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Data-Driven Approaches to Laser-Based Manufacturing Using Machine Learning

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Introduction

Machine learning is revolutionising laser-based manufacturing by addressing complex correlations between laser parameters and material properties. It enables better process understanding, optimisation, and real-time monitoring toward zero-defect manufacturing. In one case study, a gradient boosting regression model—an ensemble technique combining weak learners—was developed for laser beam oscillation welding of Al-Cu joints used in EV battery packs. The model accurately predicted interface width, penetration depth, breaking force, and resistance factor using laser peak energy (Ed), oscillation diameter (D), and absorbed energy (Q) as inputs. In another ongoing project within our group, WAVETAILOR (EU Horizon-funded project www.wavetailor.eu), a digital twin with machine learning-driven predictive capabilities is under development. It continuously analyses real-time sensor data to foresee future states of the physical twin (i.e., the additive manufacturing process). These applications demonstrate the transformative potential of machine learning in enhancing precision, reliability, adaptability, and sustainability in laser-based manufacturing systems.

Case study 1: Gradient boosting regression (GBR) model for Laser beam oscillation welding

Materials and Methods

Materials

0.3 mm-thick commercially pure Al 1050 (99.5% Al) and 1 mm Cu C101 (99.9% Cu) sheets were used for experiments to represent Al-Cu tab-to-busbar joints in pouch-cell-based EV battery packs. The chemical compositions of the materials used for experiments are given in Table 1.

Table 1 The chemical composition (wt.%) of the Al and Cu sheets

Materials	Al	Cu	Fe	C	Mn	P	S	Pb	Bi
Al 1050	Bal.	0.01	0.3	-	0.02	-	-	-	-
Cu C101	-	Bal.	-	-	-	<0.007	-	<0.005	<0.001

Welding setup

Weld experiments were conducted by a single-mode Yb:fibre laser (YLR-150/1500-QCW, IPG Photonics Corporation, Massachusetts, US). For the delivery of beam oscillation, an FLW-D30 wobble head from (IPG Photonics Corporation, Massachusetts, US) was utilised. The wobble head was integrated with the IPG's fibre laser. A clockwise circular oscillation pattern was used, and parameters, including diameter, frequency, were controlled using variables.

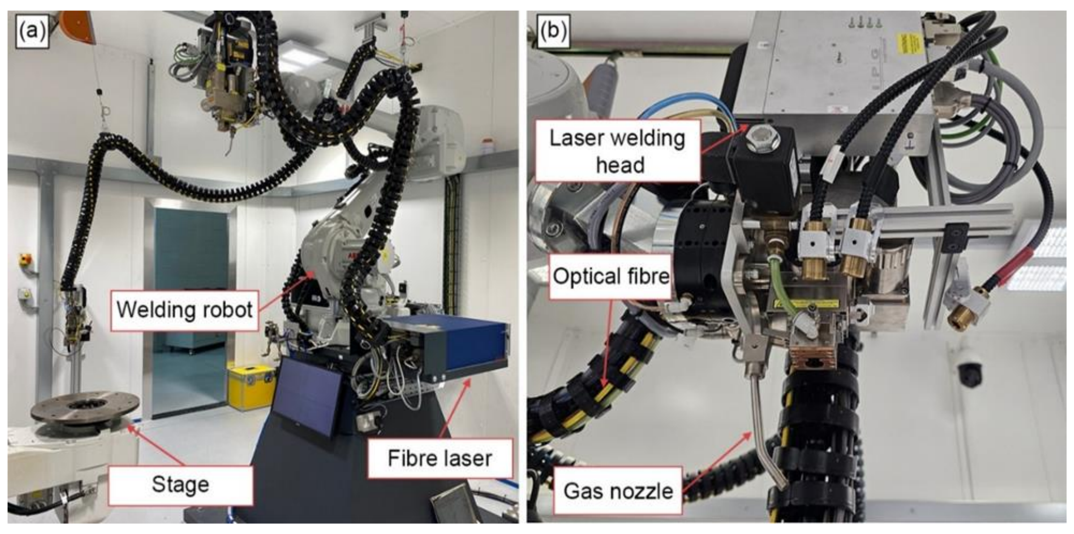


Figure 1 (a) The robotic laser welding setup (b) close-up of the optics and shielding gas nozzle setup.

GBR model

When dealing with a limited number of available data, neural networks run the danger of overfitting and usually require large datasets for optimal training. Thus, GBR is chosen instead due to its strong performance on small-to-medium data sets, ability to model complex, non-linear relationships. The goal is to estimate interface width, penetration depth, maximum breaking force (Fc), and resistance factor (K) using input features, laser peak energy (Ed), oscillation diameter (D), and total absorbed heat input (Q) that describe energy density and distribution. The maximum breaking force for the ML model was calculated as the total amount of the maximum peel and lap shear forces. The data set consisted of 76 distinct data points.

