AN INVERSE MODELING FRAMEWORK FOR LPBF ADDITIVE MANUFACTURING

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Background and motivation

- LPBF inputs can produce similar geometry but different thermal histories and properties.
- Trial-and-error parameter selection is slow, expensive, and does not ensure target outcomes.
- Multiple power-speed combinations may satisfy the same melt-pool geometry.

Inverse Modeling for Targeted LPBF Design

- Forward models predict outcomes; inverse models identify parameters for desired outcomes.
- Multiple power-speed combinations can produce similar melt-pool geometry.
- Develop physics-guided predictions of feasible process conditions from target attributes.

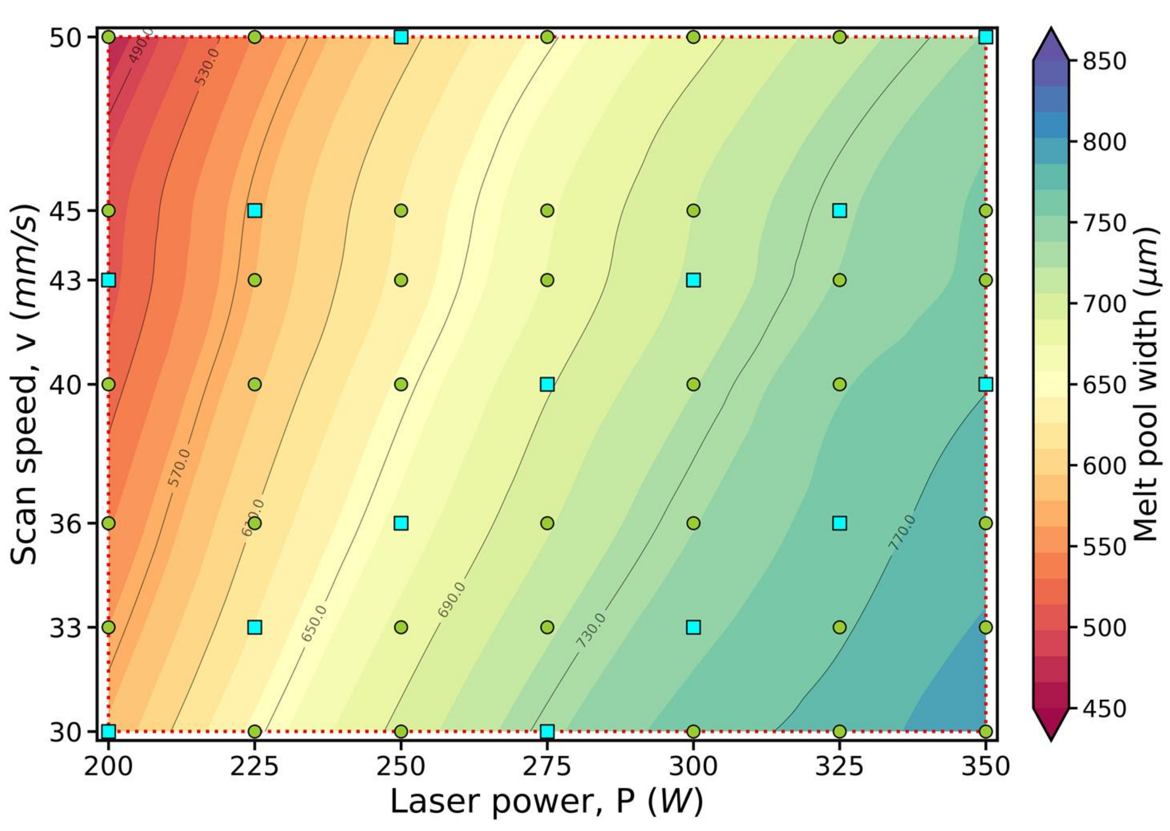


Figure 1. Process parameter design space for single-track LPBF used to define the inverse search domain and connect process inputs to melt-pool response.

