



Article

Spatter, Melt Pool Stability, and Their Correlations Using Deep Learning for Laser Directed Energy Deposition

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Abstract

Laser directed energy deposition (LDED) is a promising metal additive manufacturing process, but printed parts' quality highly depends on spatter formation and melt pool stability. In this work, a high-speed camera is employed to capture and record the complex interaction between the laser, fed powders, and fusion region under various LDED process conditions. A deep learning algorithm, the YOLOv7 model, is trained to automatically detect and track the location and motion of the melt pool and spatter particles. The well-trained YOLOv7 model achieves a precision of 0.94 and is then applied to extract information on spatter count, spatter size, and melt pool geometry. We find that an elevated laser power intensifies spatter formation due to augmented vapor recoil pressure, while a high scanning speed promotes spatter ejection through Plateau–Rayleigh capillary instability. A low powder feed rate further exacerbates spatter formation owing to high metal evaporation and hydrodynamic instability within the small melt pool. In addition, this work introduces a novel melt pool stability index for real-time process assessment based on the melt pool length change rate. A stable melt pool with a high stability index generates less spatter. Otherwise, more spatters are detected. These findings advance the mechanistic understanding of spatter dynamics in LDED, introduce a novel quantitative metric for real-time melt pool stability assessment, and establish a direct correlation between the detected spatter amount and the melt pool stability. This work provides a practical framework for spatter mitigation, melt pool stability enhancement, and in-process control in advanced manufacturing.

Keywords: additive manufacturing; laser directed energy deposition (LDED); deep learning; spatter; melt pool stability; high-speed imaging



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1. Introduction

Additive manufacturing (AM) is a digital manufacturing process that builds parts layer by layer from a 3D model, allowing shapes that are hard or inefficient to make with traditional methods [1–6]. The main advantages of AM are its ability to move quickly from design to a finished part and its highly efficient material utilization [2,7]. Laser directed energy deposition (LDED) is an AM technology in which a focused laser creates a melt pool on a substrate while metal feedstock is fed into that pool to build tracks and layers [8]. It is widely used because it is well-suited for repairing or rebuilding high-value parts,

producing specially designed materials, such as compositionally tailored or graded regions, and achieving relatively high deposition rates on large parts [9,10].

However, achieving consistent quality in LDED remains challenging, as it depends on various process parameters, such as laser power, scanning speed, and powder feed rate. These parameters directly affect spatter, melt pool geometry and stability, surface quality, and the part's mechanical properties [11,12]. Spatter is usually known as an important factor that affects the part's surface quality. For example, some works have shown that adjusting the LDED process conditions can reduce the adverse effect of the adhesion of spattering droplets and contribute to printing high-quality parts [13–17]. It is also known that spatter formation is associated with heat input, surface tension force, vapor recoil force, overheating of the melt pool, and vaporization [16,18]. In addition, some studies suggest that spatter is one of the most visible indicators of process stability [15,19–22]. For example, excessive or abnormal spatter is often associated with unstable melt pool behavior, inefficient powder catchment, and strong vapor–plume interactions [15,16,23–25]. Although the aforementioned studies have investigated spatter formation mechanisms and behavior during AM processes, the influence of laser power, scanning speed, and powder feed rate on spatter generation in LDED remains insufficiently understood. Furthermore, the correlation between spatter formation and melt pool stability in the LDED process has yet to be established.

To capture spatter behavior and dynamics during the AM process, high-speed imaging systems are employed [26,27]. Given the large volume of recorded footage, machine learning (ML) and deep learning (DL) methods are subsequently applied for automated analysis. It is worth noting that, compared to other AM processes, such as laser powder bed fusion (LPBF) and wire arc additive manufacturing (WAAM), noise reduction and spatter extraction from LDED process videos present considerably greater challenges. This difficulty stems primarily from the coaxial powder delivery configuration inherent to LDED, in which the metallic feedstock powder is introduced along the same axis as the laser beam [8,11]. As a result, the fed powder particles must be reliably identified and distinguished from spatters, a task that demands robust detection algorithms. Furthermore, three types of gas flow, the powder carrier gas, nozzle gas, and shielding gas, exert a significant influence on spatter trajectories, introducing additional complexity to accurate spatter tracking. Therefore, the selection of an appropriate DL algorithm for spatter detection and tracking in the LDED process is of critical importance.

To address the aforementioned research gaps and overcome the challenges associated with high-speed video analysis in LDED, this work presents a systematic experimental investigation of the LDED process across varying levels of laser power, scanning speed, and powder feed rate. The recorded videos are analyzed using a DL algorithm, YOLOv7, to detect and track spatters as well as to characterize melt pool geometry. A novel melt pool stability index is introduced to evaluate and compare melt pool stability based on the detected melt pool length change rate. This study elucidates the influence of laser power, scanning speed, and powder feed rate on spatter formation and establishes a correlation between spatter count and melt pool stability during the LDED process.

2. Materials and Methods

2.1. Experimental Setup

In this work, the LDED experiments are conducted using a Haas UMC750 five-axis vertical milling machine fitted with an AMBIT FLEX deposition head (Hybrid Manufacturing Technologies, McKinney, TX, USA). In this configuration, the workpiece (SS316 plate) remains stationary while the optical head containing the laser optics executes synchronized motion along the X–Y–Z axes. A continuous-wave ytterbium fiber laser manufactured by

IPG Photonics is used, operating at 1070 nm with a maximum output laser power of 1 kW. The final beam spot size focused on the top of the plate's surface is 2.5 mm in diameter.

The process atmosphere and powder delivery are managed using three separate gas lines, as illustrated in Figure 1a, argon shielding gas to isolate and protect the molten region, a carrier stream to convey powder through the nozzle, and an auxiliary nozzle gas intended to reduce fume or spatter backflow toward the optics. The shielding, carrier, and nozzle flow rates are set at 10, 5, and 4 L/min, respectively. Gas-atomized SS316L powder ($D_{10} = 47.6 \mu\text{m}$, $D_{50} = 62.7 \mu\text{m}$, $D_{90} = 79.7 \mu\text{m}$) from Carpenter Additive is used as feedstock. The powder is delivered coaxially through the optical head and focused on the laser spot. The powder feed rate is set at two levels: 8.18 g/min and 21.42 g/min. In situ observations are captured with an Edgertronic SC2+ high-speed camera across the processing conditions summarized in Table 1. The camera views the melt pool from an off-axis location at approximately 45° relative to the laser axis (Figure 1b) and is mechanically coupled to the laser system so that it translates with the deposition head during the LDED process [28]. The high-speed camera is set to 1000 fps with a 1280×760 -pixel frame size, and a spatial resolution of $17.3 \mu\text{m}/\text{pixel}$ (Figure 1c). The specific combinations of laser power, scan speed, and powder feed rate used in this study are listed in Table 1. The bounds for these values are selected based on prior experimentation, consistency with published literature for LDED of SS316L, and the AMBIT system capabilities.