GridSearchCV was used to refine the performance of the GBR model by methodically adjusting important hyperparameters to improve prediction accuracy by carefully modifying key hyperparameters. The number of boosting iterations (n_estimators) was set between 100 and 200 to balance bias and variance. The learning rate, which determines the step size during model updates, was adjusted to 0.01 and 0.1. The maximum depth (max_depth) was set at 3 to 5 to vary the tree complexity and guarantee that the model captures underlying patterns without overfitting. The minimum number of samples required to split an internal node (min_samples_split) was fixed as 2 and 5. The minimum number of samples needed for a leaf node (min_samples_leaf) was evaluated at 1 and 2.

Results

The interface width shows an excellent fit and small errors relative to true values, indicating accurate predictions. The force and resistance factor show very good fits and low errors, with the GBR model slightly overpredicting for force in low values. Penetration depth values show a moderate fit and higher error compared to the rest of the responses. The GBR model generally underpredicts the penetration depths, with some overprediction in higher values. The lower accuracy of the model for predicting penetration depth values could be due to variation in energy density and the complex relation of absorbed energy with process parameters. The effective velocity and therefore energy density are not constant during the LBOW, which affects the penetration depth more than other responses, making it more difficult to predict the actual values.

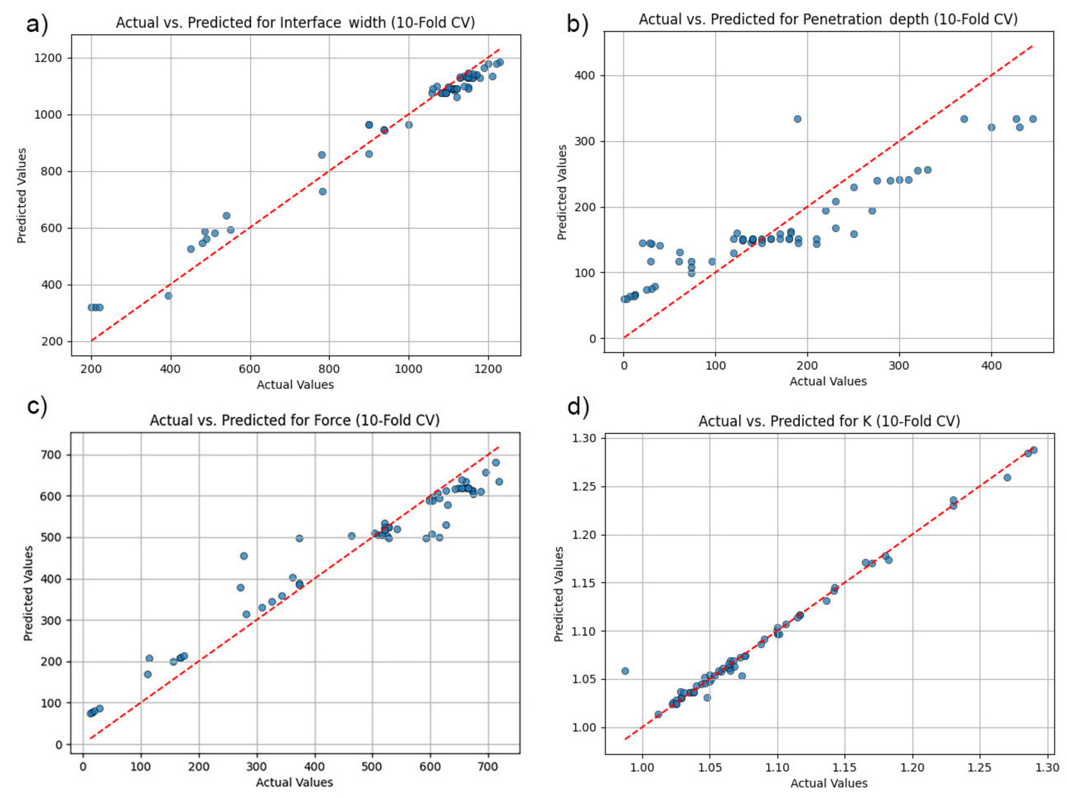


Figure 2 Predicted vs actual values for a) interface width, b) penetration depth, c) breaking force, and d) resistance factor (K).

