Photodiode-based machine learning for optimization of laser powder bed fusion parameters in complex geometries

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Background and motivation

Laser Powder Bed Fusion (LPBF) additive manufacturing is very promising but there are shortcomings. Parts often exhibit:

- Irregular quality
- Dimensional inaccuracies
- Defects: cracks, pores, spatter, etc.

We need approaches to control and optimize the additive manufacturing process

Background and motivation

Process parameters (e.g. laser power and velocity) optimization is a challenging task

- Need to incorporate effects of material, geometry, and complex underlying physics of LPBF
- Meltpool sensor data is available but often limited or noisy
- High-fidelity physics-based simulations are computationally expensive

Technical approach

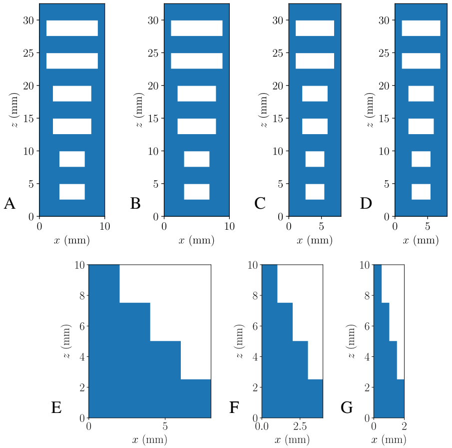
Combine optical sensor data and machine learning for the feed-forward selection of laser process parameters

1. Data generation: Print parts with varying geometry and laser parameters and collect sensor data.
2. Modelling: Build models to predict the sensor signal or laser parameters
3. Deployment: Print parts with laser parameters determined by the model.

Training data

Training parts are printed to collect photodiode signal data

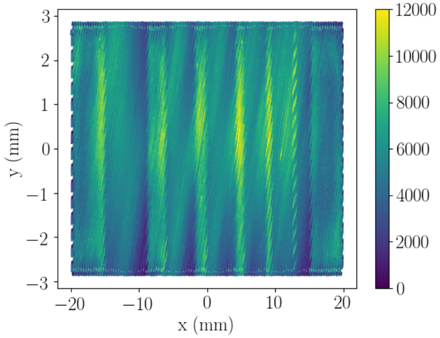
- Focus on canonical features: thin walls and overhangs
- Stainless steel (SS316L) used for all parts
- Laser power and velocity are varied across a wide range
- Each part is printed 13 times to acquire sufficient data



Forward model

Build a model to predict the photodiode signal $PD = f(\mathrm{geo}, \mathrm{laser})$

- PD: photodiode signal
- geo_i: distance to nearest edge in $x - y$ plane



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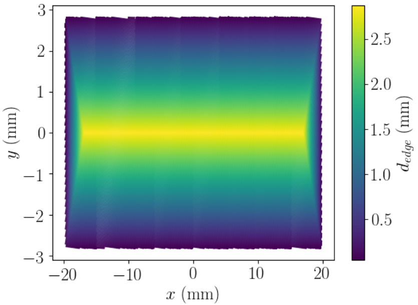

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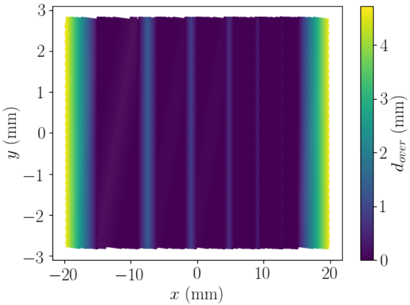

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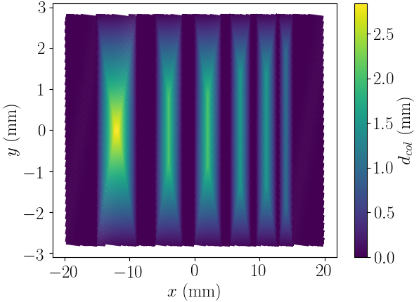
- geo_i: distance to nearest overhang in build (z) direction



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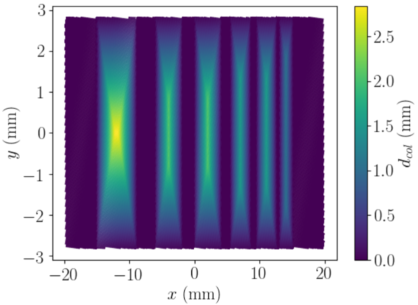
- geo_i: distance to nearest overhang in build (z) direction
- geo_i: length of the track



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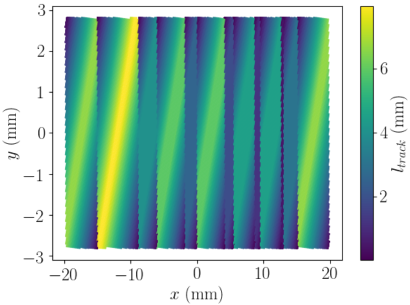
- geo_i: length of the track
- laser_i: laser power



