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Process optimization and mechanical property investigation of Inconel 718 manufactured by selective electron beam melting

Heng Dong1,2, Feng Liu1,2, Lin Ye1,2, Xiaqiong Ouyang1,2, Qiangbing Wang3, Li Wang1,2, Lan Huang1,2*, Liming Tan1,2*, Xiaochao Jin4, Yong Liu1,2

1State Key Laboratory of Powder Metallurgy, Central South University, Changsha 410083, China
2Powder Metallurgy Research Institute, Central South University, Changsha 410083, China
3Guangzhou Sailong Additive Manufacturing Co., Ltd., Guangzhou 510700, China
4State Key Laboratory for Strength and Vibration of Mechanical Structures, Xi’an Jiaotong University, Xi’an 710049, China

Abstract
To accelerate the optimization of selective electron-beam melting (SEBM) processing parameters, two machine learning models, Gaussian process regression, and support vector regression were applied in this work to predict the relative density of Inconel 718 from experimental data. The experimental validation indicated that the trained algorithms can precisely predict the relative density of SEBM samples. Moreover, the effects of different parameters on surface integrity, internal defects, and mechanical properties are discussed in this paper. The Inconel 718 samples with high density (>99.5%) prepared by the same SEBM energy density exhibit different mechanical properties, which are related to the existence of the unmelted powder, Laves phase, and grain structure. Finally, Inconel 718 sample with superior strength and plasticity was fabricated using the optimized processing parameters.

Keywords: Electron beam melting; Inconel 718; Machine learning; Parameter optimization; Defects; Tensile property

1. Introduction
Compared with traditional subtractive manufacturing techniques, additive manufacturing (AM) techniques are getting increasing attention due to their flexibility in designing and fabricating complex parts through incremental layer-by-layer manufacturing method. Selective electron-beam melting (SEBM) is one of the most promising powder bed fusion AM techniques for metal part fabrication. Compared with another powder bed fusion technology, that is, selective laser melting (SLM), SEBM has higher energy utilization rate and production efficiency, and it could reduce the risk of oxide and nitride formation due to its vacuum environment. Moreover, SEBM reduces the temperature gradient and residual stresses through preheating and, thus, avoids the strain-induced distortion. Therefore, SEBM has advantage in fabricating high-performance materials with high active elements or which are difficult to process, such as Ti6Al4V, superalloy, copper and copper alloys, and tungsten.
To accelerate the application of the SEBM, the generation of defects during the print processing must be solved in the first place since macroscopical cracks preferentially nucleate from defects region, which affect the overall property of materials\(^\text{[13]}\). The types of internal defects reported generally in SEBM process include entrapped gas porosity, lack of fusion porosity\(^\text{[14]}\), shrinkage porosity,\(^\text{[15]}\) and hot cracking\(^\text{[16]}\). In Ni-based superalloys, the formation of detrimental intermetallic phases, such as laves phases, δ phases, carbides, and nitrides, is also a kind of defect, because they reduce the number of elements used for solid solution and γ/γ’ precipitation\(^\text{[17-20]}\). Although some post-processing treatment methods, such as hot isostatic pressing (HIP), could reduce the defect density, not all defects can be repaired\(^\text{[21,22]}\). Therefore, it is of great significance to control defect generation during AM process by optimizing processing parameters. Various researchers have optimized processing parameters through experiment, such as taguchi method\(^\text{[23]}\), energy density\(^\text{[24]}\), processing window\(^\text{[25]}\) and dimensionless number\(^\text{[26]}\), and performed physical calculation simulation\(^\text{[27-29]}\) to build defect-free parts with a flat surface successfully. However, the processing parameters optimization is still a big challenge due to the high-dimensionality and complex combination of parameters, during which complex physical processes and interactions also need to be considered.

Recently, with the development of materials informatics, machine learning method has been broadly adopted to facilitate composition and process optimization for complex alloys\(^\text{[30-36]}\). Liu \textit{et al.}\(^\text{[37]}\) developed a machine learning approach based on Gaussian process regression (GPR) to identify the processing window for AlSi10Mg alloy by laser powder bed fusion, wherein the fully dense alloy with high strength and ductility was manufactured. Aoyagi \textit{et al.}\(^\text{[38]}\) proposed a simple method that combines uniform design and support vector machine to correlate processing parameters with surface conditions and generated a processing map that can obtain the best densification for SEBM CoCr alloy by fewer samples. Thereafter, Lei \textit{et al.}\(^\text{[39,40]}\) optimized multiple processing parameters of SEBM for superalloy Alloy713ELC. Sah \textit{et al.}\(^\text{[41]}\) trained multiple machine learning algorithms to predict the density and defect formation in LBPF sample.

