Deep Learning-Based Analysis of Spatter and Melt Pool Stability in LDED

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1. Background and Objectives

- Laser directed energy deposition (LDED) is promising for repair and high-rate metal additive manufacturing, but print quality strongly depends on spatter formation and melt pool stability.
- The effects of laser power, scanning speed, and powder feed rate on spatter generation and their link to melt pool stability, remain insufficiently quantified in LDED.
- Objective: use high-speed imaging and deep learning to automatically detect spatters and melt pool features, evaluate process-parameter effects, and establish a quantitative melt pool stability index.

2. Experimental Setup and Methods

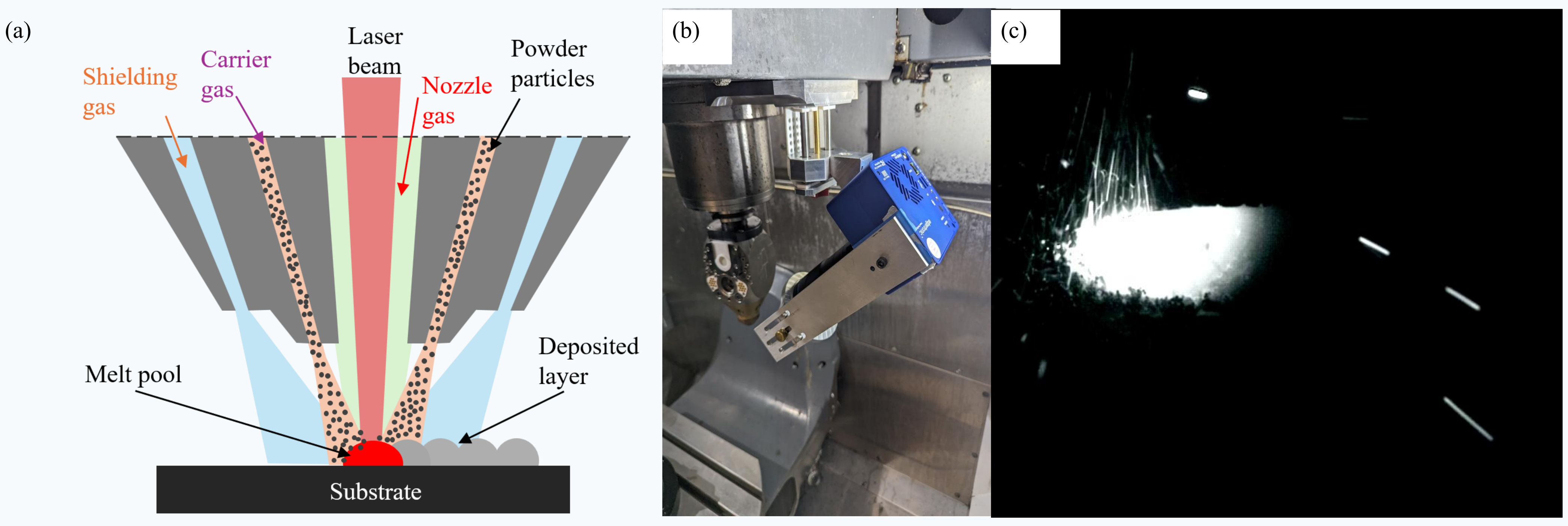

Fig 1. Experimental Setup and imaging process

- 15 single-track SS316L LDED experiments were conducted on a Haas UMC750 fitted with an AMBIT FLEX deposition head.(Fig 1 (b))
- Laser: 1070 nm IPG fiber laser, max 1 kW, 2.5 mm spot size.
- Gas flow rates: shielding 10 L/min, carrier 5 L/min, nozzle 4 L/min.(Fig 1(a))
- Camera: Edgertronic SC2+, ~45° off-axis, 1000 fps, 1280 × 760 px. 17.3 μm/pixel. For each experiment, 2000 frames were selected; 70% were used for training and 30% for testing. (Fig 1 (c))
- YOLOv7 detected melt pool and spatter features; Python tracking extracted spatter count, spatter diameter, melt pool width, and melt pool length.

