

Deliverable D3.7

Report on defect detection and classification algorithm for laser surface modification

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Executive Summary

Laser surface texturing is an advanced manufacturing technique for producing defined surface textures for a wide range of applications. One challenge for application in industry is the need for greater process control to ensure consistent and reliable textures and performance, and thus quality. In the DILAPRO project, a defect detection system is being developed for a dual laser system which can deliver precise non-thermal texturing and broad thermal surface treatment in one system. This system will monitor the laser processing with suitable sensors and use a machine learning (ML) algorithm to predict defects in the process - in particular, the deviation from targeted properties, such as hardness or contact angle, which are essential for the product quality.

This *Deliverable D3.7* report presents the framework for defect detection on the dual-laser processing system, including analysis of defects in laser surface texturing and the methodology for sensing, design of the model training dataset, and the approach for developing the defect detection algorithm. The laser system has been sensorised with an in-situ pyrometer, which measures thermal emission from the irradiated material, and an acoustic sensor, which measures acoustic vibrations emitted from the process. An eddy current sensor will be used ex-situ to characterize the laser processed surfaces, as proof-of-concept for integration into the system as an in-situ component.

For model development and cross-validation, a 256 sample 4^4 full-factorial Design of Experiments (DoE) is being carried out to create a comprehensive dataset. This dataset is designed for use in the development of predictive models on a per-quality-metric basis, to allow prediction of key parameters for varied applications, such as predicting the contact angle for anti-fouling surfaces or the surface roughness for gripping surfaces. These predictions will form the basis of an in-situ quality control system for detecting defective surfaces which if sufficiently reliable, can minimize or eliminate the need for post-process characterization in production scenarios.

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List of Abbreviations

ABR	AdaBoost Regressor
AI	Artificial Intelligence
ANN	Artificial Neural Network
BR	Bayesian Ridge
CSV	Comma Seperated Values
DCU	Dublin City University
DoE	Design of Experiments
DT	Decision Tree
ECM	Eddy Current Module
ECT	Eddy Current Testing
EN	Elastic Net
ETR	Extra Trees Regressor
GBR	Gradient Boosting Regressor
GPR	Gaussian Process Regressor
GRA	Gray Relational Analysis
GRG	Gray Relational Grade
HR	Huber Regressor
IPA	Isopropyl Alcohol
KNN	K-Nearest Neighbours
KR	Kernel Ridge
LIPSS	Laser Induced Periodic Surface Structures
LPBF	Laser Powder Bed Fusion
LST	Laser Surface Texturing

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MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MARSE	Measure Area under Rectified Signal Envelope
ML	Machine Learning
MSE	Mean Squared Error
PCC	Pearson's Correlation Coefficient
PLS	Partial Least Squares
PR	Polynomial Regression
RANSAC	Random Sample Consensus
RF	Random Forest
RFECV	Recursive Feature Elimination with Cross Validation
RMS	Root Mean Square
RMSE	Root Mean Squared Error
SGD	Stochastic Gradient Descent (SGD)
SVM	Support Vector Machine
SVM	Support Vector Machine
TSR	Theil-Sen Regressor

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1. Introduction

Laser Surface Texturing (LST) is an advanced material processing technique that uses focused laser beams to create micro- and nano-scale patterns on material surfaces, enhancing their physical and functional properties. By precisely ablating or melting localized regions, LST can modify surface topography to influence characteristics such as surface area, friction, wear, adhesion, anti-fouling, and wettability. This technique has wide-ranging applications across many industries, such as improving lubrication in automotive engine components, increasing tissue adhesion in biomedical implants, or enhancing bonding in aerospace parts. Laser systems with femtosecond duration pulses have enabled the use of "cold" ablation which removes material in short enough timeframes that heat does not have time to dissipate into the surrounding material, eliminating heat affected zones and creating more precise and defined textures than thermal ablation. As surface textures are, by definition, at the surface of a part, abrasive wear and corrosion are significant concerns for the effective lifetime of the texture in operation.

Thermal laser processing can allow for transformation of properties at the surface. By heating a thin portion of material at the surface above a transformation or melting temperature, the material can cool and quench quickly forming favourable microstructures. This can allow the enhancement of surface properties, particularly hardness and wear resistance. A dual laser system which can provide thermal surface treatment and non-thermal ablation has the potential to provide highly defined micro- or nano-scale textures with enhanced lifetimes.

Despite the benefits of these laser techniques, they face some challenges in wider industrial adoption. One key challenge is the need for precise process control to ensure reliable and consistent results. Laser processes can be quick and highly automated, but high levels of consistency are required for mass production of consumer products. This is particularly important in safety critical applications, such as medical or aerospace, where failure of parts is entirely unacceptable, and all outliers must be identified in the quality process. In-situ monitoring can provide real-time feedback on key processing signals, such as thermal emission from heated material, which provide insight into the process. Machine learning and artificial intelligence (AI) models provide a means for relating the process signals to the final part properties. Using multiple sensors, multi-modal models can be developed which can predict a range of part properties from the in-situ sensor data. These predictions provide a means for ensuring consistent and reliable results, and assuring the quality of the parts.

Deliverable D3.7 focuses on the defect detection approach for laser surface texturing. The key components of the approach are identifying the defects and suitable monitoring methods, and a strategy for developing a machine learning model which can predict key parameters from the monitoring data to detect defective surfaces. This work will leverage our machine learning and

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laser manufacturing experience, and previous work from *Deliverable D3.3* in developing predictive algorithms for laser powder bed fusion (LPBF), to develop and carry out this approach. This approach will parallel the defect detection approaches developed for LPBF and Direct Energy Deposition (DED), reported in *Deliverable 3.4* and *Deliverable 3.5*, respectively. This defect detection system will feed into the DILACERT and DILAFACT software platforms to allow in-process part qualification in laser surface texture production.