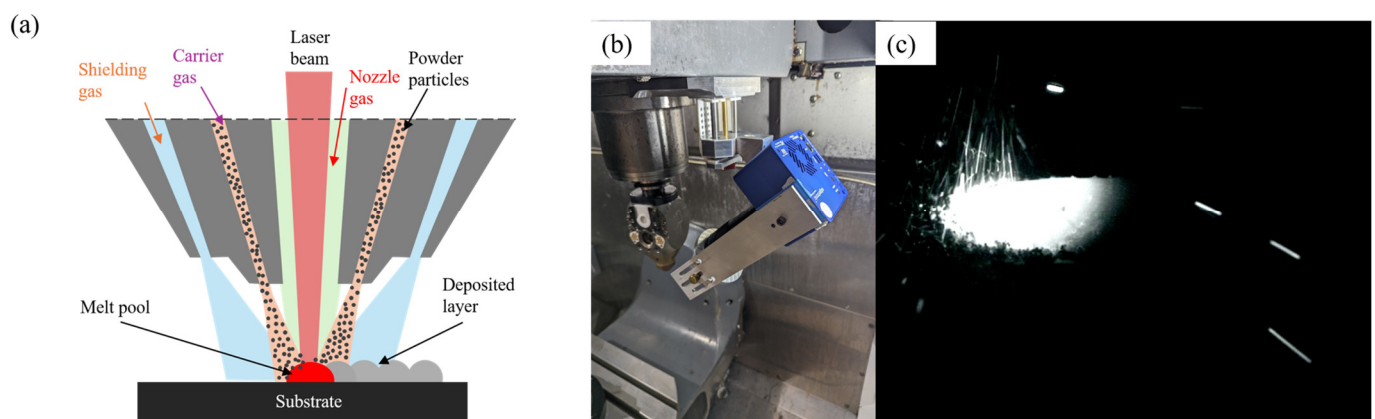


Figure 1. LDED experimental setup, high-speed imaging configuration, and an example of a recorded image. (a) Schematic of the AMBIT FLEX deposition head illustrating the laser beam, powder stream, and surrounding gas flows directed toward the substrate. (b) Photograph of the Haas/AMBIT hybrid system showing the off-axis high-speed camera mounted at $\sim 45^\circ$ to the laser axis and fixed to the deposition head to track the melt pool during scanning. (c) One selected image captured by the high-speed camera with a bright melt pool region and some ejected spatter particles.

Table 1. The LDED experimental process parameters with high-speed in situ process recording.

Test No.	Power, W	Scanning Speed, mm/s	Powder Feed Rate, g/min	Spatter Count for 600 Images	Experimental Measured Melt Pool Width, μm	Calculated Stability Index, SI_{mp}
1	500	200	8.18	198	1391	77.45
2	750	200	8.18	222	2019	51.45
3	500	350	8.18	266	1276	48.03
4	750	350	8.18	335	1695	54.54
5	750	350	8.18	383	1715	53.75
6	750	350	8.18	340	1726	56.81

Table 1. Cont.

Test No.	Power, W	Scanning Speed, mm/s	Powder Feed Rate, g/min	Spatter Count for 600 Images	Experimental Measured Melt Pool Width, μm	Calculated Stability Index, S_{Imp}
7	750	350	8.18	339	1709	56.27
8	1000	350	8.18	399	2259	44.6
9	750	500	8.18	425	1568	33.1
10	750	200	21.42	163	2419	57.95
11	1000	200	21.42	146	2967	69.51
12	750	350	21.42	117	2285	78.75
13	1000	350	21.42	129	2552	66.2
14	750	500	21.42	200	2152	60.5
15	1000	500	21.42	167	2771	58.43

2.2. Image Dataset Preparation, Processing, and Labeling

As previously described, these 15 LDED experiments are recorded using a high-speed camera, and the recorded videos are converted into image sequences for analysis. For each experiment, 2000 frames with clearly visible melt pool and particles are selected. During preprocessing, the images are converted to grayscale to enhance the contrast between the bright melt pool/particles and the darker background. It should be noted that grayscale conversion is used only for image enhancement and noise reduction, and the ground-truth labels were not assigned based on grayscale intensity alone.

During image processing, the melt pool and particles are labeled by considering their spatial location, apparent size, brightness, origin, and frame-to-frame motion. The melt pool is identified as the larger bright region that follows the prescribed scanning direction and speed. Particles moving with the incoming coaxial powder stream toward the melt pool are treated as feedstock powders and are not labeled as spatter. In contrast, particles that appear near the melt pool (and the laser-material interaction region) and then move outward away from the melt pool are labeled as spatters. Therefore, the distinction between feedstock powder and spatter is based primarily on particle origin and trajectory, supported by size and brightness information, rather than grayscale intensity alone. For each labeled melt pool and spatter, the centroid of the detected region is recorded as a (x, y) coordinate together with its corresponding classification label. This labeled dataset is then used for YOLOv7 training and subsequent melt pool and spatter analysis.

For each LDED experiment, these 2000 images are separated into approximately 1400 (about 70% of the total images) for the training dataset and the remaining 600 for the testing dataset. It is important to note that the detected spatter in this work includes three types of particles: hot metal liquid spatters, half-melted or heated-up particles, and relatively cold solid particles expelled by the gas flow without significant heating. The hot metal liquid spatters tend to be larger and brighter than the original feedstock powder. Partially melted particles and cold solid particles are typically of intermediate brightness and are similar in size and shape to the feedstock powder [18].

2.3. Melt Pool and Spatter Detection

In this study, YOLOv7 [29], a single-stage object detection DL algorithm, is selected to detect spatters and melt pools from the preprocessed, labeled images. Due to its ability to simultaneously identify and track objects, this algorithm offers rapid processing with minimal loss of accuracy. This efficiency makes it especially effective for handling large volumes of high-speed imaging data generated during the LDED experiments. Once trained, the model can automatically mark spatters and melt pools in each frame with

bounding boxes, while also recording their spatial coordinates and classification details for subsequent evaluation.

2.4. Melt Pool and Spatter Motion Tracking

To analyze the dynamic behavior of spatters and melt pools over time, a Python 3.12-based tracking algorithm is developed using OpenCV 4.12 and NumPy 2.3 [30,31]. This algorithm builds upon the YOLOv7 detection results, which provide bounding boxes and class labels for each identified spatter in consecutive image frames. Using these detection outputs as input data, the tracking routine computes the centroid and area of each spatter in every frame to characterize its motion. A matching logic based on spatial proximity and size similarity is then applied to link spatters across time steps. Specifically, two spatters in successive frames are considered identical if they lie within an 80-pixel Euclidean distance and show an area similarity above 0.85. This approach allows continuous tracking of individual spatters until they disappear from view. Each spatter is initialized with a unique identification number, which is updated as the tracking progresses through the image sequence.