High-speed imaging → preprocessing → YOLOv7 detection → tracking → stability analysis

Table 1. The LDED experimental process parameters

Test No.	Power, W	Scanning speed, mm/s	Powder feed rate, g/min	Spatter per 600 images	Stability Index
1	500	200	8.18	198	77.45
2	750	200	8.18	222	51.45
3	500	350	8.18	266	48.03
4	750	350	8.18	335	54.54
5	750	350	8.18	383	53.75
6	750	350	8.18	340	56.81
7	750	350	8.18	339	56.27
8	1000	350	8.18	399	44.6
9	750	500	8.18	425	33.1
10	750	200	21.42	163	57.95
11	1000	200	21.42	146	69.51
12	750	350	21.42	117	78.75
13	1000	350	21.42	129	66.2
14	750	500	21.42	200	60.5
15	1000	500	21.42	167	58.43

3. YOLOv7 Algorithm

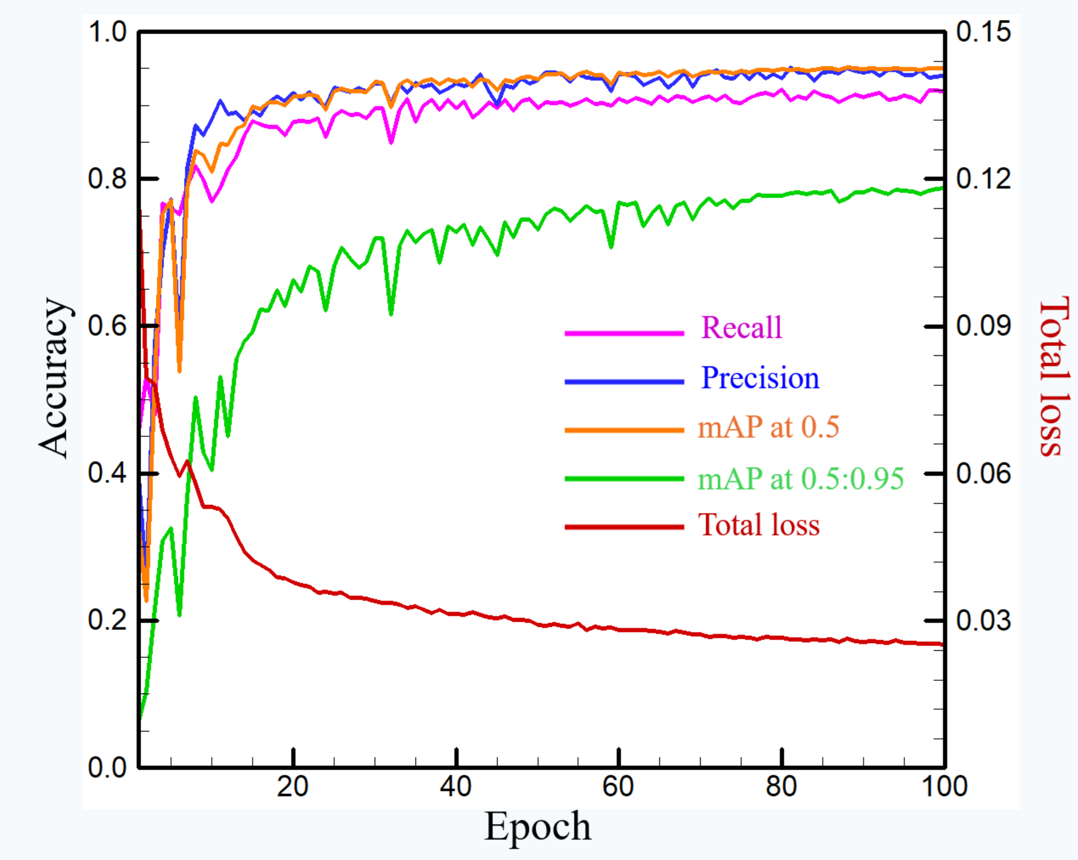

Fig 2. YOLOv7 Model Performance curves

- The trained model achieved strong detection performance, with **precision = 0.94**, **recall=0.92**, **mAP@0.5 ≈ 0.95**, and **mAP@0.5:0.95 ≈ 0.80**, while the total loss decreased below 0.03. (Fig 2)