1.1 Laser Processing Defects

There are a number of defect types which can occur in laser processing [1–3]:

- Keyholes
- Balling
- Cracks
- Heat-Affected Zone
- Spatter
- Oxidation
- Deviation from target properties

Keyholes are pores created by trapped vapour within molten material during thermal processing. Keyholes are more commonly a concern in laser welding or drilling, processes where high power densities are melting significant volumes of material, but could occur during surface hardening if the applied laser power is too high. Balling is also a phenomenon of molten material at high power densities, where liquid material forms into spherical droplets before cooling, creating an undesired surface texture. This defect is more commonly seen in Laser Powder Bed Fusion (LPBF), where powders are melted or sintered, rather than with processing of solid surfaces. Cracking can occur in thermal laser processing. Thermal expansion and contraction can lead to residual stresses in the material, and the formation of microcracks. These microcracks can interfere with the desired surface texture and act as points of failure.

The heat-affected zone is unavoidable in thermal laser processing. The laser energy absorbed into the material is transmitted from the surface into the work piece by thermal conduction, and can transform the material microstructure. In the case of laser surface hardening, this transformation is desirable, where the heating and quenching of surface material creates a harder microstructure at the surface. But in other thermal processes, such as thermal laser machining, the heat affected zone may be undesirable – changing properties away from the selected bulk properties, creating a layer which can be more brittle or less corrosion resistant, depending on the material and thermal characteristics of the process. Spatter can occur during

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thermal processing, when material ejected during ablation deposits on the surface. This material disrupts the prescribed texture. Oxidation is the formation of oxide compounds at the surface of a metal and can commonly occur during thermal laser processing in atmosphere. These oxide layers may have unfavourable properties, affecting the surface chemistry of a part and its appearance. Oxidation may also occur in non-thermal ablation, in the case of highly reactive metals that oxidise at low temperatures, however in these cases such oxidation is difficult to avoid.

Finally, deviation from the target properties is a significant defect. In production, parts will have important targeted properties, such as contact angle for hydrophobic/hydrophilic surfaces or surface roughness for bonding surfaces, with an acceptable variation. If the laser processing is inconsistent, due to influence of the other defects described above or instability in the process, and leads to the target properties falling outside the acceptable range this can be considered a defect in the part.

For the dual-laser system being used in the DILAPRO project (Figure 1), the fibre laser (IPG YLR-1000-MM-WC-Y14) which applies thermal treatment of the surface for hardening and improved wear [4,5], the thermal defects described above may be a concern. Many of these can be avoided, by careful selection of the process parameters and the use of process gas to shield the surface, but quality control is needed to ensure that they do not occur, and that target properties are met. For the femtosecond laser (NKT Origami XP) which applies non-thermal ablation [6–8], a number of the above defects should not be a concern due to their thermal nature. Deviation from the targeted dimensions and properties for the texture due to over- or under- ablation is the main concern which must be controlled for in the quality control for this process.

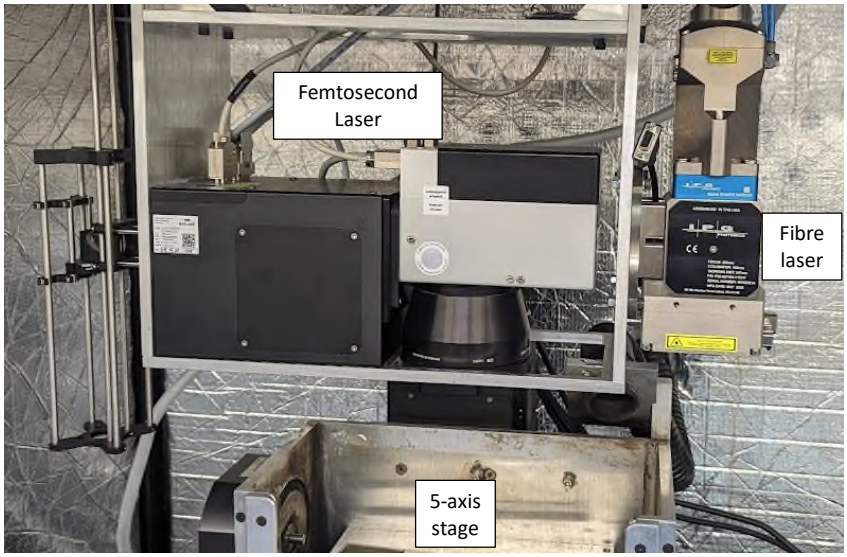


Figure 1: Dual-laser system at DCU, consisting of a fibre laser for thermal treatment, a femtosecond laser for cold ablation, and a 5-axis stage for sample positioning.

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1.2 Monitoring and Defect Detection

Traditional quality control of parts in a production environment is carried out post-process. The testing of parts may be time consuming or costly, and, in the case of destructive testing, can only be applied to a sacrificial subset of parts. Integration of quality control testing into the process with in-situ monitoring has the potential to create intelligent production lines which qualify every part against the quality control plan during the process, without the need for post-process characterisation and sacrificial test-pieces. Machine learning algorithms which relate the monitoring signals to the occurrence of defects or predict the final part properties can enable this approach, but the field is still in development.

A number of in-situ monitoring approaches have been applied to laser processing. Acoustic monitoring has been used to monitor both thermal surface treatment [9] and laser ablation [10–13]. This method uses acoustic sensors to detect soundwaves emitted by the process. These vibrations travelling through the air or through a workpiece can be detected by microphones and the intensities and frequencies of the responses used to identify defects or predict quality.

Ravnikar et al. report on acoustic monitoring of laser remelting of carbon steel using a millisecond Nd:YAG laser [9]. A VS150-M piezoelectric acoustic sensor, typically used in monitoring of pressure vessels, was used to monitor the processing in direct contact with the workpiece. The authors use a machine learning algorithm, a medium Gaussian support vector machine (SVM), to relate acoustic emission features to the laser parameters with a prediction accuracy of 97%. This paper illustrates the suitability of acoustic emission for monitoring laser thermal hardening, and the effectiveness of machine learning for this application. Artificial Neural Networks (ANN) have also been applied to acoustic monitoring. Luo et al. report on acoustic monitoring of laser welding, and the use of an ANN for defect detection [14]. In this case, a non-contact acoustic sensor was used. While direct contact may make measurement of shockwaves more straightforward, the non-contact approach is attractive for monitoring across multiple parts in a production scenario. The authors note that the strength of the acoustic emissions through the air was related to the plasma temperature, and that the ANN could detect good or defective welds with 85% accuracy from the acoustic sensing data.

