Nondestructive evaluation and in-situ monitoring for metal additive manufacturing

Hossein Taheri
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Nondestructive evaluation and in-situ monitoring for metal additive manufacturing

by

Hossein Taheri

A dissertation submitted to the graduate faculty
in partial fulfillment of the requirements for the degree of
DOCTOR OF PHILOSOPHY

Co-majors: Mechanical Engineering; Electrical Engineering

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The student author, whose presentation of the scholarship herein was approved by the program of study committee, is solely responsible for the content of this dissertation. The Graduate College will ensure this dissertation is globally accessible and will not permit alterations after a degree is conferred.

Iowa State University
Ames, Iowa
2018
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DEDICATION

To my beloved family, especially my dearest wife.
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ACKNOWLEDGEMENTS

I would like to take this opportunity to express my thanks to those who helped me with various aspects of conducting research and the writing of this thesis. First and foremost, Dr. Leonard J. Bond and Dr. Timothy A. Bigelow for their guidance, patience and support throughout this research and the writing of this thesis. Their insights and words of encouragement have often inspired me and renewed my hopes for completing my graduate education. I would also like to thank my committee members for their efforts and contributions to this work: Dr. Peter C. Collins, Dr. Nicola Bowler, Dr. Vinay Dayal and Dr. Xinwei Wang. I would additionally like to thank Dr. Lucas W. Koester for his guidance throughout the every stages of this research. I would also like to thank faculties, staff and students at Center for Nondestructive Evaluation (CNDE) at Iowa State University for their guidance and constructive comments during this work.
ABSTRACT

Powder-based additive manufacturing (AM) technologies are seeing increased use, particularly because they give greatly enhanced design flexibility and can be used to form components that cannot be formed using subtractive manufacturing. There are fundamental differences in the morphology of additively manufactured materials, when compared with, for example castings or forgings. In all cases it is necessary to ensure that parts meet required quality standards and that allowable anomalies can be detected and characterized. It is necessary to understanding the various types of manufacturing defects and their potential effects on the quality and performance of AM, and this is a topic of much study. In addition, it is necessary to investigate quality from powder throughout the manufacturing process from powder to the finished part. In doing so it is essential to have metrology tools for mechanical property evaluation and for appropriate anomaly detection, quality control, and monitoring. Knowledge of how and when the various types of defects appear will increase the potential for early detection of significant flaws in additively manufactured parts and offers the potential opportunity for in-process intervention and to hence decrease the time and cost of repair or rework. Because the AM process involves incremental deposition of material, it gives unique opportunities to investigate the material quality as it is deposited. Due to the AM processes sensitivity to different factors such as laser power and material properties, any changes in aspects of the process can potentially have an impact on the part quality. As a result, in-process monitoring of additive manufacturing (AM) is crucial to assure the quality, integrity, and safety of AM parts. To meet this need there are a variety of sensing methods and signals which can be measured. Among the available measurement modalities, acoustic-based methods have the advantage of potentially providing real-time, continuous in-service monitoring of manufacturing processes at relatively low cost. In this research, the various types of microstructural features or defects, their generation mechanisms, their effect
on bulk properties and the capabilities of existing characterization methodologies for powder-based AM parts are discussed and methods for in-situ non-destructive evaluation are reviewed. A proof-of-concept demonstration for acoustic measurements used for monitoring both machine and material state is demonstrated. The analyses have been performed on temporal and spectral features extracted from the acoustic signals. These features are commonly related to defect formation, and acoustic noise that is generated and can potentially characterize the process. A novel application of signal processing tools is used for identification of temporal and spectral features in the acoustic signals. A new approach for a K-means statistical classification algorithm is used for classification of different process conditions, and quantitative evaluation of the classification performance in terms of cohesion and isolation of the clusters. The identified acoustic signatures demonstrate potential for in-situ monitoring and quality control of the additive manufacturing process and parts. A numerical model of the temperature field and the ultrasonic wave displacement field induced by an incident pulsed laser on additively manufactured stainless steel 17-4 PH is established which is based on thermoelastic theory. The numerical results indicate that the thermoelastic source and the ultrasonic wave features are strongly affected by the characteristics of the laser source and the thermal and mechanical properties of the material. The magnitude and temporal-spatial distributions of the pulsed laser source energy are very important factors which determine not only the wave generation mechanisms, but also the amplitude and characteristics of the resulting elastic wave signals.
CHAPTER 1. INTRODUCTION

This chapter will outline the motivation for the research topic by briefly addressing the concept of additive manufacturing, quality control requirements and in-situ monitoring techniques. The state-of-the-art for in-situ monitoring for additive manufacturing process is discussed and the on-going work for acoustic-based process monitoring for additive manufacturing is introduced.

1.1 Research Motivation

Traditionally, quality is assessed on final products and the measurements constitute a significant cost. Furthermore, this procedure seldom allows for remedial treatment, so defective material must be downgraded or even scrapped with further economic loss. This can be even more challenging in Additive Manufacturing (AM) method due to complexity of the process and higher value components, which consequently have a more significant economical impact. For these reasons, a real-time process monitoring and control capability for in-process measurements with AM, is necessary to ensure quality of final parts. Several different techniques have been considered for use in on-line monitoring of the AM process, using information from characteristic signals of the process. Optical, thermal and acoustic measurements have the potential to provide characteristic signals that can be potentially be related to process and quality. However, the difficulty in using process monitoring and control systems is the accurate and reliable detection of process faults and components defects during the manufacturing. Current optical and thermal based methods are not considered to be sensitive enough to all types of process or part failures and are not found to be adequate for characterization of the condition of parts in situ. Acoustic based methods are being
considered and are on focus in the current project. Among the various potential characteristic signatures, acoustic signals are considered to be the most promising signals for providing additional data for evaluation of AM process and parts. Preliminary data has shown that particular changes in acoustic signatures contain information that can potentially be related to part quality and process performance. These signatures require precise analysis using appropriate signal processing techniques to ensure the sensitivity and correlations, particularly with regard to effectiveness for providing feedback to the control system and enable real-time detection of defects.

1.1.1 Problem Statement

The present study investigates the capabilities of acoustic methods for in-situ monitoring of AM processes. Two acoustic methods are investigated, laser ultrasound and acoustic emission. The primary goal is to assess the capability of these techniques to detect the occurrence of process faults and defects in manufactured parts in real-time. Furthermore, identification of the type of faults and defects is also necessary, and this can be achieved through the use of efficient simulation and signal processing tools. These tools will be used in this study to identify the features in manufacturing process as well as manufactured parts based on their acoustic signatures. The conceptual schematic drawing for the core problem is presented in Figure 1.1.

1.2 Research Goals and Contributions

1.2.1 Goals

Acoustic signatures of AM processes are closely related to physical effects (e.g. cracking acoustic emission) and noise that occurs due to the fabrication process (e.g. thermally induced acoustic waves due to expansion caused by laser heating) in forming parts. Such acoustic signatures are superimposed (convolved) and they can potentially provide a signature that combines process and system generated sources. It is believed that there is the potential for such a signature to contain detailed and important information regarding the process and possible defect occurrence. Previous studies show that acoustic in-situ monitoring of AM
Figure 1.1 Conceptual Schematic Drawing for the Problem

process is feasible; Rieder et al. (2014). Systems and methods are also under development for acoustic-based process monitoring; Gold and Spears (2017); Redding et al. (2017) . However, noise levels and spectral content for AM were unknown for extracting information regarding the components and process needs. Obtaining useful information requires additional investigation and more advanced signal processing to extract and characterize signatures in the time and frequency domains. Using capabilities applied to other processes and acoustic monitoring along with appropriate signal processing technique(s) can potentially identify and extract the features from the acoustic signals. The examination of various defect types in the component and the evaluation of the ultrasonic signals in view of part and system classification are further issues to be pursued. The presented approach consist of two main parts including laser ultrasound and acoustic monitoring. Laser ultrasound evaluation is based on modeling and simulation approach. Ultrasound wave generation based on laser source will be modeled with FEM method to study the wave propagation through the part during the manufacturing process. This will help to identify which possible information can be obtained by laser ultrasound during the manufacturing process and what are the potentials and limitation of the method. Signal processing of backscattered signals will allow
for the detection of pores near the surface immediately following sintering laser without the need for Rayleigh wave. In acoustic monitoring approach, the acoustic signatures are obtained by monitoring signals during AM fabrication of non-complex geometries. In this respect, a proposed standardized test artifact for AM machines and processes is the most beneficial. Process will be monitored using a modified multi-channel inspection acoustic monitoring system and sensors, originally designed for monitoring acoustic emissions. Wavelet and statistical signal processing techniques are proposed for evaluation of the signals.

1.2.2 Tasks

This research goal can be expanded into the following tasks:

• Evaluating laser ultrasound for defect detection and in-situ monitoring in AM parts and process by means of simulation study

• Signal processing and evaluation of laser ultrasound signals for increasing signal to noise ration (SNR) and sensitivity

• Experimental setup and performed experiments to measure and investigate acoustic signatures for in-situ monitoring of AM parts and systems

• Signal processing (time-frequency analysis and data clustering) techniques for evaluation of acoustic signatures recorded for process characterization, under various operating conditions

1.2.3 Contributions

The main contribution of this study is that it provides novel methods for on-line monitoring of additive manufacturing (AM) processes that improves fault detection in AM processes and parts. This contribution is a complementary and an improvement to the already implemented in-situ monitoring techniques such as thermography; Krauss et al. (2015) and optical methods; Fallis (2013). It also acts as a design tool to accommodate end user requirements. The particular simulations, finite element modeling, experimental work,
data collection, and signal processing techniques introduced in this study bring new applications to AM in-situ monitoring which cover the following aspects:

- Ex-situ AM material characterization for quantifying material properties used in modeling and simulation
- Proof of concept for acoustic methods by recording acoustic signal at different build condition
- Non-stationary signal processing on collected data under varying build conditions both with and without defects present
- Modeling, simulation and signal processing of laser ultrasound for additive manufacturing process and part evaluation, considering the matemperature dependent and local material properties.

1.3 Thesis Organization

This research will be more established and detailed in the following chapters. Chapter 2 familiarizes the reader with AM, AM defects and their formation mechanism and provides a more detailed literature review on the state-of-the-art in quality inspection and control in metal AM. It also provides background knowledge on quality monitoring and control, and provides introductory knowledge of several signal processing definitions of concepts and algorithms. Chapter 3 describes the system and sensor setup and procedure of additive manufacturing process monitoring using acoustic emission sensors. Chapter 4 formulates the methods of acoustic emission signal processing, feature extraction and classification techniques and the results for the experimental parts. Chapter 5 describes the modeling and simulation of laser-ultrasound for additive manufacturing process and parts.
CHAPTER 2. BACKGROUND

The chapter starts with definition of additive manufacturing (AM) in general with a special focus on laser and powder based AM to give a broad knowledge basis. Then it focuses down to process and material parameters that can affect formation of inhomogenities (defects) in the parts to give process and material oriented knowledge on the most influential factors. Next, the possible inhomogenities and defect formation mechanisms in powder metal AM are introduced. Material evaluation and nondestructive inspection techniques for quality control of finished AM parts are introduced and finally Past and concurrent works on in-situ monitoring techniques are discussed. Different monitoring techniques have been evaluated with emphasis on acoustic techniques.

Metal industrial products have traditionally been produced using various forms of casting and molding in combination with forming that can include forging, rolling, and extrusion. In many cases these methods are combined with machining using subtractive processes and then joining to produce a part or other product. Along with traditional and subtractive methods, powder-based processing routes have been used for part production especially for geometrically complex structures. Over decades, experience and analysis has been combined to formulate codes and standards as well as to mature various characterization, testing and evaluation methods which have identified classes of defects\textsuperscript{1}, selected alloys for particular applications, and assessed their significance when incorporated into deformation models in which stress is applied to a part or system. Additive manufacturing is defined by ISO 17296 and ASTM F2792

\textsuperscript{1}The technical term defects can create a negative perception regarding a material or process. In this work, the term defect is used in the traditional sense of a deviation away from a perfect material (i.e., a microstructural anomaly or discontinuity e.g., a pore). In this context, all materials have defects. The size and type of defect is what is important. Further, in keeping with a fundamental understanding of materials, the term defect is not meant to imply a loss of functionality. Rather, defects may reduce the lifetime of components under cyclic loading, or reduce some properties in a probabilistic sense under some defined set of stressors.
to be the process of joining materials to make parts or objects from 3D model data, usually layer upon layer, as opposed to subtractive manufacturing methodologies; ISO/ASTM (2015). There is now an increasingly diverse range of additive manufacturing (AM) process techniques that provide the ability to produce parts from computer-generated models with little to no additional material removal.

The manufacturing flexibility of AM processes provides the possibility of developing novel designs (e.g., topology optimized structures; Gaynor et al. (2014) for products which are simply not possible with casting or subtractive (e.g., machining) methods. Powder-based methods for metal manufacturing are versatile and have been explored for various applications; Yap et al. (2015); Thornton (2015); Sing et al. (2015); Foster et al. (2015); Yeong et al. (2014); Frazier (2014); Sames et al. (2016). Despite the promise of AM, there exist a number of significant impediments to its widespread utilization, particularly in industries that produce low production volume and high value components like aerospace. Quality control and mechanical characterization remains a major challenge; Huang and Ming C. Leu (2014); NIST (2013); Urabe et al. (2014); Criales et al. (2016); Koester et al. (2016). The quality and mechanical properties of the manufactured parts are influenced by the generation and existence of microstructural features and potential defects; Song et al. (2015); Olakanmi et al. (2015); Collins et al. (2014, 2016). Reliable control of mechanical properties needs to be achieved for AM to see increased use with novel designs that utilize the methods full potential, particularly for high value components; Haden et al. (2015). For this reason, it is necessary to develop new and to adapt current metrology tools for the assessment of microstructural features and provide reliable detection and characterization of defects. Integrating these tools with a good understanding of the mechanisms of defect formation during the manufacturing process should enable AM methods to be more widely adopted. It is also necessary to understand the significance of the various classes of defects on part functionality and life under the influence of operational stresses. When considering a components life cycle, it is desirable to optimize the manufacturing process and then plan monitoring and replacement of parts before they fail. Several studies have evaluated the causes and occurrence of defects in AM and their influence on mechanical properties and the
life of parts; Gong et al. (2014, 2015); Bauereiß et al. (2014). Conventional nondestructive methods for the detection of defects and other evaluation of the deposited material of AM parts are considered in several papers e.g.; Everton et al. (2015); Brien and James (1988); Slotwinski (2014). Taheri et al. (2017) studied the types of defects that can potentially occur in fabrication using AM and reviewed the capabilities of detection, sizing, and monitoring methodologies; Taheri et al. (2017d).

2.1 Additive Manufacturing

There is a variety of AM processes which can be categorized based on the type of process and materials. Initially techniques such as stereolithography; Hull (1986), fused deposition modeling; Crump (1992), and laminated object manufacturing (LOM) allowed for manufacture of parts made of plastic, polymer, wax, and similar materials; Gausemeier et al. (2012); Kruth et al. (1998). With the invention of selected laser sintering (SLS); Deckard (1989) and its commercialization in 1992, and later on Selective Laser Melting (SLM); Meiners et al. (2001), build of a large variety of metallic parts and components was made possible, extending the application to a large variety of parts and components in automotive and aerospace industries. Powder Bed Fusion (PBF), Sheet Lamination and Directed Energy Deposition (DED) are additive manufacturing processes that can be used for production of metal part. Among additive manufacturing techniques, Powder Bed Fusion (PBF) and Directed Energy Deposition (DED) are two AM processes where powders are the feedstock. In both methods, the processing parameters and raw material characteristics influence quality and mechanical properties of the as deposited part. The physical mechanisms by which the various processing parameters and powder characteristics influence the parts microstructure, defect populations, and attendant mechanical properties are topics of multiple on-going research efforts across the AM community. These processes are presented in Figure 2.1 according to ASTM F42 based on the type of process and materials.

While the mechanisms by which various process parameters influence defects and microstructure may not be completely known, several parameters associated with PBF and DED powder-based AM technologies have been correlated with defects and microstructure.
These parameters include the quality of the powder feedstock and the power imparted by the heat source. Although there are more parameters that are common to PBF and DED than there are differences, the differences are important and will impact the thermal gradients of the molten pool and surrounding material. For example, DED creates a mobile molten pool that is intimately coupled with the continuous injection of powder into the pre-programmed tool path of the heat source. The molten pool size, powder feed rate, and shielding gas flow are all critical process parameters; Yu et al. (2010). In the PBF method, pre-heating of the powder bed influences the solidification process and thermal gradient in the part; Savalani and Pizarro (2016); Lee and Farson (2015).

In both processes, powder is consolidated after imparting energy with a heat source. Both sintering and melting of powder are used to affect near-net shape structures in AM. Sintering-based AM processes generally achieve a green or brown compact that requires additional processing to achieve a fully dense part. Alternatively, fusion-based AM processes require no further consolidation, but may benefit from secondary processing steps such as hot isostatic pressing or subsequent heat-treatments. The process parameters and material attributes known to affect final part properties are summarized in Table 2.1.

---

2Sintering in AM is simply partial melting and is a legacy term for incomplete consolidation (ASTM F2792). The use of this term is understood to be a distinction between a partial and full melting process, especially for metallic materials.

