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Detecting microscale surface impurities in powder bed fusion through light scattering and machine learning

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Declaration

I, Ahmet Selim Koca, hereby declare that this thesis is my own work, except where specific reference is made to the work of others. The work presented in this thesis was carried out entirely during my doctoral studies at the University of Nottingham, under the supervision of Prof Richard Leach, Dr Helia Hooshmand and Dr Mingyu Liu. The contents of this thesis have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university.

Abstract

Laser beam powder bed fusion (PBF-LB) is a leading metal additive manufacturing technique capable of producing complex components with high precision. However, the process is prone to forming microscale surface impurities such as balling, spatter, and surface pores, which can affect mechanical properties, surface finish, and overall part reliability. Detecting these impurities, particularly during fabrication, remains a significant challenge due to limitations in current inspection methods.

Although ex-situ techniques provide high-resolution analysis, they are often time-consuming, expensive, and/or unsuitable for real-time monitoring. In contrast, in-situ sensing approaches, while promising, frequently suffer from limited resolution, inconsistent accuracy across different machines, and a lack of reliability in detecting microscale impurities. Moreover, the real-time implementation of such methods is hindered by limitations in data acquisition, reconstruction, and analysis speed.

This thesis presents a novel method for detecting microscale surface impurities, which combines light scattering with machine learning (ML) to address these challenges. An optical setup was developed to capture light scattering patterns from PBF-LB surfaces. Experimental results demonstrated that surfaces with and without microscale impurities produce distinct scattering signatures. These signatures were subsequently used to classify the surfaces using ML algorithms.

To reduce the dependency on extensive experimental datasets, a simulation framework was established. Within this framework, light scattering patterns were generated using a model based on Beckmann-Kirchhoff (BK) theory. The surfaces input into this model were synthetically created using a generative adversarial network (GAN), enabling the generation of a large and diverse dataset. This approach considerably reduced the time and effort required to develop robust classification models.

The ML algorithms, once trained, achieved an accuracy of over 90% in detecting surface impurities. The system operates efficiently and possesses the potential for integration into a PBF-LB machine, enabling real-time, in-situ defect detection without interrupting the build process.

This study presents the first application of simulated light scattering patterns derived from synthetically generated surfaces detecting microscale impurities on PBF-LB surfaces. It demonstrates a rapid, cost-effective, and highly accurate method for assessing surface quality. Although currently implemented ex situ, the system architecture is well-suited for future integration as a real-time, in-process monitoring solution, thereby supporting more reliable and intelligent additive manufacturing workflows.

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Table of contents

Declaration.....	iii
Abstract.....	i
Acknowledgements.....	iii
Table of contents.....	v
List of figures	ix
List of tables.....	xv
1. Introduction.....	1
1.1. Motivation, aim and objectives	1
1.2. Research novelty	5
1.3. Thesis outline	7
1.4. List of publications.....	8
2. Literature review	10
2.1. Additive manufacturing	12
2.1.1. Metal AM	15
2.2. Defects and surface impurities in PBF.....	21
2.2.1. Porosity	22
2.2.2. Cracking and delamination	23
2.2.3. Recoater related defects	24
2.2.4. Balling.....	25
2.2.5. Spatter	26
2.2.6. Surface pores	27
2.3. In-situ measurement methods	28
2.3.1. Visible sensing	29
2.3.2. Thermal sensing	32
2.3.3. Electronic imaging	36
2.3.4. Height mapping.....	38

2.3.4.1.	Fringe projection	38
2.3.4.2.	Coherent imaging	41
2.3.5.	Blade-mounted sensing	42
2.3.6.	Acoustic sensing	44
2.3.7.	Combination of methods	45
2.3.8.	Summary of the section.....	47
2.4.	Machine learning methods for measurement and monitoring of defects and impurities.....	49
2.4.1.	Supervised learning.....	50
2.4.1.1.	Bayesian classifier.....	55
2.4.1.2.	K-nearest neighbour	56
2.4.1.3.	Artificial neural network	57
2.4.1.4.	Convolutional neural network.....	61
2.4.2.	Unsupervised learning.....	68
2.4.2.1.	K-means clustering.....	68
2.4.2.2.	Self-organising map (SOM).....	69
2.4.2.3.	Deep belief network (DBN).....	70
2.4.2.4.	Autoencoder	71
2.4.2.5.	Anomaly detection algorithms	72
2.4.2.6.	Density-based spatial clustering of applications with noise (DBSCAN) 73	
2.4.3.	Semi-supervised learning	73
2.4.4.	Reinforcement learning (RL)	75
2.5.	Light scattering.....	77
2.5.1.	Modelling of light scattering.....	78
2.5.1.1.	Rigorous approaches	82
2.5.1.2.	Approximate approaches.....	83
2.5.2.	Theory of the BK light scattering model.....	85
2.6.	Summary	88
3.	Surface analysis of PBF-LB samples	92
3.1.	Fabrication of the samples	92
3.2.	Analysis of the microscale surface features	94

3.2.1.	Spatter particles	94
3.2.2.	Agglomeration.....	95
3.2.3.	Bulge	96
3.2.4.	Holes and gaps	97
3.2.5.	Marangoni flow	98
3.2.6.	Surface Pit	98
3.2.7.	Unknown features	99
3.3.	Investigating the effect of process parameters on surface morphology ...	102
3.3.1.	Laser power and energy density.....	103
3.3.2.	Scanning speed.....	104
3.3.3.	Layer thickness.....	105
3.4.	Summary	106
4.	Impurity detection	108
4.1.	Impurity detection on SEM images with image processing.....	109
4.2.	Topography analysis.....	113
4.2.1.	Slope angle distribution	114
4.2.2.	Areal surface texture parameters comparison	118
4.3.	Summary	120
5.	Development of the experimental light scattering	122
5.1.	Experimental light scattering setup based on beam focusing	122
5.1.1.	Analysis of the illumination beam	126
5.1.1.1.	Measurement of the beam profile with a beam profiler.....	126
5.1.1.2.	Analysis of the beam profile on PBF-LB surfaces.....	127
5.1.2.	Effect of polarisation and neutral density filter.....	128
5.1.3.	Comparison of scattering patterns generated by surfaces with and without impurities.....	130
5.2.	Summary	131
6.	Classification of scattering patterns with ML.....	133
6.1.	Surface generation.....	134
6.2.	Simulation of scattering patterns.....	137
6.3.	Unsupervised ML for classification	142

6.3.1.	Autoencoders.....	142
6.3.2.	Anomaly detection algorithms	143
6.4.	Machine learning classification results	145
6.5.	Summary	147
7.	Conclusion and future work	149
7.1.	Concluding remarks	149
7.2.	Contributions to Knowledge	151
7.3.	Future work	152
7.4.	Final remarks.....	153
	References	154
	Appendix A: The Transformation Code	190

List of figures

Figure 1.1. The number of published papers about in-situ methods on PBF based on the Scopus database.....	3
Figure 2.1. Metal AM sales between 2002-2023, Wohlers Report 2024 [45].....	13
Figure 2.2. Flow diagram of AM fabrication stages.	15
Figure 2.3. The schematic of a generic PBF machine.....	16
Figure 2.4. Schematic of laser/electron beam scanning process.....	17
Figure 2.5. Laser power versus scanning speed map for Ti6Al4V on PBF [59].	19
Figure 2.6. a) tensile test results for three different orientations, 0° ,45° and 90° in b) [65]......	20
Figure 2.7. a) surface connected, gas entrapped, lack of fusion, and [83] b) keyhole induced porosities [84]......	23
Figure 2.8. a) delamination [91] and b) cracking [40].	24
Figure 2.9. a) recoater hopping, b) incomplete powder spreading, and c) recoater streaking [95].	25
Figure 2.10. SEM images showing the balling characteristics under different scan speeds [98].	25
Figure 2.11 a) SEM image showing an open pore and spatters [121].	27
Figure 2.12. a) Powder bed images using different lighting conditions [134]......	30
Figure 2.13. a) Optical image captured during printing, b) binarized image after processing [138]......	30
Figure 2.14. a) dynamic monitoring system [141], In-situ temperature measurement setup [145]......	33
Figure 2.15. a) Spatter detection from a thermal image in [147], b) and in [42].	35

Figure 2.16. a) Schematic diagram of a PBF-EB with a BSE detector installed [153], b) Surfaces of powder-bed samples taken by the in-situ ELO method (left), confocal laser scanning microscopy (centre), and laser scanning microscopy (right) [156].	38
Figure 2.17. a) Schematic of fringe projection integration into a PBF machine [160], b) a portion of the imaged build area is shown as a height map in greyscale with vertical and horizontal line profiles in the right and bottom, respectively [160].	39
Figure 2.18. a) 3D visualisation of a small section of the measurement result [161], b) Measurement result of the in-situ fringe projection method [163].	41
Figure 2.19. a) An example of the implementation of CI as in-situ measurement[36], b) PBF-LB surface, c) resulting profile scans of the structure [166].	42
Figure 2.20. a) Computer-aided design of the experimental setup used for the powder bed scanner, b) schematic cross-section view of a layer and its corresponding top- view scan [39].	43
Figure 2.21. a) Schematic diagram of the multi-sensor system [171], b) Neural network prediction of defects on a layer (10 μm per pixel) [172].	46
Figure 2.22. Classification of ML algorithms based on the training paradigms.	50
Figure 2.23. a) linear and b) logistic regression graphs.	52
Figure 2.24. Linear SVM graph.	53
Figure 2.25. Non-linear SVM, kernel processing.	54
Figure 2.26. Classification performances of both SVM and NN [185].	55
Figure 2.27. The predicted values compared to the true values of the BN Model [192].	56
Figure 2.28. Class of the new input after KNN is applied.	57
Figure 2.29. The architecture of an ANN.	58
Figure 2.30. A generic schematic of a CNN.	61
Figure 2.31. Confusion matrix of the CNN trained for classification [223].	64
Figure 2.32. Different types of powder layering defects [231].	66
Figure 2.33. Detection of defected and homogenous surface [235].	66

Figure 2.34. Schematic representation of unsupervised learning.	68
Figure 2.35. Porosity detection by a) SOM, and b) CT-scan [248].	70
Figure 2.36. Accuracy and classification time comparison of ML algorithms [256].	71
Figure 2.37. Input and prediction of semi-supervised ML algorithm [273].	74
Figure 2.38. Reinforcement learning (RL) process [280].	77
Figure 2.39. The propagation of light during transmission, refraction, and reflection.	79
Figure 2.40. Optical theories describing light become progressively more complex, evolving from ray optics to quantum optics.....	80
Figure 2.41. a) Specular reflection, b) specular reflection dominant, c) and d) diffuse reflection dominant with protrusion and recess.	81
Figure 2.42. Schematic representation of scattering from a 3D object.	86
Figure 2.43. Observation point P is distant from the scattering medium - Ω	86
Figure 3.1. a) As-fabricate PBF-LB sample, b) RenAM 500Q PBF-LB machine [320].	93
Figure 3.2. SEM images of the top surface of as-manufactured PBF-LB samples, showing spattering.	95
Figure 3.3. SEM images of the top surface of as-manufactured PBF-LB samples, showing agglomeration.	96
Figure 3.4. SEM images of the top surface of as-manufactured PBF-LB samples, showing bulges.....	96
Figure 3.5. SEM images of the top surface of as-manufactured PBF-LB samples, showing holes and gaps.....	97
Figure 3.6. SEM images of the top surface of as-manufactured PBF-LB samples, showing the surface pit and reversed Marangoni flow.....	98
Figure 3.7. a) Circular ripples, b) Explosion-like feature.	100
Figure 3.8. a) Pentagon-shaped feature, b) Fleck adhered particle.	101

Figure 3.9. a) Half dirty half clean surface, b) Plume-surrounded particle.	101
Figure 3.10. a) Zigzag-shaped defect line, b) Stick-shaped features.	102
Figure 3.11. a) SEM image of a black mark, b) magnified image of the black mark.	102
Figure 3.12. SEM images of top surfaces fabricated with different laser powers. ..	104
Figure 3.13. SEM images of top surfaces fabricated with different laser scanning speeds.	105
Figure 3.14. SEM images of top surfaces fabricated with different laser powers and layer thicknesses.....	106
Figure 4.1. a) The input image and b) the binarised image.....	110
Figure 4.2. a) The image before and b) after applying the morphological operation.	111
Figure 4.3. a) The image before applying the boundary extraction and b) after the boundary extraction.....	111
Figure 4.4. The result of surface impurity detection for both good and poor quality surfaces.....	112
Figure 4.5. Schematic representation of α and β	114
Figure 4.6. Slope angle distribution of selected surface areas extracted from surface topography measurements.....	115
Figure 4.7. Mode, mean and main values of slope angle distribution of selected uniform surface areas without impurity.	116
Figure 4.8. Mode, mean and main values of slope angle distribution of selected non- uniform surface areas with impurity.	117
Figure 4.9. The graphs of mode, main and mean values of slope angle distribution.	117
Figure 4.10. a) Uniform and b) non-uniform surfaces with their corresponding surface texture parameters.....	119

Figure 5.1. a) Experimental setup of the light scattering technique, and b - c) its schema.....	124
Figure 5.2. a) Microscopic image of a PBF-LB surface with weld tracks highlighted by red dashed lines, b) and c) microscopic surface images with and without impurities, respectively, d) and e) height maps with and without impurities, respectively.....	125
Figure 5.3. Beam profile and the calculated Gaussian beam diameter obtained by a) beam profiler and, b) obtained by the simulation.	127
Figure 5.4. Microscopy images a) without and b) with illumination, and c)-e) image processing steps to evaluate the beam size.	128
Figure 5.5. Recorded scattering patterns at various polarisation angles.	129
Figure 5.6. Effect of energy amount on scattering patterns.	130
Figure 5.7. Recorded scattering patterns from surfaces, a) with impurities and b) without impurity.	131
Figure 6.1. Process flow of the ML-based classification of the scattering patterns.	134
Figure 6.2. Analysed specimen produced by PBF-LB.....	135
Figure 6.3. Examples of a) real and b) synthetic uniform surface images in grayscale.	136
Figure 6.4. Examples of a) real and b) synthetic uniform surface topographies.	137
Figure 6.5. a) Three-dimensional representation of the surface topography; b) extracted surface profile with a fitted circle based on the three highlighted points.	138
Figure 6.6. a) Two randomly selected uniform surface height maps; b) corresponding slope angle distributions, with red arrows indicating the mean values; c) corresponding radius of curvature distributions.....	139
Figure 6.7. Projecting the scattering from the spherical wavefront propagation to the planar screen.....	140

Figure 6.8. Examples of a) experimental and b) simulated scattering patterns from uniform surfaces, and c) experimental scattering patterns from non-uniform surfaces.	141
Figure 6.9. Structure of a) CNN-based autoencoder, b) ANN-based autoencoder. .	143
Figure 6.10. a) iForest graph showing data points classified as outliers and inliers, along with a path length map, b) LOF graph showing data points with their corresponding outlier scores.	144
Figure 6.11. Testing of trained CNN- and ANN-based autoencoders on scattering patterns from uniform and non-uniform surfaces.	145
Figure 6.12. Classification results of the ML algorithms, a) CNN based autoencoder, b) ANN based autoencoder, c) iForest, d) LOF.....	147

List of tables

Table 2.1. In-situ measurement methods using visible range imaging.	32
Table 2.2. In-situ measurement methods using thermal sensing for PBF.	34
Table 2.3. In-situ measurement methods based on ELO for PBF.	37
Table 2.4. In-situ measurement methods for PBF using the fringe projection technique.	40
Table 2.5. In-situ measurement methods for PBF using coherent and blade-mounted sensors.	43
Table 2.6. In-situ measurement methods for PBF using acoustic sensors.	44
Table 2.7. In-situ measurement methods for PBF using a combination of sensing methods.	46
Table 2.8. Overview of in-situ measurement methods' principal benefits and drawbacks.	48
Table 3.1. Ranges of the process parameters for the fabrication.	94
Table 3.2. Process parameters of the analysed samples.	99
Table 3.3. Process parameters of samples shown in Figure 3.12.	103
Table 3.4. Process parameters of samples shown in Figure 3.13.	104
Table 3.5. Process parameters of samples shown in Figure 3.14.	105
Table 4.1. Threshold values for surface topography parameters to discriminate surface types.	119
Table 5.1. Lens specifications.	123
Table 5.2. Specifications of the camera and the plastic viewing screen.	124
Table 5.3. Beam profiler specifications.	126
Table 6.1. Light scattering simulation parameters using the BK model.	134
Table 6.2. Manufacturing process parameters of the specimen shown in Figure 6.2.	136

1. Introduction

1.1. Motivation, aim and objectives

Additive manufacturing (AM) is a rapidly growing fabrication method that can produce complex geometries by adding/fusing material layer-by-layer according to the three-dimensional (3D) models of the parts [1]. AM offers a significant advantage over traditional fabrication methods in terms of design freedom [2]. AM parts can be designed without considering the tools and fixtures required for conventional manufacturing. This feature allows for parts with complex geometries and features that are difficult or impossible to fabricate using traditional methods [3]. Additionally, time and cost savings can be achieved by minimising the need for various fabrication processes and the accompanying fixturing requirements. However, in order to fabricate an AM part with the desired quality, an understanding of the underlying processes, materials, and their limitations is required. Despite improvements and optimisation studies in AM, defects still occur due to the lack of fabrication stability, robustness and repeatability of the manufacturing processes [4–6]. As such, it is essential to detect and analyse defects to inspect and monitor the fabrication quality of components.

Powder bed fusion (PBF) is the most widely used mature metal AM technique [7]. It uses a laser (laser beam powder bed fusion, PBF-LB) or electron beam (electron beam powder bed fusion, PBF-EB) to melt and fuse powder layers to fabricate 3D parts. During the fabrication process, microscale surface impurities, such as balling [8], spatter [9] and surface pores [10], may form on layer surfaces. These impurities can significantly compromise the integrity of the part by diminishing its quality. In this thesis, 'part quality' refers to the properties of the fabricated parts, including their mechanical, thermal, and dynamic characteristics, as well as the quality of their surface finish. Several studies have demonstrated that surface impurities can reduce mechanical properties such as strength [11], microhardness [12] and fatigue life [13]. Moreover, they play a critical role in crack initiation [14].

Surface impurities can also be the source of other defects and further negatively impact the part quality [15,16]. For instance, Gu et al. [8] investigated that the amount of partially melted particles increases the formation of lack of fusion (LOF). Zhang et al. [17] presented a positive correlation between surface impurities and internal porosities. Sanviemvongsak et. al [18] suggested that surface impurities can cause oxidation. Romano et al. [19] observed that surface cracks, exacerbated by impurities, decrease fatigue resistance and Zhu et al. [20] explored a correlation between surface texture and porosity. In other words, the presence of surface impurities not only indicates poor surface quality but can also be a sign of overall poor part quality [16–20].

Microscale surface impurities in PBF-LB can be measured after the fabrication using high-resolution ex-situ methods such as X-ray computed tomography (XCT) [21,22], optical methods, such as CSI [23,24], confocal microscopy (CM) [23–26] and focus variation (FV) [24,27]. In ex-situ methods, the part may need to be transported from a manufacturing site to a metrology site, which involves significant delays and potential harm from sample degradation or contamination. It should be noted that most of these measuring techniques, though having high resolution, can be relatively costly.

On the other hand, the layer-by-layer fabrication method enables in-situ monitoring of surface impurities on each layer during the fabrication process [28–30], which is valuable because it allows for real-time data collection and analysis to help identify defects. It can also enable closed-loop feedback control to correct defects during their formation.

Some of the earliest research on in-situ monitoring was conducted in 1994 by Melvin et al. [31] and Benda [32]. Melvin et al. [31] utilised video microscopy to gain insights into the behaviour of powder during fabrication, whilst Benda [32] was the first to measure melt pool temperature using an in-situ infrared (IR) sensor. These pioneering studies marked the beginning of using in-situ sensors for analysing PBF fabrication. Following these initial studies, researchers increasingly focused on in-situ methods, primarily based on visible and thermal sensing [33]. Particularly after 2010, there was a growing interest in the defect detection capabilities of in-situ methods. One of the first defect detection methods using in-situ sensing was

proposed by Berument et al. [34], who concentrated on detecting issues related to powder coating, such as insufficient or excessive powder layering. With advancements in sensor technology and ML algorithms, research in defect detection has expanded significantly [35]. Figure 1.1 shows the number of papers published on in-situ measurement and monitoring methods for PBF since 1994 according to the Scopus database, highlighting the rapid growth of interest in this area.

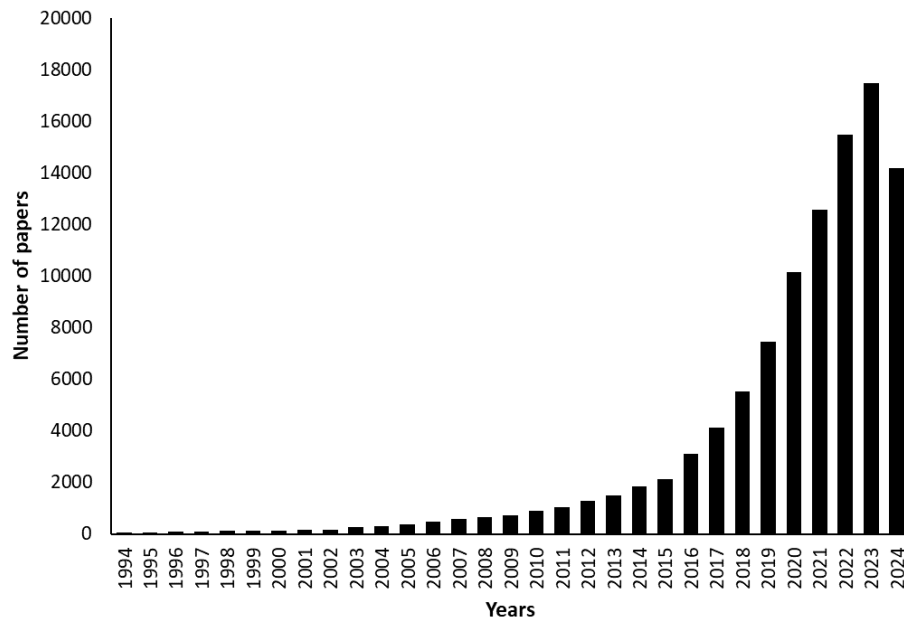


Figure 1.1. The number of published papers about in-situ methods on PBF based on the Scopus database.

Microscale surface impurities need to be detected in real-time using in-situ methods to evaluate fabrication quality or to correct these impurities during fabrication through real-time feedback control. Several recent review papers have examined in-situ measurement and monitoring methods in PBF [6,29,35].

The latest in-situ techniques specifically developed for the detection of microscale surface impurities on PBF-LB were reviewed in this thesis. The capabilities and limitations of each method are critically evaluated, with emphasis placed on detection accuracy and the range of detectable impurity sizes.

Visible and thermal sensing methods are the most used in-situ measurement methods as they can produce a large amount of data when using high-resolution and high-speed sensors. It is essential to mention that the arrangement of cameras and lighting

significantly influences detection accuracy in imaging. Variations in these configurations across different machines can affect brightness and contrast, resulting in varying detection quality from one machine to another. Backscattered electron (BSE) sensors show robustness in harsh environments; however, it should be noted that these sensors can occasionally overestimate the dimensions of porosities, and beam current and voltage can influence the BSE-acquired data, leading to unstable results. Acoustic sensing, which benefits from positioning flexibility, offers a cost-effective method for detecting impurities. Nevertheless, current research involving acoustic sensors for detecting microscale impurities is limited to single weld tracks, potentially requiring the capture of real-world construction conditions.

Unlike 2D imaging techniques, 3D height mapping of the surface provides additional information by revealing variations in surface elevation, which is particularly important for detecting impurities as they often lead to changes in surface height. Various methods for measuring surface topography in PBF, including coherent imaging [36], fringe projection [28,37] and blade-mounted systems [38,39], have been used for detection. Among these methods, coherent imaging, as a coaxial approach, can be costlier to integrate. The fringe projection systems might entail longer computation times than other methods, and installing projectors and cameras into a PBF machine can also be challenging. Blade-mounted systems, however, have resolution tied to the recoater's speed.

One of the key gaps in the literature on in-situ measurement and monitoring methods is their limited applicability to real-world industrial fabrication processes [29]. Although many techniques are capable of collecting data in real time, detection often takes place after processing due to time-consuming data analysis steps. Furthermore, numerous studies fail to report the total time required for detection, despite the fact that the feasibility of implementing these methods as real-time feedback control systems depends critically on this overall time. Additionally, variations in materials, process parameters, sensor positioning, and machine types can impact the sensor's efficiency and the detection accuracy of the algorithms [29]. The installation of sensors may also be challenging or impossible on certain machines. For methods employing ML algorithms to detect impurities, generating datasets for training supervised ML algorithms presents an additional challenge – data labelling [40]. This

process often relies on manual input from human operators, making it time-consuming and subjective. Even with unsupervised learning, a significant amount of data is still required to effectively train ML algorithms effectively.

It has also been reported that some impurities, which can degrade the fabrication quality, are even smaller than 100 μm [41]. However, the accuracy of most detection methods declines as impurity size decreases, particularly when impurities are smaller than 100 μm , primarily due to limitations in resolution [41]. For a detection system to provide robust quality evaluation, it must maintain consistent accuracy across all impurity sizes. Furthermore, while some methods are designed to detect only specific types of defects [42–44], a quality evaluation system must be capable of identifying all microscale impurities, including those smaller than 100 μm [41].

The aim of this thesis is to develop a measurement system capable of detecting microscale impurities, including those smaller than 100 μm , with consistently high accuracy, and doing so efficiently and cost-effectively. The objectives are to:

- Examine microscale surface impurities on PBF-LB components, investigate their correlations with process parameters and analyse their impact on overall part quality
- Develop an experimental ex-situ method that has the potential for future in-situ application, providing a rapid, cost-effective, and computationally efficient approach for detecting microscale impurities based on light scattering
- Employ a ML machine learning model capable of fast and automated detection, optimised for in-situ implementation
- Design a data generation model to eliminate the real-world data collection process for training machine learning algorithms

1.2. Research novelty

In this thesis, common microscale surface impurities observed on PBF-LB parts are outlined, and their impact on part quality is discussed. The methods used to detect these microscale impurities are also reviewed, and a key research gap is identified: the need for a measurement system that can infer surface topography information,

detect microscale impurities with consistently high accuracy, and operate in an efficient and cost-effective manner and adaptable for integration as an in-process tool within the manufacturing equipment.

The novelty of this work lies in the development of a method to detect microscale impurities smaller than 90 μm on PBF-LB parts. A light scattering-based technique has been designed and optimised for detecting microscale impurities. The decision to use light scattering is supported by several advantages: it is fast, cost-effective, capable of inferring surface information, and can be integrated coaxially into a PBF-LB machine for in-situ detection. To the best of our knowledge, this is the first study to apply light scattering for the detection of defects on this scale on PBF-LB surfaces.

An experimental setup based on light scattering was designed to generate scattering patterns from illuminated regions of the as-manufactured surface. A microscopy was integrated into the setup to enable data labelling and facilitate further validation of the illuminated areas. Following the observation of clear distinctions between scattering patterns from surfaces with and without impurities, a ML-based model was developed to classify surfaces according to the presence or absence of these impurities.

The scattering patterns used to train the machine learning algorithms were generated using a simulation model that takes surface topography data as input. This topography data is produced through a synthetic data generation algorithm. By simulating scattering patterns from synthetically generated surfaces, this approach removes the need for time-consuming and labour-intensive experimental data collection. After simulating the scattering patterns, ML algorithms were trained to classify scattering patterns based on the quality of the illuminated surface. Although training these algorithms demands considerable time and computational resources, once trained, the models are fast and well-suited for in-process defect detection.

In conclusion, this thesis introduces a microscale impurity-detection method for PBF-LB based on light scattering, combined with ML algorithms trained with simulated scattering patterns from synthetic surfaces. Although the method

developed in this study operates offline, it has the potential to be implemented as an in-process, real-time technique when integrated coaxially into a PBF-LB machine.

1.3. Thesis outline

Chapter 2 presents a comprehensive literature review, beginning with an overview of AM in general, followed by a focused discussion on PBF. Common surface defects associated with PBF are analysed, along with their effects on surface integrity and part quality. In-situ measurement techniques used for defect detection are reviewed, and existing research gaps are identified. Additionally, the chapter presents an overview of ML algorithms applied to defect detection and concludes with a discussion on the modelling of light scattering.

In Chapter 3, a microscale surface analysis was conducted on several Ti6Al4V alloy specimens fabricated using PBF-LB processing. The microstructural features of the as-built surfaces were examined using SEM. Several surface anomalies, previously unreported in the literature, were identified, and their potential formation mechanisms were proposed. The relationship between these microscale features and the corresponding process parameters was investigated. Finally, the impact of these surface defects on the overall quality of the fabricated components was evaluated, thereby highlighting the importance of their detection and understanding in enhancing the consistency and reliability of PBF-LB manufacturing.

In Chapter 4, impurity detection in PBF-LB manufactured components is examined through both image-based and topography-based methods. Two principal approaches were developed and evaluated. In the first approach, a custom image processing algorithm was applied to SEM images, and the defect ratio was introduced as a practical metric for the quantification of surface quality. In the second approach, surface topography data acquired using a CSI instrument were analysed. Three surface texture parameters - Sa , Sp , and Sdr – as defined in ISO 25178-2, were employed to differentiate between surfaces with and without microscale impurities.

In Chapter 5, the development and validation of a light scattering setup – designed for the detection of microscale surface impurities on components manufactured via PBF-LB – were presented through experimental investigation. The experimental setup was constructed and integrated with a microscopy unit to facilitate beam

alignment and surface visualisation. Beam profile consistency with simulated predictions was verified through the use of a beam profiler and image processing algorithms. The effects of parameters, including beam polarisation and light intensity, on scattering patterns were examined. The setup was subsequently applied to PBF-LB surfaces with and without microscale impurities. Analysis of the resulting scattering patterns demonstrated that surfaces containing impurities produced irregular, diffused patterns, while impurity-free surfaces exhibited more uniform, curved structures. These findings confirm the capability of the developed system for reliable, non-destructive detection of microscale surface impurities, supporting its potential application in quality assurance for advanced manufacturing.

In Chapter 6, the development and application of ML algorithms for the detection of microscale impurities on PBF-LB surfaces using the light scattering technique are presented. The algorithms were initially trained on simulated scattering patterns generated from synthetically created uniform surfaces, thereby avoiding the need for time-consuming real-world data collection. Furthermore, unsupervised one-class classification algorithms were employed, removing the requirement for manual data labelling. After training, the algorithms were tested on experimentally obtained scattering patterns from both uniform and non-uniform surfaces. The results indicate that the best-performing ML algorithm achieved a classification accuracy of over 95%. The experimental setup presented in this thesis serves as a proof-of-concept to validate the proposed machine learning approaches. The primary goal is to demonstrate the feasibility and effectiveness of the method, rather than to provide an exhaustive performance evaluation across all possible scenarios.

The principal findings of the study are summarised in Chapter 8, and the contributions to the existing body of literature are emphasised. Recommendations are also offered for future work to further enhance the proposed methodology for impurity detection on PBF-LB surfaces.

1.4. List of publications

The work presented in this thesis resulted in two peer-reviewed journal papers and three conference papers, all of which have been published.

Peer-reviewed journal papers:

- Koca A, Hooshmand H, Leach RK, Liu M 2025 In-situ measurement methods for microscale surface impurities in powder bed fusion: a review Meas Sci Technol 36(1):012001, <https://doi.org/10.1088/1361-6501/ad824c>.
- Koca A, Hooshmand H, Leach R, Liu M 2025 Detecting microscale surface imperfections in powder bed fusion through light scattering and machine learning – validation of inspection principles Precis Eng 94:761–72, <https://doi.org/10.1016/j.precisioneng.2025.04.010>.

Conference papers:

- Koca A, Hooshmand H, Liu M, Leach RK. Detecting microscale impurities on additive surfaces using light scattering. euspen Special Interest Group Meeting: Structured & Freeform Surfaces, June 2024, Dublin, Ireland.
- Koca A, Liu M, Leach RK. Microscale surface structure analysis of additively manufactured Ti alloy parts. euspen's 24th International Conference & Exhibition, September 2022, Huddersfield, UK.
- Koca A, Liu M, Leach RK. Microstructure analysis of laser-based powder bed fusion. ASPE/euspen topical meeting on Advancing Precision in Additive Manufacturing, July 2022, Knoxville, US.

2. Literature review

Additive manufacturing (AM), often referred to as 3D printing is capable of producing complex, functionally demanding components. Among the different AM techniques, metal-based methods – particularly PBF-LB – have gained considerable traction in sectors such as aerospace, biomedical engineering, and automotive manufacturing [45]. These sectors usually demand not only complex geometries but also tight tolerances, robust mechanical properties, and long-term reliability. PBF-LB has the ability to fabricate components with high design freedom withing the demanding tolerances. However, these advantages come with challenges, especially concerning the assurance of build quality.

In PBF-LB, each new layer builds upon the last, creating a compounding effect where microscale impurities can propagate or worsen through successive layers. This makes PBF-LB particularly susceptible to a range of process-induced defects. Microscale surface impurities such as pores, spatter, balling, and unmelted powders, which may be visually subtle or even undetectable by basic inspection, can significantly impact the final part's mechanical performance, fatigue life, surface integrity, and even corrosion resistance.

Process stability in PBF-LB is further complicated by its sensitivity to numerous interrelated parameters – laser power, scan speed, hatch spacing, powder size distribution, layer thickness, and environmental conditions within the build chamber. Many of these parameters exhibit non-linear relationships, making it difficult to predict outcomes through analytical modelling alone. This complexity underscores the importance of monitoring variations in real time. Despite extensive research efforts to optimize parameter sets for specific materials and geometries, the manufacturing process remains prone to defects due to the lack of repeatability, robustness and stability.

Traditionally, quality assurance in PBF-LB can be done by ex-situ methods such as XCT, ultrasonic inspection, and destructive testing. While these methods offer high-resolution insights, they are time-consuming, costly, or infeasible for in-line process control. As a result, there has been a growing emphasis on developing in-situ sensing

technologies capable of identifying anomalies as they arise during fabrication. The rationale behind in-situ monitoring is straightforward: if deviations can be detected and addressed immediately, it may be possible to halt or adjust the process before defects become embedded in the final part. In this way, in-situ monitoring represents a critical step toward intelligent, closed-loop control systems and aligns with the broader objectives of Industry 4.0.

Various sensing modalities have been proposed and implemented for this purpose. Visible imaging systems are among the most widely adopted due to their straightforward integration and interpretability. These systems capture high-speed, high-resolution images of the powder bed or melt pool and can detect features such as recoater streaks, spatter, and irregular deposition. Thermal imaging, using infrared or near-infrared sensors, offers insights into temperature gradients and heat flow, both of which are key indicators of melt pool stability and potential defect formation. Methods such as fringe projection and coherent imaging add a third dimension by reconstructing the surface topography of each layer, thereby enabling the detection of anomalies from the height data.

Electronic imaging techniques, including those based on backscattered electron (BSE) detection, have also been introduced in more controlled research environments. These offer the benefit of robustness under high temperatures and noisy conditions but can introduce complexity in calibration and interpretation. Acoustic sensors provide captures the sound profile of the melt process, which can be correlated with events like balling or delamination. While promising, each of these methods presents its own set of limitations – whether in terms of resolution, real-time capability, or integration complexity. Hence, there is increasing interest in developing in-process measurement and monitoring approaches that assess the quality of the fabrication.

Even with the best sensors, extracting actionable insights from high-dimensional, high-frequency data streams remains a significant challenge. This is where ML comes into play. ML techniques are particularly well-suited to handling the complex, nonlinear data generated by in-situ sensors. By training algorithms on labelled datasets of known defects, ML models can learn to recognize subtle patterns and anomalies in sensor data that would be impossible to detect manually. Supervised

learning methods such as convolutional neural networks (CNNs) and support vector machines (SVMs) have shown considerable success in classifying defect types and locations from optical or thermal imagery. Unsupervised methods, including clustering algorithms and anomaly detection frameworks, offer opportunities for discovering previously unknown defect signatures. Moreover, semi-supervised and reinforcement learning techniques open new pathways toward adaptive systems that can operate with limited training data or in dynamically changing conditions.

This chapter systematically reviews the landscape of defects and microscale surface impurities specific to PBF-LB, with a particular focus on their formation mechanisms and the implications they carry for mechanical performance and structural integrity. It also examines in detail the range of in-situ sensing technologies currently employed or under development, evaluating their resolution capabilities, practical integration constraints, and suitability for real-time feedback control. The chapter also explores how ML algorithms are being leveraged to automate defect detection, and enable closed-loop, self-optimizing PBF-LB systems. Finally, the chapter provides an overview of light scattering method, with particular emphasis on the modelling of the method using various approaches, especially the Beckmann-Kirchhoff (BK) model, which is employed in this study.

By bringing together insights from manufacturing, sensing technology, and data analytics, this chapter aims to present a cohesive overview of the state of the art in anomaly detection and quality control in PBF-LB. In doing so, it establishes the critical need for approaches to overcome the reliability and scalability challenges currently facing PBF-LB. The discussions here lay the groundwork for developing a robust fabrication quality assessment framework for PBF-LB.

2.1. Additive manufacturing

Additive manufacturing (AM) has been defined in ISO/ASTM 52900:2021 [46] as “process of joining materials to make parts from 3D model data, usually layer upon layer, as opposed to subtractive manufacturing and formative manufacturing methodologies”. Although the origins of AM date back to the 1860s, the first commercial AM machine was introduced by 3D Systems in 1987 [47]. The pace of development significantly accelerated with advancements in computer technology

and the introduction of powerful graphical interfaces. According to the Wohlers Report 2024 [45], sales of metal AM systems have steadily increased since 2002 (Figure 2.1), growing by more than 700% over the past decade. Some of the key applications are automotive, medicine, aerospace, sports and the construction industry [48].

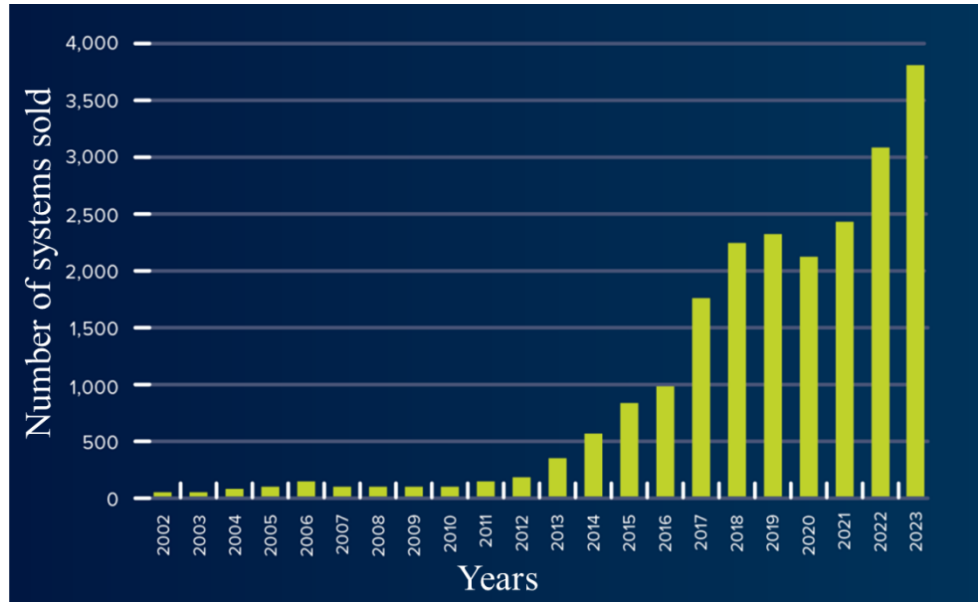


Figure 2.1. Metal AM sales between 2002-2023, Wohlers Report 2024 [45].

The AM types have been categorised into seven in ISO 17296-2 [49] as:

1. Vat photopolymerisation: an AM process in which liquid photopolymer in a vat is selectively cured by light-activated polymerisation.
2. Material jetting: an AM process in which droplets of build material are selectively deposited.
3. Binder jetting: an AM process in which a liquid bonding agent is selectively deposited to join powder materials.
4. Powder bed fusion: an AM process in which thermal energy selectively fuses regions of a powder bed.
5. Material extrusion: an AM process in which material is selectively dispensed through a nozzle or orifice.
6. Directed energy deposition: an AM process in which focused thermal energy is used to fuse materials by melting as they are being deposited

7. Sheet lamination: an AM process in which sheets of material are bonded to form an object.

Some fundamental principles of AM can be summarised as follows:

- Layer-by-layer fabrication: In contrast to subtractive manufacturing techniques such as machining, where material is removed to create the desired shape, AM builds parts by adding material layer by layer. This results in greater design freedom and reduced waste.
- Digital design: AM processes begin with a digital 3D model, typically created using Computer-Aided Design (CAD) software. This model is then sliced into layers, and each layer is sent to the AM machine for production.
- Material versatility: One of the significant advantages of AM is the ability to use various materials, including metals, polymers, ceramics, and composites. The choice of material depends on the desired properties of the final product, such as strength, flexibility, and thermal resistance.
- Customisation: Since AM operates from digital models, it allows for the mass customisation of products. Items can be produced with unique geometries tailored to individual needs without the need for specialised tooling or moulds.

On the other hand, AM also has some drawbacks compared to the traditional fabrication techniques. For example, AM can be an expensive and time-consuming alternative if the part can be fabricated with traditional methods [1]. In addition to that, post processing such as removing support structures, surface finish and heat treatment may decrease the cost and time efficiency. Additionally, not all of the material types are suitable for AM fabrication. For the material and geometry of the product, the process parameters may need to be optimised, which can take some cost, time and proficiency. Dimensional accuracy is another drawback of industrial AM methods, which is normally in the tens of micrometre scale [1]. One of the most important disadvantages of AM is its lack of repeatability, robustness and stability despite the improvements and optimisation studies [6].

Although the details of some steps can vary for different AM methods, there are eight main fabrication steps (Figure 2.2) for AM in general [50]. The fabrication

steps start with designing the CAD model of the part, then the CAD model is converted into a triangulated model. The triangulated model is then uploaded to the AM machine and the position is set according to the build volume. After these arrangements, the process parameters are set up. After the fabrication ends, the part is removed from the build volume, and then it is cleaned. The final part is ready to be used.

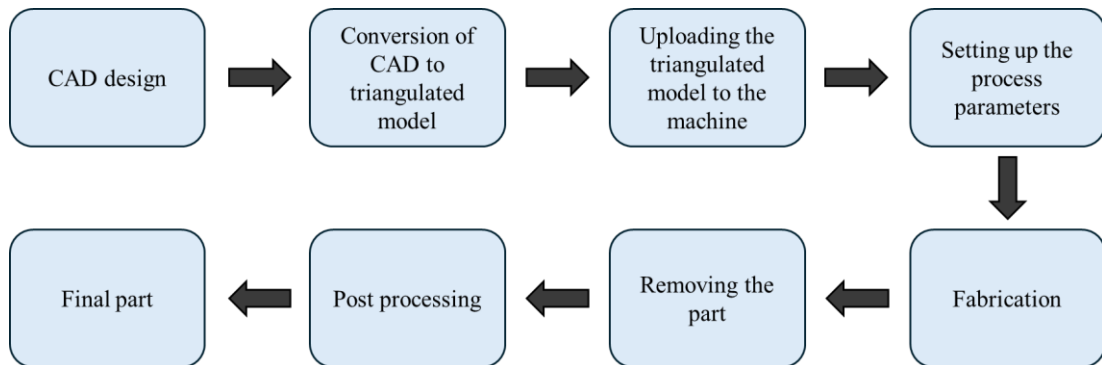


Figure 2.2. Flow diagram of AM fabrication stages.

2.1.1. Metal AM

Metal AM has the capability to fabricate parts with complex geometries as the manufacturing industry demands [2]. Components from various materials such as stainless steel, maraging steel, aluminium, titanium, and nickel alloys etc. can be manufactured by metal AM [51]. With variety of the material option and the capability of the production of complex geometries, the metal AM finds usage areas in industries such as aerospace [52] biomedical [53], automotive [54], marine [55] and etc. However, the lack of fabrication quality assurance may prevent this technology from being used directly after the fabrication process without assessment [30,35]. This thesis focuses on developing a fabrication quality assessment method for PBF which is one the most widely used mature metal AM technique [7].

Metal AM can be classified into three categories according to the feeding mechanism as powder bed, powder feed and wire feed [56]. PBF is one of the methods that falls under the powder bed category. Numerous commercial names are given to PBF, such as selective laser sintering, electron beam melting or direct metal printing. Based on the energy source types, they can be categorised as PBF-LB and PBF-EB.

