

Deliverable D3.8

Report on Validated Intelligent Control System

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Revision	Date	Author/Organisation	Description
1	29/07/2025	Gavin Chapman, Medad Monu, Eanna McCarthy, Josiah Chekotu, Dermot Brabazon	ML algorithm development and closed loop control implementation using Aconty L-PBF
2	30/07/2025	Gaetano Patrimia	Prima Additive sensor integration and data acquisition

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Action number: #101138859

Action Acronym: DILAPRO
Action Name: Digital Laser Production

Deliverable Due date: 30th June 2025
Deliverable hand-in date: 31st July 2025

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Executive Summary

This deliverable presents the validation of an intelligent control system developed for different additive manufacturing processes. The system integrates real-time monitoring and adaptive feedback mechanisms to improve part quality and reduce defects during production.

Validation activities focused on assessing the system's performance in detecting process anomalies and enabling timely corrections. The evaluation was based on the quality of the manufactured parts and the system's responsiveness, allowed by the integration of different sensors systems inside the machine platforms of the pilot line identified in the DILAPRO project.

The results confirm the system's potential to enhance process reliability and support quality assurance in industrial AM environments: this report outlines the validation setup, criteria, and outcomes, providing clear evidence of the system's effectiveness and readiness for integration into production-level AM workflows. The intelligent control system represents a step forward in achieving closed-loop quality control and supports the broader goal of certifiable, digitally controlled manufacturing.

The main focus of the work has been on L-PBF, as that is the machine available at DCU, the main responsible partner for developing the feedback control system. However, CRM and P.ADD have also implemented smaller and/or commercially available feedback control systems at their respective DED machines. These will be described at the end of the deliverable.

This deliverable was delayed of 1 month due to machine availability and sensor installations and therefore lack of data for training the ML algorithm ahead of the development of the feedback system. To address the initial data shortfall, we acquired both historical datasets and newly generated data enriched with integrated sensors. This comprehensive input significantly strengthened the machine learning algorithm's training process and enabled more reliable and accurate predictions.

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1. Introduction

Laser Powder Bed Fusion (LPBF) is an advanced additive manufacturing (AM) process that creates complex metal parts by precisely melting successive layers of metal powder with a high-powered laser. Valued for its capability to produce detailed geometries and high-performance components, LPBF has been adopted in industries like aerospace and automotive, where accuracy and strength-to-weight efficiency are essential. However, as a complex and dynamic process, the process parameters can be challenging to optimize. Additionally, small fluctuations through-out a build can lead to defects like gas porosity, incomplete fusion, or spatter, which compromise part quality and reliability. Automated control systems enable real-time monitoring and adjustment, ensuring consistency and reducing the risk of human error. As LPBF is increasingly used for critical applications in aerospace, medical, and automotive industries, robust process control is essential to meet stringent quality standards, improve repeatability, and enhance production efficiency.

The intelligent control architecture could also be extended to support Directed Energy Deposition (DED), a versatile AM process used to build or repair metal components by depositing material through a nozzle and simultaneously melting it with a focused energy source. For the acquisition of process data in DED, commercially available monitoring and control cameras, including coaxial melt pool cameras, thermal imaging systems, and eddy current sensors were integrated into the control system of Prima Additive and CRM machine solutions.

Predictive machine learning (ML) algorithms provide a means of predicting key final part properties, such as the relative density. If an algorithm can be trained to predict the final property through-out a build using in-situ monitoring data, it provides not only quality control information that is easily understood by the operator, but also a useful metric for process control. If the ML algorithms are “white-box” interpretable algorithms, the relationship between the process parameters and the quality factor can be better understood, indicating the kind of corrective adjustments that may be useful. An intelligent control system may make use of these predictions to warn the user, to automatically pause a build, or to make corrections by adjusting process parameters.

Building on the work reported in *Deliverable D3.3* and *Deliverable 3.4*, in this deliverable the validation of an intelligent ML-based control system for additive manufacturing is described. The system was developed and implemented, with real-time adjustment of process parameters on the basis of prediction of quality factors using in-situ monitoring and bespoke machine learning model.

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2. Description of the Intelligent Control System

2.1 System Architectures and Components

The system at DCU is a AconityMINI PBF-LB metal additive manufacturing machine. For the development of the prediction quality and process control system, three sensors were integrated with this machine: a pyrometer, an acoustic sensor, and an eddy current sensing module. The elements of the control system, as detailed previously in *Deliverable D3.3*, are:

- **The Process:** The manufacturing or physical process which is subject to control. In this case, the fusing of the metal powders by laser in the AconityMINI machine.
- **The Process Variable:** The specific quantity being controlled for. This is a chosen quality control factor, which may vary by process or application. The relative density of the manufactured parts has been chosen as the initial quality factor to focus on.
- **The Measuring Device:** The device(s) that measures the process or in-production part in some way to generate process signals. In this work, the three sensing methods - pyrometer, acoustic, and eddy current fill this role.
- **The Controller:** The component that decides what action to take based on the process signals, to bring the process variable as close as possible to a target value. In this work, a machine learning (ML) algorithm will use the process signals to predict the relative density. These predictions can be used in three ways: to flag to the user that the variable has fallen outside an acceptable range (>98%) while continuing the build; interrupting the build when the process variable falls outside the acceptable range; or adjusting the process parameters to move the process variable closer to the target density (100%).
- **The Final Control Element:** The component responsible for the direct control of the process. In this work, this is the control Application Programming Interface (API) for the AconityMINI. The Controller component will issue commands to this API to take actions in the process, such as pausing the build or changing the process parameters.

The overall structure is shown in Figure 1.

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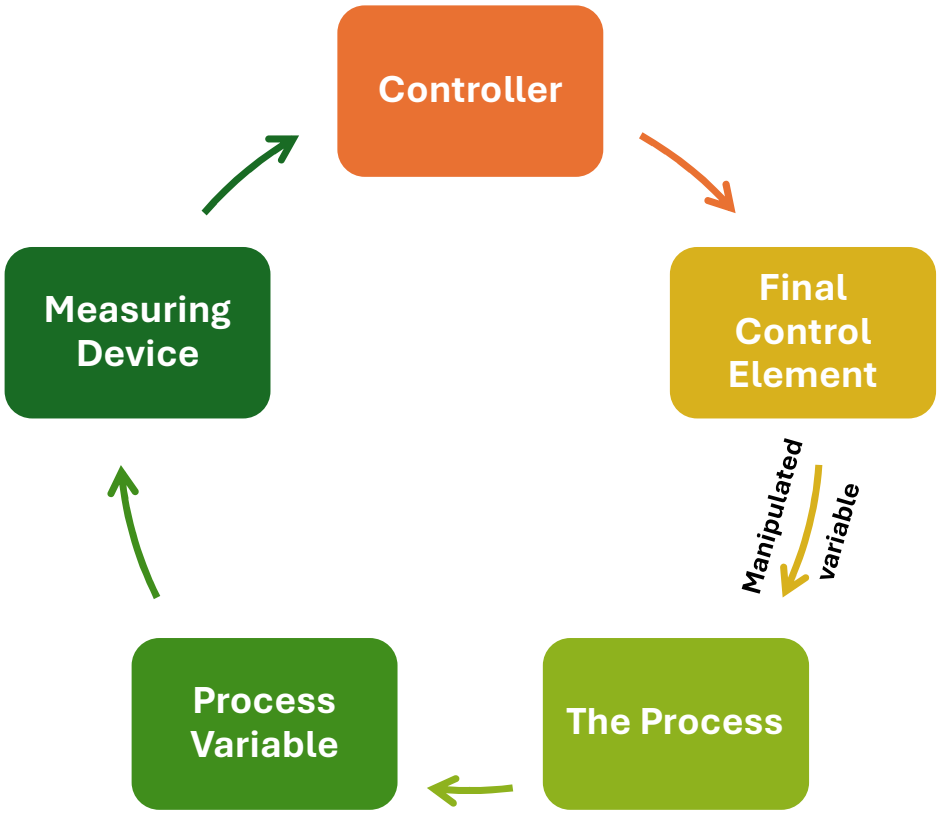


Figure 1: Elements of control system loop

2.2 Sensor Integration and Data Acquisition

Three sensors were integrated with the AconityMINI LPBF system at DCU with a pyrometer, acoustic sensor, and eddy current module.

