Article

Process Parameter Optimization in Metal Laser-Based Powder Bed Fusion Using Image Processing and Statistical Analyses

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Abstract: The powder bed fusion additive manufacturing process has received widespread interest because of its capability to manufacture components with a complicated design and better surface finish compared to other additive techniques. Process optimization to obtain high quality parts is still a concern, which is impeding the full-scale production of materials. Therefore, it is of paramount importance to identify the best combination of process parameters that produces parts with the least defects and best features. This work focuses on gaining useful information about several features of the bead area, such as contact angle, porosity, voids, melt pool size and keyhole that were achieved using several combinations of laser power and scan speed to produce single scan lines. These features are identified and quantified using process learning, which is then used to conduct a comprehensive statistical analysis that allows to estimate the effect of the process parameters, such as laser power and scan speed on the output features. Both single and multi-response analyses are applied to analyze the response parameters, such as contact angle, porosity and melt pool size individually as well as in a collective manner. Laser power has been observed to have a more influential effect on all the features. A multi-response analysis showed that 150 W of laser power and 200 mm/s produced a bead with the best possible features.

Keywords: additive manufacturing; powder bed fusion; statistical analysis; process optimization

1. Introduction

The powder bed fusion (PBF) additive manufacturing process uses an electron or laser beam to fuse metallic powders over a build platform to print one layer of the build dictated by a computer-aided design (CAD) software. The machine takes design instruction from the CAD software and creates the part by adding layers. After the first layer is created, another layer of metal powder is distributed over the build plate using a powder hopper. This layer is then melted and solidified based on the CAD design. The process continues until the final product is built. Additive processes have the ability to produce lightweight materials with a complicated design, as well as to reduce the tooling cost, which gives them an edge over conventional manufacturing processes, such as machining in aerospace and medical industries [1,2]. The laser powder bed fusion process has been the subject of extensive research lately [3–6]. Melt pool physics is one of the most crucial and complicated phenomena during the process. Many factors impact the final quality of the melt, including the energy balance, thermo-physical properties of materials and the types of heat source used for the process. Researchers showed that melt pool and bead features, such as contact angle, porosity, voids and melt pool size, can change depending on the intensity of input energy that is supplied to the powder bed [7–11]. The energy input in turn depends on the process variables, such as laser power, scanning speed, and thickness of the layers, etc. Due to the variability of these parameters, the molten region possesses distinguished features. These features, such as lower value of contact angle, are desirable as they ensure proper adhesion with previous layers [12], and some features, such as high amount of porosity that results in distortion of the part, are not very desirable.
Researchers have tried to analyze the characteristics of different aspects of the build to optimize the parameters that can influence the process. Geometrical features such as contact angle between the present and the preceding layers, which dictates the wetting behavior of the melt pool, have been studied by several scientists. Fateri et al. [12] investigated the effect of temperature and viscosity towards the evolution of contact angle using hot stage microscopy. The study showed that contact angle decreases as the powders start to sinter at higher temperature points. Haley et al. [13] used a computational fluid dynamics (CFD) simulation technique to observe the influence of particle size, melt pool shape and surface tension on wetting dynamics. They found out that powder particle residence time, which is termed as the time between the interaction of the powder and heat source, and complete melting are dependent on particle size and surface tension, and contact angle varies inversely with residence time. Triantafyllidis et al. [14] experimentally established a relationship between power and contact angle during a laser surface treatment of Al2O3-based refractory ceramics and deduced that contact angle increases with reduced power. Hu et al. [15] used a computational model to show that contact angle decreases with increasing number of tracks and decreasing scan speed during selective laser melting. Process defect in melt pool is another important feature that has been a major concern in additive manufacturing (AM) processes. It will not be feasible to move towards large-scale production without addressing these defects. Extensive research has been dedicated towards the physics behind the formation of these defects. Brennan et al. [16] discussed different defects, such as porosity, voids, lack of fusion defects and how they can be reduced using a hot isostatic process (HIP). Other papers [17,18] have also tried to investigate defects from a different perspective. These papers mainly focused on the formation of defects, such as the lack of fusion, porosity, surface roughness, etc., on the build direction. An analysis of these defects along the bead cross section based on process parameters such as laser power and scan speed is largely missing from the literature.