The maximum Fc values are predicted for oscillation diameters between 0.7 mm and 1.2 mm, while the optimum range of Ed=~5 × 10^3-20 × 10^3 J/cm^2 results in the highest Fc values. The optimum region for minimum K shows a very good overlap with the optimum range of Fc. Thus, the above values for D and Ed could be considered the optimum range in Al-Cu joints studied in this investigation.

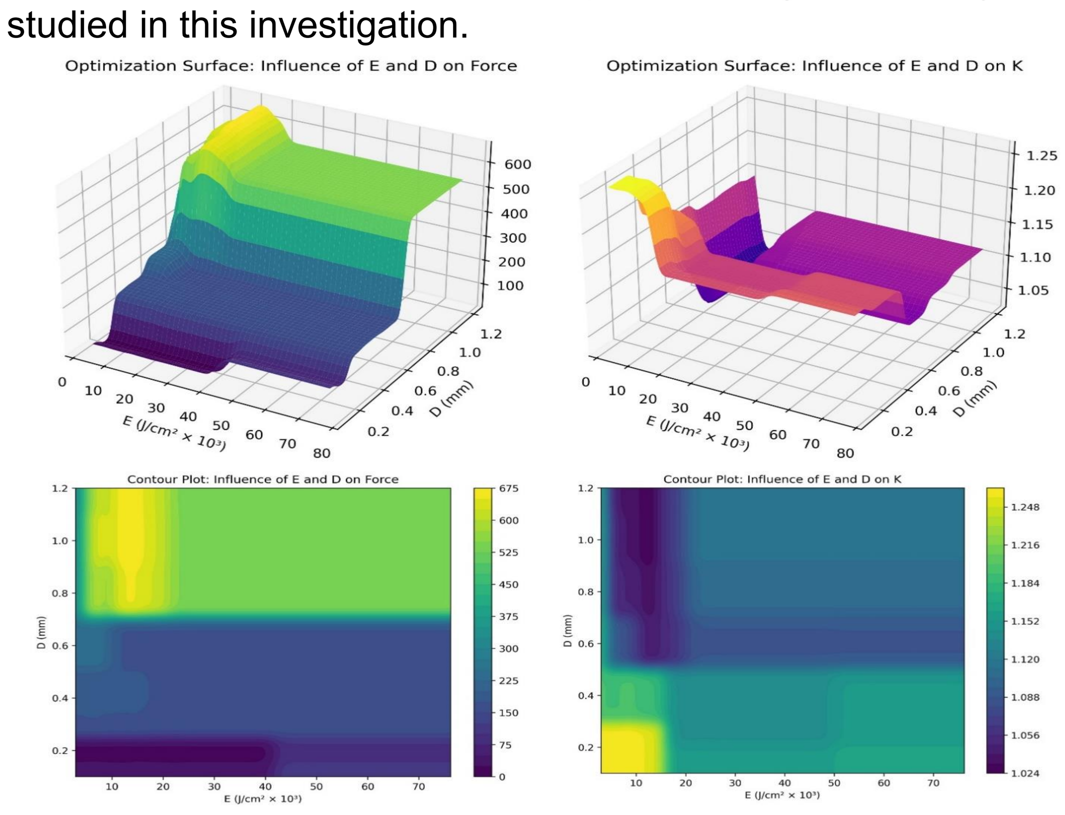


Figure 3 3D optimisation surface and 2D contour plots.

Case study 2: Digital twin in laser-based additive manufacturing

Materials and Methods

The Digital Twins represent the past, current, and future state of a system or a product. For this purpose, all relevant data, such as engineering data, telemetry data, sensor values, data sheets, and test results from various sources, must be defined, presented, and integrated into a single model (Digital Twin Model). It must also be considered that all sub-systems, as well as components and their parameters, may change during the lifetime of a system. The methods of configuring these data sets, as well as their interfaces, must therefore define reusable data models that are independent of the components used.

WAVETAILOR focuses on two industrial scenarios which are related to the complex multi-material component and assembly. DED of a multi-material leading edge for a hypersonic hydrogen-driven aeroplane, while the second is on LPBF of complex multi-material assembly of a drone for urban delivery.