Powder bed fusion

A generic schematic of PBF can be seen in Figure 2.3. The flow diagram of AM (Figure 2.2) is valid for the PBF, and the details of the fabrication step are as follows:

- An appropriate atmosphere is created in the build chamber
- Preheating is applied to reduce thermal gradients
- A powder layer with a predefined layer thickness is spread from the feeding site to the fabrication site with a roller or rake
- A high-power laser or electron source scans the surface according to the part geometry and melts and fuses the powders
- The fabrication site is lowered according to the predefined layer thickness
- The last three steps are repeated until the fabrication is complete

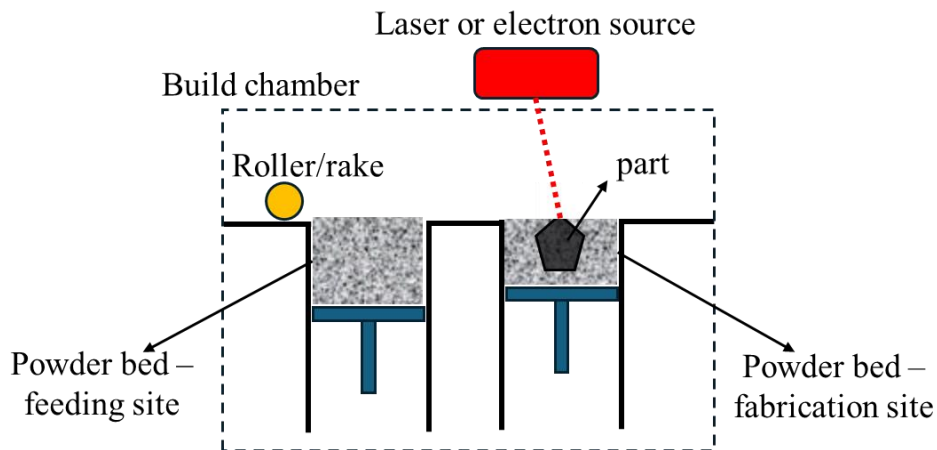


Figure 2.3. The schematic of a generic PBF machine.

In principle, any materials that are capable of being melted and subsequently resolidified may be utilised in PBF; however, some materials with high solidification rates may not be suitable for PBF [1]. A wide range of metals is available for PBF fabrication, such as titanium and its alloys, nickel-based alloys, steels, aluminium and cobalt-chrome alloys [57]. In addition to the metals, ceramics, and their composites are also available for the PBF process. These materials need to be produced in powder form by using methods such as gas atomisation with a size range of the powders approximately from 15 μm to 100 μm [58]. The size range and the morphology of the powders affect the layer thickness, porosity, packing density,

energy absorption, the thermal conductivity of the powder bed and also the surface quality of the final part. Therefore, it needs to be optimised according to the application.

Among the PBF methods, PBF-LB is the most commonly used one in the industry; therefore, with regard to this thesis, I focus on only PBF-LB. However, because of the similarities between both methods (PBF-LB and PBF-EB), the studies and the works may be applicable to PBF-EB.

Laser beam powder bed fusion (PBF-LB)

PBF-LB uses a high-energy density laser beam to melt powders selectively according to the parts' geometry. With PBF-LB, it is possible to produce nearly fully dense metal parts having complex shapes. The interaction between the laser beam and the powder influences the quality of fabrication, and in terms of the process stability, it is important to control melting, sintering and fusing of the powder, which depend on the local temperature fields. Undesired local temperatures may result in impurities or defects such as spatters, balling, cracks, etc. The schematic of the laser scanning is depicted in Figure 2.4. During the scanning, a high-energy density laser beam melts the powder and creates the melt pool. The formation of the melt pool influences the formation of the weld track, surface quality, and finally, part quality. In the next section, the process parameters of PBF-LB, including the ones affecting the formation of the melt pool, will be presented with their possible effects on the fabrication.

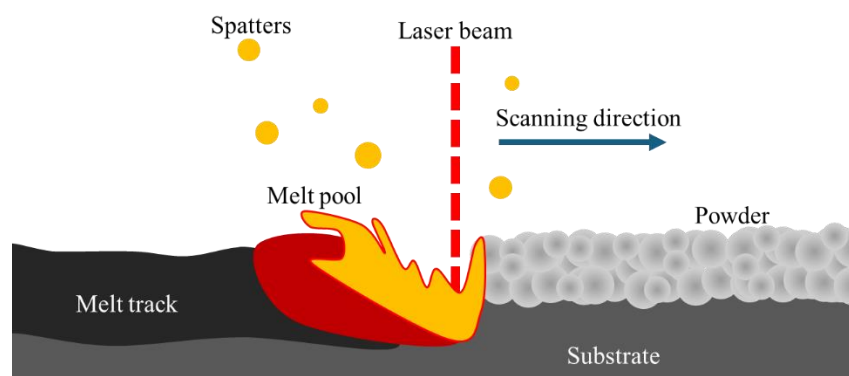


Figure 2.4. Schematic of laser/electron beam scanning process.

Process parameters

There are numerous process parameters in PBF-LB. These parameters need to be optimised according to the applications. Specific materials, geometries and also positions may need specific process parameters. Despite the optimisation studies of process parameters, there may still be defects or low-quality fabrication due to the lack of fabrication stability, robustness and repeatability of the manufacturing processes. However, it is still important to know what the main process parameters are and how they affect the fabrication process.

The process parameters of PBF-LB can be categorised into four categories [1]:

- Laser related parameters
 - Laser power, spot size, pulse duration, etc.
- Scan related parameters
 - Scan speed, scan spacing, etc.
- Powder related parameters
 - Powder size range, powder bed density, layer thickness, etc.
- Temperature related parameters
 - Powder bed temperature, build chamber temperature, etc.

Although some of these parameters can be changed independently on a PBF-LB machine, most of them are dependent on each other. For example, changing layer thickness can change the powder bed density and also affect the required power to melt the powder layers. There are lots of relations between the process parameters like these. Some of these relations are linear and easily interpretable; however, some of them are non-linear and can be hard to interpret. Therefore, an optimisation study needs to be performed to improve the quality of the fabrication.

During the laser beam scanning process, the melt pool is formed, and its characteristics are mostly related to the total amount of absorbed energy by the powder bed. The absorbed energy is not only related to the applied energy by the machine but also to the powder properties. It is complicated to calculate the absorbed energy because of the non-linear interactions; however, the applied energy density can be expressed as:

$$E = \frac{P}{vht}, \quad (2.1)$$

E : applied energy

P : power

v : scanning velocity

h : hatch spacing

t : layer thickness

The energy density is a parameter that quantifies the amount of laser power delivered per unit volume of material during the powder bed fusion process. It affects the melting behaviour of the powder. Some researchers have examined energy density in relation to laser power and scanning speed for Ti6Al4V (see Figure 2.5) [59]. The graph has been split into four zones: fully dense (I), over-melting (II), under-melting (III) and over-heating (OH). The shape of the map for different materials may not be the same; however, it should be similar to this map. According to the graph, there needs to be a balance between the power and scanning speed to fabricate fully dense parts.

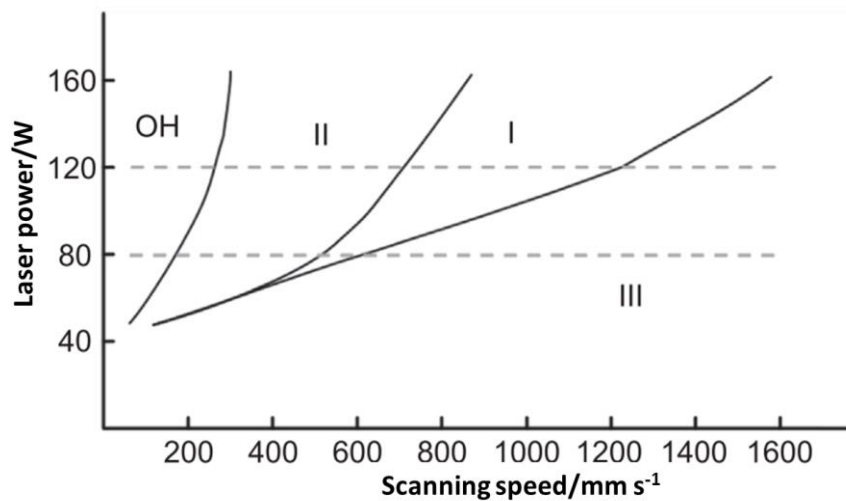


Figure 2.5. Laser power versus scanning speed map for Ti6Al4V on PBF [59].

In case not optimised energy parameters, undesired melt pools can be formed, which then results in undesired weld tracks such as non-continuous weld tracks or weld tracks with impurities. These phenomena can diminish the integrity, density and also surface finish of the part.

Mechanical properties of PBF parts

The mechanical properties, including yield strength and ultimate tensile strength, of parts fabricated through conventional methods and PBF have been compared in several studies [60]. The mechanical characteristics of these parts vary depending on the material used. For certain materials, PBF-fabricated components exhibit mechanical properties that are comparable to or superior to those of conventionally manufactured counterparts [61,62]. However, for some materials, conventionally fabricated parts demonstrate superior mechanical performance [63,64].

Several studies have investigated the mechanical properties of parts produced by PBF in relation to their build and loading orientations. The mechanical properties are observed to be superior when the load is applied parallel to the build direction (the samples fabricated with 0°), rather than perpendicular (the samples fabricated with 90°) to it (see Figure 2.6) [60,65]. In Figure 2.6 a), $\dot{\epsilon}_1$ - $\dot{\epsilon}_2$ denote the strain rates. In Figure 2.6 b), the x-y plane represents the powder bed plane, while the z-axis corresponds to the build height. However, on the other hand, some research presents findings that contradict this trend [66,67]. The discrepancies in findings may be attributed to defects or impurities present in manufactured parts, such as pores, unmelted powder particles, lack of fusion between layers, and cracks. These imperfections negatively impact the density, structural integrity, and ultimately the mechanical properties of the parts.

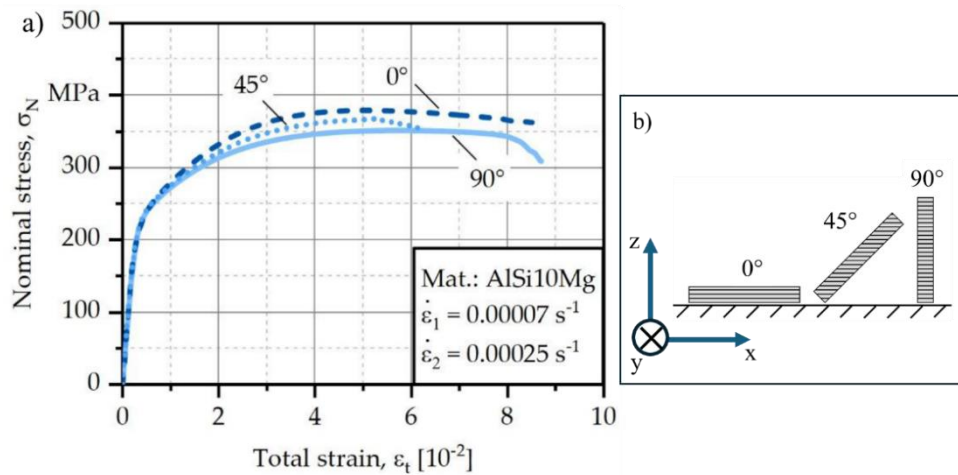


Figure 2.6. a) tensile test results for three different orientations, 0° , 45° and 90° in b) [65].

Part removal and post processing

After the fabrication process finishes, the part needs to be removed from the powder bed. This is done basically by raising the build plate and brushing off the excessive powders. In most cases, support structures are used to reduce the thermal gradients. These structures also need to be removed by using some machining operations. After these steps, some heat treatment and/or surface finish operations may be performed. The purpose of the heat treatments is to increase the parts' density and improve the microstructure and mechanical properties. On the other hand, surface finishing can be performed to improve the surface texture in order to obtain the desired surface quality.

2.2. Defects and surface impurities in PBF

Without optimising the process parameters for a specific material and geometry, it is common to have defects and surface impurities on PBF parts. Moreover, despite the optimisation studies, defects and impurities may still occur due to the lack of repeatability, robustness and stability. Therefore, it is important to analyse these features in terms of their causes and effects. The causes of these features can be categorised according to the sources as powder related defects, processing related defects and post-processing related defects.

Powder production type defines the characteristics of the powder, which is one of the most influential powder related factors for defect formation. Undesired powder characteristics, surface contamination and trapped gas in powders may induce or influence defects such as pores and balling, and diminish the final part quality.

Processing related defects are the major source of defects, and they have been widely investigated in the literature. From the processing parameters, it has been focused mainly on laser power, scan speed, layer thickness and scan strategy. These parameters have been found to cause defects such as lack of fusion, spattering, cracking and distortion.

After the fabrication, heat treatment may be applied to the part in order to improve the microstructure and the density of the part. Although the heat treatment can reduce

the porosity and improve the fatigue properties of the part, it can also negatively affect these properties if the applied time and temperature are chosen incorrectly.

Apart from the mentioned sources of defects, other sources, such as the machine itself and build preparation, can also cause defect formation. Improper setting of the machine, nonhomogeneous powder spreading can cause defects such as spattering, porosity and part integrity. Improper baseplate, improper build orientation and improper support structures may result in defects which degrade the parts' mechanical properties.

The surface quality of each layer in PBF fabrication can play a crucial role in determining a part's overall performance [20], which is due to the layer wise fabrication process, where the quality of each layer can influence the subsequent layers' quality. Microscale surface impurities refer to protrusions or recesses, such as balling, spatter and pores found on a surface. These impurities can decrease the quality of the fabricated parts. In the literature, several studies have demonstrated a direct correlation between these impurities and part quality [10,68–72]. Furthermore, other studies have indicated an indirect correlation, as these impurities can contribute to forming other defects such as internal pores, LOF and cracks, further impacting the overall part quality [9,73–78].

This section focuses on common defects and microscale surface impurities that can arise during fabrication, their influence on part quality, and the correlations between these impurities and other defects. Understanding and managing these features is vital to ensuring the overall performance and reliability of PBF-fabricated parts.

2.2.1. Porosity

In PBF-LB, porosity can be formed in different morphologies, mainly gas porosity, keyhole porosity and lack of fusion porosity [79]. The formation of pores is primarily influenced by process parameters, except in cases where it is related to the feedstock. For example, keyhole pores develop when the laser power is high and the scan speed is low. In contrast, lack of fusion pores occurs when the laser power is low, and the scan speed is high [80]. On the other hand, feedstock related pores, such as gas porosity, form mainly independently of the process parameters. The formation mechanism of pores has been widely investigated in [81].

Porosity in PBF-LB parts can negatively affect mechanical properties, including ductility, fatigue, and tensile strength, by reducing the effective load-bearing area and serving as sites for crack initiation [81]. The extent of this impact depends on factors such as the location, size, quantity, and morphology of the pores. However, it is important to note that studies have shown that a small amount of porosity has a minimal effect on mechanical properties [81]. In addition to mechanical properties, porosity can also influence the corrosion resistance by acting as corrosion sites, especially when they form on or close to the surface [82].

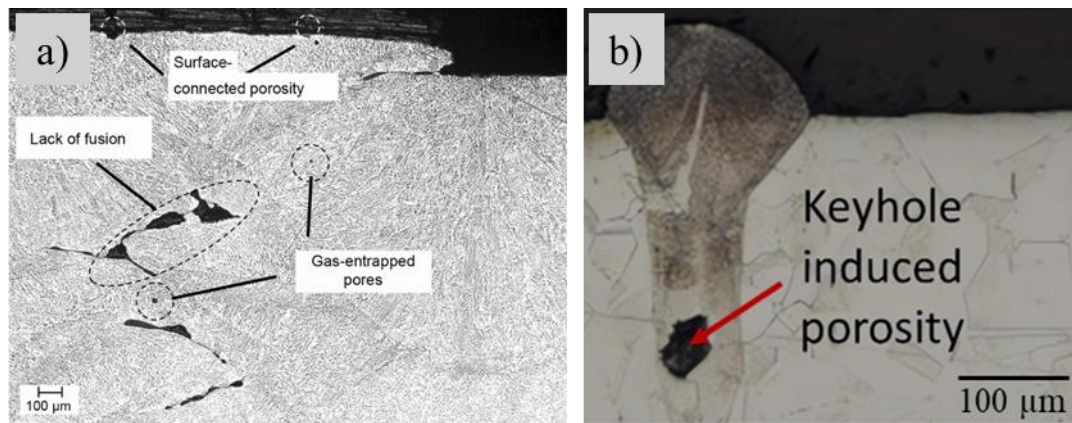


Figure 2.7. a) surface connected, gas entrapped, lack of fusion, and [83] b) keyhole induced porosities [84].

Porosities can be mitigated through post-processes such as heat treatments and hot isostatic pressing[85], although it can sometimes cause the regrowth of the pores when they contain gases like argon [86]. These mitigation strategies can also improve the mechanical properties of the fabricated PBF-LB parts, such as fatigue and tensile strength [87].

2.2.2. Cracking and delamination

Cracking can form at either in microscale or macroscale (Figure 2.8) on the surface of a layer, both during and after fabrication. In case it occurs between layers, it may cause delamination. During the fabrication, cracking and delamination can occur because of the non-optimal process parameters and build chamber environments, which can cause rapid cooling rates and high thermal stresses [88]. Apart from the parameters and the environment, material properties can also influence the cracking behaviour. For example, materials having a wider solidification temperature range

are more prone to cracking [83]. Slow cooling, reheating and preheating reduce the thermal stresses and these defects in PBF-LB parts [89,90]. Microscale cracks can decrease mechanical properties such as fatigue strength of the part by compromising its structural integrity.

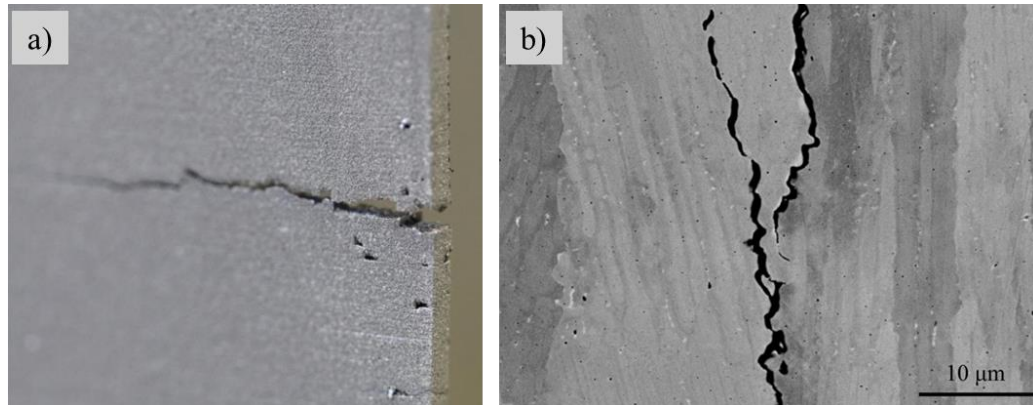


Figure 2.8. a) delamination [91] and b) cracking [40].

2.2.3. Recoater related defects

In PBF-LB, each layer of powder is spread using a mechanism, such as a roller, hopper, or blade, to achieve a consistent layer thickness. The choice of spreading mechanism significantly impacts the quality of the fabricated parts. For instance, the mechanism affects the powder bed density, which in turn influences the quality of the fusion process [92].

Typically, slower recoating speeds result in better layer uniformity and higher powder bed density, but this may increase the overall fabrication time [93]. However, certain defects can arise during the spreading process, such as recoater hopping, incomplete powder spreading, and recoater streaking (Figure 2.9), which can negatively affect the quality of PBF-LB parts. Additionally, if the layer thickness is set to be smaller than the average powder particle size, sparse layers may form, leading to defects such as balling, porosity, and shrinkage [94].

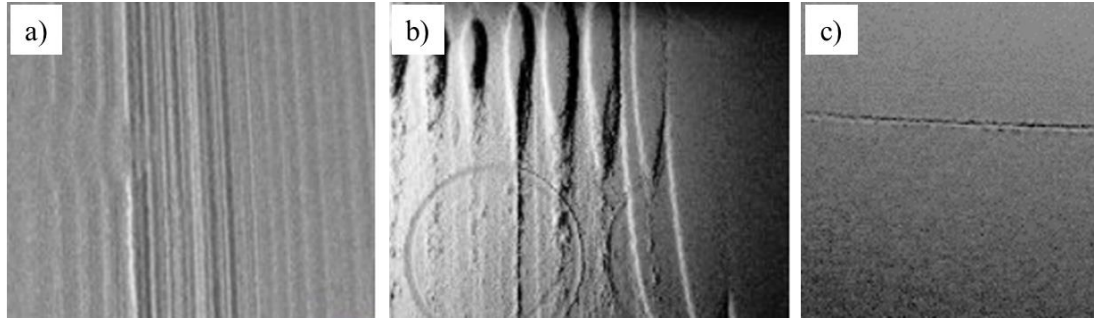


Figure 2.9. a) recoater hopping, b) incomplete powder spreading, and c) recoater streaking [95].

2.2.4. Balling

Balling is one typical fabrication defect encountered in PBF, which is formed by breaking the molten metal into droplets in the shape of separate beads (see Figure 2.10 and Figure 2.11) [96]. This phenomenon arises during the process of powder melting, wherein the weld track experiences a reduction in surface energy due to surface tension, often resulting from inadequate wettability and non-optimal process parameters [97,98]. Figure 2.10 shows that non-optimal scan speeds cause balling, especially higher than 350 mm/s, while the other parameters are fixed. Balling has been categorised based on its shape and dimensions into ellipsoidal and spherical forms, with reported dimensions ranging from approximately 3 μm to 500 μm [8,98,99].

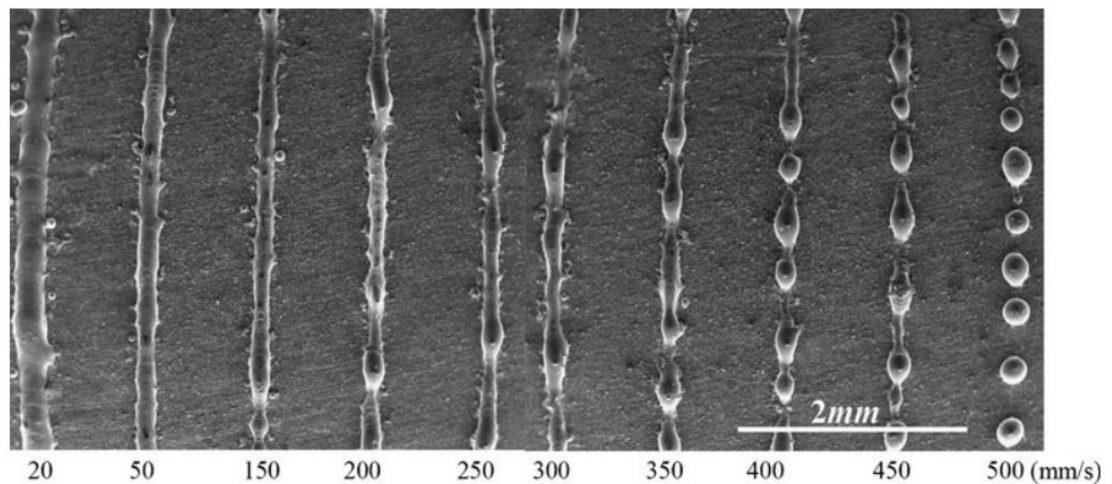


Figure 2.10. SEM images showing the balling characteristics under different scan speeds [98].

The balling phenomenon causes the interaction between the laser beam and the surface to become unstable, leading to the formation of irregular weld tracks. These irregular weld tracks lead to insufficient bonding between layers, resulting in phenomena such as rough surfaces [100–104], porosity [73–75] and reduced part density [99,105,106].

High local temperatures at the melting point can lead to surface contamination, such as oxidation. This oxidation can affect the stability of the melt pool and the melting process, reducing the wettability between the molten material and the solidified material. As a result, balling may occur, where the molten material forms spherical shapes rather than spreading smoothly [107].

2.2.5. Spatter

Spatter, a common occurrence in PBF (see Figure 2.11), is generally undesirable in many applications due to its adverse effects on part quality [9,70,108,109]. It is a by-product of the PBF process, resulting from material ejection from the melt pool due to a combination of physical phenomena, including vapour pressure, laser-induced plasma and gas flow [110–112]. Notably, spatter particles typically exhibit larger sizes compared to virgin powder particles, consequently requiring higher energy to melt [70].

The size of spatters depends on the powder used in the fabrication process. The smallest spatters can be as small as the smallest powder particles, while the largest spatters can be up to ten times larger than the average powder size. Ali et al. [76] observed that the size of spatters in D10 and D50 was similar to that of virgin powder, approximately 30 μm and 45 μm , respectively. Additionally, Liu et al. [69] reported spatters measuring around 400 μm , which is about ten times larger than the average powder size of 42.83 μm .

Spatters can induce high surface irregularities [113], leading to incomplete fusion between layers [68,69]. As a consequence, defects such as internal pores [9,76,77] and LOF [78] can form. Spatters and other potential defects caused by spatters can lead to fatigue strength degradation, reduced part density and poor tensile strength [68–70]. Furthermore, large spatter particles attached to the layer surface can be

removed by the recoater during subsequent layering, leaving pits behind and potentially compromising the recoating mechanism [77].

2.2.6. Surface pores

The surface pore is another type of impurity that occurs as dents, craters or cave-like open pores (see Figure 2.11) on the surface of PBF parts [71,114]. Several hypotheses have been proposed regarding the formation mechanism of the surface pores, focusing on the emergence of pores on the layer surface and insufficient liquid feeding [71,115,116]. Empirical studies indicate that non-optimal process parameters, such as high scanning speeds and large hatch distances, contribute to the increased occurrence of surface pores [71,117–120].

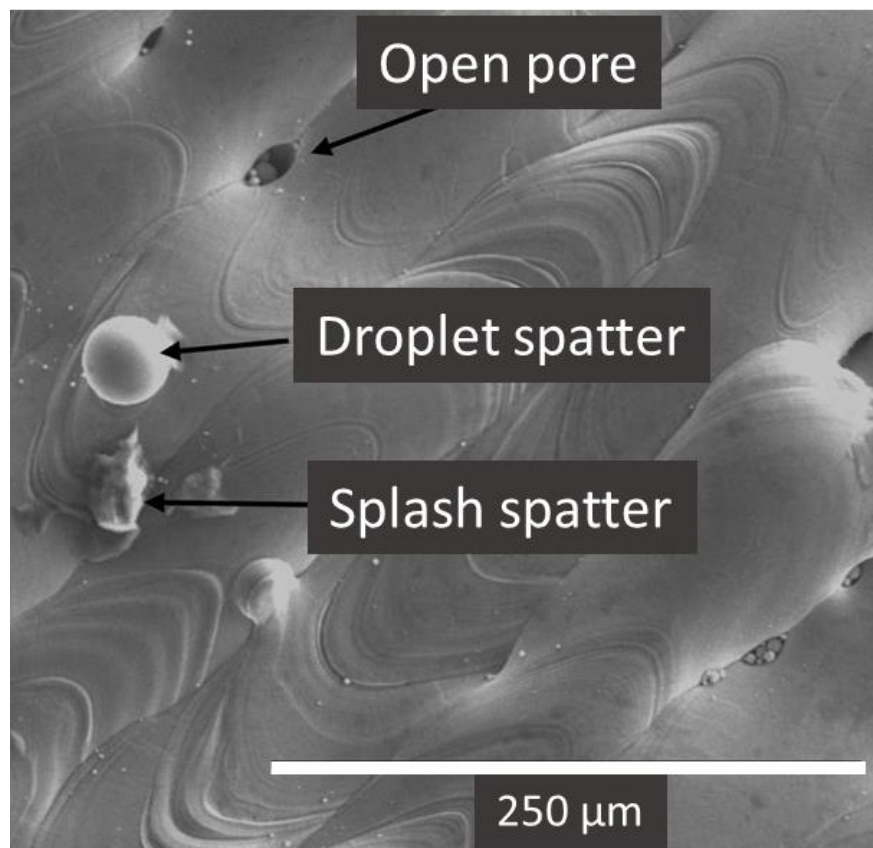


Figure 2.11 a) SEM image showing an open pore and spatters [121].

Surface pores have a notable association with internal pores, leading to diminished part density and compromising the mechanical performance of the parts [10,71,72,122]. Furthermore, the presence of surface pores escalates surface roughness and can act as initiation points for crack defects [10,117,120,123]. Some

studies have noted the presence of pores on the fractured surfaces or within product sizes ranging from 2 μm to 10 μm . These studies have proposed that these pores may be a possible source of reduced part quality [73,74].

Overall, microscale surface impurities in PBF could impact the fabrication quality, necessitating their measurement and assessment in the context of quality control. The main challenges lie in detecting them on-machine and real-time. Because they are small, the detection method must be capable of monitoring fine details and operating quickly enough for real-time detection. The following section reviews in-situ measurement methods developed for impurity detection, with particular attention to their capability and efficiency in identifying small-scale impurities.

2.3. In-situ measurement methods

Layerwise fabrication in PBF enables the implementation of in-situ measurement techniques during the manufacturing process [35]. In-situ measurement methods involve using sensors to collect data about process stability and product quality directly from where the process is taking place. Employing in-situ measurement techniques in PBF makes it feasible to detect and analyse surface impurities that may form on each layer.

The occurrence of impurities at any layer can significantly impact the quality of subsequent layers, consequently affecting the final part's overall quality [72,108]. In-situ measurement methods can provide the means to identify impurities formed on each layer. Although certain defects, such as shrinkage and distortion, may not be directly observable through in-situ measurements, anomalies associated with these defects can be detected. By enabling real-time defect detection, it becomes possible to prevent/decrease the formation of subsequent defects through active control of process parameters [124].

In certain instances, in-situ measurements may not provide a straightforward depiction of surface impurities, particularly when dealing with data that could be more intuitively interpretable, such as acoustic signals [125]. In such scenarios, surface impurities can still be detected using correlations between the non-interpretable in-situ data and interpretable ex-situ data [125–127].

In the following section, various in-situ measurement methods specifically aimed at the detection and characterisation of microscale surface impurities formed on PBF parts are presented and examined.

2.3.1. Visible sensing

Visible range sensors can capture images of the powder bed or melt tracks continuously during the fabrication or a small number of times after melting and/or after the deposition of a new layer [128,129]. In order to enable in-situ measurement, the camera vision system must have sufficient speed so as not to disrupt the ongoing fabrication process. Seminal studies have shown that visible imaging systems have the potential to detect powder bed irregularities [130,131]. Currently, visible imaging systems find applications in industrial PBF machinery for in-situ process quality measurement [29].

In visible images, surface impurities exhibit a distinctive contrast compared to the regular surface. In order to accurately identify surface impurities from the images recorded by visible range cameras, accurate segmentation and contour identification are essential [128,132,133]. The accuracy of detection and the minimum detectable size of surface impurities depend not only on the spatial resolution but also on the illumination of the vision system, as the interaction between the layer surface and lighting may give rise to undesirable reflections [134,135]. Gobert et al [134] installed eight flashing modules at different positions within a PBF machine to investigate the effect of lighting on impurity detection. They captured images of the powder bed by alternately switching the modules on and off, as illustrated in Figure 2.12, which demonstrates how different lighting settings influence the visibility of impurities on the powder bed surface.

Micro-scale protrusions on the PBF surface can be detected using the contrast between the elevated area and raw powder in surface images taken after the powder deposition process [136]. Jacobsmuhlen et al. [137] investigated the detection of the elevated areas on PBF surfaces by using a monochrome CCD camera to record surface images having a spatial resolution of approximately 30 $\mu\text{m}/\text{pixel}$. While disregarding small regions measuring 90 μm in diameter, it has been indicated that

their method yields a minimum resolvable detail of approximately $50\text{ }\mu\text{m}$ in size for a field of view measuring $180\text{ mm} \times 120\text{ mm}$.

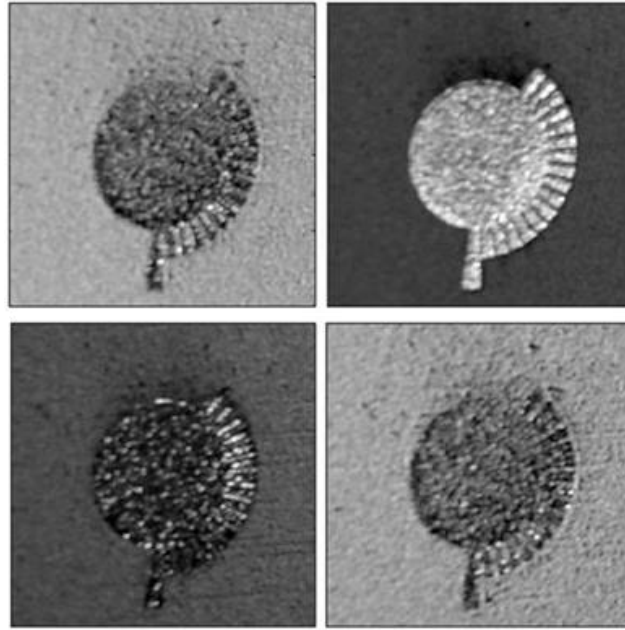


Figure 2.12. a) Powder bed images using different lighting conditions [134].

In some studies, XCT is used as “ground truth” data to validate their findings or correlate them with in-situ data. Lu et al. [138] designed a vision setup with a digital single-lens reflex (DSLR) camera and LED light sources, in which intensity values were employed for detecting surface irregularities (see Figure 2.13 a) and b), and the results were validated using XCT data. This method can detect holes with a minimum diameter of $500\text{ }\mu\text{m}$ and squares with a minimum length of $500\text{ }\mu\text{m}$.

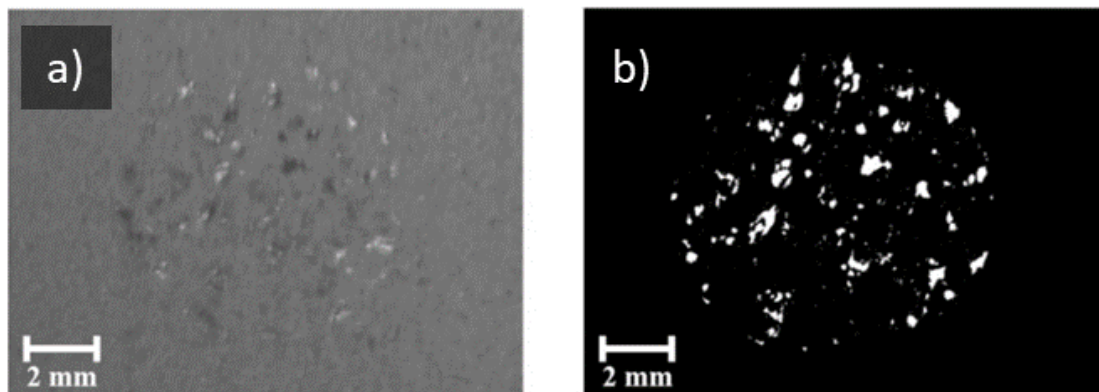


Figure 2.13. a) Optical image captured during printing, b) binarized image after processing [138].

Snow et al. [139] employed a ML algorithm to detect defects from in-situ layer images, utilising ex-situ XCT data as labelled defects for training. They attained more than 85% accuracy in defect detection for defects larger than 200 μm , both within the same dataset and with unseen data. Additionally, the study compared spatters detected through in-situ measurements and LOF identified via ex-situ XCT analysis. Notably, they presented a significant correlation between spatters and LOF defects smaller than 500 μm .

Designing synthetic defects has been proposed as a way of evaluating the system's defect detection performance. Abdelrahman et al. [132] developed a defect detection algorithm using surface images of parts with intentional defects. They demonstrated around 87% detection accuracy with the targeted defect size ranging from 50 μm to 750 μm .

Modaresialam et al. [140] showed that in-situ visible imaging can be used for real-time defect detection. They developed an algorithm using LabView software to halt fabrication when critical defects were detected. The method includes a visible range camera with a resolution of 1696 pixels $\times$ 1710 pixels and can detect microcracks and porosities as small as 10 μm .

The above imaging systems were all in fixed positions. Fischer et al. [141] implemented a dynamic image-capturing approach to address the limitation of fixed positioning. They mounted a line camera on the recoater of a PBF machine (see Figure 2.14 a) to capture powder bed images during powder deposition, obtaining images with a width of 97.67 mm and a lateral resolution of 5.97 $\mu\text{m}/\text{pixel}$. This setup allowed them to identify features such as spatter, balling and unmelted powder with a minimum size of 12.4 μm .

Table 2.1 summarises and compares the in-situ measurement methods mentioned in this section based on visible-range imaging, along with their specifications where available.

Table 2.1. In-situ measurement methods using visible range imaging.

Reference	Sensor	Resolution	Detectable features / Size range	Detection method/algorithm	Detection Accuracy
[137]	Monochrome CCD Camera	Spatial resolution: $\sim 30 \mu\text{m}/\text{pixel}$	$>90 \mu\text{m}$	Image processing	Not specified
[138]	DSLR Camera	Spatial resolution: $10\text{--}13 \mu\text{m}/\text{pixel}$	$\sim 500 \mu\text{m}$	Image processing	Not specified
[139]	DSLR Camera	Spatial resolution: $\sim 62.5 \mu\text{m}/\text{pixel}$	$\geq 40 \mu\text{m}$	Convolutional neural network	Depends on the size: less than 50% for $\sim 40 \mu\text{m}$, around 90% for $\sim 200 \mu\text{m}$, and 100% for larger than $475 \mu\text{m}$
[132]	DSLR Camera	Pixel size range: $45 \mu\text{m} \times 47 \mu\text{m}$ – $67 \mu\text{m} \times 88 \mu\text{m}$	$50 \mu\text{m} - 750 \mu\text{m}$	Image processing	$\sim 87\%$
[140]	Monochrome CCD Camera	Not specified	$\geq 10 \mu\text{m}$	Particle analysis	Not specified
[141]	Line Camera	Spatial resolution: $5.97 \mu\text{m}/\text{pixel}$	$\geq 12.4 \mu\text{m}$	Feature-based analysis	Not specified

2.3.2. Thermal sensing

In the manufacturing process, defects may arise due to thermal inhomogeneity [142] or, conversely, may lead to thermal inhomogeneity [143]. Consequently, thermal data can be harnessed to detect defects by identifying thermal inhomogeneities, offering valuable insights into process quality. Furthermore, thermal data has been previously utilised to predict the internal microstructure of parts [144].

During the PBF process, in-situ thermal information about layer surfaces or melt tracks can be collected using sensors operating in the infrared (IR, with a wavelength of $0.78 - 1000 \mu\text{m}$) or near-infrared (NIR, with a wavelength of $0.78 - 1.4 \mu\text{m}$) range (see an example implementation in Figure 2.14 b) [42,43,145–152], which can be achieved through continuously recording images of layers using high-frame-rate sensors [149]. However, continuous recording presents challenges, such as generating substantial amounts of data and being sensitive to metallisation when

employing sensors [144]. One approach to mitigate the impact of these challenges is to opt for single image recording for each layer using a mechanical shutter or placing the sensor outside the building chamber [147]. However, capturing a single image delays temperature information, as the scanning process takes time, and recording data from outside the chamber necessitates coordinate transformation. Table 2.2 summarises in-situ measurement methods using thermal sensing along with their specifications.

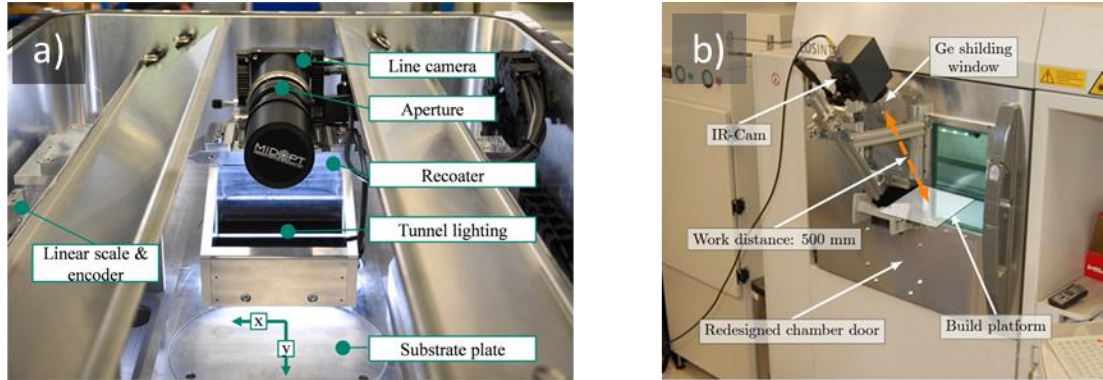


Figure 2.14. a) dynamic monitoring system [141], In-situ temperature measurement setup [145].

Some in-situ thermal sensing methods focused on detecting spatters and demonstrated their impact on process quality. For instance, Schwerz et al. [147] focused on the detection of spatters using long-exposure NIR range imaging of the layer surface (see Figure 2.15 a). The spatters were examined using SEM and exhibited a bimodal size distribution, with peaks at 30 μm and 90 μm , and the largest size measured approximately 200 μm . They conducted an ex-situ ultrasonic inspection to validate the findings and observed LOF in areas where the spatters were redeposited. Afterwards, Schwerz et al. [42] used an embedded in-situ monitoring system (EOSTATE exposure optical tomography) which included a three-megapixel sCMOS camera with a 900 nm bandpass filter for spatter detection. EOSTATE exposure optical tomography is an optical measurement system designed to monitor the exposure process during fabrication. The system continuously records the process radiation throughout production. Any deviations in this radiation are linked to variations in the fabrication process, which may potentially result in defect formation. An image processing algorithm was employed to detect bright regions

indicative of spatter defects (see Figure 2.15 b). A correlation was observed between the spatters detected using the OT system and LOF defects detected through XCT. However, a slight offset between the two detection systems was noted, potentially attributed to spatters causing LOF in subsequent layers.

Yakout et al. [43] also investigated spatter detection using an in-situ high-speed IR thermography system. In this study, the size, shape and distribution of the spatters were analysed, and the correlation between these features and the processing conditions was investigated. The sensor was positioned outside the chamber, and data was recorded through a protected window to ensure the sensor's safety in the harsh environment.

Table 2.2. In-situ measurement methods using thermal sensing for PBF.

Reference	Sensor	Detectable features / Size range	Detection method/algorithm	Detection Accuracy
[42]	NIR range imaging	$>\sim 200\ \mu\text{m}$	Image processing	79%
[43]	IR range imaging	$0.1 \times 10^6\ \mu\text{m}^2 - 2.0 \times 10^6\ \mu\text{m}^2$	Image analysis software (MIPAR)	Not specified
[148]	NIR range imaging	$>100\ \mu\text{m}$	Image processing	Not specified
[151]	IR range imaging	$600\ \mu\text{m} - 900\ \mu\text{m}$	Image processing	100%
[145]	IR range imaging	$>\sim 300\ \mu\text{m}$	Manual analysis (by looking at the graphs)	Not specified
[152]	NIR range imaging	$150\ \mu\text{m}$ (can detect smaller features with low accuracy)	A specific algorithm to correlate the OT and X-ray tomography data	90/95% (probability of detection)
[150]	IR range imaging	$50\ \mu\text{m} - 500\ \mu\text{m}$	Image processing	Depends on the size: less than 50% for $<50\ \mu\text{m}$, 100% for $>500\ \mu\text{m}$
[149]	IR range imaging	$750\ \mu\text{m}$	Image processing	Not specified

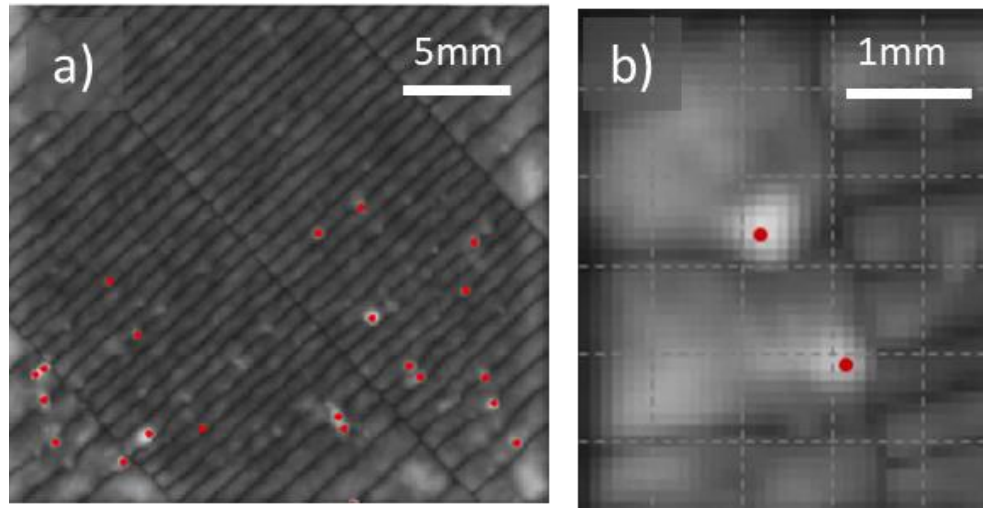


Figure 2.15. a) Spatter detection from a thermal image in [147], b) and in [42].

Another focus of in-situ thermal sensing is detecting porosity defects. Nandwana et al. [148] studied porosity detection from NIR images captured immediately after the melting process using image processing techniques. They used variations in surface emissivity to detect pores larger than $100\text{ }\mu\text{m}$. Furthermore, a correlation was established between the outcomes of fatigue performance testing and the results of pore detection. Notably, failures were observed to coincide with the regions where the most prominent pores were identified. Yoder et al. [146] utilised the same experimental setup to explore the connection between in-situ thermal data and the mechanical performance of topology-optimised parts. The study demonstrated a correlation between pores detected from in-situ data and premature failure in a sample.