2.2.1 Infrared (IR) Pyrometery

Pyrometers monitor infrared electromagnetic radiation from a surface emitted due to thermal radiation. The intensity of the infrared radiation, and thus the electric signal recorded by the pyrometer is proportional to the temperature of the surface. This signal can be used as a process signature, and with calibration can be converted into a temperature value - allowing greater understanding of the physical process and greater transferability to other calibrated systems. The meltpool temperature is an extremely important characteristic in LPBF and may indicate over- or under-heating which can lead to flaws like spatter or lack-of-fusion. Two *Kleiber® KG 740-LO pyrometers* fitted to the AconityMINI machine to perform real-time in-situ monitoring of the meltpool temperature, in-line with the laser beam. The specifications of the pyrometers are:

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- Measurable temperature range: 500–2500 °C
- Field of view: 0.5 mm
- Spectral range: 1.58–1.80 µm
- Response time (T90): 10 µs
- Resolution: 10-bit
- Data acquisition rate: 100 kHz

The pyrometer data is stored as .PCD files, with one file for each layer. The file name represents the total thickness at the current layer (e.g: 2.44.pcd corresponds to a total thickness of 2.44 mm). The data is formatted in columns for the x coordinate, y coordinate, and the meltpool temperature from each pyrometer. An example of the raw data is shown in Figure 2.

```
-20139 -15428 820 820
-20139 -15428 804 804
-20139 -15428 811 811
-20139 -15428 803 803
-20139 -15428 812 812
-20139 -15428 812 812
-20139 -15428 808 808
-20139 -15428 815 815
-20139 -15428 808 808
-20139 -15428 815 815
-20139 -15428 799 799
```

Figure 2: An example of raw data from the pyrometer.

2.2.2 Acoustic Emission Sensor

The acoustic emission sensor is a non-contact ultrasonic microphone which can capture acoustic signals produced by a physical or manufacturing process. The characteristics of the acoustic signals emitted by a process may vary with the quality of the process, and discrete events in the signal may be produced by discrete events such as the formation of flaws. An Avisoft-Bioacoustics CM16/CMPA ultrasonic microphone was mounted inside the build chamber of the AconityMINI, and used to monitoring the builds in a long waveform stream approach - recording across the frequency range continuously through-out the build. The specifications for the sensor are:

- Frequency range: 2-200 kHz
- Acquisition rate: 100 kHz

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The acoustic emission data is recorded as raw audio in the .WAV file format. Each build has a single file which is then processed using an in-house python script. This script automatically segments the data into layers by detecting the commencement and conclusion of the laser firing in the high frequency signal (>49 kHz).

2.2.3 Eddy Current Module

Eddy current testing functions by generating an electromagnetic field with a testing coil and passing it over the material to be examined. In conductive materials, the electric field passing over the material will induce an eddy current in the material. This eddy current will produce its own electric field opposing the field which created it. The interaction between the original field and the opposing field results in measurable changes in impedance within the testing coil. These changes can be monitored and analyzed to detect variations in the material's composition, microstructure, porosity, and thickness. The presence of a flaw, such as a pore, disrupts the flow of the eddy current, altering the impedance signal and allowing the detection of flaws. This method of monitoring supports the previous two, which monitor the process, by inspecting the powder bed and part in-situ during production.

An *AMiquam* W1 ECM module with two (2) eddy current sensors was installed on the AconityMINI system. It is mounted on the recoater blade and is passed over the build surface between each layer. The specifications for the module are:

- Excitation frequency: 200kHz
- Acquisition rate: 375Hz
- Average lift-off: 670 to 714 µm
- Sensor separation: 45 mm

The eddy current data is stored in .AMIDB files, which are SQLite formatted databases. The files contain the real and imaginary impedance values for the two sensors, along with the x-y position and layer number.

2.3 Real-Time Feedback and Control Mechanism

Real-time feedback on the process is provided by the sensors described above. Machine learning algorithms were developed using a 256-sample training dataset produced on the AconityMINI system. Monitoring data was captured during production of the samples, and the samples were all characterised in terms of their relative density. The trained algorithm predicts the density of the parts using process parameters and monitoring data. A number of ML algorithms were tested, training them using features extracted from the processing parameters and the

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pyrometer data. The selected algorithms were all interpretable or "white-box" algorithms, which provide insights into the relationship between the process data features and the final quality factor, unlike "black-box" algorithms such as neural networks. These insights make the algorithm more adaptable for real-time process control. The best performing model, ExtraTreesRegressor, predicted unseen validation data with an R^2 value of 0.7403.

This layer-by-layer prediction of the density forms the basis of the control system. The predicted density is used to probabilistically map the likelihood of a defect using a sigmoid function. This helps avoid the presence of borderline cases or outliers leading to over- or under- detection of defects, while providing interpretable feedback to the user. The sigmoid function is:

$$P_{(defect)} = \frac{1}{1 + e^{-k(x-x_0)}}$$

where: $P_{(defect)}$ is the probability of a defect, x is the predicted relative density (%), x_0 is a relative density threshold around which the transition from defect to no defect occurs (e.g. 98%), and κ is a steepness parameter which controls the sharpness of the transition. Values of $P_{(defect)}$ close to 0 indicate low likelihood of a defect and high confidence in quality, and values close to 1 suggest high probability of a defect. Layers where the value is >0.5 can be classified as defective and layers where the value is <0.5 can be classified as non-defective. This layer-by-layer prediction approach is described in greater detail in *Deliverable D3.4*.

The value of this sigmoid function can be used to decide actions to be issued to the final control element, the AconityMINI's API. Interventions could be the display of a clear warning to the user, interrupting the build, or adjusting the process parameters. This classification method has not been implemented yet; however, now that closed loop control has been achieved within the Aconity L-PBF machine, as noted below, this would be possible in future work.

Real time feedback control for AI active control of the relative density within the AconityMINI

For the development and validation of the process control system for the AconityMINI LPBF machine, a smaller ML model was developed. This model was formed from a smaller 100 sample data set of NiTi cubes, given material availability, with the same geometry as the 316L SS samples. A K-Nearest Neighbour (KNN) regression white box ML algorithm was deployed. KNN regression models predict the value of a process variable by searching at the *k* most similar examples from the dataset and averaging their values to form a new prediction. This ML algorithm is computationally efficient making it ideal for real-time process control applications. This model uses four features collected from the IR data as well as the laser power of the machine which is

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the process control variable used with the control mechanism. This trained model produced an R^2 value of 0.66 as illustrated in Figure 3.

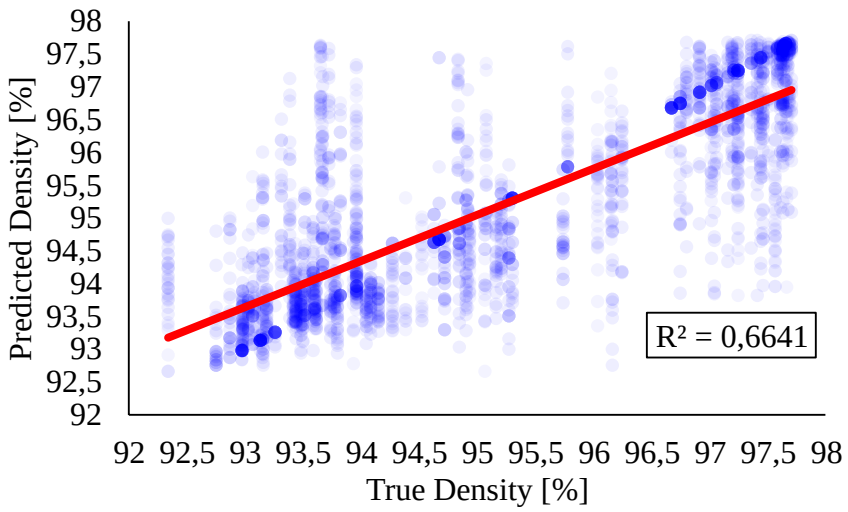


Figure 3 Actual versus predicted scatter plot from trained KNN regression model.

