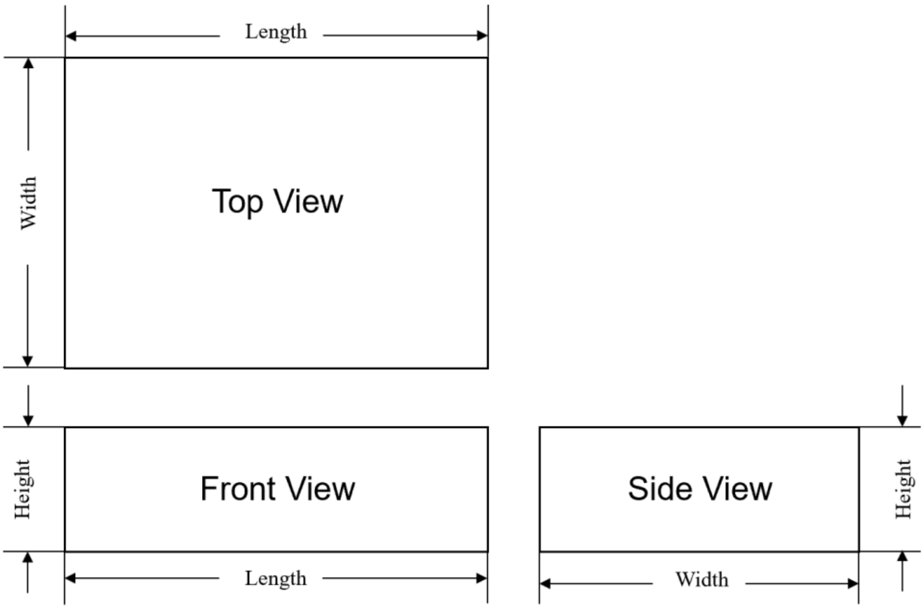

Figure 4. Top, front, side views and dimensions of the CAD model

Table 1. Data example

Types of references for dimensional measurement	Dimensions of the samples		
	Length (mm)	Width (mm)	Height (mm)
CAD dimensions	20	15	6
Dimensions before sintering process	Measured by micrometer	Measured by micrometer	Measured by micrometer
Dimensions after sintering process	Measured by micrometer	Measured by micrometer	Measured by micrometer

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. The parameters of the printing and sintering process are given in Table 2.

Table 2. Parameters of the printing and sintering process

Printing parameters	Values			Sintering parameters	Values						
Layer thickness (mm)	0.1	0.2	0.3	Layer thickness (mm)	0.1		0.2		0.3		
Nozzle temperature (°C)	220	230	240	Sintering temperature (°C)	870	875	880	885	890	895	900
Printing speed (mm/s)	10	15	20	Temperature increasing ratio (°C/min)	2		3		4		

This research resulted in 450 groups of data points. Table 3 shows an example of the combination of the process parameters and their relationship with the sample dimensions. The part was printed with a layer thickness of 0.1mm, 240 °C as nozzle temperature and a 10mm/s printing speed. The sample was sintered in at 870 °C and the temperature increasing ratio is 2 °C/min. The CAD dimensions of the part is 20×15×6mm, but after printing, the real dimensions of the part are bigger than the CAD. During the sintering process, the part undergoes a shrinkage process that reduces the dimensions to below CAD dimensions. Thus, compared to the CAD dimensions, the final dimensions will be significantly different. Therefore, a prediction of the CAD dimensions is needed.

Table 3. Combination of the process parameters

Printing parameters	Sintering parameters	Sample Type	Dimensions of the sample		
			Length (mm)	Width (mm)	Height (mm)
0.1 mm 240 °C 10 mm/s	0.1 mm 870 °C 2 °C/mm	CAD	20	15	6
		Non-sintered	20.452	15.318	6.226
		Sintered	18.787	13.922	5.236

2.4 Prediction algorithms

The three types of algorithms used in this research were single Linear Regression (LR), Linear Regression with Interactions (LRI) and Neural Networks (NN).