Real-time defect detection makes controlled fabrication possible by changing process parameters or stopping the fabrication. Mireles et al. [151] presented a closed-loop automatic feedback control for PBF-EB by integrating an IR camera into a PBF-EB machine. An algorithm was developed to automatically detect porosity by processing the IR images recorded during the process. The algorithm achieved a 100% detection rate of the artificially made porosity defects ranging from $600\text{ }\mu\text{m}$ to $900\text{ }\mu\text{m}$ in size on the cylindrical parts. Krauss et al. [145] designed artificial defects in parts by creating holes of different sizes to simulate gas pores and cracks. An IR camera with a lateral resolution of $250\text{ }\mu\text{m}/\text{pixel}$ was employed for in-situ thermal sensing of the powder bed. The thermal diffusivity data showed that the minimum

detectable defect size is approximately 300 μm . Additionally, the correlation between the formation of ejected particles and the thermal distribution was investigated.

Several studies have explored the detection of LOF defects using in-situ thermal sensing methods. For instance, Bamberg et al. [152] utilised an sCMOS camera with an NIR filter. Their system was capable of capturing images with extended exposure times. This approach demonstrated the capacity to detect LOF as small as 150 μm in size, yielding a probability of detection (POD) of 90/95%. The system's capability to detect smaller defects was enhanced, albeit with a slightly reduced POD. In another investigation conducted by Bartlett et al. [150], an IR camera sensitive to long-wave IR wavelengths was positioned externally to the PBF machine. This setup facilitated the capture of relative temperature distributions across the printed layer. Through the analysis of IR images, LOF with diameters below 50 μm were detected with a success rate of 50%. Additionally, defects exceeding 500 μm exhibited a 100% detection success rate.

Mahmoudi et al. [149] investigated the detection of cavity defects from in-situ thermal data of the melt pool. They used high-speed sensors to collect in-situ thermal information. Their study demonstrated that their method successfully detected defects of 750 μm in size.

2.3.3. Electronic imaging

Electronic imaging, also called electron optical (ELO) imaging, operates on the same fundamental principle as traditional SEM [153]. In this technique (see an example of an integrated system in Figure 2.16a), a detector captures backscattered or secondary electrons resulting from the interaction between the process beam and the powder material [154]. The intensity of the collected signal is influenced by both the current of the electron beam and the atomic number of the material [153–155]. Notably, the surface topography is determined by the scattering angle of the electrons, allowing for the reconstruction of surface topography through electronic images [153]. Compared to other sensor types, such as visible or thermal-based sensors, backscattered electron (BSE) detectors demonstrate robustness, particularly in the fabrication environment characterised by high process temperatures, X-ray radiation

and contamination. Furthermore, BSE detectors are unaffected by metallisation, enhancing the overall durability of the method [153]. Table 2.3 summarises in-situ measurement methods based on ELO.

Arnold et al. [156] implemented in-situ ELO imaging on a custom-built PBF-EB machine equipped with a BSE sensor, offering a lateral resolution range from 50 $\mu\text{m}/\text{pixel}$ to 100 $\mu\text{m}/\text{pixel}$. The study exhibited the detection of micrometre-scale surface porosities using in-situ ELO imaging (see Figure 2.16 b). Similarly, Franke et al. [157] focused on detecting porosities using ELO images. They utilised a BSE detector with a lateral resolution of 60 $\mu\text{m}/\text{pixel}$, which was installed in a PBF-EB machine to capture ELO images after the melting process. Areas with low intensities on the images were detected as porosities, with a minimum range of 100 μm to 200 μm .

Table 2.3. In-situ measurement methods based on ELO for PBF.

Reference	Sensor	Detectable features / Size range	Detection method/algorithm
[156]	BSE sensor	$\sim 300 \mu\text{m}$	Based on the correlation between ELO images, optical images, and surface topography data
[157]	BSE sensor	100 μm – 200 μm	Based on the correlation between ELO images and optical images
[158]	BSE sensor	$> \sim 100 \mu\text{m}$	Image processing (contour identification, edge detection)

Gardfjell et al. [158] used an in-situ ELO system, utilising a BSE detector with a resolution of 1500 pixels $\times$ 1500 pixels and a pixel size of 80 $\mu\text{m} \times 80 \mu\text{m}$, covering a field of view of 120 mm $\times$ 120 mm. By employing image processing methods, the ELO images were analysed to detect surface impurities. The method achieved a minimum detectable feature size of around 100 μm .

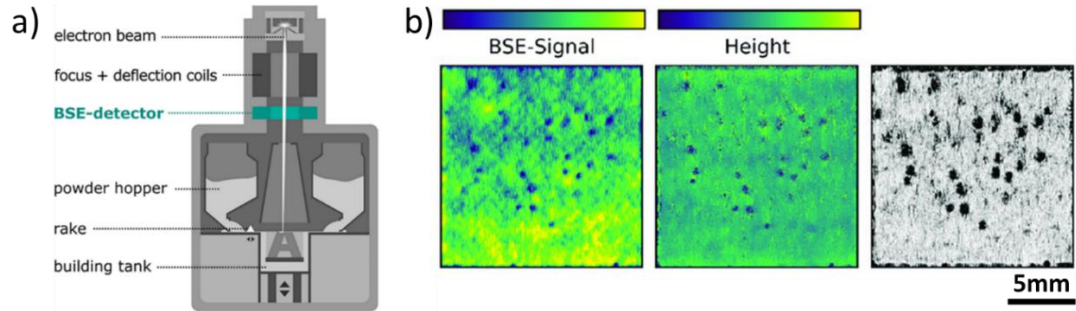


Figure 2.16. a) Schematic diagram of a PBF-EB with a BSE detector installed [153], b) Surfaces of powder-bed samples taken by the in-situ ELO method (left), confocal laser scanning microscopy (centre), and laser scanning microscopy (right) [156].

2.3.4. Height mapping

As apparent from the imaging methods discussed in earlier sections, 2D imaging techniques offer significant information about the layer surface. Nevertheless, obtaining height information can provide extra insights into process quality in addition to the 2D data. To achieve 3D information about layer surfaces, researchers have documented various in-situ techniques in the literature, including fringe projection and the use of specific blade-mounted sensors.

2.3.4.1. Fringe projection

The fringe projection method involves the integration of a projector and one or more cameras (see Figure 2.17 a). In this technique, the projector emits structured light onto the layer surface of interest, typically in a one-dimensional sinusoidal fringe pattern distribution. Subsequently, the camera or cameras capture the deformed fringe pattern resulting from the interaction of light with the layer surface. Surface height values are determined by decoding the deformed fringe pattern. The computational complexity in the fringe projection method is higher than that of the other methods based on cameras, which can make this method slower [159]. Table 2.4 presents the in-situ measurement methods for PBF, employing the fringe projection technique, along with their specifications.

Land et al. [160] used a fringe projection system consisting of an SLR camera and a digital light processing (DLP) projector for in-situ surface topography

measurements. This approach can detect micro-scale surface impurities (see Figure 2.17 b) with a noise level of approximately $18\text{ }\mu\text{m}$ in the vertical measurements.

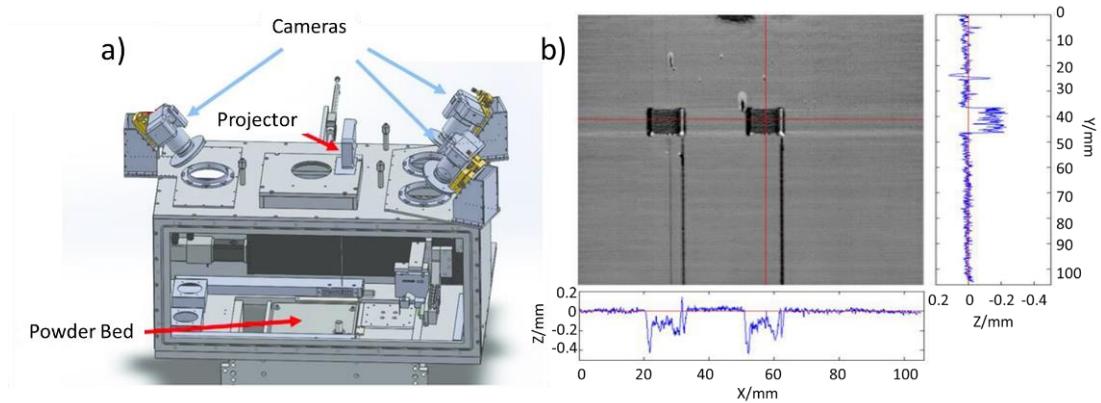


Figure 2.17. a) Schematic of fringe projection integration into a PBF machine [160], b) a portion of the imaged build area is shown as a height map in greyscale with vertical and horizontal line profiles in the right and bottom, respectively [160].

Kalms et al. [161] developed a fringe projection system with a vertical resolution of less than $10\text{ }\mu\text{m}$ and an approximate lateral resolution of $100\text{ }\mu\text{m}$. The fringe projection setup consisted of two 6-megapixel CCD cameras and a programmable LCD projector. Data collection was performed after both the powder deposition and melting processes. They stated that the method can detect unfused powder particles larger than $100\text{ }\mu\text{m}$ in size (see Figure 2.18a).

The fringe projection system described by Zhang et al. [162] consists of a commercial camera with a resolution of $5184\text{ pixels} \times 3456\text{ pixels}$ positioned about 70 cm above the powder bed, along with a DLP projector with a resolution of $1280\text{ pixels} \times 800\text{ pixels}$ positioned 56 cm above the powder bed. This setup enables a lateral resolution of $60\text{ }\mu\text{m}$ and a vertical resolution of $20\text{ }\mu\text{m}$. Moreover, in a subsequent study, Zhang et al. [163] enhanced the resolution using different cameras and positioning techniques. In this case, a camera with a resolution of $4096\text{ pixels} \times 2160\text{ pixels}$ was placed 20 cm above the powder bed, while a DLP projector with a resolution of $1280\text{ pixels} \times 800\text{ pixels}$ was positioned 60 cm above the powder bed. The improved arrangement achieves a lateral resolution of $6.8\text{ }\mu\text{m/pixel}$ (an example of measurement in Figure 2.18b). As a result, the proposed

in-situ surface topography measurements can be used to detect microscale surface impurities.

Table 2.4. In-situ measurement methods for PBF using the fringe projection technique.

Reference	Sensor	Resolution	Detectable features / Size range
[160]	DSLR camera and DLP projector	Noise level in vertical measurements: $\sim 18 \mu\text{m}$	Not specified
[161]	Two CCD cameras and an LCD projector	Vertical resolution: $< 10 \mu\text{m}$ Lateral resolution: $100 \mu\text{m}$	Unfused powder particles larger than $100 \mu\text{m}$
[162]	DSLR camera and DLP projector	Vertical resolution: $20 \mu\text{m}$ Lateral resolution: $60 \mu\text{m}$	Not specified
[163]	CMOS camera and DLP projector	Lateral resolution: $6.8 \mu\text{m}$	Not specified
[37]	NUB3D SIDIO XR	Point spacing: $75 \mu\text{m}$	Height variations of around $50 \mu\text{m}$
[164]	Four CMOS cameras and a DLP projector	Point spacing: $73.4 \mu\text{m}$	Not specified
[165]	Four CMOS cameras and a DLP projector	Lateral resolution: $57.62 \mu\text{m}$	Can detect defects smaller than $125 \mu\text{m}$

Southon et al. [37] used a commercial fringe projection system (NUB3D SIDIO XR) for in-process measurement of the PBF of polymer. The fringe projection system was positioned outside the PBF machine to perform measurements, with the capability to detect height variations of around $50 \mu\text{m}$.

Dickins et al. [164] built a multi-view fringe projection system including four cameras and a projector. A physical replica representing the build space of the Renishaw AM250 system was constructed, and the components were positioned within it. The transition from a single-camera to a multi-camera approach resulted in

a reduction of the mean point spacing from $136.7\ \mu\text{m}$ to $73.4\ \mu\text{m}$, which indicates the potential applicability of the system in defect detection, particularly for defects larger than $100\ \mu\text{m}$. Following this [164], Remani et al. [165] improved the fringe projection method described in [164]. They reported a lateral resolution of $57.62\ \mu\text{m}/\text{pixel}$ with the capability of detecting defects smaller than $125\ \mu\text{m}$.

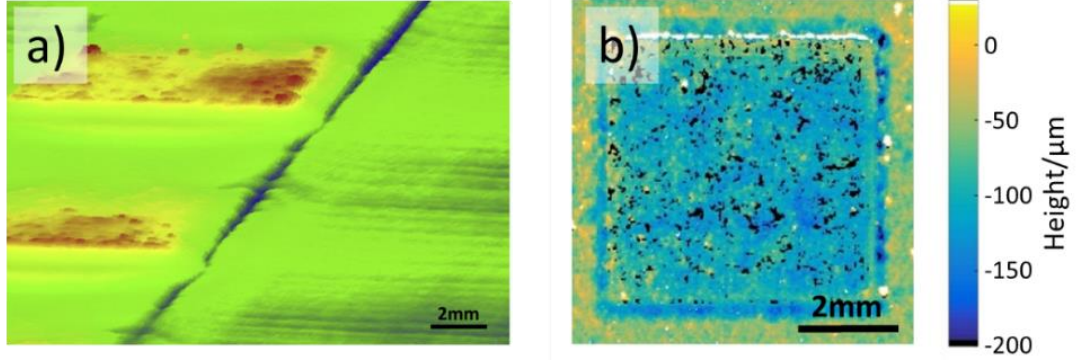


Figure 2.18. a) 3D visualisation of a small section of the measurement result [161],
b) Measurement result of the in-situ fringe projection method [163].

2.3.4.2. Coherent imaging

Coherent imaging (CI), also known as low-coherence interferometry, has been applied for in-situ surface topography construction in PBF, as demonstrated in [36,166,167]. This method can be coaxially integrated into a PBF machine (see Figure 2.19 a), thereby eliminating the need for coordinate transformation, as required in off-axis approaches. Nevertheless, it is important to note that the integration cost can be high [30]. By employing coherent imaging, surface height values are obtained through raster scanning of the layer surface with light. The interference between the backscattered imaging and a reference light beam, caused by the optical path difference, can be encoded to calculate layer surface heights. Detailed information about the working principle of coherent imaging can be found elsewhere [168].

Neef et al. [166] used a coherent imaging method for in-situ measurement with a broadband light source utilising the same optical path as the processing beam of PBF. The CI sensor in this study can scan a $3\ \text{mm} \times 3\ \text{mm}$ area with a sampling distance of $4\ \mu\text{m}$ (see Figure 2.19 b, c). The resulting height map detected single powder particles as small as $20\ \mu\text{m}$ to $40\ \mu\text{m}$. Similarly, DePond et al. [167]

implemented CI to a larger area, specifically a $4.4\text{ cm} \times 4.4\text{ cm}$ area. The scanning was performed after switching off the processing laser, which reduces the overall fabrication speed. The system in this study demonstrated an axial resolution of $25\text{ }\mu\text{m}$ and a lateral resolution of $100\text{ }\mu\text{m}$, with a scan speed of 1 m/s . The study highlights that the method can detect spatters within the size range from $200\text{ }\mu\text{m}$ to $700\text{ }\mu\text{m}$.

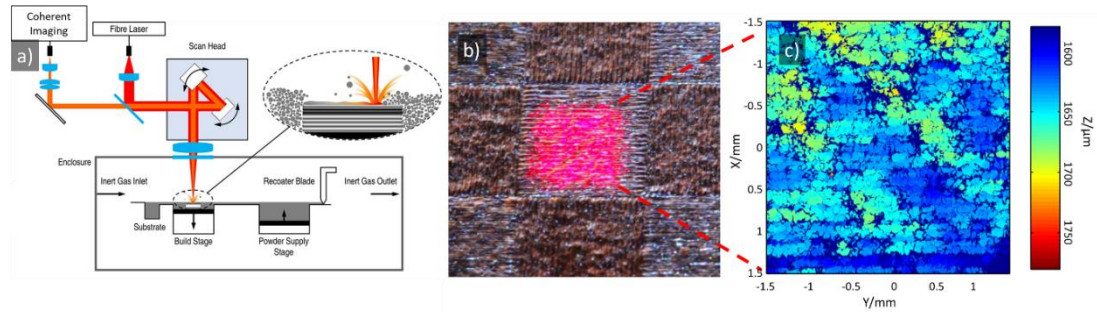


Figure 2.19. a) An example of the implementation of CI as in-situ measurement[36], b) PBF-LB surface, c) resulting profile scans of the structure [166].

Fleming et al. [36] developed a manual closed-loop control system utilising a CI method. This system could detect microscale protrusions and recesses using a CI system with vertical and lateral resolution of $7\text{ }\mu\text{m}$ and $30\text{ }\mu\text{m}$, respectively. Subsequently, the system compensated for detected impurities manually by applying additional processes.

2.3.5. Blade-mounted sensing

Another method for measuring surface height values involves mounting a sensor on the PBF machine's recoater blade. These sensors utilise the motion of the blade as the scanning direction of the surface. Table 2.5 shows the in-situ measurement methods for PBF, employing coherent imaging and blade-mounted sensors, with their respective specifications. Barrett et al. [38] used this approach by mounting a laser line scan profilometer, employing the triangulation method, on the recoater blade to obtain powder bed height measurements after melting. The scanner's spanning width was 15 mm , and the lateral profile data interval was $200\text{ }\mu\text{m}$. This study shows that blade-mounted sensing has the potential to detect LOF and spatters.

Table 2.5. In-situ measurement methods for PBF using coherent and blade-mounted sensors.

Reference	Sensor	Resolution	Detectable features / Size range
[166]	Coherent Imaging	Sampling Distance: 4 μm	20 μm – 40 μm
[167]	Coherent Imaging	Vertical Resolution: 25 μm Lateral Resolution: 100 μm	200 μm – 700 μm
[36]	Coherent Imaging	Vertical Resolution: 7 μm Lateral Resolution: 30 μm	Not specified
[38]	Blade-Mounted Laser Scan Profilometry	Lateral Profile Data Interval: 20 μm	An ellipse with a size of 1.00 mm $\times$ 0.25 mm
[39]	Blade-Mounted Contact Image Sensor	Spatial Resolution: $\sim 5 \mu\text{m}$	$\sim 14 \mu\text{m}$

Phuc et al. [39] introduced a practical blade-mounted sensing system which employed a contact image sensor (CIS). The sensor was detached from a flatbed document scanner and mounted onto a recoater blade (see Figure 2.20 a). The study explored the impact of varying scanning speeds on spatial resolution. The highest spatial resolution achieved was approximately 5 μm , with the ability to resolve features of approximately 14 μm in size. This study's height data was derived from the degree of blurriness observed in the acquired images (see Figure 2.20 b).

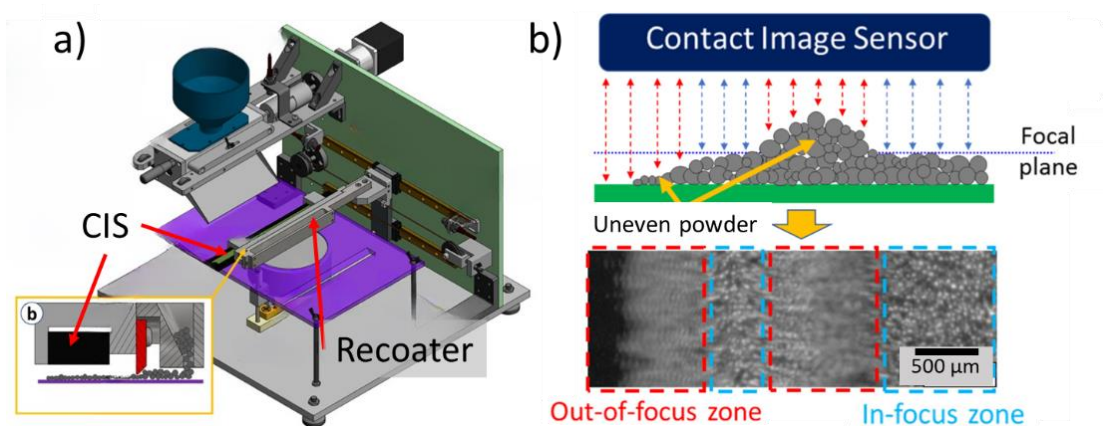


Figure 2.20. a) Computer-aided design of the experimental setup used for the powder bed scanner, b) schematic cross-section view of a layer and its corresponding top-view scan [39].

2.3.6. Acoustic sensing

Acoustic sensors are applicable for in-situ measurements in PBF. However, the data provided by these sensors might be challenging to interpret due to the absence of visual information, in contrast to sensors such as visible or thermal imaging sensors. Unlike imaging sensors, acoustic sensors do not require direct observation of the layer surface, so they offer more flexible positioning. Yet, factors such as acoustic reflection and resonance must be considered when designing these sensors' positions [169]. Table 2.6 presents the in-situ measurement methods for PBF, employing acoustic sensors, along with the features of interest and detection algorithms.

Table 2.6. In-situ measurement methods for PBF using acoustic sensors.

Reference	Sensor	Detectable features / Size range	Detection method/algorithm
[127]	Microphone	Balling and overheating on single weld tracks	Deep belief network model
[169]	Microphone	Balling on single weld tracks	Signal processing algorithms on LabView
[170]	Spatially resolved acoustic spectroscopy	Pores and cracks	Image processing

Ye et al. [127] installed a microphone into a PBF-LB machine to collect in-situ acoustic signals. Weld tracks with different morphologies, including tracks with balling and overheating defects, as well as a defect-free weld track, were produced. The acoustic signals of five different weld tracks were classified using a deep belief network model, achieving classification rates of approximately 70% for the original data and 95% for the data after applying the fast Fourier transform and denoising algorithms.

Similarly, Kouprianoff et al. [169] focused on analysing the acoustic signals of weld tracks with various qualities. The anomalies, such as balling and irregular weld tracks, were detected from acoustic signals using the signal processing algorithms in LabView.

In a study conducted by Pieris et al. [170], the capability of spatially resolved acoustic spectroscopy (SRAS), a laser ultrasonic technique, in the online measurement of PBF-LB was investigated. They utilised PBF-LB parts with polished surfaces and manufactured them using various laser power and hatching strategies. The findings indicated that SRAS is capable of identifying not only microscale surface impurities (such as cracking and unfused powders) but also sub-surface anomalies (such as pores).

2.3.7. Combination of methods

In addition to employing individual sensing methods, researchers have proposed integrating multiple sensing techniques to enhance defect detection accuracy. Combining different sensing methods, each with unique strengths, can overcome the limitations inherent in each technique. Table 2.7 outlines the in-situ measurement techniques for PBF discussed in this section, along with their specifications. Peng et al. [171] developed a coaxial multi-sensor defect detection system, integrating visible, infrared and polarisation imaging systems (see Figure 2.21 a). It has been demonstrated that multi-sensor systems exhibit superior results in extracting micro-scale defects, such as cracking, scratches and porosity, compared to individual sensor systems.

Petrich et al. [172] integrated visible range, acoustic and multi-spectral emission sensors to collect in-situ layer images, acoustic and laser emission data. Following data preprocessing, an ML algorithm was trained for defect detection using the in-situ data, scanning vector data and ex-situ XCT data as “ground truth”. It has achieved more than 98% accuracy for the binary classification of the surface status. A prediction result of the algorithm of a layer with a classification threshold of 0.9 can be seen in Figure 2.21 b. This study also presented the contributions of each sensing method to the performance of the defect detection algorithm and concluded that visible imaging demonstrates the highest contribution.

Snow et al. [173] used a combination of in-situ data, including visible range images, multi-spectral emissions, and laser scan vector data, and established correlations between these data and fatigue performance. The convolutional neural network has been used as a classifier to detect defects. The minimum detectable defect size was

limited to 200 μm by the camera resolution. The best classifier they trained exhibited a 100% accurate prediction for defects of 380 μm and above.

Table 2.7. In-situ measurement methods for PBF using a combination of sensing methods.

Reference	Sensor	Resolution	Detectable features / Size range	Detection method/algorithm
[171]	Combination of visible, infrared, and polarisation imaging	Pixel size on visible range imaging: 1.1 μm Pixel size on infrared range imaging: 30 μm Pixel size on polarisation imaging: 3.45 μm	$\sim 40 \mu\text{m}$	Image processing
[172]	Combination of visible range imaging, acoustic sensing, multi-spectral emission sensing, and laser scan vector data	Spatial resolution on visible range imaging: 10 $\mu\text{m}/\text{pixel}$	$\sim 30 \mu\text{m}$	Neural network
[173]	Combination of visible range imaging, multi-spectral emission sensing, and laser scan vector data	Spatial resolution of visible range imaging: 62.5 $\mu\text{m} \times 62.5 \mu\text{m}$	$> \sim 200 \mu\text{m}$	Convolutional neural network

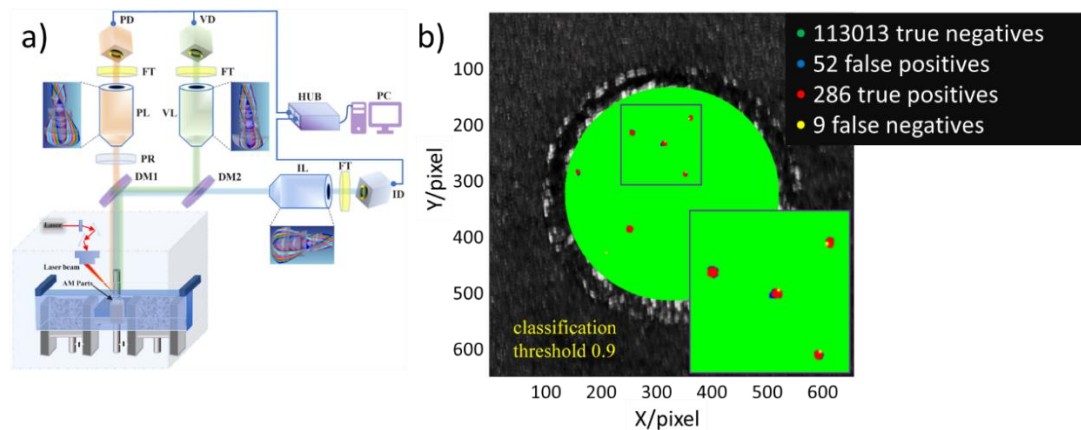


Figure 2.21. a) Schematic diagram of the multi-sensor system [171], b) Neural network prediction of defects on a layer (10 μm per pixel) [172].

Lastly, Remani et al. [28] combined three in-situ measurement methods: fringe projection and thermal imaging for measuring layers, and visible imaging for measuring melt pools. Their preliminary findings indicated that the system can be used to detect surface impurities such as protrusions and recesses.

2.3.8. Summary of the section

This section summarises the microscale surface impurities generated during the PBF process, along with their formation mechanisms and influence on the quality of the fabricated parts. In-situ measurement methodologies, which provide detection of these microscale surface impurities, are reviewed, along with their capabilities and limitations, and summarised in Table 2.8. Visible and thermal sensing methods are the most used in-situ measurement methods as they can produce a large amount of data when using high-resolution and high-speed sensors. It is essential to mention that the arrangement of cameras and lighting significantly influences detection accuracy in imaging. Variations in these configurations across different machines can affect brightness and contrast, resulting in varying detection quality from one machine to another. BSE sensors show robustness in harsh environments; however, it should be noted that these sensors can occasionally overestimate the dimensions of porosities, and beam current and voltage can influence the BSE-acquired data, leading to unstable results. Acoustic sensing, which benefits from positioning flexibility, offers a cost-effective method for detecting impurities. Nevertheless, current research involving acoustic sensors for detecting microscale impurities is limited to single weld tracks, potentially needing to capture real-world construction conditions.

Unlike 2D imaging techniques, 3D height mapping of the surface provides additional information by revealing variations in surface elevation, which is particularly important for detecting impurities as they often lead to changes in surface height. Various methods for measuring surface topography in PBF, including coherent imaging, fringe projection and blade-mounted systems, are discussed in detail. Among these methods, coherent imaging, as a coaxial approach, can be costlier to integrate. The fringe projection system might entail longer computation times than other methods, and installing projectors and cameras into a PBF machine can also be

challenging. Blade-mounted systems, however, have resolution tied to the recoater's speed.

Table 2.8. Overview of in-situ measurement methods' principal benefits and drawbacks.

Sensing Method	Benefits	Drawbacks
Visible Imaging	Straightforward implementation	High-resolution and high-speed sensors generate large datasets Detection efficiency varies due to the arrangement of cameras and lighting, resulting in varying detection qualities among machines
Thermal Imaging	Identification of thermal signatures	High-resolution and high-speed sensors generate large datasets
Electronic Imaging	BSE sensors demonstrate robustness in harsh environments	BSE-acquired data can be influenced by beam current and voltage
Fringe Projection	Generation of height maps	Installation of projectors and cameras into a PBF machine can be challenging Longer computation times
Coherent Imaging	Generation of height maps	Integration of this coaxial method may incur higher costs
Blade Mounted Sensing	Generation of height maps	Resolution is dependent on the movement and speed of the recoater
Acoustic Sensing	Offers positioning flexibility Cost-effective method	Limited applicability to single weld track experiments
Combined Sensing	Overcomes limitations of individual sensing methods	Registration of different types of data is required Large amount of data from different sensors

In-situ measurement and monitoring methods for detecting microscale impurities have been presented, each with its own advantages and limitations. However, there are significant gaps in general in the applicability of these methods in real-world industrial fabrication settings. While most methods collect data in real-time, the actual detection often occurs afterwards due to the high computational costs involved. Moreover, many studies do not specify the time required for detection, making it impractical to implement these methods as real-time feedback control systems.

Furthermore, variations in machine types and associated process parameters can influence both the efficiency of the sensing process and, subsequently, the accuracy

of the assessment. For methods that utilise machine learning (ML) algorithms to detect impurities, an additional challenge lies in the generation of suitable training datasets. This task typically involves the manual collection and labelling of data by human operators, rendering the process both time-consuming and inherently subjective.

In section 2.2, certain microscale surface impurities, along with their influences on part quality, have been presented. It has been reported that some impurities are even smaller than 10 μm . However, the accuracy of most detection methods diminishes as the size of the impurity decreases, especially when it falls below 100 μm , mostly due to their resolution limits. In order to provide a robust evaluation system, detection accuracy needs to be stable. On the other hand, real-time detection is also desired to meet the industry criteria. However, instead of detecting only some specific defects, the detection method needs to target all microscale impurities (even smaller than 100 μm in size) to be a general quality evaluation system. The average total cost of a PBF part typically ranges from several thousand to tens of thousands of US dollars [174]. High-resolution post-processing systems, such as micro-CT scanners, generally cost between approximately USD 100,000 and over USD one million, while outsourced scanning services for parts can also be both costly and time-consuming [175]. Given that high-resolution post-processing is expensive and slow, such inspection is often impractical. This challenge underlines the need for in-situ monitoring to identify microscale defects at an earlier stage.

2.4. Machine learning methods for measurement and monitoring of defects and impurities

The integration of digital systems with physical manufacturing processes is a key characteristic of Industry 4.0. Within this framework, data is collected during the fabrication with sensors and is transferred to the digital environment for further analysis or measurement such as quality assessment and defect detection. Advancements in sensor technology have led to a substantial increase in both the volume and dimensionality of collected data. The complexity and scale of this data render manual analysis by humans virtually unfeasible. While statistical methods can be applied in certain cases, they often fall short in uncovering hidden or non-linear

patterns within the data. ML techniques, by contrast, are capable of rapidly processing and analysing large datasets, enabling the detection of complex and non-obvious relationships in the data [176].

ML approaches can uncover patterns and relationships within extensive and complex datasets, often with little or no prior domain knowledge. In the context of PBF-LB, ML models have been applied to various tasks, including process optimisation, classification, and defect detection. This section specifically focuses on ML methods utilised for defect detection and quality assessment.

In this thesis, one of the main goals is to develop ML algorithms capable of responding rapidly enough for in-process detection, achieving a minimum accuracy of 90%. These algorithms will be further optimised by adapting their structures to the dimensions of the input data, thereby maximising both speed and accuracy. The details of the ML algorithms employed in this study are presented in Chapter 6.

The performance of ML-based defect detection is heavily influenced by the quality of the input data [176]. In addition, selecting an appropriate ML model is essential for achieving high detection accuracy. ML techniques can generally be categorised into four types based on their training paradigms: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning (see Figure 2.22).

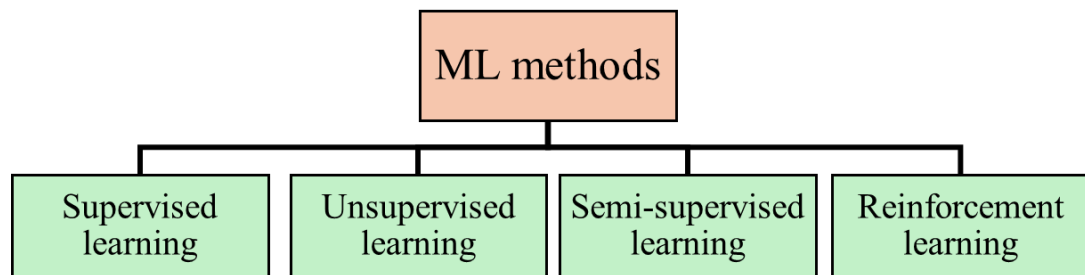


Figure 2.22. Classification of ML algorithms based on the training paradigms.

2.4.1. Supervised learning

In supervised ML models, training is conducted using a labelled dataset, where each input is paired with its corresponding output. Input data can be in the spatial, time or frequency domain. The ML model learns the relationship between the input and the output. These labels can be either numerical or categorical, depending on the nature of the training. Once trained, the model attempts to predict the output for new,

unseen inputs. A key disadvantage of supervised learning is that the labelling process can be time-intensive, and human errors during labelling may negatively affect the model's performance.

In the context of PBF-LB processes, the input typically consists of in-situ collected data, while the output may represent process parameters, defects, mechanical properties, or surface characteristics of the printed part. The registration of input and output data can be performed either automatically or manually, depending on the situation.

A supervised ML model has an objective function, called the cost function, that calculates the error between predicted and actual output. During the training, some parameters are updated in order to reduce the cost function. The supervised learning models can be trained by using regression and classification-based algorithms.

A regression model establishes a mathematical relationship between the target variable (output) and the independent variables (input). In the context of defect detection in PBF-LB processes, the output typically represents process anomalies or defects, while the input consists of process parameters or in-situ data.

The choice of regression model depends on the nature of the relationship between the variables and the number of inputs involved. For continuous relationships, polynomial regression models - such as linear or higher-degree polynomial correlations - can be applied to model the behaviour of the process. On the other hand, for discrete or categorical outcomes, logistic regression models are more appropriate as they map inputs to probabilities, making them suitable for classifying the occurrence of specific defects or anomalies. Figure 2.23 illustrates how difference between the two models.

Compared with artificial neural networks, linear regression is a simple and highly interpretable model that predicts outputs as a linear combination of input parameters. It can be trained relatively quickly and performs well with small datasets [177].

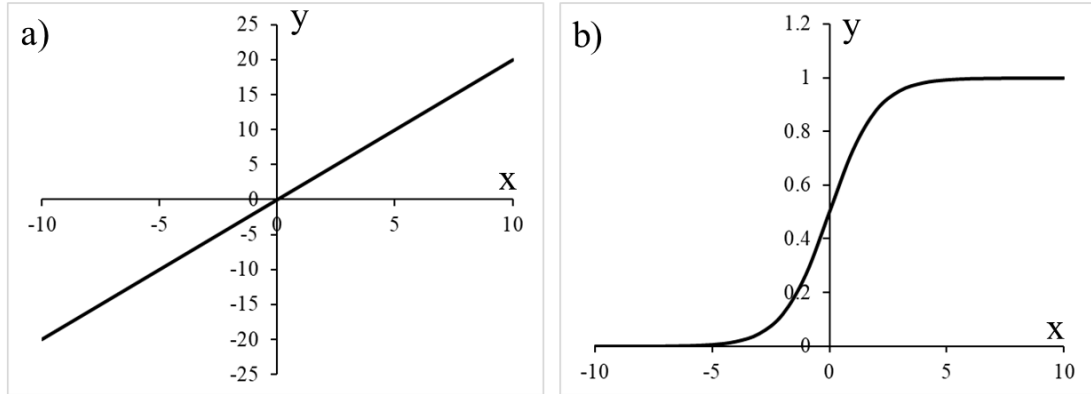


Figure 2.23. a) linear and b) logistic regression graphs.

In PBF-LB processes, the input and output data often exhibit high dimensionality and complex non-linear relationships. Commonly employed regression models for analysing and predicting such data include linear regression and logistic regression, along with other widely used models such as:

1. Linear Regression Technique
2. Logistic Regression Technique
3. Stepwise Regression Technique
4. Ridge Regression Technique
5. Lasso Regression Technique
6. Elastic Net Regression Technique

The details of these regression models can be found in [178]. Regression algorithms have been extensively employed in PBF-LB processes for process optimisation, defect detection, and classification. Logistic regression, in particular, has been frequently applied to identify fabrication anomalies and defect classification. For instance, Mahmoudi et al. [149] used thermal imaging to detect cavity defects on PBF-LB surfaces and evaluated four different classifiers, finding that logistic regression provided the highest classification accuracy with the lowest error rate. Paulson et al. [179] utilised logistic regression with infrared and X-ray images to predict subsurface porosity formation. Similarly, Repossini et al. [180] developed a logistic regression model using high-speed imaging to examine the relationship between spattering phenomena and various melting conditions. Gaja et al. [181] applied acoustic emission signals as input data to detect cracking and porosity in

laser metal deposition, comparing logistic regression with artificial neural networks (ANN), and concluded that the performance of both models was comparable. Tapia et al. [182] also developed a regression model based on a Gaussian process to predict porosity. These studies show that the regression models, especially logistic regression models, have the capability to detect and classify the defects in PBF-LB.

Support vector machine (SVM) is another type of traditional algorithm based on ML used for regression and classification problems in PBF-LB. SVM can be used for either linear or non-linear classification. In linear SVM classification problems, each sample is defined by a support vector and support vectors in different categories can be separated by several classifiers. SVM finds the best classifier called optimal separating hyperplane by maximising the margin between the support vectors and the classifier (Figure 2.24).

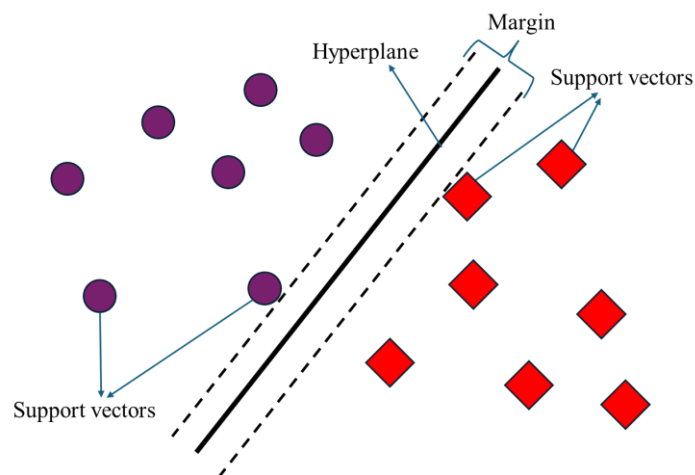


Figure 2.24. Linear SVM graph.

In non-linear SVM, the support vectors may not be separated with a linear hyperplane; therefore, a kernel function simulates each data in higher dimensions in order to separate the support vectors linearly. Figure 2.25 explains kernels' processing where a two dimensional data (x, y) is mapped into a three dimensional data (z, k, t). While the two dimensional data cannot be separated with a linear classifier, three dimensional data can be separated with a linear classifier.

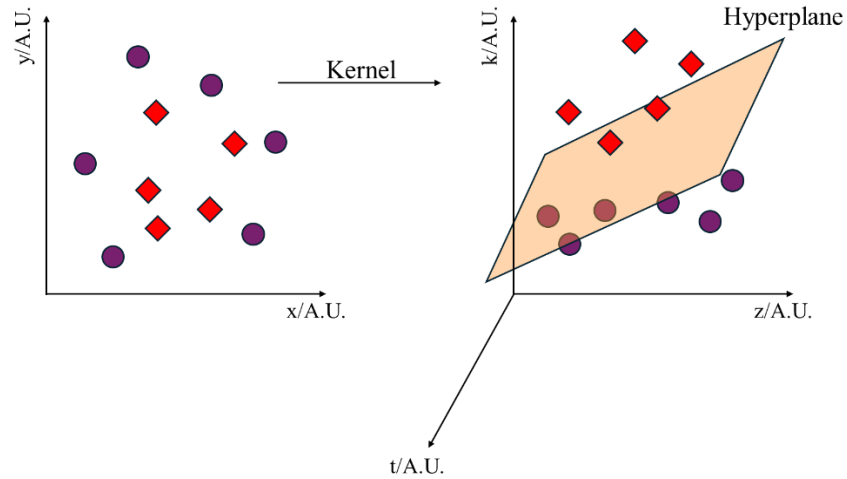


Figure 2.25. Non-linear SVM, kernel processing.

Gobert et al. [134] developed an SVM model to detect defects such as pores and cracks. They used the correlation between the in-situ images and offline computed tomography data and achieved more than 80% detection accuracy.

Imani et al. [183] investigated the effects of process parameters on the formation of porosity and developed several supervised ML algorithms, including SVM, KNN and ANN, for porosity detection. It has been achieved around 90% detection accuracy with SVM.

Ye et al. [184] developed a linear SVM in order to distinguish acoustic signals of different processing conditions, resulting in different weld track quality. Single weld tracks were fabricated with different process parameters, and acoustic signals were recorded by a microphone installed in a PBF-LB machine. Petrich et al. [185] trained two ML algorithms, SVM and NN, in order to classify the surface as defective or defect-free. The algorithms were trained with in-situ optical images and 3D computed tomography data. They showed that both algorithms have more than 85% classification accuracy (Figure 2.26).

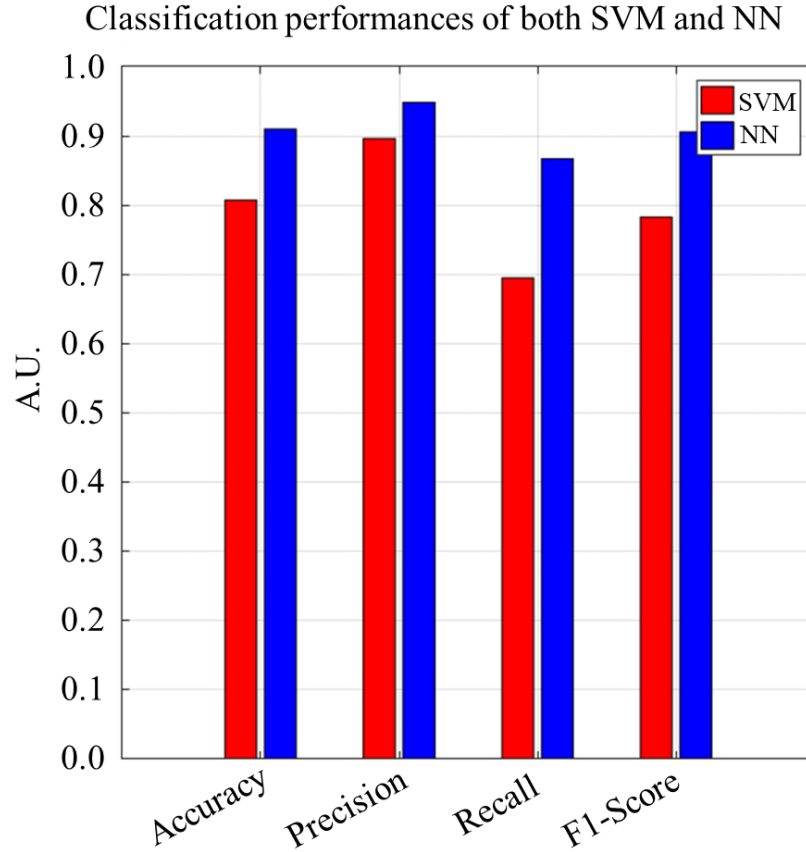


Figure 2.26. Classification performances of both SVM and NN [185].

2.4.1.1. Bayesian classifier

Bayesian classifier (BC) is a probabilistic classifier and a statistical inference system, which can provide statistical information about the probabilities of occurrence using likelihood and a priori probability as [186]

$$P(y|x) = \frac{P(x|y)P(y)}{P(x)}, \quad (2.2)$$

where, y represents the class, x represents the features of the object, $P(y|x)$ represents the posterior probability, $P(x|y)$ represents likelihood which is the conditional probability of occurrence of feature x given a class y , $P(y)$ represents class prior probability, $P(x)$ represents predictor prior probability.

BC have been used in various applications, such as lithology identification [187], classifying genes [188], risk prediction [189] and leak localisation [190]. BC have also been used in PBF-LB for various purposes, for example, to calculate the probabilities of the surface being defective or not, to analyse surface quality

quantitatively. For example, Aminzadeh et al. [133] applied BC in order to detect defective regions or layers on PBF-LB from the in-situ surface images. They first trained an ML algorithm to label the surfaces as being defective or not, and then trained the BC. They achieved a classification ratio with a true positive rate of 89.5% and a true negative rate of 82%.

