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Surface Roughness Analysis of Low-Cost Metal Material Extrusion Fabricated Parts and Prediction by Machine Learning Methods

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Abstract: Additive Manufacturing (AM), also know as 3D Printing (3DP), is a widely used layer-by-layer manufacturing process, it is evolving rapidly both in research and industry. Among all AM methods, Material Extrusion (ME) is one of the most popular techniques. Based on ME, another new AM method is developed, which is Low-cost Metal Material Extrusion (LCMME). In this newly developed process, pure metallic parts could be fabricated after sintering the metal infused additively manufactured parts. Both AM and sintering process parameters will have influence on the quality of the final pure metallic parts. In this research, several statistics methods were used to analyze the data gotten from the experiment. Then two Machine Learning (ML) algorithms were used to predict the Surface Roughness (SR) of the final specimens. Additionally, the results show that the neural network (NN) is more accurate than the support vector regression (SVR) on prediction.

Keywords: Additive Manufacturing (AM); Surface Roughness (SR); Low-cost Metal Material Extrusion (LCMME); Machine Learning (ML)

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1. Introduction

Additive manufacturing (AM) or 3D Printing (3DP), is a widely used technology to fabricate parts layer-by-layer from the computer-aided design (CAD) model [1]. There are seven different AM categories: material extrusion (ME), vat photopolymerization (VAT), powder bed fusion (PBF), direct energy deposition (DED), sheet lamination (SL), material jetting (MJ), and binder jetting (BJ) [2]. ME is the most widely used AM technology because of its numerous advantages such as using less material and time to produce complex parts, low-cost, environmental friendliness , etc [3–5]. ME already has many applications in several areas, such as the food industry, medicine, aerospace, and so on [6–8]. Also, ME is used in metal object manufacturing now[9].

However, Metal ME is a challenge because the working temperature is a difficult point [3]. The working temperature of most ME 3D printers varies from 200 to 280°C and the melting points of most metal materials are much higher. In recent years, new metal-infused polymer filaments have been developed as a feedstock material for ME and Low-cost Metal Material Extrusion (LCMME) is the new method to fabricate parts by using this kind of new material [10].

Figure 1 is the sketch of LCMME. The first several steps are the same as traditional AM, but after AM process, the parts fabricated by using metal-infused polymer filament will be sintered to melt out the internal polymer. And then the sintered part will be made from pure metal.

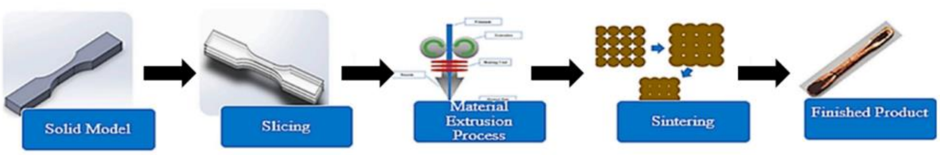

Figure 1. Sketch of LCMME.

In Figure 2, the process of sintering is introduced. In the sintering process, the sintering temperature is lower than the melting temperature [11]. As the temperature increases, the plastic melts out and the metal powders gather together to form pure metal parts.

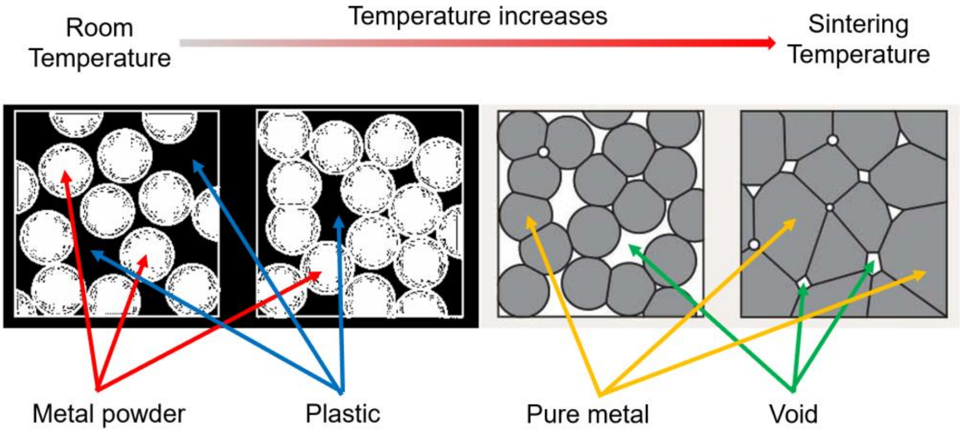

Figure 2. Process of Sintering.