In laser surface texturing, Aliff et al. related the acoustic signal from a non-contact sensor to the surface roughness produced in nanosecond laser texturing of 316L stainless steel [13]. They report the amplitude and Root Mean Square (RMS) of the acoustic signal had a significant correlation with the surface roughness. Xie et al. used acoustic emission monitoring with femtosecond laser texturing of SiC [11]. Two Nano30 acoustic sensors were placed in contact with the SiC wafer, which was processed with an 8 W, 290 fs laser to produce hole and groove

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surface structures, as well as Laser Induced Periodic Surface Structures (LIPSS) – nanoscale ripples created by interference at the surface. The authors found close relation between the acoustic signals, in number of “events” and the Measure Area under the Rectified Signal Envelope (MARSE), and the amount of material removal. The different types of surface structure (hole, hole-groove, shallow groove, and deep grove) could be classified from the acoustic data based on the frequency response. These results indicate the suitability of acoustic monitoring for defect detection in laser machining, where deviation from expected values of the MARSE or frequency response could indicate under- or over- ablation or straying from the intended structure.

Pyrometry is an attractive method of monitoring for laser processes. In this method, the temperature of an object is remotely sensed at a distance by capturing of the thermal radiation at one or more frequencies. The intensity of this radiation will be proportional to the temperature of the object and can act as a process signal or, with calibration, give a temperature value. For femtosecond ablation, monitoring of the workpiece temperature may not yield useful information, due to the speed of material removal limiting dissipation of heat into the surrounding material. It may be of use in scenarios where cold ablation is used on pre-heated substrates [15]. However for *thermal* laser processing, thermal monitoring is of high interest.

Pyrometers have been applied to the monitoring of thermal laser treatments such as surface hardening [16–18]. Raza et al. explored the use of a 2 kW fibre laser in hardening high carbon steel using a pyrometer to monitor the surface temperature [18]. The fibre laser is focused at a fixed position, and the workpiece translated linearly beneath it. The pyrometer was mounted off-axis, aimed at the laser spot position to capture the surface temperature at this point as the sample moves beneath it. This allowed the temperature profile to be recorded for the laser processing as different laser powers and scan speeds were applied. The authors found that the maximum temperature reached during processing could be related to the microstructure, in particular the amount of dendritic growth. The temperature was also related to the residual stresses, where working in the temperature range between recrystallisation and melting leading to tensile stresses, while working above the melting temperature or below the recrystallisation temperature lead to compressive stresses. These results indicate the potential of in-situ pyrometer monitoring in predicting final part properties.

Pyrometry has been used for process control of hardening [19,20], but the application of machine learning or multi-sensor approaches, while common in research of other laser processes such as laser additive manufacturing, as not be used for laser surface hardening. Exploring these approaches has the potential to enable in-situ quality control of thermal laser processing.

Eddy current testing (ECT) is a non-destructive, non-contact method of inspection where an electric field is passed over a part or weld. For a conductive material, the electric field acts on the charges within the material to produce an eddy current. This eddy current generates its own

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electric field, which is opposed to the field producing the eddy current. The impedance of the probe generating the original current can be related to material properties such as the relative density or microstructure. ECT has commonly been used in quality control as a post-process inspection method, capable of finding flaws such as pores or cracks at or near the surface of the workpiece. Integrating ECT into a production line could allow automatic testing and validation of every part as it is completed, or even examination of parts through-out the production process (such as layer by layer in additive manufacturing). In a multi-sensor system, this inspection of the part *itself* could synergise well with methods which inspect the *process*, such as pyrometery.

ECT has been applied to characterisation of laser hardened parts. Makarov et al. describe the use of ECT on steel drill bits after laser transformation hardening [21]. Carburized chromonickel steel drill bits were laser heated, with and without liquid nitrogen quenching, and characterised in terms of the microstructure and abrasive wear resistance, as well as ECT characterisation. The ECT had an estimated measurement depth of 0.17 mm, and the drill bits were ground down and ECT carried out layer-by-layer. They found that the ECT signal varied with the microstructure, and as such could be related to the wear resistance of the drill bits. Underheating, overheating, and insufficient depth of transformation could be classified from the ECT data. Savrai et al. applied the technique to laser heat treatment of a cast Al-alloy [22]. Here, the surface layer was heated above the melting point to create a harder, wear-resistant surface. ECT testing was found to be sensitive to the changes in the surface layer, such as changes in alloying element concentrations and the residual stresses. Different ECT parameters, such as the amplitude of the signal and the phase angle, allowed the estimation of different part characteristics, such as the depth of the melted zone and the level of residual stress. These works suggest the suitability of ECT testing for inferring final part properties, which is desirable for in-situ quality control.

ECT has also been applied to characterisation of surface roughness and texture. Ko and Schehl describe the estimation of the root mean square roughness (Rq) for corroded steel plates using ECT [23]. They report good agreement with white light interferometry. Gao et al. investigated the use of ECT for defect detection in finely grooved surfaces [24]. Grooved cylinders were examined by rotating and applying a probe of 48 coils to perform ECT, and then using a Deep Learning approach developed a defect detection system. Abrupt changes in the continuous groove structure lead to changes in the eddy current which can be used to flag defects. By manually labelling defects the authors were able to carried out supervised training of a network which could detect defects, achieving highest precisions of 89.29%. The work in this space indicates the potential for characterising laser textured surfaces by ECT.