2.4.1 LR

LR is a type of supervised ML algorithm that is used to predict continuous outcomes using a constant slope [32]. Since there are 8 independent variables, the polynomial regression is not a suitable method. LR is used in this research because of its briefness on learning and using, accuracy in multiple variables, and reliability [33]. In this research, multiple features are used to do prediction and the equation of the LR is:

$$\mathbf{y} = \mathbf{X\theta} + \boldsymbol{\varepsilon}$$

Here, **y** is the vector of response variables, **X** is the matrix of independent variables, **θ** is the coefficient vector and **ε** is the vector of the error term. 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). The LR algorithm will generate the **θ** and ε and the matrix of independent variables X is shown below:

$$\mathbf{X} = [\mathbf{LT} \quad \mathbf{ST} \quad \mathbf{TR} \quad \mathbf{NT} \quad \mathbf{PS} \quad \mathbf{L} \quad \mathbf{W} \quad \mathbf{H}]$$

2.4.2 LRI

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 [34]. The equation of the LR is the same as LR,

$$\mathbf{y} = \mathbf{X\theta} + \boldsymbol{\varepsilon}$$

Here, **y** is the vector of response variables, **X** is the matrix of independent variables, **θ** is the coefficient vector and **ε** is the vector of the error term. In this research, the CAD dimension is the response variable. But the matrix of independent variables X is different, LRI involved the interactions between independent variables but LR does not. The **X** for LRI is shown below:

$$\mathbf{X} = [\mathbf{LT} \quad \mathbf{ST} \quad \mathbf{TR} \quad \mathbf{NT} \quad \mathbf{PS} \quad \mathbf{L} \quad \mathbf{W} \quad \mathbf{H} \quad \mathbf{LT{*}L} \quad \mathbf{LT{*}W} \quad \mathbf{LT{*}H} \quad \mathbf{ST{*}L} \quad \mathbf{ST{*}W} \quad \mathbf{ST{*}H} \quad \mathbf{TR{*}L} \quad \mathbf{TR{*}W} \quad \mathbf{TR{*}H} \quad \mathbf{NT{*}L} \quad \mathbf{NT{*}W} \quad \mathbf{NT{*}H} \quad \mathbf{PS{*}L} \quad \mathbf{PS{*}W} \quad \mathbf{PS{*}H}]$$

2.4.3 NN

NN is a kind of ML algorithm which uses a set of network layers to translate an input data into an output [35]. NN uses multiple layers of linear processing units for feature extraction and transformation. Each layer uses the output from the previous layer

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as input, learning in supervised or unsupervised manners [36]. In this research, supervised manners are used since the response variables are labeled data. Also, a deep NN model is developed since we will involve more than a single hidden layer. The schematic of the NN is represented in Figure 5, starting at the input layer, data is analyzed in the hidden layers and then output. The output of the NN is the CAD dimensions, the inputs are the sintered data and printing/sintering parameters.

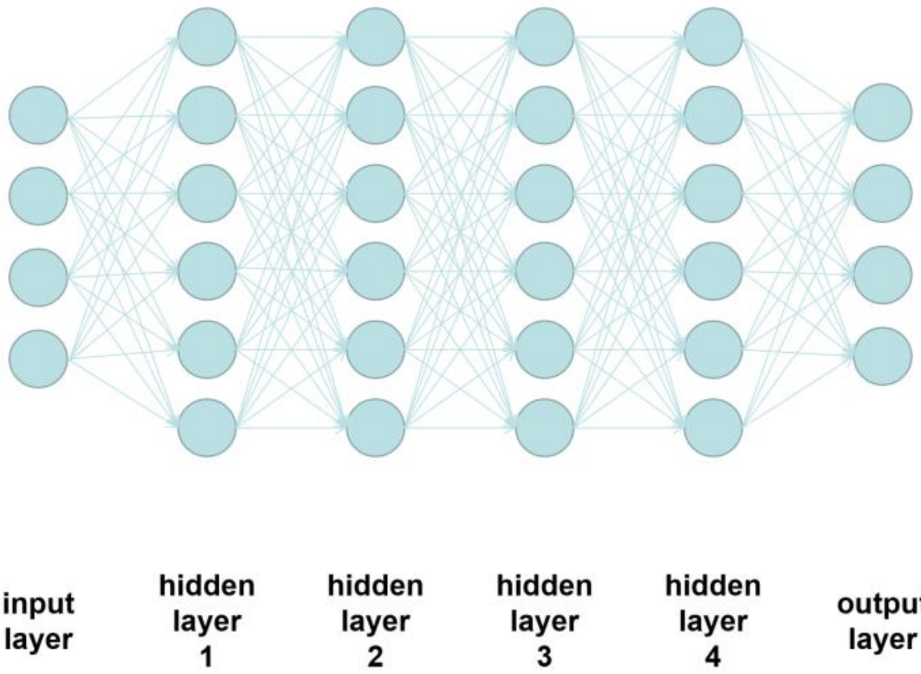

Figure 5. Schematic of the NN [37]

3. Results and Discussions

In this section, the results collected by from the two analysis different algorithms adopted in this paper are shown by figures presented. Firstly, the printing accuracy of the 3D printer is shown. Then, the dimensional changes between the CAD and sintered data were analyzed by LR, LRI and NN algorithms. the results from the three analysis algorithms adopted in this paper are presented.