Physics-Guided Inverse Modeling Framework

- Power and scan speed control melt-pool geometry and thermal response.
- Mechanistic simulations generate physics-consistent data for neural-network training.
- Genetic algorithms identify feasible parameters that satisfy specified melt-pool targets.

Neural Network K-fold validation

- Seven-fold validation used 42 training and 7 unseen test samples per fold.
- Test performance averaged R_2= 0.9956 with *RMSE* = 4.46 *μm*.
- Consistent train-test accuracy supports reliable surrogate-guided inverse optimization.

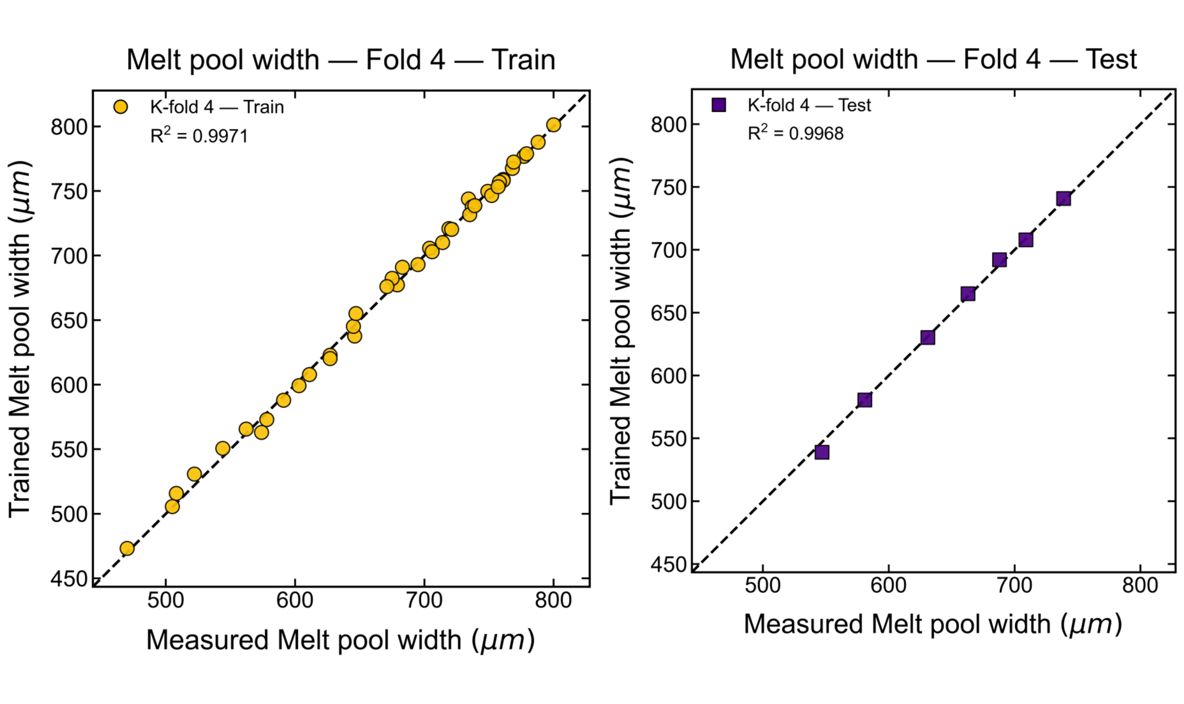


Figure 2. K-fold cross-validation: Across seven folds, unseen test predictions achieved R_2=0.9912–0.9983 and *RMSE* =3.13–6.48 *μm* for melt-pool width.

Sensitivity and surrogate-model training

- Sensitivity analysis identifies process regions strongly affecting predicted melt-pool responses.
- Objective distributions guide calibration and inverse-search performance.
- K-fold validation evaluates surrogate-model generalization across unseen samples.