How process control optimisation works

The KNN ML model predicts the density of the sample in real-time (at every printed layer). From this model, an optimisation strategy needs to be developed to determine the optimum process parameter (in this case the machine's laser power) to improve the predicted density value. The approach carried out in this study, utilised an iterative scanning technique to determine which laser power setting would provide the highest predicted density response within the process range (80-200W) for the given IR feature list. This strategy runs the KNN model for each possible laser power configuration and stores only the best predicted value.

Furthering on, large changes in laser power could produce a level of unsteadiness in the machine. Therefore, an incremental limit of $\pm$20W was set to regulate this. For example, if the current laser power was set to 80W and the AI model determined 160W would be optimum, the laser power would only increase to 100W for that layer and then 120W the next until reaching the desired 160W. This condition was implemented in order for excessively large power swings not to be allowed between layers.

API integration

The API is a code-driven interface that allows communication to and from the LPBF system through in-house Python scripts. The API controls the AcontiyMINI machine using a HTTP protocol called REST API. A REST API (Representational State Transfer - Application Programming Interface) is a way for computer programs to talk to each other over the network. The REST API

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operates by establishing a WebSocket connection to the LPBF system. WebSockets are a method used for communicating to and from a system in real-time. This communication method allows a client to send and receive requests to/from a server. In this case, the process control python code is the client and the AconityStudio. Basic HTML requests which are supported by the API are:

- GET

  GET requests receive information from the server. For example, this could be to get the status of the machine, to get information regarding parts etc.

- POST

POST requests sends new information to the server. For example, a new part or a new process parameter.

- PUT

PUT requests updates information on the server. For example, the initialisation script which contains instructions for the machine to know which parts to print and their process parameters.

An example of how these requests can be used by the API is; "*functions = await client.get('machines/functions')*". The client calls the GET request from the server to get information on the machine's functions. Behind this GET request, the server receives a URL (Uniform Resource Locator). This URL contains the network address of the server, the port in which it is being run on and then the GET request itself. For example, "*http://192.168.1.1:9000/machines/functions*". Where 192.168.1.1 is the IP address for AconityStudio REST API, 9000 is the port and /machines/functions is the location on server that contains the information that we are requesting via the API.

Before the API can send this HTML requests, it needs to first establish a connection to the server, this is done by initially creating a client. A client contains the IP address of the REST API server, the web socket server and the login credentials needed to access the system. This is done by using the code snippet below. Line 1 imports the API into the Python program. This allows us to utilise the API's built-in functions to interact with the AconityStudio server. Line 3-8 contains a dictionary variable which contains all the information required to establish a connection. Line 10 calls the create function from the API which establishes the WebSocket connection to the server.

```
1  from AconitySTUDIO_client import AconitySTUDIOPythonClient
2
3  login_data = {
4      'rest_url' : 'http://192.168.1.1:9000',
```

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```
    'ws_url' : 'ws://192.168.1.1:9000',
    'email' : 'admin@yourcompany.com',
    'password' : '<password>'
}

client = await AconitySTUDIOPythonClient.create(login_data)
```

Additional information is required from the API, this includes the machine, config and job ID. Each of these ID's allows the API to identify which LPBF machine to connect to (for situations where multiple machines are in place), and the job that you wish to access via the API. The job contains the desired printed parts and their coordinates on the build plate as well additional process parameters. All these ID's can be obtained using the following lines of code:

```
await client.get_machine_id('my_unique_machine_name')
await client.get_config_id('my_unique_config_name')
await client.get_job_id('TestJob')
```

To start a job (i.e., to begin a print), initialisation and execution scripts are required. The initialisation script configures the parts and assigns process parameters for each layer planned on being printed. This script can be automatically generated by AconityStudio. The execution script determines the laser behaviour, the use of the pyrometers and to add a new layer of powder. An example of the execution script is given below:

Execution Script

```
EXECUTION_SCRIPT_SENSORS = \
   '''layer = function(){
     $m.record_sensor($s[2Pyrometer])
   for(p:$p){
     $m.expose(p[next;$h],$c[scanner_1])
   }
     $m.stop_record_sensor($s[2Pyrometer])