3Sintering and complete melting represent the extreme ends of a continuum that includes partial melting. The degree of melting depends upon the energy density. We adopt these terms to reflect the legacy publication and research.
Table 2.1  PBF and DED process and material variables affecting the parts characteristics

<table>
<thead>
<tr>
<th>Process Parameters</th>
<th>Powder Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>PBF/DED</td>
<td>Particle Size and Distribution</td>
</tr>
<tr>
<td>Heat Source (Laser/Electron Beam) Energy</td>
<td>Internal Porosity</td>
</tr>
<tr>
<td>Scanning Rate (Speed)</td>
<td>Particle Shape and Topography</td>
</tr>
<tr>
<td>Scanning Spot Size (Radius/Length)</td>
<td>Surface Tension/Wettability</td>
</tr>
<tr>
<td>Scanning Raster Spacing and Pattern</td>
<td>Viscosity</td>
</tr>
<tr>
<td>Sintering/melting Environmental Condition</td>
<td>Specific Heat</td>
</tr>
<tr>
<td>Shielding Gas Flow Rate</td>
<td>Melting Temperature</td>
</tr>
<tr>
<td>Laser Beam Type and Characteristics</td>
<td>Thermal Conductivity</td>
</tr>
<tr>
<td>PBF</td>
<td>Absorptivity/Reflectivity</td>
</tr>
<tr>
<td>Bed Temperature</td>
<td>Emissivity</td>
</tr>
<tr>
<td>DED</td>
<td>Chemical Composition</td>
</tr>
<tr>
<td>Powder Flow Rate</td>
<td></td>
</tr>
<tr>
<td>Shielding Gas</td>
<td></td>
</tr>
</tbody>
</table>

The physical processes that occur during AM are very complex, and are just beginning to be fully understood and quantified; Markl and Korner (2016); Collins et al. (2016); Matthews et al. (2016). Indeed, as shown by Matthews et al, the particles not only move during the AM process, but that the fundamentals physics of the process (e.g., metal vapor flow) are highly variable, and can create, effectively, vortexes which cause the powder to move. Once entrained in the liquid, the melt pool dynamics are equally complex, with Marangoni convection, evaporation, wetting and capillarity playing strong roles (among many other operating physics). The liquid metal velocity is quite high, and results in features that resemble comet tails as melting particles leave molten material behind them as they move through the molten pool; Mendoza et al. (2017). These physics present challenges in understanding and modeling AM processes, which needs efforts towards the knowledgebase of the heat source / particle interactions.

2.1.1  Processing Mechanisms

Powder Bed Fusion (PBF) and Direct Energy Deposition (DED) are the main powder-based additive manufacturing processing methods. Powder Bed Fusion (PBF) systems normally include a heat source, an automatic powder layering mechanism, a computer control system and related sensors and accessories. Such a system is shown in schematic form as Figure 2.2. An electron beam source requires a vacuum environment while laser sources typically utilize
an inert gas environment or gas shielding to prevent excessive oxidation. Powder is spread over the previous layer in each step of production using a roller or a blade. After each step of layering, the build platform lowers the part so the process can be repeated for subsequent layers. Typically, melting processes are faster than sintering, but require higher energy expenditure; Gibson et al. (2015).

![Figure 2.2 Powder Bed Fusion Additive Manufacturing System](image)

The concept of Direct Energy Deposition (DED) is very similar to the other additive manufacturing methods. However, the powder is supplied through feed nozzles into an inert gas shielded delivery system. The beam and powder nozzles are focused coincidently at the deposition plane. It is possible to incorporate up to 6 degrees of freedom for the position and motion of the deposition head, allowing for deposition to occur below a part in an unsupported geometrical sense. The incoming material is heated prior to deposition as it passes through the beam, and may be melted either during this pass through the beam or by thermal conduction once the powder is in the molten pool through the nozzles into the path of a laser or electron beam. Figure 2.3 shows a schematic of a DED process and representative configuration of the nozzles relative to the beam. DED may be used to repair high value components where the existing high value components acts as the substrate.
2.1.2 Process Parameters

2.1.2.1 Heat Source Characteristics

The type of heat source and the energy density (see Scanning Characteristics) selected depend upon the material to be deposited. Lasers and electron beams are the most commonly used sources of energy in AM. Lasers supply monochromatic coherent light and can be used for a wide range of materials. Electron beams are characterized by a spot size that is typically far smaller than that of a laser, although the beam can be steered by electromagnetic lenses very rapidly, effectively allowing the melt pool size and position to be controlled and varied very quickly; Soylemez et al. (2010). Electron beams can only be used for conductive materials. Among the materials most suitable for electron beam AM technics are weldable metals, including titanium and Ti-based alloys, Ni-based superalloys, Co-based alloys, Fe-based alloys, tantalum, tungsten, niobium, stainless steels (300 series), 2319 and 4043 aluminum, and Zircalloy. AM laser heat sources are generally Q switched resulting in ultra-short pulse times. CO₂ and Nd:YAG lasers are operating with power in the range from 50 – 500 W, but very high power CO₂ lasers up to 18kW have also been used; Chua and
Nd:YAG lasers $\lambda = 1064\ nm$ have a shorter wavelength, a capability of tighter focusing, and have higher energy absorption for metallic materials. In pulsed wave mode, the energy is delivered in a short time window of milliseconds ($10^{-3}$ seconds) for melting and sintering applications; Majumdar and Manna (2013), resulting in a shorter interaction time when compared with a continuous wave laser. Pulsed laser systems have been shown to be more suitable for use in sintering processes since good metallurgical bonding with less heat accumulation can be obtained; Majumdar and Manna (2013); Santos et al. (2006). In electron beam based AM techniques, a high power electron beam (typically 50 W to 40 kW) is generated in a thermionic electron gun where electrons are emitted by a heated tungsten filament. The electrons are then accelerated with an electrical field and are focused and steered by electromagnetic coils. In certain cases, it is possible to use close-loop control to tune the energy of the electron beam thereby maintaining constant build temperature. Another capability of electron beam methods is that it is possible to deflect (steer) the beam at very high rates (faster than thermal diffusion), which can be used to establish and maintain several melt pools simultaneously, a technique known as multi-beam heating; Vayre et al. (2013). Other types of heat sources which are traditionally used in processes similar to additive manufacturing can be considered as the potential source of energy for AM. The development and control of robotic manipulation systems in multiple dimensions has enabled novel implementation of a broad range of welding-like processes in additive layer manufacturing. In plasma deposition techniques, a controlled plasma heat source forms a molten pool where a flow of metal powder is deposited; Zhang et al. (2003). In plasma heat sources, an electric arc is created between a cathode (tungsten electrode) and an anode (copper) under inert gas (Argon) shielding between the cathode and anode terminals; Messler (1999). In addition to plasma methods, other arc-based heat sources were also reported to be used for additive manufacturing. Gas Tungsten Arc Welding (GTAW) is an arc-based method which has been used for depositing metallic materials; Jandric and Kovacevic (2004). Both gas metal arc welding (GMAW) and gas tungsten arc welding (GTAW) have been used by Almeida et al. (2010) for fabrication of titanium alloy parts; Almeida and Williams (2010). Net shaping of metallic parts has also been achieved using processes such as Metal Inert Gas
(MIG) and Metal Active Gas welding (MAG) techniques; Akula and Karunakaran (2006). These methods tend to have larger absolute melt pool dimensions and thus are generally used to form large near net shaped parts when compared with those formed using laser or electron beam methods.

2.1.2.2 Scanning Characteristics

Scanning speed (\(mm/s\)), spot size and the pattern of the scanning spot are all important parameters in the AM process. The energy density can be defined as 2.1; Glardonl et al. (2001):

\[
E = \frac{P}{v_b d}
\]

where \(P\) is the average laser power (rate of energy flow averaged over one full period), \(v_b\) is the scan velocity, and \(d\) is the beam diameter. In practice, the equality in this equation should more correctly be a proportionality, given variations in the shape of the molten pool. It has been observed that there is a minimum energy density above which the properties of the material are acceptable; Sears (2002); Collins (2004). Thus, energy density is directly proportional to the average laser power and inversely proportional to the scanning speed. Balancing these parameters generally leads to an operational window within which the systems can be operated to give desired part characteristics. The optimum scan velocity may be correlated with the thermal gradient experienced by the material (e.g., its cooling rate) and desired production rate of the machine. The former can be related to microstructure, texture, compositional homogeneity ; Collins et al. (2016). while the latter is limited by the capability of the positioning or control systems for beam placement while maintaining process parameters within the optimal operational window that result in desired and ideally optimized material properties. While laser-based AM methods typically use a single beam, multi-beam laser-based AM techniques have been demonstrated and shown to provide higher precision and improved deposition rates. In multi-beam laser-based AM, it is necessary to consider new process variables that influence the quality of the deposited material, including the percentage of beam overlaps, relative spatial positions, power and frequency variations;
Patwa et al. (2013). During AM deposition, for each layer, the heat source melts or sinters the powder in a predefined scanning pattern which generally consists of sequential scanning vectors (although parallel scanning vectors are possible in multi-beam laser-based AM and electron-beam based AM). Scanning vectors are co-optimized with scanning speed by considering uniform heat flow in the part. The scanning patterns and related scanning vectors greatly influence the thermal history of the part. Their optimization is dependent upon the part geometry and multiple material thermophysical properties (e.g., thermal conductivity, heat capacity, surface tensions). Some common scanning patterns used in AM include zig-zag, parallel and hexagonal patches; Clijsters et al. (2012).

2.1.3 Powder and Substrate Characteristics

**Powder**

Both pure metal and alloy powders have been used in AM processes. However, powders of metal alloys are more commonly used for high value parts. A critical assessment of the literature indicates that the majority of investigations have focused on titanium; Wauthle et al. (2015); Gu et al. (2012) and aluminum; Bartkowiak et al. (2011); Buchbinder et al. (2011); Louvis et al. (2011); Vora et al. (2016); Brice and Dennis (2015) in pure powder processing, while Ti, Ni and Fe-based materials are typical for alloy powders; Santos-Ortiz et al. (2015). Ti-based alloys are used extensively in aerospace applications due to their high tensile strength and toughness, lightweight and the ability to withstand extreme temperatures; Dinda et al. (2008); Li et al. (2016); and in medical applications; Krishna et al. (2007); Liu et al. (2016); Dobrzańska-Danikiewicz et al. (2015); Brånemark et al. (2011); Singh et al. (2006); Banerjee et al. (2005b); due to their biocompatability. Ni-based alloys have superior creep, tensile strength, and corrosion resistance properties which make them ideal materials for jet engine and gas turbine components. Powder attributes, such as morphology, surface chemistry, size, internal porosity and any entrained defects or foreign materials have a significant influence on the quality of the as-deposited material, the transmission of prior defects, generation of new defects, and the attending mechanical properties. Thus, the characterization of powder is critically important when seeking to measure and/or predict the presence of inhomogeneities.
in the final product; Bond et al. (2014). Regarding the measurable attributes of powder, the particle shape, average size and particle size distribution are important for packing and processing; Slotwinski et al. (2014); in PBF, while flowability is important for both PBF and DED; Herzog et al. (2016).

**Substrate**

Due to large temperature gradients created between the molten pool and surroundings in powder based additive manufacturing, parts are usually made on a base plate or substrate which acts as both a mechanical support and a heat sink. The substrate and its thermal characteristics are therefore important to provide adequate cooling and support during the forming process. In general, there is a significant economic advantage if the substrate can also be incorporated into the final shape of the additively manufactured component. The incorporation of the substrate into the final component can reduce build time and cause the process to consume less energy. In contrast, for cases when the substrate is not included in the final structure, it must be removed at the end of fabrication process using some form of cutting or machining.

### 2.1.4 Material (Powder) Parameters

**Absorptivity**

Absorptivity is the ratio of the absorbed radiation to the incident radiation, and is a function of both the material and the wavelength of the incident radiation. The absorptivity for metal powders is a variable in the energy balance of the process, and influences the critical (minimum) energy density. Table 2.2 provides examples of reported absorptivity of common metals used in AM. However, as can be seen from the table, the absorptivity of the materials in their powder form is significantly higher than their absorption in dense form. This is due to multiple scattering of the laser beam in the powders; Boley et al. (2015); Tolochko et al. (2000). In addition, for powder bed AM, the physical depth where the intensity of the radiation falls to $\frac{1}{e}$ ($\approx 37\%$) of the original radiation intensity is called the optical penetration depth and depends on the absorptivity of the powders; Gu (2015); Gusarov and Smurov (2010); Tolochko et al. (2000). Although rarely possible, ideally the laser wavelength would be matched with the powder characteristics as energy density will change with both the powder absorptivity and frequency (wavelength) of the laser; Kruth et al. (2003).
Table 2.2 Absorptivity of common materials used in additive manufacturing corresponding to Nd:YAG and CO\textsubscript{2} lasers

<table>
<thead>
<tr>
<th>Material</th>
<th>Nd:YAG laser $\lambda = 1.06\mu\text{m}$</th>
<th>CO\textsubscript{2} laser $\lambda = 10.6\mu\text{m}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Powder form</td>
<td>Dense form</td>
<td>Powder form</td>
</tr>
<tr>
<td>Cu</td>
<td>0.59</td>
<td>0.03</td>
</tr>
<tr>
<td>Al</td>
<td>-</td>
<td>0.04</td>
</tr>
<tr>
<td>Fe</td>
<td>0.64</td>
<td>0.35</td>
</tr>
<tr>
<td>Ni</td>
<td>0.64</td>
<td>0.27</td>
</tr>
<tr>
<td>Ti</td>
<td>0.77</td>
<td>0.45</td>
</tr>
<tr>
<td>TiC</td>
<td>0.82</td>
<td>-</td>
</tr>
<tr>
<td>Cr</td>
<td>-</td>
<td>0.37</td>
</tr>
<tr>
<td>$Al_2O_3$</td>
<td>0.03</td>
<td>-</td>
</tr>
</tbody>
</table>

Surface Tension (Wettability)

In both sintering and fusion-based AM processes, the liquid-solid surface tension impacts the resulting product. This tension is a temperature and composition dependent variable. The surface tension of the solid-liquid interface ($\gamma_{sl}$), solid-vapor interface ($\gamma_{sv}$), and liquid-vapor interface ($\gamma_{lv}$) influence wettability which can be measured by the contact angle ($\theta$) as

$$\cos \theta = \frac{\gamma_{sv} - \gamma_{sl}}{\gamma_{lv}}$$

(2.2)

As $\cos \theta \rightarrow 1$, the liquid completely wets the solid. Spatial variation of temperature within the melt pool causes variation in surface tension and drives the melt pool to move from lower to higher surface tension regions, due to Marangoni convection.

Viscosity

The viscosity and wettability of the liquid metal enable the melt pool to spread across the previously deposited layer. Viscosity of the molten pool, $\mu$, in a solid-liquid mixture in sintering systems is presented as

$$\mu = \mu_0 (1 - \frac{1 - \varphi_l}{\varphi_m})^{-2}$$

(2.3)

where $\mu_0$ is the base viscosity, $\varphi_l$ is the volume fraction of liquid phase, and $\varphi_m$ is the volume fraction of solids. In melting based processes where the liquid formation is complete, the dynamic viscosity of the liquid is defined as

$$\mu = \mu_0 (1 - \frac{1 - \varphi_l}{\varphi_m})^{-2}$$

(2.4)
\[ \mu_0 = \frac{16}{15} \sqrt{\frac{m}{kT\gamma}} \quad (2.4) \]

where \( m \) is the atomic mass, \( k \) is the Boltzmann constant, \( T \) is the temperature and \( \gamma \) is the surface tension of the liquid.

**Thermal conductivity**

The effective thermal conductivity of a packed powder can be estimated by 2.5; Glardonl et al. (2001):

\[ K_p \approx (1 - \omega)K \quad (2.5) \]

where \( \omega \) is the packing density of the powder bed and \( K \) is the conductivity of the dense material. This effective thermal conductivity strongly depends on particle-to-particle contact. Based on experimental measurements, Fischer et al. (2003) found that a loose pack has thermal conductivity that can be more than one order of magnitude smaller than for fully dense materials; Fischer et al. (2003). Thermal conductivity for different metal powders were measured in several studies; Hadley (1986); Swift (1966). More recently, other researchers have used simulation and found that conductivity for an AM material is almost decoupled from bulk properties; Turner et al. (2015). It was found that the combination of the thermal characteristics of the material, substrate and environmental processing conditions affect the cooling and solidification rates that strongly influence the resulting part microstructure; Hofmeister and Griffith (2001).

### 2.2 Defects in Metal AM and Defect Formation Mechanism

Variations in process parameters and powder attributes influence not only the microstructural features present in AM components (e.g., grain size, texture, solute distribution), but may lead to the generation of defects. Laser power, scan speed, layer thickness, spacing of scan lines, powder feed rate, powder size distribution, and surface chemistries are among the many parameters that influence the quality of the deposited material. Many studies have been conducted which seek to understand and quantify the
effects of these parameters on the final microstructural characteristics, e.g. Rombouts et al. (2006); Slotwinski and Garboczi (2014). However, as the combined influence of all related parameters is not completely understood, robust process models still need to be developed; Rombouts et al. (2006); Ng et al. (2009); Gong et al. (2014) and other critical experiments are required.

2.2.1 Microstructural Anomalies

Any feature seen in the microstructure of AM parts that deviates from what is desired can be considered as an anomaly (or a defect) depending upon the end application. As noted previously, in this work, defect is in reference to any structural deviation away from an otherwise uniform, isotropic, fully dense solid of the target alloy. Examples are seen in the form of: porosity, lack of fusion, microcracks and hot-tears, variations in crystallographic texture and grain size, unwanted variations in composition, unexpected or metastable phases, and nonmetallic inclusions.

Porosity

Porosity is a common defect found in AM parts. Many process parameters and feed material attributes have been associated with porosity. Further, the porosity that exists can occur at different length scales. For sintering-based AM processes, micro-porosity (sub-powder scale) is generally related to pores inside the starting powder that are transmitted to the final deposition. For both sintering-based and fusion-based AM, porosity that is present at the macroscale may be categorized into two main classes: gas porosity and lack of fusion (LOF); Ng et al. (2009).

- **Gas Porosity**

At the present time, most research articles attribute gas porosity to trapped shielding gas that arises from three primary sources. In DED methods, a high powder flow rate can lower the specific energy of the melt pool, resulting in increased gas entrapment. Care must be taken to not include unmelted particles that can be pulled out during metallographic sectioning in this category, as this leads to false positive indications of gas porosity. The second source in deposition methods is entrapped gas within the starting powder particles. Lastly, Marangoni
flow, which is defined as the mass transfer along an interface between two fluids due to surface tension gradient, causes gas retention bubbles within the melt pool which lead to large pores; Barua et al. (2014).