2.5. Melt Pool and Spatter Information Extraction

In the post-processing step, the detected melt pool and spatter features are analyzed to extract quantitative information from the high-speed image sequences. Key parameters, like spatter count, spatter diameter, melt pool width, and melt pool length, are extracted from the detection results of YOLOv7 and the tracking outputs. These measurements are first extracted in pixel units from the 2D image frames and then converted to physical dimensions using the calibrated spatial resolution and frame rate of the imaging system.

It is important to note that the extracted spatter counts have some uncertainty as they are obtained from high-speed image data and not physically collected. Some spatters may leave the camera's field of view, become blurred, overlap with other particles, hit nearby droplets, or move too quickly to be reliably tracked from one frame to the next. False spatters can also be detected in some cases as feedstock powder particles. Thus, some spatters may be missed or counted twice. However, the same trained detection and tracking models and post-processing procedure are used consistently across all experiments. Nevertheless, the relative trends across different LDED processing conditions remain valid for comparative analysis of spatter count and melt pool stability in this work.

3. Results

3.1. LDED Samples' Top Surface Morphology

For all 15 LDED samples, the deposited region's top-surface morphology is characterized using a Keyence VK-X1000 laser confocal microscope. This analysis provides the deposited region width and the top-surface height distribution relative to the base plate (taken as height 0), as shown in Figure 2. For each LDED test, the deposited region width is measured at five different locations, and the average value is taken to represent the melt pool width of that case and reported in Table 1. For the deposited region top-surface height distribution in Figure 2, the color legend represents height values ranging from 0 (blue, corresponding to the base plate) to 2.8 (red, corresponding to the maximum measured top-surface height among all 15 samples). To check the LDED experiments' repeatability, Tests 4–7 are fabricated under the same process condition, and their resulting surface profiles are consistent (Figure 2). This indicates that the LDED process is repeatable under the same processing condition, although minor variations in spatter distribution and local surface height are observed; these differences, however, fall within acceptable experimental error.

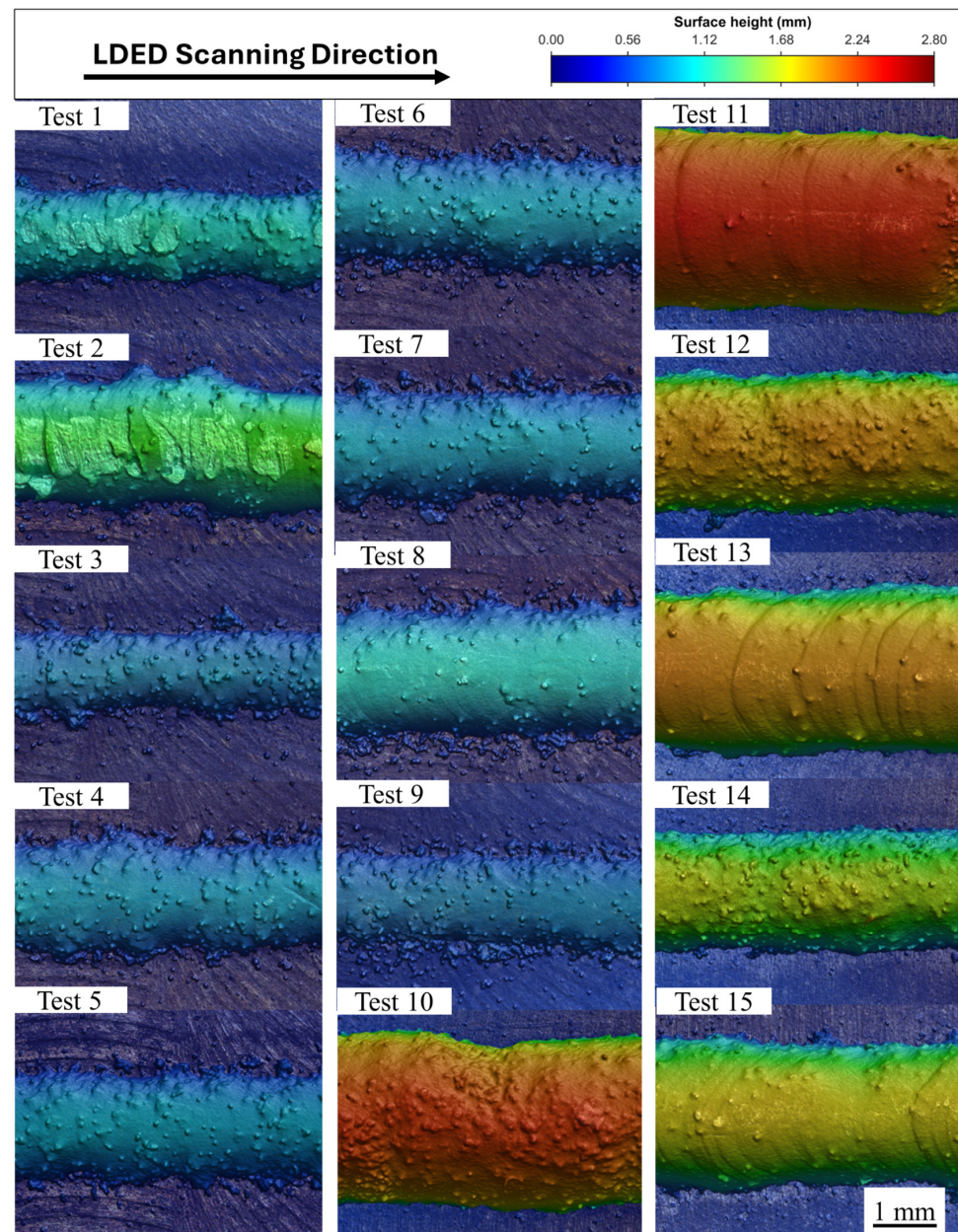


Figure 2. Optical top-view images of single-track LDED deposits for Tests 1–15 with surface height maps.

The LDED process parameters, especially laser power, scanning speed, and powder feed rate, have a strong influence on the melt pool geometry and surface quality of the deposited tracks. Tests 1–4 show continuous tracks with moderate surface integrity and scattered spatters along the track edges. As the laser power increases, the melt pool becomes wider because more energy is delivered to the material. For example, Test 2 produces a wider track than Test 1. Among Tests 1–9, Test 8 has the maximum deposited width due to the highest laser power of 1000 W. A similar influence can also be observed by varying the scanning speed. For example, compared to Test 6, the deposited region of Test 9 shows a narrower width because of a high scanning speed.