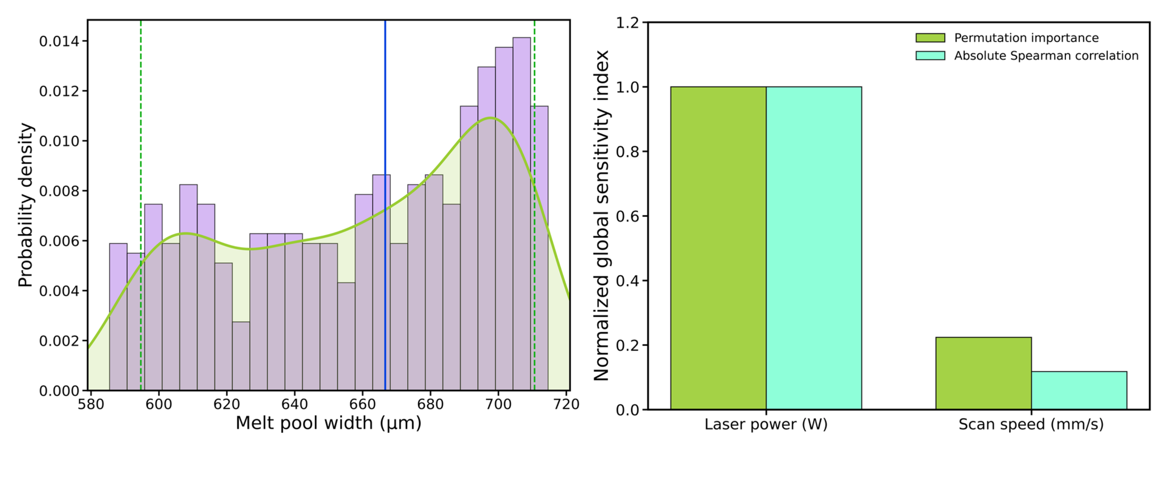


Figure 3. Sensitivity of the computed response and distribution of objective-function values across the design space.

Forward-model validation

- Predicted temperature fields reproduce expected power-dependent thermal behavior.
- Calculated melt-pool widths agree with experimental measurements.
- Training and testing R_2 values quantify surrogate prediction accuracy.