For laser based methods, the Equation 2.6 can be used as a predictor of porosity percentage indicator through the normalized enthalpy $\frac{\Delta H}{h_s}$; Wu et al. (2014); Hann et al. (2011):

$$\frac{\Delta H}{h_s} = \frac{\eta P}{\rho h_s \sqrt{\pi \alpha \sigma^2 \nu}}$$

(2.6)

where $\Delta H$ is the specific energy (J/kg), $h_s$ is the enthalpy at melting (J/kg), $\eta$ is the surface absorptivity, $P$ is the power (J/s), $\rho$ is the density at melting (kg/m$^3$), $\alpha$ is the thermal diffusivity (m$^2$/sec), $\sigma$ is the half width of beam spot (m) and $\nu$ is the speed msec. Increasing the normalized enthalpy will decrease the porosity percentage. A correlation between the normalized melt depth and normalized enthalpy is presented in Figure 2.4, which is a comparative evaluation based on data from several studies and for different materials. This figure captures results from multiple studies, including data from two different laser fiber diameters (200 and 400 $\mu$m) and two scanning velocities (1 and 2 m/min) with data from Rai et al (2007) for a range of metals; Hann et al. (2011); Rai et al. (2007). Importantly, there is a minimum heat input (enthalpy) that is required to result in melting. Deviations from an ideal energy input, and hence melt pool depth and enthalpy, will change the attributes of the molten pool, including the potential to entrap gas resulting in gas porosity.

Porosity in structural applications is generally detrimental to part performance. The influence of both the starting powder and the process parameters have been investigated with the objective of reducing/eliminating the porosity in final components. It has been found that samples fabricated using powders produced by gas atomization (GA) show three times higher interlayer porosity than those formed using powders produced by Plasma Rotating Electrode Process (PREP) at all powder feed rates and laser powers; Ahsan et al. (2011). This has been attributed to the increased levels of entrapped porosity within the powders produced by GA compared with PREP powders, and explained by considering the fact that smaller particle sizes should result in higher melt pool temperatures/fluid flow and thus the elimination of
Increasing the energy density can eliminate some of these smaller pores. However, other types of inhomogeneities can form at higher energy densities; Meier and Haberland (2008); Bauereiß et al. (2014). According to these authors, the inhomogeneities that occur at higher energy densities are part morphologies including increased surface roughness and density variation. Regarding the former, this is most likely due to complex (and offsetting) molten pool physics that operate at higher molten pool temperatures, including the spreading of the molten pool due to decreased surface tension, and a concurrent vaporization of some elements which can lead to local cooling. The selective evaporation of some elements has been associated with a reduction of density of the final components. At lower energy densities, insufficient melting leads to cavities in the part. Irregular, lattice like pores form when the scan line spacing is too large and energy density is insufficient. The effect of scanning speed
on the finish of the build plane and sidewalls has also been investigated. In these studies, it was shown that an increase in scanning speed initiates fragmentation in both surfaces; Meier and Haberland (2008). Since any new layer is built on the rough and corrugated surface of a previous layer, the thickness of the new layer has significant variability. When compounded with the dependence of melt pool depth and normalized enthalpy in Figure 2.4, process related defects such as lack of adequate binding and porosity can occur; Bauereiß et al. (2014).

- **Porosity due to lack of fusion (LOF)**

When there is insufficient energy in the melt pool, the resulting inability to melt the powder particles can cause lack of fusion (LOF) porosity in AM parts. In DED, an incorrect or varying standoff distance between the deposition nozzle and substrate causes defocusing of the laser beam and reduced energy density (i.e., higher spot diameter in the energy density equation of Glardon), which can cause LOF porosity; Barua et al. (2014). The size and composition of the substrate can also affect the thermal diffusion away from the melt pool and cause LOF, as well as substrate-deposit delamination. LOF defects are usually found along boundaries between layers, are irregularly shaped, and often contain unmelted powder as shown in Figure 2.5; Liu et al. (2014); Olakanmi et al. (2015). LOF can be divided into three categories; Liu et al. (2014): (a) separated surface with un-melted powder, (b) separated surface without un-melted powder and (c) narrow and long shaped with un-melted powder. In general, it is found that increasing the scanning speed decreases the specific energy and therefore increases the risk of causing LOF defects; Ng et al. (2009) The occurrence of LOF increases as the powder feed rate increases and as the normalized enthalpy of the melt pool is decreased. In looking at mitigation strategies, it has been found that increasing the track overlap will not have a significant effect on reducing the tendency for LOF defect formation; Ng et al. (2009).

**Anisotropy and Phase Stability**

Changing process parameters such as laser power and scanning parameters, specifically scanning speed and its effects on energy density, has been shown to cause a considerable change in the grain structure; Gong et al. (2014), the phases present (including the promotion of
Figure 2.5 Optical micrographs of LOF defects in the cross-sections of SLM Ti64 with 30 m layer thickness shown as a cross section of the build direction at high scanning speed (both cross-sections were etched to reveal the microstructures and defects): (a) Along the layer boundary and (b) LOF defect with un-melted powder particle; Liu et al. (2014).

metastable phase formation), their distribution within the microstructure; Scharowsky et al. (2015), and tendencies for defect generation; Zhong et al. (2015) in AM parts; Liang et al. (2014a,b). The variation in the temperature gradient in the melt pool result in variation in the solidification rate, resulting in concurrent variations in microstructure, including phase stability; Marya et al. (2015). Further, the atmosphere can have an influence on phase stability, microstructural features/morphology, and defects. For example, even a small amount of oxygen contamination can cause oxidation changing the resulting texture and adding impurities to the microstructure in some AM methods which are processed under inert gas shielding or environments; Murgau (2016). Several studies have reported the anisotropy seen in material properties caused by the different scanning patterns and process parameters used Ahn et al. (2002); Shamsaei et al. (2015) and has also been shown to be dependent upon the material employed Zhu et al. (2015); Carroll et al. (2015).

Inclusions

For the sake of completeness, it is useful to consider the formation of dispersoids of varying types in the microstructure. From the perspective of physical metallurgy, these dispersions may be either intentional (and thus beneficial), or an undesirable (and deleterious) microstructural feature. When they are intentional, they are often dispersions that are (often) incoherent with
the matrix, but of a size that is sufficiently small ($< 250\,nm$) that they do not lead to large stress concentrations in the microstructure, and tend to improve the mechanical properties, such as yield strength. However, while this size may be intentionally introduced and is attainable in additively manufactured materials; Banerjee et al. (2005a); Brice and Fraser (2003), it is not the only type of dispersion present. In other cases, the material can chemically react with the shielding gas, forming exogenous intermetallic particles such as oxides and sulfides. The size of these inclusions are generally in the range of $0.5\,\mu m$ to 1 millimeter - a size scale that is a cause for concern when considering the mechanical properties, specifically ductility, fracture toughness, and fatigue. Impurities in powders can exacerbate the size of these inclusions. The number, size, shape (morphology) and distribution of inclusions over the part significantly affect final part performance, particularly fatigue strength; Wilby and Neale (2015).

Current methods of materials characterization are often destructive, requiring that the material be sectioned and appropriately prepared to quantify the microstructural features present. For example, scanning electron microscopy (SEM) and electron backscattered diffraction (EBSD) techniques can be used to observe and quantify porosity, grain size, shape, and orientations to determine the local anisotropy. Similarly, various spectroscopic techniques can be used to measure the composition of the material as well as of phases in the material (e.g., inclusions). A challenge for some types of additive manufacturing is that the length scales of the important features, especially as it relates to anisotropy, where the domains over which different orientations exist may span several millimeters; Brice et al. (2016). Such length scales are not compatible with current analysis techniques, such as EBSD. However, there are exciting new techniques, including spatially resolved acoustic spectroscopy (SRAS); Smith et al. (2014); Sharples et al. (2006); Li et al. (2012); Smith et al. (2016b) which may provide a way to conduct large scale analysis of variations in the orientation of grains, providing a way to correlate processing with properties and performance; Haden et al. (2015). There are some non-destructive methods to assess anisotropy, including x-ray based tomographic approaches, but they are sensitive to sample thickness and can be hindered by a spatially varying crystallographic texture.
2.2.2 Geometrical Anomalies

Dimensional inaccuracy for an AM produced part can be problematic, particularly when considering a prototype or high value part where the end use is for a component requiring fine dimensional control; Smith et al. (2016a). The layering process used in AM methods can result in rough surfaces and possible deviations from specified CAD model tolerances or other geometrical anomalies in the final part. Typically, the CAD model is converted to a stereolithography (*.stl) file format where the designed geometries and surfaces are discretized into geometric meshes. A macro-level stair-case effect can occur on part surfaces due this discretization; Moroni et al. (2014). In addition it has been shown that melt pool dynamics have a large influence on sidewall dimensions for the finished parts; Lee and Farson (2015). The risk of occurrence for curling, waviness and surface roughness are also all influenced by the previously discussed process and material parameters.

Melt pool dimensions and fluid flow have been shown to influence the sidewall dimensions and surface finish in deposited parts; Gockel et al. (2015). To minimize geometrical anomalies, a stable melt pool size/shape is required; Lee and Farson (2015). The Marangoni effect has a strong influence on melt pool size and shape and can introduce anomalies in deposited layers due to its dependence on composition and the local thermal gradients.

Balling Phenomenon

The balling phenomenon represents a type of defect that is generated in laser sintering-based AM processes. Several researchers have investigated and sought to explain the balling mechanism; Shen et al. (2006); Gu and Shen (2009); Bauereiß et al. (2014). A sub-critical energy density has been identified as the primary cause of balling which resulted in insufficient material being present in the liquid phase to promote sintering. In addition, balling at higher scanning speeds has been attributed to instabilities in the molten pool due to a capillary effect. Formation of oxide layers on both the solid and molten material due to presence of oxygen in the powder or built chamber will change the wetting process of surrounding material and cause balling phenomenon; Louvis et al. (2011). These factors then change the viscosity of the semi-molten phase, limit the liquid flow and melt pool morphology, leading to balling occurring
on the sintering surface. Remedies include increased the laser power, reducing the scan speed, and decreasing the layer thickness to achieve higher energy density. Adding deoxidants to the powder can generate a smooth sintering surface and consequently lower the risk of ball formation by mitigating formation of an oxide layer on the melt pool. Figure 2.6 shows a schematic of the balling phenomenon exhibited by coarsening spherically-shaped sintered particles and limited liquid formation.

![Figure 2.6 Schematic of balling phenomenon featured by coarsening spherical-shaped sintered particles and by limited liquid formation.](image)

**2.2.3 Cracks (and similar linear features)**

Several different physical factors and process parameters can cause cracking in AM parts. Melted powder can merge with the closest surface contact point, often a solid or liquid neighboring particle and not the previous layer. Continuation of this phenomenon can cause a change in the distribution of thermal energy and generation of large channels devoid of material bound to the substrate that resemble cracks in the final part; Bauereiß et al. (2014). Melt pool movement also causes mass transfer/movement along the interface due to surface tension gradients (known as the Marangoni effect) and can cause entrapped gas porosity, or cracks; Shifeng et al. (2014); Scharowsky et al. (2012). Thermal gradients can generate cracks in the parts when there are differences in thermal properties between the substrate and the
build material, or when there are large thermal gradients in the molten pool while solidification is proceeding (i.e., hot tearing). In addition to these cracks that can form during service, it is possible to have cracks form during service. Powder contamination, especially inclusions or un-melted particles originating from the feedstock, can cause subsequent cracking in service due to stress concentrations around inclusions under fatigue loading. Geometric anomalies can form stress concentrators that can potentially form the starting point for crack growth in service.

2.2.4 Defects in Powder Materials

As noted previously, internal voids in feedstock powder materials have been identified as a source of defects in AM components. Poor packing density during consolidation can create internal voids in as-deposited materials. Impurities in the powders can also lower the quality of the final part and generate porosity and inclusions; Benson and Snyders (2015). Sieving the as-atomized powders; Lee et al. (2006) and triboelectric separation; Stencel et al. (2000) are reported as potential methods for removing impurities from powder feedstock. The particles themselves can also contain geometric defects including voids; Moylan et al. (2014a); Philtron and Rose (2014). One such example is that of an x-ray image of titanium particles that exhibit internal voids, as well as powder particle size and shape variations is shown in Figure 2.7. Smaller sized powder particles exhibit better compaction and lower defect rates than when compared with larger particle. However, smaller particles may also lead to increased interstitial contents in the final components or safety issues during powder processing and handling. It has also been found that the final part surface roughness increases with larger particle and consequently larger layer thickness is employed; Abd Elghany and Bourell (2012).

2.3 Influence of Raw Material Properties, Process Parameters and Inhomogeneities on Mechanical Properties

Whether due to process parameters, environmental conditions, or material (powder) attributes, all of the defects discussed above contribute to mechanical property variations seen in AM products. The microstructures of AM processes are from, typically, non-equilibrium
processes with significant thermal gradients and complex thermal histories that vary spatially within a component. Not surprisingly, the post-processing heat treatment can alter many of the mechanical properties for a finished part. However, the anisotropic characteristics of AM fabricated materials, due to the thermal gradients and previous layer that template the next layers grains (e.g., epitaxial growth) are likely to persist unless recrystallization can be promoted or multiple variants of a dominant second phase can be promoted. Several studies discuss the mechanical behavior of different AM parts; Leuders et al. (2013); Song et al. (2015); Shifeng et al. (2014), including orientation-induced variations in the mechanical properties; Brice et al. (2016). There has also been work that reported the influence of different types of defects on final part mechanical performance; Liu et al. (2014); Lu et al. (2015).

The mechanical properties of the final part are affected by and related to the feedstock materials properties, specific manufacturing method used, as well as to particular process
parameters. Several studies have investigated the influence of manufacturing methods and process parameters on finished part mechanical properties; Abd Elghany and Bourell (2012); Simchi (2006); Yadroitsev et al. (2013). For example, process evaluation on Ti-6Al-4V samples manufactured by SLM and EBM revealed that yield and tensile strength of the samples produced by SLM are higher than for those produced by an EBM method. This is most likely attributed to differences in composition (including aluminum loss under vacuum), as that has been determined to have a strong influence on the mechanical properties of Ti-6Al-4V; Collins et al. (2014). However, the ductility, hardness, and consequently the fatigue strength of the samples produced by both methods are similar; Gong et al. (2015), and are less dependent upon composition.

In addition to microstructural inhomogeneities and mechanical property variation, the as-deposited density of AM components depends on powder characteristics, process parameters, layer thickness and scan line spacing; Simchi (2006). Laser power in the top range of the operational window results in higher density. Increasing the thickness of layers likely decreases the final part density unless the energy density is adjusted to account for the increase in melt pool depth required. However, several parameters limit the minimum layer thickness that can be employed, such as the maximum particle size. The powder spreading mechanism can disrupt previous layers when the layer thickness is close to or smaller than the maximum particle size. This is particularly detrimental during the early stages of the build process where disturbances propagate geometric errors into the successive layers; Agarwala et al. (1995). In Simchi’s (2006) study, density seems to be linearly proportional to the scan rate on a semi-log scale.

Simchi’s study also analyzed the influence of oxygen content, particle shape, size and its distribution on the porosity, and concluded that higher densities are obtained when the powder particles are fine and oxygen content is low while processing within the operational window, which likely correlates with reduced internal porosity. By decreasing scan speed and hatch distances (i.e., increasing energy density) the volumetric mass density of the resulting material increases, and, not surprisingly, has an influence on the mechanical properties. For example, the effect of layer thickness and scanning speed on tensile strength of 304L stainless steel samples was studied by Elghany et al (2012). Three different layer thicknesses 30, 50, and 70 µm at two
scanning speeds of 70 and 90 \textit{mm}/s were considered. The samples with higher layer thickness were more brittle in nature due to the occurrence of higher porosity; Abd Elghany and Bourell (2012).

The existence of defects can cause parts to have poor mechanical properties under certain loading conditions. It has been found that fatigue cracks are usually initiated from stress concentrations associated with pores and LOF defects and that the elimination of these defects would significantly increase the fatigue life; Liu et al. (2014); Tammas-Williams et al. (2016). These results have also been confirmed for Ti-6Al-4V samples where porosity of 5 vol. \% of the defects is shown to be a limiting factor for mechanical properties acceptance produced with a high energy density. However, it has been found that defect occurrence at a rate as low as 1 vol. \% has a considerable effect on mechanical properties. For LOF defects caused by lower energy density, even 1 vol. \% of defects has been shown to strongly affect both tensile and fatigue properties; Gong et al. (2015), most likely due to stress concentrators (e.g., small radii of curvatures) in such defects. It was also found that defects closer to the surface affected fatigue life more, when compared to the defects that were deeper or far from the surfaces due to higher stress concentrations for the near-surface defects; Liu et al. (2014).

2.4 Material Evaluation and Quality Monitoring in AM

In order to improve product quality and minimize the risk of failure caused by defects, it is important that defects be detected as early as possible in the manufacturing process. This, in principle, could then allow corrective action during the process to be taken to minimize material waste and increase both quality and yield. It would also minimize the extra costs needed for repair and rework of sub-standard items; Koester et al. (2016). Inspection and monitoring data can also be used to provide feedback and materials characterization which can be used to optimize the manufacturing process and to determine the operational window of a particular material system and AM method. Several reviews of current monitoring methods including non-destructive evaluation (NDE) tools, new approaches to total quality management for the characterization of materials from metal powder to finished parts, and a discussion of in-line metrology needs and techniques for AM processes can be found in the literature; Koester et al.
Global activities and industrial interest in AM technology, as well as rapidly expanding research and number of technical journals dedicated to AM topic shows the importance of quality control and performance evaluation in additively manufactured parts; Seifi et al. (2016).

2.4.1 Application of Nondestructive Techniques on Material Evaluation and Flaw Detection of AM Parts

Nondestructive evaluation techniques have been extensively studied and used for quality and property evaluation of additively manufactured parts. Application of each of these methods is related to the properties of the target material, geometry and physical feature of the part, and characteristics of the feature which needs to be evaluated or detected by the metrology. In this section, nondestructive evaluation methods which have been used for material evaluation of additively manufactured parts are introduced.

Optical Inspection Techniques

Optical inspection is a useful tool for NDE of parts and process monitoring and is attractive due to its low cost and ease of implementation. In an AM process, in-line vision monitoring systems are a promising candidate for defect detection and quality monitoring; Barua et al. (2011); Sparks et al. (2009). However, there are significant challenges faced in its implementation. Several methods of visual inspection can be applied for visualization of defects which are used with or without mechanical or optical aids.