In this study, the most commonly used superalloy Inconel 718 was selected to investigate the effects of different parameters on the surface morphology and internal defects. The beam current and scan speed were used as the input of GPR and support vector regression (SVR) to establish the relationship between different processing parameters and relative density, and the optimized processing window is determined. Then, four high-density Inconel 718 samples with different microstructures and properties were built according to the processing window. The relationship among SEBM processing parameters, defect, microstructure, and property of Inconel 718 was studied.

2. Methodology

2.1. Inconel 718 powder and SEBM process

Pre-alloyed powders were supplied by Guangzhou Sailong Additives Manufacturing. Co., Ltd., Guangzhou, China. The chemical composition of powder is listed in Table 1. Figure 1 shows the surface morphology and microstructure of the Inconel 718 alloy powder. The powders mostly exhibit a spherical shape (>90%), only few satellites (red arrow) and non-spherical powders (white arrow) were observed, as indicated in Figure 1A. On the smooth surface of the powder, dendrite structure can be seen, as shown in Figure 1B. Inconel 718 powder consists of fine equiaxed grains with average grain size of 5.8 μm.

![Figure 1. Surface morphologies and microstructures of pre-alloyed Inconel 718 powder. (A) SEM in low magnifications. (B) SEM high magnifications. (C) IPF map are based on EBSD measurements with a step size of 0.3 μm.](https://doi.org/10.18063/msam.v1i4.23)

Table 1. Chemical composition of Inconel 718 powder.

<table>
<thead>
<tr>
<th>Ni</th>
<th>Cr</th>
<th>Fe</th>
<th>Nb</th>
<th>Mo</th>
<th>Ti</th>
<th>Al</th>
<th>Co</th>
<th>Ca</th>
<th>Si</th>
<th>C</th>
<th>O</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bal.</td>
<td>21</td>
<td>17.2</td>
<td>5.12</td>
<td>3.21</td>
<td>0.85</td>
<td>0.45</td>
<td>0.2</td>
<td>0.089</td>
<td>0.039</td>
<td>0.032</td>
<td>0.0149</td>
<td>0.0146</td>
</tr>
</tbody>
</table>

https://doi.org/10.18063/msam.v1i4.23
and random orientation, as shown in Figure 1C. The average powder particle size is approximately 35 μm, as illustrated in Figure 2. A flow time of 12.0 ± 0.1 s for 50 ± 0.1 g of powders is determined by going through a 2.5 mm diameter Hall flowmeter orifice. Therefore, the pre-alloyed powders with the above-mentioned properties are suitable for the selective electron-beam melting.

The SEBM was conducted on a commercial SEBM machine (Sailong-Y150 SEBM System) provided by Xi’an Sailong Metal Materials. Co, Ltd., Xi’an, China. During SEBM, the powder bed was preheated to 900°C to prevent “smoking” phenomenon. Then, the contour scanning was performed before hatching. The scanning direction of the electron beam was rotated by 90° after each successive layer. In this study, beam current and scan speed were chosen as variables with a certain acceleration voltage of 60 kV, a line offset of 100 μm, a layer thickness of 50 μm, and a spot size of 150 μm. Cuboid samples with a size of 20 × 20 × 10 mm³ were built using the processing parameters, as shown in Table 2, which generate 63 parameter combinations in total. The volume energy density (J/mm³) is calculated as follows:

\[ E_{\text{volume}} = \frac{P}{\nu \times l \times t} \]  

where \( \nu \) is scan speed (mm/s), \( l \) is line offset (mm), \( t \) is layer thickness (mm), and the power \( P \) is determined by

\[ P = U \times I \]  

where \( U \) is acceleration voltage (V), and \( I \) represent beam current (mA).

### 2.2. Machine learning

SVR and GPR are two classical regression algorithms of machine learning in the field of process optimization. Both models have advantage in update and suitable for small data set. It is necessary to evaluate, in which one is suitable for data in this work. Other common algorithms have been evaluated. Linear regression and logistic regression were too simple to learn effectively. Artificial neural network was so complex that it can easily cause overfitting. Although Decision Trees, Random Forest, and K-Nearest Neighbor obtained an optimized processing window, they did not obtain a smooth boundary curve between different relative density due to their characteristics. The SVR constructs a hyper-plane or set of hyper-planes in a high or infinite dimensional space, and the nearest data points on either side of the hyper-plane are termed as support vectors which are used to plot the boundary line\(^{41}\). All data in a set are closest to the regression plane. The model produced by SVR only depends on a subset of the training data, because the cost function ignores samples whose prediction is close to their target\(^{42}\). The GPR implements Gaussian processes (a generic supervised learning method) for regression purposes. The collection of random variables has a joint Gaussian distribution with a continuous domain and the prediction interpolates the observations\(^{37}\). In this study, beam current and scan speed are input, while relative density is output, and SVR and GPR were used to predict relative density and generate processing windows.

