X-Disciplinarity

DOI: https://doi.org/10.63174/xdi.ZVHP5789

Original Article

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

https://doi.org/10.63174/xdi.ZVHP5789

Volume 2 Issue 1

Received: 12 Mar 2026

Accepted: 16 Mar 2026

Published: 17 Mar 2026

Open Access

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Abstract: Additive manufacturing (AM), also known as 3D printing (3DP), is a widely used layer-by-layer manufacturing process that is evolving rapidly in both research and industry. Among all AM methods, material extrusion (ME) is one of the most popular techniques. Based on ME, a new AM method was developed, namely low-cost metal material extrusion (LCMME). In this newly developed process, pure metallic parts can be fabricated after sintering metal-infused additively manufactured parts. Both the AM and sintering process parameters influence the quality of the final pure metallic parts. In this study, several statistical methods were used to analyze the data obtained from experiments. Then two machine learning (ML) algorithms were used to predict the surface roughness (SR) of the final specimens. The data were divided into two groups, SR_Top and SR_Edge. The mean square error (MSE) metric was used to evaluate the performance of each algorithm. The results show that the neural network (NN) is more accurate than the support vector regression (SVR) in prediction, because the MSEs of SR_Top are 8.39 (NN) and 9.41 (SVR) and the MSEs of SR_Edge are 3.68 (NN) and 6.87 (SVR).

1. Introduction

Additive manufacturing (AM) or 3D printing (3DP), is a technology that is widely used to fabricate parts layer by layer from a 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 its use of less material and time to produce complex parts, its low cost, and its environmental friendliness [3-5]. ME is already applied in several areas, such as the food industry, medicine, and aerospace industry [6-8]. ME is also now used in metal object manufacturing now [9, 10].

Despite the wide use of ME, Metal ME presents a challenge due to working temperature requirements [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) isa new method for fabricating parts with this new type of material [11, 12].

Surface roughness (SR) refers to deviations in the direction of the normal vector of a real surface from its ideal form [13]. It is an important mechanical property of metal. The SR of parts manufactured using AM processes has been studied in some works. Ciracì et al. performed 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 [15]. This work aimed to generate a comprehensive understanding of the turned surface roughness in theoretical modeling. Alfieri et al. studied the influence of SR in AM applications [16].

Machine learning (ML) is a subset of artificial intelligence that can be used to predict the mechanical properties of AM-fabricated parts [17, 18]. ML has plenty of applications in AM; for example, ML is used to improve the quality of design [19], it can help manufacturers perform anomaly detection [20], and, with the help of ML, doctors can read the CT images and answer questions accurately [21]. However, in specimen fabrication, ML has not been sufficiently studied. Since SR is an important parameter in specimen fabrication, its control is a key question in the industry. After reviewing previous researches, it was found that there is no research on using ML to predict and improve the SR of LCMME-fabricated parts. Thus, this work will compensate for this shortcoming. In this study, the author chose different manufacturing parameters, and the SR was collected based on different parameters. Totally, 327 groups of data were collected from LCMME-fabricated parts. The influence of different manufacturing parameters was analyzed, and two ML algorithms—support vector regression (SVR) and neural network (NN)—were generated to predict the SR values.

With the development of 3DP technology, metal 3DP is a hard point in this research area. Also, ML algorithms already have been widely used in quality evaluation in 3DP. Thus, this work provides a newly developed metal 3DP technology and the SR was chosen to be evaluated.

2. Materials and Methods

2.1. Manufacturing Process

Figure 1 presents a sketch of LCMME. The first several steps are the same as those in traditional AM, but after the AM process, parts fabricated by using metal-infused polymer filaments are sintered to melt out the internal polymer. The sintered part is then composed of pure metal.