- **Scanning Electron Microscopy (SEM)**

Scanning Electron Microscopy (SEM) is commonly used for obtaining images from cross sectional or other desired sections of materials after the final part is completed. Data obtained using SEM techniques can be used to analyze both the starting powders and finished parts at higher spatial resolutions than x-ray computed tomography; Slotwinski (2014). SEM micrographs can be used to verify the crack formation which initiates in the brittle phase, assess microstructural variations, or coupled with other SEM-based analytical tools that can be used to obtain compositional information (via energy dispersive spectroscopy) or texture.
(via electron backscattered diffraction). However, these SEM techniques are neither in-situ nor real-time. Further, analysis by SEM requires that metallographic samples be prepared, which is inherently a destructive method, making it only an off-line process analysis tool.

- **Optical Tomography**

The general steps of defect detection and process control in vision systems include image acquisition, image processing, detection algorithms and a control system. For camera-based monitoring systems, images of deposited layers are usually obtained by a single lens reflective camera; Zenzinger et al. (2015). However, Iravani and Toyserkani (2007) used a trinocular optical detector composed of three CCD cameras and interference filters for real-time measurement of deposition height and used a neural network model to determine optimal threshold value for the images; Iravani-Tabrizipour and Toyserkani (2007). Although optical (and infrared; Sames et al. (2016); Peter (2015); Turner et al. (2015); Dehoff (2015)) imaging systems are promising methods for defect monitoring and detection, at least in research studies, there also several challenges that will limit in-process use. These include the inability to visualize instability of the melt pool and fundamental limits of optical detection wavelengths. Real time monitoring and analysis for typical builds also generate large data sets and in-process implementation on an industrial scale machine is a non-trivial problem.

**Ultrasonic Techniques**

Ultrasonic based testing (UT) techniques have a wide range of applications in material testing and evaluation. This family of methods has been extensively applied for inspection and characterization of conventional materials and advanced materials and systems; Taheri et al. (2017b, 2014); Taheri (2014). Ultrasonic techniques have also shown some promise as methods for characterization of AM materials such as porosity detection in aeronautical structures; Ciliberto et al. (2002) and in more routine application to finished parts. In addition to defect detection, microstructure and mechanical properties of materials can be evaluated by ultrasonic techniques. In the cases non-contact ultrasonic methods such as using laser ultrasound, the advantage is to be able to be applied on rough surfaces, at higher temperature and during manufacture. The application of laser ultrasound for in-line
inspection of Laser Powder Deposition (LPD) Inconel samples with machined artificial flaws has been evaluated by Cerniglia et al. (2015). An infrared Nd:YAG pulsed laser was used as the transmitter and a continuous wave laser combined with an interferometer was used as the receiver for the generation and detection of UT waves, respectively. The results show the ability to detect micro-scale defects in layer-by-layer deposition process and this have been confirmed by use of an ultra-high sensitivity X-ray technique; Ciliberto et al. (2002). The ultrasonic velocity is a bulk material dependent parameter that demonstrates sufficient sensitivity to detect small changes (≈ 0.5%) in total porosity. Porosity measurement by this method has also been demonstrated to map spatial variations in porosity; Slotwinski and Garboczi (2014). Mapping porosity, elastic moduli and density using ultrasonic techniques can also be used for material testing and evaluation, at least in a finished part; Bond et al. (2014). Ultrasonic (and acoustic) emissions from manufacturing processes can also be used for health monitoring and fault diagnosis of additive manufacturing systems. Some defect generation events produce acoustic emissions that can be monitored and located in space, such as spontaneous crack formation caused by large thermal gradients. Acoustic emission has been extensively used in monitoring and flaw detection in welding; Homsawat et al. (2015); Charunetratsamee et al. (2013). Several studies have considered its application to additive manufacturing technology; Strantza et al. (2015). Furthermore, based on previous applications giving real time NDE for different manufacturing processes; Clavette and Klecka (2015), it appears to have the potential to be used for in-line monitoring of the inhomogeneities in parts at relatively low cost.

**Electromagnetic and Eddy Current Techniques**

Changes in electrical and dielectric properties of electrically conductive materials can be used to detect changes in capacitance due to porosity or other defects; Rogé et al. (2003); Taheri et al. (2017a, 2013). Direct current resistivity technique appears to be capable of not only detecting cracks but also measuring hardness and density. Eddy current testing can be used for surface crack detection but it is not suited for detecting internal cracks; Brien and James (1988). Advanced techniques and devices using eddy current techniques make it a promising method for some defect detection and inspection applications. High resolution
and array eddy current techniques may enable use of this method for inspection and testing of additively manufactured materials. However, similar to conventional materials evaluation, material properties and surface finish will impact the potential application and success of the method.

**X-ray Radiography and Computed Tomography**

X-ray imaging and x-ray computed tomography (XCT) can be used for defect detection and material characterization for either powder or finished parts. Based on several investigations; Bond et al. (2014); Du Plessis et al. (2015); Siddique et al. (2015), micro computed tomography (micro-CT) is now a relatively rapid and cost effective way to obtain structural information at the very early stages in a manufacturing process. The size distribution, shapes and internal features of the particle such as porosity can be determined quickly from a CT scan. Radiography techniques with image or volumetric processing can also be used to assess porosity, particle shape distribution, and size; Bond et al. (2014). XCT was compared with Archimedes’ method and mass/volume measurement in Slotwinski’s et al (2014) study to monitor porosity where 5 mm CoCr cylindrical AM samples were cut from the larger reference cylindrical disk samples, 40 mm in diameter and 10 mm thick. The measured porosity given by all three methods were similar and were used to evaluate the resultant change in ultrasonic wave speed caused by porosity; Slotwinski and Garboczi (2014). The trend for porosity generation can also be evaluated using micro-CT. Optical sections of powders have also confirmed the existence of entrapped voids in raw powder materials; Ng et al. (2009). In addition to many research articles on application of x-ray imaging and XCT for AM, Thompson et al. (2016) provide a review article on XCT for AM; Thompson et al. (2016). In Thompson’s article XCT is introduced as not only an imaging technique, but also a volumetric dimensional measurement tool used for porosity and internal defect metrology. The current barriers in application of XCT in AM are the resolution for porosity measurement and measurement of surface texture; Thompson et al. (2016).

**Thermography**

Laser and electron beam sintering and melting methods of additive manufacturing are based on thermal evolution of feedstock materials. Monitoring and detection of the
temperature profile of layering steps can potentially be used for determination of the quality of the material. Thermal dissipation is influenced by the microstructural characteristics of the part. Geometrical anomalies, material loss, inclusions and voids can be detected by a number of thermographic techniques. This method is noncontact and potentially full-field making it a promising candidate for in-line monitoring and complex structures inspection similar to optical methods; Dinwiddie et al. (2013).

Calibrated red, green and blue (RGB) intensity values of the colors of the obtained images and radiant surface temperature can be used to approximate a value for the temperature of each pixel in an image from visible emissions in melting processes. Infrared filters, a high speed shutter, and pulsed energy delivery systems can be synchronized with image acquisition and used in conventional techniques; Kizaki et al. (1993a,b). CCD cameras have been used to monitor surface temperature, to determine mass flow rate of the powder and to monitor the dimensions of the deposited track; Grevey and Vannes (1997). The color gradient of the melt pool and deposited track can provide a metric for process monitoring and identification of sintered and un-melted particles of powder and appears as sources of noise in image processing. For a research system, the temperature profile shape versus pixel data can be extracted to give a signature for an acceptable deposition or for deposition over a defect; Barua et al. (2011). Some other work in this field has made some progress using similar infrared thermography; Rodriguez et al. (2012); Moylan et al. (2014b), near-infrared thermography; Price et al. (2012) and thermography approaches for in-line monitoring; Krauss et al. (2012). Figure 2.8 summarizes the application of NDE methods for defect detection and material evaluation of AM parts.

2.5 Past and Concurrent Work on In-Situ Monitoring in AM

When there is not a quality monitoring module in an AM machine, quality control and inspections are performed on the finished part. Like subtractive manufacturing methods, mechanical repair or re-building the part is required if the quality or mechanical properties do not meet the expectations. Furthermore, if it is found that the lower quality of the part than the design requirements is due to the manufacturing process or build strategy, different
Figure 2.8  Comparison of potential and capabilities for application of NDE methods for defect detection and material evaluation for finished additive manufacturing parts. A, Applicable; B, Possible but Needs development for use in AM; C, low probability of successful application to AM; D, Not applicable to AM. 1, Larger cracks can be detected by visual inspection when the part condition is closer to failure which is not desirable.

<table>
<thead>
<tr>
<th>NDE Technique</th>
<th>Defect or Material Characteristics</th>
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<tbody>
<tr>
<td></td>
<td>Poreosity</td>
</tr>
<tr>
<td>Visual</td>
<td>C²</td>
</tr>
<tr>
<td>Ultrasonic</td>
<td>A</td>
</tr>
<tr>
<td>Electromagnetic</td>
<td>B</td>
</tr>
<tr>
<td>Radiography</td>
<td>A</td>
</tr>
<tr>
<td>Thermography</td>
<td>D</td>
</tr>
</tbody>
</table>

Advances in additive manufacturing are needed to address the challenges and uncertainties that currently exist around input materials and processing technologies. Uncertainties in the properties of input materials and equipment and processing lead to uncertainties in how final parts will perform as well as quality and characteristics. The solutions to address the uncertainties and increase the quality and performance of additively
manufactured parts include advancement in design step, material characterization, and in-situ monitoring and quality inspection of part and processes. These relationships are described in Figure 2.9. While there is an extended amount of work done on real-time process monitoring over the past two decades, the amount of work on in-situ quality monitoring and inspection is very limited and the work is very preliminary. Past and concurrent work on in-situ monitoring in metal AM is extended in the next section.


2.5.1 Application of In-Situ Monitoring Techniques in AM

There are variety of techniques that can be used for process monitoring in additive manufacturing. Each of these techniques are based on a physical parameter that is known to have influence on formation of defect. These parameters can be defined as quality indicators (QI). QIs play a major role for part quality monitoring. Possible process monitoring signals are optical and acoustic process emissions, optical camera observations, temperature measurements and eddy current measurements of the built in process. Hence, sensor concepts
can monitor different signals like acoustic noise, reflected laser light, or radiation emitted from the melting process (e.g. the melt pool) in order to receive information about possible processes inconsistencies. Efficient quality monitoring therefore relies on the identification of relevant operating parameters and on a continuous process monitoring, i.e. measuring and analyzing those parameters during the process; Schmidt et al. (2017). As there are several processing parameters that have the most significant influence on the final part quality and so can be monitored and correlate to the part quality. For example, it has been known that the energy density is one of the influential factors in defect formation; Mohammad et al. (2017). One of the physical parameters that is directly related to the energy density is the melt pool area. Monitoring of melt pool parameters such as shape, size, or temperature have been successfully practiced for additive manufacturing process monitoring; Clijsters et al. (2014); Craeghs et al. (2012). However the process monitoring can be based on melt-pool monitoring, but further solutions need to be developed in order to assess not only the quality of the manufacturing process, but also the quality of the consolidated material. Several review articles introduced variety of approaches for in-situ monitoring of AM processes which can be referred to for more detailed discussions and literatures on this topic; Reutzel and Nassar (2015); Everton et al. (2016); Chua et al. (2017); Grasso and Colosimo (2017). In the following sections, different monitoring approaches which have been proposed or studied for AM process and part quality monitoring are introduced based on the main physical parameter used for monitoring. Table 2.3 provides a summary for comparison of in-situ monitoring techniques for AM.

<table>
<thead>
<tr>
<th>Monitoring technique</th>
<th>Optical-Based</th>
<th>Thermal-Based</th>
<th>Acoustic-Based</th>
</tr>
</thead>
<tbody>
<tr>
<td>Performance</td>
<td>Converting the received reflected light to the signal or image</td>
<td>Monitoring melt pool/sintering location temperature</td>
<td>Monitoring the acoustic signatures</td>
</tr>
<tr>
<td>Advantages</td>
<td>Contactless detection, Fast observation using high-speed camera</td>
<td>Low cost, Ability to be placed near processing zone</td>
<td>Can include many information Can be used both in contact and noncontact way</td>
</tr>
<tr>
<td>Limitations</td>
<td>Sensitivity to harsh manufacturing environment (smoke and spatter)</td>
<td>Interference with other possible emissions</td>
<td>Complexity</td>
</tr>
<tr>
<td>Applications</td>
<td>Monitoring melt pool behavior, Defect detection</td>
<td>Monitoring melt pool behavior, Cooling rate monitoring</td>
<td>Online thickness measurement, Defect detection</td>
</tr>
</tbody>
</table>

**Thermal-Based Monitoring**

Most of the current monitoring systems for AM are based on thermal detection. Several
approaches have been investigated for thermal-based monitoring of AM processes. 50 $\mu$s temporal resolution was achieved using a two-color pyrometer and a charge-coupled device (CCD) camera, which are coaxially mounted in a LBM set-up; Chivel and Smurov (2010). Using high speed near-infrared complementary metaloxidesemiconductor (CMOS) camera is another approach that has been used for monitoring of melt pool behavior; Craeghs et al. (2011). for determination of the temperature distribution in the powder bed and homogenity analysis of the surface analysis, a successful integration of a thermal imaging system has been performed; Wegner and Witt (2011). Process observation with an IR-camera and evaluation regarding process errors originating from insufficient heat dissipation have been investigated as well as the limits for detecting pores and other irregularities by observation of the temperature distribution; Krauss et al. (2012).

Barriers in thermal-based monitoring (thermal imaging) are due to limited camera’s view angle, camera focusing, and dependency of the reference values on movement direction of the processing zone. In addition, in temperature measurement for AM processes, spatial resolution, tracking large temperature ranges, extreme gradients and fast transient response are the major challenges; Price et al. (2014). Better understanding of fundamental correlation between process parameters, the melt pool temperature, and the part properties is necessary which needs thermal imaging systems with better optical and temporal resolutions.

**Optical-Based Monitoring**

There are several parameters in AM process which can be measured and monitoring using optical measurement techniques and optical sensors. Build height is one of the manufacturing parameters that is strongly influenced by distortion and changes in powder capture efficiency. Optical sensors are most often used for non-intrusive measurements of build height. Hand et al. (2000) developed a chromaticaberration-based technique which takes advantage of variations in intensity of each spectral range with working distance, due to chromatic distortions, to measure and monitor the build height; Hand et al. (2000). Deposition parameters were also measured using other optical techniques and devices such as regular charge-coupled device CCD imaging sensors; Fathi et al. (2007) and high-speed CCD cameras; Song and Mazumder (2011). Furthermore, spectra analysis from optical emissions during a build designed to have
intentional lack-of-fusion defects suggests that optical emissions may contain information that can be related to build defects; Nassar et al. (2014). Optimal lighting and visibility (resolution) are the main concern in IR signatures, and optical images; Holzmond and Li (2017).

**Acoustic-Based Monitoring**

State of the art in acoustic monitoring of manufacturing processes includes both active and passive measurements, using laser-based and sensor-based techniques.

- **Laser Ultrasound**

Laser ultrasound techniques show great promise for in-situ evaluation of material during the manufacturing processes. In laser ultrasound, applying a laser pulse onto a metal surface causes the surface temperature of the metal to raise due to absorption of the optical energy. The resultant thermal expansion, due to changes in temperature, at lower energy densities, or ablation of particles from the surface at higher energy densities generates elastic waves (ultrasound) in the material; Scruby and Drain (1990). The ablative regime is defined by the presence of a strong normal force component caused by the generation of plasma at the surface. At low power levels of the thermoelastic regime, surface damage is avoided, but the normal force component is lost. Each of these regimes, shown in Figure 2.10, provides a distinct source for ultrasonic wave propagation.

![Figure 2.10 Ultrasound generation regimes in a solid medium by a pulsed laser](image)

**Thermoelastic regime**

**Ablation regime**
The main strengths of laser ultrasound methods for in-situ monitoring are their wide bandwidth (typically in the range of 1-70 MHz) and their ability to operate in harsh environments (high temperature, dust and noisy). They however have the challenge of limited efficiency in ultrasound generation and detection sensitivity. This is particularly more challenging in nondestructive evaluation where the level of energy is limited to thermoelastic regime. Different modes of wave can be generated from the thermoelastic interaction of laser with materials. These wave modes can be used for NDE purposes, however, there might be limitations regarding each of the wave modes. In case of Rayleigh wave generation, larger regions are needed for the waves to interrogate and since the early detection of defects will be delayed. Also, the time gap that laser generated ultrasound heat source can be applied to the part and the sintering/melting laser heat source is a limiting factor that needs to be investigated. Laser ultrasound technique for in-situ monitoring of AM process is known to be under evaluation by several research groups at the time of this project; Millon et al. (2017).

- **Acoustic Signatures**

Acoustic/ultrasound techniques based on contact transducers have been used for in-situ monitoring and obtaining signatures for a wide range of chemical and manufacturing processes. Gaja (2016) used acoustic emission sensor for defects monitoring of laser metal depositions. They distinguished two types of acoustic emission signals which are corresponding to two kinds of defects, cracks and porosities; Gaja and Liou (2016).

Considering the successful application of acoustic-based monitoring techniques for other manufacturing processes, these techniques seem to have the potential for in-situ additive manufacturing process monitoring and some new systems and techniques have been developed and few are patented for this purpose; Gold and Spears (2017); Redding et al. (2017). To be able to use these techniques in industrial applications and for precise defect detection and control purposes, the correlation of the acoustic signatures with process and parts quality needs to be further investigated.

The parameters influencing the part quality are manifold and the impact of changing process parameters and their correlation with process defects are not fully understood.
Hence, in the course of the ongoing and upcoming industrialization of AM technologies, process monitoring becomes more and more important and needs to be further developed. On one hand, this is motivated by a desire to deepen the understanding of the process and on the other hand to achieve higher process stability. Each AM material forming processes has characteristics associated with the incident heat source, material feed stock, and material transfer mechanisms which combine to influence physical processes of the molten pool and which determines properties of the final products, including the potential for occurrence of flaws and anomalies in the parts. The so-called material state and allowable manufacturing anomalies for additive manufactured materials are still the subject of investigation. The nature of additive manufacturing provides opportunities to implement new approaches to defect assessment during processing. These new approaches are still under developed. In order to select the appropriate detection and monitoring methods, it is essential to understand the different types of defects, their critical sizes and how and when they evolve during processing. Knowledge of how and when the types of defects appear will increase the potential for early detection of defects in additively manufactured parts, offers the opportunity for in-process intervention and decrease the time and cost of repair or rework.