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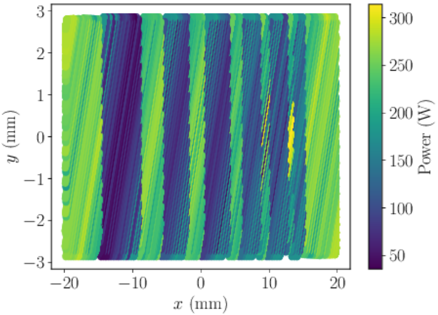
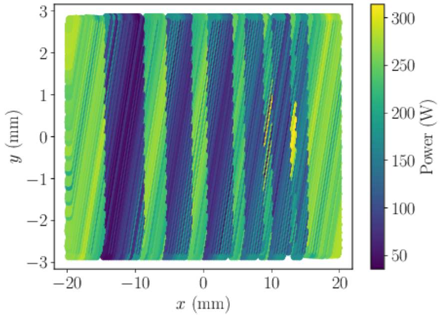
- geo_i: distance to nearest column in $x - y$ plane
- geo_i: distance to nearest overhang in build (z) direction
- geo_i: length of the track
- laser_i: laser power
- laser_i: laser velocity



Forward model

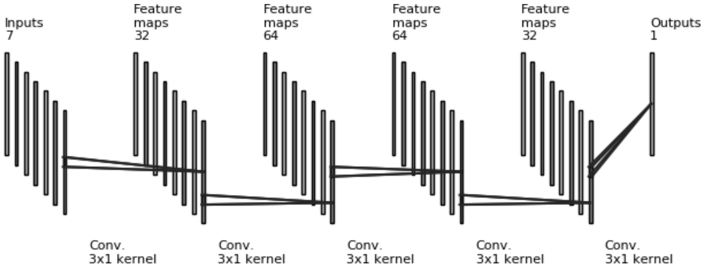
Build a model to predict the photodiode signal $PD = f(\text{geo}, \text{laser})$

- PD: photodiode signal
- geo_i: distance to nearest edge in $x - y$ plane
- geo_i: distance to nearest overhang in $x - y$ plane
- geo_i: distance to nearest column in $x - y$ plane
- geo_i: distance to nearest overhang in build (z) direction
- geo_i: length of the track
- laser_i: laser power
- laser_i: laser velocity



Forward model

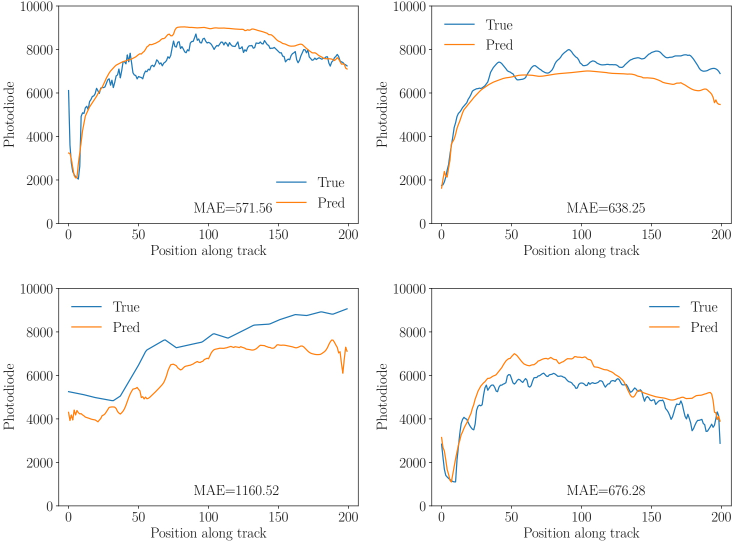
1D CNN to predict track-wise signal



- Inputs: trackwise geometry and laser parameters
- Output: trackwise PD signal
- Fully convolutional model with $\sim$ 30K parameters
- 550K tracks used for training

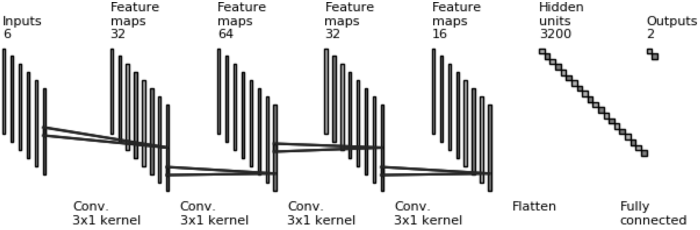
Forward model results

MAE on held-out validation data: 1060. Predicted tracks:



Inverse model

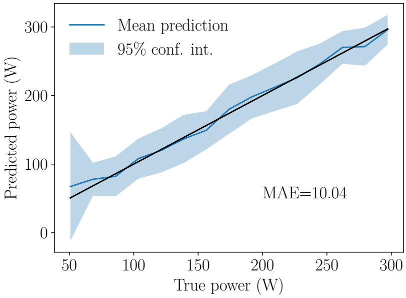
Build a model to predict the laser parameters given the geometry and the desired PD signal. $\text{laser} = f(\text{geo}, PD)$

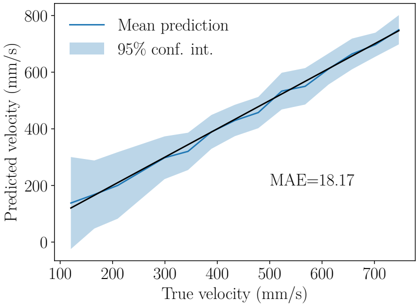


- Inputs: trackwise geometry and PD signal
- Output: laser power and speed (single value per track)
- CNN regressor with $\sim$ 33K parameters
- Same 550K tracks dataset used for training

Inverse model results

MAE on laser power: 10 W
MAE on laser speed: 20 mm/s

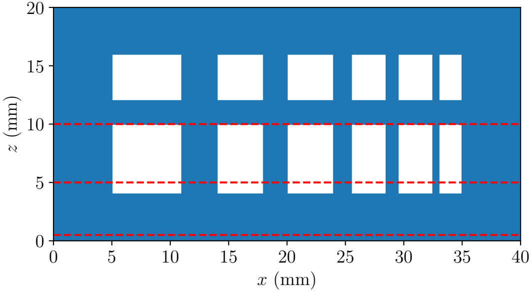




Deploy inverse model on test geometry #1

Test inverse model on simple “window block” geometry

- Create ML model inputs from geometry
- Predict track-wise laser power/speed for a desired constant PD signal
- Reduced power in corners, thin walls, and overhang regions



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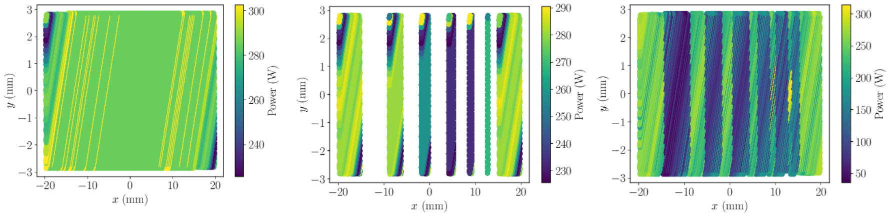
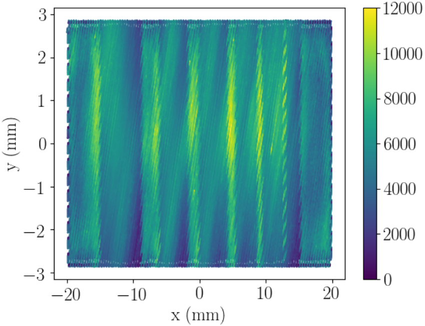
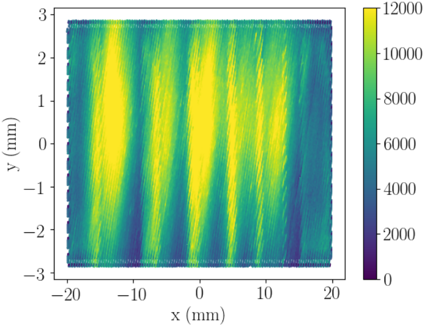


Deploy inverse model on test geometry #1

Comparison of photodiode signal with optimized (left) and nominal parameters (right)





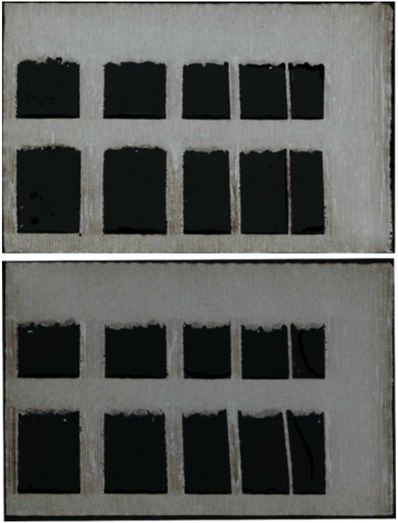
Optimized laser parameters predicted by the inverse model lead to lower photodiode signal in overhang and reduce fluctuations.