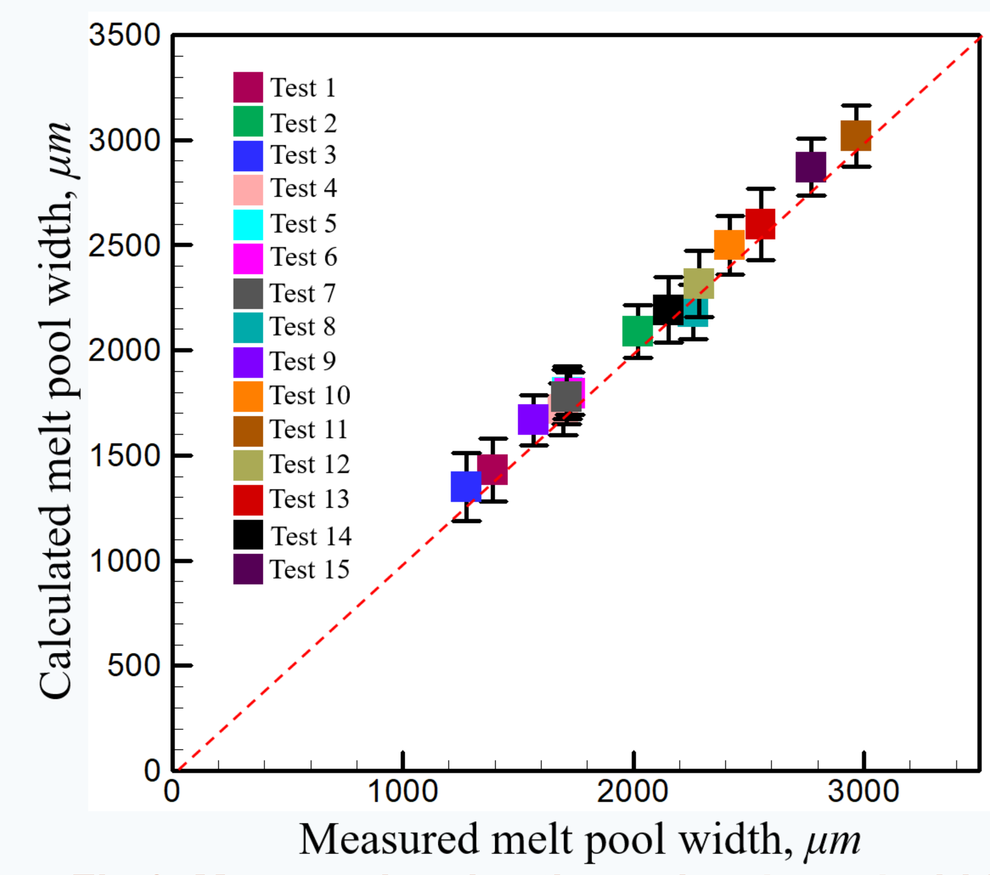

Fig 3. Measured and estimated melt pool widths

- Camera-detected melt pool widths closely follow the measured values, with most points located near the 1:1 agreement line. (Fig 3)
- The error bars are relatively small, with a maximum error range of approximately **±135 μm**. This strong agreement validates the high-speed imaging method for reliably measuring melt pool geometry.