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

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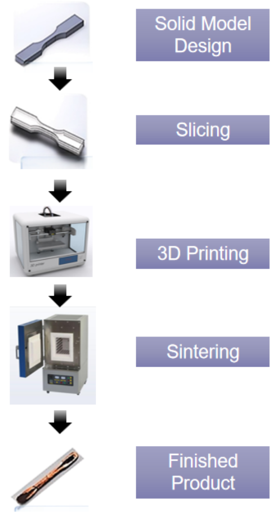

Figure 1. Sketch of LCMME

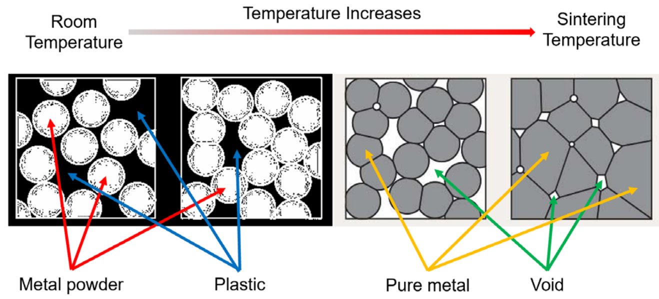

Figure 2. Process of Sintering

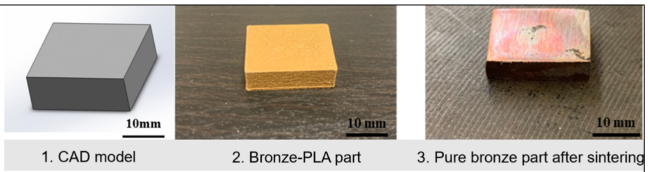

Figure 3. Samples in different status

2.2. Material Used in the Study

As a widely used plastic material, polylactic acid (PLA) has plenty of applications in both research and manufacturing [22, 23]. Bronze is a metallic material that also has many applications [24] having been used by human beings for more than 5000 years [25]. Thus, in this study, the samples were fabricated using bronze-PLA filaments. The filament was made by The Virtual Foundry, it has a diameter of 2.85mm, contains 90% bronze, and has a density of 4.5g/cc. **Figure 3** shows the metal-composite part as a CAD model, when it was 3D printed, and after sintering. In this research, the author used LCMME technology fabricated several samples and the micro view of four different samples are shown in **Figure 4**. The CAD model is designed in SolidWorks and sliced using Cura. The bronze-PLA parts were 3D printed using an Ultimaker S5 3D Printer, and a KSL-1100X muffle furnace was used to sinter the parts. The SR of the pure bronze parts after sintering was measured using a SJ-210 SR Tester. **Figure 5** shows the SR tester used in this study.

2.3. Data Preparation

There are several SR parameters, such as R_a, R_{ms}, R_z, R_v, and so on. In this research, R_a is used since its accuracy and simplicity. R_a is the arithmetical mean deviation of the assessed profile; the equation is shown below:

$$R_a = \frac{1}{l_r}\int_0^{l_r} |\, z(x) \,|\, dx \qquad (1)$$

where l_r is the measured length. In this research, the value of l_r is chosen as 20% of the specimen length. For example, if the length of the part is 20mm, the l_r of this part is 4mm.

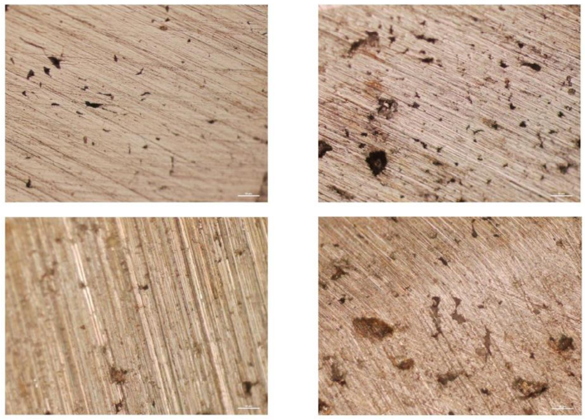

Figure 4. Micro View of Four Different LCMME Fabricated Parts

Figure 5. SJ-210 SR Tester

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	

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;
Printing Speed (PS): the moving speed of the nozzle during the 3DP process.
Table 1 shows the units and values of different manufacturing parameters.