The raw data set will affect the results of machine learning algorithms. Data preprocessing methods, including unbalanced data, data partitioning, and standardization, were applied to reduce the impact of raw data distribution and improve the accuracy of prediction. As shown in Figure 3, relative density values are mostly concentrated between 98% and 100%, and only a few original data are lower than 98%, resulting in unbalanced data. Unbalanced data reduce the prediction accuracy of low-density areas. To improve the prediction accuracy, the data of relative density lower than 98% were copied once to improve the weight of low-density data. The total data set was increased to 65 (remove unformed build). Machine learning parameters are divided into parameter and hyper-parameter. Parameter obtains value by the process of training data, but hyper-parameter is set manually. The choice of hyper-parameter will change the learning ability of machine learning model. When the data and hyper-parameter are fixed, the machine learning model is usually fixed. Therefore, raw data set should be partitioned to obtain the appropriate hyper-parameter, and the train-set

![Figure 2. The powder size distribution of the studied Inconel 718 alloy.](https://doi.org/10.18063/msam.v1i4.23)

<table>
<thead>
<tr>
<th>Processing parameter</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beam current (mA)</td>
<td>7.5, 10, 12.5, 15, 17.5, 20, 22.5, 25, 27.5</td>
</tr>
<tr>
<td>Scan speed (mm/s)</td>
<td>2000, 3000, 4000, 5000, 6000, 7000, 8000</td>
</tr>
</tbody>
</table>

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### References

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Process optimization of SEBM IN718 via ML

3. Results

3.1. Processing parameters on surface integrity

There is a total of 63 combination of scan speed (m/s) and beam current (mA) in this study. The samples were divided into four types: even, uneven, porous, and unformed, according to the surface morphology observed from the optical images, as shown in Figure 4A. According to processing parameters window of surface morphology, porous surface was observed in the samples built with low beam current and high scan speed, while uneven or unformed surface was observed in the samples built with high beam current and low scan speed. Most samples can obtain a flat and even surface. Figure 4B-D shows the typical surface morphology and corresponding cross-sections of samples. There were two different cross sections of uneven surface. Large irregular pores were inside undular surface, while no pores were inside arched surface, as shown in Figure 4B. The even surface had a cross-section without defects or with a few defects, as shown in Figure 4C. There were a large number of lack-of-fusion pores beneath the porous surface, and the lack-of-fusion defects were generally perpendicular to the build direction, as shown in Figure 4D.

The energy input or energy density is often used to investigate the influence of SEBM processing parameters. Figure 5A shows the relationship among surface morphology, energy density, and beam current. To a certain extent, the energy density reflects the
characteristics of surface morphology. Low-energy density results in porous surfaces, while high-energy density results in uneven surfaces. Despite the same energy density, it is still easy to get uneven or unformed surfaces when the beam current is too high. The surface morphology is also related with the relative density, as shown in Figure 5B. The porous surface has a low relative density due to the lack-of-fusion defects mentioned above. Samples with even surfaces usually own higher relative density, compared to those with uneven surfaces. Different from SLM which uses laser as energy source, there was no reduction in relative density due to keyhole when the energy density is too high\(^{46}\).

### 3.2. Prediction of relative density by machine learning

In this study, SVR and GPR machine learning algorithms were trained to predict the relative density. There were 65 groups of basic data (including six repeated low relative density data), in which 52 data were for training, while 13 data were for testing, as shown in Figure 3. Training the machine learning model by the method is described in section 2.2. The appropriate hyper-parameter was selected by the Grid-Search method. Hyper-parameter is critical to machine learning's performance. SVR has the radial basis function kernel and hyper-parameters \(C = 300, \gamma = 3.5\), and GPR has squared exponential kernel and hyper-parameter...
alpha = 5 × 10⁻³. Kernel and hyper-parameters affect the learning ability and generalization of the model⁴⁷. The predicted value matched well with the measured value, indicating that the selection of hyper-parameter was appropriate, as shown in Figure 6A and 6C. Compared with the “big data” in the field of artificial intelligence, the data volume obtained by SEBM was small. To make full use of the limited data, all data were taken as input to train the machine learning model with the same hyperparameters. New machine learning model predicted the relative density from the parameter space. There were 61 discrete scan speed values from 2000 mm/s to 8000 mm/s with an interval of 100 mm/s and 201 discrete beam current values from 7.5 mA to 27.5 mA with an interval of 0.1 mA. The combination of these parameters gave rise to a parameter space of 12261. The scoring of SVR model and GPR model is shown in Table 3. Both models have learned data well and exhibited good performance. The relative density contour map was produced by GPR model and SVR model, as shown in Figure 6B and D. Both maps displayed similar structure, while a high relative density region of low beam current and high scan speed predicted by SVR did not exist. Hence, the map obtained by GPR model may be more applicable.