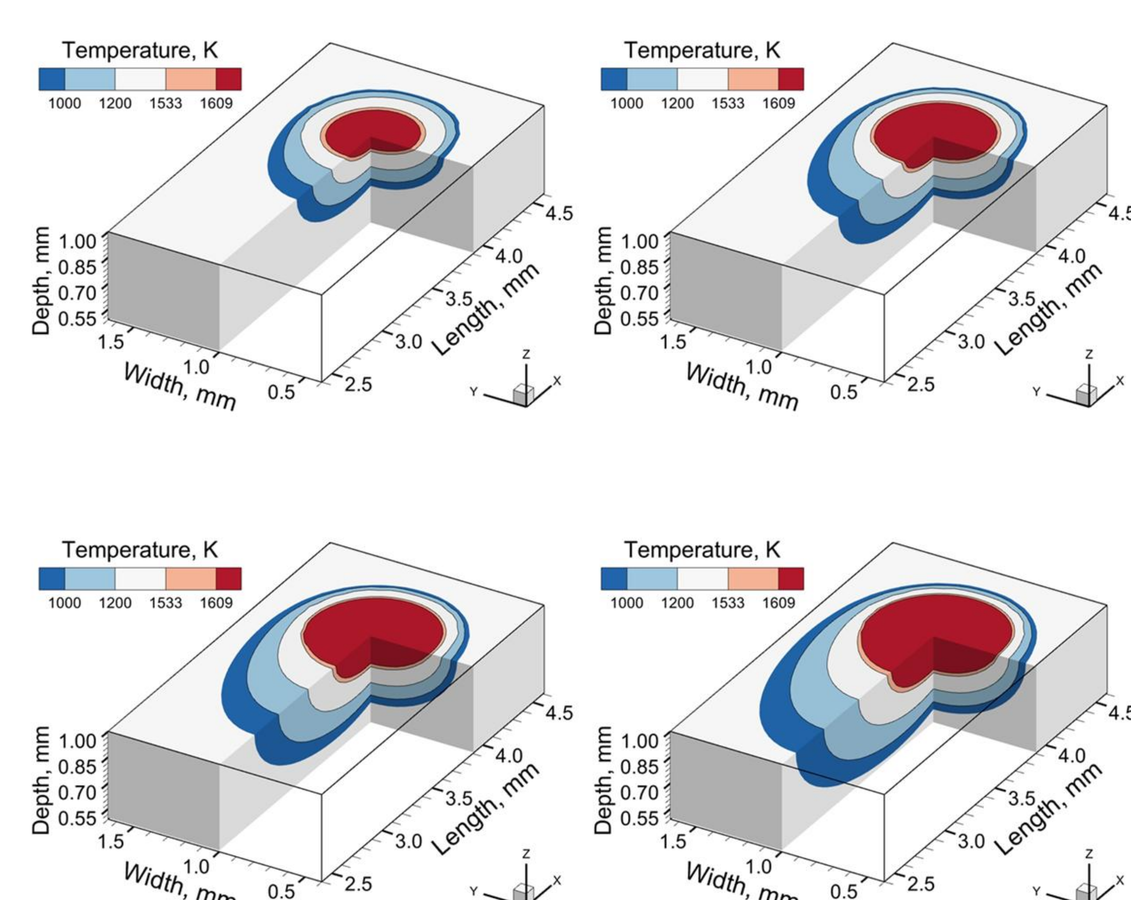


Figure 4. Validation case showing 3D temperature field predictions for laser powers from (a) 200W (b) 250W (c) 300W (d) 350 W at constant speed.

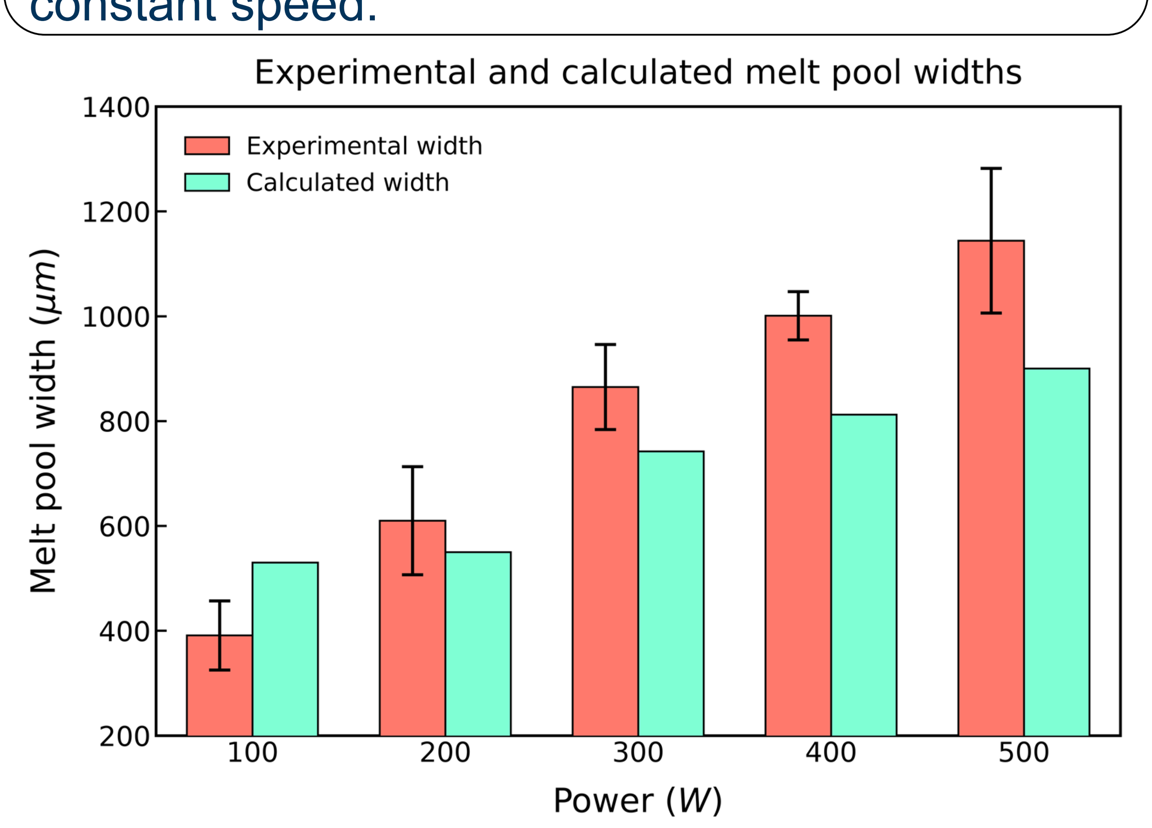


Figure 5. Comparison of experimental and calculated melt-pool width for different powers at the same scan speed