In addition, in Figure 2, Tests 1–9, which use a relatively low powder feed rate of 8.18 g/min, exhibit lower top-surface heights in the deposited regions because of the limited volume of melted material. By contrast, Tests 10–15, conducted at a higher powder feed rate of 21.42 g/min, show substantially greater deposited-region surface heights. Among Tests 10–15, Test 11 shows the largest measured melt pool width due to the combined effect

of high laser power, low scanning speed, and high powder feed rate. This combination increases both the energy input and the amount of deposited material.

At the higher powder feed rate, increasing laser power generally increases the track width. This trend can be seen by comparing Tests 10 and 11 at 200 mm/s, as well as Tests 12 and 13, at 350 mm/s. However, the surface morphology is not controlled by laser power alone. Scanning speed also plays an important role because it changes the interaction time between the laser and the powder. With all other conditions constant, a slow scanning speed allows more heat input per unit time and more powder to feed into the region, producing a wider and higher deposited region.

3.2. Comparing the Measured and Camera-Detected Pool Widths

To make sure that recorded videos provide reliable information on the fusion region and spatters, we compare the measured deposited width with the melt pool width detected from the videos. The measured melt pool width is provided in Table 1. The melt pool width can also be calculated using the high-speed videos by converting the number of pixels into real distance using the spatial resolution of $17.3 \mu\text{m}/\text{pixel}$. For the 15 LDED tests, the melt pool widths extracted from the high-speed videos are mathematically corrected by multiplying by a factor of $1/\sin(45^\circ)$ to account for the 45° camera viewing angle. These corrected widths are then compared with the experimentally measured melt pool widths, and the results of this comparison are shown in Figure 3. The red dashed line indicates that the calculated melt pool width exactly agrees with the corresponding measured data. The points lie close to the red dashed line, which means the video-based widths match the direct measurements within the error range. This strong agreement confirms that the recorded high-speed videos provide a reliable and effective means of characterizing melt pool geometry and analyzing spatter behavior during the LDED process.

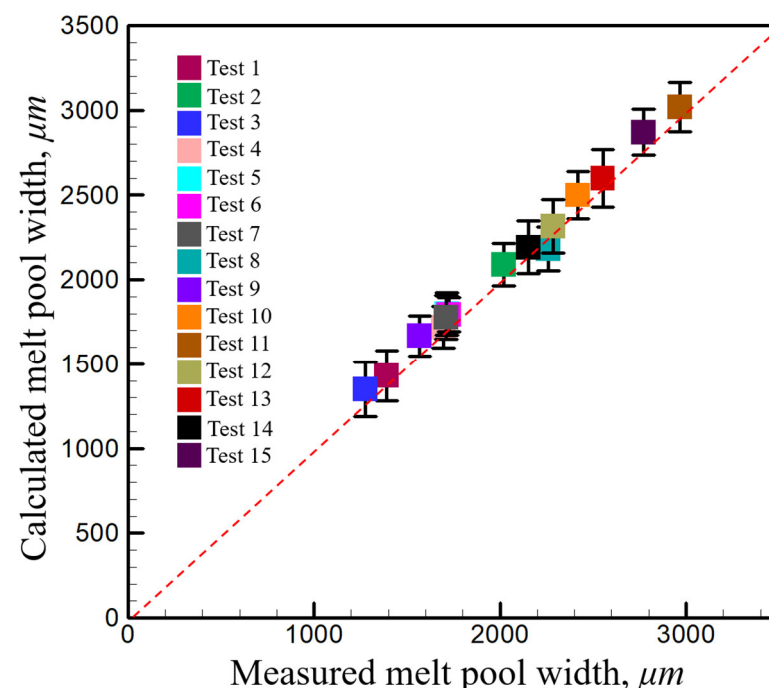


Figure 3. Comparison of melt pool width estimates from the high-speed video analysis against the measured melt pool widths for Tests 1–15. Each colored marker represents a test condition, with error bars showing the spread in the measurements (maximum error range within $\pm 135 \mu\text{m}$). The red dashed line indicates perfect agreement between the measured and calculated values.

3.3. Model Performance for YOLOv7

The training performance is quantified using precision (P), recall (R), mean average precision (mAP) at 0.5, and mAP at 0.5:0.95, with P and R defined in Equations (1) and (2), respectively. Precision represents the proportion of predicted spatters and melt pools that are correctly detected, whereas recall denotes the fraction of true spatters and melt pools in the images that the model successfully identifies. The mAP at 0.5 serves as an overall performance indicator that measures how effectively the model detects objects whose predicted bounding boxes overlap the ground truth by at least 50%, thereby reflecting its ability to recognize both spatters and melt pools and localize them with an intersection over union (IoU) of at least 0.5. In comparison, mAP at 0.5:0.95 offers a more rigorous evaluation by averaging precision across IoU thresholds from 0.5 to 0.95 in steps of 0.05, capturing not only whether spatters and melt pools are detected but also how closely the predicted boxes conform to their true spatial extents over a range of overlap criteria. Higher values for both mAP metrics indicate that the model achieves accurate detection and produces bounding boxes well aligned with the actual positions of spatters and melt pools.

$$\text{Precision } (P) = \frac{\text{True Positive } (TP)}{\text{True Positive } (TP) + \text{False Positive } (FP)} \quad (1)$$

$$\text{Recall } (R) = \frac{\text{True Positive } (TP)}{\text{True Positive } (TP) + \text{False Negative } (FN)} \quad (2)$$

In these definitions, True Positives (TP) correspond to correctly detected spatters or melt pools, False Positives (FP) are regions that are incorrectly classified as spatters or melt pools, and False Negatives (FN) occur when true spatters or melt pools are missed by the model. For the training set, the evolution of P , R , mAP at 0.5, mAP at 0.5:0.95, and total loss over the training epochs is depicted in Figure 4. Both precision and recall surpass 0.9 within the first 20 epochs and remain stable thereafter, while mAP at 0.5 approaches 0.95 and mAP at 0.5:0.95 gradually increases and stabilizes near 0.80. Also, the total loss steadily decreases to below 0.03, which indicates smooth optimization without overfitting or training instability.

Following training, the model is assessed on the testing datasets. The trained algorithm achieves strong performance on these test images, with $P = 0.94$, $R = 0.92$, mAP at 0.5 = 0.95, and mAP at 0.5:0.95 = 0.79. These results confirm that the model can reliably detect and track spatters as well as the melt pool, supporting its suitability for subsequent analysis and application.