3.3. Optimized SEBM processing window for Inconel 718

The SEBM processing window for Inconel 718 was obtained by the combination of GPR relative density contour map and processing parameters window of surface morphology, as shown in Figure 7A. The area with high relative density and even surface is the optimized SEBM processing window. The low, middle, and high scan speed areas in the processing window were used to fabricate Inconel 718 samples with a high relative density and even surface. Compared with SVR model, an apparent feature

Figure 6. Relative density value prediction results: Comparison between predicted value and measured value from test-set (A) GPR and (C) SVR, and relative density contour map with beam current and scan speed (B) GPR and (D) SVR (the red circle is the area of error prediction). GPR: Gaussian process regression, SVR: Support vector regression.

Table 3. Scoring of SVR and GPR.

<table>
<thead>
<tr>
<th>Machine learning algorithm</th>
<th>R²</th>
<th>MSE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Train-set</td>
<td>Test-set</td>
</tr>
<tr>
<td>SVR</td>
<td>0.9975</td>
<td>0.9942</td>
</tr>
<tr>
<td>GPR</td>
<td>0.9994</td>
<td>0.9913</td>
</tr>
</tbody>
</table>

GPR: Gaussian process regression, SVR: Support vector regression
of GPR is that it can output prediction error directly. The error of relative density prediction in parameter space is provided in Figure 7B. All the area had low error except for the unformed surface area.

Four new points of processing conditions within the area with high relative density and even surface in this optimized processing window were selected to validate the GPR model. It should be noted that P1, P2, and P3 have the same energy density. New samples were fabricated with corresponding processing parameters. The specific SEBM processing parameters of new samples and the results of measured and predicted values are shown in the Table 4. In the 95% confidence interval (error × 1.96), the predicted value matched with the measured value and exhibited high accuracy, as shown in Figure 7C. In addition, the relative density obtained under the new processing parameter was generally higher than the previous training data. The microstructure and mechanical properties of the four new samples were further characterized.

3.4. Microstructure of the SEBM-fabricated Inconel 718

As shown in Figure 8, no cracks and lack-of-fusion pores were found in the building samples. BSE images at low

![Figure 7](https://example.com/figure7.png)

Figure 7. (A) The selective electron beam melting processing window for Inconel 718 and selected four new points for validation. (B) The error of relative density prediction by GPT model. (C) The measured relative density values compared to the predicted relative density values by Gaussian process regression model from four new points of parameter combination.

<table>
<thead>
<tr>
<th>Point</th>
<th>Beam current (mA)</th>
<th>Scan speed (m/s)</th>
<th>Energy density (J/mm²)</th>
<th>Measured relative density</th>
<th>Predicted relative density</th>
<th>Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1</td>
<td>9.6</td>
<td>2.4</td>
<td>48</td>
<td>99.72%</td>
<td>99.82%</td>
<td>-0.10%</td>
</tr>
<tr>
<td>P2</td>
<td>16.8</td>
<td>4.2</td>
<td>48</td>
<td>99.68%</td>
<td>99.63%</td>
<td>+0.05%</td>
</tr>
<tr>
<td>P3</td>
<td>25.6</td>
<td>6.4</td>
<td>48</td>
<td>99.63%</td>
<td>99.57%</td>
<td>+0.06%</td>
</tr>
<tr>
<td>P4</td>
<td>22.5</td>
<td>7.5</td>
<td>36</td>
<td>99.52%</td>
<td>99.29%</td>
<td>+0.23%</td>
</tr>
</tbody>
</table>

Table 4. Processing parameter of new samples for validation and relative density of measured and predicted value.
magnification present the similar microstructure of slender columnar grains from SEBM-fabricated Inconel 718 with processing parameters, as shown in Table 4. The columnar grains were parallel to the BD, which was also observed in other works about SEBM process\(^{25,45,48}\).