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1.3 Objectives of *Deliverable D3.7*

The primary goal of *Deliverable D3.7* is lay out the approach for delivering a defect detection system for the dual-laser surface processing system at Dublin City University (DCU). To achieve this, the team at DCU outlined the following objectives:

1. **Identification:** Review of the literature to understand the suitable monitoring methods.
2. **Sensor approach:** Defining the sensors and their application for the dual-laser system.
3. **Data approach:** Defining the training dataset which can be used to develop the defect detection system.
4. **Algorithm approach:** Defining the machine learning approach to train and test varied algorithms to select the best algorithm or combination for detecting defects.

2. Defect Detection Approach

This section describes the overall strategy for development of the defect detection system. A diagram of the approach is shown in Figure 1. The strategy involves the gathering of a training data set. This dataset will include the known laser parameters such as power and scanning speed, and potentially derived parameters such as the power density or irradiance. Monitoring data will be captured from the selected sensors during and immediately after laser processing. The samples will then be characterised in terms of target parameters which are identified in the quality strategy for a given application. These could be the contact angle for a superhydrophobic self-cleaning surface, or the surface roughness for a gripping surface. Multiple quality factors may be considered for a single application, with measures of robustness such as wear resistance being of interest for multiple applications due to their influence of lifetime. Due to the high volume of samples needed for training data, target properties must be considered in terms of the time for characterisation, and whether the characterisation is destructive. For destructive or time consuming tests, they may not be feasible to consider, or a downsampled subset of the samples may need to be produced for testing. While the downsampled dataset may not be sufficient for training of an algorithm, it could be used for the development of simulations in other DILAPRO work packages.

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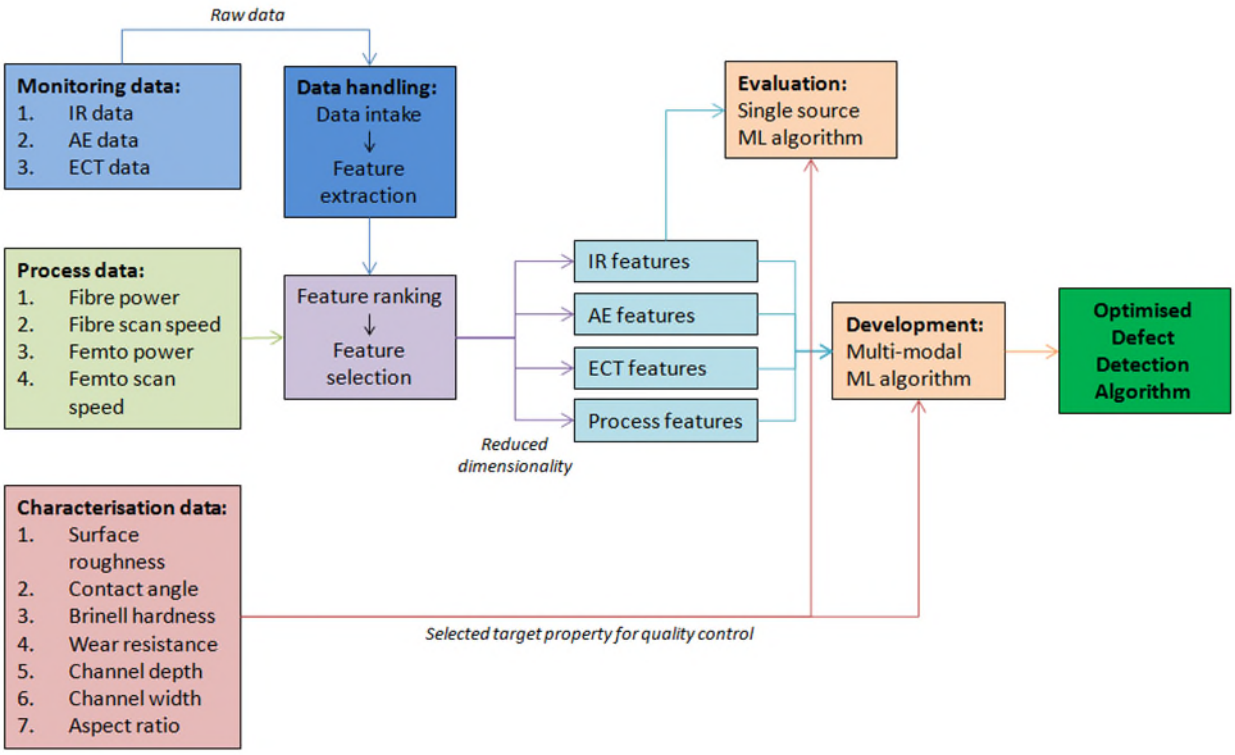


Figure 2: Approach for development of system for detecting defective laser surfaces based on in-situ monitoring data.

The monitoring data from each source will then be processed from its raw form into an exploitable form, such as a Pandas dataframe. From the monitoring data features will be extracted. The high volumes of raw data which can be generated from each experiment could be fed directly into machine learning algorithms - however this may be computationally intensive, leading to long training times and higher energy usage. Additionally, much of the information in the raw data may not have any strong correlation with the target property or be redundant, making the approach inefficient, and creating noise that may lead to worse predictive accuracy. By taking features, such as averages, standard deviations, etc., which can compress more information about a given experiment into a smaller number of values to be fed to the machine learning algorithm, greater efficiency can be achieved. In machine learning, each value we have for an individual experiment/sample is considered a dimension, and extracting and using a limited number of features is a way of reducing the dimensionality of a dataset.

Features can be ranked in terms of their correlation with the target property, to allow for the most useful features to be selected. The dimensionally reduced monitoring data, along with the process parameters for each sample, and the selected target property can be used to train the machine learning algorithms. For evaluation, models can be trained using just the process parameters, and using individual sensors to understand the effectiveness of each method. Finally, multi-modal algorithms will be trained using multiple sensors, to create an optimised algorithm

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which can be used to detect defective surfaces and validate or invalidate the quality of a given surface.

2.1 In-situ monitoring

The three monitoring methods selected for the dual-laser system were pyrometer, acoustic sensing, and eddy current. These methods have already been deployed successfully for the laser powder bed fusion system at DCU, and show promise for application on laser surface processing, as discussed in **Section 1.2**.