Shen et al. [191] employed BC to predict the relative density of parts produced through PBF-LB based on process parameters. Additionally, they compared the performance of BC with a multilayer perceptron, demonstrating that the multilayer perceptron proved to be more efficient in their specific case. Similarly, Li et al. [192] applied BC to predict the density of the parts fabricated by PBF-LB from the process parameters. The predicted values with the true values are presented in Figure 2.27.

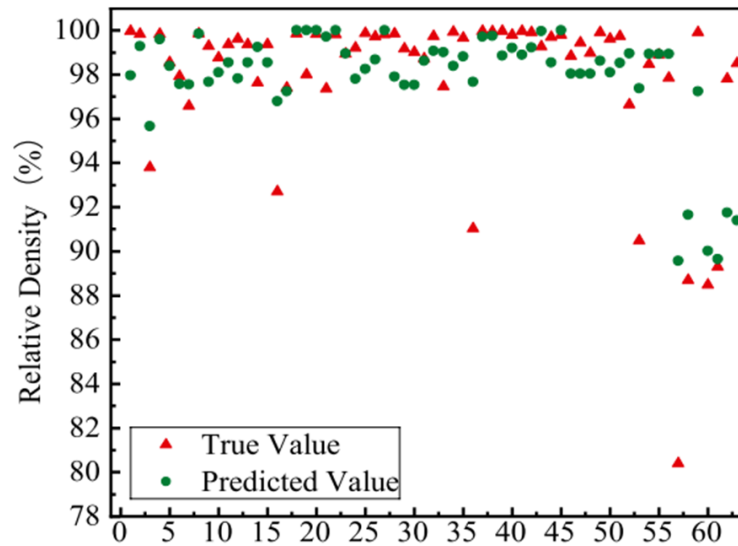


Figure 2.27. The predicted values compared to the true values of the BN Model [192].

Nath and Mahadevan combined the Bayesian method with a physics-based method in order to build a predictive quality control mechanism for PBF-LB by using in-process data [193]. The model predicts the porosity formation from thermal data and changes the process parameters according to the predictions.

2.4.1.2.K-nearest neighbour

K-nearest neighbour (KNN) is one of the most widely used supervised ML algorithms that can be used for classification and regression problems based on how

close a data point is to others. KNN is simple in interpretation, easy to implement, and it works with both numerical and categorical data. It can be applied in the case where there is no information about data distribution, including defect detection in PBF-LB.

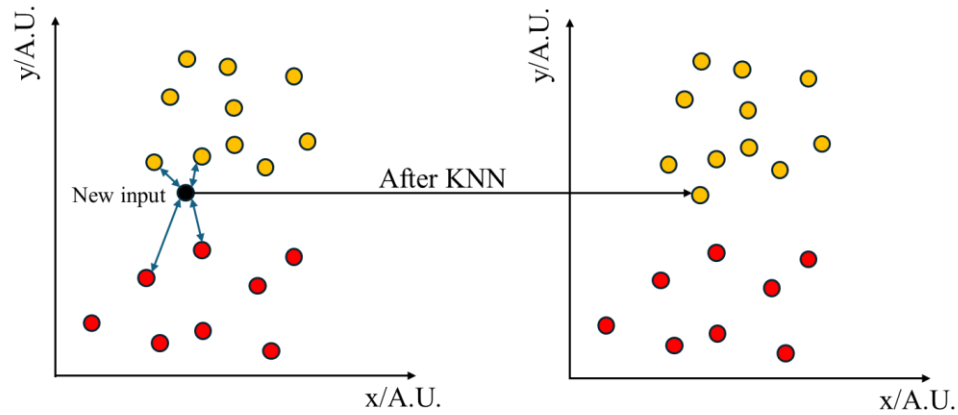


Figure 2.28. Class of the new input after KNN is applied.

Bewans et al. [194] developed a digital twin for PBF-LB by training a KNN model. The model has been trained with simulated thermal history and in-situ sensor data as input, and ex-situ porosity and microstructure data as output. Jatti et al. [195] have applied various ML models in order to predict the tensile strength of PBF-LB parts from their fabrication process parameters. Within the classification models, KNN showed the highest accuracy with 92.5%.

Smyrnnow et al. [196] built various classification models including KNN in order to predict material toughness for PBF-LB parts from AlSi10Mg0.5. The models establish the correlations between process parameters and Charpy impact testing results. Similarly, Gorgannejad et al. [197] trained KNN, SVM and Gaussian Naïve Bayes algorithms for predicting the porosity formation during PBF-LB fabrication process. They correlated in-situ acoustic and thermal data with the porosity formation obtained from in-situ X-ray data.

2.4.1.3. Artificial neural network

An ANN is a ML algorithm designed to address both regression and classification tasks. It is modelled after the structure of the human brain, consisting of artificial

neurons that simulate biological neurons. These neurons are organized into interconnected layers, typically comprising an input layer, one or more hidden layers, and an output layer. Each layer plays a specific role in processing information, with the neurons collectively working to learn patterns from data and make predictions.

Each neuron in a layer transmits the input to the neurons in the next layer by applying a weight and a bias value. During the training, these weight and bias values are adjusted in order to reduce the error between the targeted and predicted output. In case the ANN is fed with labelled data, the ANN can be used for classification and defect detection.

Each neuron within a layer processes the input by applying a weight and bias before transmitting it to the neurons in the subsequent layer. During training, these weight and bias values are iteratively adjusted with an optimisation algorithm to minimise the error between the predicted output and the target output. When an ANN is trained using labelled data, it can be employed for tasks such as, process optimisation, defect detection and classification.

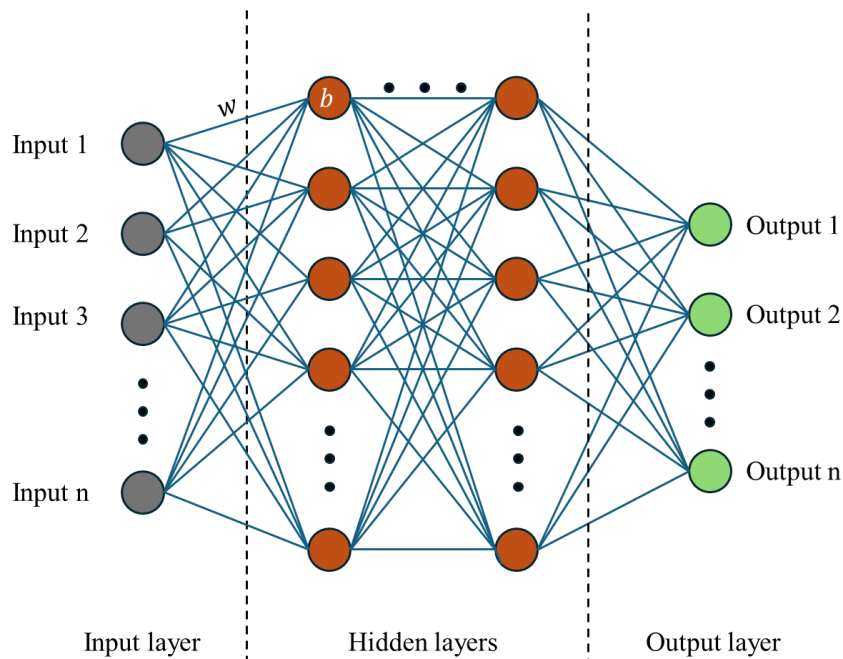


Figure 2.29. The architecture of an ANN.

Centola et al. [198] used different ANN types, i.e. feed-forward neural network, physics-informed neural network, and bi-linear feed-forward neural network, in

order to create a model which can predict the fatigue strength of PBF-LB parts from the fabricating parameters and post-process treatments. Similarly, Tridello et al. [199] trained two ANN algorithms, feed-forward neural networks, to assess the probability of the formation of defects and their size distribution.

The ANN has been widely used for process optimisation. For example, Simson et al. [200] investigated the influences of process parameters on the geometry of single weld tracks. They trained an ANN algorithm with three process parameters, which are laser power, scanning speed and layer thickness as input and with three geometric features of the weld track, which are track width, remelting depth and track height as output. Jahan et al. [201] trained a graph based ANN with simulated process parameter data, such as scanning speed and laser power, in order to predict the behaviour of the next layer based on the previous layer.

Malekipour et al. [202] designed a closed-loop hybrid-control system to modify the process parameters in PBF-LB. The system utilises ANN to optimise the energy density to prevent defect formations. Shin et al. [203] developed an optimisation method for PBF-LB specifically for Ti-5Al-5V-5Mo-3Cr alloy. Through this study, various components were fabricated under different processing conditions – including variations in laser power, laser scanning speed, and hatching distance – and the resulting densities were measured using the Archimedes method. An ANN model was then trained on these data, enabling prediction of relative density based on the specified processing parameters.

In addition to the process optimisation ANN has been used for prediction/detection of defects and impurities, specifically the porosity. For example, Mohammed et al. [204] applied an ANN model to predict the porosity/density ratio on PBF-LB parts. They used experimental and synthetic X-ray computed tomography data to train the algorithm and achieved a good prediction accuracy with 0.9981 of R^2 . Schlicht et al. [205] introduced a method for inline porosity assessment in polymer parts produced by PBF-LB technology. This approach utilises an ANN to analyse the correlation between optical data, captured by a camera, and the resulting porosity in the manufactured parts.

Babakan et al. [206] developed four models, including ANN, in order to predict the porosity from processing parameters – laser power, scan speed, hatch space, and island size – on PBF-LB parts fabricated from AlSi10Mg alloy. Schlicht et al. [205] proposed an inline porosity assessment method for PBF-LB of polymer parts. The correlation between the optical data collected by a camera and porosity was processed by an ANN.

Gaja et al. [181] trained an ANN to detect and classify defects, including porosity and cracks, based on acoustic emission signals. The network architecture comprised 25 neurons and was trained over 30 iterations using a dataset of 25 data points. Model performance was validated with an additional 6 data points and further tested with a separate set of 6 data points. Imani et al. [207] developed a defect detection method utilising a deep artificial neural network approach that analyses in-situ optical images of the powder bed in PBF-LB processes. Their findings indicate that the model successfully identifies cylindrical and cubic defects with dimensions of 750 μm , achieving an accuracy rate of 92.5%. Xu et al. [208] proposed a laser ultrasonic method combined with ANN to detect surface defects, holes. They used a multi-feature fusion imaging to mitigate the effect of noise.

Mohammadi et al. [209] proposed an approach for real-time defect detection – specifically for identifying porosity and cracks – using various ML techniques, including ANN. The ANN model was trained with in-situ acoustic emission data collected during the fabrication of H13 tool steel. Upon completion of training, the model was tested on 316L samples, where it successfully identified trends in build quality. Jahan et al. [210] developed defect prediction and defect correction models based on ANN and game theoretic modelling, respectively. The ANN model is trained with processing parameters and temperature data collected by the IR camera during the fabrication to map surface irregularities, voids and other defects.

Ozel et al. [211] used ANN model to predict the surface texture parameters such as Sa , Sq , Ssk , and Sku from the PBF-LB laser scanning parameters. They build various nickel alloy parts by PBF-LB and measured the surface topographies of the parts by using a focus variation microscopy. It has been used a feed forward neural network with a quasi-Newton backpropagation algorithm.

2.4.1.4. Convolutional neural network

A Convolutional Neural Network (CNN) is a specialised form of ANN primarily used in computer vision tasks, including image classification, object detection, and image segmentation. A CNN architecture consists of three core types of layers: convolutional, pooling, and fully connected layers (Figure 2.30).

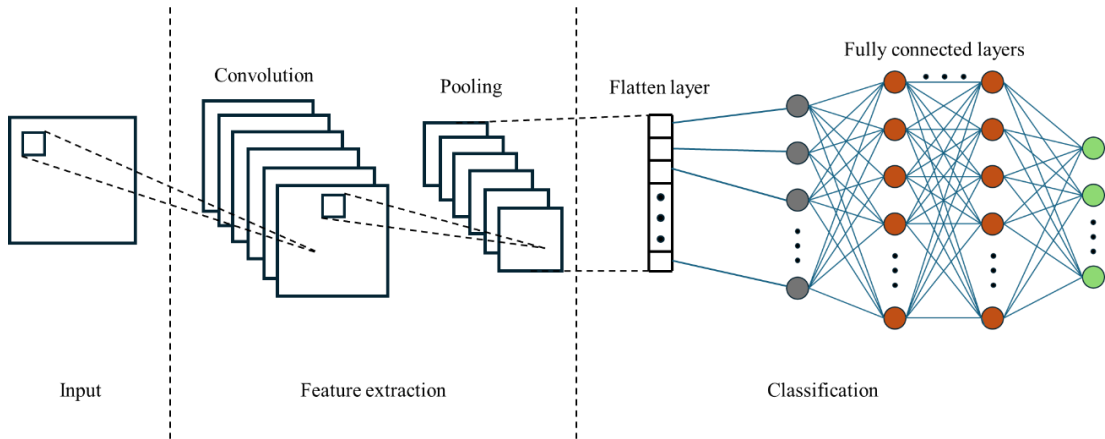


Figure 2.30. A generic schematic of a CNN.

The convolutional and pooling layers work together to extract key features from images. In the convolutional layer, a kernel operator is applied, allowing different kernels to identify specific features in images, such as edges and curves. Following this, the pooling layer selects the most relevant features from the output of the convolutional layer. Finally, the fully connected layer maps these extracted features to the desired output, enabling the network to make predictions based on the processed image data.

The CNN has been applied to defect detection tasks within the PBF-LB additive manufacturing process. One of the main defects focused on in the literature is the porosity. For example, Li et al. [212] proposed a framework to detect the porosity ratio of the samples fabricated by PBF-LB. They developed a deep transfer learning model integrating CNNs and transfer learning to predict porosity ratios on PBF-LB surfaces. To train their model, they fabricated 316L stainless steel samples using various processing parameters, resulting in samples with differing porosity ratios. During the fabrication process, optical images of the sample surfaces were recorded and subsequently labelled according to the porosity ratios measured post-fabrication

from cross-sectional images. Based on the three levels of porosity ratio, the model achieves more than 99% classification accuracy.

The CNN algorithm with acoustic sensing has also been used for porosity detection. Ahmmed et al. [213] developed a CNN model trained using in-situ collected acoustic data as input and ex-situ collected X-ray radiography data as output, specifically to identify porosities. To enhance the model's robustness, they applied data augmentation techniques to the acoustic dataset. Li et al. [214] also introduced a method for detecting porosity using acoustic data, following a series of data transformations. Their approach utilised CNN algorithms designed to capture multi-scale information and to fuse spatial information at multiple levels, resulting in a detection accuracy of 99.12%.

Several studies have demonstrated that in-situ thermal data can be used to establish a correlation with porosity formation. Lee et al. [215] proposed a method for detecting porosity using a 3D CNN algorithm. The algorithm was trained on melt pool data gathered via an in-situ measurement system employing photodiodes, alongside micro-computed tomography data collected post-fabrication. Oster et al. [216], in contrast, trained a one-dimensional CNN using in-situ thermography data to detect porosity formation in Haynes 282 samples produced by PBF-LB. Following feature extraction, the thermography data was registered with X-ray computed tomography data. The CNN model achieved a good prediction accuracy with R^2 score of 0.90.

Mao et al. [217] proposed a framework to predict future porosity formation by analysing the in-situ thermal properties of previously deposited layers. Their approach employs a CNN model, consisting of two convolutional layers, each followed by a pooling layer, and concluding with a fully connected layer. The framework was tested on computed tomography data, achieving a precision of 0.72. Oster et al. [218] developed a porosity prediction model using in-situ thermography data, leveraging a custom CNN algorithm. This approach involves reconstructing the thermal history of an AISI 316L stainless steel component from thermogram data. After preprocessing, this data is used to train and validate the CNN algorithm for porosity prediction. The model achieved a prediction accuracy of 96%.

Smoqi et al. [219] developed a methodology for detecting porosity using in-situ melt pool images captured by a pyrometer. They compared a CNN algorithm, trained solely on melt pool images, with other ML algorithms such as KNN and SVM, which were trained on process signatures, including melt pool length, temperature, and distribution. The findings demonstrate that the CNN approach achieved comparable classification accuracy without requiring feature extraction.

In addition to experimental data, simulated data has also been used to develop a detection method. Ansari et al. [220] developed a model for detecting porosity using a CNN and synthetically generated porosity data. They examined two distinct training approaches: one using CAD data and the other using XCT data. Their findings indicate that the model trained with XCT data achieved a higher accuracy in detecting pores as small as 200 μm .

In addition to its use in defect detection, CNN has also been applied for defect classification in PBF-LB. Jiang et al. [221] employed an off-axis camera to capture images of the powder bed during the fabrication process of PBF-LB. They then trained a CNN algorithm using a defect parameter vector along with the powder bed images, achieving a defect classification accuracy exceeding 80%. Zou et al. [222] proposed defect classification methods using CNN combined with in-situ signal fusion of photodiode data. Their approach demonstrated varying classification accuracies depending on the signal fusion technique used and the defect sizes. The optimal signal fusion method achieved classification accuracies ranging from 74.41% to 98.83% for defect sizes between 100 μm and 500 μm .

Schwerz et al. [223] developed an algorithm for defect detection and classification based on OT and CNNs. They produced Hastelloy X samples with varying processing parameters, resulting in distinct types of porosity formations, namely lack of fusion, keyhole, and residual porosity. The CNN algorithm was trained using in-situ OT data collected during fabrication, which included intentionally induced defects, and was subsequently tested on unseen data, achieving a classification accuracy exceeding 96% (see Figure 2.31).

Luo et al. [224] developed a method for monitoring spattering behaviour by utilising acoustic signals in conjunction with ML algorithms, specifically CNNs, recurrent

neural network, long short term memory and gated recurrent unit. To train these ML models, spattering behaviour data was captured via a coaxial high-speed camera, enabling the algorithms to correlate acoustic signals with the observed spattering data. For the category with two spattering levels, the 1D-CNN achieves the highest accuracy, reaching 85.08%.

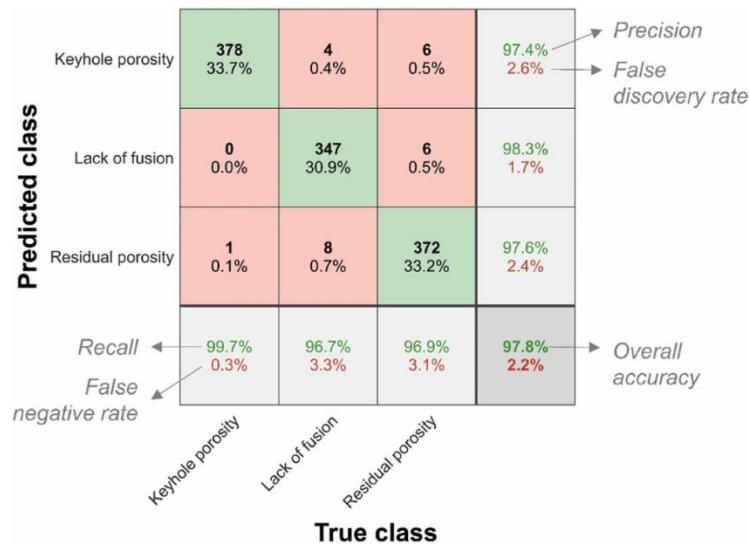


Figure 2.31. Confusion matrix of the CNN trained for classification [223].

CNN algorithms have also been used for defect segmentation purposes on PBF-LB surfaces. For instance, Wang et al. [225] employed a CNN algorithm to segment surface irregularities such as balling and porosity from secondary electron microscopy images collected after the fabrication. Fang et al. [226] developed a melt pool monitoring system using an off-axis high-speed camera and a U-Net-based CNN algorithm. Following the preprocessing of the melt pool images, the CNN algorithm was trained to perform segmentation.

Pan et al. [227] used a type of CNN, DeepLabV3 + network, for the purpose of defect segmentation on tomographic imaging of PBF-LB parts fabricated from Ti6Al4V alloy. Similarly, Gu et al. [228] employed CNN for image segmentation tasks. Their approach involved using CNN to segment melt pools in microscopy images of cross-sections from PBF-LB samples, as well as to detect porosities. They compared various CNN architectures, including U-Net, LinkNet, and FPN, using different backbone models, specifically EfficientNet-B7 and DenseNet-201. The

results demonstrated that the combination of U-Net with EfficientNet-B7 achieved the highest detection accuracy.

Some studies have focused solely on weld tracks rather than the entire powder bed, as the quality of the weld track can influence both the surface finish and the overall quality of the final product. Chen et al. [229] conducted an investigation into weld track quality using in-situ acoustic sensing combined with various classification algorithms, including SVM, ANN, and CNN. They fabricated single weld tracks from a copper-tin alloy with varying laser power and scanning speed. Across three categories – over-melted, normal, and unmelted – the CNN demonstrated the highest classification accuracy, achieving a rate of 99%. Similarly, Cao et al. [230] evaluated weld track quality by categorising the weld track status into three distinct conditions: over-melted, normal, and under-melted. During the fabrication of PBF-LB samples under various processing parameters, photodiode signals were collected. These 1D photodiode signals were then converted into 2D grayscale images and subsequently analysed using a CNN algorithm. The approach achieved an accuracy rate of 95.81%, with a minimal processing time of 15 ms.

Despite ongoing development and optimisation of PBF-LB machines, defects related to the recoater and other powder delivery systems may still occur. Several studies have identified such defects using CNN algorithms. For example, Wei et al. [231] proposed an online monitoring system utilising a CNN algorithm to detect powder layering defects – including insufficient layering, scraper stripes, and strip powder stacks (see Figure 2.32) – using in-situ optical images. Their test results demonstrated a detection accuracy of 98.63%, with a detection time of approximately 3.5 seconds. Similarly, Qiu et al. [232] developed a surface quality evaluation model leveraging a CNN algorithm to predict the balling level of surfaces in PBF-LB processes. They trained a CNN algorithm, referred to as a finite depth separable convolution network, using microscopy images of PBF-LB surfaces exhibiting various balling levels – categorised as slight, moderate, and severe. Their model achieved a recognition accuracy of 100% during testing, demonstrating its high efficacy in surface quality assessment. Similar to the approach in [232], Xin et al. [233] investigate assessing the quality of the powder layering process in PBF-LB. They utilise various types of CNNs to detect layering defects from optical images.

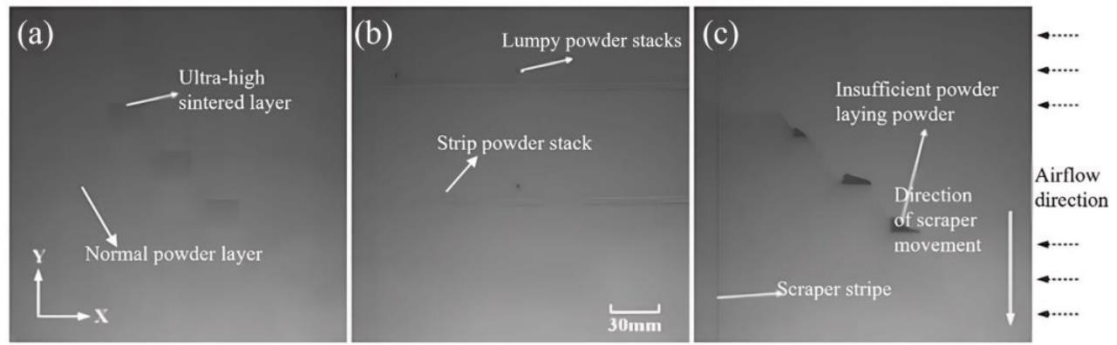


Figure 2.32. Different types of powder layering defects [231].

Ansari et al. [234] utilised powder bed images collected via the EOSTATE monitoring system provided by the machine's manufacturer. They fabricated samples with overhang geometries to intentionally induce surface deformation. After categorising the images as either defective or normal, they trained a CNN algorithm to predict surface deformation. Their testing demonstrated that the model achieved a classification accuracy exceeding 99%. Fischer et al. [235] developed a surface deformation classification algorithm that utilises CNN by analysing powder bed images, captured dynamically by a camera mounted on the recoater. The algorithm was trained on 45 data sets, enabling the classification of surface irregularities (see Figure 2.33) – such as spatters, incomplete fusion, and balling – with a peak accuracy rate of 99.15%.

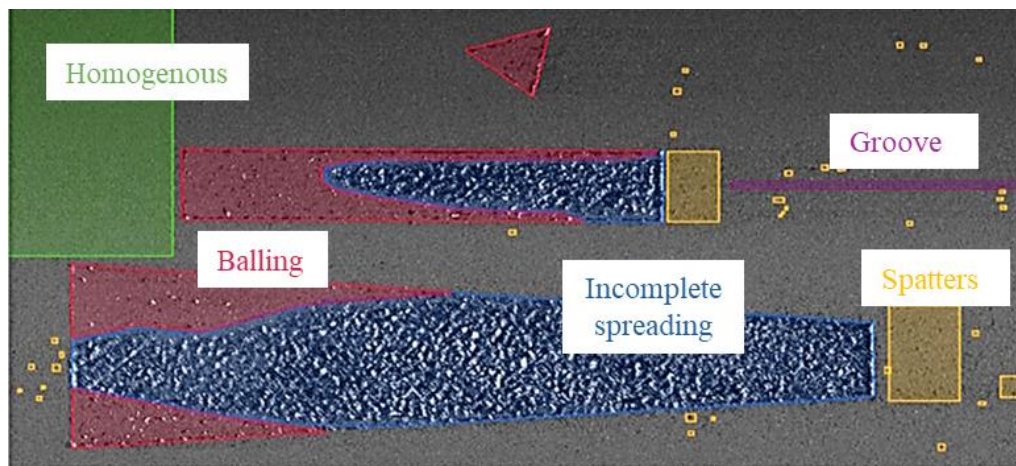


Figure 2.33. Detection of defected and homogenous surface [235].

Chen et al. [236] proposed a framework utilising CNN to detect defects in powder layering, based on images of the powder bed recorded during the fabrication process.

They trained and tested the algorithm on the production of FeSiCr magnetic samples, enabling it to identify and classify three types of defects: uncovered powder, uneven powder, and recoater scratches. The results demonstrated a classification accuracy of approximately 93%, achieved within an average processing time of 0.22 seconds.

Xing et al. [237] conducted a comparative analysis of various CNN algorithms to assess melt pool quality using a coaxial high-speed camera. In-situ data was collected during the fabrication of Q235A steel samples across five distinct laser energy levels. The algorithms demonstrating the highest classification accuracy were ResNet and Inception, both achieving an accuracy of approximately 97%.

Several studies employing CNNs have integrated multiple sensing systems to improve detection accuracy, despite the associated increase in data volume. For instance, Li et al. [238] developed a multi-fusion sensing framework to evaluate the fabrication quality of PBF-LB processes using CNN algorithms. This framework employs three distinct sensing systems – optical imaging, acoustic emission sensing, and photodiode detection – to individually train the algorithms and subsequently assess the effect of sensor fusion. The findings indicate that this multi-sensor fusion approach significantly enhances the accuracy in detecting porosity ratios. Pandiyan et al. [239] proposed a defect classification model for PBF-LB processes, utilising CNN and long short-term memory algorithms. They employed four distinct sensing technologies – visible light, infrared, back reflection, and acoustic emission – to gather in-process data for detecting three classes of defects: lack of fusion, conduction mode, and keyhole defects. To train their model, they fabricated 316L stainless steel samples containing these defects using a small-scale PBF-LB system equipped with the sensing technologies and X-ray imaging to confirm defect formation.

Gaikwad et al. [240] developed a framework to detect porosity formation in 316L samples produced by a PBF-LB process with varying laser spot sizes. Alongside SVM and multilayer perceptrons, a CNN-based algorithm was employed to identify porosities using in-situ data from optical and thermal imaging sensors. These sensors capture process signatures, including melt pool morphology and spattering. Snow et al. [173] employed CNNs for defect detection using in-situ multi-sensor data, including optical images of the powder bed, multi-spectral emissions, and machine

vector data. Ti6Al4V samples were fabricated using PBF-LB and subsequently scanned via XCT to identify defects and label the in-situ data accordingly. The authors then compared the classification accuracy of CNNs trained on individual in-situ data types as well as on fused data from multiple sources.

In addition to defect detection, prediction, and classification, CNNs have also been employed to predict surface characteristics. Gerdes et al. [241] proposed a framework that utilises CNN to predict surface roughness values of magnesium alloy samples produced via PBF-LB based on hyperspectral imaging data.

2.4.2. Unsupervised learning

Unsupervised learning is a type of ML that analyses data without the need for labels or categorisation provided by human supervision (Figure 2.34). This makes unsupervised learning particularly effective for tasks where there is no prior knowledge about the data. Unlike supervised learning, unsupervised learning does not rely on output data for training; instead, it uses only input data to identify patterns and relationships within the dataset. Despite its advantages over supervised learning algorithms, unsupervised learning has been relatively underutilised in defect detection tasks within PBF-LB processes compared to supervised learning approaches.

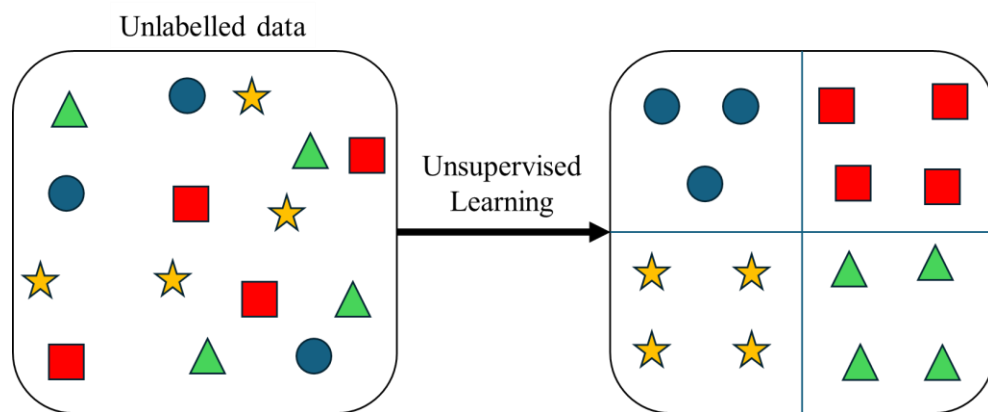


Figure 2.34. Schematic representation of unsupervised learning.

2.4.2.1.K-means clustering

The K-means clustering (KNN) algorithm categorises input data into a predefined number of clusters. Cluster centres are initially estimated, serving as starting points

for subsequent iterations. During each iteration, data points are assigned to the nearest cluster centre, and the distances between data points and cluster centres are calculated. New cluster centres are then determined to minimise these distances.

Jayasinghe et al. [242] utilised the K-means clustering algorithm and a Gaussian Mixture Model (GMM) to classify the density of PBF-LB parts based on in-situ photodiode data. Their approach achieved classification accuracies of approximately 83% and 93%, respectively. Scime and Beuth [243,244] proposed anomaly detection methods based on K-means clustering using optical powder bed and melt pool images. Similarly, Snell et al. [245] compared supervised and unsupervised classification algorithms to analyse pores in metal specimens produced by PBF-LB. Their findings indicated that the K-means clustering algorithm yielded the most accurate results for 3D X-ray computed tomography data.

Grasso et al. [246] proposed an automated method for defect detection, utilising off-line recordings of melt pool images in conjunction with the K-means clustering algorithm. Before clustering, the melt pool images were pre-processed using Principal Component Analysis (PCA). Their findings demonstrated that this approach was effective in identifying defects related to localised overheating.

2.4.2.2. Self-organising map (SOM)

A Self-Organising Map (SOM), also referred to as a Self-Organising Feature Map (SOFM) or Kohonen Map, is an unsupervised ML model rooted in ANN. SOMs are commonly utilised for tasks such as dimensionality reduction, clustering, and data mapping. Unlike other artificial neural networks, SOMs employ competitive learning rather than error correction techniques like backpropagation. Additionally, they use a neighbourhood function to maintain the topological relationships inherent in the input data.

The SOM algorithm has been widely applied to defect detection tasks in PBF processes [247–249]. For instance, Schur et al. [247] investigated the impact of powder reuse on fabrication quality in PBF-EB by examining microstructural characteristics, oxygen content, and porosity, alongside mechanical properties, using SOM analysis. Similarly, Taherkhani et al. [248] employed light intensity data from a coaxial photodiode to detect porosity formation in PBF-LB samples (see Figure 2.35

for the detection results). Their analysis utilised SOM to process the one-dimensional light intensity data and identify the locations of pores. Ero et al. [249] applied a SOM algorithm to predict porosity formation in PBF-LB samples, analysing in-situ optical tomography data and validating the predictions against ex-situ computed tomography results.

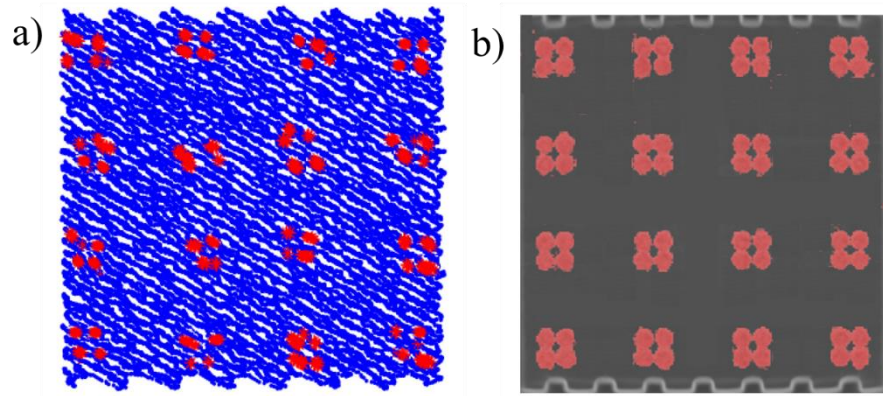


Figure 2.35. Porosity detection by a) SOM, and b) CT-scan [248].

Beyond PBF, the SOM algorithm has also been utilised for defect detection in other AM techniques, including laser metal deposition (LMD) [250], directed energy deposition (DED) [251–253], and fused filament fabrication (FFF) [254].

2.4.2.3. Deep belief network (DBN)

Deep Belief Networks (DBNs) are a type of ANN specifically designed to automatically learn patterns from large datasets through unsupervised learning. A DBN operates in two primary stages: pre-training and fine-tuning. During the pre-training stage, the network learns the probability distribution of the input data. In the subsequent fine-tuning stage, typically involving supervised learning, the model's parameters are adjusted to perform tasks such as clustering or regression.

The DBN has been utilised for various applications in the analysis of PPBF-LB processes by processing in-situ data. For instance, Ye et al. [127] identified five distinct melting stages from in-process acoustic data using a DBN with unsupervised pretraining steps. Similarly, Ye et al. [255] applied the same methodology to classify five distinct melting stages from off-axis near-infrared (NIR) data, which captured plume and spatter information, again leveraging a DBN.

The DBN has also been employed for defect classification. For example, Li et al. [256] proposed a method for porosity classification based on in-situ melt pool data collected using a coaxial high-speed camera. Their approach incorporated several ML algorithms, including BPNN (back propagation neural network), DBN and SVM, for clustering porosities. Figure 2.36 presents the accuracy and classification results of these ML algorithms, showing that the DBN performs better than the others in this case.

Additionally, the DBN has been utilised to predict the mechanical properties of parts fabricated via PBF-LB. For example, Jia et al. employed a DBN-based algorithm to predict the fatigue life of samples fabricated through PBF-LB processes [257].

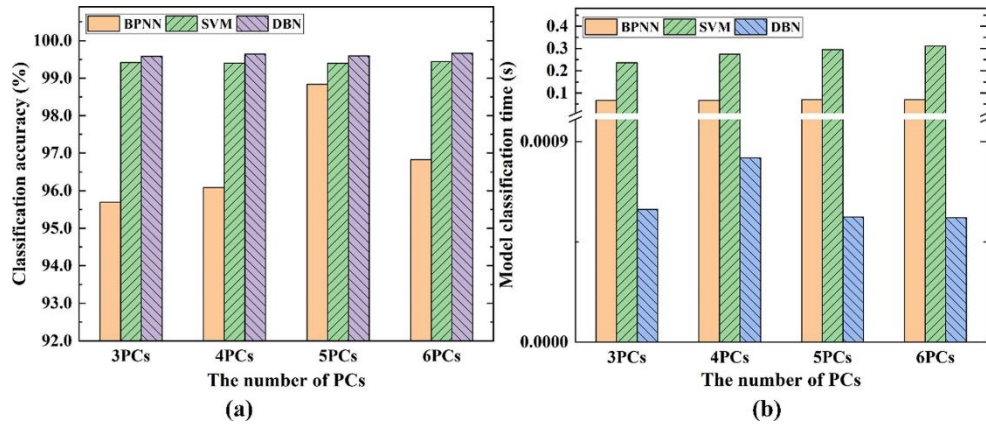


Figure 2.36. Accuracy and classification time comparison of ML algorithms [256].

2.4.2.4.Autoencoder

An autoencoder operates by first encoding the input data into a lower-dimensional representation, known as the latent space, and then decoding this compacted data back to its original dimensions. The primary goal is to reconstruct the input as accurately as possible by minimising the error between the original input and the reconstructed output during the training process. The magnitude of this error reflects the performance of the autoencoder. Once an autoencoder is trained on a particular class of data, testing it with data from a different class usually results in higher error rates. By examining the error values, one can determine whether the test data belongs to the same class as the training data or to a different class. It can be used for clustering, keyword detection and image generation tasks.

Liu et al. [258] proposed a defect detection method for PBF-LB surfaces using light scattering in combination with a convolutional autoencoder. The autoencoder was trained using simulated light scattering data from non-defective surfaces and subsequently tested on both simulated and experimental datasets. The method demonstrated classification accuracies of 89.3% and 99.1%, respectively.

2.4.2.5. Anomaly detection algorithms

Anomaly detection algorithms, such as isolation forest (iForest) and local outlier factor (LOF), can determine whether new test data is consistent with the trained data (inlier) or represents a distinct category (outlier). The iForest algorithm isolates each data point by partitioning the data through random decisions [259,260]. These partitions create a tree structure, where each data point progresses from the root to a terminal node. The number of partitions required to isolate a data point is recorded as the path length. Anomalies are typically isolated more rapidly than normal points, resulting in shorter path lengths within the trees. The LOF algorithm calculates a score, known as the local outlier factor, which indicates the degree of abnormality in observations [261]. It evaluates how much the local density of a given data point deviates from that of its neighbouring points. Typically, anomalous data points exhibit much lower local density and higher outlier scores.

The iForest algorithm has been used to detect anomalies and defects in metal AM recently. Li et al. [262] has proposed a real-time, unsupervised anomaly detection framework using iForest for wire arc additive manufacturing (WAAM) using video data collected during industrial production. The goal is to detect defects like slag inclusions and geometric holes without requiring labelled data. The framework achieves real-time detection (under 10 seconds for 600 frames) reaching an F1-score of 0.93.

Mattera et al. [263] evaluated and compared unsupervised ML methods, including iForest and LOF, for real-time anomaly detection in WAAM using exclusively defect-free training data. Their study addressed key challenges such as the absence of labelled data, dynamic operational environments, and the high cost of data generation. Both iForest and LOF achieved a validation accuracy of 100%; however, their precision scores in the time domain were 0.92 and 0.94, respectively.

2.4.2.6. Density-based spatial clustering of applications with noise (DBSCAN)

The DBSCAN algorithm has been utilised in PBF-LB processes for defect and pattern clustering. Bordekar et al. [264] introduced a hybrid defect detection model incorporating both supervised and unsupervised learning algorithms. In their approach, defects in CT data from PBF-LB samples were first identified using a supervised learning algorithm, followed by the application of DBSCAN to classify these defects as pores or inclusions. Similarly, Malashin et al. [265] employed DBSCAN to categorise melt pool images based on the thermal impact applied to the powder bed, distinguishing between overheated, underheated, and normal states. Voigt et al. [266] developed a methodology to investigate the impact of edge effects on the fabrication process, using DBSCAN to identify patterns in in-process coaxial melt pool monitoring data obtained via photodiode measurements.

In addition to clustering defects, DBSCAN has also been applied to classify specific features of PBF-LB samples. For instance, Wang et al. [267] utilised DBSCAN to identify texture orientations in 316L stainless steel samples fabricated using PBF-LB.

2.4.3. Semi-supervised learning

Semi-supervised learning, a hybrid approach combining elements of supervised and unsupervised learning, utilises both labelled and unlabelled data. The inclusion of some labelled data helps to mitigate the risks associated with unsupervised learning methods. Conversely, the reliance on only a subset of labelled data significantly reduces the time required for data labelling, addressing a key limitation of supervised learning.

In the literature, both supervised and unsupervised models have been adapted for use as semi-supervised models in tasks such as defect detection and process optimisation within PBF-LB. For example, Pandiyan et al. [268] employed a semi-supervised approach to train two CNN models using acoustic emission signals collected during the PBF-LB fabrication process. These models were designed to identify defects, including balling and porosities. Larsen and Hooper [269] introduced a deep CNN model utilising semi-supervised learning to identify defects in high-speed video

recordings captured during fabrication and laser input. Their findings demonstrated that the model achieved a porosity detection accuracy of 0.2%, with an AUC of 0.999.

The semi-supervised approaches have also been used to analyse the quality of weld tracks. Li et al. [270] proposed a semi-supervised model employing a deep CNN to classify PBF-LB weld tracks into three categories: over-melted, under-melted, and normal-melted. The model was trained using surface images captured after the scanning, and its performance was tested on a real-world dataset. The results demonstrated the model's robustness in quality identification. Wilkinson et al. [271] employed a semi-supervised model based on CNN to determine the optimal process parameters for PBF-LB technology when working with new powders. The model was trained using optical images of single weld tracks exhibiting varying levels of quality, enabling it to predict processing maps for different materials.

The semi-supervised models have also been implemented for finding the correlation between in-process data and post-process characteristics. Okaro et al. [272] proposed a semi-supervised method for fault detection in PBF-LB samples, utilising in-process photodiode data and ultimate tensile strength measurements. The Gaussian mixture model, trained using a semi-supervised approach, achieved a detection accuracy comparable to that of a supervised model. Nguyen et al. [273] developed a surface classification model of PBF-LB (see Figure 2.37 for the classes) using semi-supervised ML techniques combined with optical imaging. They established correlations between optical surface images and post-processing characteristics, such as surface roughness and tensile strength, to facilitate defect detection.

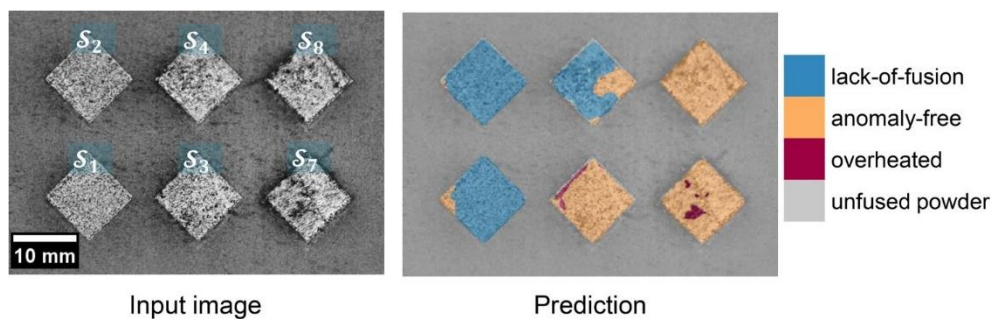


Figure 2.37. Input and prediction of semi-supervised ML algorithm [273].

Semi-supervised methods can be used to label the data with the help of manually labelled data. Yadav et al. [274] employed the K-means clustering algorithm to assign labels to 200 OT datasets, utilising 40 manually labelled datasets. The manual labelling process involved comparing the OT data with the corresponding CT data. This approach improved the accuracy of the clustering algorithm and significantly reduced the time required for the labelling process. Manivannan [275] introduced a semi-supervised deep learning model for defect detection in PBF-LB samples. He evaluated the performance of his model against other models using a publicly available dataset.

2.4.4. Reinforcement learning (RL)

Reinforcement Learning (RL) is a dynamic control framework that learns by interacting with an environment. It operates on a trial-and-error basis, where actions are taken, and their consequences are observed. Based on these consequences, the framework receives rewards for successful outcomes and penalties for unsuccessful ones. The primary goal of RL is to maximise the cumulative rewards received over time. This approach has proven effective in applications such as self-driving vehicles and game theory, where continuous adaptation and optimisation are critical for success.

However, there are some challenges for RL to use in defect detection tasks on PBF-LB. Firstly, while RL is well-suited to determining discrete actions, the control of PBF-LB processes entails a high-dimensional continuous space with numerous parameter combinations, rendering evaluation highly complex. Secondly, although immediate rewards can be assessed through thermal and structural features, evaluating the cumulative impact of actions on subsequent layers remains challenging due to intricate interactions. Finally, RL necessitates a substantial number of training samples, which are both costly and labour-intensive to obtain experimentally. Simulations are often used as a substitute for real experiments; however, they may fail to fully represent physical realities, thereby limiting the practical applicability of the control policies developed.