Further, characterization shows that the main defect in the sample with even surface morphology was the voids parallel to the BD, as shown in Figure 9A. This defect was also observed in samples with uneven and porous surface morphology. The voids were distributed at the interdendritic region with a width of 2–3 μm and a length of 20 μm. These voids are considered the shrinkage porosity\(^{49}\).

The reason for the formation of shrinkage porosity was that insufficient liquid reached the channel that was isolated by dendrite bridging during solidification\(^{50}\). Three precipitates can be observed in the matrix of these samples, as shown in Figure 9B, and Figure 9C is the corresponding EDS map. According to the morphology and element enrichment, the block shape precipitate “a” is enriched in Nb and Mo, which is determined as Laves phase\(^{47}\). The long plate shape precipitate “b” is the δ phase. Laves phase is mainly formed on the grain boundaries and mixed with a few of δ phase somewhere. The polygonal precipitate “c” is enriched in N and Ti, indicating the existence of TiN phase. The spherical precipitate “d” in the core of TiN is rich in Al and O, which suggests that the precipitate is the Al\(_2\)O\(_3\) phase. No gas pore defects were observed inside the sample.

The difference between grains was observed by EBSD. Figure 10 shows the EBSD-IPF maps on the cross-section parallel to the BD. Strong texture in the as-built samples along the BD was observed in the EBSD-IPF maps. The as-EBM-built samples mainly consist of columnar grains with preferential orientation <001>, decorated with few equiaxed fine grains. Figure 11 shows the pole figures and multiple of uniform density (MUD) maximum of four samples. Sample P2 shows a strong texture in BD with a MUD maximum of 30.73, sample P1 and P3 shows a reduced texture, and sample P4 has the lowest MUD maximum, which is 17.21. Completely equiaxed grain

Figure 8. BSE images at low magnification showing the similar slender columnar grains in different samples: (A) P1, (B) P2, (C) P3, (D) P4.

Figure 9. BSE images of defects and phase in selective electron beam melting-fabricated Inconel 718: (A) shrinkage porosity, (B) Laves phase, δ phase, and TiN/Al\(_2\)O\(_3\) phase, (C) EDS map of the inclusion in (B).
structure has a MUD value of 1. In comparison, sample P2 has the least area of grains in random orientations.

The bottom half of these regions reserved a hemispherical shape. Compared with the microstructure of pre-alloyed powder, it indicated that the fine grains may be inherited from the incompletely melted powder. Columnar grains were formed after <100> preferential growth on equiaxed grains. The columnar grains are interrupted when coming across the next unmelted powder. Variations of the columnar grain width measured using the interception method according to ASTM E112-2013 standard are listed in Table 5. Samples P1, P2, and P3 with the same energy density had similar columnar grain width, and sample P4 with the fastest scanning speed and smaller energy density had finer columnar grains.

3.5. Mechanical properties of SEBM-fabricated Inconel 718

The hardness of Inconel 718 fabricated by SEBM with the parameters listed in Table 4 is shown in Table 5. It can be seen that the as-built samples without heat treatment had high hardness, because high temperature was maintained.

![Figure 10. Electron back-scattered diffraction-Inverse pole figure maps on cross-section of as-built samples: (A) P1, (B) P2, (C) P3, and (D) P4.](image)

![Figure 11. Pole figures in the XY-plane: (A) P1, (B) P2, (C) P3, (D) P4.](image)
during SEBM process resulting in precipitation of $\gamma'$ and $\gamma''$ phase. However, the deviation indicates that the microstructures and the precipitates were not uniform. The tensile strength, yield strength, and elongation at room temperature of the as-built samples are shown in Figure 12, and the detailed values are shown in Table 5. Although the four samples fabricated by optimized processing parameters obtained high relative density, the mechanical properties were different. Sample P1 had the worst mechanical properties, while sample P2 had the best, although both P1 and P2 were fabricated with the same energy density. Samples P1 and P3 had relatively higher relative density and similar hardness values, but the mechanical properties of sample P3 were significantly higher than that of sample P1, especially the elongation. Thereby, as for the SEBM-fabricated fully dense Inconel 718 specimens, it is far from adequate to take energy density or relative density into consideration to optimize the mechanical properties.

### 4. Discussion

#### 4.1. Relationships between surface morphology and internal defects

The pre-alloyed powder in this study was prepared by plasma rotating electrode process; hence, the gas pore inside the powder and gas pore induced defects can be ignored. As shown in Figure 4, different combinations of parameters will give rise to different surface morphology in SEBM process. Different surface morphology is related to various types of internal defects. Uneven surface included lack-of-fusion defect or no defects, even surface included shrinkage porosity defect, while porous surface included lack-of-fusion defect.