2.1.1 Pyrometer

Pyrometers capture the thermal radiation from the workpiece during processing. The pyrometer signal will be proportional to the temperature, and with calibration can give a temperature value. This method is applicable for thermal treatment with the fibre laser on the dual-laser system, where the temperature behaviour is key for achieving the desired result and avoiding quality failure.

As such the pyrometer was mounted off-axis on the side of the optical head of the fibre laser using a bespoke fixture (Figure 3). The fixture aims the pyrometer to be at the centre of the laser spot (a 6x6 mm square) at the focal position. A stage translates the sample below this fixed point during processing. The pyrometer is a Kleiber KG-740-LO. This pyrometer uses a spectral range of 1.58 - 1.80 µm, and has a measurement field diameter of 1.2 mm, a temperature range of 500-2500 °C, a response time of 10 µs, and an acquisition rate of 100 kHz.

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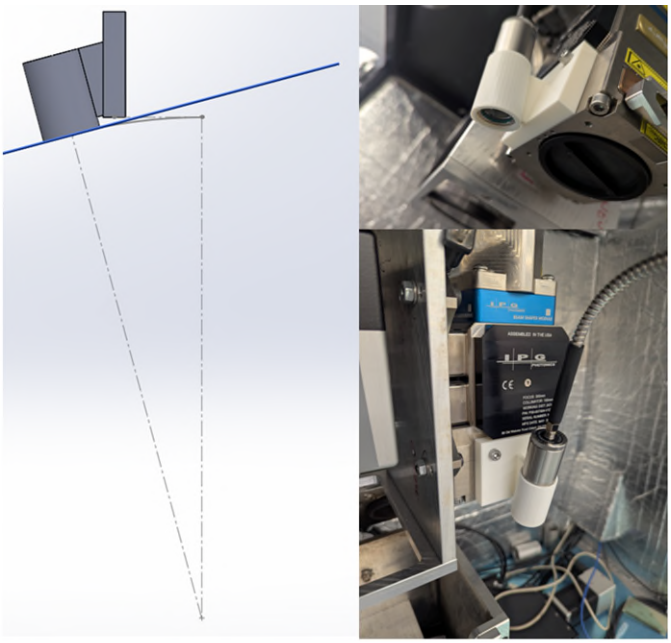


Figure 3: Mounted pyrometer aimed at focal position of the fibre laser.

2.1.2 Acoustic

Non-contact ultrasonic microphones can capture the acoustic signals produced by the laser process and transmitted through the air. As with the LPBF approach, *long waveform streams* will be used per ASTM E749/E749M-17 AST [25]. In this approach, signals are recorded throughout the process.



Figure 4: Avisoft-Bioacoustics acoustic emission sensor.

Two Avisoft-Bioacoustic sensors (Figure 4) were used, with a measuring range of 2-200 kHz and an acquisition rate of 100 kHz. One sensor was aimed at the fixed focal point beneath the fibre laser, and one at the centre of the scanfield beneath the femtosecond laser galvanometric beam scanner.

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2.1.3 Eddy Current

Eddy current sensors pass an electric field over the sample, inducing eddy currents (in conductive materials). These eddy currents generate their own electric fields opposing the original field. The eddy current behaviour can give insights into the sample's surface and near-surface properties and structure.

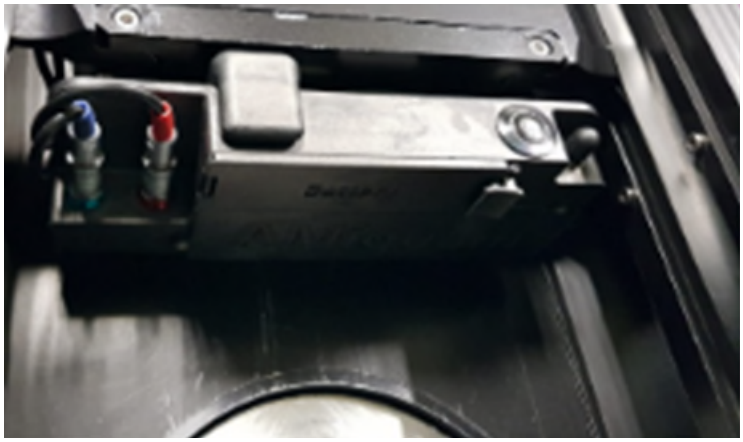


Figure 5: AMiquam W1 ECM module mounted on AconityMini recoater blade.

For this an AMiquam W1 ECM module with two eddy current sensors is being used (Figure 5). As only one module was received at DCU, this test is being performed ex-situ. The module is already mounted on the LPBF system, and transferring it between the two systems would be disruptive. On the LPBF system, the ECM module is passed over the build area after each layer as the 3D part is built. Laser surface processing is a “2D” process, consisting of a single layer, so the eddy current testing will be performed once, after the processing is finished to validate the processing. Carrying out the eddy current testing ex-situ will act as proof of concept for using it as an in-situ method of validation/quality control. The substrates for laser processing have been designed to allow two of them to fit on the AconityMini build plate beneath each of the eddy current sensors, so they can be positioned vertically and scanned by the ECM.

2.2 Training Data Generation

To train the machine learning algorithms a high volume of data is required. A set of experiments was planned to generate a dataset for dual laser processing – treating the surface with the fibre laser first to produce a more durable surface and then processing with the femtosecond laser to texture the surface – so that the developed algorithm would make predictions accounting for the interaction of the two techniques. A 4^4 full-factorial Design of Experiment (DoE) was planned, using two process parameters from the fibre laser and two process parameters from the

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femtosecond laser. The levels of these factors were selected based on experience with the laser system and pre-trial experiments. The factors and levels for this DoE can be seen in Table 1.

Table 1: Design of Experiments (DoE) for laser surface processing.