Despite the challenges, RL is used in PBF-LB for defect mitigation and process optimisation tasks. For instance, Ogoke and Farimani [276] proposed a dynamic

control method capable of adjusting process parameters to prevent defect formation. This method, based on deep RL, was trained and validated through simulations. Malik et al. [277] employed RL within the digital twin they developed for PBF-LB to optimise process parameters, with the aim of preventing defects. To achieve this, a physics-based model was implemented to simulate fabrication under varying process parameters, and a classification algorithm was used for defect prediction.

Wasmer et al. [126] utilised reinforcement learning alongside in-process acoustic data to classify part quality into three categories: poor, medium, and high quality. The acoustic data was collected during the fabrication of 316L stainless steel components at three distinct laser speeds. The findings demonstrated classification accuracies ranging with a corresponding confidence level of 74% to 82%.

In order to reduce the porosity formation, RL is used to optimise the process parameters. Knaak et al. [278] developed a dynamic control method for adjusting process parameters to increase the fabrication quality. Their method initially employed a CNN trained with on-machine optical imaging to predict the surface roughness of the powder bed. Subsequently, reinforcement learning was utilised to optimise the process parameters based on the predicted surface roughness maps. Mohamed et al. [279] developed a parameter optimisation model to reduce the porosity formation based on RL. The reward function was formulated using a physics-informed principle. The model was experimentally validated on A205 aluminium alloy samples fabricated using a PBF-LB machine, demonstrating effective prediction capabilities.

The RL model is also employed to optimise the laser scanning process and address anomalies associated with laser scanning. Park et al. [280] proposed an RL-based control mechanism (see Figure 2.38) for the laser scanning process in PBF-LB. The RL model was trained using data from the scanning path and melt pool characteristics, and its performance was evaluated through both simulation and experimental validation on a PBF-LB machine. The results demonstrated that the model effectively reduces melt pool inhomogeneities. Qin et al. [281] developed an algorithm for tool path generation based on deep RL, with the goal of reducing thermal gradients. They demonstrated that the algorithm effectively reduces thermal gradients in both simulated and experimental datasets.

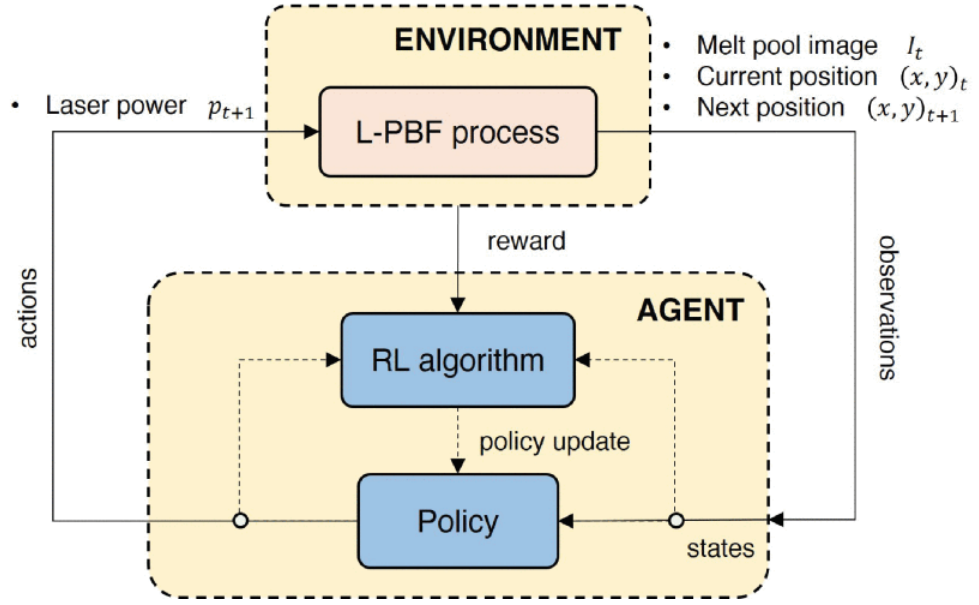


Figure 2.38. Reinforcement learning (RL) process [280].

2.5. Light scattering

As discussed in Sections 2.2 and 2.3, the measurement and monitoring of layers are critical in PBF-LB, as any microscale impurities in the layers can degrade the quality of the final component. A light scattering method, which is used in this study, can be employed to detect surface impurities on PBF-LB layers. This technique is fast, non-contact, and cost-effective, and it infers surface topography information [282], which can be critical for evaluating fabrication quality.

In the optical surface topography instruments such as coherence scanning interferometry and confocal microscopy, the light scattered from the object is collected, propagated through the optical system and is recorded by a sensor [283,284]. The surface topography is reconstructed by analysing the recorded intensity pattern [285,286]. These instruments could be used for off-process quality assessment after fabrication is complete because of the limited space in the PBF-LB machine, long measurement time and small field of view. In contrast, scatterometry, a light scattering technique, is suitable for in-process measurement and has been applied to measure surface roughness and dimensions in semiconductor chips [287,288]. However, full reconstruction of the surface topography using this method

is time-intensive and challenging due to the complexity of the inverse scattering problem. In this thesis, a light scattering approach has been developed to detect microscale surface impurities on PBF-LB surfaces without requiring surface reconstruction. The method involves illuminating the surface of interest with a light source and capturing the reflected light as a scattering pattern, which is recorded as an intensity image on a screen. Variations in the scattering pattern are attributed to changes in the surface topography, potentially caused by surface impurities. Similarly, this approach has been proposed as a measurement method to assess the quality of AM samples focusing on larger-scale surface anomalies [258].

Although statistical methods can be employed to classify scattering patterns, they may be limited in their ability to identify hidden or non-linear structures within the data. In contrast, ML techniques are well-suited to the rapid processing and analysis of large datasets, facilitating the discovery of complex and non-obvious relationships – often with minimal or no prior domain knowledge [176]. When employing unsupervised ML, the need for manual labelling is also eliminated, thereby reducing the considerable time and effort typically required. In light of these advantages, unsupervised ML algorithms were adopted in this study for the classification of scattering patterns.

Given the large data requirements of ML, this thesis proposes the use of simulated scattering patterns. To generate such data, the light scattering models must be used. Several models exist for this purpose, ranging from rigorous to approximate methods. This section introduces the fundamental principles of light scattering, followed by an overview of commonly used simulation models, highlighting both rigorous and approximate approaches. As the BK theory – a widely used approximate model – is applied in this thesis, its theoretical basis is presented at the end of the section.

2.5.1. Modelling of light scattering

The propagation of light through different media, including its transmission, reflection, and refraction (Figure 2.39), can be described using ray, wave or electromagnetic optics (see Figure 2.40) [289]. As the explanation of light and its

behaviour becomes more detailed from ray to quantum optics, the complexity and difficulty of understanding it also increase [290].

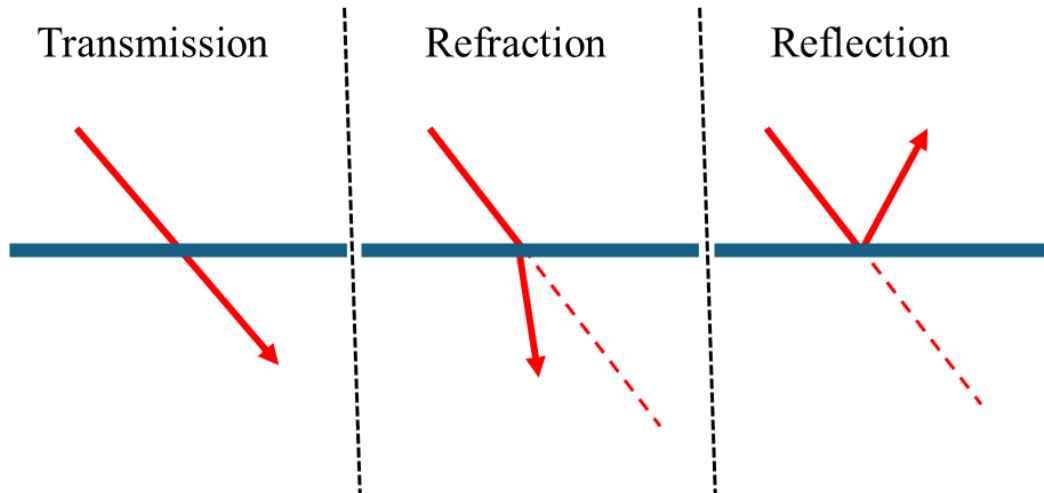


Figure 2.39. The propagation of light during transmission, refraction, and reflection.

Ray optics, also known as geometric optics, provides the simplest macroscopic perspective for describing light and its propagation. This theory is straightforward because many of the phenomena it explains are observable in everyday life. The principles governing the propagation of light in ray optics are mostly based on Hero's principle, Fermat's principle, and Snell's law [290,291]. Ray optics is particularly useful for designing and aligning optical systems, such as those involving beam alignment.

However, ray optics has certain limitations. It is valid only when the wavelength of light is significantly smaller than the characteristic dimensions of the object or medium it interacts with [290]. When the wavelength of light is comparable to the dimensions of the medium, the wave nature of light, evident in phenomena such as diffraction and interference, becomes apparent [292]. In such cases, wave optics, which models light as a scalar waves, provides a more accurate representation of light propagation [289].

At a more advanced level, electromagnetic wave theory describes light as an electromagnetic wave consisting of oscillating electric and magnetic vector fields. These two fields are perpendicular to each other and to the direction of propagation [289]. Electromagnetic wave theory offers a more comprehensive explanation compared to ray theory of light by accounting for incident, reflected, and transmitted

electromagnetic field, thereby providing a deeper understanding of light propagation in complex media.

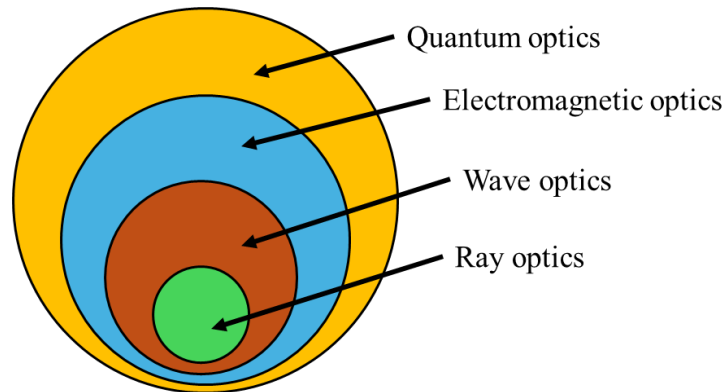


Figure 2.40. Optical theories describing light become progressively more complex, evolving from ray optics to quantum optics.

Transmission refers to the propagation of light through a material [289]. Refraction is the bending of light as it passes from one medium to another [289]. Reflection involves a change in the direction of light as it bounces off a surface [289]. The processes of transmission, reflection, and refraction are macroscopic phenomena resulting from light-matter interactions at the submicroscopic level [289]. In cases where the surface is rough, the incident light is reflected in various directions – a phenomenon known as scattering or diffuse reflection.

The surface topography, material properties and the properties of the illumination light, including the angle of incidence, wavelength, and polarisation determine the scattering of light [292]. When the properties of the incident light and material properties are fixed, the scattering depends on the surface topography. As such, the scattered light contains information about the surface topography, enabling its reconstruction [293].

Surface topography measuring instruments capture the scattered light field via the optical system and subsequently apply surface reconstruction methods to the acquired data to generate the surface topography [283]. In this thesis, a non-imaging method is introduced to evaluate surface uniformity directly from the scattered light pattern, without the need to reconstruct surface topography. This approach avoids the complexity, cost, and time associated with conventional surface reconstruction, offering a more efficient alternative for assessing surface characteristics.

When a surface is illuminated by a light beam, the light scatters upon impinging on the surface. Under a fixed illumination geometry, the direction of the scattered beam is influenced by the surface topography (Figure 2.41) [289,294]. If the surface is optically flat, the light scatters primarily in the specular direction. In the case of flat surface with a small amount of height variation, specular reflection dominates. However, a small fraction of the incident light is also reflected in other directions as diffuse reflection, deviating from the primary specular direction. In the presence of surface impurities causing significant texture, diffuse reflection becomes predominant than the specular reflection. A surface may be classified as rough when the specular component of reflected light is negligible compared to the diffuse component [14]. In Figure 2.41, the propagation of light was visualised with rays, which are perpendicular to the wavefronts, in order to prevent the cluttering.

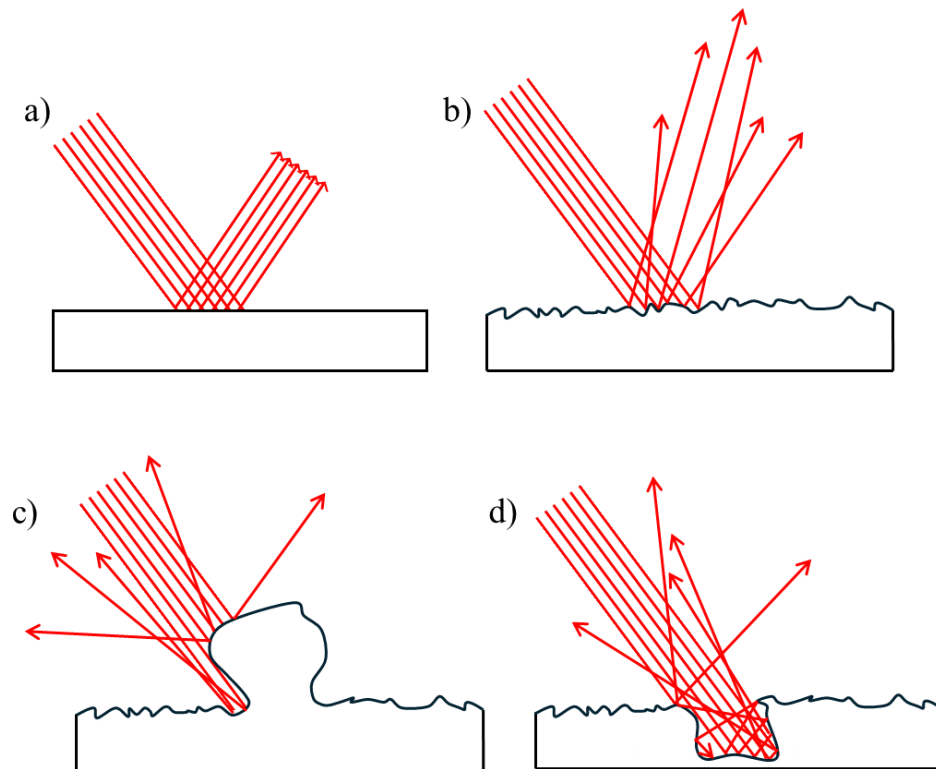


Figure 2.41. a) Specular reflection, b) specular reflection dominant, c) and d) diffuse reflection dominant with protrusion and recess.

The propagation of light, that is, electromagnetic waves, through an inhomogeneous medium is governed by Maxwell's equations [292]. Formulated by James Clerk

Maxwell in 1861, these equations form the foundation of electromagnetic theory. To determine the total electromagnetic field at a point in space resulting from light scattering by a surface, it is necessary to solve Maxwell's equations using either rigorous or approximate methods, employing both analytical and numerical approaches [295,296]. These methods include:

- analytical approximate methods
- numerical rigorous methods
- numerical approximate methods

Notably, there is no analytical rigorous method available for solving the scattering problem, particularly for strongly rough surfaces. This is because, in the case of strongly rough surfaces, the total field at a given point is influenced by the total field at other locations (a phenomenon known as multiple scattering) [294]. Such interdependencies render an analytical solution to the scattering problem unfeasible.

2.5.1.1.Rigorous approaches

Rigorous models are capable of accurately modelling scattered light without simplifying assumptions, even in scenarios involving multiple scattering, [283]. This applies to surfaces with high slope angles and small radii of curvature features.

Among the principal rigorous numerical approaches are the finite element method (FEM) [297,298], finite difference time-domain (FDTD) [299], rigorous coupled wave analysis (RCWA) [300,301] also known as Fourier modal method (FMM) and boundary element method (BEM) [302,303] also called as moments of methods (MoM) [304]. Each method possesses distinct advantages and limitations with respect to various applications. The FEM is a numerical technique capable of solving scattering problems from complex structures [305]. It achieves this by solving partial differential equations using boundary conditions derived from the discretisation of the domain of interest [305]. However, the computational time may increase significantly when smaller mesh sizes are employed during the discretisation [306]. FEM is highly accurate and offers considerable flexibility in handling structurally complex geometries [307]. It has been applied to both periodic and non-periodic structures for modelling of scattering [308,309] and is particularly efficient for addressing monochromatic scattering problems [297,298].

The FDTD method, on the other hand, discretises Maxwell's equations in space and time domain expressed in differential form [310]. To achieve sufficient accuracy, FDTD often requires fine mesh grids and small time-steps. However, both fine meshes and small time-steps can lead to increased computational time [311]. Despite this, FDTD is well-suited for modelling systems with partially coherent illumination [299].

The RCWA method provides an effective solution for problems involving inhomogeneous and near-planar surface structures [300,301]. It is widely used for modelling diffraction efficiencies and simulating grating structures [306,312]. RCWA employs a staircase approximation for periodic structures [306]. The method is less efficient for highly complex geometries [304]. In terms of computational speed, RCWA is generally faster than FEM, while FEM is faster than FDTD [306]. Finally, the BEM utilises the integral form of Maxwell's equations to solve scattering problems. This approach is typically faster than other methods, as it solves partial differential equations only along the surface boundaries [302,303].

2.5.1.2. Approximate approaches

In order to predict the scattered light from complex surfaces containing features such as overhangs, rigorous models rather than approximate models need to be applied because they take into account multiple scattering. Rigorous methods provide exact solutions for scattering from any surface geometry, as they do not rely on approximations. Nevertheless, certain rigorous models may yield more accurate results for specific geometries or materials [313]. Despite their precision, rigorous models are generally more complex and computationally demanding. In contrast, approximate models, while neglecting phenomena such as multiple scattering, offer the advantages of simplicity and greater computational efficiency [296]. This section provides a general overview of the commonly known approximate methods.

Perturbative approach

The vector perturbation theory, also known as Rayleigh-Rice theory, provides an approximate analytical solution for light scattering from weakly scattering surfaces [314]. Due to the small surface height variations, only a small proportion of light is

scattered away from the specular direction. This approach is based on the assumption that the scattered field can be expressed as an expansion of the scattering amplitude in powers of the surface profile. The model remains valid provided that the root-mean-square height of the surface is smaller than the wavelength of the incident light. Although Rayleigh-Rice theory is one of the oldest and most widely recognised perturbation methods, numerous other perturbation theories have also been developed to describe light scattering from weakly rough surfaces [315]. Most of these perturbation theories are derived from the reduced Rayleigh equations, and are valid when the surface is weakly scattering [313].

Numerical approaches

There exist numerical solutions to the reduced Rayleigh equations that are neither perturbative nor rigorously derived. Their primary advantage lies in their ability to solve scattering problems for larger surface areas while requiring similar or less memory resources to those of rigorous numerical solutions. However, their applicability depends on the validity of the Rayleigh hypothesis. Consequently, these methods cannot address scattering from arbitrary surfaces but are effective for surfaces that cannot be resolved using perturbation theories.

Born and Rytov

The Born (or First-order Born) and Rytov approximation methods are two widely utilised approaches for solving light scattering problems in media where the refractive index variation is small. The Born approximation is particularly effective when the scattering potential is weak when the refractive index variation is minimal [292]. In this model, the total electric field can be approximated by the incident electric field [296].

The Rytov approximation, in contrast to the Born approximation, is more suitable for problems involving longer propagation paths or larger scatterers [292]. Both the Born and Rytov approximations are valid for weakly scattering media [292], with the Born approximation being more effective for small objects and the Rytov approximation being better suited for larger objects [316]. To reduce computational

complexity, a cylindrical surface is recommended for the Born approximation, while plane surfaces are suggested for the Rytov approximation [316].

Beckmann-Kirchhoff (BK)

The BK model which is used in this study to model light scattering, is one of the most widely used approximate methods to solve light scattering problems [285,294]. Under the assumption that multiple scattering is negligible, the BK model consider the scattering process as a linear filtering operation applied to the foil model of the surface [286]. This filtering process is characterised by a transfer function [286] that depends on the optical system and illumination configuration. By making these simplifications, the BK model reduces the computational complexity associated with solving the scattering problem.

The BK model has the capability to simulate scattering of light from surfaces having larger height variations compared to other models, such as perturbative approaches [296]. However, the model assumes the surface slope is not too large. The validity of the BK model is subject to certain conditions [296], including a constant Kirchhoff reflection coefficient across the range of incident angles, the neglect of shadowing and multiple scattering effects, and distant observation of the scattered field [283].

2.5.2. Theory of the BK light scattering model

This section outlines the derivation of the measured scattering field according to BK theory. Most derivation steps have been omitted, as the model itself was not developed within this thesis; however, the complete derivation can be found in references [283,286,317].

Under the Born approximation for incidence with a wave vector of $\mathbf{k}_i$, all possible scattered wave vectors, $\mathbf{k}_s$, are determined by the Ewald vector [292] which is $\mathbf{K} = \mathbf{k}_s - \mathbf{k}_i$, and, in a Cartesian coordinate system $\mathbf{K} = K_x \hat{\mathbf{x}} + K_y \hat{\mathbf{y}} + K_z \hat{\mathbf{z}}$. Please note strong scattering occurs when Ewald vector is parallel to the surface normal. Figure 2.42 illustrates the scattering of light from a 3D object, where E_i , E_s and E_t represent the incident, scattered and total electric fields, respectively, and $E_t = E_i + E_s$.

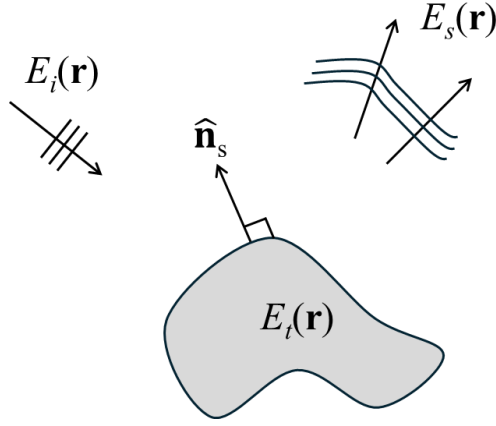


Figure 2.42. Schematic representation of scattering from a 3D object.

$\hat{\mathbf{n}}_S$ in Figure 2.42 is the outward surface normal and expressed as

$$\hat{\mathbf{n}}_S = \frac{\mathbf{k}_s - \mathbf{k}_i}{|\mathbf{k}_s - \mathbf{k}_i|}, \quad (2.3)$$

for elastic scattering $|\mathbf{k}_s| = |\mathbf{k}_i| = k_0$. $k_0 = 2\pi/\lambda$ is the wavenumber and λ is the illuminating wavelength, and $\mathbf{k}_s = \mathbf{K} + \mathbf{k}_i$.

The scattered field from a medium, Ω (Figure 2.43), in the far field can be expressed as

$$E_s(\mathbf{r}) = f(\mathbf{k}_s, \mathbf{k}_i) \frac{e^{ik_0 r}}{r}, \quad (2.4)$$

which shows that the scattered field behaves as outgoing spherical waves.

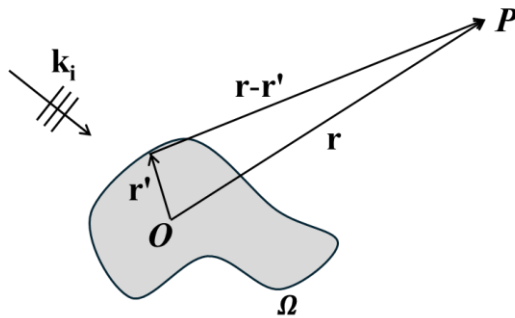


Figure 2.43. Observation point P is distant from the scattering medium - Ω .

In Eq. (2.4), $f(\mathbf{k}_s, \mathbf{k}_i)$ represents the scattering amplitude which can be expressed under the BK theory [283] as

$$f_{BK}(\mathbf{K}) = \frac{\mathbf{K}^2}{2\mathbf{K}_z} \int F_{BK}(\mathbf{r}) e^{-i\mathbf{K}\mathbf{r}} d^3r, \quad (2.6)$$

where $F_{BK}(\mathbf{r})$ is the foil model representation of the surface [286] and is expressed as

$$F_{BK}(\mathbf{r}) = RW(\mathbf{r})\delta[r_z - Z_s(r_x, r_y)], \quad (2.5)$$

where δ is a 1D Dirac delta function that follows the surface height $Z_s(r_x, r_y)$ of a homogeneous material as a function of the lateral position and $W(\mathbf{r})$ is a shading function. Eq. (2.7) shows that the scattered field is a weighted Fourier components of the foil model. With the Ewald sphere definition [292], the scattering amplitude can be written as a filtering operation applied to the Fourier transform of the foil model as

$$f_{BK}(\mathbf{K}) = \frac{\mathbf{K}^2}{2\mathbf{K}_z} \tilde{F}_{BK}(\mathbf{K}) \cdot \tilde{G}_E(\mathbf{K}, \mathbf{k}_i), \quad (2.7)$$

where $\tilde{F}_{BK}$ is the Fourier transform of the foil model. $\tilde{G}_E(\mathbf{K}, \mathbf{k}_i)$ is the Ewald sphere which can be expressed by a 1D Dirac delta function as

$$\tilde{G}_E(\mathbf{K}, \mathbf{k}_i) = \delta\left(\frac{|\mathbf{K} + \mathbf{k}_i|}{k_0} - 1\right). \quad (2.8)$$

When the integral theorem of Helmholtz and Kirchhoff is used, the scattered field can be defined as a surface integral. Kirchhoff's boundary conditions can be applied to solve this problem. The first condition approximates the total field as the sum of the incident and reflected field:

$$E_t(\mathbf{r}) = (1 + R)E_i(\mathbf{r}), \quad (2.9)$$

where R is the reflection coefficient. And the normal derivative of this boundary condition can be expressed as:

$$\frac{\partial E_t(\mathbf{r})}{\partial n} = i\mathbf{k}_i \cdot \hat{\mathbf{n}}(1 - R)E_i(\mathbf{r}), \quad (2.10)$$

where $\hat{\mathbf{n}}$ is normal to the surface.

Up to this point, the equations demonstrate how the illuminated field relates to both the total field and the scattered field, and how the surface relates to the scattered

field. The intensity observed on the screen, however, corresponds to the square of the amplitude of this scattered electric field and can be expressed as:

$$I = |E_s(\mathbf{r})|^2. \quad (2.11)$$

The code developed in this study calculates the intensity viewed on the screen in accordance with Eqs. (2.3)-(2.11). Given that the scattering material employed is non-transparent, the scattered field propagates over a hemispherical shell. To model the projection of the scattered field from the surface onto a planar detection screen, the field distribution over the hemispherical surface is mapped onto a plane. This projection is based on the configuration of the experimental light-scattering setup described in Chapter 5, where further details of the projection process are also provided.

2.6. Summary

This chapter has provided a comprehensive overview of the current state of knowledge concerning PBF-LB additive manufacturing, with a particular emphasis on microscale surface impurities, in-situ measurement technologies, and ML methods for fabrication quality assessment. It has been established that PBF-LB is a promising technique for fabricating complex geometries with high resolution making it well-suited for critical applications in the aerospace, biomedical, and automotive sectors. Nevertheless, the technique is inherently prone to a variety of defects and surface anomalies due to its complex thermophysical processes, sensitivity to numerous interdependent parameters, and lack of inherent process stability.

The chapter began by outlining the principles and classification of AM, highlighting PBF-LB as a widely adopted metal AM method. The fundamental steps of AM, its advantages - such as design freedom and material customisation – and limitations, including high cost, post-processing requirements, and limited repeatability, were critically examined. Particular focus was given to the process parameters of PBF-LB, categorised into laser, scanning, powder, and temperature-related factors. These parameters govern melt pool formation, which is instrumental in defining the integrity and performance of the fabricated components.

Following this, the chapter examined the formation mechanisms, characteristics, and implications of various microscale surface impurities, including porosity, cracking, balling, spatter, and recoater-related defects. It was demonstrated that these impurities can significantly degrade mechanical properties such as tensile strength and fatigue life, while also acting as initiation points for further subsurface defects. The literature review illustrated that despite extensive parameter optimisation, PBF-LB remains susceptible to these anomalies due to non-linear interdependencies, powder inconsistencies, and environmental variables. Moreover, the surface integrity of each layer plays a critical role in determining the quality of subsequent layers, reinforcing the necessity for layer-wise defect monitoring. Therefore, this thesis aims to develop a quality evaluation method targeting to detect microscale surface impurities.

In addressing the limitations of conventional ex-situ inspection methods, the chapter transitioned to an in-depth review of in-situ measurement technologies. These methods aim to detect defects in real time, thus enabling corrective actions before flaws become embedded. The review encompassed a variety of sensing modalities: visible imaging, thermal sensing, electronic imaging, height mapping (including fringe projection and coherent imaging), blade-mounted sensors, and acoustic sensing. Each method was evaluated in terms of resolution, integration complexity, detection accuracy, and practical limitations. While visible and thermal imaging are among the most mature and widely adopted approaches, methods such as fringe projection and coherent imaging offer three-dimensional insights into surface topography, albeit with increased complexity and cost.

Importantly, the integration of multiple sensor modalities has emerged as a promising avenue for enhancing defect detection capabilities. Multi-sensor systems can mitigate the limitations of individual methods and improve detection robustness. However, challenges remain in data registration, sensor calibration, and computational efficiency, particularly in industrial environments characterised by varying materials, geometries, and machine configurations. One of the main limitations of the methods developed lies in their capability to detect small impurities at the microscale. This thesis seeks to develop an in-situ detection method

that is both cost-effective and sufficiently rapid to enable real-time monitoring of such impurities.

The chapter also reviews ML algorithms used for interpreting high-dimensional in-situ sensor data. ML algorithms - particularly supervised models such as CNNs and logistic regression - have demonstrated considerable promise in identifying complex, non-obvious defect patterns. Unsupervised, semi-supervised, and reinforcement learning techniques further broaden the possibilities for adaptive defect detection under uncertain or dynamically changing process conditions. Nonetheless, issues such as data labelling, training dataset generation, and generalisability across different systems continue to present barriers to widespread industrial implementation. This thesis aims to develop machine learning approaches for impurity detection, as these methods are capable of rapidly interpreting high-dimensional data, thereby enabling in-situ detection.

This chapter also presents an overview of the modelling of light scattering, with a particular focus BK model. In the literature a variety of models, both rigorous and approximate, have been developed to address the scattering problem. Rigorous approaches offer high levels of accuracy but are computationally intensive. In contrast, approximate methods, including BK model, offer simplified solutions under specific conditions. Notably, the BK model demonstrates an effective trade-off between computational efficiency and accuracy, particularly for surfaces with moderate roughness. Given the advantages of the BK model, this thesis aims to simulate scattering patterns using the model, thereby avoiding the need for time-consuming data collection.

In summary, the chapter has highlighted that while significant development has been made in detecting and understanding microscale impurities in PBF-LB, there remains a pressing need for robust, scalable, and real-time defect monitoring solutions. A multidisciplinary approach – combining process engineering, sensor technology, and data analytics – is essential to develop intelligent quality assurance systems that are both accurate and practical for industrial deployment. This sets the stage for future research directed at achieving reliable, closed-loop fabrication systems aligned with the broader objectives of Industry 4.0.

As a conclusion, the aim of this thesis is to develop a measurement system capable of detecting microscale impurities, including those smaller than 100 μm , with a detection accuracy of at least 90%, while operating sufficiently quickly to enable real-time detection in a cost-effective manner.

3. Surface analysis of PBF-LB samples

As discussed in Section 2.2 the surface quality of each layer in PBF-LB can play a crucial role in determining a part's overall performance. Microscale surface impurities which refer to protrusions or recesses, such as spatter and holes found on a surface can decrease the quality of the fabricated parts. Section 2.2 also highlights that these impurities are either directly correlated with part quality, or indirectly associated, as they may contribute to the formation of additional defects or imperfections, thereby further compromising the overall integrity of the part.

In this study, PBF-LB samples were fabricated with the aim of detecting microscale impurities formed on the top surface using a method suitable for in-situ integration. Prior to detection following part fabrication, the top surface of the as-manufactured components was examined in this chapter using an ex-situ high-resolution technique, scanning electron microscopy (SEM), in order to investigate the microscale impurities present on the surface. This chapter also provides the possible effects of these impurities on the surface and fabrication quality. Section 3.1 presents the details of the fabrication of the samples and details of the analysis method.

The formation of the microscale surface impurities is significantly influenced by the processing parameters employed during fabrication. Accordingly, Section 3.2 and 3.3 explores the effects of these parameters explicitly the laser power, scanning speed, and layer thickness on the microscale surface impurities, with particular focus on defects such as spatter, agglomeration, bulges, holes, and some other microscale anomalies.

The parts analysed have been fabricated from Ti6Al4V alloy by using a PBF-LB machine and the analysis has been done by using a SEM. Some parts of the research described in this chapter have been presented at a conference in [319].

3.1. Fabrication of the samples

The specimens were fabricated in a simple cubic shape (see Figure 3.1a) from Ti6Al4V alloy using a Renishaw RenAM 500Q (Figure 3.1b) PBF-LB machine. The

RenAM 500Q features a four-laser scanning system that can operate in either continuous wave or pulse-width modulated modes. Each laser has a wavelength of (1070 ± 10) nm, with a beam diameter of approximately $80 \mu\text{m}$ at the focus. The machine's build volume is $(25 \times 25 \times 35) \text{ cm}^3$. The scan speed is controlled by three parameters: hatch spacing, exposure time, and the delay between two successive points. Further details about the machine are provided in [320].

Ti6Al4V is a titanium alloy that is widely used in biomedical applications due to its high strength, good fabricability, excellent corrosion resistance, and capability for heat treatment to optimise properties [321]. Although it was originally developed for aerospace, its outstanding mechanical properties and biocompatibility make it highly suitable for medical applications [322]. Given these advantages, Ti6Al4V was selected for fabricating and analysing the surfaces in this study.

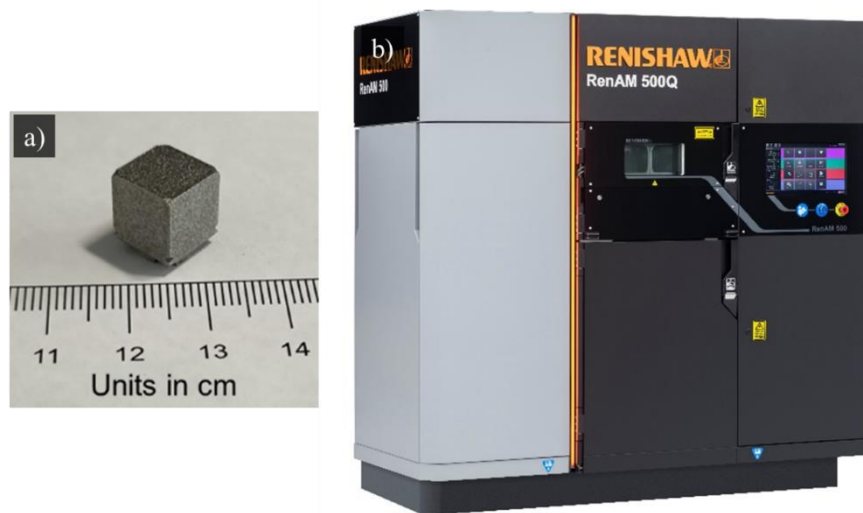


Figure 3.1. a) As-fabricate PBF-LB sample, b) RenAM 500Q PBF-LB machine [320].

The samples were manufactured using a range of process parameters (see Table 3.1). The 3D energy density was calculated using the Eq. (2.1). The selection of these parameters was based on recommendations from the PBF-LB machine manufacturer and findings from the literature. Certain parameters were deliberately chosen to deviate significantly from the optimal values in order to investigate their impact on surface quality.

Table 3.1. Ranges of the process parameters for the fabrication.

Laser power / W	Scan speed / m s ⁻¹	Layer thickness / μm	3D Energy density / J mm ⁻³
120-370	1.0-2.0	30, 60	40-90

3.2. Analysis of the microscale surface features

In this section, a microscale surface analysis was performed on multiple Ti6Al4V alloy specimens produced via PBF-LB. Surface characteristics were examined using an FEI XL30 at the Nanoscale and Microscale Research Centre (nmRC), University of Nottingham. To preserve the true surface morphology and avoid obscuring or altering microscale features, no coating was applied prior to SEM imaging. The microscale features on the as-built surfaces were examined, and their potential implications for fabrication quality were discussed. Additionally, several novel abnormal surface micro-features were identified, and potential formation mechanisms were proposed.

3.2.1. Spatter particles

Spattering (see Figure 3.2 for examples) is a common phenomenon in PBF-LB processes and is generally undesirable due to its detrimental effects on part quality. Both the literature (see Section 2.2) and the SEM analyses presented in this study identify various types of spatters. The primary categories of spatter are powders, partially melted powders (those located around the liquid melt pool), and droplets (ejected from the liquid melt pool). The formation of all spatter types can be attributed to the interaction between the laser beam and the powder material [9,109]. During the melting process, the recoil pressure generated by the laser beam displaces powders. Once these powders land on the solidified area, they form powder spatters. In cases of insufficient power, some powders are only partially melted, leading to the formation of partially melted powder spatters [9]. When partially melted particles form between two narrow melt tracks, they can link these tracks, acting as bridges.

Additionally, recoil pressure can eject liquid material from the melt pool, which, upon landing on the solidified surface, creates droplet spatters [69,108].

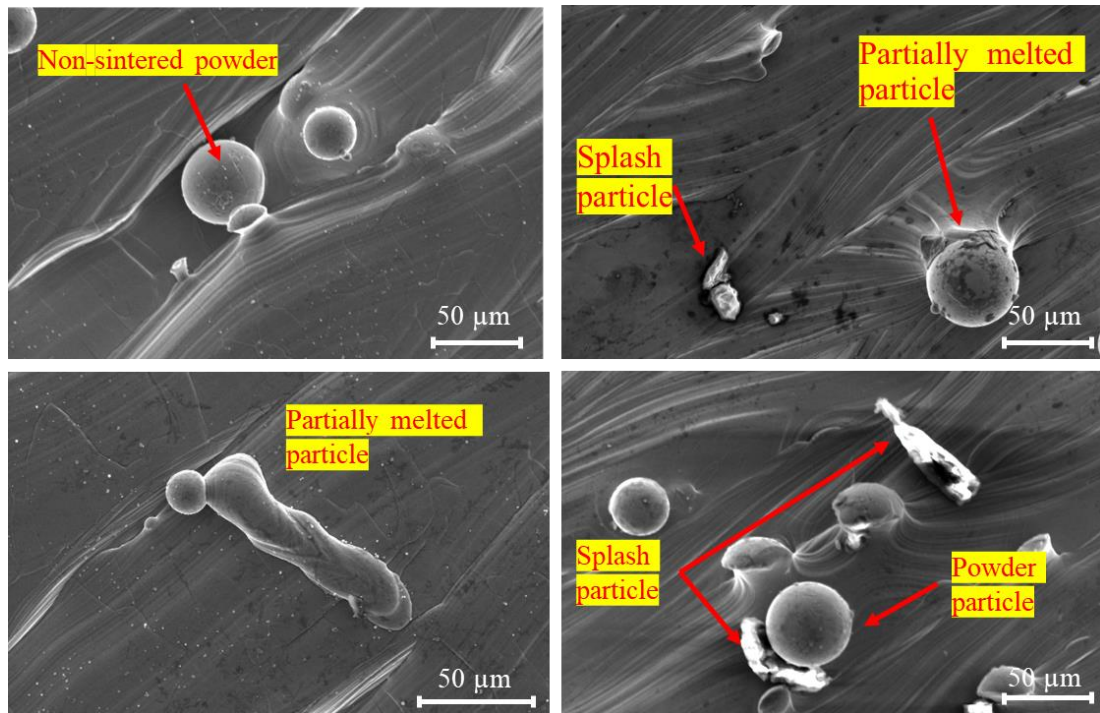


Figure 3.2. SEM images of the top surface of as-manufactured PBF-LB samples, showing spattering.

Powder spatters and droplet spatters often exhibit similar shapes, whereas partially melted powders are distinct in appearance. Regardless of their type, these spatter formations can increase surface roughness and adversely affect the mechanical properties of the manufactured samples [70]. When spatter particles are too large and fail to melt completely, they can act as crack initiation points, potentially leading to premature failure [70,76].

3.2.2. Agglomeration

When partially melted powders adhere to one another or when clusters of powder are partially melted, they can form agglomerations on the surface (see Figure 3.3). Research indicates that agglomeration occurs more frequently when a low hatch spacing is employed [323]. Further interaction between the agglomerated material and the laser can result in the formation of large spherical particles [324]. The substantial aggregation of material may obscure surrounding powders, leading to

incomplete melting. Additionally, the agglomerated particles can contribute to increased surface roughness similar to the effects caused by spattering.

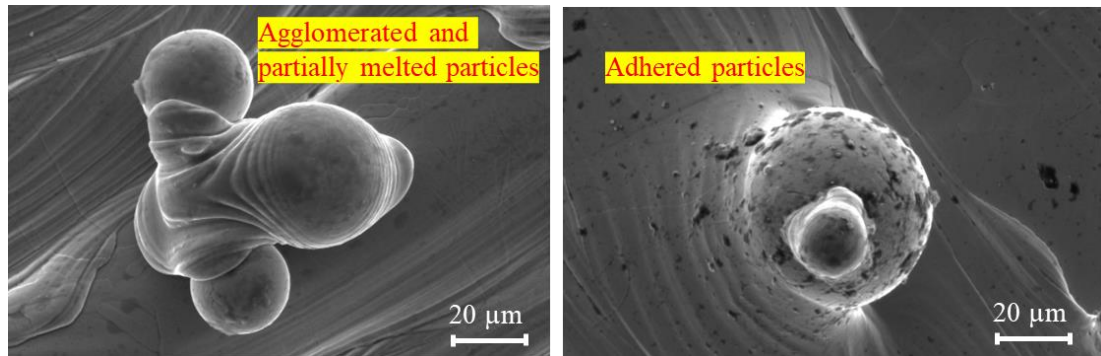


Figure 3.3. SEM images of the top surface of as-manufactured PBF-LB samples, showing agglomeration.

3.2.3. Bulge

As observed in the SEM images presented in Figure 3.4, bulges are formed as excess material between the weld tracks. A possible explanation for the formation of these bulges is insufficient melting at the edges of two adjacent weld tracks. Factors such as low energy density or the remelting of spattered particles between adjacent melt tracks may contribute to this phenomenon.

A lower scanning speed combined with higher energy density increases the width of the weld track and the overlap area between adjacent melt tracks, thereby reducing the formation of bulges. Conversely, a higher scanning speed leads to an increase in the number of bulges. Bulges have a similar effect on part quality as spatter and agglomeration as they have similar characteristics.

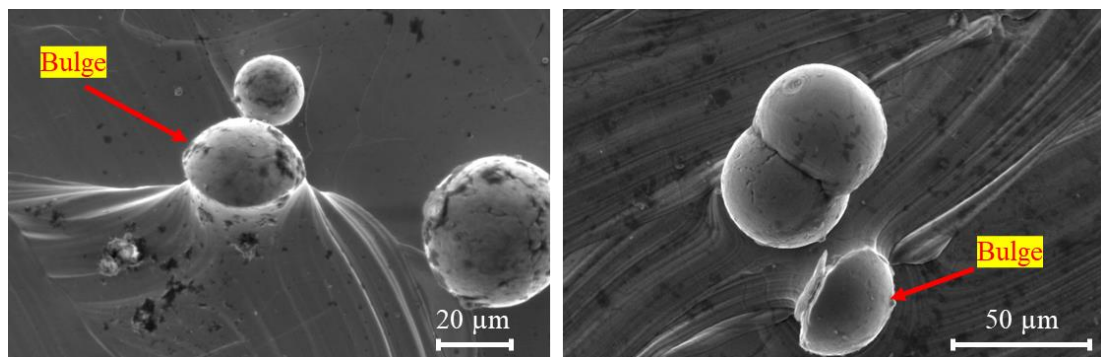


Figure 3.4. SEM images of the top surface of as-manufactured PBF-LB samples, showing bulges.

3.2.4. Holes and gaps

Large holes and gaps (see Figure 3.5) primarily form between melt tracks, predominantly due to insufficient laser power. Low laser power is unable to adequately melt the powder along the melt tracks, resulting in narrower tracks. These narrower melt tracks fail to merge effectively, leading to the formation of holes and gaps between them.

Additionally, larger hatch spacing, which reduces the overlap between melt tracks, can also contribute to the occurrence of gaps.

Another potential cause arises during the laser scanning process, where some areas of the surface may become devoid of powder due to interactions between the laser beam and the surface. The reduced availability of powder leads to the production of an insufficient quantity of liquid metal, which cannot adequately fill the gaps between the melt tracks, thereby resulting in large holes and gaps.