Figure 13A shows the effect of beam current on relative density, and input energy increases with the increase of current by fixing scanning speed. When the input energy gradually increases, the surface morphology changes from even to uneven, and the relative density first decreases and then increases. The combined effect of the Marangoni effect, vapor recoil pressure, and electron-beam agitation results in an uneven surface.\(^{[52]}\). The convex and concave of the uneven surface led to a large difference in the thickness of the powder layer, and the input energy (beam current < 15 mA) is not enough to melt the thicker powder layer, resulting in a huge lack-of-fusion defects, as shown in Figure 4B. With the further increase of input energy (15 mA < beam current < 25 mA), the molten pool is enough to pass through the thick powder layer and prevent lack-of-fusion defects, and the relative density increases correspondingly. When the input energy (beam current > 25 mA) is too high, the splashing of metal liquid or metal vapor makes it impossible to form. Figure 13B shows the effect of scan speed on relative density, and input energy decreases with the increase of scan speed by fixing beam current. When the input energy gradually decreases, the surface morphology changes from even to porous, and the relative density decreases. As shown in Figure 14, the sample with porous surface had a large number of lack-of-fusion defects, which is the main reason for the low relative density. Small and shallow molten pool was generated due to the low input energy. The molten pool cannot effectively penetrate the new layer of powder and combine with the previous solidified layer. Balling effect causes the partially melted powder to form an isolated molten liquid. Due to surface tension and rapid solidification, molten liquid could not flow into pores and thus combine with nearby powder.\(^{[53]}\). Therefore, the lack-of-fusion defects

<table>
<thead>
<tr>
<th>Sample</th>
<th>Columnar grain width (μm)</th>
<th>Hardness (Hv)</th>
<th>Yield strength (MPa)</th>
<th>Tensile strength (MPa)</th>
<th>Elongation (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1</td>
<td>20.7±(16.51)</td>
<td>427.70±(32.59)</td>
<td>908.0±(5.0)</td>
<td>1009±(50)</td>
<td>7.6±(1.3)</td>
</tr>
<tr>
<td>P2</td>
<td>22.36±(16.85)</td>
<td>440.15±(15.81)</td>
<td>954.5±(14.5)</td>
<td>1270±(9)</td>
<td>34.0±(1.7)</td>
</tr>
<tr>
<td>P3</td>
<td>19.11±(15.30)</td>
<td>424.09±(17.34)</td>
<td>914.5±(10.5)</td>
<td>1215±(22)</td>
<td>22.1±(6.5)</td>
</tr>
<tr>
<td>P4</td>
<td>14.36±(10.30)</td>
<td>410.82±(12.88)</td>
<td>876.0±(4.0)</td>
<td>1216±(30)</td>
<td>17.5±(3.9)</td>
</tr>
</tbody>
</table>

Figure 12. Tensile tests at room temperature of as-built Inconel 718 samples with the parameters listed in Table 4.
are generally irregular, and the defect direction may be either vertical to the powder layer or parallel to the powder layer. When the input energy is appropriate, the surface morphology is even. Although the surface is even and free of defects, the properties of the Inconel 718 fabricated by SEBM vary greatly when specific parameters are different. Therefore, the internal defects can be roughly judged by the surface morphology, while the mechanical properties need further evaluation.

4.2. Machine learning models for optimizing SEBM processing window

SVR and GPR models have exhibited good ability of learning and prediction in this study. As shown in Figure 6, SVR model incorrectly predicted that Inconel 718 fabricated in the region with low beam current and high scan speed had high relative density. Error in prediction may be caused by overfitting. Overfitting led to wrong prediction in the test-set in spite of good performance of the machine learning model in the train-set. The composition and preprocessing of data set or the inappropriate hyper-parameters could result in overfitting. Compared with GPR, SVR had better R² and MSE in the test-set, but the robustness and generalization were worse. Therefore, the results of GPR model were better in this study to represent the predicted value of relative density in parameter space. However, it does not mean that any data set related to SEBM process is applicable to GPR model. Complex machine learning model does not necessarily have better learning performance. Model selection is based on the performance, interpretability, complexity of model, size, dimension of data set, and training time and cost. For a new data set, especially when the feature number is large, it is necessary to conduct performance tests on different machine learning algorithms to select the appropriate algorithm, such as ten-fold cross-validation. SVR and GPR chosen here are suitable for few-shot learning, because the data are limited in this study. Another feature deserved that more attention of GPR model is that the prediction error can be directly obtained. Updated GPR model is also convenient for small databases obtained in engineering application. When more measured data are obtained, the new data can be further added to the data set, and the model can be trained again to enhance the prediction performance and accuracy.