	Fibre Laser Power (W)	**Fibre Scanning Speed (mm/s)**	**Femtosecond Laser Power (W)**	**Femtosecond Scanning Speed (mm/s)**
Level 1	300	20	3	2
Level 2	400	30	3.5	3
Level 3	500	40	4	4
Level 4	600	50	4.5	5

The material chosen to examine first was 316L stainless steel. Substrates of 316L were produced with the dimensions 25 x 6 x 135 mm. The length of the strips was chosen to allow two to fit onto the build plate of the AconityMini for eddy current testing. The surface was prepared by cleaning with Isopropyl Alcohol (IPA).

During the thermal laser processing with the fibre laser, pyrometer and acoustic data is captured. During the femto-second laser texturing, acoustic data is captured. Eddy current testing is then carried out ex-situ on the AconityMini as proof-of-concept for in-situ testing. Two strips can be placed on the build plate and positioned vertically relative to the ECM, and then scanned simultaneously, covering multiple sample patches on each in a single pass.

The samples will then be characterised in terms of key quality parameters. The first characterisation method will be non-contact profilometry (3D Bruker Contour GT-X Profilometer). This technique is non-destructive, relatively fast, and can automatically capture a number of important surface characteristics, such as a variety of roughness quantities (Sa, Sq, Sz). Further details can also be manually extracted, such as channel width, depth, and aspect ratio. The automatically captured roughness will be used as the first quality factor for developing the algorithms, as it can be determined quickly and is an important characteristic for a number of applications (gripping surfaces, joining, anti-fouling, etc.). Other quality factors being considered are:

- Channel geometry (width, depth, aspect ratio)
- Brinell hardness
- Contact angle
- Wear resistance

The same algorithm development approach will be followed for the subsequent quality factors, to identify the important sensors and features, and most suitable algorithm for the different

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factors. This will allow for a multi-modal defect detection system for quality control and validation.

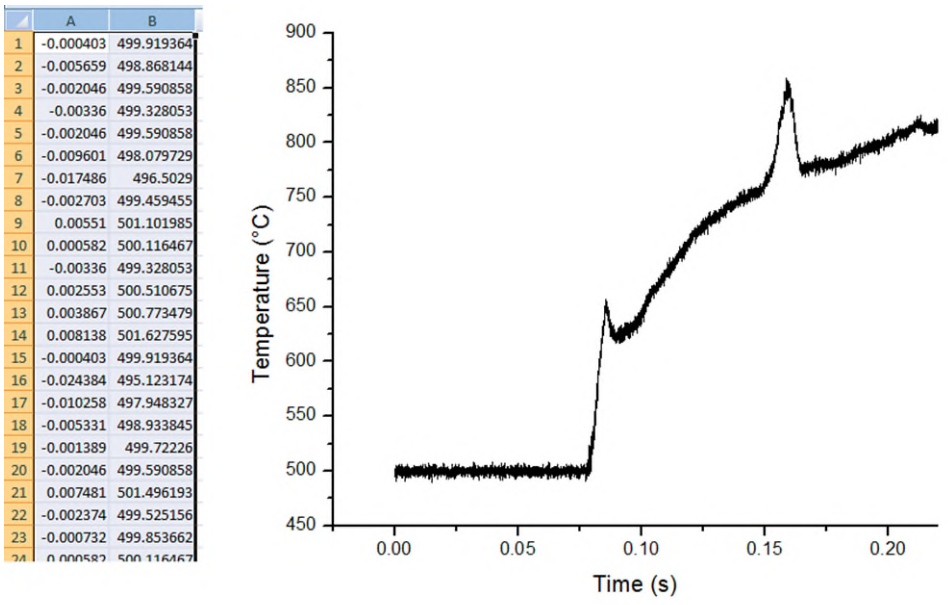
2.3 Data Handling

The data generated from the sensorised dual-laser system contains various sources, creating multi-modal data for each experiment performed or part produced. The dataset for one experiment/part will contain the processing parameters and the data from the three sensors. For the training dataset which is in production, the processing parameters, sensor data, and characterisation data will make up the full dataset.

2.3.1 Sensor data

Pyrometer data

The pyrometer data is stored as a CSV text file. The file contains comma-delimited values for the raw voltage signal from the pyrometer sensor, and for the temperature. Example data from a laser hardening pre-trial can be seen in Figure 6. As the range of the pyrometer is 500-2500 °C, the base temperature reading is 500 °C. Using the capture rate of 100 kHz, a time series can be generated. The file sizes are relatively small, on the order of megabytes for a single laser hardening pass. The data can be manually analysed using software such as excel or origin, and can easily be imported into python into a Pandas dataframe or similar manageable data format.



	A	B
1	-0.000403	499.919364
2	-0.005659	498.868144
3	-0.002046	499.590858
4	-0.00336	499.328053
5	-0.002046	499.590858
6	-0.009601	498.079729
7	-0.017486	496.5029
8	-0.002703	499.459455
9	0.00551	501.101985
10	0.000582	500.116467
11	-0.00336	499.328053
12	0.002553	500.510675
13	0.003867	500.773479
14	0.008138	501.627595
15	-0.000403	499.919364
16	-0.024384	495.123174
17	-0.010258	497.948327
18	-0.005331	498.933845
19	-0.001389	499.72226
20	-0.002046	499.590858
21	0.007481	501.496193
22	-0.002374	499.525156
23	-0.000732	499.853662
24	0.000582	500.116467

Figure 6: Pyrometer data as captured from the Kleiber KG-740-LO.

Acoustic emission data

The acoustic emission data is recorded in the .WAV format. The data files are moderately large, with a single fibre laser experiment generating a file on the order of tens of megabytes for each

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sensor, and a laser texturing experiment generating a file on the order of hundreds of megabytes for each sensor. In the system, there are two sensors, one pointed at the fibre laser site and one pointed at the centre of the galvanometric beam scanner's scanfield. It is possible the audio data from the sensor which is not aimed at the laser site current in use *may* provide some useful information, but recording only with the aimed sensor when performing either laser operation would reduce the data overhead. The data is an audio file, and can be manually analysed in Avisoft's own software, SASLab, or in other audio software such as Audacity.