Additive manufacturing encompasses a wide range of materials, processes and coupled factors that affect the type and properties of defects that can be generated. Porosity, cracking, microstructure and geometrical anomalies are among the most common types of defects encountered that can significantly alter the mechanical properties of the finished parts. Fatigue resistance appears to be the property most sensitive to these types of defects, based on data reported in the literature, although it must be emphasized that the literature tends to be limited to tests that can be conducted on small specimens and in a typical laboratory setting. Thus, other weak-link driven properties (e.g., fracture toughness), slower tests (e.g., creep), or less common tests (e.g., torsional or shear tests) may occur. It has been already found that tensile strength will drop considerably if the volume fraction of porosity increases above \( \sim 1\% \). Surface roughness and crack generation are significantly affected by process parameters such as scanning speed and energy density. Speed of crack growth can have a considerable influence on fatigue resistance. Several nondestructive techniques have been
identified for detection of defects, process monitoring and evaluation of materials in AM parts and are in varying stages of development. Among these methods ultrasonic and radiographic techniques appear the most promising. Non-contact implementations of methods of these NDE techniques do appear to have more potential for use in quantitative in-line monitoring and defect detection. Process monitoring is also the source for the development of future closed-loop feedback control structures. Such process monitoring solutions need to be correlated with Non-Destructive-Testing (NDT) data taken from the final produced part, in order to build up knowhow on how to interpret monitoring data, and to generate intervention and acceptance limits for defect types and sizes, as discussed in; du Plessis et al. (2016); Jacobsmühlen et al. (2013).
CHAPTER 3. ACOUSTIC TECHNIQUE FOR IN-SITU MONITORING

In this chapter, initial concepts and conditions for in-situ monitoring of AM process using acoustic technique are explained, and experimental design and procedure are introduced. A range of sensors are used for process monitoring for additive manufacturing, including in-situ signals such as force, acceleration, temperature, pressure, infrared (IR) signatures, and optical images as well as acoustic signals; Bi et al. (2006); Fallis (2013); Krauss et al. (2015). Acoustic emission has been widely used for condition monitoring and fault diagnosis in manufacturing processes. Compared to other Non-Destructive Testing (NDT) techniques, acoustic and ultrasonic-based methods have the advantage of being able to be deployed to give real-time continuous monitoring of in-service manufacturing processes. Acoustic sensing techniques have been employed for a range of process monitoring tasks and also for monitoring of a variety of processes that involve melting and solidification; Lee et al. (2014); Gu and Duley (1996). Acoustic sensing has the potential to identify defect generation such as keyhole formation; Li (2002), a range of crack propagation phenomena; Wang et al. (2008) and with processes involving rapid phase change; Purtonen et al. (2014). Acoustic (ultrasonic) techniques can be used for process monitoring with different forms of sensors; Rieder et al. (2014), with laser generated and detected ultrasound; Addison et al. (1992); Miller et al. (2002); Taheri et al. (2017c), and monitoring the acoustic emission from cracking events; Farson and Kim (1999); Steen and Weerasinghe (1986).

Analytical model and experimental observations by Farson and Kim showed that acoustic emission signals are correlated with the laser welding parameters; Farson and Kim (1999), while Steen showed that acoustic emission signals are capable of in-process monitoring for laser material processing and can detect some process variables; Steen and Weerasinghe (1986). Considering the successful application of acoustic-based monitoring techniques for
other manufacturing processes, these techniques seem to have the potential for in-situ additive manufacturing process monitoring; Bigelow et al. (2017), and some new systems and techniques have been developed for this purpose; Gold and Spears (2017); Redding et al. (2017); Clavette and Klecka (2015).

For reliable monitoring of the additive manufacturing process, it is important to identify signatures, develop metrics and the transient process-related signals in the presence of high levels of time-varying noise, generated by the AM machine and processing environment. The major challenge is how to differentiate the base signatures and discrete events of interest, such as those due to defect generation / growth or imminent failure, the process moving out of its optimal operating envelope, and from noise due to a diverse array of other sources. This becomes a problem of pattern recognition and classification for what in many cases are near-random signal generation processes. The lack of adequate understanding of the process, in terms of the acoustic signature generation and details for sources of the signals and noise, may result in both un-related and redundant feature identification; Shao et al. (2013). In many cases, traditional signal features such as amplitude, energy, and rise time, which are used in analysis of acoustic emission in Nondestructive Testing (NDT) applications, are insufficient to separate the noise and events of interest, as the noise can be near continuous rather than discrete events and it often has similar temporal and frequency features as the acoustic signals caused by process variations. As a result, new approaches for signal processing, pattern recognition, and classification methods have to be explored.

There are varieties of classification methods which are potentially very appealing for the analysis of complex processes like additive manufacturing; Zanon et al. (2014). These classification methods include k-means clustering, principal component analysis (PCA); Gaja and Liou (2016); Taheri (2017), and wavelet analysis; Guo et al. (2012); Nikravesh et al. (2013) all of which have been demonstrated to be very useful when there are a large number of input variables. Another approach is to use neural networks that are capable of automatically discovering related features and patterns in a larger collection of near random observations; Barga et al. (1990); Sun et al. (1999); Wasmer et al. (2018). In acoustic signals, frequency content as well as temporal data can exhibit significant signatures. There are also
many wave propagation related signal characteristics, such as attenuation, harmonics and modal parameters of vibration, which are best investigated in the frequency domain. The use of frequency spectral features has proven to be particularly useful when there are a variety of different noise generation mechanisms in the system, such as in manufacturing machinery; Hassaan (2014), processing systems including boilers and heat exchangers, and in turbo-machinery fault diagnosis; Al-Hashmi (2012). If defined appropriately, the frequency-related features and signatures of the acoustic signal are very effective in terms of feature extraction and their use for discrimination and classification purposes.

### 3.1 Experimental Setup and Description of The Data

An instrumentation system together with an experimental fixture that supports piezoelectric acoustic sensors was designed to enable attachment to the control stage of a Direct Energy Deposition (DED) system. Figure 3.1 shows the conceptual design of experiment for in-situ monitoring using acoustic sensors. Titanium 6Al-4V powder was deposited on a steel substrate under a variety of conditions. The fixture that was built to support sensors for process monitoring is shown in Figure 3.2. It consists of two optical adapter plates (Figure 3.2 a) separated by four mounting posts to provide enough clearance to attach the acoustic sensors to the system. The adapter plates have a grid of 6.35 mm (¼") holes, which provides the capability to bolt them to the main stage of the DED machine and build plate at a range of desired locations. Also, the mounting plate and posts can be attached to the adapter plates by bolts. The build plate (Figure 3.2 a), which is the substrate for the additively manufactured parts, is a 6.35 mm (¼") thick steel plate, bolted to the upper adapter plate at its four corners. The mounting plate (Figure 3.2 b) is a 101.6 × 101.6 mm (4 × 4") steel plate which is bolted to the upper adapter plate. Eight 12.7 mm (½") diameter steel cylindrical risers separate the sensors from direct contact with the upper adapter plate and the build plate to ensure the transducers remain at a temperature where it is safe for their operation (below 150°C) (Figure 3.2 b).
3.1.1 Experimental Setup, Data Acquisition System and Transducers

Direct deposition method of additive manufacturing system is considered. The system is available at The Quad City Manufacturing Laboratory (QCML). Figure 3.3 shows the available system and the designed experimental fixture setup inside the machine. An eight-channel data acquisition system adapted from a commercial (Digital Wave Corp.) acoustic emission research system was used to continuously monitor and collect data from the acoustic transducers with various system operating conditions, which included baseline (system signature), operation solely with powder spray, and during various settings for deposition processes. Figure 3.4 shows the data acquisition system, amplifiers, and measurement fixture. An external pulser receiver was used for triggering at $\sim 300 \, Hz$, so that trigger levels did not necessarily affect data collected. The setting for recording the data used in this study are shown in Table 3.1.

Figure 3.5 shows the detailed arrangement of the acoustic sensors related to build plate. To keep the acoustic sensors within an acceptable operating temperature range, metallic spacers were designed to act as buffer rods between build plate and acoustic sensors as illustrated in.
3.1.2 Description of the Test Data

The data used in this study was collected when the DED system was operating and performing single layer depositions on a 5 × 5 array on the two build plates (Figure 3.7). The feedstock material was Titanium 6Al-4V powder which was deposited on steel build plates. The arrangement and dimensions of the specimens and the sensor locations are shown in Figure 3.6. Four sensors were used in this study. Three of them were placed on the bottom of the build plate (attached to the mounting plate), as described in Figure 3.7, and connected to the designed fixture. The last sensor was placed on the top of the build plate, as shown in Figure 3.7b.
Table 3.1  The settings of the acoustic data acquisition system

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Parameters’ Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Preamplifier gain</td>
<td>20 dB (inline) + 36 dB</td>
</tr>
<tr>
<td>Signal setting</td>
<td>Filter: 50 kHz ~ 5 MHz; Gain: 36 dB</td>
</tr>
<tr>
<td>Trigger setting</td>
<td>Filter: 50 kHz ~ 5 MHz; Gain: 12 dB</td>
</tr>
<tr>
<td>Trigger level</td>
<td>0.1 v</td>
</tr>
<tr>
<td>Sampling rate</td>
<td>5 MHz</td>
</tr>
<tr>
<td>Record length</td>
<td>800 µs (117 µs pre – trigger)</td>
</tr>
</tbody>
</table>

Figure 3.7. Each zone of material deposited was 12.7 mm (0.5”) in length and consisted of 4 parallel passes. Deposition was performed with the machine operating in five different states. The acoustic signals that were generated were recorded for these five different cases, including three different machine states. Figure 3.8 shows a typical acoustic signal recorded during the depositions. In addition to the deposition states, the other states included control under which there was just powder spray and a baseline during where there were no active deposition activities. Table 3.2 shows the different conditions under which depositions were performed and acoustic signals were recorded, as well as the abbreviations used to identify the corresponding data in the analysis.
Figure 3.5  Detailed Arrangement of the Acoustic Sensors Related to Build Plate

Figure 3.6  Thermal Separator (spacer rods) Between Build Plate and Acoustic Sensors

Figure 3.7  Thermal Separator (spacer rods) Between Build Plate and Acoustic Sensors
Table 3.2  The settings of the acoustic data acquisition system

<table>
<thead>
<tr>
<th>Conditions name</th>
<th>Conditions description</th>
<th>Conditions abbreviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>Machine at inactive status</td>
<td>BL</td>
</tr>
<tr>
<td>Control</td>
<td>Powder spray situation solely</td>
<td>CO</td>
</tr>
<tr>
<td>Condition 1</td>
<td>Optimum (Normal) process</td>
<td>C1</td>
</tr>
<tr>
<td>Condition 2</td>
<td>Low laser power</td>
<td>C2</td>
</tr>
<tr>
<td>Condition 3</td>
<td>Low powder feed</td>
<td>C3</td>
</tr>
</tbody>
</table>

Figure 3.8  Typical acoustic signal recorded during the depositions
CHAPTER 4. SIGNAL PROCESSING AND CLASSIFICATION
FRAMEWORK FOR ACOUSTIC SIGNATURES

The type of information extracted from the acoustic signatures depends on the signal processing technique used for data analysis. Former studies used traditional acoustic features such as velocity of wave propagation and reflection signals from defects for evaluation of the process; Addison et al. (1992); Rieder et al. (2014). In this study, feature-based signal processing techniques is used for analyzing the acoustic signals. Data analysis has been done in temporal as well as spectral domains. In each domain, related signal metrics have been extracted and analyzed. This section considers passive acoustic (ultrasonic) monitoring of an additive manufacturing process and use of the algorithms, which have been shown to be efficient for clustering and separation of events based on multiple spectral and temporal features extracted from the original test data. The signatures and metrics given by the in-situ monitoring technique and data acquisition have been shown to correlate with a variety of process conditions.

For acoustic signals, in addition to evaluate the data for basic parameters, statistical signal processing techniques was used. Statistical signal processing techniques were used for clustering the signals from acoustic monitoring of AM process; Gaja and Liou (2016). The new contribution of using statistical signal processing technique is to classify the different states of the manufacturing process based on temporal and spectral features as described in related sub-sections in this chapter.
4.1 Temporal Domain Signal Processing and Data Analysis

A process for the data recording was developed that used commercially available acoustic emission equipment (Digital Wave). Intermittent sampling was performed to reduce data set size due to hardware limitations when compared to continuous collection and to sample process noise in addition to capturing event data, in contrast to classical event based triggering used with acoustic emission. Data collection consisted of an A/D card (8 bit) connected to a personal computer digitizing at 5 MHz sampling frequency. All transducers were connected with shielded coaxial cable through a 20 dB in-line amplifiers coupled to the A/D card through a Digital Wave FM-1 signal conditioning unit. In addition to inline amplification, an additional analog gain of 36 dB was applied through the FM-1 signal conditioning unit, with hardware band-pass filtering of 150 - 5,000 kHz. The system sampled process noise intermittently by utilizing an FM-1 channel specifically for triggering connected to a commercial NDT pulser/receiver (Panametrics Type 5052). The pulse repetition rate was adjusted to approximately 300 Hz, with an acquisition duration of approximately 820 milliseconds (4096 points at 5 MHz), which effectively reducing data-file size by 75% when compared to continuous monitoring and thus enabled data sampling throughout a longer total build period. A block diagram showing the measurement system is given in Figure 4.1.

![Figure 4.1 Block diagram for data collection using an external trigger at 300 Hz to sample noise intermittently, rather than HAE triggered data in conventional AE.](image)

4.1.1 Temporal Signal Processing

Data was collected for two different builds, using nominally identical process conditions for sequences of variations in parameters and powder. Between the builds, the process consisted
of a complete removal of the fixture from the DED machine. A new build plate and upper transducer, were installed followed by a replicate build with randomized locations of the same build condition variants as occurred in the first build. The data recorded for the two builds were generally similar, but those presented here are taken from the second build which included more frequent Baselines taken to evaluate drift, and the process did not contain any identified build errors. Differences and anomalies seen between the two builds will be discussed briefly for completeness at the end of this article. The signal processing used consisted of digital signal conditioning in addition to the hardware based filtering described previously. All gains applied to signals during collection by inline amplifiers and the signal conditioning unit were removed digitally prior to filtering. The data was band-pass filtered across the approximate bandwidth of the transducer (50 - 2,000 kHz) using a Kaiser-order filter design. The lower limit of the band-pass was increased slightly from the stated lower bandwidth of the transducers (50 kHz) due to hardware based band-pass filtering applied during testing (150 kHz - 5,000 kHz) while the upper limit corresponded to the upper bandwidth limit of the transducers (2,000 kHz, below the Nyquist frequency). The data was filtered with an impulse response convolution filter in the time domain. The induced phase delay was removed and temporal characteristics were then extracted from the filtered signals. Some Baseline drift was observed over the course of the builds and was removed by spectral subtraction, which is a common noise reduction technique employed in audio (vocal) signal processing. Intermittent Baseline testing was used as the noise sample to establish the average spectral data to be removed from the build acoustic data; Boll (1979). Waveforms were collected beginning immediately with the start of each build, throughout the entirety of the build, and for a short time after build completion. The analysis was restricted to the first 2000 waveforms collected which corresponded to waveforms sampled during deposition only for all data files collected. Temporal signal characteristics considered included simple measures such as the root-mean-squared noise (RMS), standard deviation of the rectified signal (STD), average amplitude of the rectified signal (MEAN), and maximum voltage of the rectified signal (MAX). High amplitude events (HAE) were identified as those waveforms having a peak voltage exceeding two standard deviations from the median of the data collected during the builds. These HAEs, referred to as Hits were then characterized
using conventional acoustic emissions metrics, including the amplitude, energy and average frequency; Grosse and Ohtsu (2008). These metrics will be described in more detail as they are introduced.

4.1.2 Temporal Signatures Results and Discussion

An exemplary HAE from one transducer is depicted in Figure 4.2, showing the temporal run sequence (voltage over time), lag-plot, histogram, and comparison to a normal distribution through a normal probability plot. An increased number of counts around small voltage values were observed and attributed to low amplitude process noise which can be easily seen in the distribution and run sequence plots (before the HAE). The lag plot is random, indicating no repeating trends in the data. The normal probability plot shows that high amplitude events skew the data from a normal distribution towards longer tails, with a flatter, higher sloped region at low amplitude from voltages collected before the event. The data appears to be a summation of two approximately normal distributions, presumably one for process noise and the other for an event. Also shown (Figure 4.2) is the RMS values calculated after signal processing for 4000 waveforms collected intermittently throughout the build and during a short time after build completion. These data show indications of low amplitude process noise with HAEs interspersed throughout the build. A similar example is shown in Figure 4.3 for a low amplitude, process noise waveform. The four-plot (Figure 4.3 a-d) exhibits a weak correlation in the lag plot (slight oval shape), and an approximately normal distribution with slightly elongated tails in the normal probability plot. Also shown (Figure 4.3 e) are the RMS values calculated after signal processing with HAEs removed for data collected intermittently throughout the build and for a short time after build completion. These data show the change in low amplitude RMS values more clearly.
Figure 4.2  Four-plot showing the (a) Run sequence (voltage over time), (b) Lag-plot showing no correlation, (c) voltage distribution, and (d) Normal probability plot showing deviations from a normal distribution for the complete event signal. The (e) evolution of the RMS noise level is also shown, showing HAEs as spikes in RMS values and an abrupt drop at the time of build completion (both for Normal condition).
Figure 4.3  Four-plot showing the (a) Run sequence (voltage over time), (b) Lag-plot showing a weak positive (oval) correlation, (c) voltage distribution, and (d) Normal probability plot showing an approximately normally distributed process noise signal with slightly elongated tails. The evolution of the RMS noise level is also shown, showing an abrupt drop at the time of build completion with high amplitude events removed (both for Normal condition).
4.1.3 Trends in Temporal Signatures with Build Condition

Slight variations in the Baseline amplitude are attributed to electronic drift due to environmental temperature variations of the equipment and sensors. These trends were monitored by recording Baselines as previously described. This effect can be observed in data given in Figure 4.4 for the time domain metrics calculated for each waveform grouped by condition (with the exception of Baselines taken before, between and after all build conditions). For clarity, the means of the data for each build are indicated with a marker unique to the build condition. The data are shown in the order of collection (from left to right) to examine results for any potential effects of electronic or other drift with time on time domain metrics calculated for the varying build conditions. It can be seen that some Baseline drift does occur (data marked x) even after attempted removal, but significant RMS noise elevations away from this Baseline are observed for all build conditions including the Powder Only (data marked o) condition. This suggests that powder impacts and potentially motion stage noise from bearings or motors produced significant acoustic energy and signals in the bandwidth of the transducers used. The same time domain metrics, but calculated with HAEs removed to examine distributions of process noise are shown in Figure 4.5. The effect of removing HAEs on central tendencies can be observed with the skew of the process noise data to higher amplitudes, particularly for build states that entailed material deposition.