3.1 Printing Accuracy

The errors between the non-sintered and CAD data are shown in Figure 6. For the length and the width, non-sintered dimensions are larger than the CAD dimensions, which means that the real parts will expand in length and width than the 3D models after the printing process. As for the height, the real parts will shrink or expand than the 3D models.

In the AM design process, the CAD dimensions can be controlled by the users. Thus, it is required to predict the CAD data, but not the non-sintered data.

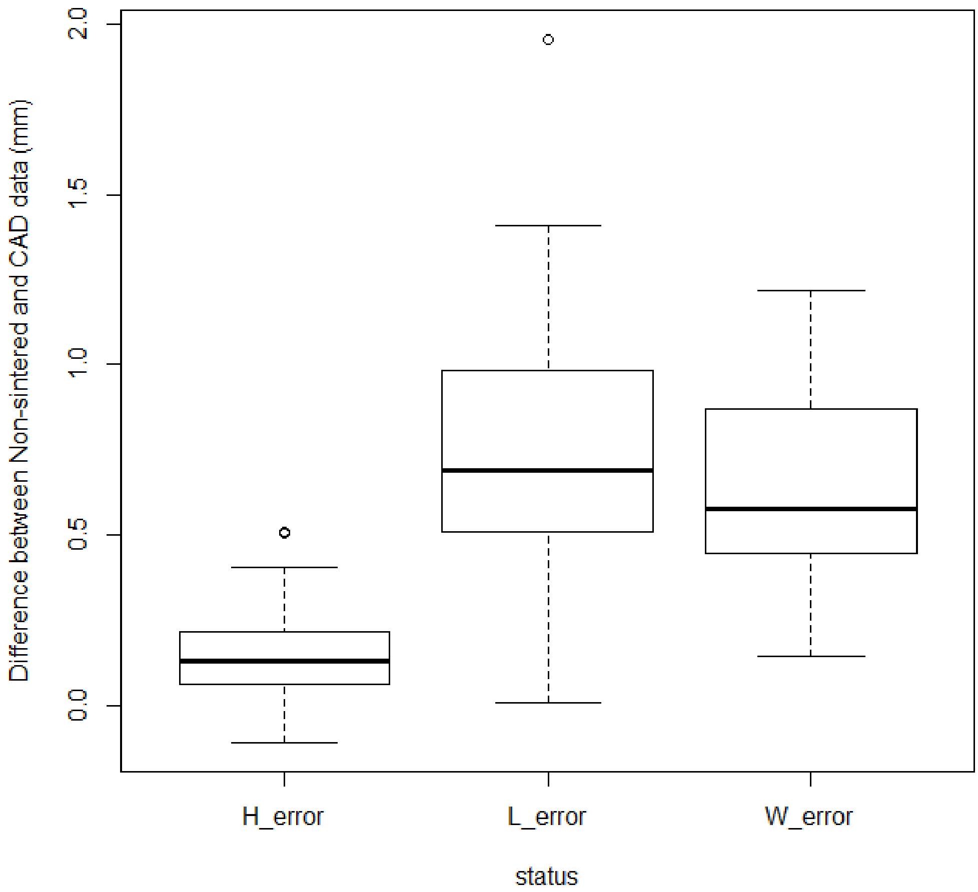

Figure 6. Difference between Non-sintered and CAD data

3.2 Analysis of dimensional variations of CAD and sintered samples

In this subsection, the results of the prediction of CAD dimensions of three different algorithms are shown separately.

3.2.1 Results of prediction by LR

After parameter optimization, the equations to predict the initial CAD dimensions are:

$$\mathbf{CAD\_L = X * [-0.000220\ 0.0649\ 0.0136\ 0.000300\ -0.0321\ 0.647\ 0.118\ 0.0793]^T + [-0.0231]} \quad (1)$$

$$\mathbf{CAD\_W = X * [-0.00733\ 0.0698\ 0.0134\ -0.0364\ -0.100\ 0.250\ 0.556\ 0.0801]^T + [0.0260]} \quad (2)$$

$$\mathbf{CAD\_H = X * [-0.00146\ 0.0633\ 0.0121\ -0.00729\ -0.0517\ 0.517\ 0.219\ 0.0757]^T + [-0.0154]} \quad (3)$$

The prediction of CAD dimensions by the LR is shown in Figure 7. The medians of all three errors are close to zero and most absolute values of maximum and minimum errors are less than 1mm. But for length and width, there are also several outliers of 2mm and 1.5mm respectively.