2.4. SVR and VV

In this study, support vector regression (SVR) and a neural network (NN) were used to predict the SR results of LCMME fabricated parts. SVR provides flexibility to define whether the error in a model is acceptable or not. An 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. **Figure 6** shows the structure of the NN algorithm. Operators input the manufacturing parameters, and the algorithm generates the predicted SRvalue.

3. Results

In this ssction, the results are shown.
Figure 7 shows the top, front, and side views of a sample, and **Table 2** shows the SR values of different surfaces of two different specimens. These two specimens that were chosen had different manufacturing parameters; for example, the LT was 0.3mm for the first one and the second specimen had an

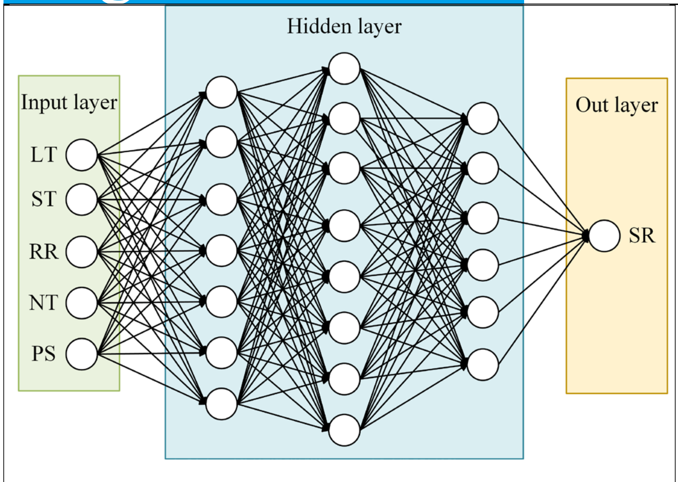

Figure 6. NN Structure

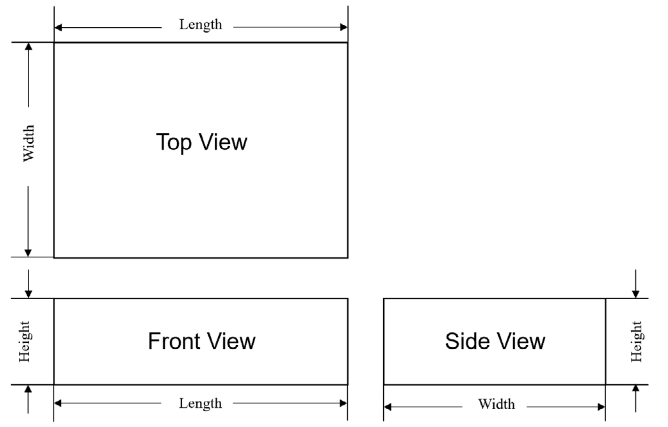

Figure 7. Top, Front, Side Views of the Samples

Table 2. SR Examples

Manufacturing Parameters					SR (μm)		
LT (mm)	ST (°C)	RR (°C/min)	NT (°C)	PS (mm/s)	Top	Front	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

Table 3. ANOVA Result of Three Groups of Data

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

LT of 0.2mm LT. In this study, the data were firstly divided into three groups, which were the top, front, and side. Different manufacturing parameters lead to different SR values for different surfaces.

3.1. Results of ANOVA

This study used R to apply ANOVA for two main purposes. The first was to determine whether all surfaces had the same SR values for each cubic sample. The second was to determine whether all manufacturing parameters had an influence on the SR values.