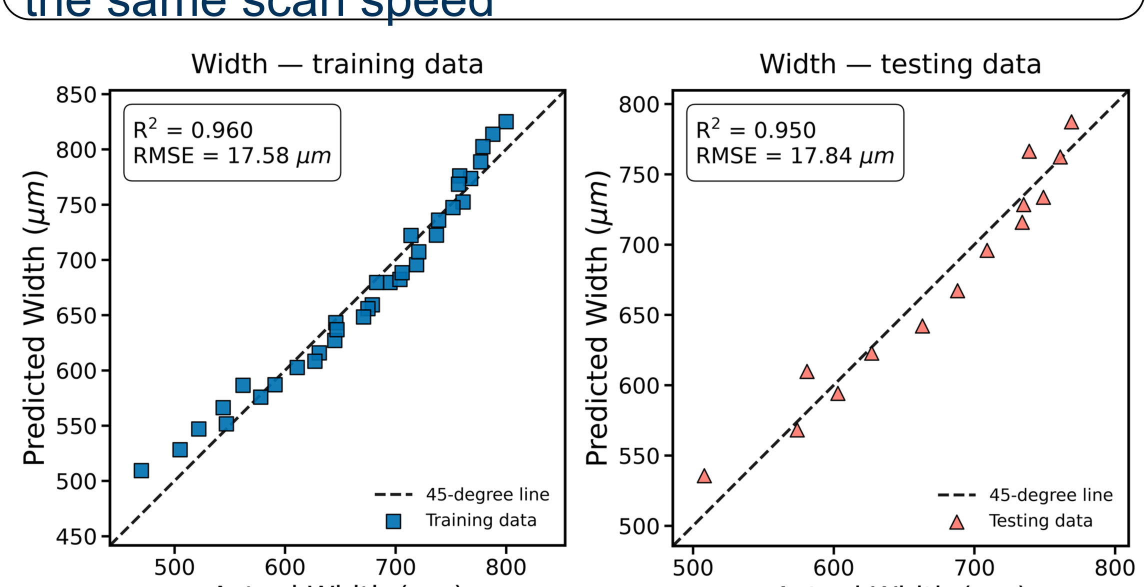


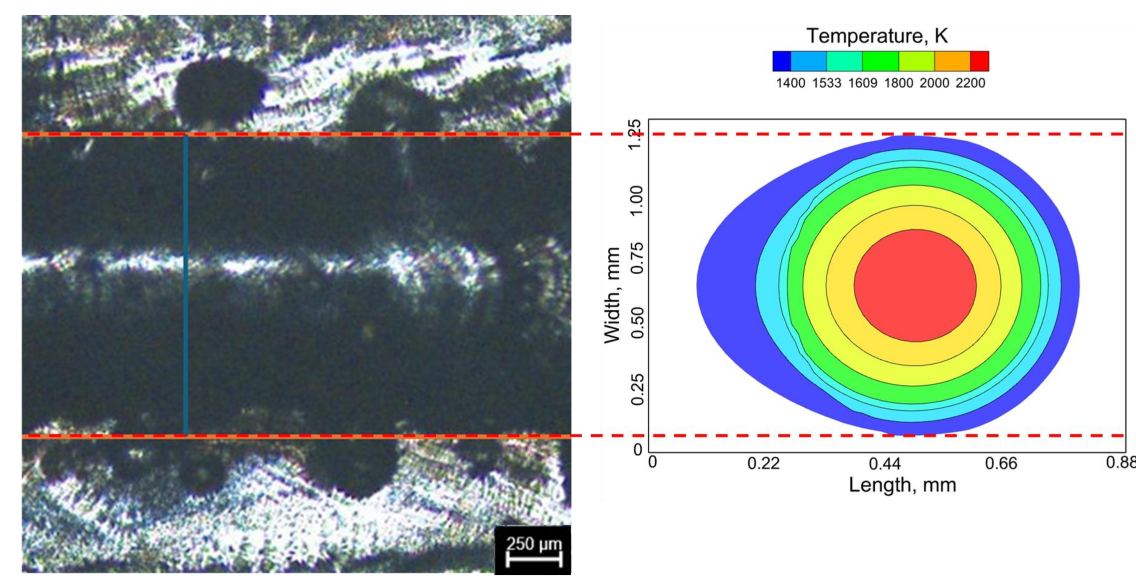
Figure 6. Training and testing R^2 values for width and depth, demonstrating predictive accuracy of the surrogate model