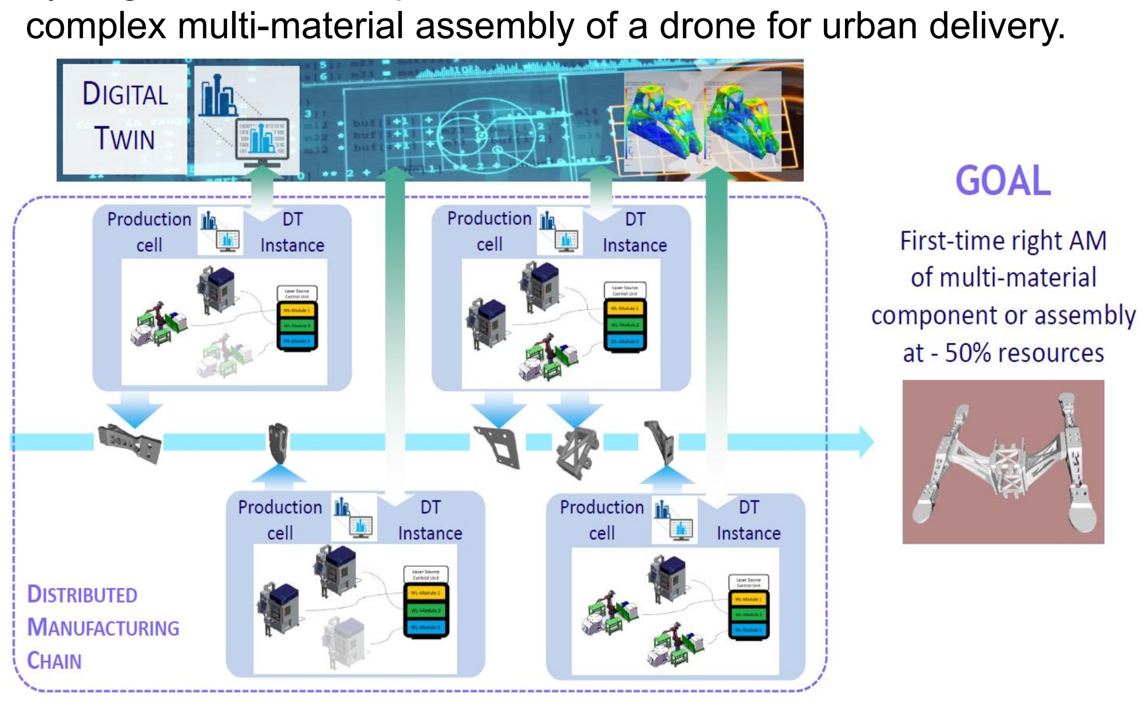


Figure 4 Overall concept of WAVETAILOR

Results

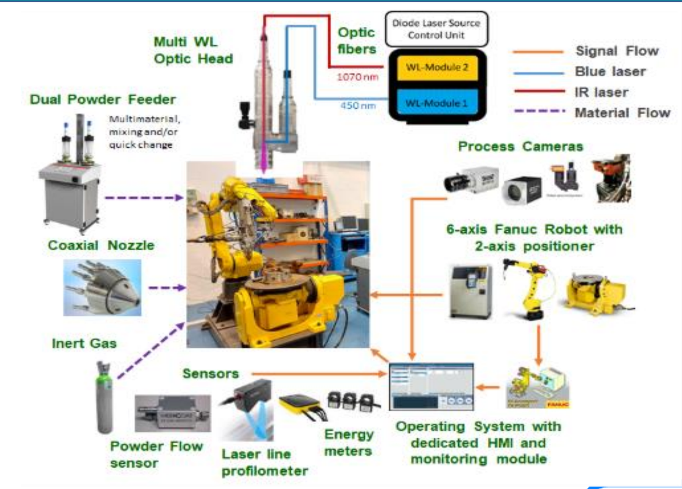


Figure 5 Reconfiguration of a single-optic Laser DED cell (Robot or CNC),

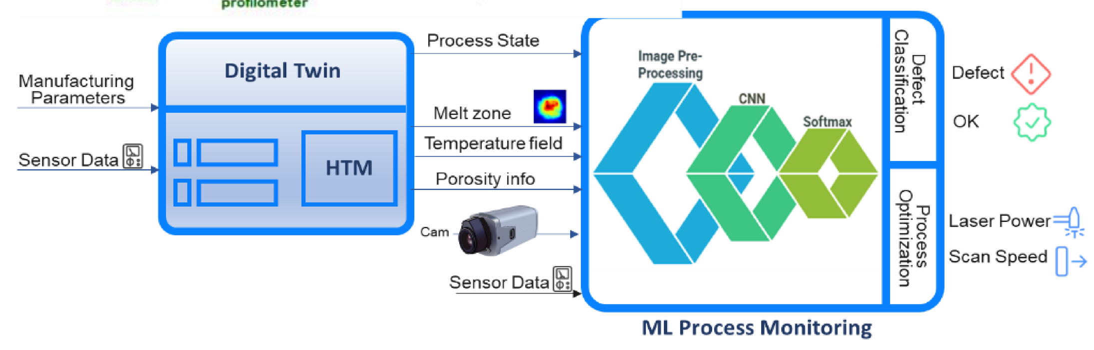
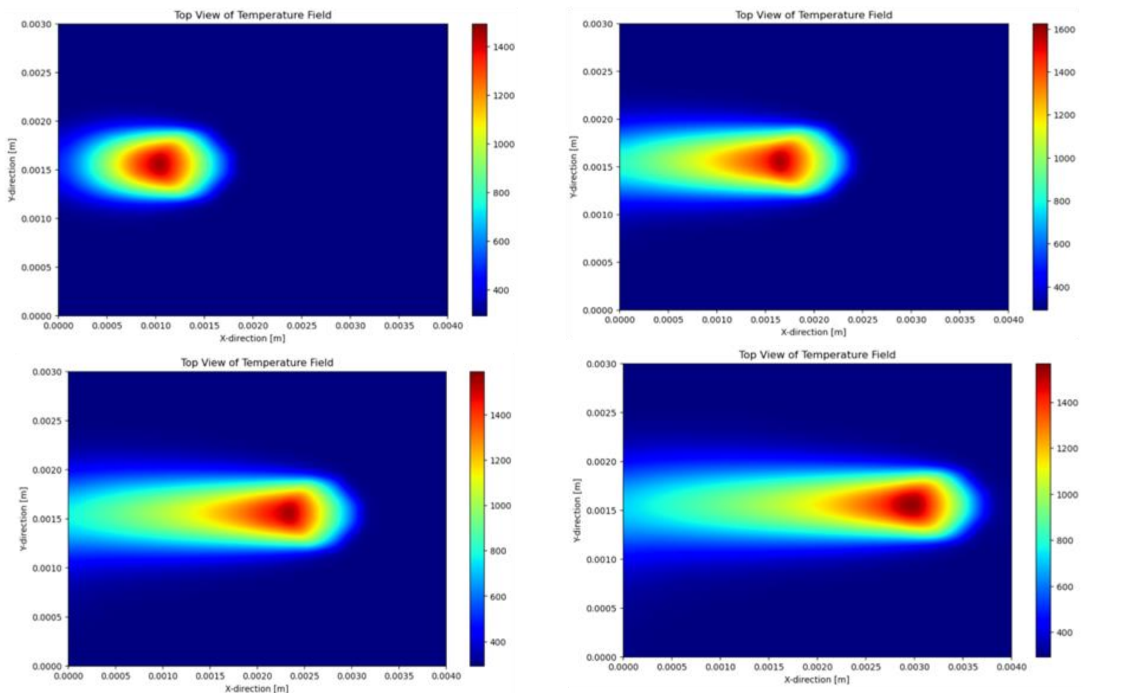


Figure 6 Machine learning multi-scale model



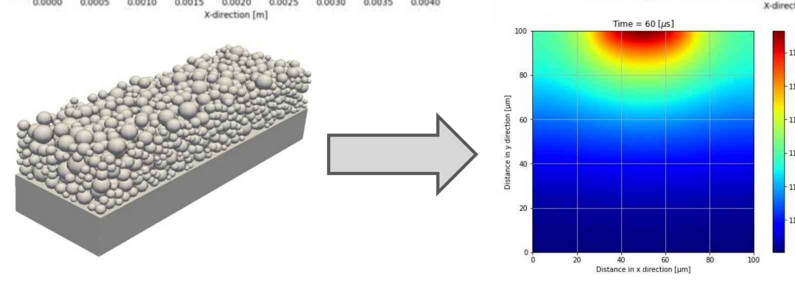


Figure 7 Thermal model to simulate powder melting and predict porosity levels

Conclusions and Future Works

-Two use cases on AI/ML in laser-based manufacturing were investigated. First, the use of the GBR ML model in optimising laser beam oscillation welding of Al-Cu was investigated. Second, the use of the digital twin model in multi-material additive manufacturing via LPBF and DED was discussed.

-The optimal range for maximum breaking force and K shows a good overlap, resulting in a desirable oscillation diameter of 0.7≤D≤1.2 mm and peak energy density of =~5 × 10^3-20 × 10^3 J/cm^2. However, it should be noted that the model was trained on a rather limited dataset (76 data points), which may limit its generalizability. Thus, the model provides valuable insights for process optimisation, but further investigations could refine the model by providing new data outside the range of this study.

-WAVETAILOR will develop universal LBAM (DED-LB and PBF-LB) tools that will enable the production of 3D printed components with complex geometries made of multi-materials (including difficult-to-process materials) and end-products (including near-net-shape geometries and complex assemblies) from various industrial sectors.

References and Acknowledgements

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Wavetailor

Contact Information