3.4. Influence of Laser Power and Scanning Speed on Spatter Formation

The well-trained YOLOv 7 algorithm is applied to extract information on spatters. Figure 5 compares the spatter size distributions under different LDED processing conditions. Each histogram shows how many spatters are detected within each diameter range, allowing the effects of laser power and scanning speed to be compared more clearly. Keeping the same scanning speed of 350 mm/s, Tests 3, 4, and 8 show the influence of laser power (Figure 5a–c). When the laser power increases from 500 W to 750 W and then to 1000 W, the total spatter amount also increases. The maximum number of spatters among these three cases is detected for Test 8. Most of the spatters are concentrated in the 100–300 μm range, showing that medium-sized spatters are dominant. This indicates that higher laser power provides more heat to the melt pool, which can increase melt pool temperature, enlarge the molten region, and result in a high vapor recoil force and more evaporation from the melt pool. Therefore, more spatters are ejected from the melt pool under high laser power.

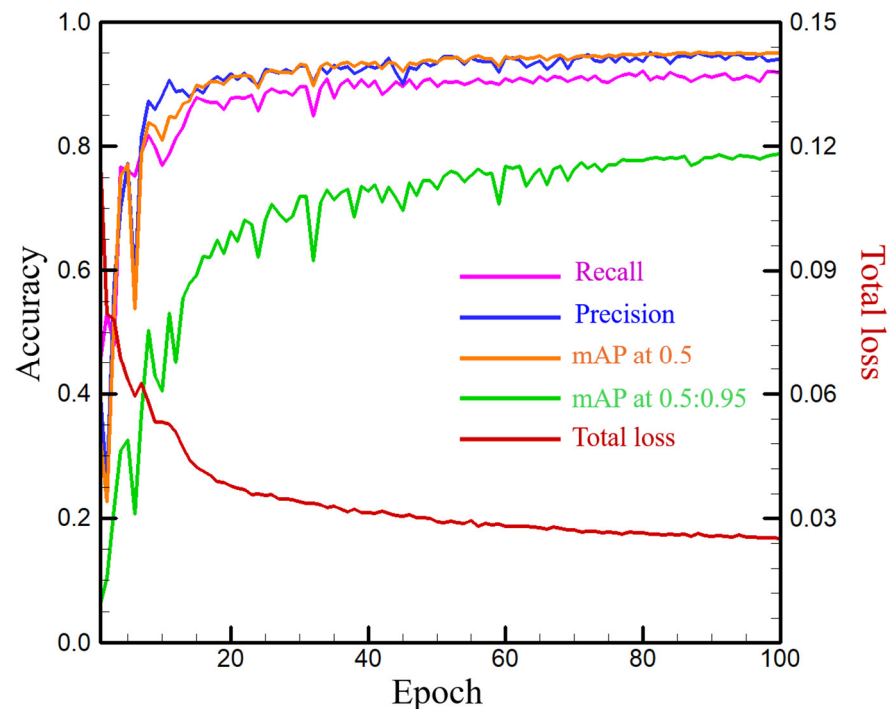


Figure 4. Training curves of the YOLOv7 model over 100 epochs. Curves show the evolution of key detection metrics (left axis, e.g., precision/recall and mAP) and the corresponding loss (right axis), indicating fast convergence in the early epochs followed by gradual stabilization.

The effect of scanning speed can be seen by comparing Tests 2, 4, and 9, where the laser power is fixed at 750 W while the scanning speed changes from 200 to 350 and 500 mm/s. In these cases, the spatter count increases as the scanning speed increases. Test 2, with the lowest speed of 200 mm/s, has the lowest spatter count, while Test 9, with the highest speed of 500 mm/s, produces the largest number of spatters. Similar to the results shown in Figure 5a–c, most spatters are found in the 100–300 μm diameter range in Figure 5d–f. As the scanning speed increases, the melt pool tends to elongate, becomes unstable, separates, and forms spherical balls to maintain the uniform capillary pressure within the pool. In short, under a high scanning speed, more spatters are detected due to the Plateau–Raleigh capillary instability of the melt pool [2].

Overall, the results show that both higher laser power and higher scanning speed promote spatter formation. Higher laser power increases the melt pool energy and metal evaporation, while higher scanning speed can result in the Plateau–Raleigh capillary instability. Therefore, selecting proper laser power and scanning speed is important for reducing spatters and improving process stability during the LDED process.

3.5. Influence of Powder Feed Rate on Spatter Formation

Not only the laser power and scanning speed, but the powder feed rate also affects spatter formation. The influence of the powder feed rate on spatter is compared and explained in Figure 6. Keeping the laser power at 750 W, reducing the powder feed rate from 21.42 g/min to 8.18 g/min leads to a noticeable increase in spatter generation (Figure 6a,c). The low-powder-feed condition produces many more spatters, especially in the 100–200 μm and 200–300 μm size ranges. This suggests that when the powder supply is too low compared with the laser energy input, the melt pool becomes more likely to overheat, resulting in significant evaporation and an unstable melt pool, making droplet ejection easier. A similar trend is observed at 1000 W in Figure 6b,d. When the powder feed rate is reduced to 8.18 g/min, the total number of spatters increases significantly compared with the 21.42 g/min condition. The 1000 W and low-feed cases show the highest spatter

amount among the four conditions in Figure 6, indicating that a high laser power combined with a low powder feed rate can strongly disturb the melt pool and generate more spatters.