Surface Roughness (SR) is the deviations in the direction of the normal vector of a real surface from its ideal form [12]. It is an important mechanical property of metal. The SR of parts manufactured in AM process has been studied in some works. Ciracì et al. did research on the impact of SR in several metallic systems [13]. Due to the fabrication-induced surface roughness, most metallic systems suffer from some degree of inhomogeneity. He et al. reviewed the influencing factors and related modeling methods [14]. This work aims to generate a comprehensive understanding of the turned surface roughness in theoretical modeling. Alfieri et al. studied the influence of SR in AM applications [15].

Machine Learning (ML) is a subset of artificial intelligence and it can be used to predict the mechanical properties of AM fabricated parts [16]. In LCMME, ML has been used to do dimensional accuracy prediction [3]. ML has plenty of applications in AM [17–19]. However, there is no research on using ML to predict and improve SR of LCMME fabricated parts. In this study, 150 cuboid samples were made by LCMME. The influence of different manufacturing parameters was analyzed and two ML algorithms were generated to predict the SR values.

2. Materials and Methods

2.1. Material and Equipment

In this research, the samples were fabricated by bronze-PLA filament and Figure 3 shows the metal-composite part as a CAD model, 3D printed and after sintering. Figure 4 is the micro view of the final pure metallic parts. The SR of pure bronze part after sintering was measured by a SJ-210 SR Tester and Figure 5 is the SR tester used in this research.

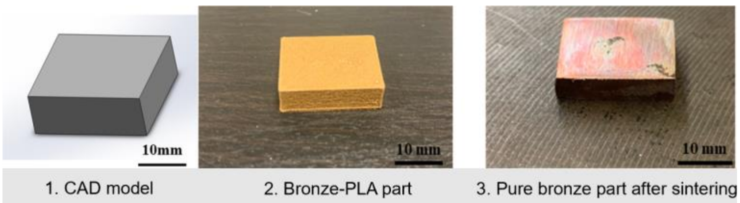

Figure 3. Samples in different status.

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Figure 4. Micro View of LCMME Fabricated Part.

Figure 5. SJ-210 SR Tester.

2.2. Data Preparation

There are several SR parameters, such as Ra, Rms, Rz, Rv, and so on [20]. In this research, Ra is used since its accuracy and simplicity [21]. Ra is the arithmetical mean deviation of the assessed profile [20]; the equation is shown below:

$$\mathrm{Ra} = \frac{1}{\mathrm{lr}}\int_0^{\mathrm{lr}} |\, z(x) \,|\, dx$$

Where lr is the measured length. Figure 6 shows the definition of Ra.

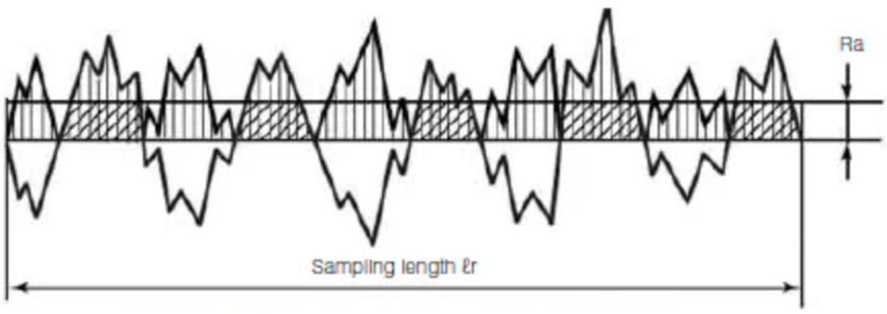

Figure 6. Definition of Ra [22].