The SEBM processing window established through machine learning model with limited data has larger parameter selection range than before, which is conducive to selecting the appropriate processing parameters and controlling microstructure. High beam current and scan speed could improve production efficiency. Moreover, using machine learning to predict, the surface integrity is meaningful. There is a high relative density area at high-energy density, but this area is not suitable to manufacture due to the severe loss of dimensional accuracy. Four new samples that were manufactured according to processing window proved...
the reliability of processing window. Although the sample manufactured by the optimized processing parameters still contain some defects, post-treatment such as HIP could heal those defects, and the original grain structure can be maintained as much as possible[21]. The formation of shrinkage porosity defects in Figure 9A may be ascribed to the existence of some imperfect spherical powders in the pre-alloyed powders, which resulted in low-energy absorption rate and thermal conductivity, and it prevented the liquid flowing into the inter-dendritic region to compensate voids[12].

4.3. Mechanical properties and fracture mechanisms

Inconel 718 samples, especially samples P1 and P2, with high relative density (>99.5%) were fabricated by SEBM after process optimization, which displayed different strength and elongation. Samples P1 and P2 had the same energy density. Although P1 had the highest density in this study, its mechanical properties were the worst. As shown in Figure 10, the difference in mechanical properties may be caused by different microstructures. According to the analysis of section 3.4, the unmelted powder resulted in equiaxed grains. The fracture surfaces of P1 and P2 were analyzed to explore the reason, as shown in Figure 15A-F. The samples exhibited dimple fracture, which indicates the ductile fracture mode. Both of them showed fine and equiaxed dimples in the center, and there were no significant differences between the size and depth of dimples. This is consistent with high elongation of P2, while P1 showed low elongation. Brittle fracture was observed at the boundary in Figure 15G, and complete and broken powders in P1 were observed, as shown in Figure 15H and I, respectively. The size of complete powder particle is about 88 μm, which is relatively large among pre-alloyed powder. These unmelted powders did not reduce the relative density of the sample, but retained the original structure of the pre-alloy powder. This, further, suggests that the equiaxed grains in Figure 10 may stem from the unmelted powder. The unmelted powder also resulted in the decrease of plasticity of Inconel 718 sample, because the smooth surface reduced the intergranular bonding force, and Laves phase inside powder perpendicular to the tensile direction also decreased the strength. The unmelted powder in each part of the sample became the breach of fracture. Although P3 and P4 had finer columnar grains, the increase in the number of mixed-equiaxed grain reduced its strength and plasticity. The large area of mixed-equiaxed grain that appeared randomly is the reason for the large variance of the elongation in P3 and P4. Sun et al.[51] fabricated the Inconel 718 by SEBM with similar microstructure to P1, whose strength and plasticity were also poor. Therefore, it is necessary to improve energy input to fully melt the original pre-alloyed powder. Reducing the particle size distribution is

![Image](https://example.com/image.jpg)

**Figure 15.** SEM images of fracture surface: (A–C) P2; (D–F) P1; (G), (H) and (I) are the corresponding regions in (D).
also beneficial to the energy absorption of the powder. The above results suggest that energy density is not good enough to represent the energy absorbed by the powder.

In this study, the mechanical properties were measured in the as-built state. As shown in Figure 16, compared with SEBM and wrought Inconel 718 in other reports, P2 had considerable strength and elongation, because the sample with no defects and finer columnar grains was fabricated in processing window. Laves phase and δ phase (Figure 9B) were rich in strengthening elements such as Nb and Mo which reduced the effect of solid solution strengthening and inhibited the precipitation of γ’ and γ’’ strengthening phase[17]. The bulk Laves phase is also the initiation region of the crack. Under normal conditions, solution treatment can make Laves phase dissolve into the matrix, and aging treatment can make strengthening phase precipitate uniformly. Therefore, heat treatment is suggested to further improve mechanical property of Inconel 718.

5. Conclusions

In this study, SEBM processing window was established for Inconel 718 using machine learning model to obtain high relative density. The relationship between the SEBM processing parameters, surface morphology, defects, microstructure, and mechanical properties has been investigated. The main conclusions are as follows:

(i) Excessive energy input leads to uneven surfaces or unshaped samples. Insufficient energy input results in porous surface with lack-of-fusion defects, which is the main reason for low density.