   $m.add_layer($g)
}

repeat(layer)
'''
```

The workflow for using the API to control the LPBF system is shown in Figure 4. The process control system operates by scanning and collecting IR data after printing a singular layer. The IR

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data gets fed into the ML model where the predicted density and optimum laser power is returned. If the model proposes a different laser power than what is currently set, the API gets called to change this process parameter on the system. The process repeats for every layer until the printed component is complete.

The developed control algorithms as presented in Deliverable 3.4, can be used to predict the density and in future other physical properties of produced parts, supporting directly the Dilafact software development. In addition, the developed algorithms could be used to provide the verification data required for implementation of the Dilacert software.

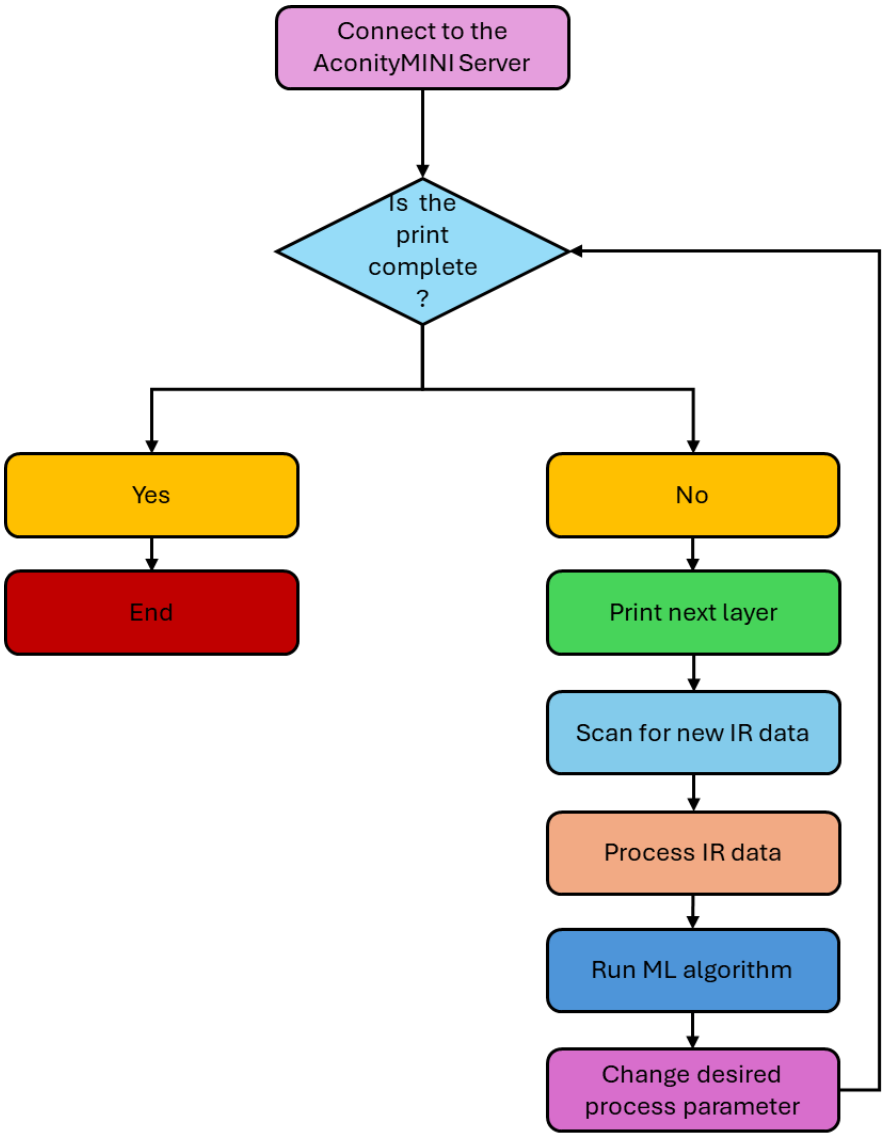


Figure 4 API workflow for AconityMINI.

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2.4 Software and Communication Interfaces

A rough GUI design has been drafted and shown in Figure 5. This user interface contains all the necessary information required for an operator to easily implement real-time process control on their system. The top left of the GUI allows the operator to select the given print job and the targeted control parameter. The right of the GUI has all the machine connectivity and control settings. The user can select the process parameters that can the control system has permission to modify. The bottom of the UI shows an example of real-time data collected. The left plot showing the machine learning models predicted results for each printed layer and the right show an IR thermogram of the last printed layer. This GUI design and development will be discussed more in Work Package 7.

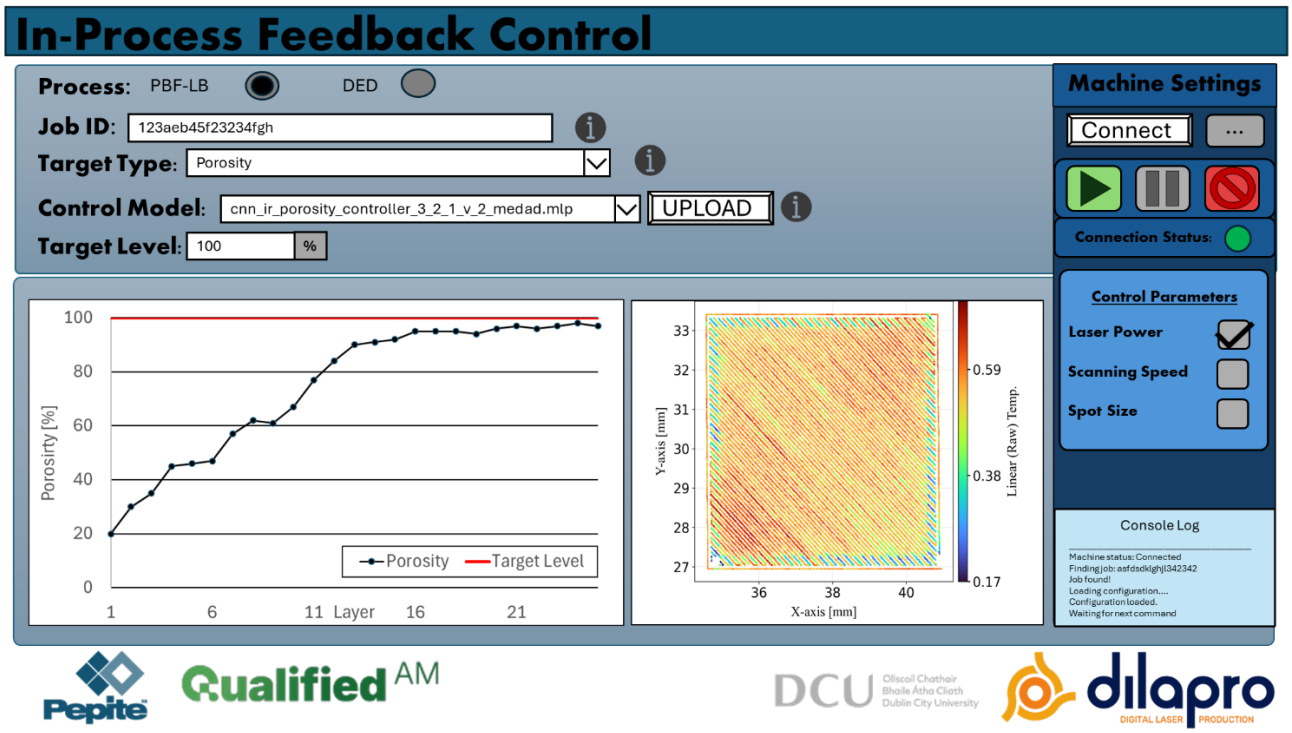


Figure 5 GUI design for real-time process control.

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3. Experimental Setup for System Validation

3.1 AM Pilot Lines and Parameters Used

The AconityMINI LPBF machine was purged with high purity argon gas (N5.5) with the gas flow rate kept below 4 l/min and the pump set to 15%. The oxygen level inside the print chamber of the machine was kept below 600ppm for the duration of the experiment. During the printing process, the IR pyrometers were enabled capturing the IR data for every layer as well as the acoustic emission sensor for future analysis. The breakdown for all the process parameters used to produce the samples are shown in Table 1.

Table 1 Process parameters for LPBF samples.

Layer Thickness	50 um
Inert gas	Argon N5.5
Inert gas flow rate	~ 4l/min
scan strategy	bi-direction
first layer angle	45 degrees
angle increment per new layer	90 degrees
Laser Power	[100, ML controlled] W
Scanning Speed	1000 mm/s
Hatch Spacing	90 um
Laser Spot Size	90 um

3.2 Sample Types and Part Specifications

To validate the process control system on the AconityMINI LPBF machine, a double stacked cube was printed with four support structure prongs to provide easy separation as shown in Figure 5. The bottom cube was printed with the process control system active and was printed with a ML controlled laser power. The top cube was printed as a control for comparison and was printed without the feedback control system active but instead printed with a constant laser power of 100W. A stacked cube approach was implemented to simply the IR data processing stage as no IR segmentation and isolation techniques would be required.

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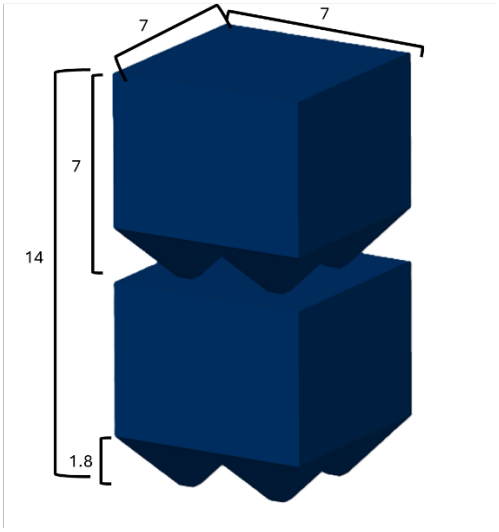


Figure 6 Sample geometry for LPBF process control validation print.

The stacked cubes were printed using NiTi alloy then the captured data was used for training the model. Testing the ML performance on different alloys, including 316L and Inconel, will be conducted which would allow further investigation regarding the generalizability these ML models have for different materials.