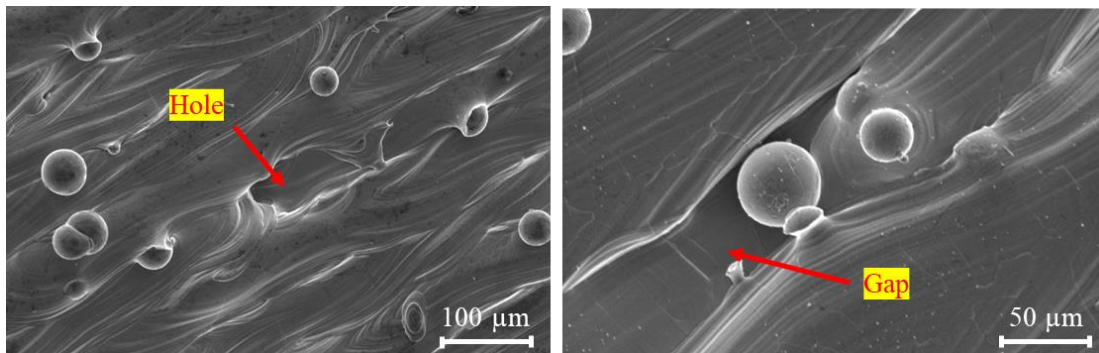


Figure 3.5. SEM images of the top surface of as-manufactured PBF-LB samples, showing holes and gaps.

Surface gaps and holes can lead to the formation of porosity during the fabrication of subsequent layers. Porosity in PBF-LB components can adversely affect mechanical properties – such as ductility, fatigue resistance, and tensile strength – by reducing the effective load-bearing area and providing sites for crack initiation [81]. The severity of these effects is influenced by factors including the location, size, distribution, and morphology of the pores. Nevertheless, it is worth noting that previous studies have indicated that a small amount of porosity has a negligible

impact on mechanical performance [81]. Beyond mechanical considerations, porosity can also compromise corrosion resistance, particularly when pores are located at or near the surface, as they may act as initiation sites for corrosion [82].

3.2.5. Marangoni flow

The oxygen content in the surrounding environment and the powder material can locally alter surface tensions [325]. Such localised variations in surface tension can reverse the direction of Marangoni flow, with the reversed flow potentially leading to the formation of islands, as illustrated in Figure 3.6. Additionally, these local changes in surface tension may compromise the stability of laser scanning and reduce the wetting and spreading behaviour of the liquid melt flow.

3.2.6. Surface Pit

When ejected molten material solidifies and settles on the powder bed surface, or when a powder particle lands on the powder bed surface without fully melting, a protrusion is formed on the surface [59]. Material agglomeration resulting from mass transfer can also lead to the formation of surface protrusions. Protrusions larger than the layer thickness may be removed by the recoating mechanism during the layering process, leaving pits (see Figure 3.6) on the surface. If these pits are small, they can be rectified by subsequent layers. However, larger pits may be irreparable, potentially causing defects in both the current and subsequent layers.

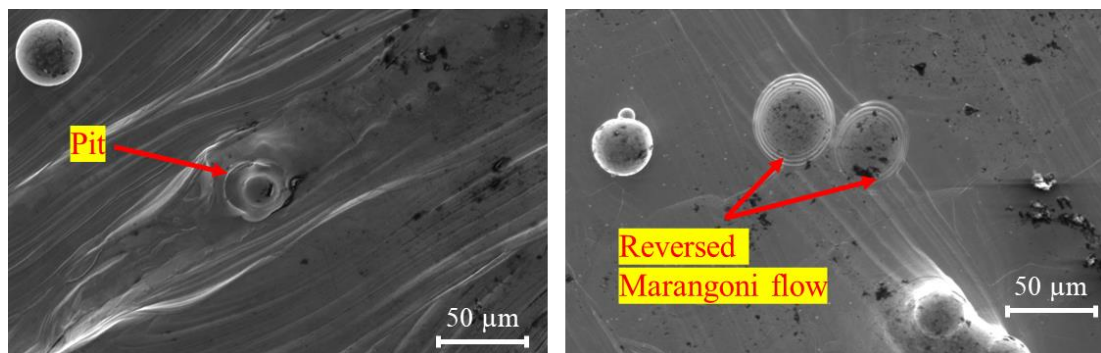


Figure 3.6. SEM images of the top surface of as-manufactured PBF-LB samples, showing the surface pit and reversed Marangoni flow.

3.2.7. Unknown features

This section introduces certain microscale surface features, which are reported for the and presented in [319]. Additionally, it outlines the potential mechanisms responsible for the formation of these features. The PBF-LB specimens exhibiting these features were produced using the process parameters outlined in Table 3.2.

Table 3.2. Process parameters of the analysed samples.

Profile name	Laser power / W	Scan speed / m s^{-1}	Layer thickness / μm	3D Energy density / J mm^{-3}
5-30	145	1.25	30	59.49
6-30	220	1.25	30	90.26
6-60	370	1.5	60	63.29

Figure 3.7 illustrates two types of round-shaped features, which we named “circular ripples” and “explosion-like feature”. The features of the circular ripples (see Figure 3.7a) are similar to the ripples on the weld tracks on the surface, whilst having a circular shape and some particles in the centre. The shape of the surface ripples formed nearby appears to be influenced by the circular features. This may be because the ripples on the weld tracks were formed while the surface was in a liquid state; whilst the ripple structures were pushed around the circular ripples. The circular ripples may be caused by pores that escaped from the surface. It should be noted that the circular ripples were observed on all samples we manufactured.

For the explosion-like feature, as shown in Figure 3.7b, a dynamic impact may be the cause of its formation as it seems there was a force pushing the upper layer from below, and the upper layer was therefore shaped. Note that the centre of the feature contains some debris.

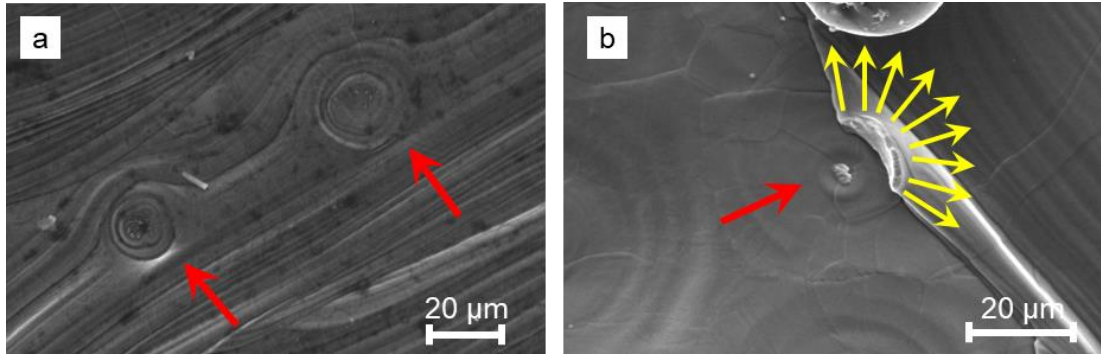


Figure 3.7. a) Circular ripples, b) Explosion-like feature.

Figure 3.8a shows a feature that has a pentagonal shape whose centre looks similar to those of the circular ripples and explosion-like features, but with a different outer shape. It can be observed that there are dendritic structures on its edges and a collapse-like centre. These dendritic structures look similar to those reported in [326], probably having the same causes – the impact of particles remelting around the surface or solidifying the melt pool on contact. It appears that there is a sharp distinction at the edge area of the pentagon-shaped feature, which may be because this feature was formed due to cracking after solidification, e.g. spattered material may have hit the solidified surface after attaining high temperature and velocity.

Figure 3.8b shows one partially melted or buried powder or spatter particle on the border of two adjacent scan lines. What distinguishes it from other surface particles is that it has many small shiny flecks on it. These flecks may have stuck to the particle while the spatter was airborne and adhered to the particle before falling to the surface.

The sample with the explosion-like feature, the pentagon-shaped feature and fleck-adhered particle were manufactured with profile 6-60, which has the highest laser power value among the three profiles. Therefore, high laser power may be responsible for the formation of these features.

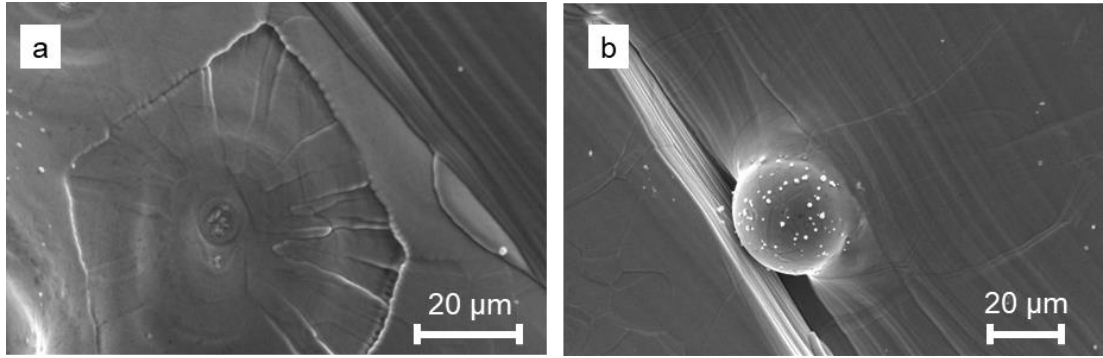


Figure 3.8. a) Pentagon-shaped feature, b) Fleck adhered particle.

Figure 3.9a shows an area with dark markings on the right side, and Figure 3.9b shows a particle surrounded by plume-like material. These two figures were taken from the same sample. The sample having these structures was fabricated with profile 6-30. The formation of the dark markings and the plume-surrounded particle may be related to the high 3D energy density.

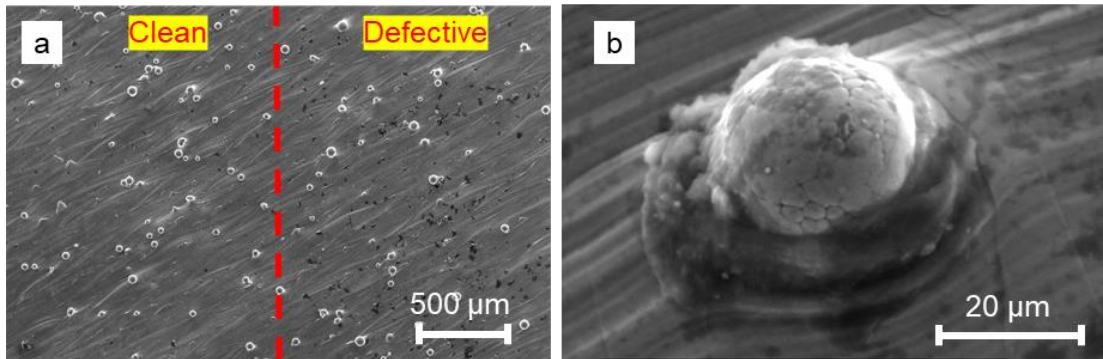


Figure 3.9. a) Half dirty half clean surface, b) Plume-surrounded particle.

Figure 3.10a shows dark spots which are formed like a zigzag-shaped line, whose width is about 30 μm to 50 μm . It seems there are no correlations between the zigzag-shaped line and the laser scan tracks. A motion error due to vibration or a material defect may be the cause of the zigzag-shaped line.

Figure 3.10b shows stick-shaped features located near the zigzag-shaped structure. Similar structures to the stick-shaped features were reported in [327] and named “needle-formed precipitates”. They were claimed to have a negative effect on the quality of the parts.

The sample that has the zigzag-shaped line and stick-shaped features was fabricated using profile 5-30. As profile 5-30 has the lowest laser power and 3D energy density, it may be the cause of these features.

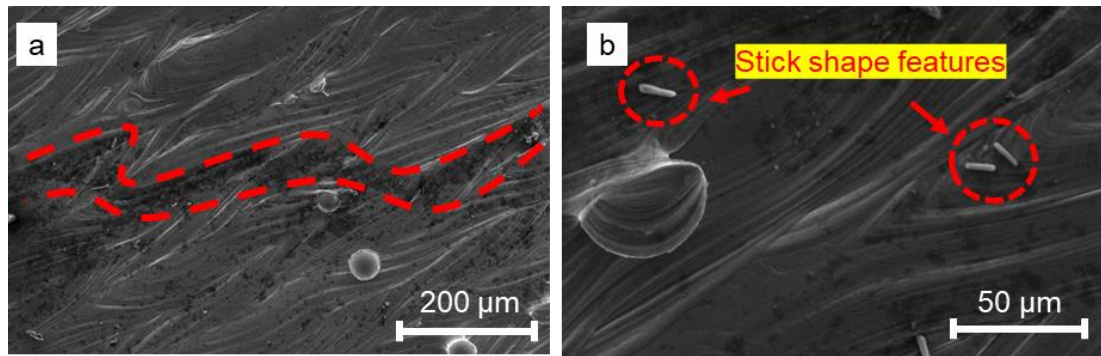


Figure 3.10. a) Zigzag-shaped defect line, b) Stick-shaped features.

As shown in Figure 3.11, there is a large dark mark on the surface whose width is about 100 μm . A powder spreading error or contamination of powder material may be the cause of this feature.

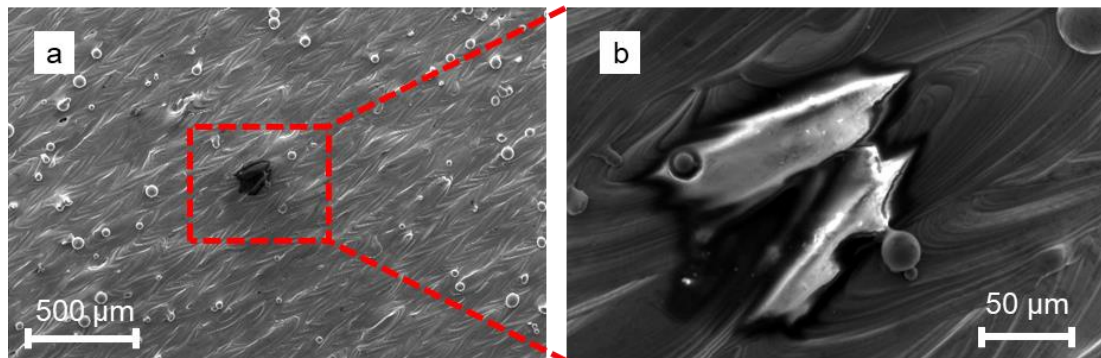


Figure 3.11. a) SEM image of a black mark, b) magnified image of the black mark.

3.3. Investigating the effect of process parameters on surface morphology

Additive manufacturing processes such as PBF-LB are highly sensitive to processing parameters, which can influence the quality and properties of the fabricated components. Although there are some process optimisation studies for PBF-LB fabrication, it may not be possible to find the optimised parameters for any machine, material and geometry. Among the process parameters, laser power, scanning speed,

and layer thickness play significant roles in determining melt pool dynamics, surface morphology, and defect formation. This section aims to investigate the effect of these parameters on surface quality, particularly focusing on spatter formation and melt track uniformity. By evaluating the top surfaces of fabricated samples using SEM imaging, insights into how each parameter individually contributes to surface characteristics are obtained.

The findings further shows that small deviations of the process parameters can cause the microscale surface impurities which can diminish the surface quality. Therefore, the microscale surface features need to be measured and monitored during the fabrication to assess the fabrication quality.

3.3.1. Laser power and energy density

In the initial set of experiments, the energy density was decreased by reducing the laser power, while all other process parameters were kept constant. Figure 3.12 presents SEM images of the fabricated samples, with the corresponding process parameters detailed in Table 3.3. The layer thickness and scan speed were maintained at $30\text{ }\mu\text{m}$ and 1.25 m s^{-1} , respectively. The laser powers of the samples were 170 W, 145 W, and 120 W, corresponding to 3D energy densities of 69.74 J mm^{-3} , 59.49 J mm^{-3} , and 49.23 J mm^{-3} , respectively.

The SEM images in Figure 3.12 reveal that, as the laser power and energy density decrease (from profiles 1-30 to 5-30 and subsequently to 4-30), the uniformity of the weld tracks progressively deteriorates. However, the quantity of spatter particles observed on the surfaces remains relatively consistent across all three samples.

Table 3.3. Process parameters of samples shown in Figure 3.12.

Profile name	Laser power /W	Layer thickness / μm	Scan speed / m s^{-1}	3D Energy density / J mm^{-3}
1-30	170	30	1.25	69.74
5-30	145			59.49
4-30	120			49.23

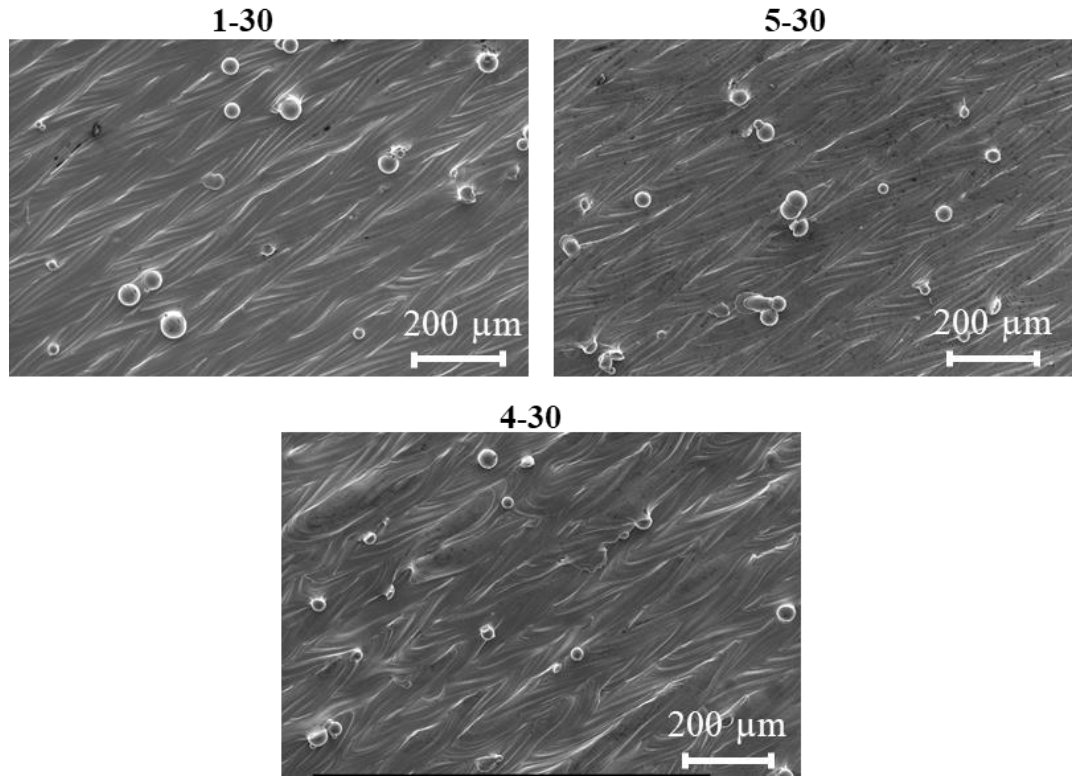


Figure 3.12. SEM images of top surfaces fabricated with different laser powers.

3.3.2. Scanning speed

The second set of samples was manufactured using varying scanning speeds while maintaining all other parameters, such as power and layer thickness, constant (see Table 3.4 for the process parameters). The purpose of fabricating this set was to examine the effect of scanning speed on surface quality. As illustrated in the images in Figure 3.13, the number of spattered particles increases as the scanning speed rises from 1.0 m s^{-1} to 1.5 m s^{-1} and 2.0 m s^{-1} . Additionally, the uniformity of the melt tracks deteriorates with an increase in scanning speed.

Table 3.4. Process parameters of samples shown in Figure 3.13.

Profile name	Laser power /W	Layer thickness / μm	Scan speed / m s^{-1}	3D Energy density / J mm^{-3}
1-60	320	60	1.0	82.05
2-60			1.5	54.70
3-60			2.0	41.07

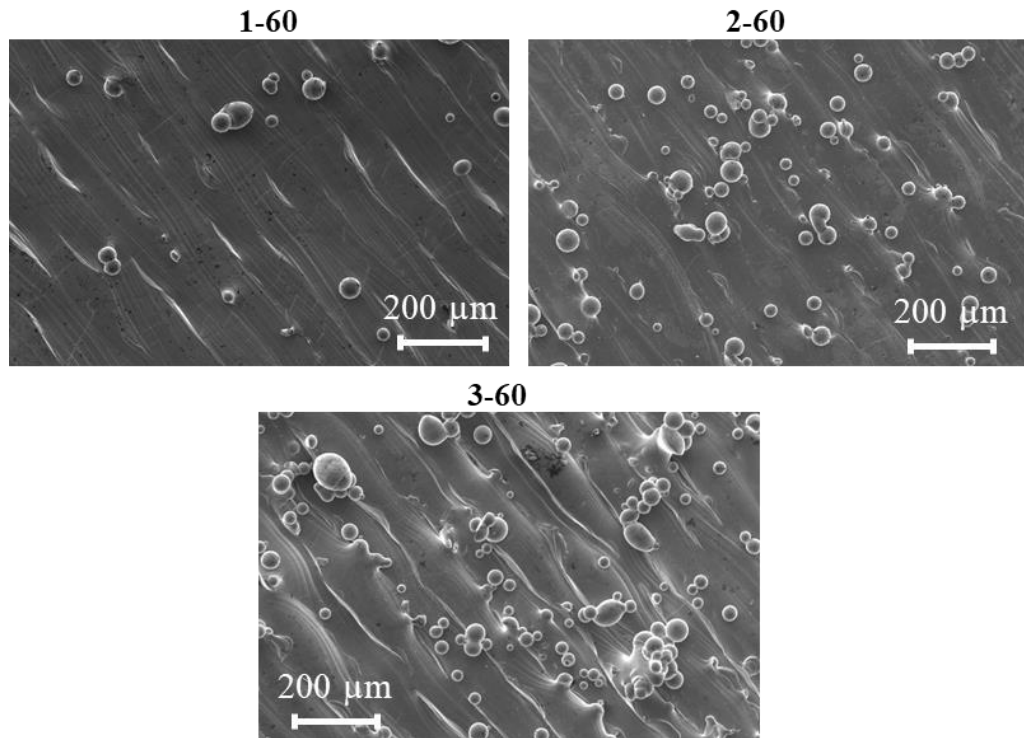


Figure 3.13. SEM images of top surfaces fabricated with different laser scanning speeds.

3.3.3. Layer thickness

Figure 3.14 illustrates two samples fabricated using the same scanning speed of 1.5 m s^{-1} , but with differing laser powers and layer thicknesses. The sample fabricated with the profile 2-60, has a larger layer thickness and higher laser power (see Table 3.5), exhibits a significant amount of powder spattering. This observation suggests that the occurrence of spattering is influenced not only by scanning speed but also by other parameters. The substantial spattering observed in this instance is likely attributable to the increased layer thickness, as higher laser power typically produces smoother surfaces.

Table 3.5. Process parameters of samples shown in Figure 3.14.

Profile name	Laser power /W	Layer thickness / μm	Scan speed / m s^{-1}	3D Energy density / J mm^{-3}
2-30	170	30	1.5	58.12
2-60	320	60		54.70

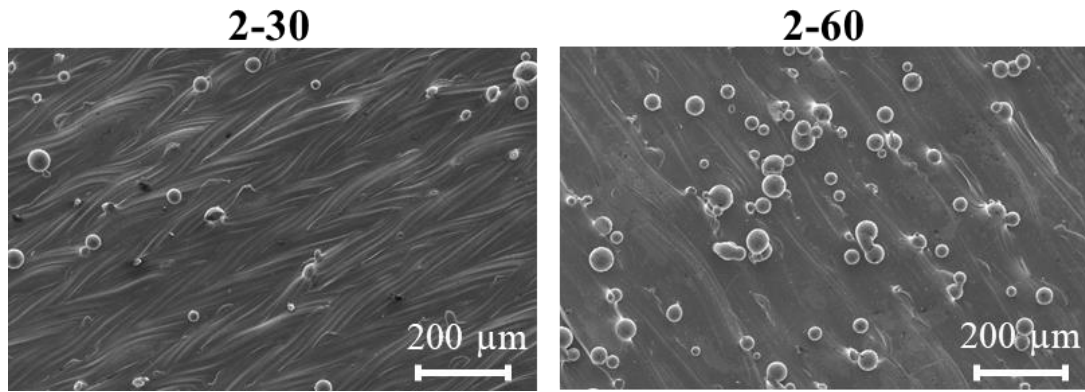


Figure 3.14. SEM images of top surfaces fabricated with different laser powers and layer thicknesses.

The experimental observations clearly demonstrate that variations in laser power, scanning speed, and layer thickness have a considerable impact on surface morphology in PBF-LB parts. A reduction in laser power and energy density leads to poorer weld track uniformity, while increased scanning speeds correlate with a higher presence of spatter. Furthermore, increased layer thickness amplifies spattering effects, even when compensated with higher laser power. These findings highlight the need for a balanced optimisation of process parameters to minimise surface defects and improve the overall quality and consistency of additively manufactured parts.

3.4. Summary

One of the aims of this thesis is to develop a method for detecting microscale impurities formed during the PBF-LB process. Prior to devising such a method, PBF-LB samples were fabricated under a range of process parameters and subsequently subjected to microscale surface analysis. This chapter presents the findings of that analysis, the primary objective of which was to observe microscale impurities using a high-resolution technique, SEM, as a precursor to developing the detection method.

Additionally, several previously unreported surface anomalies were identified, and their potential formation mechanisms were proposed. The relationship between these microscale features and the corresponding process parameters was also investigated. Finally, the impact of such surface defects on the overall quality of the fabricated

components was evaluated – emphasising the importance of detecting and understanding these features in order to improve the consistency and reliability of PBF-LB manufacturing.

4. Impurity detection

Section 2.2 reviews key microscale surface impurities reported in the literature and discusses their potential impact on surface quality and overall part integrity. Building on this, Chapter 3 presents a detailed microscale surface analysis of as-manufactured PBF-LB samples, highlighting the types of impurities observed and their associated effects on component quality. These sections collectively emphasise the necessity of detecting such impurities, either to assess the quality of the build or to enable real-time intervention—potentially including corrective actions or the termination of fabrication if the defects are critical.

Although the concept of detecting surface impurities may appear straightforward, precisely defining what constitutes a defect is more complex, as certain types of impurities may either be corrected in subsequent layers or persist and propagate into them. The methods for detecting impurities during the fabrication of PBF-LB components (see Section 2.3), can broadly be classified into two main categories: direct detection using fabrication data, and indirect detection via process signatures. Indirect methods rely on correlations between the formation of impurities and process signatures—such as acoustic or thermal data—collected during fabrication. These techniques establish a relationship between the recorded process signals and known ground truth data, enabling impurity detection. In contrast, direct methods focus on detecting impurities from in-process data, such as images or surface topography measurements, without using correlations.

Detection methods employ a sensing technology to collect in-process data such as acoustic [328], image [233], thermal [329] or height map [164] data. In order to detect the impurities from the collected data, data processing such as analytical approaches [330], image processing algorithms [331] or ML algorithms [256] can be used.

This chapter presents two approaches developed to quantitatively identify surface impurities through image processing and surface topography analysis. The first approach, described in Section 4.1, utilises a custom image processing algorithm implemented in MATLAB to detect microscale surface impurities and assess the

overall surface quality from SEM images. The fabrication details of the surfaces and the procedure for SEM image acquisition are provided in Chapter 3. As the focus of Chapter 4 is on the development of impurity detection methods, those details are not repeated here.

The second approach, outlined in Section 4.2, involves the analysis of surface topography data, in line with the overarching methodology of this thesis, which prioritises the detection of surface features using topographical information. This method includes acquiring surface topography measurements using a CSI instrument and evaluating the surface parameters defined in ISO 25178-2 [332] to identify and distinguish surfaces exhibiting impurities. Although the methods developed in this study are applied offline, the investigation lays the groundwork for future implementation in in-process applications with further development.

4.1. Impurity detection on SEM images with image processing

In this section, a defect detection algorithm for SEM images is proposed, utilising image processing. The algorithm was developed in Matlab and is designed to analyse SEM images of PBF-LB surfaces to detect and evaluate non-uniform features such as spatters, balling, and other surface defects. The Matlab code identifies non-uniform objects within the image, calculates their total area, and determines the proportion of the image pixels that these objects occupy. Based on this calculated defect coverage (referred to as the defect ratio), the code assigns a quality classification – either "Good Quality" or "Poor Quality".

Here's a breakdown of the purpose and functionality of each section:

Read and Prepare the Image

```
RGB = imread("input image");  
I = rgb2gray(RGB);  
bw = imbinarize(I);
```

The initial step involves loading the image with RGB channels using “input image”. The loaded image subsequently converted to grayscale using “rgb2gray” function. This enhances computational efficiency for further analysis. The grayscale image is subsequently binarised with “imbinarize”, separating it into black and white pixels

by setting the values 0 and 1, respectively. This function uses Otsu's threshold to select the values. Figure 4.1 illustrates the loaded image and final image after binarisation.

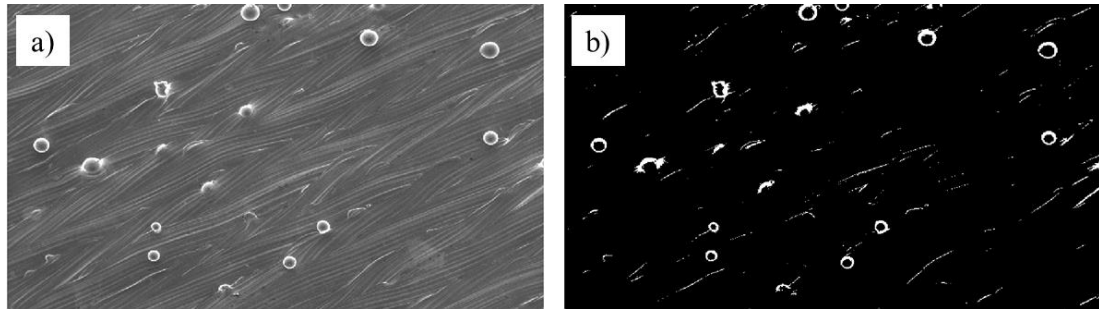


Figure 4.1. a) The input image and b) the binarised image.

Morphological Processing

This section of the code applies morphological operations to the binarised images in order to eliminate noise and enhance the visibility of surface features.

```
bw = bwareaopen(bw,5);
se = strel('disk',8);
bw = imclose(bw, se);
bw = imfill(bw,'holes');
```

The first two lines of this section remove the noise on the binarised images. The function “*bwareaopen*” removes small objects – fewer than 5 pixels are selected here based on the size of the impurities. In order to close small gaps in the impurities, morphological closing is performed using “*Imclose*” with a disk-shaped structuring element named “*strel*” having a radius of 8 pixels. The function “*imfill*” ensures that all objects, such as holes and connected regions, are filled (e.g., circles become solid). Figure 4.2 illustrates before and after applying morphological operations to the binarised image. By adjusting the pixel threshold in “*bwareaopen*” and the diameter of the circular shape of “*strel*” disk, the size of the smallest feature can be determined.

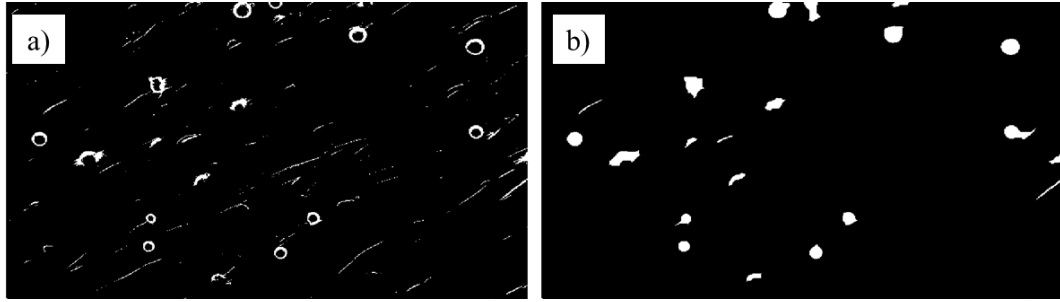


Figure 4.2. a) The image before and b) after applying the morphological operation.

Boundary Extraction and Visualisation of Compute Area

```
[B,L] = bwboundaries(bw,'noholes');
for k = 1:length(B)
    boundary = B{k};
end
stats = regionprops(L,'Area');
areas = ones(length(B),1);
for k=1:length(B)
    areas(k)= stats(k).Area;
end
sumAreas = sum(areas);
```

The function “*bwboundaries*” extracts the boundaries of all objects (B) and labels each connected component (L) in the binary image. The first loop here iterates through each boundary found and extracts the boundary coordinates. The second loop extracts the area of each detected object. After the area extraction, the total area of all objects, “*sumAreas*” is computed by summing the individual areas. Figure 4.3 shows before and after applying the boundary extraction.

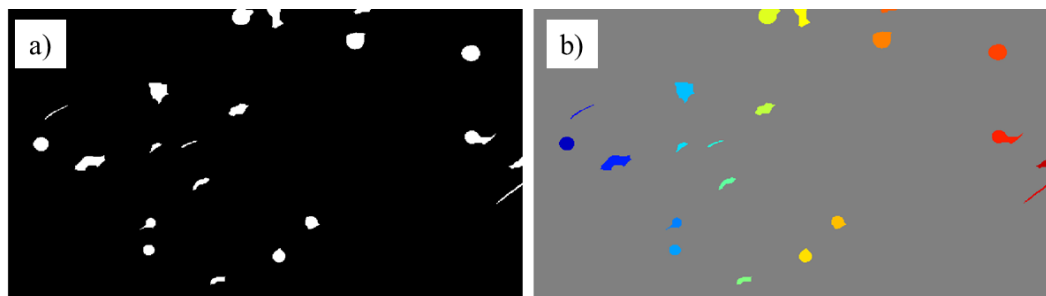


Figure 4.3. a) The image before applying the boundary extraction and b) after the boundary extraction.

Defect Ratio Calculation

```
[a, b, c] = size(RGB);
```

```
TotalArea = a*b;
```

```
areaRatio = round(sumAreas/TotalArea*100);
```

The last section of the code here determines the quality of the surface by calculating the defect ratio. It initially calculates the total area of the image “*TotalArea*” by multiplying its dimensions. It subsequently computes the percentage of the image covered by the detected objects “*areaRatio*”. The original image is shown alongside the segmented image in Figure 4.4. The defect ratio is displayed on the segmented image.

When the defect ratio is below 5%, the quality is deemed "Good Quality" (green text). Otherwise, it is "Poor Quality" (red text). This threshold may be adjusted depending on the acceptable level of defects for a given application. Figure 4.4 presents the results of the algorithm for both good-quality and poor-quality cases.

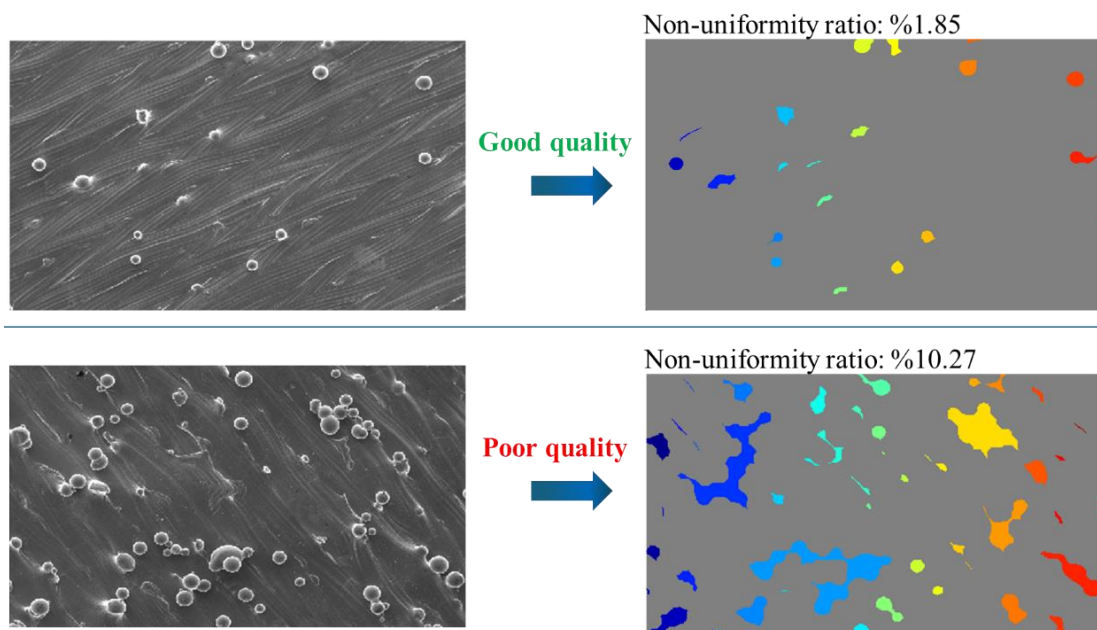


Figure 4.4. The result of surface impurity detection for both good and poor quality surfaces.

4.2. Topography analysis

Image processing techniques, such as the method described in Section 4.1, require the careful selection of optimal image processing parameters to achieve maximum detection accuracy. However, this selection process is typically conducted through a trial-and-error approach. Consequently, a systematic and quantitative methodology is essential for the effective detection of impurities [333].

The pixel values in digital images represent the intensity or brightness recorded by the imaging system; however, there is no direct or reliable correlation between these pixel values and surface height measurements. The ISO 25178-2 standard [332] defines a set of surface topography parameters that describe surface topography. These parameters are geometrically based and can offer valuable insights into the manufacturing process and the mechanisms underlying defect formation. Therefore, an approach based on the analysis of surface topography and the application of ISO 25178-2 metrics is deemed essential.

Surface topography parameters derived from topographical measurements provide detailed information about variations in surface elevation. These parameters capture the geometric structure of the surface – specifically its form and texture [334]. Owing to their well-established use within manufacturing environments [335], they offer practical and intuitive means of characterising physical surface features. They are particularly valuable for identifying correlations between fabrication processes, the resulting surface morphology, and the functional performance of the final component.

Several studies in the literature have investigated surface topography to evaluate manufacturing quality. For example, Janson et al. [336] examined the relationship between surface height parameters and the tribological and mechanical properties of certain nanostructured coatings. Likewise, Das et al. [337] aimed to identify and systematically select the most appropriate surface height parameters for monitoring manufacturing processes.

In this section, surface topography analysis was carried out on fabricated PBF-LB samples to assess surface quality and detect impurities. The surfaces were measured using the Zygo NexView™ NX2 CSI instrument with the $5.5\times$ magnification lens.

Following data acquisition, surface analysis was performed using MountainsMap software.

4.2.1. Slope angle distribution

Surface topography plays a critical role in determining the functional performance and quality of components. One parameter of increasing relevance in surface analysis is the slope angle – also referred to as the gradient – distribution, which provides a statistical representation of local surface inclinations. As defined in ISO 25178-2 [332], the slope distribution is:

“The density function calculated from the scale-limited surface showing the relative frequencies against the angle of the steepest gradient $\alpha(x, y)$ with respect to the z -axis and direction of the steepest gradient $\beta(x, y)$ anticlockwise from the x -axis.”

The schematic representations of the gradients, α and β , are illustrated in Figure 4.5. These gradients can be calculated using equations (4.2) and (4.1), respectively.

$$\alpha = \tan^{-1} \left(\frac{n_u}{n_z} \right) = \tan^{-1} \left(\frac{\sqrt{n_x^2 + n_y^2}}{n_z} \right), \quad (4.2)$$

$$\beta = \tan^{-1} \left(\frac{n_y}{n_x} \right). \quad (4.1)$$

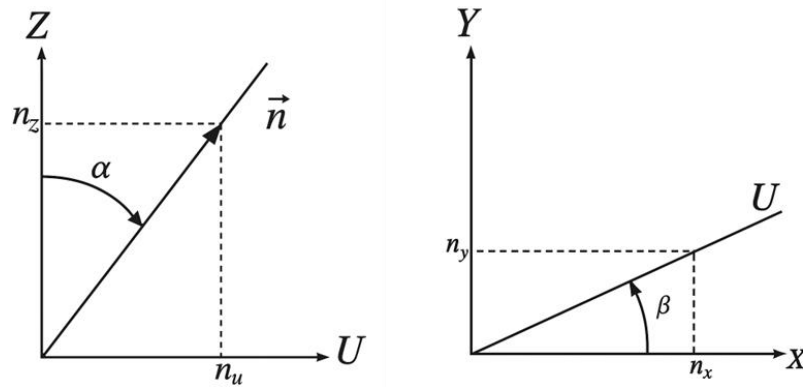


Figure 4.5. Schematic representation of α and β .

In the context of impurity detection, slope angle analysis can serve as a powerful tool for distinguishing between surface regions affected by impurities – such as

protrusions or recesses – and those that are uniform. This section investigates the slope angle distributions of PBF-LB manufactured surfaces, comparing areas with and without observable impurities. The objective is to evaluate whether variations in slope characteristics can be used as reliable indicators of surface anomalies. Through quantitative analysis using MountainsMap software (see Figure 4.6), statistical metrics such as mode, mean, and main slope angle values are examined to assess their potential for classifying surface conditions and supporting defect detection efforts.

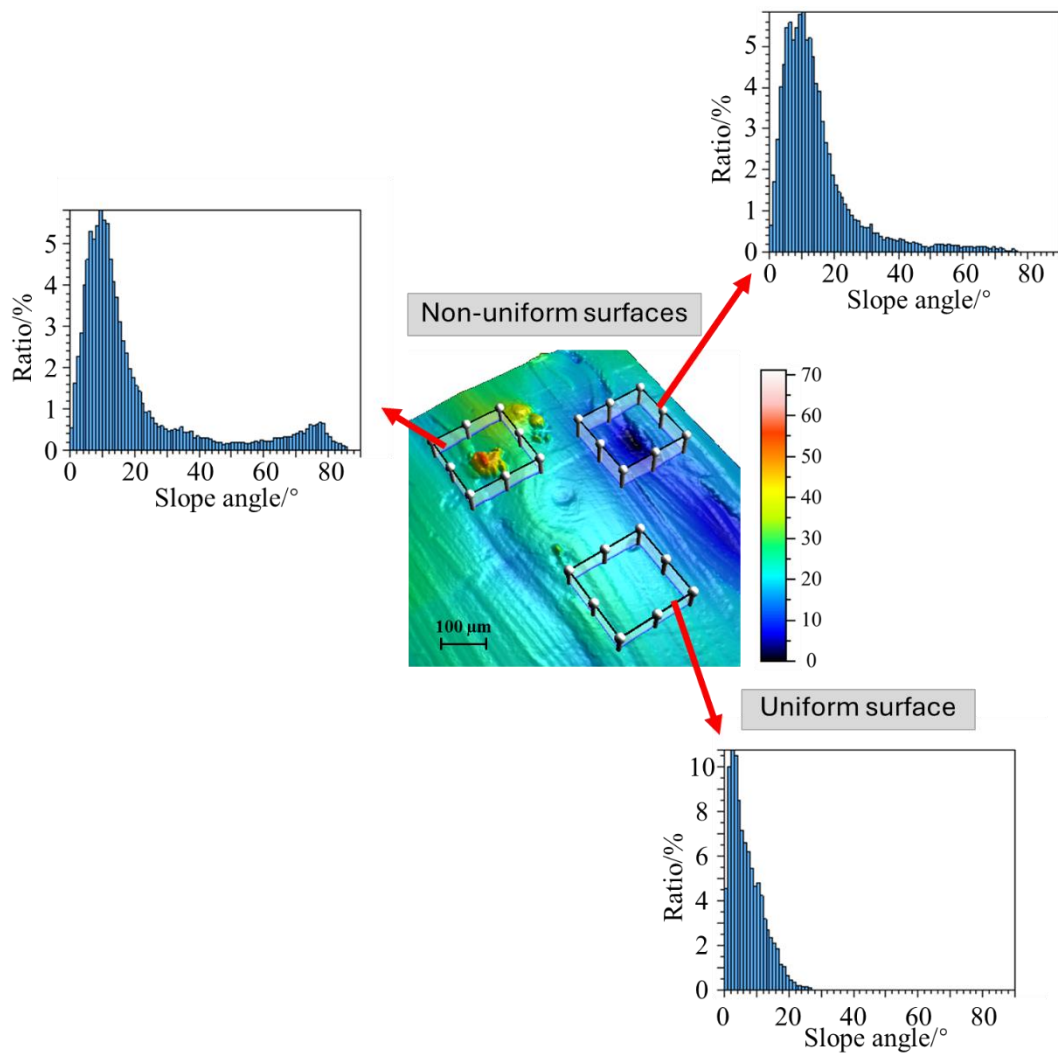


Figure 4.6. Slope angle distribution of selected surface areas extracted from surface topography measurements.

The slope analysis was performed on two sets of surface portions, those with and those without impurities. Figure 4.7 and Figure 4.8 depict the selected surface

portions alongside their respective slope angle distribution characteristics. Figure 4.9 provides graphs displaying the results for uniform and non-uniform surface areas, focusing on mode, mean, and main values of slope angle distribution. In Figure 4.9 it has been compared the slope angle distribution of the uniform and non-uniform surfaces extracted from the areas shown in Figure 4.7 and Figure 4.8. It can be observed that the mode and main exhibit similar characteristics. While some overlap between these two metrics is evident for certain surfaces, they show promise for use in surface classification. In contrast, the mean demonstrates distinct characteristics compared to the mode and main, showing greater potential for surface classification. This is due to the absence of overlap between the results for the two surface types, enabling the establishment of a threshold value to differentiate between uniform and non-uniform surfaces.