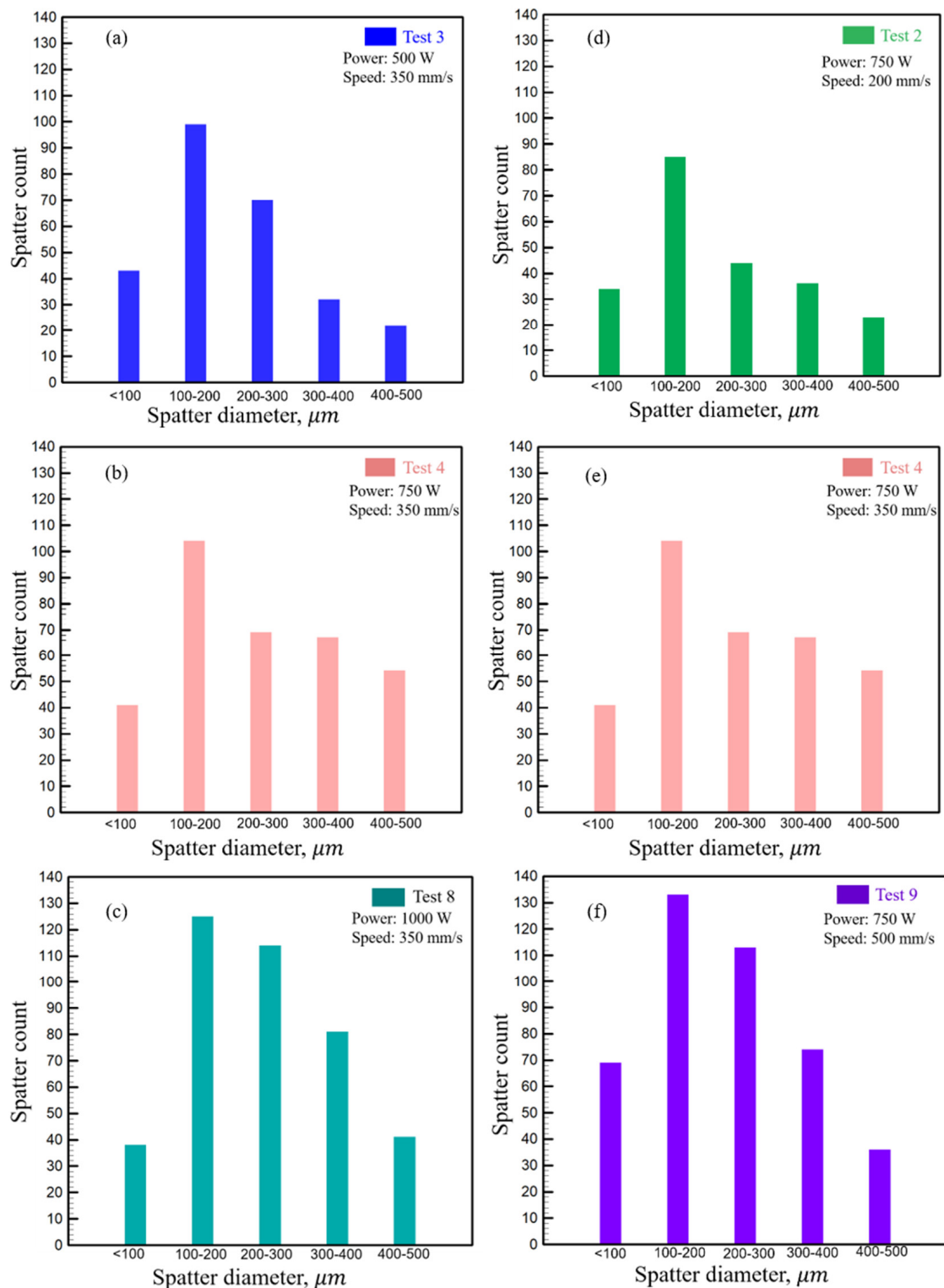


Figure 5. Influence of laser power and scan speed on spatter formation at a constant powder feed rate (8.18 g/min). (a–c) compares spatter size distributions for different laser powers at the same scanning speed (350 mm/s), showing the effect of power on spatter count. (d–f) compares spatter size distributions for different scanning speeds at a fixed laser power, showing the role of scanning speed on spatter generation.

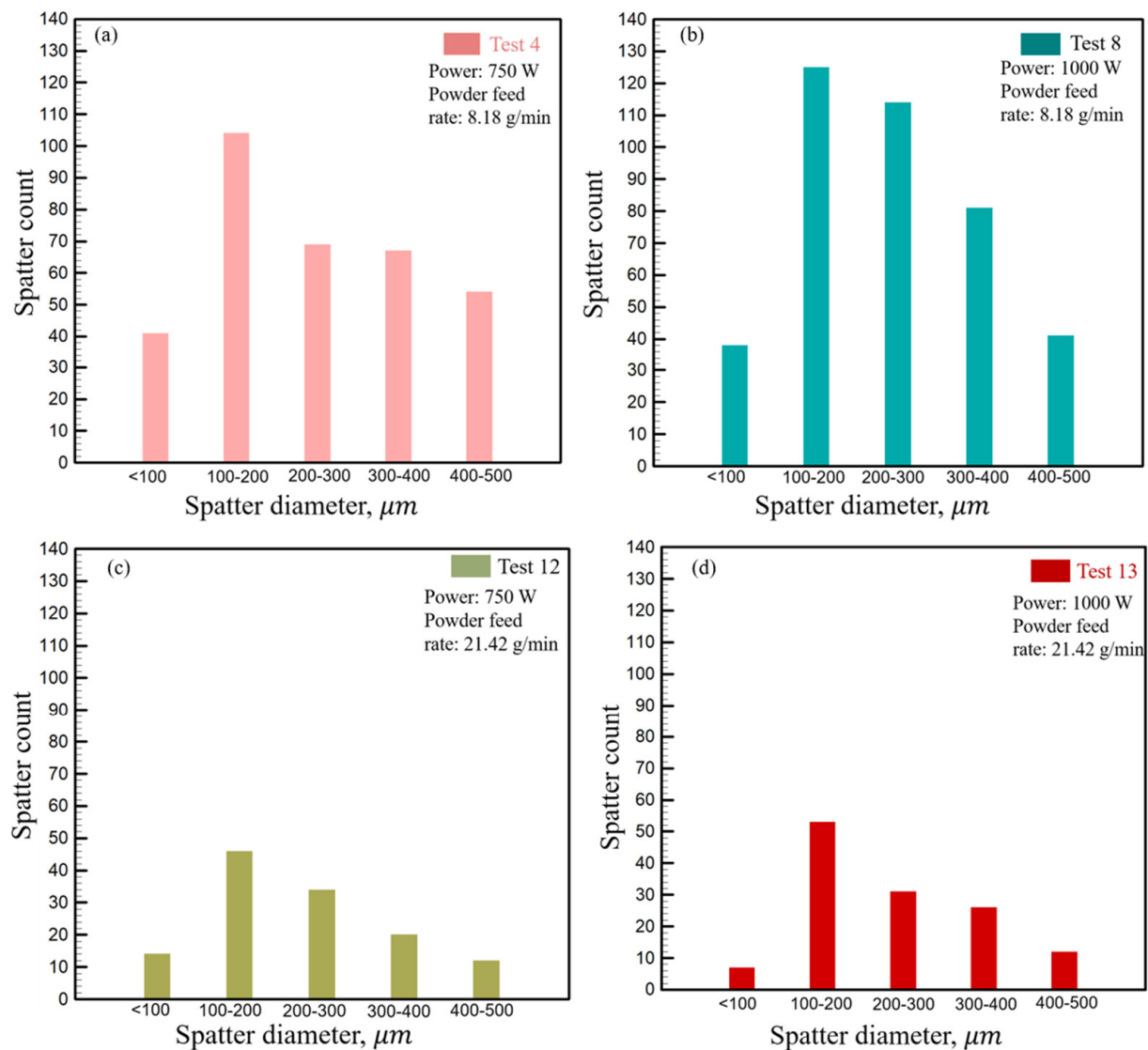


Figure 6. Effect of powder feed rate on spatter size distributions at a fixed scan speed (350 mm/s). (a,c) Compare two powder feed rates (21.42 vs. 8.18 g/min) at a constant laser power of 750 W, highlighting how changing the feed rate impacts the spatter count. (b,d) show the same comparison at 1000 W, showing the influence of powder feed rate under higher power conditions.