Similarly, PRIMA conducted validation experiments on the Laserdyne 811 DED system by printing Inconel 625 samples arranged on a platform-based geometry. Instead of a stacked configuration, the samples were spatially distributed to suit the DED process characteristics and to facilitate targeted monitoring. Eddy current sensors were integrated into the build setup to capture electromagnetic responses in real time during deposition. These signals enabled PRIMA to track process stability and detect deviations correlated with material integrity and deposition dynamics. The collected data was used to train machine learning models, in order to evaluate model generalizability across multiple material systems and DED process configurations.

3.3 Metrics for Quality and Defect Detection

Print quality is evaluated based on density characterisation. The density values get scaled based on a theoretical density value typically found across literature or in datasets. The theoretical density value used for NiTi in this study is 6.6g/cm^3 to match the value used in the trained ML model. Density is evaluated using Archimedes method. This involves measuring the weight of the sample in air and then when submerged in fluid. The following formula can be applied to calculate the density of the sample:

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$$\rho = \frac{W_a \cdot (\rho_{fl} - \rho_a)}{W_a - W_{fl}} + \rho_a$$

Where ρ_{fl} is the density of the fluid submerged, ρ_a is the density of the air, W_a is the weight of the sample in air and W_{fl} is the weight of the sample submerged in fluid.

4. Results

4.1 Quality of Produced AM Parts

The two stacked cubes were easily separated by twisting, no tools required. A close-up visual inspection with no magnification is shown in Figure 8. From the two samples side by side, a clear improvement in part quality is seen in the process-controlled sample (a) when compared to the non-controlled sample (b). The sample with fixed parameters and no closed loop control in place (top) shows signs of cracking and surface delamination whereas with process control (bottom produced sample), no surface level cracking or other surface abnormalities could be seen.

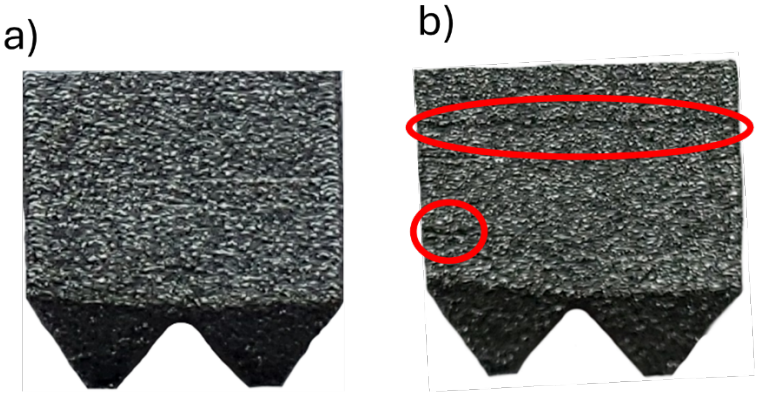


Figure 7 a) Figure of printed sample with process control active. No signs of any visual defects from visual inspection. b) Sample produced without control. Small cracks and surface imperfections identified and highlighted by red circles.

From literature and other studies conducted at Dublin City University, thermal fields can change during the LPBF process when printing samples greater than 20mm in height. To ensure that the thermal field for each of the two stacked cubes was not significantly different, a visual inspection of the IR data thermograms was conducted as shown in Figure 9. The IR data was visualised during the end of the support structures where both samples were printed with the same process parameters. From this, differences in the thermal behaviour caused by the difference in layer height were deemed negligible as both thermograms shows near identical thermal data.

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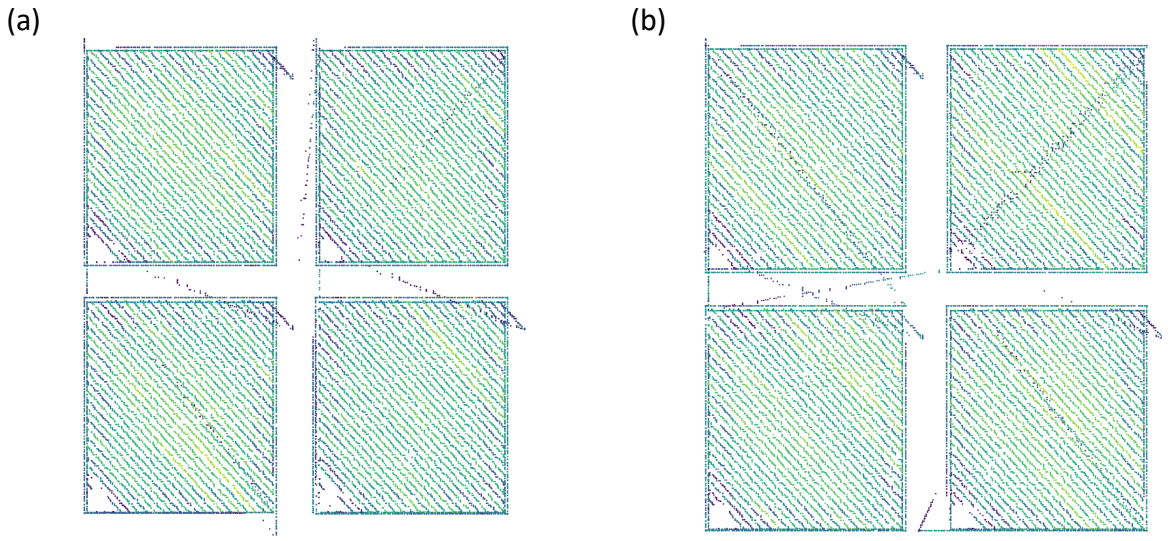


Figure 8 Visualization of IR data for (a) layer 30 and (b) layer 170.

4.2 Accuracy of Defect Detection

The true density was measured three times using Archimedes method. No outliers were found during the characterization. The density results for the process controlled and the non-controlled cube are shown in Figure 11. A clear and significant difference between the two sample's relative density is observed with the process-controlled cube having a true relative density value nearing 98% whereas the non-controlled cube having a true relative density of below 95%. The process-controlled cube had a higher true density then what the ML model predicted with an improvement of over 3% density compared to the predicted 2%.