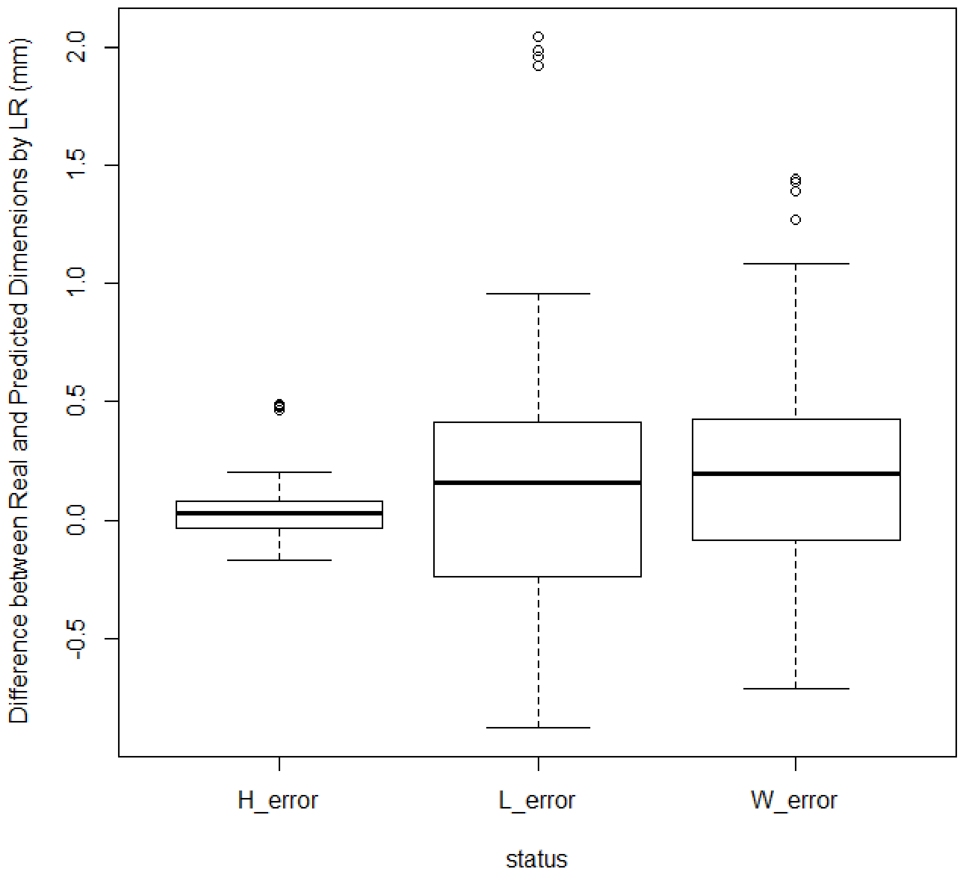

Figure 7. Difference between Real and Predicted CAD dimensions by LR.

3.2.2 Results of prediction by LRI

The prediction of CAD dimensions by the LR is shown in Figure 8. The medians of all three errors are close to zero and most absolute values of maximum and minimum errors are less than 0.8mm. But for length and width, there are also several outliers of 1.4mm and 1.2mm respectively.