In this research, there are five different manufacturing parameters, which are:

- Layer Thickness (LT): the height of each layer during the printing process;
- Sintering Temperature (ST): the temperature to sinter the bronze-PLA parts;
- Ramp Ratio (RR): the temperature increasing ratio from room temperature to ST;
- Nozzle Temperature (NT): the temperature of the printing nozzle during the 3DP process;

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- Printing Speed (PS): the moving speed of the nozzle during the 3DP process.

Table 1 shows the units and values of different manufacturing parameters.

Table 1. Manufacturing Parameters.

Manufacturing Parameters	**Values**						
LT (mm)	0.1			0.2			0.3
ST (°C)	870	875	880	885	890	895	900
RR (°C/min)	2			3			4
NT (°C)	220			230			240
PS (mm/s)	10			15			20

Figure 7 is the top, front, and side views of the sample and Table 2 shows two examples of the manufacturing parameters and SR values in this research. In this research, the data are divided into three groups, which are SR_Top, SR_Front, and SR_Side. From Table 2, these two samples have different manufacturing parameters, and the SR values of different surfaces are different either.

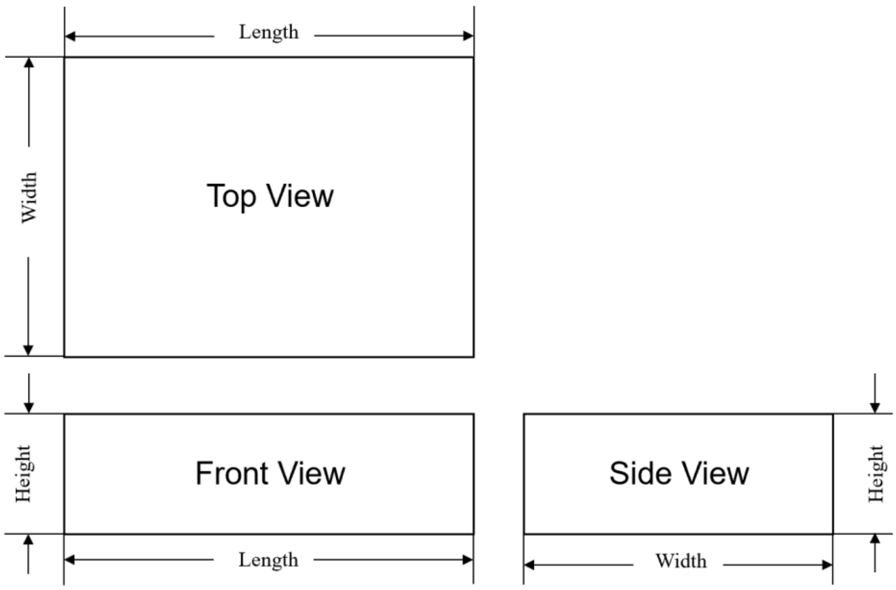

Figure 7. Top, Front, Side Views of the Samples.

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Table 2. SR Examples.

Manufacturing Parameters					SR (μm)		
LT (mm)	ST (°C)	RR (°C/min)	NT (°C)	PS (mm/s)	SR_Top	SR_Front	SR_Side
0.3	895	3	220	10	5.13	1.50	1.36
0.2	870	4	240	15	12.51	2.51	2.40

3. Statistical Methods Results

In this subchapter, the statistical and ML algorithms used in this part of research are introduced. Also, the results are shown.

3.1. ANOVA

ANOVA analysis has two main applications in this section. The first is to determine for each single cubic sample if all surfaces have the same SR values or not. The second is to find if all manufacturing parameters have influence on SR values or not.

A one-way ANOVA model is developed to determine whether the SR is the same in different surfaces. The following hypothesis is set:

H0: $\mu_{SR\_Top} = \mu_{SR\_Front} = \mu_{SR\_Side}$

Ha: at least one group of SR values is different

The result of this one-way ANOVA result is shown in Table 3. F crit < F, which means the H0 is rejected. Thus, the three groups of surfaces do not have the same SR values.

Table 3. ANOVA Result of Three Groups of Data.