The specific features of the beads discussed above can be utilized to optimize the process parameters in the powder bed process. Traditionally, process parameter optimizations are implemented using experimental and computational methods [8,19,20]. Although computational modeling can reveal important information about melt pool, microstructure, temperature history, etc., that change with the input variables, due to the complications in the process, these models possess a lot of simplified assumptions, which result in a deviation from actual experimental results [21–24]. To solve the issue, many researchers have recently opted to use machine learning algorithm techniques to optimize the process parameters. Kwon et al. [25] used a convolutional neural network (CNN) to forecast laser power from images of the molten pool taken during the experiment and built a model with 96% accuracy. Caiazzo et al. [26] built a three-layer cascade forward propagation artificial neural network (ANN) to predict the process parameters needed to print the optimum part dimension. They produced a result with 2% error for laser power and 5.8% for scan speed. Although machine learning models have become increasingly popular as they can predict data with high accuracy, these techniques are still not good enough to predict process parameters with smaller datasets [27]. These techniques require a large number of experimental data set to train [25,28], which is both time-consuming and expensive. Statistical analysis techniques have also been employed to identify patterns in additive manufacturing. Sanaei et al. [29] analyzed the defects in an AM part based on specific locations, such as the narrow section and at the perimeter of the dog-bone samples. They used a K–S statistical test to show that the distribution of defects are different in the neck and perimeter region. Casalino et al. [30] investigated the impact of laser power and scan speed on mechanical properties, such as hardness and tensile strength of the final build. They found out that increasing energy density decreases surface roughness and increases hardness. Whip et al. [31] used an analysis of variance method to observe the effect of process parameters in melt pool and surface roughness. They found out that increasing laser power increases the melt pool size, which facilitates in a smoother surface due to
proper wettability. The effect of process parameters on the evaluation of bead formation has been discussed in several works [32–34].

Although there is a handful of research discussions about the defects of AM parts, a comprehensive analysis of different features of the bead cross section is missing. Moreover, most of this research focuses on an analysis of defects on the surface and beneath. This work attempts to provide a detailed analysis of different features of the bead cross section for a nickel-based Inconel 718 sample, which has a high strength over a wide range of temperatures. Contact angle, porosity, void, melt pool area and keyhole formation are quantified. Individual significance of each parameter is analyzed using a full factorial design of experiment and analysis of variance (ANOVA). Process parameter optimization in terms of multiple response parameters is largely missing from the literature as well. A multi-response analysis is conducted in this work, including all the features as a part of process parameter optimization.

### 2. Experimental Setup

An EOSINT M280 machine was used to fabricate 24 base blocks of 25.4 mm × 25.4 mm × 4 mm using 285 W of laser power and a scanning speed of 960 mm/s to ensure that microstructure was uniform throughout all the samples [35]. Evenly spaced parallel lines were built on top of the base blocks while changing laser power and scan speed on each specimen, according to a factorial Design of Experiment (DoE). Inconel 718, an alloy based on nickel, was chosen due to its superior properties over a wide temperature range and high corrosion resistance. After the samples were built, they were cut into several sections to expose the bead cross sections. A Meiji Techno optical microscope equipped with a Nikon DS-Fi1 camera was used to take the images of the solidified beads. A magnification of 200× was used for beads with smaller dimensions. Magnifications were reduced to 100× to incorporate larger bead sizes. Samples were encased in resin, polished and etched to prepare it for micrography observation. A total of 8–12 images from each sample were taken for proper representation of the samples. Table 1 contains the laser power and scan speeds that were used during the experiments. Samples are numbered as T1, T2 and so on. ImageJ was used to quantify the features. ImageJ is a widely used open access processing and analysis software. As it was mostly a manual process, measurements were taken multiple times for the same sample to ensure precision.

| Power/Speed  | 40 W  | 100 W | 150 W | 200 W | 300 W |
|--------------|-------|-------|-------|-------|-------|
| 200 mm/s     | T1    | T4    | T10   | T13   | T19   |
| 700 mm/s     | T2    | T5    | T11   | T14   | T20   |
| 1200 mm/s    | T3    | T6    | T12   | T15   | T21   |
| 1700 mm/s    | T7    |       | T16   | T17   | T22   |
| 2200 mm/s    | T8    |       | T18   |       | T23   |
| 2500 mm/s    | T9    |       |       | T18   | T24   |

### 3. Melt Pool Features

#### 3.1. Contact Angle

Contact angle is the angle between the bead section and the layer beneath it [36]. It determines the wettability of the molten powder particle with the previous layer. Proper wettability ensures there is a good adhesion between the layers. Inadequate adhesion between layers can result in a warped build [12], as the surface tension forces become dominant over the adhesive forces. A high contact angle (>90°) can result in a balling phenomenon, which distorts the material. Thus, it is desirable to have a low contact angle to ensure proper wetting and adhesion between layers. Image analysis software ImageJ was used to measure the contact angle of the experimentally obtained bead. The bead images were obtained using optical microscopy. Pixel units were converted to micron
units for convenience. Figure 1 shows two yellow straight lines making the contact angle between the substrate and the surface of the bead.