4. Results and Discussion

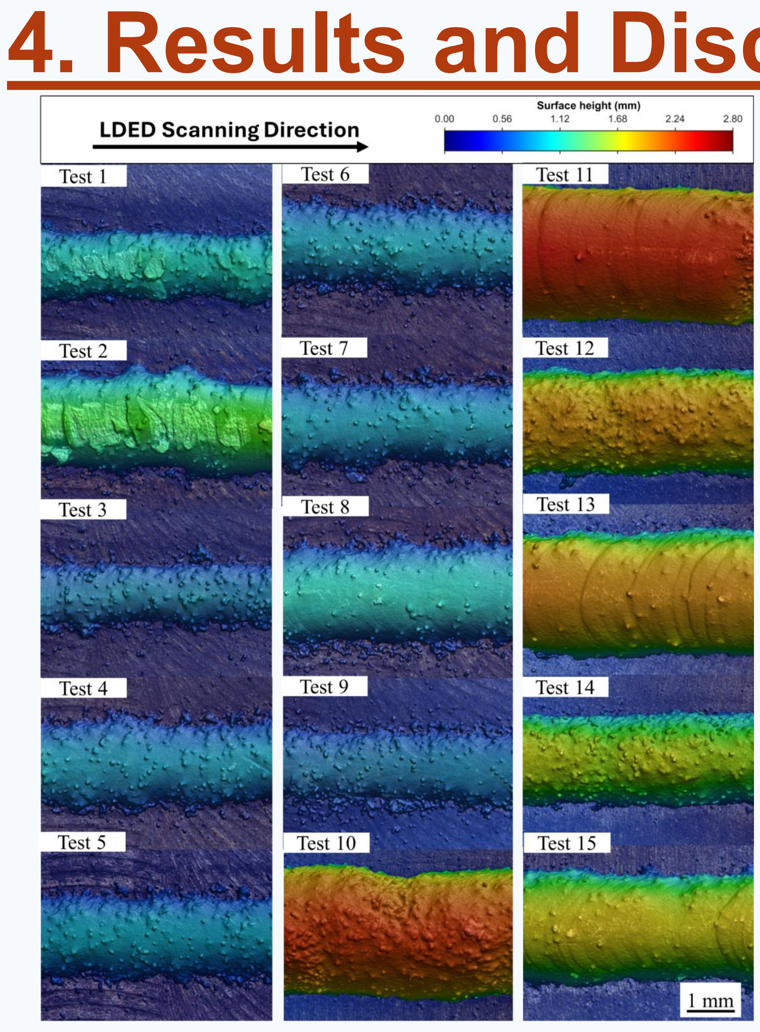

Fig 4. Surface height maps

- Tests 10–15, produced using the higher powder feed rate, generally exhibit greater track heights than Tests 1–9 because more material is supplied to the melt pool. (Fig 4)