	Df	Sum Sq	Mean Sq	F value	F crit	Pr (>F)
dim	2	2902297	1451149	93.39663	3.00648	2.44e-37 ***
Residuals	837	13004875	15537.48			

However, during the data collection, the researcher found that the SR_Front and SR_Side are similar. So the research group did another one-way ANOVA model is developed to determine if the SR_Front and SR_Side of a part are the same or not. The following hypothesis is set:

H0: $\mu_{SR\_Front} = \mu_{SR\_Side}$

Ha: $\mu_{SR\_Front} \neq \mu_{SR\_Side}$

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The result of this one-way ANOVA result is shown in Table 4. F crit > F, which means the H_0 is not rejected. Thus, the two groups of surfaces have the same SR values.

Table 4. ANOVA Result of SR_Front and SR_Side.

	Df	Sum Sq	Mean Sq	F value	F crit	Pr (>F)
dim	1	9163.768	9163.768	0.681879	3.858178	0.409293
Residuals	558	7498976	13439.03			

Thus, the three groups of data can be simplified into two groups, which are SR_Top and SR_Edge (including SR_Front and SR_Side). Then, further ANOVA analyses were generated to find if all manufacturing parameters have influence on SR values or not. Tables 5 and 6 show the results.

Table 5. ANOVA Result of SR_Top.

	Df	Sum Sq	Mean Sq	F value	Pr (>F)
LT	2	41801	20901	1.6415	0.1962310
ST	6	299781	49964	3.9240	0.0009817***
NT	2	276153	138076	10.8441	3.337e-5***
PS	2	26087	13043	1.0244	0.3608456
RR	2	656636	328318	25.7850	1.026e-10***

Table 6. ANOVA Result of SR_Ed.

	Df	Sum Sq	Mean Sq	F value	Pr (>F)
LT	2	221884	221884	34.5064	9.746e-15***
ST	6	468760	78127	12.1499	9.603e-13***
NT	2	74548	37274	5.7967	0.0032521**
PS	2	141323	70662	10.9890	2.150e-05***
RR	2	83375	41687	6.4830	0.0016651***

The results from the above two tables show that the P-values of ST, NT, and RR on SR_Top are smaller than 0.001, which means that these three parameters have influence on SR_Top. Besides, All parameters on SR_Edge have p-value numbers smaller than 0.01. Thus, in manufacturing process, all parameters will affect the SR_Edge values.

From the results of all ANOVA analysis, The data can be simplified into two groups, which are SR_Top and SR_Edge. And in ML algorithms, only three parameters will be used as independent variables in SR_Top analysis. All five parameters will be used as independent variables in SR_Edge analysis.

3.2. Results of ML Algorithms

In this research, Support Vector Regression (SVR) and Neural Network (NN) are used to predict the SR results of LCMME fabricated parts. SVR could provide flexibility to define the error in the model whether it is acceptable or not. NN uses a set of network layers to translate an input into an output. These two methods have been proven to be effective tools in real-value estimation.

In this research, Mean Square Error (MSE) metric is used to evaluate the performance of each algorithm. Table 7 shows the MSE results. It shows that NN behaves better in predicting the SR of LCMME fabricated parts.

Table 7. MSE Values of Each ML Algorithm

Data Group	MSE	
	SVR	NN
SR_Top	9.41	8.39
SR_Edge	6.87	3.68

4. Conclusions

In AM manufacturing process, SR is an important value in quality evaluation. In this research, as a new metal AM technique, LCMME is developed to fabricate pure metal parts in low temperature situation and without laser. Two different ML algorithms are used to do prediction on SR of LCMME fabricated parts. And the following conclusions are generated in this research:

1. The top side of the LCMME fabricated parts has different SR values with the edge sides.
2. Only three manufacturing parameters have influence on the SR_Top, which are ST, NT, and RR.
3. All five parameters will affect the SR_Edge values.
4. The MSE of NN is smaller than SVR in overall.

5. Future Work

In this research, the influence of different manufacturing parameters are evaluated by ANOVA analysis. Besides, two ML methods to predict the SR values of LCMME fabricated parts. In the further research, more parameters, such as flow rate, build-plate temperature, fan speed, and so on, could be added to increase the accuracy of prediction. Also, different materials could be used to do fabrication by this newly developed method.

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