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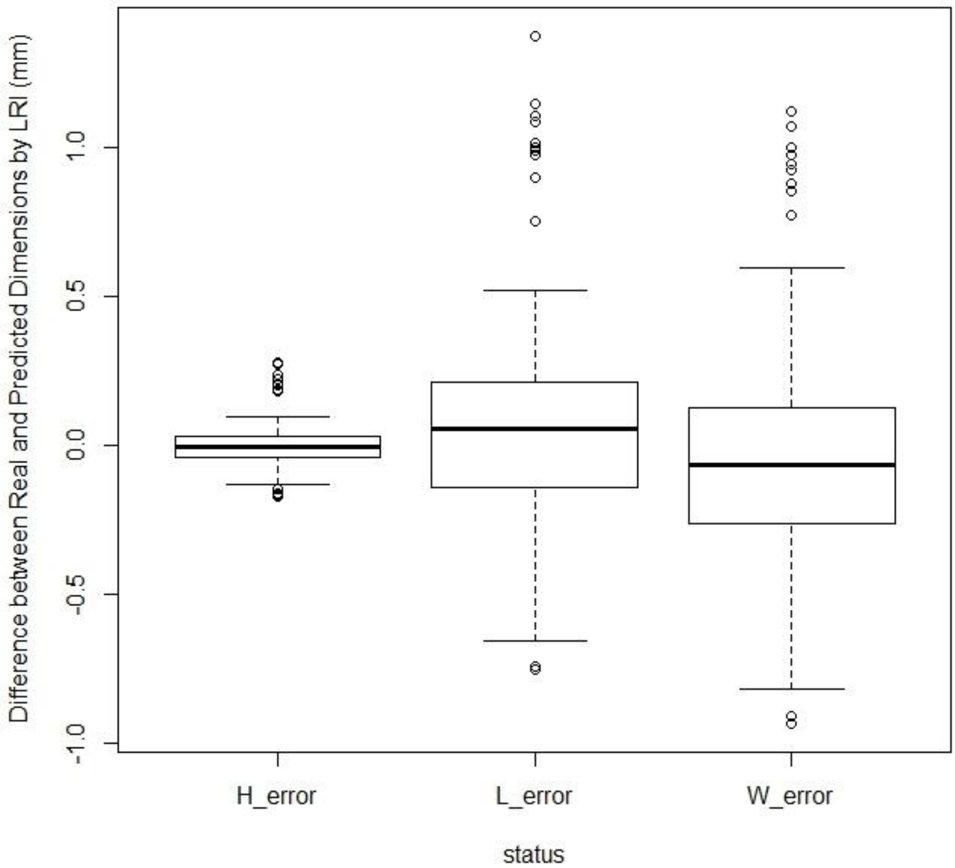

Figure 8. Difference between Real and Predicted CAD dimensions by LRI.

3.2.3 Results of prediction by NN

After parameter optimization, the structure of the NN is shown in Table 4:

Table 4. Structure of the NN

Number of hidden layers	5
Number of neurons in each hidden layer	128
Activation function at hidden layers	ReLU

In Figure 9, the results generated by NN are shown. The medians of all three errors are close to zero and most absolute values of maximum and minimum errors are less than 0.1mm. For length and width, there are also several outliers but most of them are less than 0.4mm. Comparing with LR and LRI, NN is more accurate. This can be attributed to the fact that NN can extract complex features within the data and hence yield better results compared with LR and LRI.