Inverse optimization results

- Genetic algorithms search multiple feasible parameter combinations.
- Surrogate predictions make inverse optimization computationally efficient.
- Returned solutions satisfy target attributes while preserving physical consistency.

Optimization performance

- Global and local fitness curves show stable convergence during optimization.
- Fitness reduction indicates progressively improved agreement with target attributes.
- Multiple low-fitness solutions reveal feasible LPBF processing windows.



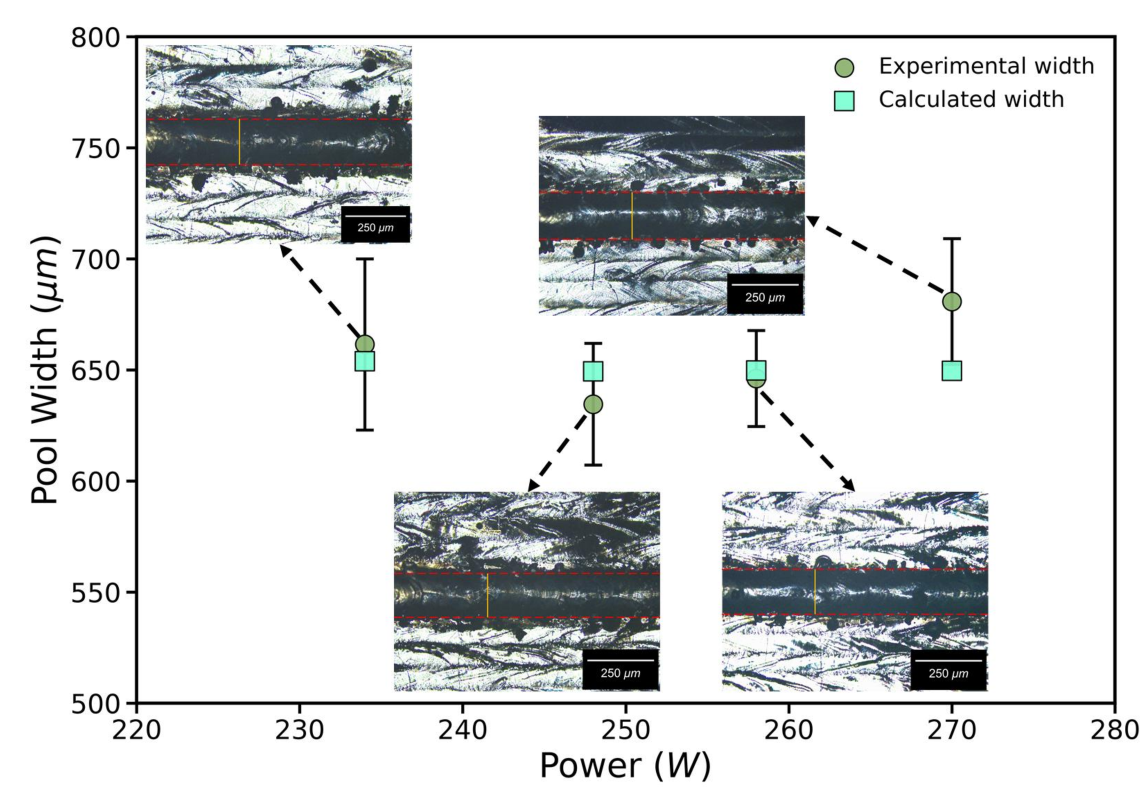


Figure 7. Comparison between experimental melt-pool width and GA-predicted melt-pool width.