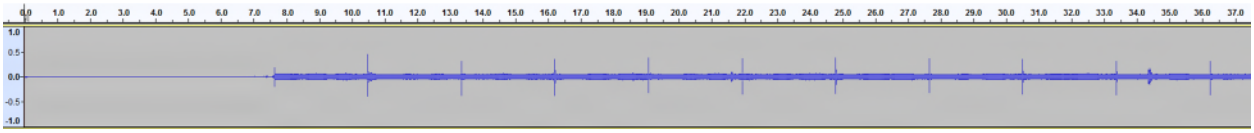
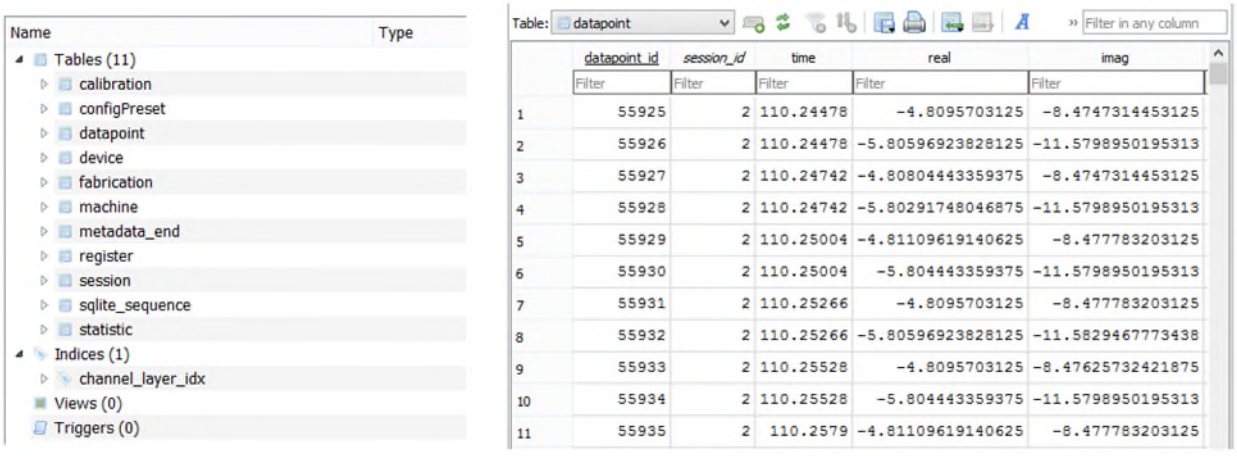


Figure 7: Acoustic emission data of a laser texturing experiment captured using the Avisoft-Bioacoustic sensor.

An example file from a laser texturing sample of parallel lines can be seen in Figure 7. The commencement of the laser ablation can be discerned between 7 and 8 seconds, and periodic spikes where the laser jumps from one parallel line to the next line in the texture. The .WAV files can also be imported into python as a NumPy array, using the SciPy package.

Eddy current data

The eddy current data is in the .AMIDB format, which is a SQLite formatted database (see Figure 8). The files contain calibration information, the position of the sensors, time, and the real and imaginary impedance of the sensors. File sizes are on the order of a megabyte for a single pass, with several samples being scanned in one pass. The AMIDB data can be opened in Amiquam's software, or using other SQLite tools. The data can also be imported into python using the sqlite3 package.



	datapoint_id	session_id	time	real	imag
1	55925	2	110.24478	-4.8095703125	-8.4747314453125
2	55926	2	110.24478	-5.80596923828125	-11.5798950195313
3	55927	2	110.24742	-4.80804443359375	-8.4747314453125
4	55928	2	110.24742	-5.80291748046875	-11.5798950195313
5	55929	2	110.25004	-4.81109619140625	-8.477783203125
6	55930	2	110.25004	-5.804443359375	-11.5798950195313
7	55931	2	110.25266	-4.8095703125	-8.477783203125
8	55932	2	110.25266	-5.80596923828125	-11.5829467773438
9	55933	2	110.25528	-4.8095703125	-8.47625732421875
10	55934	2	110.25528	-5.804443359375	-11.5798950195313
11	55935	2	110.2579	-4.81109619140625	-8.477783203125

Figure 8: Eddy current data example, showing the database structure (left) and the table of data (right).

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2.3.2 Feature selection

Feature selection is a method for reducing the dimensionality of data for machine learning to reduce training time and energy consumption. Features are individual values which describe a larger set of data, values such as average, standard deviation, first quartile, etc.. These features can contain a significant amount of information about the overall data in a single value. The features are then ranked in terms of how well they correlate with or explain the target (the selected quality factor). Low ranking features can then be eliminated, selecting the features with the best relationship to the target. This process creates a dimensionally reduced dataset to allow efficient training of the algorithm. The features that are important for each quality factor may differ greatly, and as such the feature selection approach will be applied for each target.

The approach to feature selection for this work follows the successful feature selection approach used for the LPBF system for *Deliverable D3.3*. Gray Relational Analysis (GRA) and Pairwise Pearson's Correlation Coefficient (PCC) are used to rank the features. GRA assigns a coefficient, the Grey Relational Coefficient (GRC), which indicates the closeness of a given feature to the target quality factor. The GRC is given by:

$$\gamma_i(k) = \frac{\Delta_{min} + \xi\Delta_{max}}{\Delta_i(k) + \xi\Delta_{max}}$$

where $\gamma_i(k)$ is the GRC between the reference sequence X_0 and the i^{th} sequence Xi at the k^{th} data point. $\Delta_i(k)$ is the absolute difference between the reference sequence X_0 and the i^{th} sequence at the k^{th} data point:

$$\Delta_i(k) = |\mathrm{X}_0(k) - \mathrm{X}_i(k)|$$

The minimum and maximum differences across all data points are respectively represented by Δ_{min} and Δ_{max} , and ξ is a distinguishing coefficient (usually between 0 and 1) that adjusts the relative importance of the minimum and maximum differences (typically set to 0.5).