A restriction of the analysis to HAEs shows a similar trend seen in time domain statistical measures of the total dataset. The various traditional acoustic emission HAE metrics including hits (defined here as both an outlier described previously, and with sufficient temporal amplitude to trigger a classical acoustic emissions system), amplitude (maximum amplitude of the hit), energy (area under the rectified waveform) and RA value (a measure used to classify AE events defined as the ratio of the time to peak amplitude during an event divided by the amplitude); Grosse and Ohtsu (2008) are shown in Figure 4.6.
Figure 4.4  Time domain metrics of signals including HAE and noise for 5 build conditions plotted in the order in which they were collected for all waveforms (from left to right) for transducer 4: average rectified time domain voltage (mean), root-mean-square voltage level (rms), standard deviation of the rectified time domain voltage (std), and maximum voltage (max). Top includes 2000 waveforms taken during the build and analyzed while the bottom depicts the same data with outliers (HAEs) removed as described in the text. Mean values are indicated by symbols unique to each build condition.
Figure 4.5  Time domain metrics of signals with HAE removed for 5 build conditions plotted in the order in which they were collected for all waveforms (from left to right) for transducer 4: average rectified time domain voltage (mean), root-mean-square voltage level (rms), standard deviation of the rectified time domain voltage (std), and maximum voltage (max). Top includes 2000 waveforms taken during the build and analyzed while the bottom depicts the same data with outliers (HAEs) removed as described in the text. Mean values are indicated by symbols unique to each build condition.
Figure 4.6 Classical acoustic emissions metrics for HAE’s for various build conditions (from left to right): hits (temporal amplitude greater than two standard deviations from the rectified mean), amplitude of the rectified signal, energy, and RA Value.

### 4.2 Spectral Domain Signal Processing and Data Analysis

Traditional spectral features such as amplitude and frequency have been previously used for classification of acoustic signals; Kozhisseri and Bikdash (2009); Ludeña-Choez and Gallardo-Antolín (2016), and pulsed eddy current signals; Pan et al. (2013). The method used for data analysis is based on feature extraction from the frequency response of the acoustic signature signals. The analysis has been done in two parts. First, spectral features have been defined and extracted form the frequency response of the signals. These features have been tested for their efficiency in classifying different process conditions. It has been shown that defined spectral metrics are capable in classifying different process conditions. Next, quantitative statistical signal processing method has been used to quantitatively analyze the separation of process clusters at different conditions.
4.2.1 Clustering of Acoustic Signals Based on Spectral Features

This section describes the steps that are implemented for successfully extracting the acoustic spectral features from the event signals in the recorded data set. In order to improve the signal-to-noise ratio, signals were filtered to match the bandwidth of the transducers ($150 \text{kHz} \sim 2 \text{MHz}$) using a Kaiser band-pass filter; Kaiser (1974). A Fourier Transform was applied to the signals (2000 waveforms) to obtain the spectra of the waveforms for each operation/build condition.

Homomorphic deconvolution filtering was applied to the frequency spectrum to reduce the noise and smooth the spectrum. In the application of the homomorphic deconvolution technique, each of the time domain waveforms was converted to the frequency domain and then filtered to reduce the impact of noise; Proakis and Manolakis (1996). The approach implemented was to use the mathematical concept of homomorphic mapping to separate two signals (the event signal and the underlying noise signal) by linear filtering, and to retrieve the original signal by inverse mapping; Taxt (1995). A detailed description of homomorphic filtering theory is given by Oppenheim and Schafer; Oppenheim and Schafer (1989). A typical section of RF data record and a typical spectrum are shown in Figure 4.7, which indicates that there are two main frequency bands where the majority of energy occurs.
Based on this observation, the range of frequencies observed was divided into a low frequency band ($< 800 \text{ kHz}$) and a high frequency band ($> 800 \text{ kHz}$), and the dominant features in each band were investigated. The next step was to define the features in the frequency domain. These features are listed in Table 4.1 and are discussed here:

- Feature 1 is the peak (maximum) amplitude of the data from the Fourier Transform and is identified by PA abbreviation in the study and graphs.

- Feature 2 is the difference in peak amplitudes of the spectral data from the Fourier Transform for each process condition compared to peak amplitude of the data from the Fourier Transform of the baseline and is identified by PAD.

- Feature 3 is the frequency at which the peak amplitude of the spectrum is located and is identified by Pf.
- Features 4 and 5 are the centroid amplitude and centroid frequency of the data from the Fourier Transform (Figure 4.7), which are identified as CA and Cf respectively.

Table 4.1 Spectral features type and abbreviation

<table>
<thead>
<tr>
<th>Spectral Feature Number</th>
<th>Feature Type</th>
<th>Features abbreviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Feature 1</td>
<td>peak amplitudes of the spectral data from the Fourier Transform</td>
<td>PA</td>
</tr>
<tr>
<td>Feature 2</td>
<td>Difference in peak amplitudes of the spectral data from Fourier Transform for each condition compared to the one for baseline condition</td>
<td>PAD</td>
</tr>
<tr>
<td>Feature 3</td>
<td>Peak frequency of the spectral data from of Fourier Transform</td>
<td>Pf</td>
</tr>
<tr>
<td>Feature 4</td>
<td>Centroid amplitude of the spectral data from Fourier Transform</td>
<td>CA</td>
</tr>
<tr>
<td>Feature 5</td>
<td>Centroid frequency of the spectral data from Fourier Transform</td>
<td>Cf</td>
</tr>
</tbody>
</table>

Finally, extracted spectral features have been investigated and used in pairs and triples to represent the classification of process conditions. A flowchart for the steps outlined and used in this algorithm is given in Figure 4.8. The performance of the algorithm has been investigated with its implementation on two sets of experimental data (two different builds). Each has twenty-four single layer depositions that were performed under five different conditions, with data obtained using four sensors. The average values for all spectral features for all depositions in the low and high frequency bands are presented in Figure 4.9.
Figure 4.8  Flowchart for the feature extraction algorithm applied to the frequency response
Figure 4.9 The average values for all spectral features for all depositions in (a) low frequency band, and (b) high frequency band.

Using Spectral Features to Examine Clustering and Classification for the Build Cases
Clustering analysis is based on plotting the identified features in pairs and triples (2D and 3D plots respectively) to study the separation of variables and classification of process conditions for different build settings. In this method, each feature defines one axis of the plot and related data are presented as the scattered data points, when successful clusters of data are obtained which correlate to different process conditions. The results obtained and a discussion of the classification technique is given in the next section.

**Process Classification Using the Proposed Features**

The spectral features defined and listed in Table 4.1 are used for process classification. The reliability of the data given by the sensors used for monitoring during the process is studied by classification analysis using the peak amplitude of the spectrum given by the Fourier Transform (PA) and centroid amplitude of the spectrum given by the Fourier Transform (CA) features. This process is applied to data from all four sensors, and considered in the high and low frequency bands. Since data for each of the process conditions (BL, CO, C1, C2, and C3) was sampled multiple times, the reliability in data monitoring for process conditions was investigated in the next step, to evaluate the consistency of the monitoring technique at all locations and conditions during the deposition process. After testing the reliability and consistency of the process monitoring and data recording techniques, pre-defined frequency spectral features in Table 3 were used for classification of different process conditions. Statistical analysis of the cluster data such as those presented in Figure 8, shows that more than 72% of the data for the spectral features are within the $\pm 10\%$ deviation range of the data cluster centroid. The maximum deviation from the cluster centroid is approximately 34%, which occurs for the PAD feature. This shows the lower classifying efficiency of this feature compared to other spectral features. Considering these ranges of the data for different features and build conditions, the clustering analysis for both build plates, different process conditions, and measurements by different sensors showed similar classification results.

- **Reliability of Data Monitoring with Sensors**

Prior to classification of the process conditions, the performance of all four sensors in terms of data monitoring was examined for the different process conditions. Baseline and control
(powder feed only) process conditions in the low (Figure 4.10) and high frequency (Figure 4.11) bands have been chosen to demonstrate the reliable evaluation of the sensor data. These graphs show the peak amplitude of the spectrum of the data from the Fourier Transform (PA) and centroid amplitude of the spectrum of the data from the Fourier Transform (CA) features. The graphs indicate that if setup appropriately, the data obtained by the sensors can be used for classification of the various conditions.

Figure 4.10  Classification of Baseline and C0: Powder feed only process conditions for consistency evaluation of sensors in low frequency band using peak amplitude of the spectral data from the Fourier Transform (PA) and centroid amplitude the spectral data from the of Fourier Transform (CA) features.
Figure 4.11 Classification of Baseline and C0: Powder feed only process conditions for consistency evaluation of sensors in high frequency band using peak amplitude of the spectral data from the Fourier Transform (PA) and centroid amplitude the spectral data from the of Fourier Transform (CA) features.

- **Consistency in Data Monitoring for Process Conditions**

Each set of process conditions (Table 3.2) was repeated randomly over the grid for each build. To evaluate the consistency of the data monitoring and classification method for different process conditions, spectral features for each process condition have been evaluated at all build locations over the grid. Centroid frequency of the spectrum from the Fourier Transform (Cf) and centroid amplitude of the spectrum from the Fourier Transform (CA) features for all baseline conditions have been presented in Figure 4.12 and Figure 4.13 for low frequency and high frequency bands to exemplify the results of the evaluation of the condition monitoring repeatability. Clustering data analysis show that there is consistency seen in the metrics obtained from the processed acoustic data monitoring between different locations and conditions.
Figure 4.12  Classification of Baseline process condition for consistency evaluation of data monitoring in low frequency band, using centroid frequency of the spectral data obtained using the Fourier Transform (Cf) and centroid amplitude of the spectrum obtained using the Fourier Transform (CA) features.
Figure 4.13 Classification of Baseline process condition for consistency evaluation of data monitoring in high frequency band, using centroid frequency of the spectral data obtained using the Fourier Transform (Cf) and centroid amplitude of the spectrum obtained using the Fourier Transform (CA) features

- **Consistency in Different Builds**

Consistency of the in-situ monitoring technique is evaluated for different build plates used in this study. As mentioned earlier, the experiment was repeated on two different build plates, each having a $5 \times 5$ grid of depositions. The classification results show that there is consistency seen in the metrics obtained from the processed acoustic data monitoring between different builds. Data recorded by sensor 2 for baseline (BL) and optimum process (C1) conditions for randomly selected depositions is presented in Figure 4.14.
Figure 4.14  Classification of Baseline and C1: Optimum (Normal) process conditions for consistency evaluation of builds in (a) low frequency and (b) high frequency bands using centroid frequency of the spectral data (Cf) and centroid amplitude of the spectral data (CA) obtained from the Fourier Transform

- **Classification of Process Conditions Using Spectral Features**

The different process conditions (Table 3.2) were classified using the spectral features (Table 4.1). The performance of spectral features varies in terms of clustering effectiveness for the metrics determined from the acoustic signature data. Results of the process conditions classification using centroid frequency (Cf) and centroid amplitude (CA) of spectral data obtained using the Fourier Transform, for the low and high frequency bands, and for all sensors are shown in Figure 4.15 and Figure 4.16 respectively. The classification results show that clustering of different process conditions can be performed using metrics obtained from processed acoustic data. The efficiency of data clustering for acoustic signatures can vary due to location of the sensors in the system and the effect of electronic noise. Clustering results obtained from sensor 2, using peak amplitude (PA) and centroid amplitude (CA) of the spectral data obtained using the Fourier Transform are shown in Figure 4.17 for the low and high frequency bands. Distinct separation of clusters are shown to correlate with the data from different process conditions. Combination of acoustic signatures in the frequency domain can provide closer and more effective data clustering for different process conditions. Groups
of triple spectral features (Cf, Pf and CA (Table 3)) were used in 3D scatter plots to achieve better clustering representations for the metrics of data in the low and high frequency bands (Figure 4.18).

Figure 4.15 Process conditions classification using centroid frequency (Cf) and centroid amplitude (CA) of spectral data obtained using the Fourier Transform, at low frequency band, for metrics obtained for data from all sensors.
Figure 4.16 Process conditions classification using centroid frequency (Cf) and centroid amplitude (CA) of spectral data obtained using the Fourier Transform, at high frequency band, for metrics obtained for data from all sensors.

Figure 4.17 Clustering results for data from a single sensor (Sensor 2) using peak amplitude (PA) and centroid amplitude (CA) of spectral data obtained using the Fourier Transform in (a) low frequency and (b) high frequency bands
Figure 4.18 Classification of process conditions using three frequency domain features; peak frequency of the Fourier Transform (Pf), centroid frequency (Cf) and centroid amplitude (CA) of spectral data obtained using the Fourier Transform for a single sensor (Sensor 2) at (a) low frequency and (b) high frequency bands

4.2.2 Clustering Performance Evaluation Using K-means Algorithm

Clustering can be considered as one of the most important parts of the data analysis for process monitoring. A cluster is a collection of observations which are similar between each other and are dissimilar to the observations belonging to the other clusters; Jung et al. (2014). In previous section, it has been shown that the defined spectral features in Table 4.1 can be used for clustering of different process conditions during the AM process. The efficiency and effectiveness of the clustering need to be quantified. Ideally, clusters should be cohesive structures that are isolated from each other. To evaluate this criterion, for a particular application, the concepts of clustering homogeneity (cohesion) and separation (isolation) need to be tested; Landau and Chis Ster (2010). This measurement can be quantified based on the Euclidean distance between the clusters silhouette mean values using K-means as a method of interpretation and validation of consistency within the clusters of data. The silhouette value is a measure of how similar an object is to its own cluster (cohesion) compared to other clusters (separation).
**K-Means Clustering Algorithm Overview**

A K-mean clustering algorithm is typically used to determine how to measure similarity distances. Considering K number of clusters and a database containing n observations, this algorithm calculates a set of k-clusters that minimize the squared error criterion. The steps used to implement the K-mean clustering algorithm are given in Figure 4.19.

![K-mean clustering algorithm](image)

Figure 4.19 K-mean clustering algorithm

To achieve the full power of data analysis methods, a well-formulated objective needs to be applied to the empirical data coming from observations or experiments; Barga et al. (1990). For data analysis and classification, appropriate metrics must be defined and calculated. In this investigation, the spectral features of the acoustic signals (waveforms) were selected as the data metrics as explained earlier (Table 4.1). These metrics can then be used for clustering of the data. A graphical representation of two clusters (process conditions) is shown in Figure 4.20. Graphical representation of the clusters such as what is shown in Figure 4.20, as well as other conceptual descriptions are presented for one data set and two metrics, for simplicity of graphical representation and imagination. The same concept and algorithm are used for all metrics and all data sets where the graphical representations are
not easy enough or possible to show. Because of this, and to investigate the efficiency of the algorithm, the results are evaluated and presented quantitatively.

Figure 4.20 An example of application of the Cf and CA acoustic spectral features for data clustering

After calculating the spectral features metrics (Table 4.1), the silhouette mean value is calculated for each set of data, which is then used for assessment of clusters isolation. Then, the Euclidean distances of each data point from all silhouette mean values of different clusters are calculated. These Euclidean distances are used for calculating the cohesion and isolation of the data points in the datasets. Finally, the silhouette mean value of all datasets were used to calculate the cohesion and isolation of the clusters in terms of cluster efficiency. These efficiencies show that compared to a training dataset (BL or C1 in this investigation), what percentage of the observations are correctly assigned to the right cluster (have shorter distance to the silhouette mean value of the appropriate cluster than other clusters). The various different steps of this algorithm are shown in a flowchart, Figure 4.21, for the algorithm as explained above. An example of the silhouette mean values of the clusters and the Euclidean
distance of a data point from all silhouette mean values are shown in Figure 4.22.

Figure 4.21 Flowchart for the steps of algorithm for evaluation of the clustering method

Figure 4.22 A schematic and example of silhouette mean values of the clusters and the Euclidean distance of a data point from all silhouette mean values
**Evaluation of Cohesion and Isolation of Clusters Using K-Means Clustering Algorithm**

Visualization of the clusters for different process conditions can be presented using two or three different features (spectral metrics identified in Table 4.1). Using two different features, process classification can be represented by 2D graphs such as that shown in Figure 4.23, which is with data for one series of experiments. An example of the representation of process classification in the high frequency band using three spectral features is given as Figure 4.24 for all data points and mean values, as well as only showing mean values in Figure 4.25. The silhouette means values (centroid) of the clusters are also shown both with the all data points, and separately for each process condition.

![Figure 4.23 An example of 2D graphical representation of AM process condition classification using three spectral features (Cf and CA) of acoustic signals; (a) representing all data points and the silhouette means, (b) silhouette means of each cluster](image)

Figure 4.23 An example of 2D graphical representation of AM process condition classification using three spectral features (Cf and CA) of acoustic signals; (a) representing all data points and the silhouette means, (b) silhouette means of each cluster
Figure 4.24 An example of 3D graphical representation of AM process condition classification using three spectral features (Cf, CA, and PA) of acoustic signals representing all data points and the silhouette means.
Figure 4.25  An example of 3D graphical representation of AM process condition classification using three spectral features (Cf, CA, and PA) of acoustic signals showing silhouette means of each cluster

Graphical representation of the clusters is a useful technique for qualitatively evaluating the classification of different process conditions. However, this presentation depends on the features (metrics) selected and the angle of view, as well as the quantitative investigation of the cohesion and isolation of the clusters, which is necessary for the practical application of acoustic-based in-situ monitoring for AM. The acoustic signature dataset of two build plates, all replications for each process condition (total replications for each process condition: BL=7, C1=C2=C3=CO=10), four acoustic sensors, two frequency bands, and five spectral features were processed for quantitative classification of AM process conditions. The efficiency of the proposed classification approach in correctly classifying the acoustic signature waveforms into different conditions comparing to the baseline condition (BL) is shown in Figure 4.26. Uncertainties in terms of standard deviations are presented using error bars.
Figure 4.26 Efficiency of clustering compared to the baseline condition (BL) in (a) low (LF), and (b) high (HF) frequency bands

It is observed that all process conditions can be effectively classified into the appropriate clusters. The efficiency of clustering is more than 90% in the LF band and greater than 87% in the HF band for C1, C3, and CO process conditions. The lowest classification accuracy happens in the C2 process condition, which the efficiency drops to 85% in the LF band and 70% in the HF band. This analysis and the results presented in Fig. 10 show that the acoustic signature from the machine (background noise) can be distinguished by the clustering technique from the other operational process conditions (C1, C2, C3, and CO).