![Contact angle measurement](image)

**Figure 1.** Contact angle measurement.

### 3.2. Porosity

Gas-entrapped pores can have both a spherical and irregular shape. They are characterized by a size of around 5–20 microns for the powder bed fusion (PBF) process and greater than 50 microns for direct energy deposition (DED) [37]. These defects can be attributed to the manufacturing of powders using a gas atomization process that can carry some gases entrapped within the powders [17]. In addition, process parameters that create strong marangoni flow can trap some of the pores within the melt pool. The presence of porosity can induce a damaging impact on material fatigue life, as well as mechanical properties. ImageJ was used to identify the porosities in the melt pool using a color threshold. The scale bars in the images were used as a reference to ensure accurate measurement of the pores by converting the pixel size to a micron unit. For ease of measurement, the color images were converted into an 8-bit binary image. Afterwards, a fast Fourier transform (FFT) using a bandpass filter was used to maintain a uniform background throughout the image. A threshold was used afterwards to separate the pores from the rest of the image. The darker regions with 0.4–1 circularity were selected as porosities having a size of 5–30 microns. The long grey regions were considered as impurities and, as such, were ignored. The borderline thresholds were removed during analysis. Figure 2a shows the cross section of the bead obtained using the optical microscope, and Figure 2b shows the color threshold used to find the porosities.

![Bead cross section](image)

**(a)** Bead cross section, **(b)** identification of porosities across the bead cross section using a color threshold.

**Figure 2.** (a) Bead cross section, (b) identification of porosities across the bead cross section using a color threshold.
3.3. Keyhole and Voids

Although a keyhole is more dominant in welding due to high laser power and low welding speed, it can be present during additive manufacturing as well, as high laser powers are being used lately in this process. High energy density on the powder material can cause evaporation, creating recoil pressure, which depresses the melt pool, creating a narrow and deep keyhole shape [38]. The keyhole needs to be controlled, otherwise it can leave voids inside the melt pool containing vapor. Metals that have low thermal conductivity facilitate the formation of a keyhole, as they help accumulate enough heat to start evaporation. Each keyhole image was measured 5 times to remove measurement error as much as possible. Figure 3 shows the keyhole formation due to excessive energy input that creates a large void inside the melt pool.

![Figure 3. Voids associated with keyholes.](image)

3.4. Melt Pool

Melt pool shape is one of the most crucial features in additively manufactured parts. Geometry of the melt pool is extremely important. If the area of the melt pool is too large, then it repeatedly melts and solidifies 4–5 layers beneath the current layer, which can create residual stress in those layers. Residual stress can result in distortion of the part of the build. On the other hand, a shallow melt pool can cause inadequate adhesion with the previously solidified layer. Therefore, choosing the optimum process parameter is of paramount importance to create the standard melt pool. Each of the melt pool areas was measured 5 times to reduce the measurement error.

4. Results and Discussion

4.1. Single Response Analysis

As part of the statistical analysis, the features were identified and quantified. An analysis of variance (ANOVA) was used to detect if the process variables such as laser power and scan speed have any significant impact on the bead cross section, such as contact angle, porosity and melt pool size. Each combination of laser power and scan speed had 6–10 images of the bead, and each response parameter was measured five times for each image to make sure the measurement errors were reduced as much as possible. Groups are defined according to the design of experiments provided in Table 1. ANOVA starts with the assumption that there is no significant influence of the input variables on the output, termed the null hypothesis. The F-ratio or F statistic is calculated using the mean of different groups to observe if the output changes significantly based on the change in the input. If the value of the F-ratio is sufficiently large, then it can be concluded that there is a
strong correlation between the input and output, and a change in the input will affect the output substantially.

\[
F \text{ ratio} = \frac{\text{Mean of squares between (MSv)}}{\text{Mean of squares within (MSw)}}
\]  

\[
MS = \frac{\text{Sum of squares (SS)}}{\text{Degrees of freedom (DF)}}
\]  

\[
DF = \text{Number of groups of a variable} - 1
\]  

\[
\text{Sum of squares within, SSw} = \sum (Y_{ij} - Y_{i avg})^2
\]  

\[
\text{Sum of squares between, SSv} = \sum (Y_{i avg} - Y_{tot avg})^2
\]  

Here, \(Y_{ij}\) denotes the jth observation of the ith group.