A one-way ANOVA model was developed to determine whether the SR is the same on different surfaces. The following hypotheses were set:

H_0: $\mu_{SR\_Top} = \mu_{SR\_Front} = \mu_{SR\_Side}$

H_a: 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 H_0 is rejected. Thus, the three groups of surfaces do not have the same SR values.

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:

H_0: $\mu_{SR\_Front} = \mu_{SR\_Side}$

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

The result of this one-way ANOVA result is shown in **Table 4**. F crit > F, which means the H0 is not rejected. Thus, the two groups of surfaces have the same SR values.

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

In an ANOVA, if the P-value is smaller than 0.001, itindicates that this parameter does not influence the final result. The results from the two tables above show that the P-values of ST, NT, and RR on SR_Top are smaller than 0.001, meaning that these three parameters have an influence on SR_Top. In Table 5, the P-values of LT and PS is 0.1962310 and 0.3608456 respectively. Thus, these two parameters do not affect SR_Top. In addition, all parameters have p-values smaller than 0.01 for SR_Edge. Thus, in the manufacturing process, all parameters affect the SR_Edge values.

As shown be the ANOVA results, the data can be simplified into two groups, which are SR_Top and SR_Edge. In the ML algorithms, only three parameters were used as independent variables in the SR_Top analysis. All five parameterswere used as independent variables in the SR_Edge analysis.

3.2. Results of ML Algorithms

In this study, the ML algorithms were run in Python and the mean square error (MSE) metric was used to evaluate the performance of each algorithm. **Table 7** shows the MSE results, indicating that the NN behaved better in predicting the SR of the LCMME fabricated parts.

It has been proved that as the number of samples increased, the accurcy of ML will raise too[5]. Thus, in order to get a lower MSE, more data collected from new samples could be added into the database.

Table 4. ANOVA Result of SR_Front and SR_Side

	Df	Sum Sq	Mean Sq	F value	F crit	P-value
dim	1	9163.768	9163.768	0.681879	3.858178	0.409293
Residuals	558	7498976	13439.03			

Table 5. ANOVA Result of SR_Top

	Df	Sum Sq	Mean Sq	F value	P-value
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	P-value
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***

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 the AM process, the SR is an important value for quality evaluation. In this study, a new metal AM technique, LCMME, was developed to fabricate pure metal parts in a low-temperature situation without a laser. Two different ML algorithms were used to predict the SR of LCMME-fabricated parts. The conclusions of this research are as follows:

The top side of the LCMME-fabricated parts has a different SR value from that of the edge sides.

Only three manufacturing parameters have an influence on SR_Top; ST, NT, and RR.

All five parameters affect the SR_Edge values.

The MSE of an NN is smaller than that of SVR in overall.

This study focused on analyzing the SR of LCMME-fabricated parts and employed ML algorithms to perform prediction. It can help manufacturers develop a more accurate design before processing. In addition, by controlling the manufacturing parameters, better specimens will be fabricated in the future.

5. Future Work

In this study, the influence of different manufacturing parameters is evaluated using ANOVA. In addition, two ML methods are used to predict the SR values of LCMME-fabricated parts. In future research, more parameters, such as the flow rate, build-plate temperature, fan speed, and material flow rate can be added to increase the accuracy of prediction. However, the ML algorithms used in this study occupy significant time and storage sources to generate results. Thus, if the research group could use better equipments, more data could be used in the ML algorithms and more accurate results will be generated. In addition, a straightforward and simple model, such as linear regression with interactions and k-Nearest Neighbors, can be used. In addition, more metal-polymer materials can be used for fabrication with this newly developed method. Finally, the research group will try to find an industrial application of this technology

Funding

This work was supported by Shandong Agriculture and Engineering University Start-Up Fund for Talented Scholars (BSQJ-202301).

Acknowledgments

This research has been made possible with the help provided by Mr. Xin Liu.

Conflicts of Interest

The author Zhicheng Zhang is an editor of X-Disciplinarity but was not involved in the peer review or decision-making process for this article.

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