Fig. 11 shows the results for classifying the acoustic signature waveforms into different conditions while comparing to the normal process condition (C1). Uncertainties are presented by error bars. When compared to the normal process condition (C1), the overall efficiency is higher in the HF band than the LF band (85% in HF compare to 78% in LF). The lowest clustering efficiency is still in the C2 (low power laser) process condition in the HF band, but the lowest clustering efficiency belongs to the CO process condition in the LF band while the efficiency in the C2 process condition clustering increased to 88%. Overall clustering efficiency is lower in the LF band than the HF in this condition. Clustering analysis with comparison to the normal process condition (C1) indicated that different abnormal process conditions can be
differentiated from the normal runs. This capability has the potential to be used for process monitoring and control during the build.

A proof of concept study has investigated new approaches to process monitoring for additive manufacturing. Various alternatives for signal processing, pattern recognition, and classification methods were applied to acoustic signals generated by additive manufacturing. It has been shown that acoustic signal characteristics can be used to classify process and system conditions. A novel application of signal processing tools is used for the identification and use of metrics based on frequency spectrum features in acoustic signature signals for the purpose of in-situ monitoring and characterization of conditions in an additive manufacturing process. The acoustic signals were collected during the Direct Energy Deposition (DED) additive manufacturing process with different process conditions to investigate and determine if variations in process conditions can be discriminated. A spectral feature based clustering method was implemented to analyze the acoustic signals. Clustering plots for metrics in 2 and 3-D were used to facilitate the visualization of the groupings and condition discrimination. It is demonstrated that a passive acoustic monitoring approach and use of signal processing algorithm is effective at giving metrics that achieve clustering and

Figure 4.27  Efficiency of clustering compared to the normal condition (C1) in (a) low (LF), and (b) high (HF) frequency bands
separation of conditions based on multiple spectral features extracted from the original test data, and that these metrics correlate with different AM system conditions. Classification of different DED additive manufacturing process conditions exhibit successful clustering of large data sets. Evaluation of the identified features confirmed the consistency in process monitoring and data collection by all sensors, different locations on the build plate, and various process conditions. Results show that this novel approach using acoustic signal analysis can provide metrics based on acoustic signals (signatures) generated by the AM process, and classification of the signatures can be correlated with different process conditions. Monitoring of the manufacturing process using acoustic signatures would appear to have the potential to give data which can help enable early detection of off-normal conditions, generation of faults in the process, and can be used for process optimization and control. It is demonstrated that with more than 87% confidence the process conditions can be classified compared to the base line condition (BL) in low frequency (LF) and high frequency (HF) bands for normal (C1), low powder (C3), and powder spray (CO) process conditions. The lowest classification accuracy occurs in the low power (C2) process condition, where the efficiency drops to 85% in the low frequency (LF) band and 70% in the high frequency (HF) band. This analysis shows that the acoustic signature from the machine (background noise) can be efficiently distinguished and quantified by clustering techniques from the other operational process conditions (C1, C2, C3, and CO). Clustering analysis with comparison to the normal process condition (C1) indicated that different abnormal process conditions can be differentiated from a normal nominal build. This capability has the potential to be used for process monitoring and control during the AM process.
CHAPTER 5. LASER ULTRASONIC TECHNIQUE

The need for noncontact in-situ in process nondestructive evaluation of additively manufactured (AM) parts makes laser-based ultrasound a potential method for performing measurements needed in quality control for complex manufacturing processes. However, the physics and mechanism of ultrasonic wave generation by laser is a complicated process which is affected by optical, thermo-elastic and other material properties. To be able to have an appropriate experimental system and efficient signal processing, it is necessary to understand the laser-generated signal and wave propagation characteristics. Also, in order to identify the defects and determine material properties of AM materials by laser-based ultrasound, the generated ultrasonic signal must be well understood. The process needs to consider the thermal transients caused by rapid heating and cooling of the printed parts.

Laser-generated ultrasound has a history of successful applications in nondestructive testing for defect detection and characterization of materials; Scruby and Drain (1990). The fundamentals are well established for many applications requiring non-contact generation and detection of elastic waves and commercial equipment is now available. Laser systems are particularly well suited to meeting the requirements for inspection in harsh manufacturing environments, such as those found in additive manufacturing; Everton et al. (2015). In additive manufacturing to both understand the process and to better characterize materials as they form, precise measurement of ultrasound wave parameters such as speed of sound are necessary to study the material properties and potentially enable real-time assessment of the quality of the part as it forms; Koester et al. (2016).
5.1 Laser-Ultrasound Generation Mechanism

Laser ultrasonics is the technique of generation and detection of ultrasound waves in materials using laser light; Krishnaswamy (2003). This technique uses laser irradiation to induce ultrasound in either ablation regime or thermo-elastic regime. Optical (laser) detectors are also typically used to measure the ultrasonic waves. For this reason, laser ultrasound provides a non-contact method of ultrasonic inspection of materials. Laser ultrasonic is primarily generated by two main mechanisms, thermoelastic expansion and material ablation; Scruby and Drain (1990). Applying a laser pulse onto a metal surface causes the surface temperature of the metal to raise due to absorption of the optical energy. The resultant thermal expansion, due to changes in temperature, at lower energy densities, or ablation of particles from the surface at higher energy densities generates elastic waves (ultrasound) in the material. Laser ultrasonic (LU) is primarily generated by these two main mechanisms, called thermoelastic expansion and material ablation respectively. Figure 5.1 shows these two generation mechanisms. When the generation mechanism is thermoelastic, the method is considered as nondestructive. However, the ablation mechanism cannot be considered solely nondestructive, since it is characterized by material removal. This material removal can cause some pitting and inhomogeneity on the surface or the top layer of the material, and particularly in additive manufacturing has some potential for causing small defect generation in the deposited layer by increasing the possibility of entrapped gas (porosity), entrapped/un-melted powder (lack of fusion (LOF)) and by influencing of Marangoni effect in melt pool.

The characteristics of the laser-generated ultrasonic waves strongly depend on the optical parameters, thermal diffusion, elastic and geometrical properties of the materials, as well as parameters of the exciting laser pulse including the spot size, pulse duration and pulse energy; Telschow and Conant (1990). To understand the characteristics of the laser generated ultrasound waveforms, their propagation, and resulting wave field seen at probing points, it is necessary to study the complex thermoelastic process of ultrasound wave generation using pulsed lasers and for the case of additive manufacturing, the effects of locally varying material
Theoretical Background

The problem of laser based generation of ultrasound has been studied theoretically and experimentally since early 1980s. The problem of the propagation of vibrations over the surface of a semi-infinite isotropic elastic solid due to an arbitrary application of force at a point was initially studied by Lamb; Lamb (1904). Miller and Pursey; Miller and Pursey (1954), Hutchins et al.; Hutchins et al. (1981), and Scruby et al.; Scruby et al. (1982) described a laser point source by two orthogonal dipoles to obtain the directivity patterns for longitudinal and shear waves, while Rose; Rose (1984); confirmed those results using the classical thermoelastic theory. All of these studies are found to give a good agreement between the theoretical results and experimental observations based on their assumptions and simplifications for the theoretical analysis.

As a noncontact and prosperous source of elastic wave generation and a promising method for in-situ monitoring and nondestructive evaluation (NDE) of additive manufacturing (AM) materials, it is necessary to understand the features of laser-generated ultrasound such as the modes of generated waves and the directivity pattern. Solving thermal diffusion and thermal
displacement equations simultaneously, analytical expressions for ultrasound displacement can be obtained. From displacement expressions, waves directivity patterns are attained. Directivity pattern represents the sound vector condensed to the principal plane which consist of point of laser irradiation and is normal to the specimen surface. Directivity pattern of the generated ultrasound depends on many different physical and material parameters and can vary significantly in different generation mechanism or by physics and material parameters.

### 5.2.1 Ablation Regime

Laser ablation is defined as the removal of matter from metal surface which is irradiated by a laser pulse. The 1-D heat equation for propagation of heat flow into the irradiated sample is presented with Equation 5.1; Stafe et al. (2006).

\[
\rho c_p \left( \frac{\partial T}{\partial t} - \nu_\alpha \frac{\partial T}{\partial z} \right) - k_t \frac{\partial^2 T}{\partial z^2} = Q(z,t) \quad (5.1)
\]

where \( \rho \) is the material density, \( c_p \) is the specific heat at constant pressure, \( \nu_\alpha \) is the recession velocity of the irradiated surface due to ablation, \( k_t \) is the thermal conductivity, and \( Q(z,t) \) is the laser energy absorbed into the sample, per unit volume and time, that is converted into heat. A depth of \( h_m \) of samples metallic layer will melt at a moment \( t \) due to the laser energy absorbed into the sample. The resultant directivity patterns for longitudinal (\( u_r \)) and shear (\( u_\theta \)) waves are presented in Equations 5.2 and 5.3 respectively.

\[
u_r^{(\text{Ablation})}(\theta) \sim \frac{2k^2 \cos \theta (k^2 - 2 \sin^2 \theta)}{(k^2 - 2 \sin^2 \theta)^2 + 4 \sin^2 \theta \sqrt{1 - \sin^2 \theta} \sqrt{k^2 - \sin^2 \theta}} \quad (5.2)
\]

\[
u_\theta^{(\text{Ablation})}(\theta) \sim \frac{\sin 2\theta \sqrt{1 - k^2 \sin^2 \theta}}{k(1 - 2 \sin^2 \theta)^2 + 4 \sin^2 \theta \sqrt{1 - \sin^2 \theta} \sqrt{1 - k^2 \sin^2 \theta}} \quad (5.3)
\]

where \( k = \frac{c_l}{c_s} \) is the ratio of longitudinal to shear wave speeds, \( u_r \) is the radial displacement component, and \( u_\theta \) is the angular displacement component.
5.2.2 Thermoelastic Regime

In thermoelastic regime, temperature and displacement for a semi-infinite isotropic metal located in $z \geq 0$ space and irradiated by laser beam incident normally on the free surface $z=0$ can be described by the thermal diffusion equation and the thermoelastic displacement equations (Eqs. 5.4 and 5.5 respectively); Nowacki (1975).

$$k_t \nabla^2 T - \rho c_v \frac{\partial T}{\partial t} = -Q \quad (5.4)$$

$$\left(\lambda + 2\mu\right) \nabla(\nabla \cdot u) - \mu \nabla \times \nabla \times u - \rho \frac{\partial^2 u}{\partial t^2} = \alpha (3\lambda + 2\mu) \nabla T \quad (5.5)$$

where $c_v$ is the specific heat at constant volume, $\lambda$ is the Lame first parameter, $\mu$ is the Lame second parameter, and $\alpha$ is the thermal expansion coefficient. The resultant directivity patterns for longitudinal ($u_r$) and shear ($u_\theta$) waves are presented in Equations 5.6 and 5.7 respectively; Scruby and Drain (1990).

$$u_r^{(Thermoelastic)}(\theta) \sim \frac{\sin \theta \sin 2\theta \sqrt{k^2 - 2 \sin^2 \theta}}{k^2 - 2 \sin^2 \theta + 4 \sin^2 \theta \sqrt{1 - \sin^2 \theta \sqrt{k^2 - \sin^2 \theta}}} \quad (5.6)$$

$$u_\theta^{(Thermoelastic)}(\theta) \sim \frac{k \sin 4\theta}{k(1 - 2 \sin^2 \theta)^2 + 4 \sin^2 \theta \sqrt{1 - \sin^2 \theta \sqrt{1 - k^2 \sin^2 \theta}}} \quad (5.7)$$

However either of thermoelastic or ablation mechanisms might be of interest for laser ultrasonic generation, but there are some other factors which need to be considered for implementation of the LU for industrial applications. Laser power density (energy) is the main parameter which determines the generation mechanism of the laser ultrasonic. Also, since many laser ultrasonic systems are using optical fibers for directing the laser energy to the sample, laser power density must be maintained lower than damage threshold of the fibers.
5.3 Directivity Pattern for Additive Manufacturing Materials

There are several different metals available for metal additive manufacturing and this range is continuously expanding due to advances in powder metallurgy techniques; Bond et al. (2014). Stainless steels, aluminum, nickel (Inconel), cobalt-chrome and titanium alloys are all commonly used in additive manufacturing. In addition, some manufacturers offer their own particular alloys. Table 5.1 presents the most common metal alloys used in additive manufacturing together with their longitudinal and shear wave velocities used in this study.

<table>
<thead>
<tr>
<th>Alloy</th>
<th>Aluminum</th>
<th>Co-Cr Alloy</th>
<th>Tool Steel</th>
<th>Ni Alloy</th>
<th>Stainless Steel</th>
<th>Ti Alloy</th>
<th>Cu Alloy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Material</td>
<td>CL 30AL</td>
<td>ASTM F75</td>
<td>AISI 420</td>
<td>Inconel 718</td>
<td>SS 17-4 PH</td>
<td>Ti6Al4V</td>
<td>CC 480 K</td>
</tr>
<tr>
<td>DIN</td>
<td>1706</td>
<td>2.4723</td>
<td>1.2083</td>
<td>2.4668</td>
<td>1.4542</td>
<td>3.7165</td>
<td>2.1050</td>
</tr>
<tr>
<td>$c_L$ (m/s)</td>
<td>6200</td>
<td>6170</td>
<td>5900</td>
<td>5800</td>
<td>5730</td>
<td>6070</td>
<td>4660</td>
</tr>
<tr>
<td>$c_S$ (m/s)</td>
<td>3160</td>
<td>3180</td>
<td>3230</td>
<td>2960</td>
<td>3120</td>
<td>3310</td>
<td>2330</td>
</tr>
</tbody>
</table>

Neglecting any finite extent of the source as well as thermal conductivity terms, laser source can be represented as a point source (center of expansion) at the surface. In this case the far-field radiation pattern of waves is a function of $k$ and the spatial angle. Figure 5.2 shows the directivity patterns of the longitudinal wave and Figure 5.3 shows the directivity patterns of the shear wave for additive manufacturing materials (Presented in Table 5.1) by pulsed laser source in thermoelastic regime at 1 MHz detecting frequency according to Equations 5.6 and 5.7. From the directivity patterns for different additive manufacturing materials it is found that changes are more drastic for shear waves directivity.

Directivity patterns for longitudinal and shear waves in additive manufacturing materials (Table 5.1) in ablation regime based on Equations 5.2 and 5.3 are presented in Figure 5.4 for longitudinal and Figure 5.5 for shear waves by pulsed laser point source at 1 MHz detecting frequency.

One of the representative model for a laser source is the point source. The results of experimental observations showed a good correlation with theoretical results when Scruby et al. (1980); Scruby et al. (1980); described a point source as two mutually orthogonal force doublets. Later, Rose (1983); Rose (1984) derived a systematical representation of this point source.
Figure 5.2 Directivity pattern of longitudinal waves generated in additive manufacturing materials (Table 5.1) by pulsed laser point source in thermoelastic regime at 1 MHz detecting frequency.

However, the assumption for those evaluations is that the pulse of the laser can be approximated with a Dirac delta function when used for conventional LU. The comparison of a common laser pulse shape with the time domain arrival of the bulk waves in most samples, having sound travelling a distance of few millimeters, shows that the Dirac delta function is a reasonable assumption for conventional use in LU. However, when considering the application of LU in additive manufacturing, where the scale of desired travelling distance is in the range of deposited layer thickness (∼40μm in case of SS 174 PH samples in this study), the theoretical model for the pulse function needs to be modified accordingly. Figure 5.6 shows the representation of a typical Q-switched laser pulse with 10 ns pulse duration in comparison to the Time of Flight (TOF) of pulse-echo (two-way travelling) of bulk waves in one layer of AM deposition for the case of in-situ monitoring with LU, and Figure 5.7 shows this pulse for 5 mm of bulk SS 174 PH material in the case of conventional LU application. Since for more accurate evaluation of LU signals some other factors, such as thermal properties, material morphology in as built condition and geometry need to be included in the model in addition to the pulse features. In reviewing modeling options it appears that FEM would be a fast and promising method for
Figure 5.3  Directivity pattern of shear waves generated in additive manufacturing materials (Table 5.1) by pulsed laser point source in thermoelastic regime at 1 MHz detecting frequency.

evaluation of LU signals in AM applications.

5.3.1  Source Size

The results of directivity pattern presented above, were obtained when the thermal conductivity term is neglected in the thermal diffusion equation. In this case, results are in good agreement with experiments when the spatial profile of the laser beam is small and detecting frequency is low (∼ 1-5 MHz). However, differences between the theoretical predictions and experimental results become significant when beam size and/or frequency are increasing. The effect of including the thermal conductivity in the thermal diffusion equations were later studied; Zhang et al. (1997); Krylov (2015) and results show how the directivity patterns are changing due to variation in beam size and/or frequency. The results for directivity patterns, considering the effect of thermal conductivity in SS 17 4 PH additively manufactured material for longitudinal and shear waves are shown in Figure 5.8 and Figure 5.9 respectively, for changes in beam size.
5.3.2 Detecting Frequency

The results for directivity pattern when considering the effect of thermal conductivity in SS 17 4 PH additively manufactured material for longitudinal and shear waves are shown in Figure 5.10 and Figure 5.11 respectively, with changes in detecting frequency.