Equations (1)–(5) provide the steps to calculate the F-ratio. Here, between refers to the value of an output between the groups of a variable, and within means the value of an output within a specific group of a variable. For example, when we try to find out the F-ratio of the contact angle in terms of laser power, the sum of squares between refers to the variation of means of the contact angle between different laser powers (40 W, 100 W, 150 W and so on) compared to the average of all the contact angles, which can be calculated using Equation (5). On the other hand, the sum of squares within refers to the variation of the contact angle within a specific group. For instance, there are multiple values of contact angle for a laser power of 40 W. The sum of squares within calculates the variation of the contact angle within this group of 40 W, does the same for all the other groups, such as 100, 150, 200 and 300 W, and sums it all up to get the total sum of squares between, as shown in Equation (4). We get the mean of squares by dividing the sum of squares by the degrees of freedom. Finally, the F-ratio is calculated by dividing the mean of squares between by the mean of squares within. So, if the F-ratio is larger than the critical value of F provided in the F distribution table [39], then the variability of the contact angle for different laser powers is large enough to ascertain that laser power has a significant effect on contact angle. The p-value is another way to determine if the null hypothesis is true. The null hypothesis states that the mean value of the contact angle for different laser powers is the same. The p-value is the probability of accepting the null hypothesis. A smaller p-value indicates a small chance for the null hypothesis being true. For example, if the p-value is 0.05, then there is only a 5% chance that the mean contact angle value for all the laser powers will be same, which is really low. Thus, we can reject the null hypothesis.

A Pareto chart is another tool that demonstrates the significance of the process parameters on the response parameter. It is a bar chart that shows the relative effect of different parameters on a specific response or output parameter. It also provides a reference line at a 5% significant level. The process parameters are considered significant if they exceed that reference line.

### 4.1.1. Contact Angle

Figure 4 shows the effects of laser power and scan speed on the contact angle. The values of the contact angle varied between 29 degrees at 300 W/200 mm/s to 135.2 degrees at 40 W/2500 mm/s. Although literature with similar process parameters was unavailable, the trend of contact angle agrees well with the work of Triantafyllidis et al. [14] and Hu et al. [15]. The contact angle decreased with higher laser power and lower scan speed because of the high energy input. At a lower energy input, the angle was more than 90 degrees. At this level, balling phenomena occurred that could create delamination and distort the part. It can be observed from both Figure 4 and the F-value of Table 2 that both laser power and scan speed played a significant role on contact angle. The F-value for
laser power was larger than scan speed, indicating that power had a more significant effect than scan speed on contact angle. An ANOVA for the interaction between laser power and scan speed was not possible to conduct, as we did not have contact angle data for all combinations of laser power and scan speed because some of the beads were broken due to balling and other defects.

![Main Effects Plot for Contact Angle](image1)

**Figure 4.** Individual impact of laser power and scan speed on mean contact angle.

**Table 2.** Analysis of variance.

| Source | DF | Adj SS (Degree$^2$) | Adj MS (Degree$^2$) | F-Value | p-Value |
|--------|----|---------------------|---------------------|---------|---------|
| Power  | 4  | 16,439.6            | 4109.89             | 338.87  | 0.00001 |
| Speed  | 5  | 1872.2              | 374.44              | 30.87   | 0.00003 |

It can also be observed from the Pareto chart in Figure 5 that both power and speed effects were higher than the threshold detected by the 95% confidence interval (red dotted line), with laser power being the most dominant influencing factor. The values in the x axis denote deviation from the overall mean for each process parameter. The more the deviation, the more likely it is that the specific parameter is more influential on the output value.

![Pareto Chart of the Standardized Effects](image2)

**Figure 5.** Pareto chart of the standardized effect of laser power and scan speed on contact angle.
4.1.2. Porosity

The pores in the melt pool varied in the range of 5 to 30 microns in diameter. This is similar to the average size found by Everton et al. (5 to 20 microns) [37]. Due to improper melting, a lack of fusion occurred at lower laser powers and higher scan speeds, resulting in a higher number of pores. Although there was less porosity at higher laser powers due to proper wetting, some pores still existed due to the larger melt pool size. Excluding the 40 W power samples, which did not have enough power to melt the particles, porosity ranged from 1 to 8 percent (Figure 6), which is similar to the 1–5 percent range found in the literature [17].