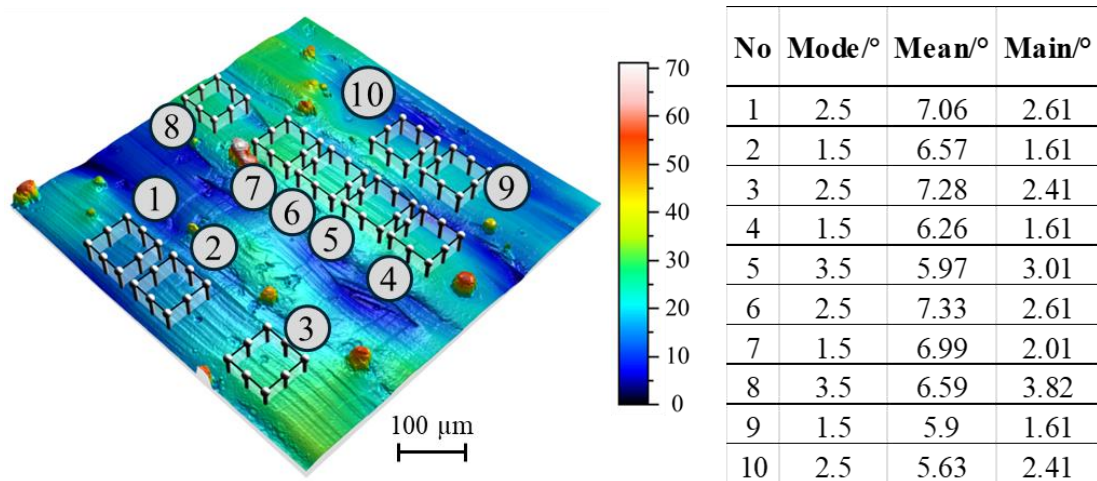


Figure 4.7. Mode, mean and main values of slope angle distribution of selected uniform surface areas without impurity.

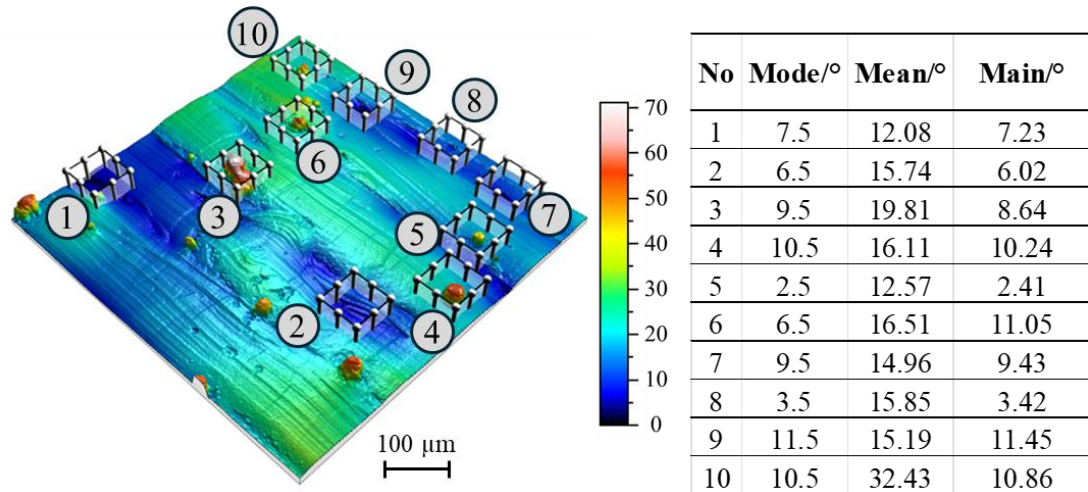


Figure 4.8. Mode, mean and main values of slope angle distribution of selected non-uniform surface areas with impurity.

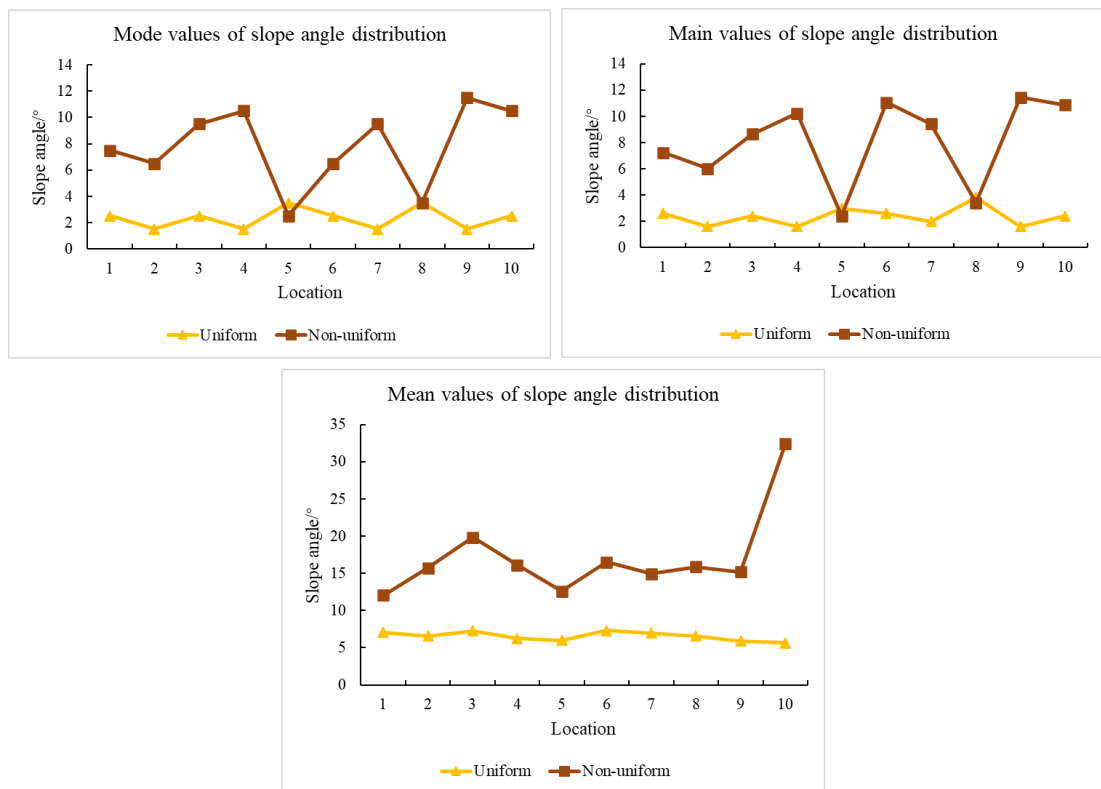


Figure 4.9. The graphs of mode, main and mean values of slope angle distribution.

Although the slope angle distribution provides a useful means of distinguishing between uniform and non-uniform surfaces, it has certain limitations. Specifically, the recorded slope angles may be constrained by the numerical aperture of the

objective lens. As a result, this method may not offer a general approach for impurity detection, as its effectiveness is dependent on the characteristics of the objective lens used.

4.2.2. Areal surface texture parameters comparison

This section examines the application of surface topography parameters – specifically those defined in ISO 25178-2 [332] – for the evaluation and classification of surfaces produced by the PBF-LB process. Particular attention is given to three key parameters: arithmetical mean height (Sa), maximum peak height (Sp), and developed interfacial area ratio (Sdr). These parameters were previously identified by Redford and Mullany [333] as effective indicators for defect classification.

The definitions of the metrics from ISO 25178-2 [332] are as follows:

- Sa represents the mean of the absolute values of the ordinate of the scale-limited surface. The Sa value can be calculated as

$$Sa = \frac{1}{A} \iint |z(x, y)| dx dy, \quad (4.3)$$

where A represents the value of the evaluation area.

- Sp represents the largest peak height value of the scale-limited surface.
- Sdr represents the ratio of the increment of the interfacial area of the scale-limited surface over the evaluation area. The Sdr value can be calculated with the equation (4.4) as

$$Sdr = \frac{1}{A} \iint \left(\sqrt{\left[1 + \left(\frac{\partial z(x, y)}{\partial x} \right)^2 + \left(\frac{\partial z(x, y)}{\partial y} \right)^2 \right]} - 1 \right) dx dy. \quad (4.4)$$

In this study, surfaces are categorised as either uniform, indicating the absence of microscale impurities, or non-uniform, indicating their presence. To facilitate this classification, threshold values were defined for each parameter, as summarised in Table 4.1.

Table 4.1. Threshold values for surface topography parameters to discriminate surface types.

Uniform surfaces	$< Sa, 2 \mu\text{m}$
	$< Sp, 4 \mu\text{m}$
	$< Sdr, 15\%$

Figure 4.10 presents representative examples of both uniform and non-uniform surfaces, together with their corresponding surface texture parameter values. As illustrated, uniform surfaces—comprising primarily of melt tracks—exhibit surface texture parameters below the defined thresholds. Conversely, non-uniform surfaces that contain microscale impurities display significantly higher values. These results demonstrate that the selected parameters, when used with appropriate thresholds, can reliably classify surface quality in a quantitative and systematic manner. This approach will be employed in Section 6.1 for the classification of surfaces.

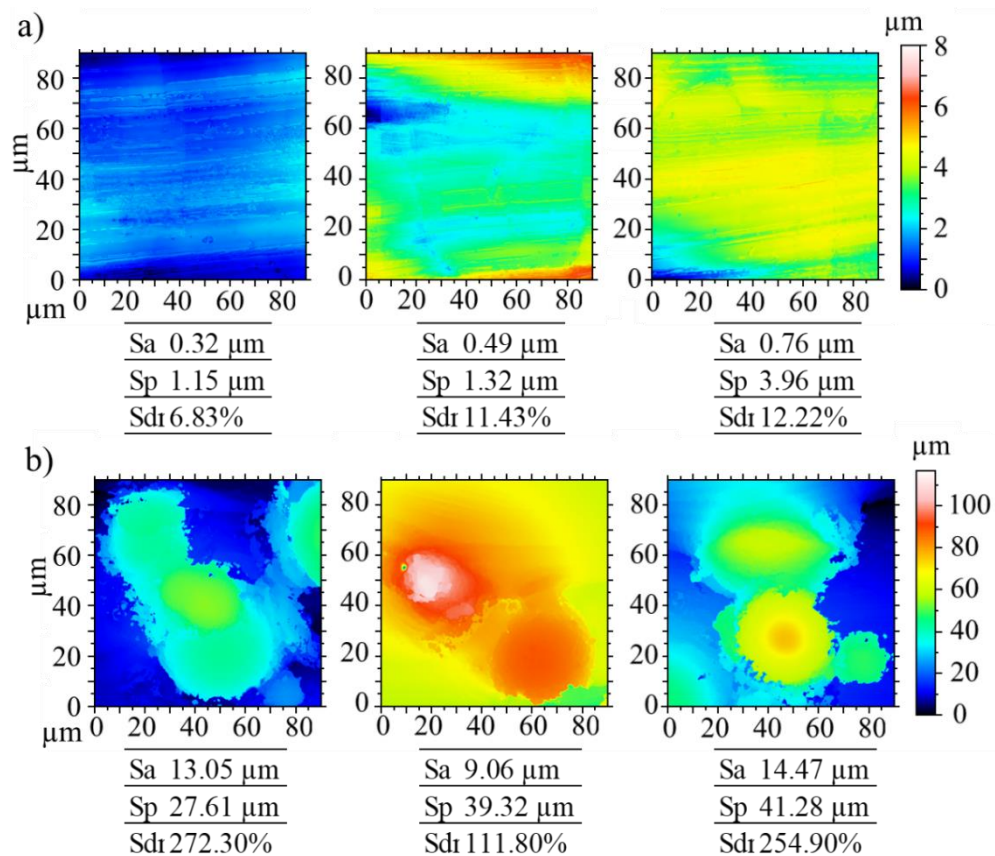


Figure 4.10. a) Uniform and b) non-uniform surfaces with their corresponding surface texture parameters.

4.3. Summary

This chapter has presented an investigation into impurity detection in PBF-LB manufactured components, employing both image-based and topography-based methodologies. Two distinct approaches were developed and evaluated. The first involved a custom image processing algorithm designed to analyse SEM images for the identification and quantification of surface defects. This approach introduced the concept of a defect ratio as a practical metric for assessing surface quality and demonstrated its effectiveness in classifying surfaces as either good or poor quality, based on the proportion of surface impurities. While this approach provides valuable insight into defect detection, a key limitation lies in the parameter selection for the image processing algorithm, which currently relies on a trial-and-error process.

The second approach focused on the analysis of surface topography data acquired through the CSI instrument. Initially, slope angle distribution analysis was introduced as a quantitative tool to detect surface irregularities and distinguish between uniform and non-uniform regions based on statistical characteristics of surface inclination. However, as previously noted, the slope angle approach is constrained in its effectiveness due to the limitations imposed by the numerical aperture of the objective lens. Finally, a method applied using three surface texture parameters – Sa , Sp , and Sdr – as defined in ISO 25178-2, to differentiate between surfaces with and without microscale impurities. This method demonstrates that, when used with appropriate threshold values, these parameters can be used to classify surface quality in a quantitative manner.

The SEM method is not suitable for in-process evaluation, as the component must be fully fabricated before measurements can be performed. Similarly, surface topography measurement using a CSI instrument is not inherently designed for in-process assessment. Nevertheless, this technique offers potential as a foundation for the development of an in-process monitoring method.

One of the purposes of this thesis is to develop a method for detecting microscale impurities that arise during the PBF-LB process. In order to identify such impurities, it is first necessary to establish a quantitative definition of the impurities. This chapter evaluates two approaches to achieving this. Given the advantages of the

second approach based on surface texture parameters, it is adopted in this thesis for the classification of surfaces.

5. Development of the experimental light scattering

While various in-situ methods show potential for detecting microscale impurities on PBF-LB, their applicability in industrial settings remains limited. Real-time data is often collected, but detection typically occurs post-process due to high computational demands. Detection delays due to high processing times further hinder implementation as real-time feedback systems. More details about in-situ measurement and monitoring methods can be found in Section 2.3. Section 2.2 highlights microscale surface impurities, some under 10 μm , which can significantly affect part quality. However, detection accuracy of the in-situ methods generally declines for features below 100 μm mostly due to their resolution limits. A reliable industrial solution must consistently detect all relevant impurities in real time, including those smaller than 100 μm . In this thesis, a light scattering method, which is a non-contact, fast, and cost-efficient system, and can infer surface topography [159], has been developed to meet these requirements.

This chapter presents designing the experimental light scattering setup for monitoring and detection of microscale surface impurities formed on PBF-LB. The chapter also introduces a microscopy unit that has been developed and integrated into the scattering setup. This unit facilitates monitoring of the illuminated area and aids in aligning the beam within weld tracks.

In addition to setting the experimental design, the chapter investigates the impact of polarisation and neutral density filters on the resulting scattering patterns. By analysing and comparing scattering patterns of surfaces with and without impurities, the system's effectiveness in differentiating between them is thoroughly evaluated. These findings demonstrate the potential of the developed setup for microscale impurity detection in PBF-LB manufacturing.

5.1. Experimental light scattering setup based on beam focusing

In the light scattering setup (see Figure 5.1), a diode laser with a central wavelength of 635 nm and a beam diameter of 1.1 mm is employed to illuminate the target surface. To reduce the beam size, a converging lens with a focal length of 75 mm is placed between the laser source and the surface. The distance between the lens and

the surface is set to 80 mm, resulting in a beam diameter of approximately 90 μm at the surface. This configuration ensures that the laser spot remains within the weld track.

Table 5.1. Lens specifications.

Lens Shape	Plano-Convex
Substrate Material	N-BK7 (Grade A)
Focal length/mm	75
Diameter/mm	50.8
Anti reflection coating	350 – 700 nm
Reflectance over Coating	<0.5%
Index of Refraction	1.515
Surface Quality	40-20 Scratch-Dig
Focal Length Tolerance	$\pm 1\%$

The light scattered from the surface forms a pattern on the plastic screen (EDU-VS1), that is specific to the illuminated surface. The relationship between the scattered light and the illuminated surface is explained in detail in Section 2.5. A Nikon D3300 camera was used to record this scattered pattern formed on the screen (see Figure 5.1). The locations and the positions of the components are illustrated in Figure 5.1. The specifications of the camera and screen are provided in Table 5.2. To minimise the effects of vibration during data collection, the camera was remotely triggered. Following the image capture of the patterns, the recorded images were cropped to extract the field of interest.

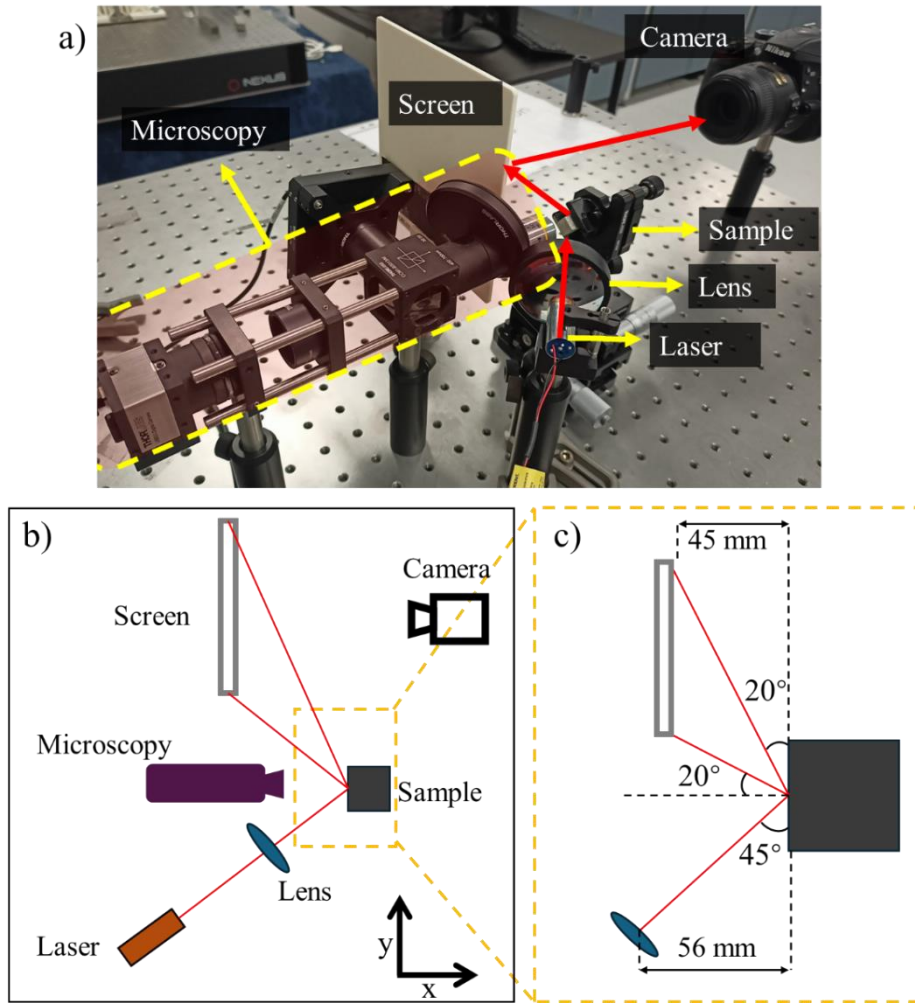


Figure 5.1. a) Experimental setup of the light scattering technique, and b - c) its schema.

Table 5.2. Specifications of the camera and the plastic viewing screen.

Camera specifications		Screen specifications	
Body type	Compact SLR	Size	150 mm × 150 mm
Max resolution/pixels	6000 × 4000	Thickness	3.0 mm
Effective pixels/megapixels	24	Material	White Polystyrene
Sensor size/mm	APS-C (23.5 × 15.6)		
Sensor type	CMOS		
Minimum shutter speed/sec.	30		
Maximum shutter speed/sec.	1/4000		
Flash range/m	12.00 (at ISO 100)		
Continuous drive/fps	5.0		
Exposure compensation	±5 (at 1/3 EV steps)		

As shown in Figure 5.1a and b, the light scattering setup was combined with a microscopy unit to inspect the illuminated area on the surface. This integration assists in aligning the beam within weld tracks (see Figure 5.2a) and in characterising the illuminated surfaces. This unit comprises an objective lens (Olympus PLN 10 $\times$), an LED light source (Liucwha - Cold White) with a diffuser (ED1-C50-MD), a beam splitter (CCM1-BS013/M), a focusing lens (AC254-060-A-ML), and a camera (DCC1240C) for capturing surface images. As direct illumination with laser can obscure surface details (see Figure 5.4a and b), images are recorded both with and without illumination to clearly reveal the illuminated area.

Examples of impurities on the weld tracks are shown in the surface image and height maps in Figure 5.2b and d. Figure 5.2c and e illustrate the surface image and height map of uniform weld tracks without impurities. In Figure 5.2, surface images were obtained using the microscopy unit, and the surface topographies were acquired using the Zygo Nexview NX2 - a surface topography measuring instrument based on CSI.

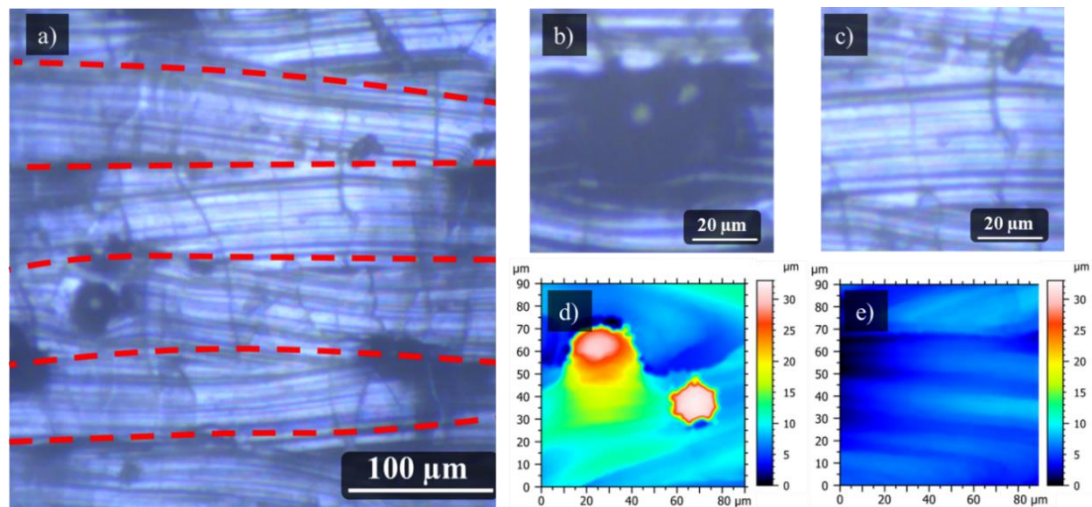


Figure 5.2. a) Microscopic image of a PBF-LB surface with weld tracks highlighted by red dashed lines, b) and c) microscopic surface images with and without impurities, respectively, d) and e) height maps with and without impurities, respectively.

5.1.1. Analysis of the illumination beam

In the proposed light scattering method, achieving a small and uniform beam size is crucial for the detection of microscale impurities. This section presents an analysis and experimental measurement of the illumination beam profile to verify this objective. The beam profile on the surface plane was measured using a beam profiler, and the results were compared with simulations described in the previous section. Additionally, the beam size on the surface was examined using an image processing algorithm applied to the microscope images.

5.1.1.1.Measurement of the beam profile with a beam profiler

To analyse the beam profile and determine the beam size at the surface plane, experimental measurements were carried out using a beam profiler (BP209 VIS/M; see Table 5.3 for specifications). During the measurements, the beam profiler was positioned at the sample location. Figure 5.3a displays the beam profile recorded at the surface plane, showing the measured intensity distribution together with their corresponding Gaussian fit. The average Gaussian beam diameter at the surface plane was calculated to be approximately 87 μm .

Table 5.3. Beam profiler specifications.

Wavelength Range/nm	200 - 1100
Detector Material	UV-Enhanced Si
Aperture Diameter/mm	9
Scan Methods	Scanning Slits, Knife Edge
Slit Sizes/ μm	5 and 25
Beam Diameter Range	2.5 μm – 9 mm

The beam profile at the surface plane was simulated by using Zemax OpticStudio[®] software (see Figure 5.3b). The Gaussian beam diameter was calculated to be approximately 93 μm , which differs slightly from the experimental measurement, possibly due to setup misalignments.

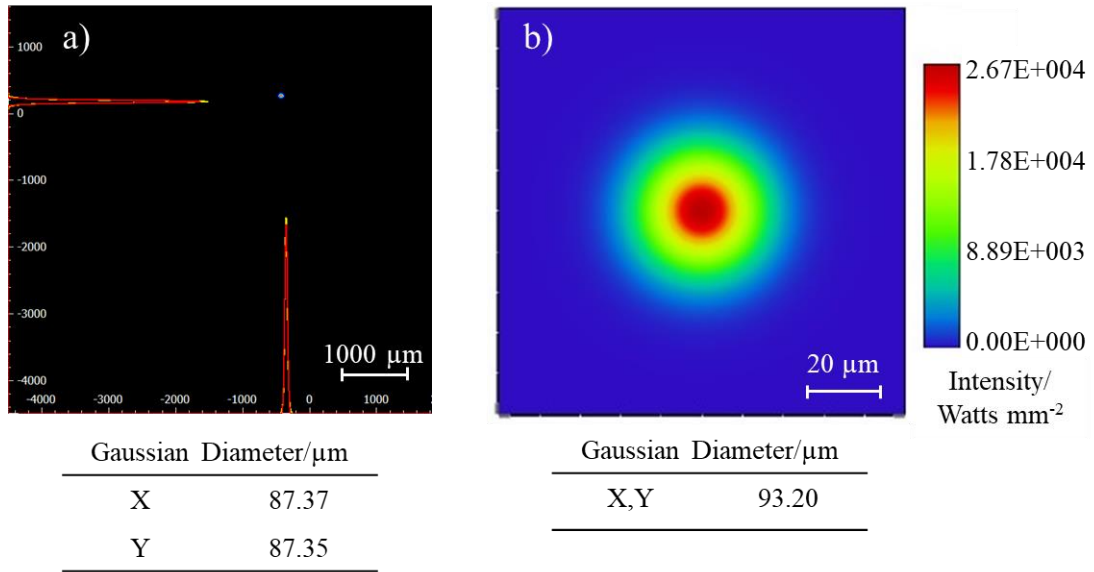


Figure 5.3. Beam profile and the calculated Gaussian beam diameter obtained by a) beam profiler and, b) obtained by the simulation.

5.1.1.2. Analysis of the beam profile on PBF-LB surfaces

The as-manufactured PBF-LB sample was securely mounted on high-precision linear stages (Thorlabs – XRN25/M) in the experimental setup. To capture scattered light from various areas, the stages enabled controlled movement of the sample along the x and y -axes, ensuring precise alignment of the laser beam with the weld track. During the surface scanning, the laser beam spot size on the PBF-LB surface was verified using images acquired by the microscope unit, analysed with ImageJ, an open-source image processing software. Figure 5.4b-e illustrate the procedure for determining the beam size at the surface, including converting the image to greyscale, generating a mask, and fitting a circle. Minor deviations in the calculated beam diameter, up to $\pm 10 \mu\text{m}$, observed during verification were deemed negligible. As the laser source remained stationary and the beam size was validated, the angle of incidence was assumed to be constant during the scanning process.

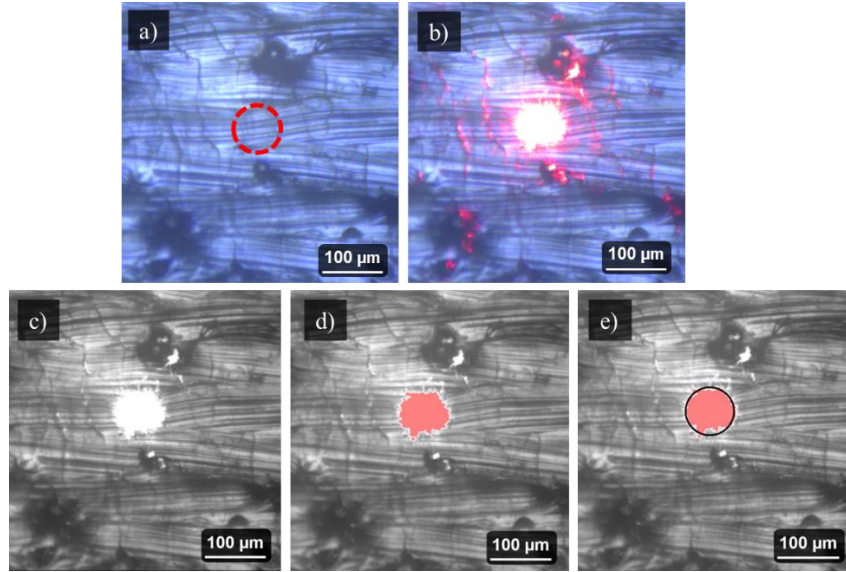


Figure 5.4. Microscopy images a) without and b) with illumination, and c)-e) image processing steps to evaluate the beam size.

5.1.2. Effect of polarisation and neutral density filter

Light is an electromagnetic wave, consisting of oscillating electric and magnetic fields [347]. The electric and magnetic fields are perpendicular to each other and to the direction of light propagation. Unpolarised (also referred to as natural) light consists of waves with randomly and rapidly varying polarisation directions [289].

The state of polarisation is determined by the orientation, relative magnitude, and phase of the electric field components perpendicular to the direction of propagation [289]. Polarisation can be classified as linear (also referred to as plane or planar), circular, or elliptical [348]. In linear polarisation, the electric field oscillates within a single plane, such as the xz or yz plane, while the light propagates along the z -axis. In circular polarisation, the components of the electric field have equal amplitude and a phase difference of $\pi/2$. In elliptical polarisation, the components of the electric field may have different amplitudes, a phase difference other than $\pi/2$, or both.

An optical device known as a polariser can be used to modify the polarisation properties of light. A polariser allows only a specific component of the electric field to pass through, producing polarised light. Polarisers are classified as linear, circular, or elliptical, depending on the orientation of the output wave.

Polarisation is a significant property of light that can influence the performance of an optical system. In this study, a linear polariser was used to investigate the effect of the polarisation of the light source on the performance of the light scattering system by placing it in front of the laser source. By rotating the polariser on a rotation stage, the polarisation angle was varied, and the resulting scattering patterns were recorded and compared (see Figure 5.5). The results indicate that the intensity of the recorded scattering pattern decreases as the polariser angle is varied, reaching a minimum at 20° , where almost no signal is detected by the camera. However, at 110° , a scattering pattern of similar intensity to the initial state is observed. This indicates that the diode laser source used in the study is predominantly linearly polarised, and that variations in the polarisation angle have little effect on the scattering pattern. Therefore, no polariser was used during data collection.

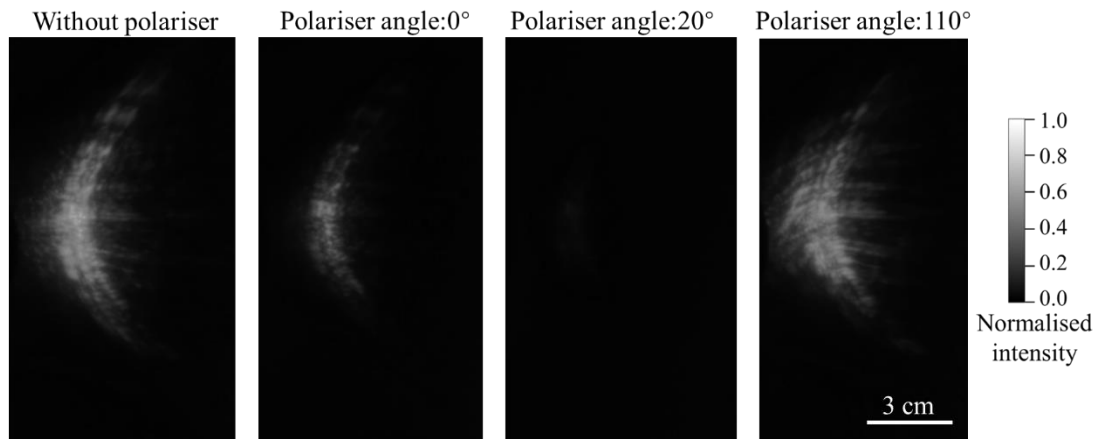


Figure 5.5. Recorded scattering patterns at various polarisation angles.

Neutral density (ND) filters are designed to reduce the amount of transmitted energy. The extent of this reduction varies depending on the optical density of the specific ND filter used. To examine the effect of different energy levels on scattering patterns, an analysis was conducted using ND filters of varying optical densities. Figure 5.6 illustrates the scattering patterns in three conditions: without an ND filter, with an ND filter of 0.1 optical density, and with an ND filter of 1 optical density. The results indicate that as the transmitted energy decreases, the intensity of the scattering pattern also reduces. However, the overall shape of the pattern remains largely unchanged. Given that the use of ND filters does not significantly alter the

shape of the scattering pattern, but does result in a reduction in intensity that may lead to a loss of information, ND filters were not utilised in this study.

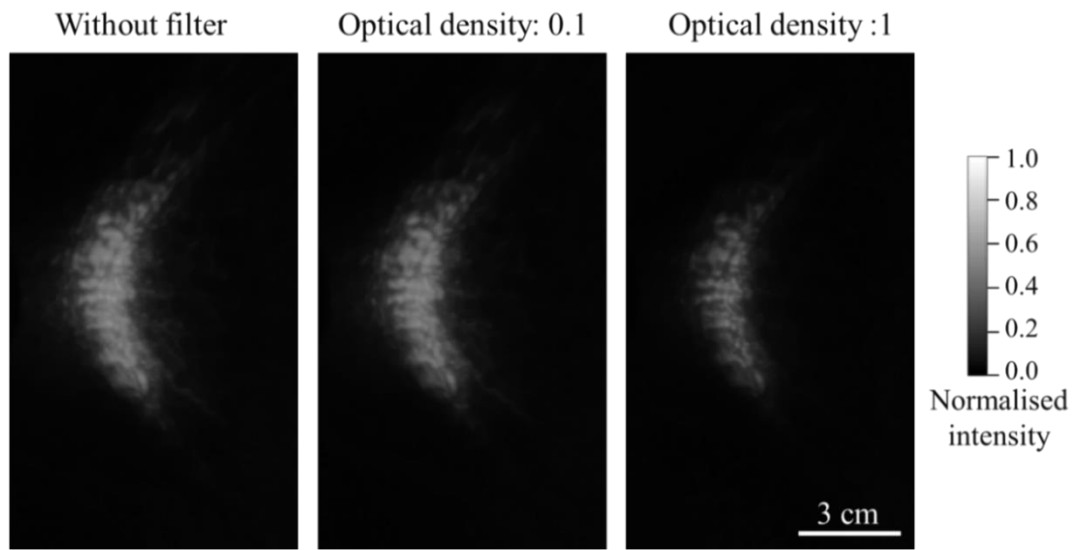


Figure 5.6. Effect of energy amount on scattering patterns.

5.1.3. Comparison of scattering patterns generated by surfaces with and without impurities

Figure 5.7a and b present randomly selected scattering patterns of surfaces with and without impurities, respectively. The images in Figure 5.7a demonstrate that surfaces with impurities produce randomly distributed scattered light patterns, whereas those in Figure 5.7b show that surfaces without impurities generate curved-like scattered light patterns. This curved-like pattern is attributed to the presence of weld ripples only on the surfaces without impurities. It appears that the presence of impurities disrupts this regular pattern.

While factors such as the size and shape of the impurities may affect the randomness of the scattering patterns, this study focuses solely on the presence of impurities rather than their specific characteristics. Consequently, the observed differences in scattering behaviour between the two types of surfaces have been utilised to propose a method for detecting microscale impurities. These findings underscore the potential of the proposed approach for impurity detection, thereby demonstrating its value in evaluating surface quality.

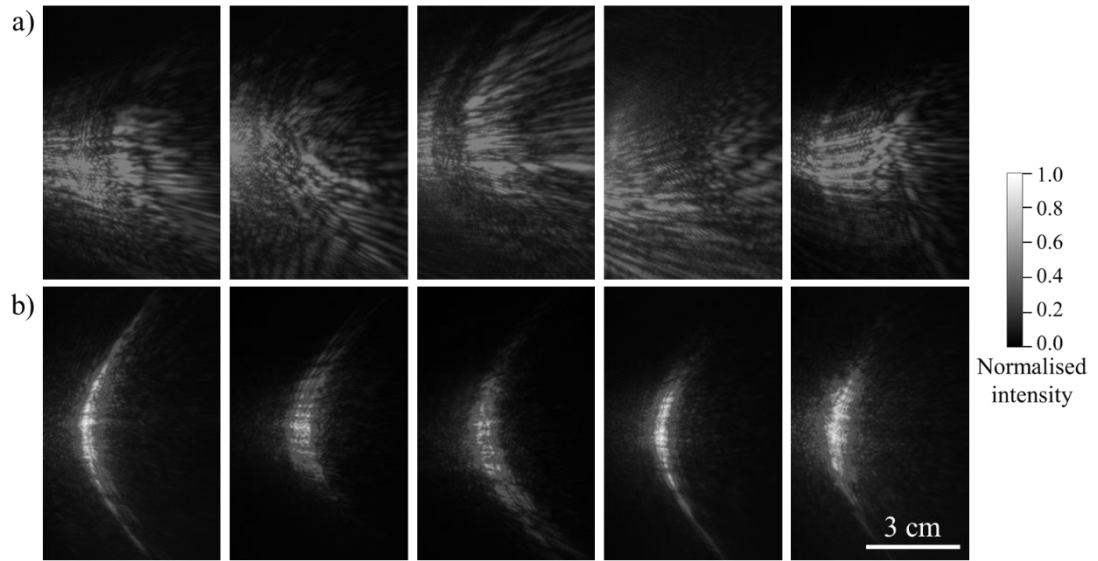


Figure 5.7. Recorded scattering patterns from surfaces, a) with impurities and b) without impurity.

5.2. Summary

One of the main objectives of this thesis is to develop a cost-effective and rapid method for measuring and monitoring microscale impurities on PBF-LB surfaces, with the aim of enabling real-time detection in the future. This chapter presented the development of this method, the light scattering technique, which is designed to detect microscale surface impurities on PBF-LB manufactured components. An optimised beam focusing setup was realised in the experimental context. A diode laser source, lens, and imaging components were assembled based on the simulated design. A microscopy unit was integrated to assist in beam alignment and surface visualisation. Experimental measurements using a beam profiler and image processing algorithms confirmed the consistency of the beam profile with simulated predictions. The influence of optical parameters – such as beam polarisation and light intensity – on the resulting scattering patterns was also examined. Results indicated that while the polarisation influenced the intensity of the scattered light, the scattering pattern's overall characteristics remained stable as the laser source is mostly polarised. Furthermore, the use of ND filters showed that reducing the beam intensity primarily affected signal strength without altering the fundamental features of the scattering patterns.

Finally, the light scattering setup was tested on PBF-LB surfaces, both with and without microscale impurities. The analysis of the recorded scattering patterns revealed clear distinctions: surfaces with impurities produced irregular, diffused patterns, while surfaces without impurities displayed more uniform, curved structures. These results highlight the potential of the developed system to reliably detect microscale surface impurities, demonstrating its value for non-destructive evaluation and quality control in advanced manufacturing contexts.

6. Classification of scattering patterns with ML

This chapter outlines the development and application of ML algorithms for classifying scattering patterns generated by PBF-LB surfaces, with the objective of distinguishing between uniform surfaces without microscale impurities and non-uniform surfaces that contain such impurities. Unsupervised ML methods based on one-class classification are employed, including isolation forest (iForest), local outlier factor (LOF), and two autoencoder models based on a deep CNN and a shadow ANN, respectively. In this classification framework, models are trained on unlabelled scattering pattern data, thereby eliminating the need for manual labelling – a process that is often labour-intensive and time-consuming.

Achieving high classification accuracy with ML algorithms typically requires large volumes of input data. However, collecting extensive real-world data is both time-intensive and impractical. To overcome this limitation, scattering patterns are generated using the BK model, which simulates light scattering based on surface topography and experimental parameters. Because experimentally collecting surface topography data for input into the BK model is similarly time-consuming and impractical, synthetic topographies are instead generated using a GAN.

In this chapter, synthetic uniform surface topographies are generated using a GAN. These are subsequently input into the BK model to simulate scattering patterns. The resulting simulated data are then used to train ML algorithms. Once training is complete, the ML models are evaluated using experimentally acquired scattering patterns of both uniform and non-uniform surfaces. The overall workflow is illustrated in Figure 6.1.

By using synthetic and simulated data for training ML models, the approach substantially reduces the time and effort required for data collection. Additionally, the use of unsupervised one-class classification removes the need for manual data labelling. Experimental validation further demonstrates that the most effective model achieved a classification accuracy of over 97%, highlighting the strong potential of this method for detecting microscale surface impurities.

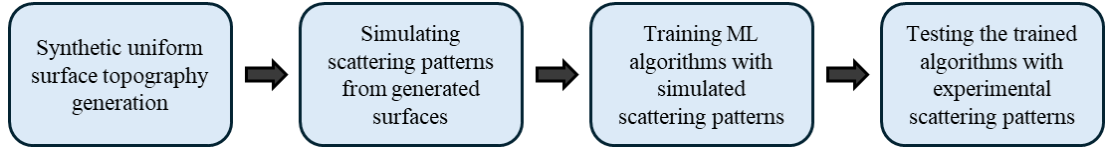


Figure 6.1. Process flow of the ML-based classification of the scattering patterns.

6.1. Surface generation

To develop an effective ML model with high classification accuracy, it is essential to obtain a substantial volume of training data [349]. In the context of this study, a large number of scattering patterns is required. To meet this demand, a simulation model is employed to generate the scattering patterns rather than using experimentally measured ones. This model generates scattering patterns based on surface topography and experimental parameters such as the specifications and configurations of the components within the light scattering setup (see Table 6.1). Therefore, a significant amount of surface topography data is needed to simulate these patterns. To address this requirement, a GAN is employed to synthetically generate topography data of uniform surfaces. This section outlines the methodology for generating synthetic surface.

Table 6.1. Light scattering simulation parameters using the BK model.

Wavelength/nm	635
Far-field distance/mm	42
Polar angle/°	45
Azimuth angle/°	0

A GAN is capable of producing synthetic data that closely resembles the original input dataset, making it nearly indistinguishable from real data. In this study, synthetic surfaces were generated using a GAN similar to the one described elsewhere [349]. However, a more advanced variant of the GAN was employed, namely the alias-free generative adversarial network (StyleGAN3). StyleGAN3, developed by NVIDIA, offers significant improvements over traditional GANs, as outlined elsewhere [350]. The StyleGAN3 was chosen for its enhanced speed, stability and compatibility with the NVIDIA A100 GPUs available at the high-performance computing (HPC) facility, named Ada, at the University of Nottingham.

StyleGAN3 comprises two sub-networks: the generator and the discriminator. The generator creates new surfaces, while the discriminator is trained to evaluate whether these generated surfaces look like input images or not. The generator network comprises two sub-networks: the mapping network and the synthesis network. The mapping network converts a latent code into a style code, which guides the synthesis process. The synthesis network initiates with a spatial map defined by Fourier features and employs fourteen layers of convolution, non-linearities, and upsampling to generate synthetic data. Low-pass filters within these layers help to prevent aliasing [350] and enhance image quality.

To generate synthetic surfaces, a dataset of real surface topographies measured by a physical instrument was used as input for training the StyleGAN3 model. To this end, fifty uniform surfaces were measured using a surface topography measuring instrument, Zygo Nexview NX2, equipped with a $50\times$ objective lens and $2\times$ zoom tube lens magnification, having a 0.55 numerical aperture. The fabrication parameters of the measured PBF-LB sample (see Figure 6.2) can be found in Table 6.2. Following the measurements, the surface topographies were levelled using MountainsMap[®] software, and then height values were normalised to fall within the range $[0, 1]$ and mapped to grayscale. Data augmentation techniques – such as cropping, mirroring, and rotation – were applied to the grayscale images covering an area of $(110 \times 110) \mu\text{m}$. This process expanded the dataset to approximately 3000 grayscale images representing an area of $(90.11 \times 90.11) \mu\text{m}$, corresponding approximately to the illuminated region in the experimental setup. This dataset was subsequently used to train the StyleGAN3 model.

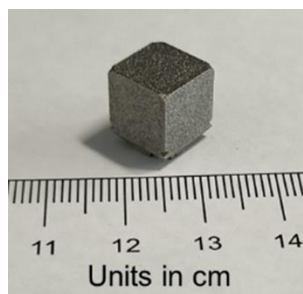


Figure 6.2. Analysed specimen produced by PBF-LB.

Table 6.2. Manufacturing process parameters of the specimen shown in Figure 6.2.