Overall, the results show that increasing the powder feed rate helps reduce spatter formation at both 750 W and 1000 W. A higher powder feed rate provides more material to absorb laser energy and contributes to a larger, more stable melt pool. In contrast, a lower powder feed rate leaves more excess energy in the melt pool, which can increase melt pool temperature, vapor recoil force, and evaporation. These effects make the melt pool more unstable and promote spatter ejection.

In short, spatter formation in LDED is strongly governed by laser power, scanning speed, and powder feed rate. Higher laser power increases energy input to the melt pool, raising its temperature, intensifying metal evaporation, and strengthening vapor recoil pressure. These effects destabilize the melt surface and promote droplet ejection, leading to increased spatter [16,18]. Likewise, higher scanning speed can induce Plateau-Rayleigh-type capillary instabilities along the melt track and enhance shear-driven disturbances [2], which also contribute to more frequent spatter formation. Therefore, carefully selecting laser power and scanning speed is essential to limit spatter and improve process stability. In contrast, increasing the powder feed rate generally reduces spatter generation. A

higher powder feed rate supplies additional material to absorb the laser energy, creating a larger, more thermally buffered melt pool that is less susceptible to violent recoil and breakup [15]. When the powder feed rate is low, surplus laser energy is concentrated in a smaller melt pool, further elevating its temperature and vapor recoil, which destabilizes the molten region and facilitates spatter ejection. As a result, optimizing powder feed rate, in conjunction with laser power and scanning speed, is critical for mitigating spatter and achieving robust LDED processing.

3.6. Melt Pool Stability Analysis

The laser power, scanning speed, and powder feed rate can affect not only the spatter but also the melt pool geometry and stability. It is important to note that, compared to the melt pool width, the detected melt pool length is more reliable and accurate due to the high-speed camera being set at a 45° viewing angle to the track. In Figure 7, we compare the detected melt pool length for some selected tests. Test 13 shows the longest melt pool length during most of the deposition process. This is expected because Test 13 was processed using a high laser power of 1000 W and a high powder feed rate of 21.42 g/min at 350 mm/s. This combination provides both greater heat input and more material for the melt pool, resulting in a larger and more extended molten region. Tests 8 and 12 also show relatively long melt pools, but for different reasons. Test 8 has a high laser power of 1000 W but a lower powder feed rate of 8.18 g/min, while Test 12 has a higher powder feed rate of 21.42 g/min but a lower laser power of 750 W.

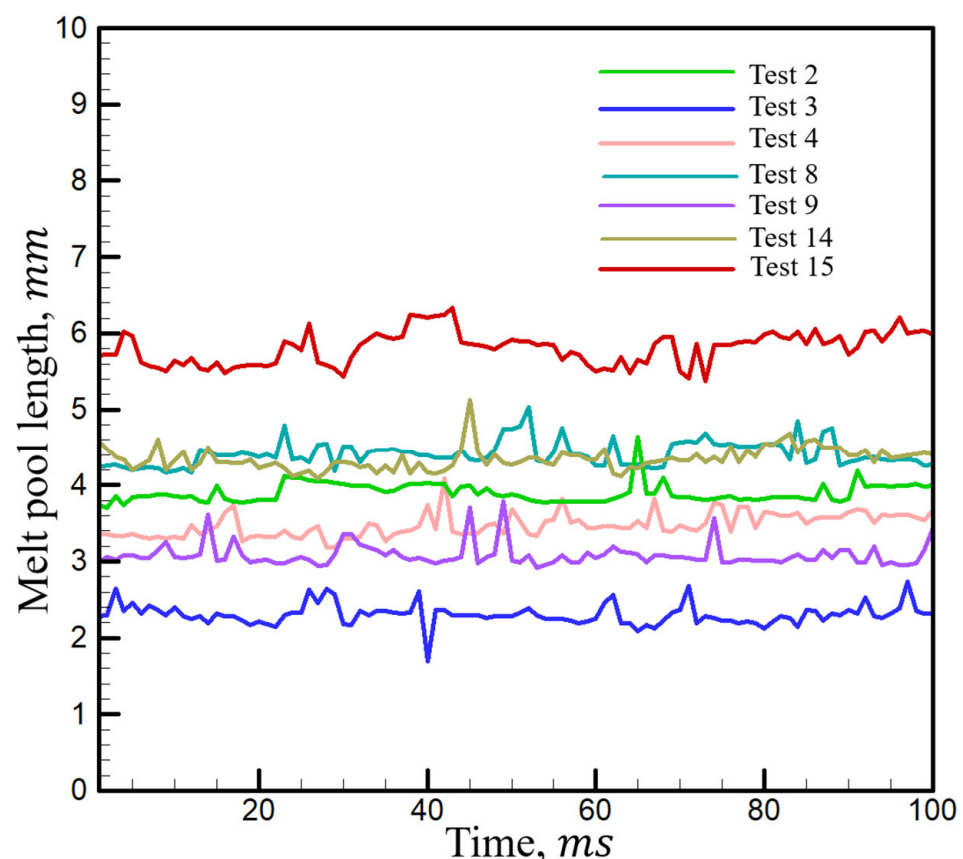


Figure 7. For some selected LDED tests, the melt pool length variation over time was obtained from the high-speed video analysis.

The effect of laser power can be seen by comparing Tests 3, 4, and 8, which are all processed at 350 mm/s with a powder feed rate of 8.18 g/min. As the laser power increases from 500 W to 750 W and then to 1000 W, the melt pool length generally increases. This shows that higher power enlarges the molten region by increasing the heat input. The effect of scanning speed can be observed from Tests 2, 4, and 9, where the laser power and powder feed rate are fixed at 750 W and 8.18 g/min. As the scanning speed increases from 200 to 350 and 500 mm/s, the melt pool length becomes shorter. This occurs because a higher scanning speed reduces the laser–material interaction time, limits heat accumulation, and shortens the melt pool length.

In addition, Figure 7 shows that the melt pool length stays mostly steady during the LDED process, but it is not completely smooth. Each test has a few small peaks or drops, which likely happen when the melt pool is briefly disturbed by changes in powder flow, heat input, or spatter ejection. For example, Tests 3, 4, and 9 show more noticeable changes with time, meaning the melt pool was less steady in those cases. In particular, Test 3 has a sudden drop near the middle of the sequence, while Test 9 shows several short spikes. In comparison, Tests 2 and 14 show smoother curves, suggesting a more stable melt pool during deposition.