![Figure 6](image)

**Figure 6.** Individual impact of laser power and scan speed on the mean of porosity.

Laser power had a considerable influence on pore percentage, as is evident from the ANOVA analysis (Table 3) and Pareto chart (Figure 7). Although scanning speed had much less significance, it was still above the threshold level, and hence could not be ignored while optimizing the process to minimize porosity in the melt pool.

**Table 3.** Analysis of variance.

| Source | DF | Adj SS  | Adj MS  | F-Value | p-Value |
|--------|----|---------|---------|---------|---------|
| Power  | 4  | 321.06  | 80.266  | 22.52   | 0.000   |
| Speed  | 5  | 68.04   | 13.607  | 6.82    | 0.027   |

![Figure 7](image)

**Figure 7.** Pareto chart of the standardized effect of laser power and scan speed on porosity.
4.1.3. Melt Pool

Power and speed had similar, but opposite effects on the melt pool area that spanned across the melt pool depth, width and height of the bead (Figure 8). Melt pool size can be extremely small and shallow for a lower energy input, while high energy can create a large enough molten pool that melts 5–6 layers of previously solidified layers. An ANOVA analysis (Table 4) showed that the p-value for power and speed was 0.007 and 0.010, indicating a significant effect on melt pool area. Contrary to contact angle and porosity, scan speed and laser power had a similar impact on the size of the melt pool. Melt pool size took a sharp increase when the power was shifted to 200 W from 150 W, and the change was rather insignificant at a scan speed beyond 1700 mm/s (Figure 9).

![Main Effects Plot for Melt pool](image)

**Figure 8.** Individual impact of laser power and scan speed on mean contact angle.

| Source    | DF | Adj SS (µm$^4$)   | Adj MS (µm$^4$) | F-Value | p-Value  |
|-----------|----|------------------|-----------------|---------|----------|
| Power     | 4  | 13,541,394,444   | 3,385,348,611   | 5.95    | 0.007    |
| Speed     | 5  | 14,474,970,343   | 2,894,994,069   | 5.49    | 0.010    |

**Table 4.** Analysis of variance.

![Pareto Chart of the Standardized Effects](image)

**Figure 9.** Pareto chart of the standardized effect of laser power and scan speed on melt pool.
4.1.4. Keyhole and Void

Keyholes were found only in three sets of beads: 300 W of laser power with scan speeds of 200 and 700 mm/s and 200 W of laser power with a 200 mm/s scan speed due to high energy input. The size of the keyhole was 18,036 square microns on average. The diameter of the voids within the keyholes due to gas entrapment was around 81 microns on average.

4.1.5. Regression Model

Table 5 shows the regression model for the melt pool features. This is an important tool, as it can be used to predict the output value for unknown values of laser power and scan speed. The model provides the regression equation for the contact angle with an $R^2$ value of 86.2% based on the process variables. This can be explained by the strong correlation between the parameters, laser power and speed with the output contact angle. Although porosity varied in a consistent manner with laser power, it was somewhat scattered for scanning speed. Melt pool size had a reasonable correlation as well. These models can be used to play with the process parameters and achieve the best $R^2$ value for each individual output parameter. However, more experimental data are needed to get a more realistic value of the regression model.

Table 5. Regression model to predict bead features.

| Bead Feature   | Model                                      | $R^2$ |
|----------------|--------------------------------------------|-------|
| Contact Angle | $111.18 - 0.2714 \times \text{Power} + 0.00834 \times \text{Speed}$ | 0.862 |
| Porosity      | $10.75 - 0.04046 \times \text{Power} + 0.001550 \times \text{Speed}$ | 0.818 |
| Melt Pool Size| $27,865 + 270.1 \times \text{Power} - 33.45 \times \text{Speed}$ | 0.774 |

4.2. Multi-Response Analysis and Optimization

To observe the combined effect of both the process parameters on the all the outputs or responses simultaneously, the response optimizer was used in Minitab, which is a statistical analysis software. Response optimization enables the identification of the optimum values of the variables to achieve the desired set of output values.