Hatch power/W	Hatch distance/ μm	Scan speed/ m s^{-1}	Layer thickness/ μm	Energy density	
				1D/ J mm^{-1}	3D/ J mm^{-3}
320	95	1.0	60	320	56

The training of StyleGAN3 was conducted on eight NVIDIA A100 GPUs with 128 GB of memory on the HPC system Ada. The training process took four days to complete, and generating 10,000 images took less than an hour on the same system. Figure 6.3a and b show examples of real and generated surface images in grayscale, respectively. The results indicate that while the generated images are visually indistinguishable from the real surface images, they appear unique and distinct from the actual surfaces, which is the intended outcome of this method. The generated synthetic data only contains uniform surfaces, as our ML model, which is based on unsupervised one-class classification, has been trained exclusively on scattering patterns of uniform surfaces.

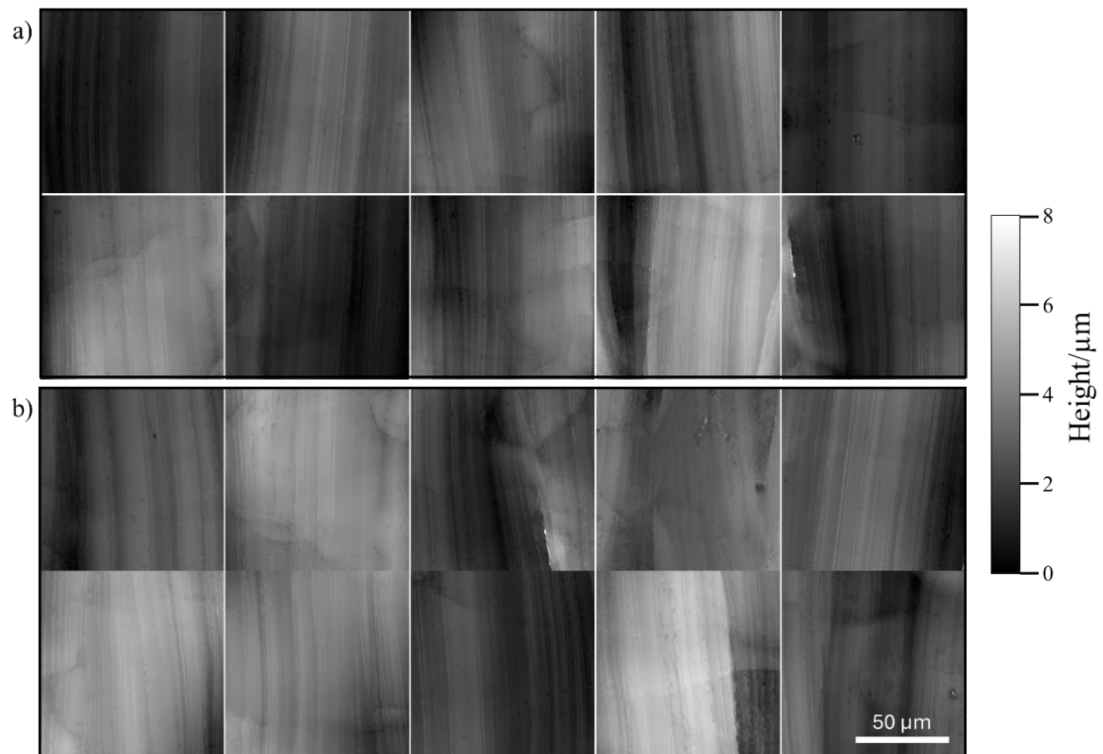


Figure 6.3. Examples of a) real and b) synthetic uniform surface images in grayscale.

The generator produces grayscale surface images that require decoding to retrieve the surface topographies. This is achieved by applying the reverse of the previously

used encoding process to the generated images. Figure 6.4 presents a comparison between several real and decoded synthetic surface topographies.

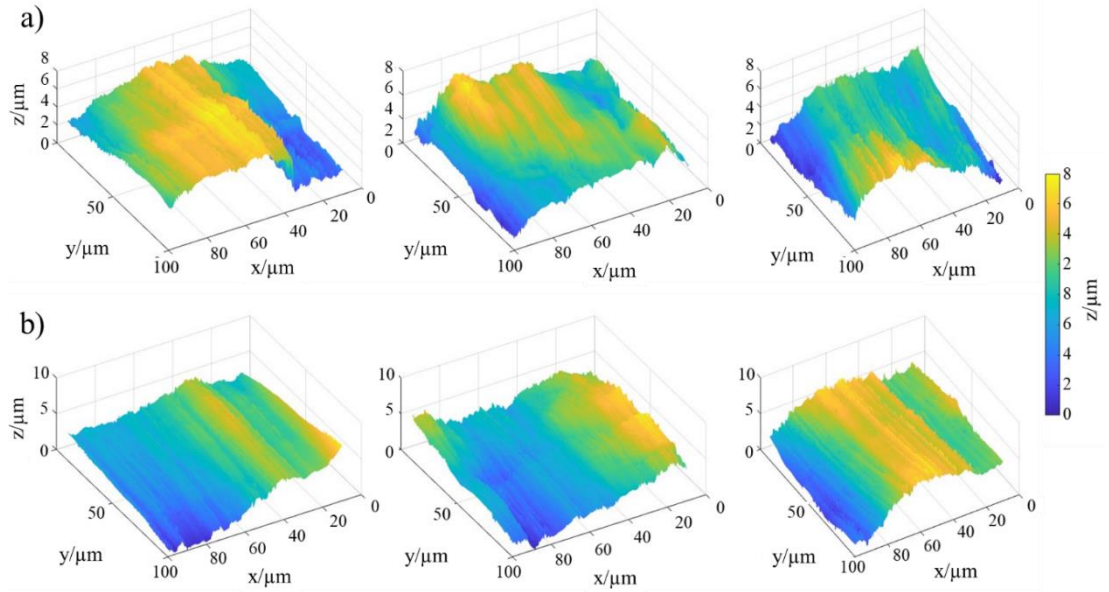


Figure 6.4. Examples of a) real and b) synthetic uniform surface topographies.

6.2. Simulation of scattering patterns

The scattering of light can be modelled to generate scattering patterns using either rigorous or approximate approaches [283]. Rigorous models are capable of calculating the scattered light even when multiple scattering occurs (where approximate approaches struggle), including scattering from surfaces with high slope angles and small radii of curvature features [296]. However, rigorous approaches are computationally complex and time-consuming [351]. In contrast, approximate models, while neglecting effects such as multiple scattering, offer simplicity and efficiency [296]. In this study, the BK model – an approximate light scattering model (see 2.5) - was employed to generate scattering patterns.

The validity of the BK model is subject to certain conditions. For example, the model fails where the surface exhibits steep slopes or small radii of curvature [296]. To assess compliance with these conditions, both the slope angle distributions and radii of curvature distributions of the uniform surfaces were calculated. Slope angle distributions were obtained using MountainsMap software, while the radii of curvature were calculated in MATLAB. For the curvature calculations, surface

profiles were extracted along the x -direction. Circles were fitted through sets of three adjacent points, with the radius of each fitted circle representing the local radius of curvature (see Figure 6.5).

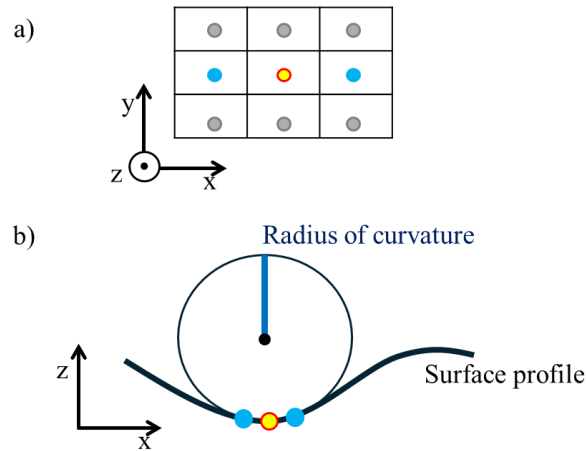


Figure 6.5. a) Three-dimensional representation of the surface topography; b) extracted surface profile with a fitted circle based on the three highlighted points.

A quantitative investigation into the validity conditions of the BK model has been concluded that the model fails in regions where slope angles exceed approximately 38° , and where radii of curvature are less than about ten times the illumination wavelength [296]. Two representative examples of the relevant surface height maps, along with their corresponding surface slope angle and curvature distributions, are presented in Figure 6.6. As shown, the uniform surfaces largely fit into the validity criteria established for the BK model, with at least 90% of the slope angles and radii of curvature values falling within the acceptable range – slope angles less than 38° and radii of curvature greater than $6.35 \mu\text{m}$ – defined in [296].

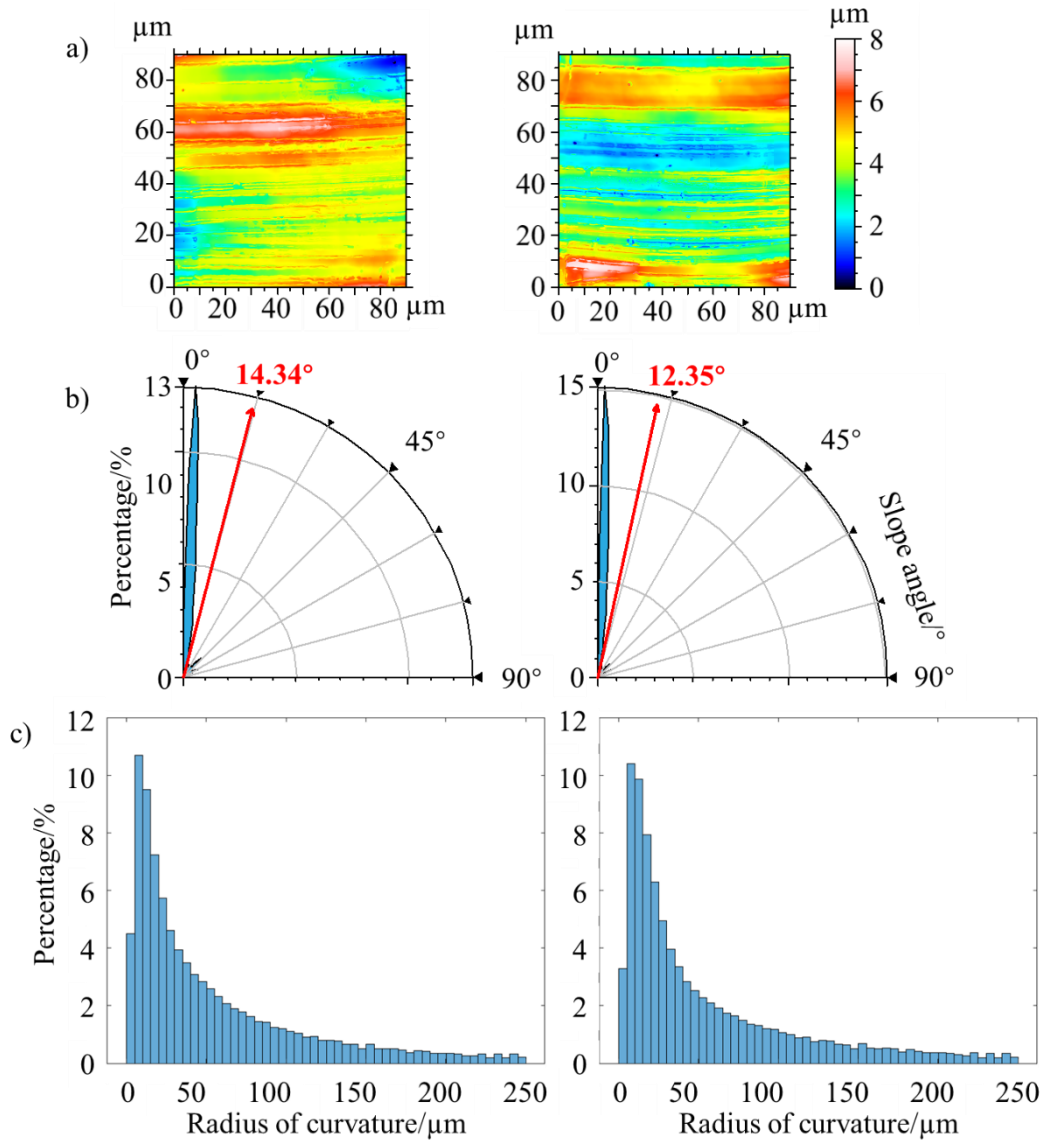


Figure 6.6. a) Two randomly selected uniform surface height maps; b) corresponding slope angle distributions, with red arrows indicating the mean values; c) corresponding radius of curvature distributions.

The BK model used in this study initially generates a 3D transfer function based on the experimental parameters listed in Table 6.1. Although the laser used is not monochromatic – exhibiting a bandwidth of $+7/-2$ nm – it is treated as monochromatic in the simulations due to the relatively narrow bandwidth. Subsequently, a foil model of the uniform surface is constructed. The Fourier transforms of foil model of the surface and transfer function are then multiplied to calculate the angular distribution of the electric fields in the Fourier domain. The result is then transformed from the Fourier domain into the space domain. These

procedures are described in detail in Section 2.5.2, and in references mentioned in that section.

The angular distribution of the scattered electric field is propagated on a semi-spherical shell, therefore the electric field needs to be projected onto a planar screen (see Figure 6.7) to replicate the experimental setup. For this purpose, a transformation code was developed as part of this thesis, and it is included in the Appendix.

The summary of the projection code is as follows:

- The polar and azimuthal angles corresponding to the spherical coordinates were calculated.
- The angular distribution of the scattered field was then defined based on these polar and azimuthal angles.
- A 2D mesh grid – represents the 2D screen – was generated in polar coordinates, taking into account the distance between the surface and the screen in the experimental setup.
- While mapping the data to the 2D screen, an interpolation method is used.

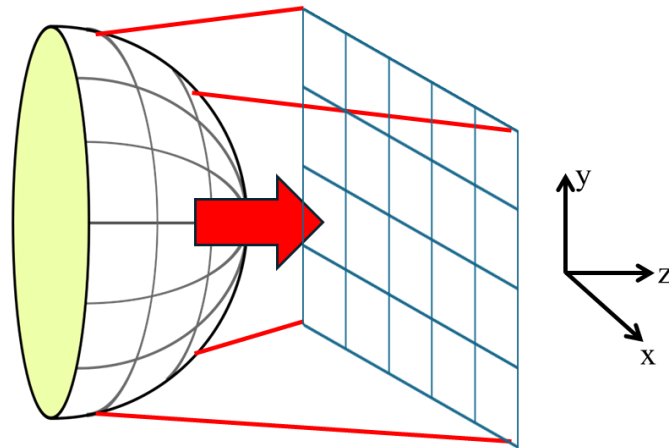


Figure 6.7. Projecting the scattering from the spherical wavefront propagation to the planar screen.

Since unsupervised learning with one-class classification is used, only uniform surfaces are employed to simulate the scattering patterns. Figure 6.8 shows scattering

patterns of uniform surfaces obtained from the experiments (Figure 6.8a) and simulation (Figure 6.8b), as well as the scattering pattern of non-uniform surfaces obtained by the experiments (Figure 6.8c). The experimental scattering patterns of non-uniform surfaces show randomly distributed scattered light patterns, whereas those in Figure 6.8a and b show that surfaces without impurities generate curved-like scattered light patterns. Although the simulated scattering patterns of uniform surfaces appear grainier than those obtained experimentally – likely due to differences in resolution between the simulation and the experiment, as the simulation treats the camera and screen as a single entity, whereas in the experiment, the scattering pattern is first formed on a screen and then captured by a camera – the overall shape of the patterns remains consistent. This consistency is further validated by the ML results presented at the end of the chapter.

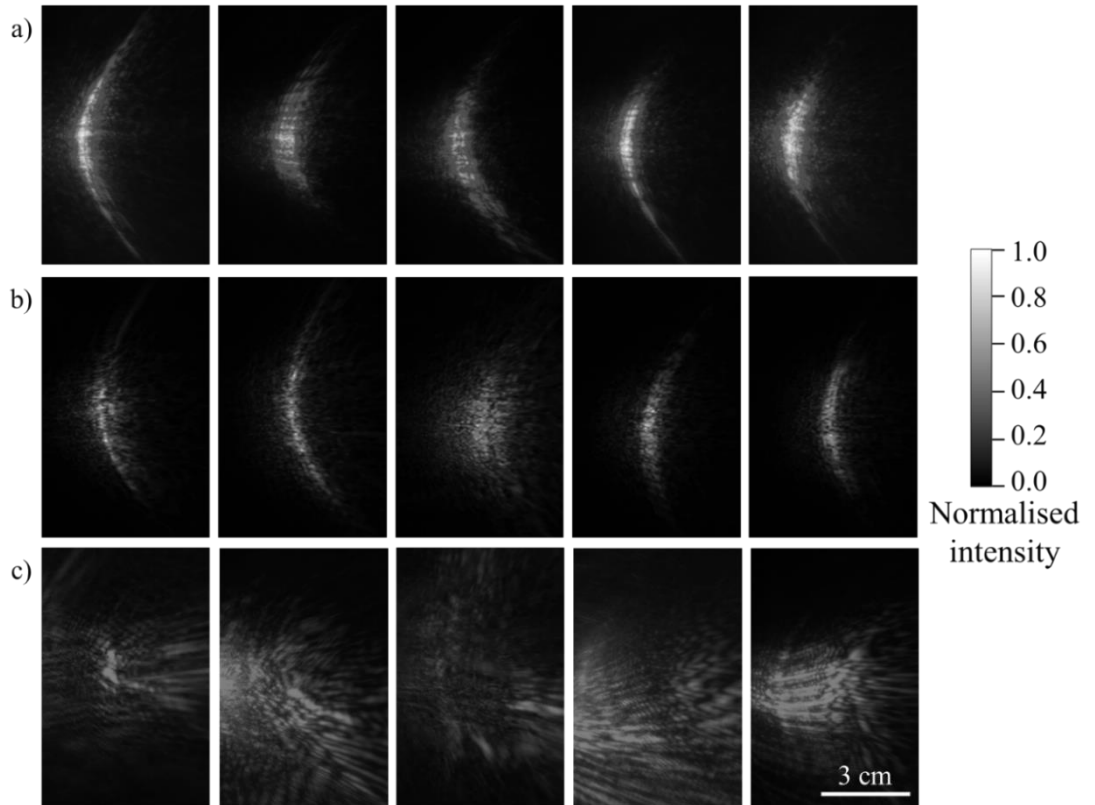


Figure 6.8. Examples of a) experimental and b) simulated scattering patterns from uniform surfaces, and c) experimental scattering patterns from non-uniform surfaces.

6.3. Unsupervised ML for classification

In this thesis, training was performed using four distinct unsupervised ML algorithms based on one-class classification: two autoencoders – one utilising a deep CNN and the other a shadow ANN – alongside two anomaly detection algorithms, iForest [259,260] and LOF [261]. The goal was to classify surfaces as either uniform without microscale impurities or non-uniform with microscale impurities without distinguishing between sub-classes. The models were trained exclusively on simulated scattering patterns of generated uniform surfaces and subsequently tested on experimentally acquired patterns from both uniform and non-uniform surfaces to evaluate their ability to distinguish between the two types.

6.3.1. Autoencoders

An autoencoder operates by first encoding the input data into a lower-dimensional representation, known as the latent space, and then decoding this compacted data back to its original dimensions. The primary goal is to reconstruct the input as accurately as possible by minimising the reconstruction error – defined as the difference between the original input and the reconstructed output during the training process. The magnitude of this error reflects the performance of the autoencoder. Once an autoencoder is trained on a particular class of data, testing it with data from a different class usually results in higher reconstruction error. By examining the error values, one can determine whether the test data belongs to the same class as the training data or represents a different class.

Two autoencoders were trained using simulated scattering patterns derived from synthetically generated uniform surfaces. After completing the training, the autoencoders were tested on scattering patterns of both uniform and non-uniform surfaces obtained through experimentation. Based on the test results, an error threshold was determined for each autoencoder to optimise classification accuracy.

In the encoding stage, the CNN-based autoencoder (Figure 6.9a) consists of two convolutional layers with sixteen and eight filters, respectively, each using (3×3) kernels. These layers are followed by downsampling, as the purpose of an autoencoder is to compress the input data through dimensionality reduction and

subsequently reconstruct the original input from this compressed representation. In this process, the data dimensions are reduced from 240×100 to $48 \times 20 \times 16$, and then further to $24 \times 10 \times 8$. The data is then reshaped to a 1920×1 format using a flatten layer. Three densely connected layers are located at the centre of the autoencoder, which has 1920, 512 and 1920 neurons, respectively. The decoding process reverses these steps, ultimately producing an output that matches the input size.

The ANN-based autoencoder, depicted in Figure 6.9b, consists of two downsampling layers, a flattening layer, and a dense layer during the encoding phase. The downsampling process reduces the data size from 240×100 to 60×25 , which is then reshaped into a 1500×1 format by the flattening layer. The dense layer in the latent space contains 150 neurons, while the other two dense layers have 1500 neurons each. During the decoding phase, reshaping and upsampling layers are employed after the dense layers, ultimately generating an output that matches the original input size of 240×100 .

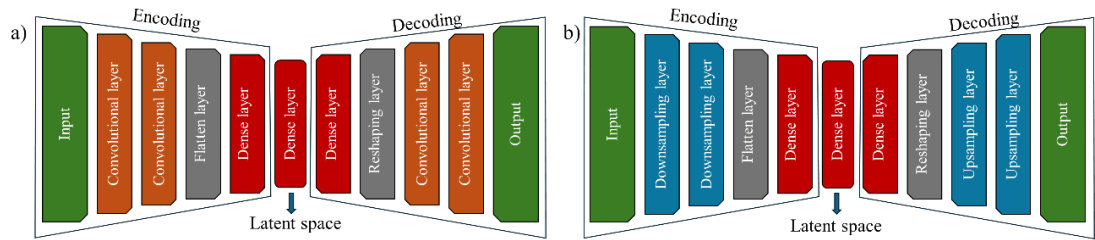


Figure 6.9. Structure of a) CNN-based autoencoder, b) ANN-based autoencoder.

6.3.2. Anomaly detection algorithms

Anomaly detection algorithms can determine whether new test data is consistent with the trained data as an inlier or represents a distinct category as an outlier. In order to distinguish between scattering patterns of uniform and non-uniform surfaces, two anomaly detection algorithms were trained using the scattering patterns of synthetically generated uniform surfaces. When applying the trained anomaly detection algorithms to the experimental dataset, it is expected that the algorithm will classify the scattering pattern of “non-uniform” surfaces as “outlier” and those of “uniform” surfaces as “inlier”.

Trained anomaly detection algorithms include iForest and LOF. The iForest algorithm isolates each data point by partitioning the data through random decisions [259,260]. These partitions create a tree structure, where each data point progresses from the root to a terminal node. The number of partitions required to isolate a data point is recorded as the path length. Anomalies are typically isolated more rapidly than normal points, resulting in shorter path lengths within the trees (see Figure 6.10a). For the training process of the iForest algorithm, the randomness parameter is enabled, the contamination ratio is set to 0.0025, a subsampling size of 100 is used.

The LOF algorithm calculates a score, known as the local outlier factor, which indicates the degree of abnormality in observations [261]. It evaluates how much the local density of a given data point deviates from that of its neighbouring points. Typically, anomalous data points exhibit much lower local density and higher outlier scores (see Figure 6.10b). For the training process of the LOF, the following parameters were specified: the number of neighbours was set to 500 and the contamination ratio was set to 0.0025. The specified parameters were chosen to achieve high detection accuracy for both iForest and LOF.

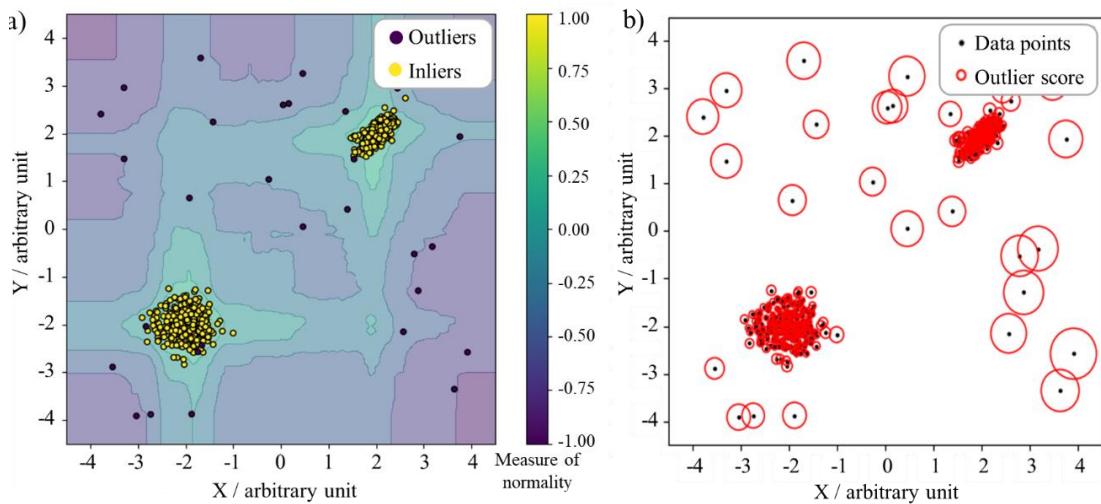


Figure 6.10. a) iForest graph showing data points classified as outliers and inliers, along with a path length map, b) LOF graph showing data points with their corresponding outlier scores.

6.4. Machine learning classification results

Following the training of the autoencoders with simulated scattering patterns of synthetically generated uniform surfaces, scattering patterns, which were not used for training, were tested on the trained models. Scattering patterns of both uniform and non-uniform surfaces from the simulation and experimentation were evaluated. Figure 6.11 shows the test results for the CNN and ANN-based autoencoders. The test results for the other two methods (LOF and iForest) have not been included, as they do not operate based on the encoding-decoding principle. The scattering images on the left represent the input scattering images, while the right-side images show the encoded scattering images, i.e., the autoencoder output. For scattering patterns of uniform surfaces, there is consistency between inputs and encoded data. However, for scattering patterns of non-uniform surfaces, the input and encoded data are less consistent, resulting in higher root-mean-square error (RMSE) values compared to those for uniform surfaces. By setting a threshold RMSE value, it is possible to classify the data as either containing impurities or not.

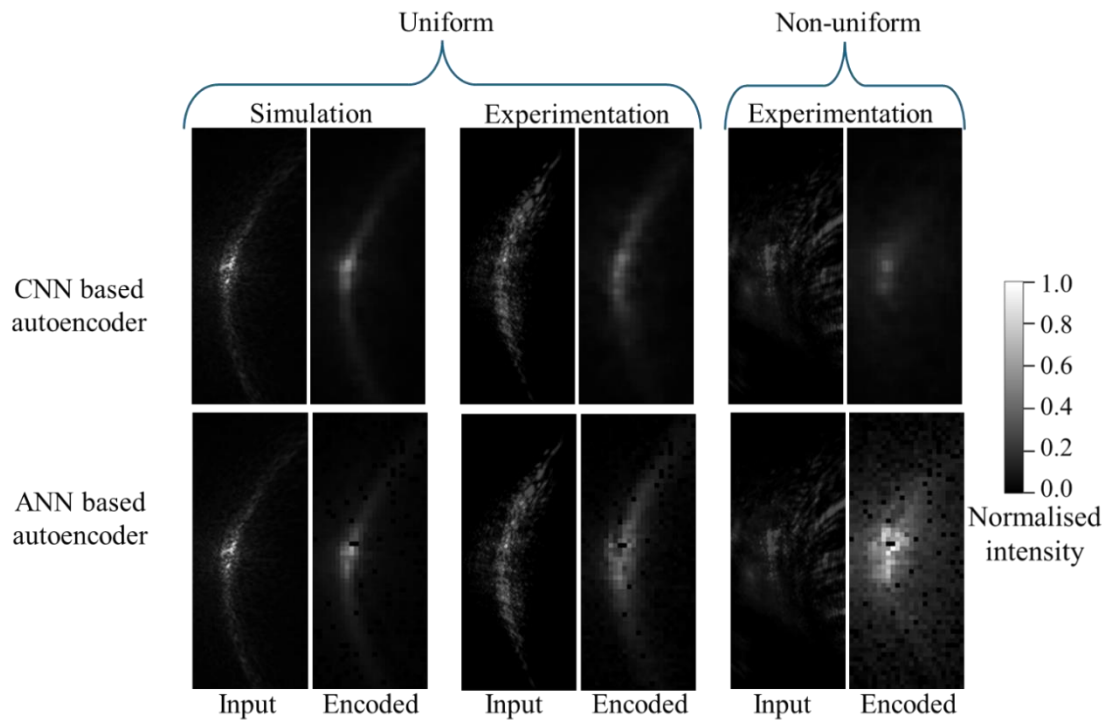


Figure 6.11. Testing of trained CNN- and ANN-based autoencoders on scattering patterns from uniform and non-uniform surfaces.

Figure 6.12 illustrates the classification results of ML algorithms based on the experimentally collected light scattering patterns of both uniform and non-uniform surfaces. Figure 6.12a and b show the RMSE values for the experimental scattering patterns processed by the autoencoders. In order to achieve optimal classification accuracy, thresholds of 0.088 and 0.091 were defined for the CNN- and ANN-based autoencoders, respectively – see Figure 6.12a and b.

For the iForest and LOF algorithms, classification is performed by analysing the test data scores after training. These algorithms calculate an anomaly score for each test data; a lower score indicates a higher likelihood of the data being anomalous. Figure 6.12c and d present the test results for the scattering patterns of uniform and non-uniform surfaces using iForest and LOF. Threshold anomaly scores of 0.02 and -1.4 were set for iForest and LOF, respectively, to achieve optimal classification accuracy. Note that the threshold values defined here are specific to the experimental configuration developed in this study. For any new configuration, it may be necessary to recalculate these thresholds.

When comparing the results of these four algorithms, it can be concluded that the autoencoders demonstrate similar classification accuracy, with the CNN-based model showing slightly higher accuracy. However, iForest achieves the highest accuracy among all anomaly detection algorithms, with a classification rate exceeding 97%. Although the LOF algorithm has the lowest accuracy, it still achieves more than 80% classification accuracy. In terms of runtime, autoencoders, CNN-based autoencoders and ANN-based autoencoders require approximately 0.12 s and 0.17 s, respectively. LOF has the longest runtime at around 0.55 s, while iForest is the fastest, with a runtime of approximately 0.04 s. Runtimes are calculated based on the specifications of a standard PC equipped with an Intel Core i3-7100 CPU, 8 GB of RAM, and running the Windows operating system.

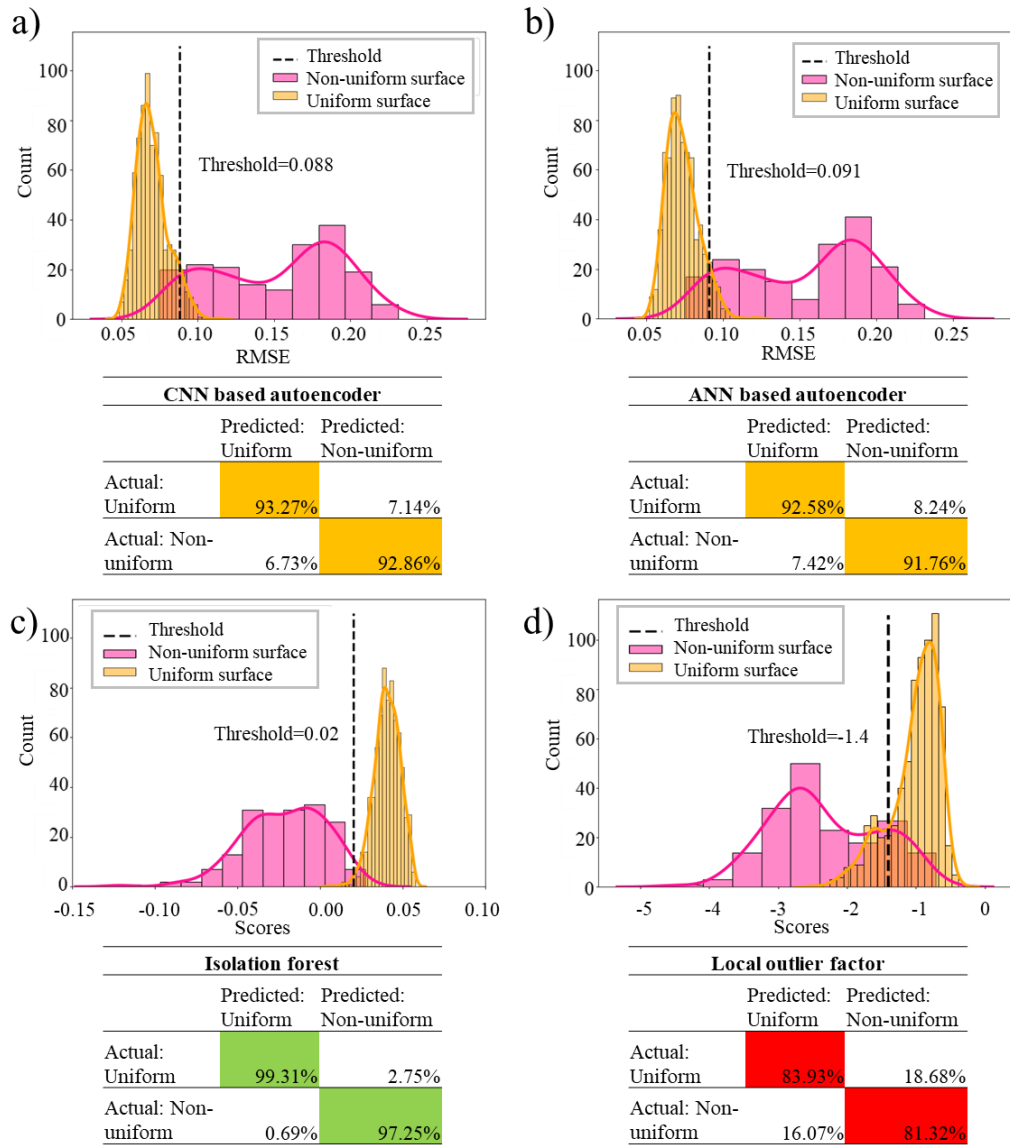


Figure 6.12. Classification results of the ML algorithms, a) CNN based autoencoder, b) ANN based autoencoder, c) iForest, d) LOF.

6.5. Summary

One of the aims of this study is to develop ML algorithms capable of interpreting high-dimensional light-scattering patterns in order to detect microscale impurities on PBF-LB surfaces. This chapter described the development and application of these algorithms. Unsupervised one-class ML classification methods were employed to remove the need for data labelling and for collecting datasets from other classes. In addition, a data-generation framework was created to replace manual experimental data collection, which is also one of the objectives of this thesis. The central

significance of the results lies in demonstrating that high classification accuracy can be achieved without relying on large volumes of experimentally collected or manually labelled training data. Instead, the innovative use of GAN-generated synthetic surface topographies and BK model-based scattering simulations provided an adaptable and efficient training dataset. This approach substantially reduces the time, cost, and effort associated with data acquisition, addressing one of the key bottlenecks in applying ML to industrial quality assurance.

The experimental validation confirmed the effectiveness of this strategy: the best-performing algorithm achieved a classification accuracy exceeding 97%, while even the least effective algorithm surpassed 80%. These results prove that synthetic and simulated training data can translate into robust real-world performance. Moreover, runtimes as low as 0.04 s highlight the near real-time capability of the models, underscoring their industrial relevance for in-situ monitoring and potential closed-loop control.

By combining light scattering, synthetic data generation, and unsupervised one-class ML classification, this work delivers a generalisable framework that is adaptable to different experimental configurations, materials, and defect types. The results not only establish a foundation for generalisable in-process monitoring in PBF-LB but also contribute to the broader vision of physics-informed ML systems capable of intelligent, autonomous manufacturing.

7. Conclusion and future work

7.1. Concluding remarks

This thesis set out to address one of the critical challenges in the field of metal AM, particularly in PBF-LB: the reliable and accurate detection of microscale surface impurities. These impurities – such as balling, spatter, and surface pores – can significantly compromise the mechanical integrity, fatigue life, and functional performance of fabricated components. Despite the growing interest in in-situ monitoring technologies, current detection methods often lack sufficient resolution, robustness, or real-time applicability, particularly when detecting features smaller than 100 μm . To bridge this gap, this research presents a novel framework for defect detection based on light scattering combined with a simulation model of light scattering, synthetic data generation and ML algorithms.

Chapter 2 began with a thorough review of the literature on AM, with particular emphasis on PBF-LB and the associated challenges of microscale surface quality assurance. A comprehensive taxonomy was developed, categorising defect types, their formation mechanisms, and existing in-situ sensing techniques. Additionally, ML algorithms employed for interpreting high-dimensional in-situ sensor data were reviewed. Some challenges of employing ML have been identified, such as data labelling and the acquisition of real-world datasets, which may hinder wider adoption in industry. Light scattering, proposed in this study as a sensing method for assessing fabrication quality in PBF-LB, was also reviewed, with particular emphasis on the modelling approaches used to describe the scattering behaviour. Chapter 2 has demonstrated that, despite substantial progress in the detection and understanding of microscale defects in PBF-LB, there remains an urgent need for robust, scalable, and real-time defect monitoring solutions. Addressing this challenge necessitates a multidisciplinary approach that integrates process engineering, sensor technology, and data analytics to develop intelligent quality assurance systems.

Chapter 3 provided an in-depth examination of the microscale surface features of PBF-LB-fabricated Ti6Al4V parts using SEM. Previously undocumented surface

anomalies were identified, and hypotheses regarding their formation mechanisms were proposed. The relationship between process parameters – such as scan speed, laser power, and powder morphology – and surface defects was carefully investigated. It was demonstrated that small variations in these parameters can significantly affect impurity size, distribution, and density. Importantly, this analysis highlighted the critical need for a microscale impurity detection system for PBF-LB.

In Chapter 4, two impurity detection approaches were developed: one based on image processing of SEM images, and another using quantitative surface topography parameters. Topographical parameters – such as Sa , Sp , and Sdr – were applied to distinguish between surfaces with and without impurities. The topography-based approach established a foundational understanding of how surface topography correlates with impurity formation, providing measurable criteria to evaluate the effectiveness of detection algorithms.

Building on these insights, Chapter 5 introduced an optical method based on light scattering which can infer surface topography information. An experimental setup was designed after performing some initial simulations on Zemax using optics to focus a laser beam (diameter $\sim 90\ \mu\text{m}$) onto the surface of fabricated parts. The scattered light was captured to detect microscale impurities. Initial results revealed a strong distinction between the scattering patterns from uniform surfaces and those with surface impurities. This confirmed that light scattering can be an effective method to detect microscale surface impurities.

ML algorithms were employed to classify patterns produced by the light scattering method, with the aim of detecting microscale surface impurities. This approach leverages the key strengths of ML algorithms, particularly their capacity to detect patterns and relationships within large and complex datasets, often with little to no prior domain-specific knowledge. However, the use of ML algorithms generally presents two main challenges: the need for substantial volumes of training data, and the difficulty of obtaining such data under real-world conditions. These challenges were addressed in Chapter 6 through the development of a simulation-based data generation pipeline. A GAN was utilised to produce synthetic surface topographies, which were subsequently fed into a light scattering simulation model based on the BK theory to generate scattering patterns. These simulated patterns were then used

as training data for a set of ML algorithms designed to classify the presence or absence of microscale impurities.

The ML models were trained on synthetic data and then tested on experimental scattering patterns. The best-performing algorithm achieved a classification accuracy exceeding 95%, even for surface impurities smaller than 90 μm . Importantly, the models were based on one-class classification, removing the need for extensive manual labelling. Once trained, the models operated in near real-time and could be integrated into a potential closed-loop control system for AM.

In summary:

Objective 1 was addressed through the systematic examination of microscale surface impurities on PBF-LB specimens, establishing their correlations with process parameters and evaluating their influence on overall part quality.

Objective 2 was achieved by the development and validation of a light scattering system, which demonstrated a rapid, cost-effective, and non-destructive means of discriminating between surfaces with and without impurities, with strong potential for future in-situ integration.

Objective 3 was met by implementing machine learning models that delivered high levels of accuracy in automated classification, thereby supporting the feasibility of fast and reliable impurity detection.

Objective 4 was fulfilled through the design of a synthetic data generation and scattering simulation framework, which successfully removed the reliance on extensive experimental datasets for training machine learning algorithms.

Collectively, these contributions confirm that the overarching aim of the thesis—developing a robust, efficient, and scalable system for the detection of microscale impurities in PBF-LB—has been realised.

7.2. Contributions to Knowledge

This thesis makes several significant contributions to the field of additive manufacturing and quality assurance in PBF-LB. One of the key innovations is the development and validation of a light scattering-based method for detecting microscale surface impurities. This technique is not only cost-effective and rapid but

also inherently compatible with coaxial integration into PBF-LB systems. As such, it offers a promising pathway for real-time, in-process monitoring.

Another major contribution lies in the simulation- and machine learning-based detection framework. Rather than relying on the laborious and time-consuming collection and labelling of experimental data, the research uses simulated scattering patterns generated from synthetic surface topographies. This approach enables the training of machine learning models that are accurate, robust, and adaptable to various deployment scenarios.

7.3. Future work

Several avenues for future research have been identified to enhance the current approach. One important direction involves the development of a compact, coaxial optical module for in-situ integration into commercial PBF-LB machines. This would require incorporating real-time alignment mechanisms, temperature compensation systems, and robust hardware capable of operating reliably in harsh industrial environments. In parallel, combining light scattering data with other sensing modalities – such as thermal imaging or acoustic monitoring – may enhance the robustness and confidence of impurity detection. Note that the experimental light scattering setup was designed and validated under controlled laboratory conditions. The integration of such a system into a commercial PBF-LB machine may present challenges related to sensor placement, optical path design, calibration under dynamic thermal environments, and vibration resistance.

Another key focus is integrating the detection system with machine control software to enable real-time feedback. Such a system could automatically adjust process parameters (e.g., laser power or scan speed) in response to detected impurities, moving PBF-LB closer to autonomous, self-correcting fabrication. Additionally, generalising the method to accommodate a wider range of materials, powder types, and geometries is essential for broad industrial adoption. Validation on larger datasets and in real-world manufacturing settings will further support its practical utility.

Lastly, advancing the theoretical understanding of light scattering could yield valuable insights. Exploring the relationship between specific impurity geometries

and their scattering signatures may not only improve model interpretability but also contribute to a deeper understanding of surface physics relevant to AM.

7.4. Final remarks

Additive manufacturing has revolutionised the way complex, high-performance parts are designed and fabricated. However, the widespread adoption of PBF-LB in critical industries – such as aerospace and biomedical – relies on robust and reliable quality assurance techniques at the microscale. This thesis addresses a major gap in current monitoring capabilities by introducing a novel light scattering-based detection method of microscale impurities by combining ML algorithms trained with simulated patterns generated from synthetic surfaces. Through a combination of light scattering, ML, simulated and synthetic data generation, this work sets a foundation for the next generation of microscale in-situ quality control systems in PBF-LB. While challenges remain, the tools and insights developed here offer a promising pathway toward fast, accurate, cost-effective, and intelligent impurity detection – bringing the vision of fully autonomous, high-precision manufacturing.

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Appendix A: The Transformation Code

This code has been used to transfer the scattering data produced by the BK model to a planar screen.

```
function [ss,tt,azz] = transformationoffoil_v2(distance, gax, gay, m2Scatter_angle )
```

```
%distance is the normal distance between the surface and the plastic screen
```

```
%gax and gay are the coordinates
```

```
% m2Scatter_angle is the scattering data
```

```
r1 = 1;
```

```
x1 = r1.*sind(gax);
```

```
y1 = r1.*sind(gay);
```

```
z1 = sqrt(r1.*r1 - x1.*x1 - y1.*y1);
```

```
%transfer gax and gay to polar and azimuth angles because for
```

```
%interpolation part angles on the sphere and screen should be the same,
```

```
%they are the same in polar coordinate but not cartesian plane, so we
```

```
%transfer angles to spherical coordinate to be able to use interpolation.
```

```
[azimuth,elevation,r] = cart2sph(x1,y1,real(z1));
```

```
elevation = (pi/2 - elevation)*180/pi;
```

```
azimuth = azimuth*180/pi;
```

```
gxx = r1.*sind(elevation).*cosd(azimuth);
```

```
gyy = r1.*sind(elevation).*sind(azimuth);
```

```
gzz = r1.*cosd(elevation);
```

```

theta = 0:0.05:90;

sai = -180:0.2:180;

[o, p] = meshgrid(theta, sai);

ss = distance*sind(o).*cosd(p)./cosd(o); %can be replaced by axx in polar
coordinate

tt = distance*sind(o).*sind(p)./cosd(o); %%can be replaced by ayy in polar
coordinate


[ gaxaysca3 ] = convert_mesh_to_xyz( elevation , azimuth, m2Scatter_angle );


azz = interpolation_3d_xyz_to_xxyyzz(double(gaxaysca3), double(o), double(p));

dist_mat = sqrt(distance^2 + ss.^2 + tt.^2);

ratio = (distance^2) ./ (dist_mat.^2); %distance

azz = azz .* ratio;


figure

mesh(ss,tt,azz);

axis equal

xlabel('x');

ylabel('y');

zlabel('z');

view([0 0 1])

xlim([0 100]);

ylim([-75 75]);

```

end