5.4 Numerical Modeling and Results

Extensive works on theoretical and experimental evaluation of laser-generated ultrasound provide valuable information about the generated ultrasound waves in materials. However, the difference between theoretical and experimental results becomes prominent when more influential factors such as beam shape and size, conductivity properties and detection frequency vary in the problem. These factors need to be considered while doing theoretical analysis or can be studied using finite element models (FEM) when solving theoretical equations is challenging. Numerical modelling can allow the interplay of the various factors to be studied, giving insights that can lead to improved experimental design. Using FEM many realistic experimental conditions can be included in the model to study the physics of the
problem. Some of the parameters which are difficult to consider in theoretical analysis but more convenient to include in FEM are the variety of boundary conditions, laser beam shape and profile, temperature dependence of material properties, and materials as built condition. FEM has been previously used for studying laser-generated ultrasound; Xu et al. (2004); Feng et al. (2012), simulation of laser-source additive processing; Ganeriwala and Zohdi (2014); Romano et al. (2015), and wave propagation in additive manufacturing materials; Taheri et al. (2017c).

5.4.1 Model Properties

The finite element model consists of a 2D axisymmetric solid domain prepared in COMSOL; COMSOL (2018). The geometrical shape of the model is a quarter circle with the radius of 1.5 times of far-filed distance. Boundary layer elements were used in the region near the irradiated surface to be able to capture the temperature and displacement field in that area. Quadratic meshes were assigned to the rest of the domain and the mesh size is not larger than $\frac{\lambda}{6}$, and the time step for the solution is obtained from Equation 5.8 considering CFL number equals to 0.2. A schematic drawing for a 2D axisymmetric models geometry and corresponding quadrilateral
Figure 5.6  Representation of a typical Q-switched laser pulse with 10 ns pulse duration in comparison to Time of Flight (TOF) of bulk waves in one layer of AM deposition in case of in-situ monitoring with LU.

meshes are shown in Figure 5.12 and Figure 5.13 respectively. Some major laser and materials parameters used are listed in Table 5.2 and Table 5.3 respectively.

\[ t_{step} = \frac{CFL \times L_{max}}{c} \]  

(5.8)

where \( L_{max} \) is the maximum mesh size and \( c \) is the compression wave velocity.

<table>
<thead>
<tr>
<th>Spot size (Dia.)</th>
<th>Pulse duration</th>
<th>Laser energy</th>
</tr>
</thead>
<tbody>
<tr>
<td>100( \mu )m</td>
<td>10ns</td>
<td>54( \mu )J</td>
</tr>
</tbody>
</table>

The spatial distribution of the zone illuminated by the pulsed laser is assumed to have a Gaussian cross section and this is considered in a cylindrical coordinate system which is adopted for the model. Based on thermoelastic theory, the thermal conduction and thermoelastic equation can be written as Equations 5.9 and 5.10 respectively; Eslami et al. (2013):
96

Figure 5.7  Representation of a typical Q-switched laser pulse with 10 ns pulse duration in comparison to Time of Flight (TOF) of bulk waves in 5 mm of bulk SS 17 4 PH material in case of conventional LU application.

\[ k \nabla^2 T(r, z, t) - \rho c_v \frac{\partial T(r, z, t)}{\partial t} = -Q(r, z, t) \] (5.9)

\[ (\lambda + 2\mu) \nabla (\nabla \cdot U(r, z, t)) - \mu \nabla \times \nabla \times U(r, z, t) - \rho \frac{\partial^2 U(r, z, t)}{\partial^2 t} = \alpha (3\lambda + 2\mu) \nabla T(r, z, t) \] (5.10)

where \( k \) is the thermal conductivity, \( T(r, z, t) \) is the temperature field distribution, \( \rho \) is the density, \( c_v \) is the thermal capacity (specific heat at constant volume), \( Q(r, z, t) \) is the laser

<table>
<thead>
<tr>
<th>Physical properties</th>
<th>Additively manufactured stainless steel 17 4 PH</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temperature ( K/\degree F )</td>
<td>( k(W m^{-1} K^{-1}) )</td>
</tr>
<tr>
<td>Thermal conductivity</td>
<td></td>
</tr>
<tr>
<td>422.04/300</td>
<td>17.9</td>
</tr>
<tr>
<td>533.15/500</td>
<td>19.5</td>
</tr>
<tr>
<td>733.15/860</td>
<td>22.5</td>
</tr>
<tr>
<td>Density ( \rho(kg m^{-3}) )</td>
<td>7740</td>
</tr>
<tr>
<td>Thermal capacity ( c(J kg^{-1} K^{-1}) )</td>
<td>745</td>
</tr>
<tr>
<td>Coefficient of thermal expansion ( \alpha(\frac{1}{K}) )</td>
<td>( 12.3 \times 10^{-6} )</td>
</tr>
<tr>
<td>Youngs modulus ( E(GPa) )</td>
<td>194</td>
</tr>
</tbody>
</table>
energy absorbed into the sample, that is converted into heat, $\lambda$ and $\mu$ are the Lam parameters, and $U(r, z, t)$ is the displacement field distribution.

Considering the effect of optical penetration, the heat source can be expressed as Equation 5.11.

$$Q(r, z, t) = \beta(1 - R)I_0e^{-\beta z} f(r)g(t) \quad (5.11)$$

where $\beta$ is the optical absorption coefficient, $R$ is the optical reflectivity of the material, $I_0$ is the maximum intensity of the incident laser, and $f(r)$ and $g(t)$ are the spatial and temporal distributions of the pulsed laser respectively which can be written as Equations 5.12 and 5.13 respectively.

$$f(r) = \exp\left(-\frac{r^2}{r_0^2}\right) \quad (5.12)$$

$$g(t) = \exp\left(-\frac{(t - t_0)^2}{\tau^2}\right) \quad (5.13)$$
where \( r_0 \) is the radius of laser spot, \( t_0 \) is the arrival time of the pulse and \( h_0 \) is half width of pulsed laser. To solve the temperature and displacement fields, the boundary and initial conditions of Equations 5.9 and 5.10 need to be determined. Assuming that there is no initial heat source, stress and mechanical displacement in the system, the initial conditions can be written as Equations 5.14, 5.15, and 5.16:

\[
T(r, z, t)_{t=0} = 293.15K \quad \text{(5.14)}
\]

\[
U(r, z, t)_{t=0} = 0 \quad \text{(5.15)}
\]

\[
\frac{\partial U}{\partial t} \bigg|_{t=0} = 0 \quad \text{(5.16)}
\]

- **Laser spot size**

The laser beam spot size at the focal point of a pulsed laser is a critical parameter in laser-generated ultrasound and laser materials processing. In laser-generated ultrasound, the
irradiated area on the surface and consequently the temperature and thermal stress distributions are strongly influenced by the incident beam spot size; Wang et al. (1993). In this study, laser spot sizes are considered to be 50, 100 and 150 µm to investigate the effect of spot size on the resulting temperature and displacement fields.

- **Laser pulse duration**

One of the major effects in laser-generated ultrasound is the influence of the pulse duration on the generated acoustic waves and evolution of the signal. It is of great interest to be able to choose the optimal pulse duration to increase the efficiency of optoacoustic response; Dehoux et al. (2006). 5, 10, and 15 ns pulse durations were studied for evaluation of the pulse duration effect on the generated acoustic waves.

- **Laser energy**

The level of laser source energy drastically changes the generated ultrasound signals in the thermoelastic regime. Further changes in the level of the laser energy can even change...
Figure 5.11 Directivity pattern of shear waves generated in stainless steel 17-4 PH additive manufacturing materials at 1 mm Gaussian profile beam size for different detecting frequencies.

The wave generation mechanism (switching between thermoelastic and ablation regimes) which have different signal characteristics. In this study, first the amplitude of the power intensity which causes the sample to melt has been calculated based on the melting point, thermal and physical properties of the sample. Then, a fraction of the calculated maximum power intensity was considered as the amplitude of the pulsed lasers power. To study the effect of laser energy, models using 25, 35, and 50% of the calculated power intensity at the melting point were considered for the pulsed lasers power.

- Thermal conductivity

The effect of the thermal conductivity of the material is very important in laser-generated ultrasound as the temperature field resulting from laser heating serves as the source for elastic displacements. This can be seen in the thermoelasticity equations presented in Equations 5.9 and 5.10. Thermal conductivity of materials varies with temperature. Three different thermal conductivities at 422.04K (300°F), 533.15K (500°F), and 733.15K (860°F) were considered for evaluation of the effect of thermal conductivity on the generated ultrasound wave fields.
5.4.2 Numerical Results and Discussion

Figures 5.14 and 5.15 show the 3D representations of total displacement and temperature distribution in the model at 200 ns respectively. Figure 5.16 shows the temperature profiles as a function of distance into the sample (z-direction) and Figure 5.17 shows this distribution on the surface of the sample (r-direction) for different time intervals. The rate of the temperature change as a function of time at different distances into the sample (z-direction) is shown in Figure 5.18.
Figure 5.13  Schematic for 2D axisymmetric models corresponding quadrilateral meshes.

Figure 5.14  3D representations of total displacement in the model at 1.25 μs.
Figure 5.15  3D representations of temperature distribution in the model at 1.25 µs.

Figure 5.16  Temperature profile as a function of distance into the sample (z-direction) for different time intervals.
Figure 5.17  Temperature profile as a function of distance on the surface of the sample (r-direction) for different time intervals.

Figure 5.18  Rate of the temperature change over time at different distances into the sample (z-direction).

Figure 5.19 shows the total displacement as a function of time at different locations into the sample (z-direction) and Figure 5.20 shows the total displacement on the surface of the sample (r-direction). A comparison of the result for the total displacement at the epicentral point of the sample for longitudinal and shear waves Time Of Flight (TOF) obtained by finite element
and theoretical models (FEM and THM respectively) are presented in Figure 5.21.

Figure 5.19  Total displacement versus time at different locations into the sample (z-direction).

Figure 5.20  Total displacement versus time at different locations on the surface of the sample (r-direction).
Figure 5.21  Total displacement at the epicentric point of the sample (L1=1st arrival of longitudinal wave, S1=1st arrival of shear wave) Theory (THM) – Finite Element (FEM).

- **Effect of optical and physical parameters on temperature and displacement fields**

Displacement and temperature fields were calculated for different values of laser spot size, pulse duration, percentage of total energy which reaches the top surface of the sample, and the thermal conductivity as described in the previous section. Figure 5.22 shows the total displacement versus time at a depth of 250 µm below the irradiated point (z-axis) and Figure 5.23 shows total displacement versus time at a radius of 250 µm from the center of the irradiated point on the surface (r-axis). As can be seen from the Figures 5.22 and 5.23, the amplitude of total displacement is increased when the laser spot size, pulse duration, and energy, as well as the conductivity of the material increases at higher temperatures.
Figure 5.22  Total displacement versus time at 250 $\mu$m distance below the irradiated point (z-axis).
Figure 5.23  Total displacement versus time at 250 µm distance from irradiated point on the surface (r-axis).

The distribution of the transient temperature field is the source of the body force in the generation of ultrasonic waves in the solid media. The transient temperature field distributions at 10 ns in r and z directions as well as the variation of temperature at 1 µm below irradiation point over time are shown in Figures 5.24- 5.26. Figure 5.24 shows that at 250 µm distance from the irradiation point on the surface, by increasing the laser spot size from 50 to 150 µm, the local temperature increases about 45% (From 293.2 K to 426.6 K). Laser pulse duration, laser energy and conductivity of the sample, are more influential on the temperature distribution on the surface of the sample at distances closer to the irradiation point (r<150 µm). Temperature distribution along the z-axis (depth of the sample) in Figure 5.24 shows that the temperature gradient decreases rapidly over the depth of the sample. This gradient is steeper when the laser beam is more focused (smaller laser spot size and shorter pulse duration for a constant laser energy). In this situation, the generated thermal stress tensors are larger in the direction perpendicular to the surface, so the generated bulk waves would be stronger. From Figures 5.24 and 5.25, it can be seen that the heat-affected zone is very localized in both the radial (r)
and depth (z) directions, however this localization is much smaller in the depth (z) direction. Figure 5.26 shows the temperature distribution over time at 1 $\mu m$ distance below the surface, under the irradiation point. As can be seen from Figure 5.26, there is a sudden increase in the temperature gradient at the time of laser pulse which generates the ultrasound wave in the sample and this is followed by a much slower cooling period.

![Temperature field distribution over distance on surface (r-axis) at t=10ns](image)

Figure 5.24 Temperature field distribution over distance on the surface (r-axis) at 10 ns.
Figure 5.25  Temperature field distribution over distance in depth (z-axis) at 10 ns.

Figure 5.26  Temperature distribution over time at 1 μm depth (z-axis) for different percentages of total laser energy.

The peak temperature of this gradient decreases about 14% (From 406 K to 349 K) when
the percentage of total energy applied to the sample decreases by 50%. As can be seen from Figure 5.26, the cooling process duration is much longer than the ultrasound waves travel time in the top few layers of additively deposited materials (Figure 5.22). Since the speed of sound is a function of temperature, the wave speed in the material will be influenced by the temperature during the additive manufacturing process.

- **Effect of the temperature-dependency of material properties on temperature and displacement fields**

  Local temperature change phenomena seen in terms of melting and solidification is the most important aspect of additive manufacturing process. The local variation of temperature, and temperature gradients, during the additive manufacturing process are not only among the main factors in defect generation mechanisms in the part, but also result in local changes in the microstructure and material properties; Taheri et al. (2017d). Thermal conductivity, specific heat (heat capacity), and coefficient of thermal expansion are among those material properties which are a function of temperature and are important in the physics of the laser-generated ultrasound phenomena. Because of the considerable temperature variations during the additive manufacturing process, as well as steep temperature gradients over short distances and times during the laser-generation of ultrasound, the temperature dependency of these parameters and their influence on ultrasonic wave displacement fields needs to be evaluated. The temperature dependency of thermal conductivity, specific heat (heat capacity), and coefficient of thermal expansion for stainless steel 17-4 PH are described by the relationships presented in Equations 5.17, 5.18, and 5.19 respectively:

\[
k(T) = 14.6 + (1.27e - 2) \times T \tag{5.17}
\]

\[
c(T) = 450 + 0.28T - (2.91e - 4) \times T^2 + (1.34e - 7) \times T^3 \tag{5.18}
\]

\[
\alpha(T) = 11.813 + (1.3106e - 2) \times T - (6.1375e - 6) \times T^2 \tag{5.19}
\]
Figure 5.27 shows the effect of temperature dependency of the thermal physical parameters of the material on displacement field. Figure 5.28 shows the effect of temperature dependency of the thermal physical parameters of the material on transient temperature field.

Figure 5.27  Effect of temperature-dependency of material properties on displacement field distribution in laser-generated ultrasound.
Figure 5.28 Effect of temperature-dependency of material properties on temperature field distribution in laser-generated ultrasound.

As can be seen from Figure 5.27, there is approximately 6% difference in maximum amplitude of displacement on the surface (r-axis) and 12% difference in maximum amplitude of displacement in depth (z-axis). This is due to change in the thermal gradient (Figure 5.28) caused by temperature dependence of the material properties.

Multiphysics numerical model is a promising way for characterization of physical mechanism of laser ultrasonics. The results show a good agreement with theoretical predictions. FEM evaluation of the laser ultrasonics problem provides the advantages of fast and efficient way of considering variety of parameters in the problem and perform the calculations in different scenarios. Once validated, these parameters can be used to setup the best experimental conditions. Despite the challenges in simulation and optimization of laser ultrasound, this technique has perspective in noncontact and in-situ measurements for additive manufacturing applications. Effects of thermal conductivity, laser spatial profile and pulse characteristics changes the directivity pattern of laser generated ultrasound. These influences are particularly important in in-situ monitoring of the additive manufacturing
materials, where the size of the deposited layers and associated possible defect are critical and the thermal behavior of the process is complicated. Considering these factors, calculation of the real sound field is necessary in deposited additively manufactured layers of materials.
CHAPTER 6. CONCLUSIONS

The aim for this project was to investigate NDE for additive manufacturing and in particular in-process metrology. The project has provided a proof of concept demonstration which established a correlation between acoustic signatures and process build conditions for a metal additive manufacturing process. The approach employed a multi-sensors configuration attached to the build plate. A variety of temporal and spectral feature extraction methods were applied to the acoustic signals. The signal processing included an assessment of the manufacturing process classifications using the acoustic signals features, including quantitative evaluation of cohesion and isolation of clusters (Clustering performance analysis). Specific and more detailed conclusions were:

i. Results shown in this work provide proof-of-concept data which establishes a correlation between acoustic signatures and operating condition in an AM process.

ii. It is demonstrated that a passive acoustic monitoring approach and use of signal processing algorithm is effective at giving metrics that achieve clustering and separation of conditions based on multiple spectral features extracted from the original test data, and that these metrics correlate with different AM system conditions.

iii. Evaluation of the identified features confirmed the consistency in process monitoring and data collection by all sensors, different locations on the build plate, and various process conditions.

iv. It has been shown that the acoustic signatures of the AM process not only can be classified so as to identified manufacturing conditions, but also can be used to quantitatively analyzed for the cohesion and isolation of the clusters.

v. It is demonstrated that with more than 87% confidence the process conditions can be classified compare to the base line condition (BL) in low frequency (LF) and high frequency
(HF) bands for normal (C1), low powder (C3), and powder spray (CO) process conditions. The lowest classification accuracy occurs in the low power (C2) process condition, where the efficiency drops to 85% in the low frequency (LF) band and 70% in the high frequency (HF) band.

vi. Statistically significant changes in temporal noise level measures could be observed based on processing condition for both classical acoustic emissions analysis and process noise characteristics.

vii. Examination of process noise, excluding HAESs that can strongly influence central tendencies, and correlations with varying process parameters, and demonstrate the capability to potentially predict and monitor passively directed energy deposition additive manufacturing system build performance and condition.

viii. FEM evaluation of the laser ultrasonics problem provides the advantages of fast and efficient way of considering variety of parameters in the problem and perform the calculations in different scenarios. ix. The evaluation of the effect of different pulsed laser source properties (spot size, pulse duration and energy), and temperature-depended material properties (conductivity, heat capacity, and coefficient of thermal expansion) on temperature fields and ultrasonic wave forms show the important influence of optical and physical properties on successful generation and detection of ultrasound waves using pulsed laser source.
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