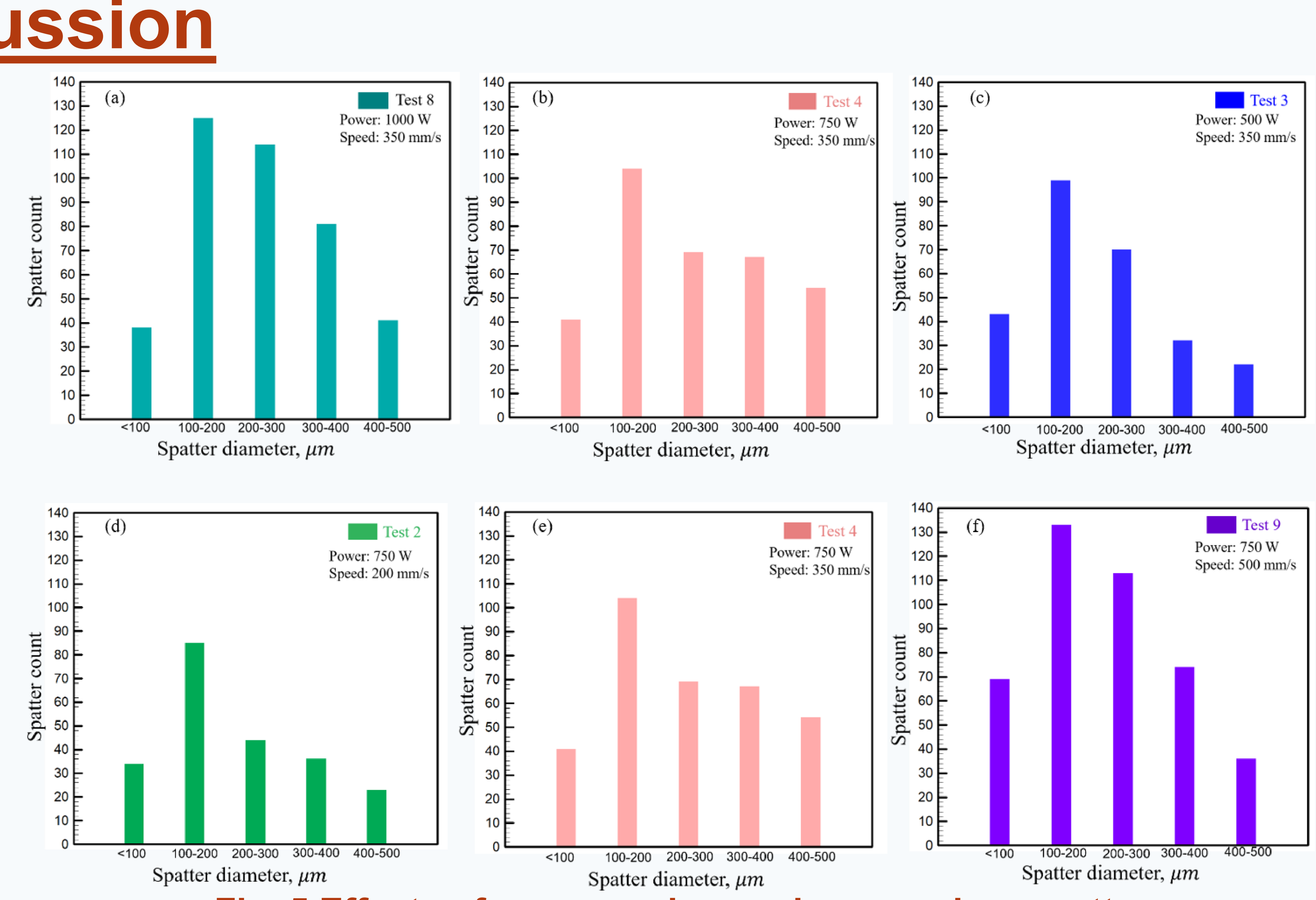

Fig. 5 Effects of power and scanning speed on spatter

- At a constant scanning speed of **350 mm/s**, increasing laser power from **500 W to 1000 W** increases the total spatter count. (Fig 5)
- At a constant laser power of **750 W**, increasing scanning speed from **200 to 500 mm/s** also increases spatter formation.
- Most spatters are concentrated in the **100–300 μm** diameter range.