Deploy inverse model on test geometry #1

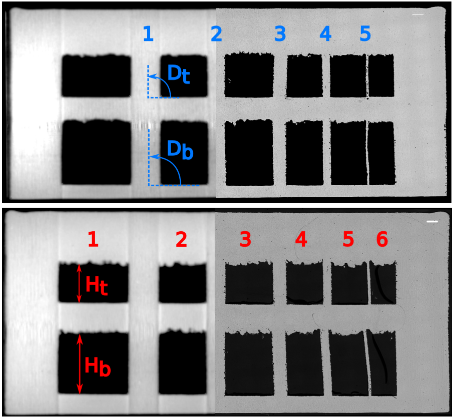
Compare prints with optimized (top) and nominal parameters (bottom)

Optimized parameters improve part quality:

- Considerable reduction of dross formation in the overhang regions
- Thinnest wall is less distorted
- No distortion compensation strategy was applied

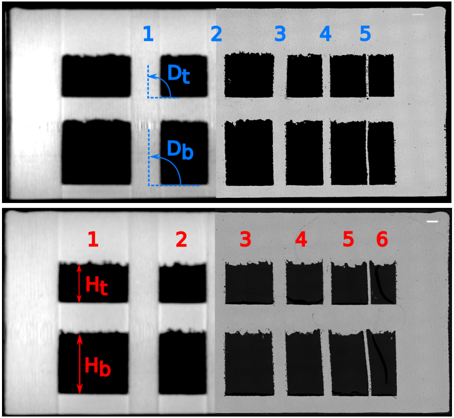


Deploy inverse model on test geometry #1



Dim.	Desired	Nom.	ML
H_{1t}	4	3.529	3.799
H_{2t}	4	3.521	3.804
H_{3t}	4	3.623	3.841
H_{4t}	4	3.610	3.828
H_{5t}	4	3.462	3.803
H_{6t}	4	3.362	3.807
Avg. dev.		**-0.482**	**-0.186**
H_{1b}	6	5.513	5.803
H_{2b}	6	5.494	5.821
H_{3b}	6	5.529	5.824
H_{4b}	6	5.586	5.752
H_{5b}	6	5.467	5.712
H_{6b}	6	5.460	5.727
Avg. dev.		**-0.492**	**-0.227**

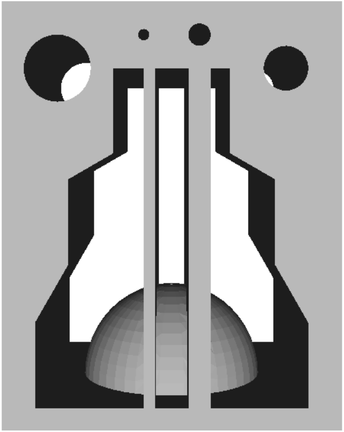
Deploy inverse model on test geometry #1



Dim.	Nom.	ML
D_{1t}	89.565	89.780
D_{2t}	90.396	90.527
D_{3t}	91.591	88.953
D_{4t}	91.005	91.413
D_{5t}	92.352	91.372
D_{1b}	90.025	90.017
D_{2b}	90.718	90.174
D_{3b}	92.726	90.508
D_{4b}	93.694	90.526
D_{5b}	95.236	91.495
Avg. dev.	**1.731**	**0.477**

Deploy inverse model on test geometry #2

Deploy model on a second, more complex, test geometry



Deploy inverse model on test geometry #2

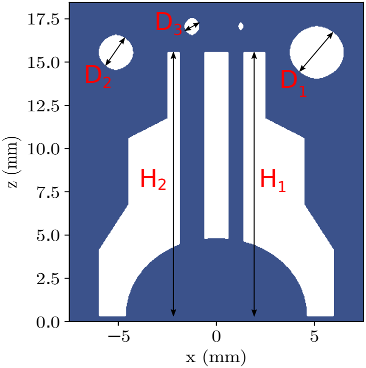
Compare prints with optimized (left) and nominal parameters (right)

Optimized parameters improve part quality:

- Considerable reduction of dross formation in both flat and angled overhang regions
- Reduction in keyhole porosity in the thin walls

Deploy inverse model on test geometry #2

Computed tomography (CT) data used to assess dimensional accuracy



Dim.	Desired	Nom.	ML
D_1	3	2.708	2.828
D_2	2	1.681	1.753
D_3	1	N/A	1.086
H_1	15.2	14.679	15.177
H_2	15.2	14.768	15.108

Dimensions of the part printed with optimized parameters are closer to the desired values for the five features considered.

Conclusion

Data-driven approach for the selection of laser process parameters

- Parts printed with varying laser parameters to collect photodiode data
- Built models to predict the track-wise photodiode signal or laser parameters
- Used the inverse model to optimize laser parameters for a desired constant photodiode signal
- Optimized parameters lead to improved part quality

Future work:

- Add geometry features to the training data: angled overhangs, circular features, angled thin walls, etc.

Questions?

The work was performed under the auspices of the U.S. Department of Energy by Lawrence Livermore National Laboratory under contract DE-AC52-07NA27344.