The model under predicted the relative density values for both samples. This can be explained by the relatively low R^2 used in this experiment as well as the different alloy composition used. From this result, it would indicate that ML generalisability is not suitable for LPBF and therefore ML models would need to be trained for specific alloy compositions for accurate density prediction. However, a general ML algorithm can still be capable for improving the overall part quality.

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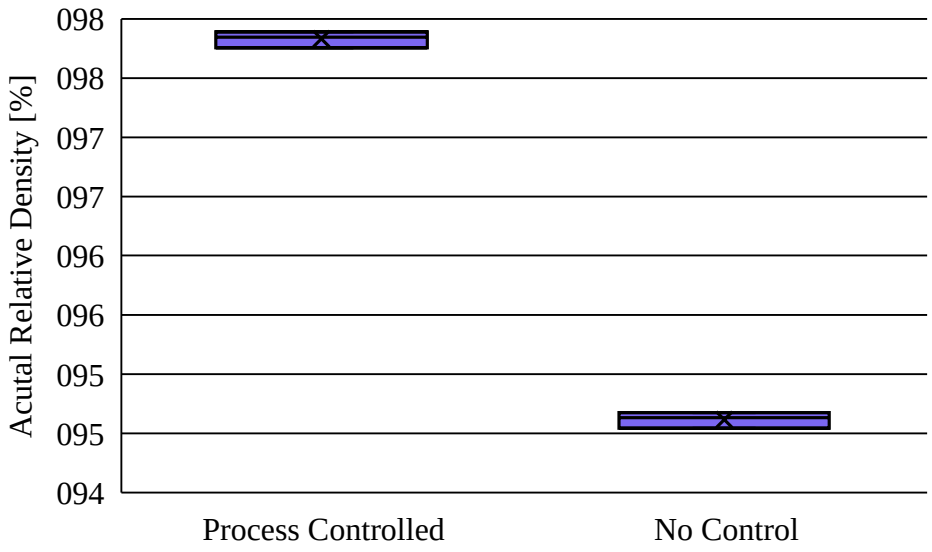


Figure 9 Box plot showing the true density values for the process-controlled cube and the cube without any feedback mechanism.

4.3 Performance of Correction Mechanisms

Figure 12 shows how the process control ML model adjusted the laser power during the printing process. The first 36 layers were kept at a constant 100W laser power. This was during the printing of the support structures. After the support structures were printed, the ML model rapidly increases the laser power to 171W before settling down to 167W for the rest of the sample. A peak of 193W was observed for a single layer, this is likely due to an abnormality in that layer's IR data.

After 140 layers the laser drops immediately down to 100W where the laser power no longer changes. This is the start of the second cube where the process control was disabled. This chart validates that the process control system is working as intended.

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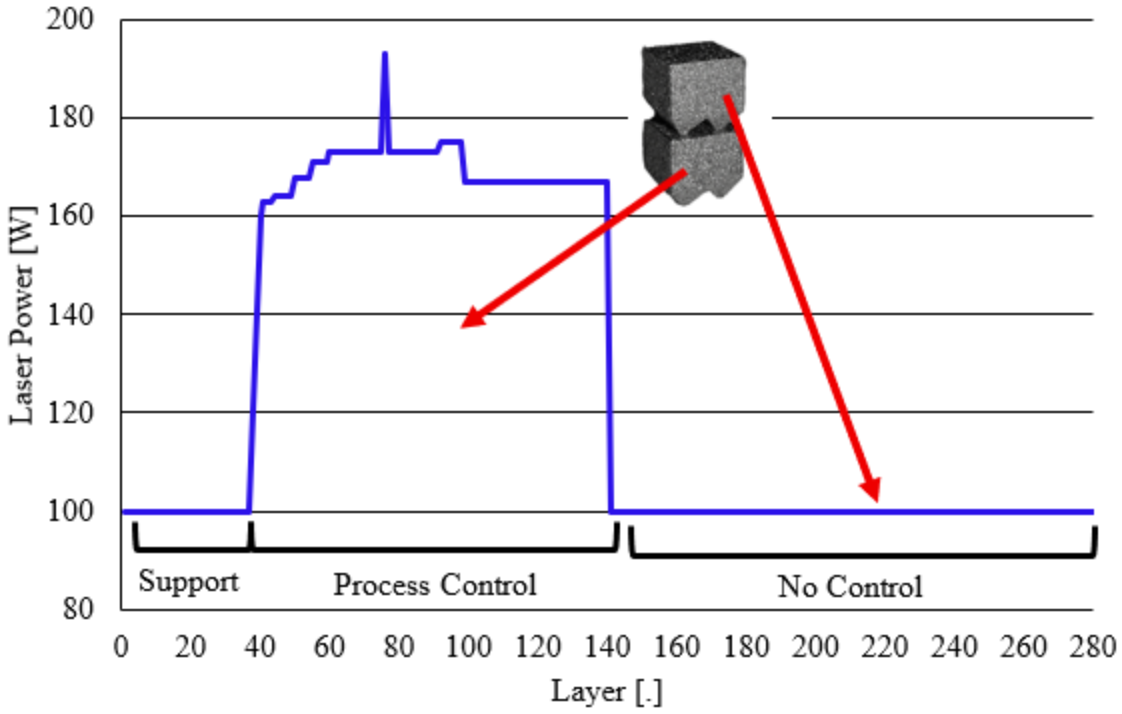


Figure 10 Laser power adjustments during LPBF printing of the double stacked cubes controlled by process feedback controller.

Figure 13 shows the ML model's predictions for both cubes for each layer that was printed. For the printing of the support structures (where both cubes had no process control active), a similar declining density prediction is observed with unsteady oscillations. Once the process feedback controller was activated, a large rise is observed in the predicted density output reaching a peak of 95.86%. Some layers shown drops in the density before stabilising near the completion of the print. This is most likely a resultant on the low R^2 value of the ML model utilised. This could be a result of the model predicting lower densities possible at certain scanning directions for certain layers due to its limited training data. The process control still however reaches an overall equilibrium.

The sample without any feedback controller active shows a consistent lower predicted relative density value compared to the process-controlled sample with a stabilised value of 94.21%. Constant drops are observed in the non-controlled sample appearing in similar spaced intervals. Strengthening the conclusion that certain scanning directions are causing the model to predict lower density values for certain layers.

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This result confirms that the process control feedback developed for the LPBF machine is being activated as expected and is influencing the meltpool behaviour during printing as reflected by different density predictions for the two samples. Furthermore, this result also validates that the ML model predicts that its impact has positively improved the parts quality compared against not using any feedback controller by approximately 2%.

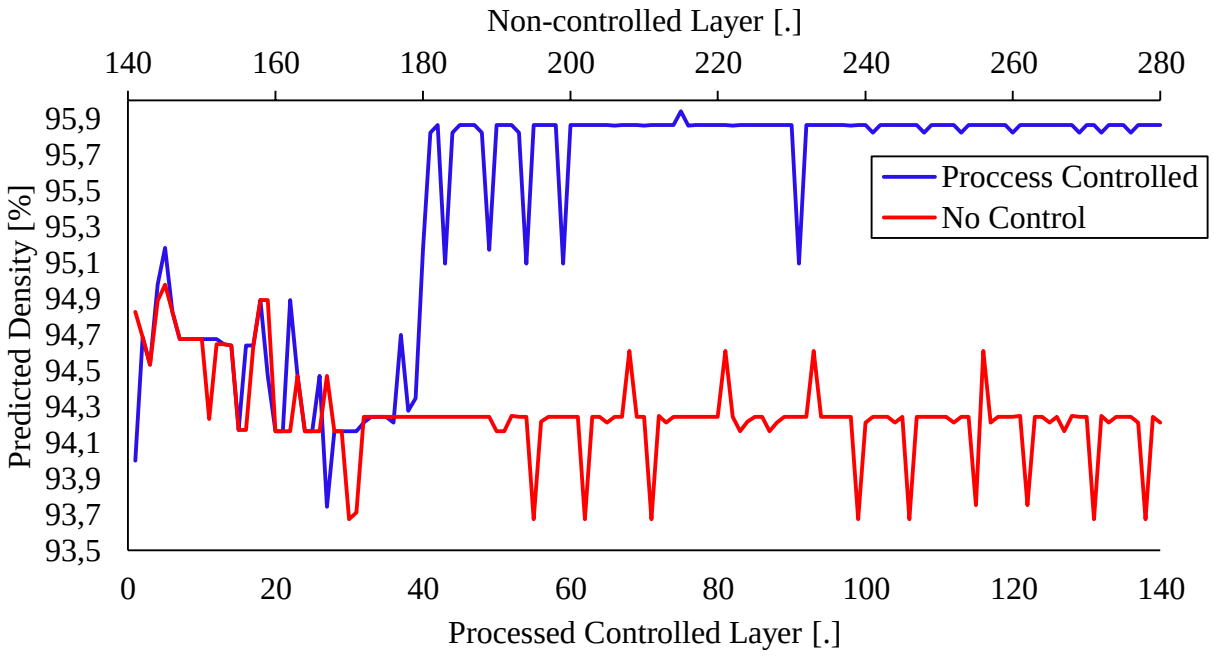


Figure 11 Predicted relative density values for each printed layer during the production of the process-controlled cube and the fixed parameter cube.

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5. Expansion to DED system

As part of the development of an advanced, prediction-based quality and process control system for Directed Energy Deposition (DED), multiple partners have implemented sensor-integrated laser cells and feedback control systems tailored to their manufacturing platforms. The following section outlines the contributions from Prima Additive and CRM.

5.1 Prima Additive DED Platform

Prima Additive deployed the LASERDYNE® 811 DED laser cell—a high-precision metal additive manufacturing system designed for layer-by-layer fusion of metal powder using a high-power laser. To enable real-time process monitoring and control, the system was enhanced with a multi-modal sensor suite:

- Infrared coaxial camera for capturing melt pool temperature and thermal gradients
- Eddy current sensor for detecting sub-surface porosity and cracks
- Acoustic and plasma sensors for additional event detection and process integrity

Material homogeneity was selected as the core process variable due to its strong correlation with mechanical performance and defect presence.

A key component of this setup is the CLAMIR NIT infrared camera, installed adjacent to the laser head to acquire thermal imagery with the following specifications:

Property	**Value**
Spectral Range	Near-Infrared (centered ~1.5 µm)
Frame Rate	200 Hz
Resolution	640 × 512 pixels

The camera collects layer-wise thermal frames across each build. A proprietary Python-based algorithm segments these frames by identifying fluctuations in pixel intensity, enabling precise timing of laser ignition and mapping thermal events to build geometry. The accompanying CLAMIR software provides a user-friendly control interface with visualizations of melt pool and process parameters, and embeds a PID feedback loop (Kp, Ki, Kd) to dynamically tune laser power.

Performance trials were conducted by systematically varying laser power, scan speed, overlap, and powder feed rate. Key insights include:

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- Higher overlap/powder feed yielded taller builds but introduced surface roughness
- Reduced power led to insufficient growth or contour collapse
- Optimal configurations maintained consistent height near the target 15 mm, indicating high process fidelity

These results illustrate how tightly coupled sensor data and adaptive control can stabilize the DED process and improve deposition quality.

Table 2 Samples process parameters and results.

	Power (W)	Speed (mm/min)	Overlap (%)	Powder feed rate (RPM)	Height (mm)	Nominal height (mm)	Evaluation	notes
standard	1000	1000	30	4				
P1	800	1000	30	4	14,36	15		Suboptimal contour
P2	1200	1000	30	4	15,82	15		Suboptimal contour
P3	900	1000	30	4	15,34	15		Suboptimal contour
P4	1000	1200	30	4	14,77	15		Suboptimal contour
P5	1000	800	30	4	16,26	15		-
P6	1000	1400	30	4	11,92	15		Insufficient growth
P7	1000	1000	50	4	16,66	15		Suboptimal contour
P8	1000	1000	75	4	18,41	15		Suboptimal contour
P9	1000	1000	20	4	14,04	15		Suboptimal contour
P10	1000	1000	30	5	16,43	15		Adhesion particles
P11	1000	1000	30	3	13,26	15		Insufficient growth
P12	1000	1000	30	6	17,06	15		Adhesion particles

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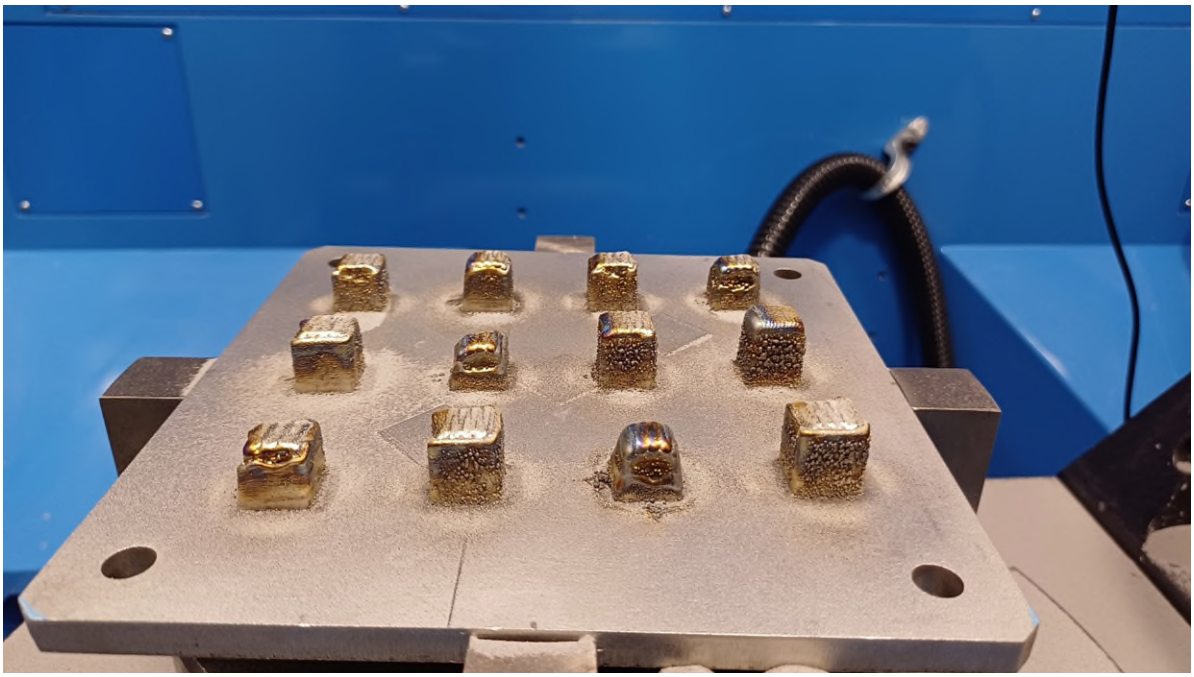


Figure 12 Final Inconel samples results on the DED powder machine

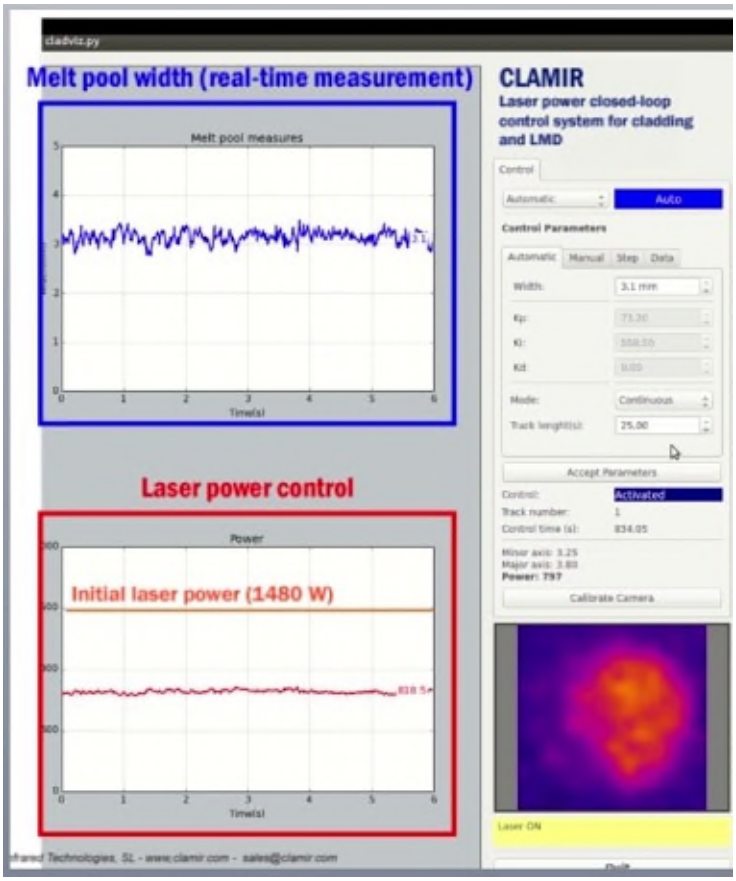


Figure 13 Clamir Software interface

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5.2 CRM: Closed-Loop Feedback with 2D Profilometry

CRM has developed a closed-loop feedback control system tailored for its DED-LB additive manufacturing platform. This system utilizes real-time geometric data gathered from a **2D profilometer**, enabling dynamic optimization of process parameters to maintain build accuracy and consistency.

At the core of the control methodology is a layer-wise evaluation mechanism:

- **After completing layer N**, the profilometer scans the surface profile and identifies deviations from the nominal target height.
- **For layer N+1**, the system adjusts **laser power**, **scan speed**, and **powder flow rate** accordingly:
    - **Increase parameters** when the previous layer is too thin
    - **Decrease parameters** when excess material results in a thicker layer

This approach effectively corrects layer height errors, maintaining vertical stability and minimizing morphological inconsistencies throughout the build. The feedback algorithm improves the geometric fidelity of complex additive structures.

A representative example (see Figure) demonstrates the system's ability to counteract fluctuations in layer height, using profilometric data to fine-tune laser energy input and deposition rates in real time.