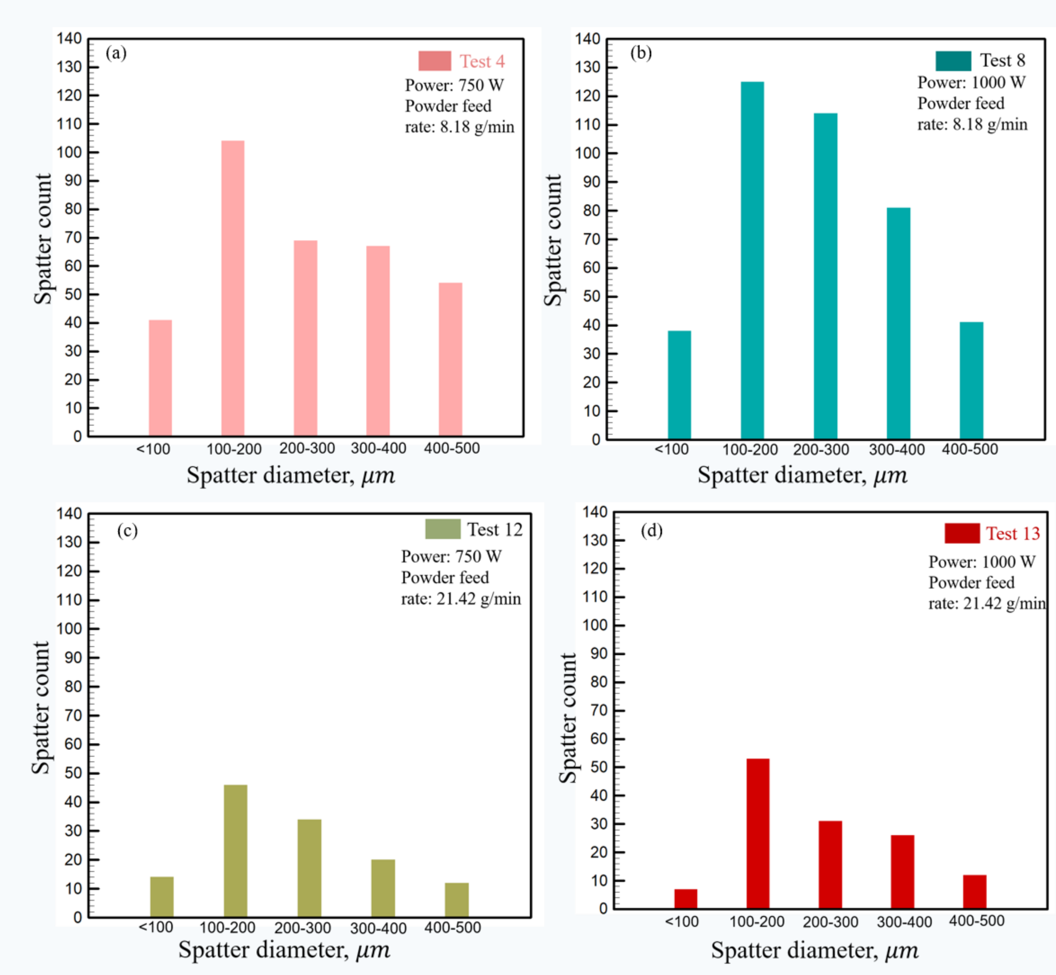

Fig 6. Effects of powder feed rate on spatter

- Increasing the powder feed rate from **8.18 to 21.42 g/min** substantially reduces the total spatter count at both **750 W and 1000 W.** (Fig 6)
- Low powder feed conditions produce more spatters because excess laser energy overheats and destabilizes the smaller melt pool.

5. Melt Pool Stability

- Melt pool length is extracted from each frame using the bounding rectangle along the scanning direction. Due to the camera's 45° angle, width is excluded. The length change per microsecond is used to define the melt pool fluctuation rate φ. So, $\varphi_i = \frac{abs(y_{i+1}-y_i)}{t}$
- Melt pool stability is evaluated by tracking length variation between frames. Smaller fluctuations indicate greater stability, quantified using a Stability Index (SI). So, $SI = \frac{1}{RMSE(\varphi)}$
- A clear negative trend was observed here. As the melt pool stability increases the spatter count decreases. (Fig 7)

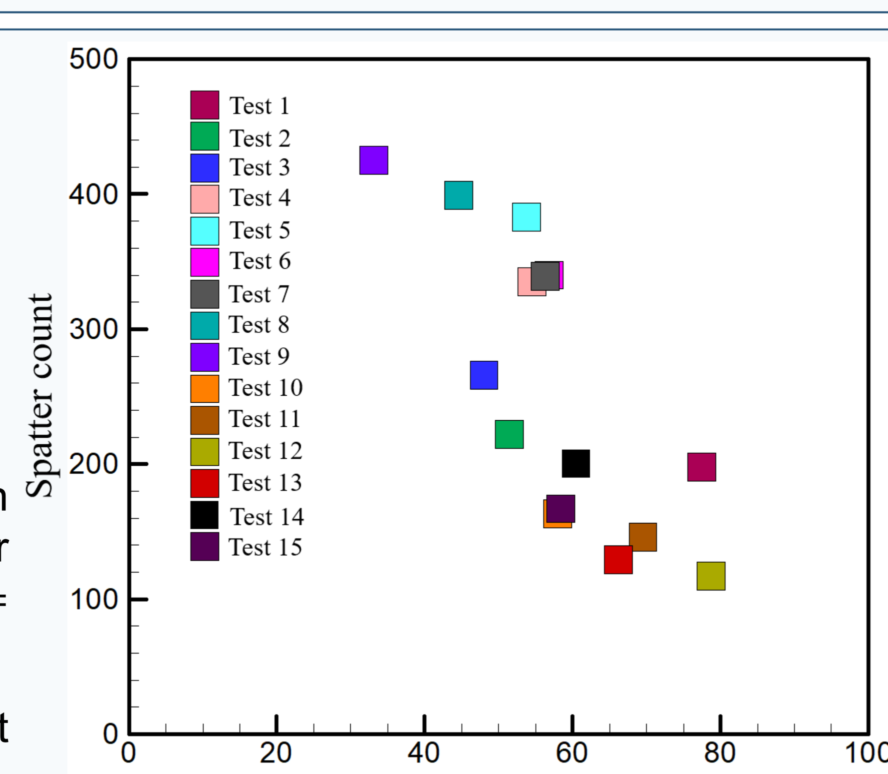

Fig 7. Melt Pool Stability Index

6. Conclusions

- The YOLOv7 model successfully automated melt pool and spatter detection, achieving high accuracy for large high-speed imaging datasets.
- Higher laser power and scanning speed increase spatters, while a higher powder feed rate reduces spatter by stabilizing the melt pool.
- A higher melt pool stability index corresponds to fewer spatters, demonstrating its potential for real-time process monitoring and optimization.

7. Acknowledgements

The authors gratefully acknowledge the valuable support from Dr. Jakob Hamilton's group, Dr. Shan Jiang's group, and the laboratory staff in the Department of Materials Science and Engineering at Iowa State University.