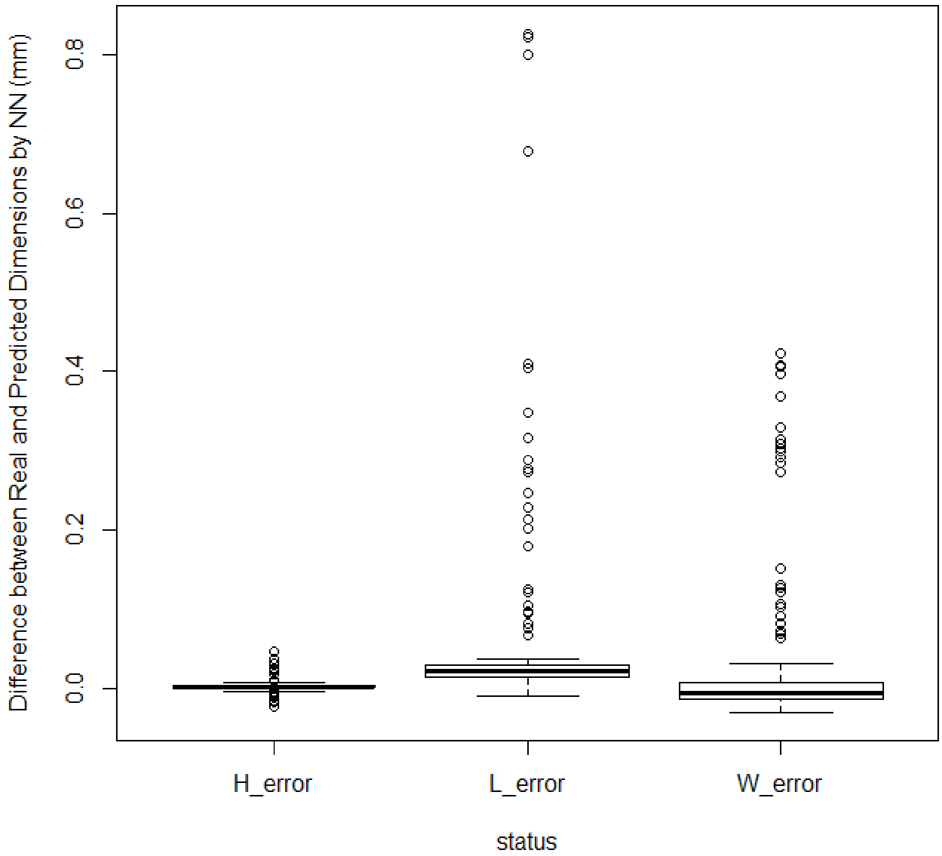

Figure 9. Difference between Real and Predicted CAD dimensions by NN.

In statistics, p-value is usually used to evaluate the probability of extreme outcomes [38]. A very small p-value means that an extreme observed outcome would unlikely occur. Table 5 shows the p-values of NN-predicted length, width, and height. All p-values are significantly small.

Table 5. P-values of NN-predicted dimensions

Dimensions	Length	Width	Height
p-value	2.99×10^{-8}	1.097×10^{-4}	1.272×10^{-6}

4. Error metrics

The results of different algorithms have been shown in figures. It is difficult to test the performance from the figures. Models that are used to predict output values must have metrics to assess the performance or the success of the algorithm. There are several error metrics that are utilized in the ML community. In this research, the mean square error (MSE) metrics was used to test the performance of the algorithms. MSE is the average squared difference between the estimated values (predicted values) and the actual value (observed values) [39]. The equation is given below:

4.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \quad (4)$$

where the MSE is mean square error, n is the sample size used to test an algorithm, $\boldsymbol{Y_i}$ is the observed value, and $\boldsymbol{\hat{Y}_i}$ is the value predicted by the algorithm.

The MSE of three algorithms are shown in Table 5. NN has the smallest MSE and thus, NN is the most accurate algorithm in this research.

Table 5. MSE results of non-sintered to sintered and sintered to non-sintered predictions.

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

5
5

5. Verification

In this section, a verification part is sintered to verify the accuracy of the algorithm. Since the MSE of NN is the lowest, the prediction is generated by NN. The verification part is printed and sintered in the following parameters:

- Layer Thickness = 0.3mm;
- Nozzle Temperature = 220°C;
- Printing Speed = 15mm/s;
- Sintering Temperature = 880°C;
- Temperature Increasing Ratio = 3°C/min.

The results are shown in the Table 6

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Table 6. Verification of the ML algorithm

Printing Parameter		Sintering Parameter		Target Dimensions		Predicted CAD Dimensions		Final Dimensions after Sintering	
Layer Thickness (mm)	0.3	Layer Thickness (mm)	0.3	Length (mm)	20	Length (mm)	20.905	Length (mm)	19.998
Nozzle Temperature (℃)	220	Sintering Temperature (℃)	880	Width (mm)	15	Width (mm)	15.394	Width (mm)	14.996
Printing Speed (mm/s)	15	Temperature Increasing Ratio (℃/min)	3	Height (mm)	6	Height (mm)	6.154	Height (mm)	6.001

The target final dimensions of this part are 20×15×6mm, and the predictions of CAD size are 20.905×15.394×6.154mm. After the sintering and polishing, the real final dimensions are 19.998×14.996×6.001mm. Comparing with the target, the dimensional errors are negligible.

6. Conclusion

AM is one of the latest manufacturing processes that is widely used in several fields. Metal AM is also relatively new and has a potential to be one commonly used low-cost metal manufacturing technologies. Low-cost metal ME does not have the disadvantages of metal AM since it uses metal-infused filament materials instead of pure metal materials. ML can assist researchers to predict the qualities of the parts fabricated by low-cost metal ME. In this research, the printing accuracy and the dimensional changes of low-cost metal ME fabricated parts are analyzed by different algorithms and the following conclusions are drawn:

- After the printing process, the non-sintered dimensions are different from the CAD dimensions, it will expand in length and width than the 3D models. As for the height, it will shrink or expand than the 3D models.
- The three types of algorithms behave differently in predicting CAD dimensions. NN has the smallest MSE and, hence, will be the best algorithm to use to predict the initial CAD dimensions.
- After verification, the errors between the real and target dimensions are negligible; the accuracy of the prediction by NN is acceptable.

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