Looking ahead, CRM is advancing this system further by:

- **Integrating machine learning models** to map the relationships between process parameters, local build conditions, and resulting part properties
- Enhancing automation capabilities to reduce operator intervention and optimize the build strategy based on predictive analytics

The ultimate aim is to achieve **real-time adaptation of process parameters** while maintaining desired **microstructural and density characteristics**, even under varying thermal and deposition conditions. This intelligent, feedback-driven architecture represents a significant step toward autonomous, quality-assured DED manufacturing.

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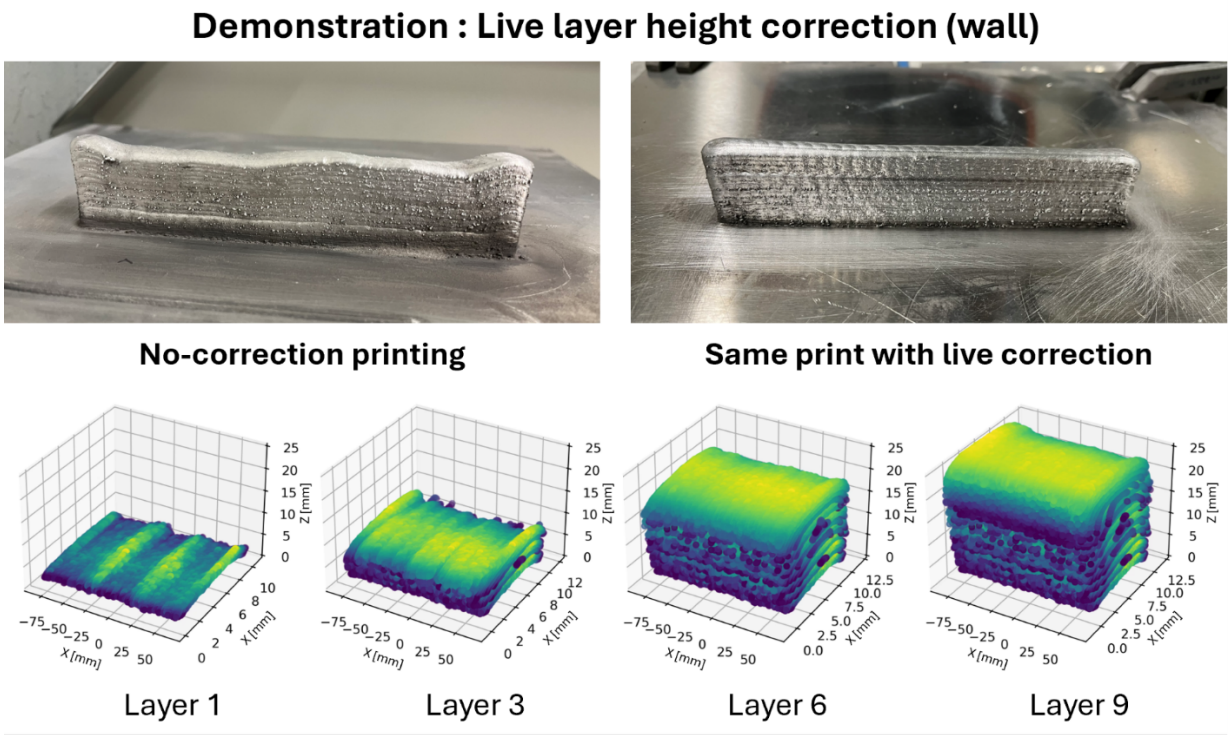


Figure 14 Demonstration of layer height and quality correction by live feedback control of laser power based on profilometer measurements.

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6. Conclusions

Validation experiments on the PBF and DED system confirmed the capability of integrated sensor data to support process control improvements for additive manufacturing. Multiple sensors were used to monitor printed samples, enabling detection of anomalies and correlation to deposition dynamics. The data were successfully used to train machine learning models that could predict part characteristics and help stabilize process parameters. Real-time process feedback controller has been developed for the AconityMINI LPBF machine at DCU. This feedback system incorporates a KNN regression model that optimises the predicted density of the printed component by modifying the machine's laser power at every layer.

The feedback-controlled sample showed a clear improvement in surface part quality compared to using a fixed laser power, where cracking and delamination was successfully prevented with the feedback-controller. The ML model did not accurately predict the actual relative density value of the cubes due to a low sample size model being used and with a different alloy composition. For example, in Figure 9 and 11, it is seen that the actual density values of the produced samples were measured as 97.8% and 94.6%, whereas the density values were predicted as 95.8% and 94.2%. This is an error of approx. 2% in the higher value and 0.4% in the lower value. From these results, ML algorithm however was able to determine well where higher and lower density regions were present. In this way, the model could predict the overall improvement in part quality with the use of the feedback controller. For accurate true density predictions, the ML model should be trained with the same alloy composition planned for that AM part.

The process controller successfully stabilised the laser power at 167W and predicted this power would provide the highest achievable density. This highlights to potential for real-time controllers to also be capable of improving process parameters optimisation by minimising the number of samples required resulting in less material waste and shorter print times for industrial applications.

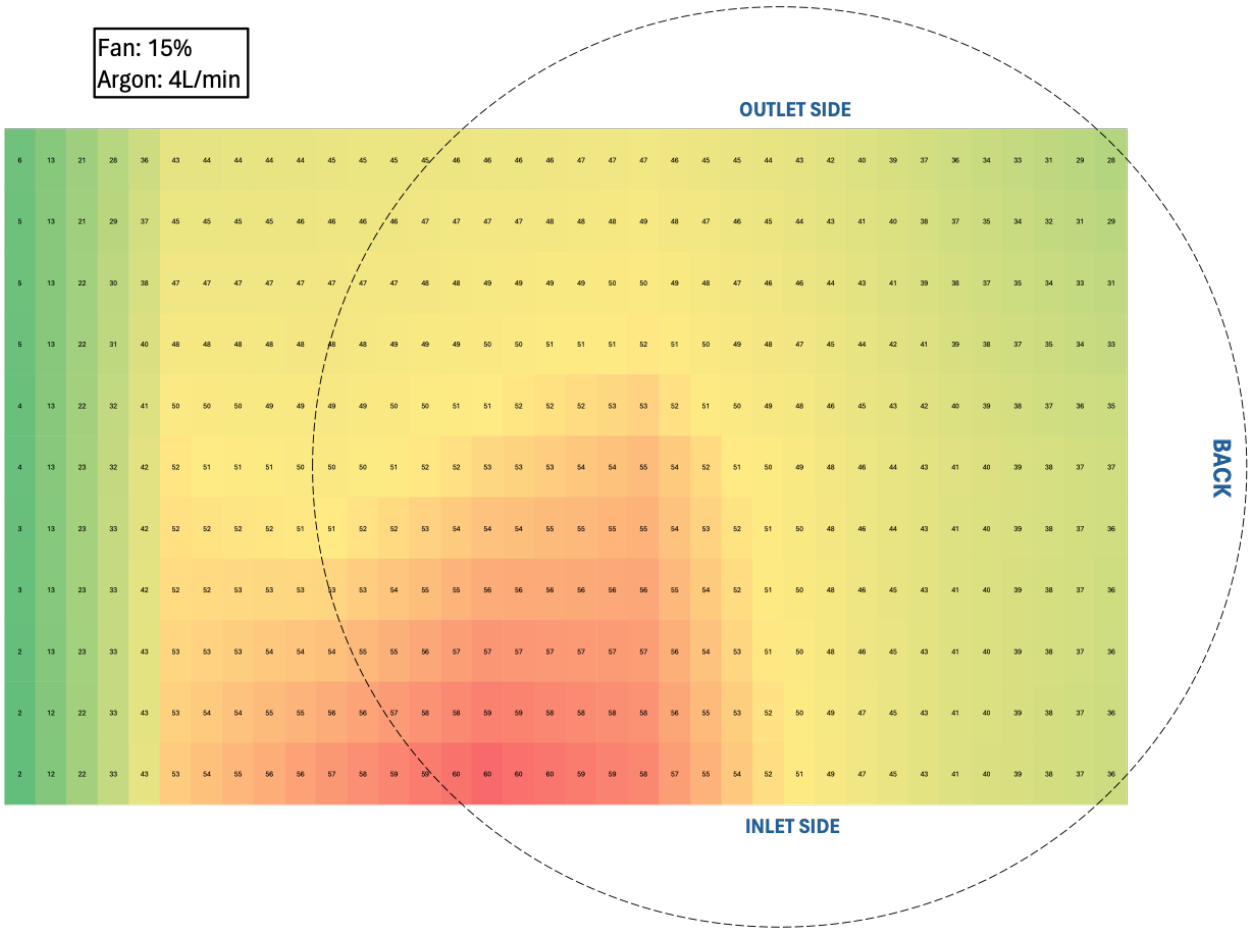
The ML model predicted an improved relative density value using the controller of approximately 2% validating that the real-time controller was operating as expected, see Figure 11. When comparing the true density for each sample, the process-controlled sample achieved just over 3% higher relative density value compared to the fixed parameter sample, see Figure 9. This further validates that the real-time process feedback control system can improve part quality in LPBF; and be used for the development of the Dilafact and Dilacert softwares.

For DED, simpler and/or proprietary versions of the feedback control system were put into action, which nevertheless also proved the concept of feedback control on both the P.ADD and CRM DED machines. These will all be integrated into the DILAFACT software.

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7. Appendices

7.1 Appendix A: Heat map of gas flow velocity in L-PBF build area



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