To quantify and compare the melt pool stability among different LDED processes, we propose a melt pool stability index, evaluated based on the detected melt pool length change rate over time. This index shows how rapidly the melt pool geometry fluctuates in time and can be calculated by differentiating the time-resolved melt pool length extracted from the high-speed images, giving the frame-to-frame change in length per millisecond (mm/ms), as shown in Equations (3)–(5).

$$\varphi_i = \frac{\text{abs}(y_{i+1} - y_i)}{t} \quad (3)$$

$$t = \frac{1}{1000} = 0.001 \text{ s} \quad (4)$$

where φ_i denotes pool length change rate at time i , y_{i+1} and y_i are the melt pool lengths at time $i + 1$ and i . The timestep t is determined from the frame rate of the camera. Using this change-rate signal, we propose a melt pool stability index, SI_{mp} . The melt pool stability index SI_{mp} is the inverse of the standard deviation of the melt pool length change rate φ_i . A higher stability index (SI_{mp}) indicates a more stable melt pool.

$$SI_{mp} = \frac{1}{\sqrt{\sum_{i=1}^n \frac{(\hat{\varphi} - \varphi_i)^2}{n}}} \quad (5)$$

where $\hat{\varphi}$ is the mean of the melt pool length change rate, the melt pool change rate at time is φ_i , and n is the number of recorded images. The calculated values of the melt pool stability index for the ten LDED tests are available in Table 1. The correlation between the detected spatter count and the melt pool stability index is plotted in Figure 8.

The correlation between the detected spatter count and calculated melt pool stability for these LDED tests is shown in Figure 8. A clear trend is observed in that a stable melt pool with a higher stability index indicates a lower number of detected spatters. Among all these LDED tests, Test 12 has the highest value of melt pool stability with the least detected spatter count. Similarly, Test 9 shows the lowest melt pool stability index but the highest spatter count. This trend also suggests that improving melt pool stability can help to reduce spatter formation in the LDED process. In addition, this inverse relationship confirms that the proposed melt pool stability index is a meaningful and effective indicator of process

stability. The LDED process conditions that suppress rapid melt pool length changes also strongly reduce spatter formation, improving the overall quality of the LDED process.

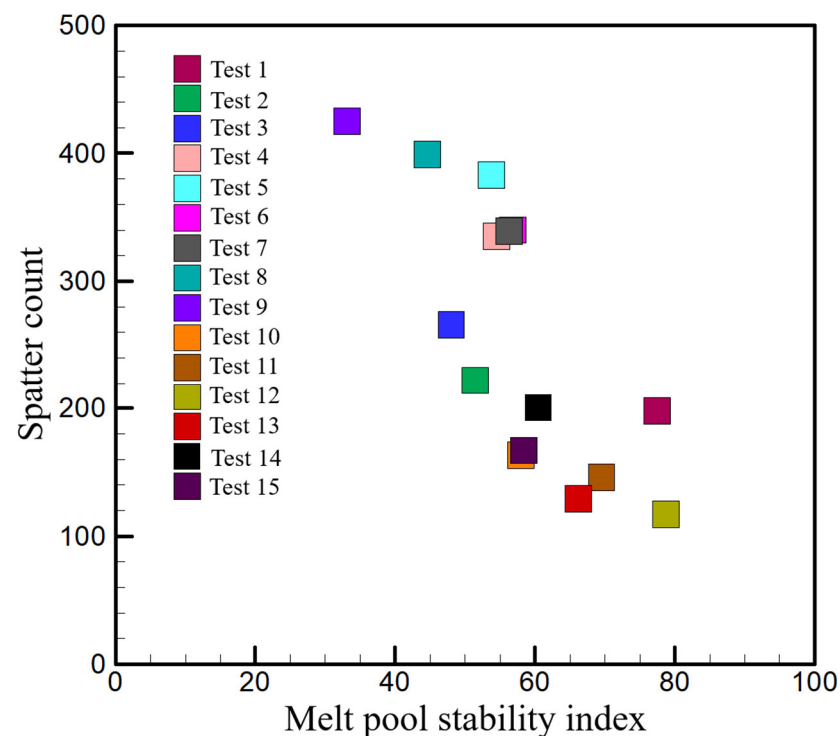


Figure 8. Relationship between melt pool stability index and detected spatter count for the LDED tests. A clear trend shows that a high stability index corresponds to a smaller number of spatters.

In future work, the trained YOLOv7 model in this work can be extended to detect and track spatter and melt pool behavior under additional LDED process conditions once the corresponding high-quality video data are available.

4. Conclusions

This work investigates the influence of laser power, scanning speed, and powder feed rate on spatter, melt pool geometry and stability using experimental tests and a high-speed camera. A DL algorithm, YOLOv7 is applied and well-trained to extract information from recorded videos for spatter and melt pool detection. The correlation between spatter formation and melt pool stability is also established. The main findings are summarized as follows:

(1) Both higher laser power and higher scanning speed promote spatter formation. Higher laser power increases melt pool energy and metal evaporation, while a higher scanning speed can result in the Plateau–Raleigh capillary instability and more spatter particles. Selecting proper laser power and scanning speed is important for reducing spatter and improving process stability during LDED.

(2) Increasing the powder feed rate helps reduce spatter formation. A higher powder feed rate provides more material to absorb the laser energy and contributes to a larger, more stable melt pool. In contrast, a lower powder feed rate leaves more excess energy in the melt pool, which can increase melt pool temperature, vapor recoil force, and evaporation. These effects make the melt pool more unstable and promote spatter ejection.

(3) According to the melt pool length change rate, a melt pool stability index is proposed as an indicator to compare melt pool stability under different LDED process conditions. A higher stability index suggests a more stable melt pool, which also generates fewer spatter particles, while a lower stability index indicates stronger melt pool fluctu-

ations with higher spatter counts. This shows that the stability index is an effective and efficient measure for connecting melt pool dynamics with spatter formation.

(4) The DL algorithm applied in this work, YOLOv7, shows great advantages in automatically detecting the melt pool and spatters across a large volume of images with high accuracy and low error. It can be applied to extract other information for different advanced manufacturing processes once high-speed videos are available.

Overall, the study shows that stable LDED processing requires a proper balance of laser power, scanning speed, and powder feed rate. A stable LDED process can reduce spatter formation. The proposed melt pool stability index and deep learning-based high-speed imaging analysis framework provide an effective pathway for high-speed in situ process monitoring, process optimization, and video and image data analysis.

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