(ii) SVR and GPR models were trained to predict the relative density, and GPR model presents superior predictability. The SEBM processing window for Inconel 718 was obtained by combining GPR relative density contour map with processing parameter window of surface morphology. Machine learning model allows the high-density area to be predicted from a data set which contains a few samples, and the parameter space is larger than before.

(iii) Inconel 718 samples with high relative density (>99.5%) were fabricated by SEBM. Mechanical properties and plasticity are different while at the same energy density. Although the unmelted powder particles did not reduce the relative density of the sample, the smooth surface and the Laves phase inside, which are perpendicular to the tensile direction of the powder, aggravate the properties.

(iv) Sample P2 with few defects and finer columnar grains was prepared using the optimized parameters, and further, mechanical test indicated its excellent combination of strength and ductility.

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Conflict of interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Author contributions

Conceptualization: Heng Dong, Feng Liu, Liming Tan
Formal analysis: Heng Dong
Funding acquisition: Yong Liu, Li wang
Investigation: Heng Dong, Lin Ye, Xiaqiong Ouyang
Methodology: Heng Dong, Lin Ye, Xiaqiong Ouyang
Resources: Qiangbing Wang
Supervision: Liming Tan, Lan Huang
Validation: Heng Dong, Feng Liu
Writing – original draft: Heng Dong, Feng Liu
Writing – review & editing: Heng Dong, Liming Tan, Lan Huang, Xiaochao Jin  
All authors have read and agreed to the published version of the manuscript.

References

https://doi.org/10.1016/j.actamat.2016.07.019

https://doi.org/10.1016/j.ijmachtools.2021.103729

https://doi.org/10.18063/msam.v1i2.13

https://doi.org/10.1080/09506608.2016.1176289

https://doi.org/10.1142/s24249130214100034

https://doi.org/10.1080/09506608.2020.1868889

https://doi.org/10.1007/s11661–014–2722–2

https://doi.org/10.1016/j.matdes.2019.107792

https://doi.org/10.1016/j.matdes.2018.107552

https://doi.org/10.1016/j.addma.2019.100877

https://doi.org/10.1002/adem.201600078

https://doi.org/10.1016/j.ijrmhm.2019.105040

https://doi.org/10.1016/j.addma.2020.101059

https://doi.org/10.1007/s11837-015-1802-0

https://doi.org/10.1016/j.msea.2019.138058

https://doi.org/10.1016/j.addma.2020.101633

https://doi.org/10.1016/j.matdes.2018.09.006

https://doi.org/10.1016/j.msea.2017.12.043

https://doi.org/10.1016/j.scriptamat.2020.113661

https://doi.org/10.1016/j.marchar.2018.02.020

https://doi.org/10.1007/s10853-020-05595-2

https://doi.org/10.1016/j.matdes.2018.08.054

https://doi.org/10.1016/j.addma.2014.08.002

https://doi.org/10.1016/j.msea.2018.08.037

https://doi.org/10.1557/jmr.2014.192


https://doi.org/10.1016/j.camwa.2013.10.001

https://doi.org/10.1016/j.promfg.2017.07.151

https://doi.org/10.1002/adfm.202109367

https://doi.org/10.1016/j.scriptamat.2019.11.019

https://doi.org/10.1016/j.actamat.2019.03.010

https://doi.org/10.1038/s41524-020-0334-5

https://doi.org/10.1016/j.mtcomm.2022.103172

https://doi.org/10.1142/s242949130200050

https://doi.org/10.18063/msam.v1i1.6

https://doi.org/10.1016/j.actamat.2020.10.010

https://doi.org/10.1016/j.addma.2019.03.013

https://doi.org/10.1016/j.msea.2020.139485

https://doi.org/10.1016/j.actamat.2021.116695

https://doi.org/10.1016/j.mtcomm.2022.103193
https://doi.org/10.1023/b:stco.0000035301.49549.88

https://doi.org/10.1016/j.jmatprotec.2021.117374

https://doi.org/10.1016/j.matdes.2020.108818

https://doi.org/10.1016/j.jallcom.2019.153320

https://doi.org/10.1016/j.msea.2021.141985


https://doi.org/10.1016/j.addma.2020.101277

https://doi.org/10.1016/j.actamat.2017.09.047

https://doi.org/10.1016/j.addma.2018.08.017

https://doi.org/10.1016/j.addma.2022.102736

https://doi.org/10.1016/j.jmatprotec.2014.05.002

https://doi.org/10.1179/026708309x12468927349451

https://doi.org/10.1016/j.msea.2017.03.085

https://doi.org/10.1016/j.msea.2016.10.069

https://doi.org/10.1016/j.msea.2021.141515