The overall Grey Relational Grade (GRG), also known as the Gray Relational Analysis score (GRA score) for each feature is then calculated by averaging the GRCs across all data points, where N is the number of data points:

$$GRA_i \; or \; GRG_i = \frac{1}{N}\sum_{k=1}^{N}\gamma_i(k)$$

A higher score indicates a more relevant feature.

PCC is a statistical measure of the linear relationship between two dimensions, in this case the feature and the target. The coefficient will be positive in the case of a direct correlation and

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negative in the case of an inverse correlation, with the absolute value (between 0 and 1) indicating the strength of the correlation. The Pearson coefficient is given by:

$$r_{xy} = \frac{\sum_{i=1}^{N}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i - \bar{x})^2 \sum_{i=1}^{N}(y_i - \bar{y})^2}}$$

where r_{xy} is the PCC between two variables x and y, x_i and y_i are the values of the i^{th} data points for x and y variables, $\bar{x}$ and $\bar{y}$ are the means of the x and y variables, respectively, and N is the number of data points.

For feature ranking, an average score of the GRA and PCC is created to produce a more comprehensive value for the significance of the feature.

Recursive Feature Elimination with Cross Validation (RFECV) is also used to remove irrelevant features which introduce noise and create inefficiency in machine learning models. RFECV is expressed by the formula:

$$Score(S) = \frac{1}{k}\sum_{i=1}^{k} score(S_i)$$

where S is the set of selected features, k is the number of folds in the cross-validation, S_i is the subset of features in fold i, and $score(S_i)$ is the model's performance score on fold i with the subset S_i.

Four regressors were identified for use in feature elimination: Random Forest, Gradient Boosting, Lasso, and Linear Regression. These four regressors are used to assess the feature importance, and cross-validation carried out using KFold from the SKlearn python package. Feature scoring is normalised for comparison across the models, and ranked in terms of the average across the four regressors. A number of top-ranked features can then be selected to be retained for the training of the machine learning model.

This feature selection approach provides a robust, model-agnostic method for selecting the most important features for the target property, allowing for efficient and effective model training.

2.4 Machine Learning

To develop a defect detection model for a given quality parameter a number of supervised regression algorithms are applied. The features and algorithm that work best for each quality parameter may vary. A final multi-modal defect detection system will make use of multiple

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models to allow the detection of defective parts for a variety of applications where different quality factors are important for validation.

Eighteen algorithms were identified and succesfully applied in the work on the LPBF system, described in *Deliverable D3.3*, and have been selected for the defect detection approach for the laser processing system. The eighteen algorithms are:

1. *AdaBoost Regressor (ABR)*
2. *Bayesian Ridge (BR)*
3. *Decision Tree (DT)*
4. *Elastic Net (EN)*
5. *Extra Trees Regressor (ETR)*
6. *Gaussian Process Regressor (GPR)*
7. *Gradient Boosting Regressor (GBR)*
8. *Gradient Boosted Trees (XGBoost Regressor)*
9. *Huber Regressor (HR)*
10. *K-Nearest Neighbours (KNN)*
11. *Kernel Ridge (KR)*
12. *Partial Least Squares (PLS) Regression*
13. *Polynomial Regression (PR)*
14. *Random Forest (RF)*
15. *Random Sample Consensus (RANSAC) Regressor*
16. *Stochastic Gradient Descent (SGD)*
17. *Support Vector Machine (SVM)*
18. *Theil-Sen Regressor (TSR)*

Training of the regression algorithms is performed by splitting the training dataset into 80% for training, and 20% for cross-validation of the model. Five performance metrics can be used to evaluate each algorithm: the confidence interval, coefficient of determination (R^2), mean squared error (MSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean squared error (RMSE).

In the algorithm development approach, a single quality factor will be selected, initially the surface roughness as discussed in Section 2.2 as the target response. To understand the utility of the different data sources in detecting defective parts, the eighteen algorithms will first be applied with the processing parameters, to see the predictive power without in-situ sensors. The eighteen algorithms will then be applied with data for the individual sensors, to understand the predictive power of each sensor for the selected quality factor. Finally, the eighteen algorithms will be applied with data for multiple sensors. This process will be repeated for each quality factor. This will allow for a system for predicting multiple selected quality factors based on the

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application, from the sensor data. By detecting unacceptable deviation from the quality targets, the system will identify defective surfaces or validate the surface.

3. Outlook

The planned 256 sample 4^4 design of experiment is currently being carried out with the sensorised laser system and prepared 316L material to produce a training dataset. The approach detailed in this deliverable will be followed to develop algorithms based on the processing parameters, individual sensors, and multiple sensors. This will focus on various quality factors, such as roughness or contact angle, to develop a system which can predict the selected quality factors from the in-situ data.

Building on this system using the training dataset, a recommender system will be developed - allowing a user to select target values, or acceptable thresholds for a target to be above/below, for quality factors and be given recommended processing parameters. The recommender system may consider lifecycle aspects, as identified in WP4, to select the least ecologically impactful option where multiple parameter sets can achieve the requested result. As the processing parameters are applied, the defect detection system then uses the sensor data, targets, and tolerances to validate that the predicted values are acceptable, thus validating the part or detecting that it is defective. These systems will feed into the DILACERT and DILAFACT software platforms to allow intelligent parameter selection and in-process part qualification in laser surface production.

4. Conclusion

This *Deliverable D3.7* presents the approach for defect detection for a dual-laser surface processing system. The sensing methods applied to the sensorised laser system were reviewed and the strategy for developing the defection detection system detailed. It outlines the approach for gathering the training dataset, which is underway. The strategy for reducing the dimensionality of the training data, to reduce the computational burden and noise in efficient training of machine learning algorithms was detailed. The strategy for developing the machine learning model was detailed, including the eighteen algorithms which will be tested. This approach will develop a system which predicts the final quality factors of a part from the sensor data. This system will allow the detection of defective parts and thus the validation of non-defective parts as an in-situ quality control system.

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