Table 6 shows the optimization parameters for each output. The target for the contact angle was set as 50 degrees. As a lower contact angle can produce higher surface roughness [14], a lower limit of 30 was chosen. On the other hand, a higher angle of contact with the substrate can facilitate a balling formation, which is why an upper bound of 80 degrees was selected. As porosity is not desirable in additively manufactured parts, a minimum value was set as the target value. For melt pool area, a range was chosen which ensured proper adhesion with the previous layer, as well as made sure that repeated solidification and melting was prevented to avoid residual stress. The keyhole area and void were avoided during the multi-response analysis, as we did not have enough data for these features.

Table 6. Parameters set for response optimization.

| Response              | Goal         | Lower | Target | Upper | Weight | Importance |
|-----------------------|--------------|-------|--------|-------|--------|------------|
| Contact Angle (Degrees)| Target      | 30    | 50.0   | 80    | 1      | 1          |
| Porosity              | Minimum      | 0.9   | 4      |       | 1      | 1          |
| Melt pool ($\mu m^2$) | Target      | 30,000| 50,000 | 70,000| 1      | 1          |

After examining all the combinations of input, 150 W of laser power and a 200 mm/s scan speed were selected as the optimum values of the process parameters to provide the desired output target values. A regression model and process parameters were used to get the best fit out of all the combination settings. The standard error of the fit (SE fit) was used to calculate the variation from the mean value for a specific set of process variables. The
smaller the standard error, the more precise the predicted mean response [40]. The standard error along with the fit could be used to calculate the confidence interval for the responses. The SE fit for all the responses is provided in Table 7, along with the confidence interval.

Table 7. Multiple response prediction.

| Variable          | Setting | Composite Desirability |
|-------------------|---------|------------------------|
| Power (W)         | 150     | 0.7647                 |
| Speed (mm/s)      | 200     |                        |
| Response          | Fit     | SE Fit                |
| Contact Angle     | 56.82   | 3.44                   |
| Porosity          | 2.01    | 0.87                   |
| Melt pool (µm²)   | 55,424  | 6578                   |

|                    | 95% CI   |
|-------------------|----------|
| Contact Angle     | (50.07, 63.56) |
| Porosity          | (0.3048, 3.71)  |
| Melt pool (µm²)   | (42,531, 68,316) |

One of the most important parameters in a multi-response analysis is composite desirability. Composite desirability indicates how effectively the settings have reached the target values. For multiple response parameters, it is difficult to get all the optimum response parameters for a single combination of process inputs. Composite desirability combines all the individual desirabilities for each of the response parameters and combines them to get the overall desirability. The individual desirability for a target response is defined as [41]:

\[
d_i = \left( \frac{Y_i - L_i}{T_i - L_i} \right)^{r_i}
\]

\[
d_i = \left( \frac{U_i - Y_i}{U_i - T_i} \right)^{r_i}
\]

Here, \( Y \) is the predicted value, \( L \) is the lowest acceptable value, \( U \) is the highest acceptable value, \( T \) is the target value and \( r \) is the importance of the \( i \)th response. Composite desirability is defined as:

\[
D = (d_1 \times d_2 \times d_3 \times \ldots d_n)^{\frac{1}{n}}
\]

Here, \( n \) is the number of responses or outputs.

For example, it can be observed that the composite desirability of a 150 W/200 mm/s combination of laser power and scan speed is 0.7647. This combination of power and speed has produced the values of the response optimizer (Fit column in Table 7) that are closest to the target values compared to other combinations of speed and power. Therefore, the composite desirability of other combinations of parameter speeds are less than 0.7647. Based on these composite desirability values, 150 W of laser power and 200 mm/s of scan speed were chosen as the optimum process parameters; that is, the closest to the target value set by the user.

5. Conclusions

- This paper discusses the different features of a melt pool, i.e., contact angle, porosity, melt pool size, keyhole area and void that were found in additively manufactured samples for different combinations of laser power and scan speed using optical micrography.
- ImageJ was used to measure and quantify the size of the features. The measured values were plotted against laser power and scan speed. Contact angle and porosity decrease with increasing laser power and declining scanning speed, while the process parameters had the opposite effect on melt pool size.
- A single response statistical analysis was conducted to assess the impact of process variables. An ANOVA as well as a Pareto chart revealed that both the process parameters have a significant impact on the measured responses because of their effect on the energy input, with laser power being the most dominant factor between them.
• A multi-response analysis was performed to optimize the process using Minitab. Composite desirability was used as the performance parameter to choose which process parameter yields the best features in terms of low porosity, lower contact angle and average melt pool size.

• A laser power of 150 W and scan speed of 200 mm/s were found to have produced a melt pool, with the most desired features having the highest composite desirability of 0.7647.

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