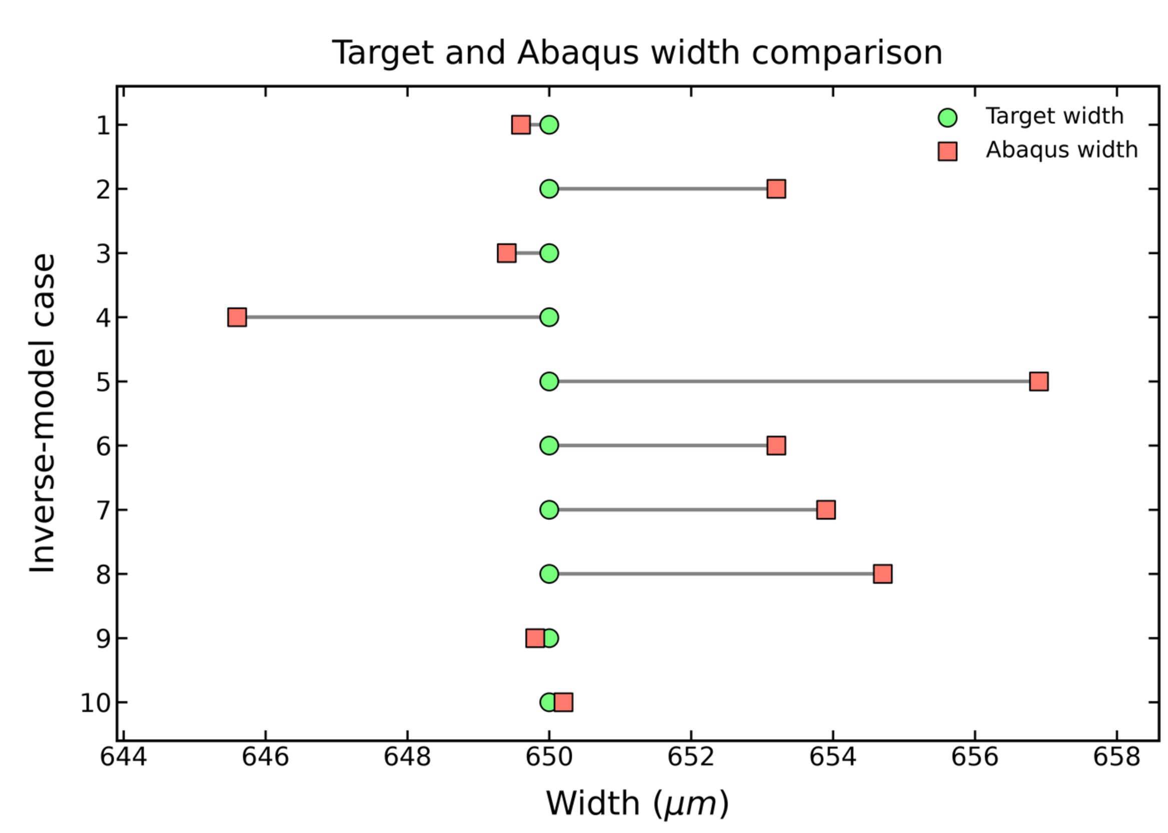


Figure 8. Validation of inverse-model-predicted power-speed combinations through comparison of experimental and calculated melt-pool width.

Conclusions and Future Impact

- The framework enables rapid, physics-informed LPBF process-parameter selection.
- Surrogate models and genetic algorithms identify multiple feasible inverse-design solutions.
- Future work incorporates microstructure, defects, cooling rate, and application-specific constraints.

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