Control Oriented Model and Control System Design for Selective Laser Melting Process

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Control Oriented Model and Control System Design for Selective Laser Melting Process

by

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Control Oriented Model and Control System Design for Selective Laser Melting Process
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Whoever takes a path upon which to obtain knowledge, Allah makes the path to Paradise easy for him

Prophets Muhammad

To my Father who wished to see me in this stage

To my Mother

To my family

Acknowledgement

In the name of Allah, the Most Gracious, the Most Merciful.

All praise is due to Allah, the Lord of all worlds. I express my gratitude to Allah for granting me strength, wisdom, and perseverance throughout my academic journey.

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Finally, I express my gratitude to all those who directly or indirectly contributed to the completion of this thesis. Your collective efforts have made an indelible mark on this scholarly endeavor.

Declaration

I, Taha Mubarak Al-Saadi, declare that the thesis titled "Control of Selective Laser Melting Process" is my original work. I confirm that:

1. This work has not been submitted in any form to any other university or institution for assessment purposes.
2. Every effort has been made to indicate clearly with proper citation and acknowledgment wherever contributions of others are involved.
3. No part of this work has been copied from any other source except where due citation is made.
4. The views, opinions, findings, conclusions, or recommendations expressed in this thesis are my own and do not necessarily reflect the views of my advisor, the university, or any other organization.
5. I have not received any assistance that has not been declared in the acknowledgments section of this thesis.

   I understand that any act of plagiarism or other forms of academic misconduct as stated above may result in serious consequences, including the possible revocation of my degree.

Sheffield, 2nd October 2024

TAHA MUBARAK AL-SAADI

Abbreviations List

AM	Additive Manufacturing
SLM	Selective Laser Melting
PBF	Powder Bed Fusion
FLC	Fuzzy Logic Controller
L-PBF	Laser Powder Bed Fusion
ASTM	American Society for Testing and Materials
ISO	International Organization for Standardization
SLA	Stereolithography/Photopolymerisation
DED	Directed Energy Deposition
BJP	Binder Jetting Process
SL	Sheet Lamination
SLS	Selective Laser Sintering
STL	Stereolithography file format
CAD	Computer Aided Design
FPGA	Field Programmable Gate Arrays
FF	Feed-Forward
P	Proportional
PI	Proportional-Integral
PID	Proportional-Integral-Derivative
CMOS	Complementary Metal-Oxide-Semiconductor
MFC	Model-Free Control
ILC	Iterative Learning Control
DL	Deep-Learning
ML	Machine Learning
FEA	Finite Element Analysis
ODE	Ordinary Differential Equation
PDE	Partial Differential Equation

Abstract

Powder Bed Fusion – Laser Beam (PBF-LB) process, a prominent additive manufacturing (AM) technology for metals, has the potential to revolutionize manufacturing by enabling the rapid production of complex parts directly from digital models. Despite its advantages in speed and geometric flexibility, the quality and repeatability of SLM-produced parts are often compromised due to the complex and fast-changing process dynamics. The literature highlights the critical need for robust online control systems to enhance part quality and consistency. However, a significant challenge lies in the lack of an adequate process model to design effective online control algorithms.

This research addresses these challenges by investigating and implementing various online control systems to mitigate heat accumulation and improve part quality and process performance. Our contributions are threefold:

1. Extending control models: We advance beyond existing track-level control to a multi-layer, variable-shape framework.

2. Fast and efficient simulation: We developed a MATLAB tool that drastically reduces simulation time (from days to seconds) while accurately capturing process behavior, facilitating rapid control system design and testing.

3. Control system exploration: We explore various control approaches for multi-layer SLM, including, for the first time, the application of Fuzzy Logic. This technique leverages human expertise and integrates seamlessly with our multi-layer model, offering unique advantages for handling inherent process uncertainties.

Our work enhances understanding of SLM process control and paves the way for more efficient additive manufacturing practices.

Contents

1

Research Project Overview

This chapter provides a brief introduction to the research investigation carried out in this project. It states the problem statement, aim and objectives of the research work. Then, based on the best of our research knowledge, a list of contributions and publications is provided. Finally, the thesis structure is described at the end of the chapter.

1.1. General introduction

Additive Manufacturing (AM) is a group of manufacturing techniques that builds 3D parts directly from a digital design. The building is achieved by printing one layer after another until the full product is completed [1]. The technology is a fast manufacturing tool since it reduces many traditional fabrication steps. It provides more flexibility and freedom in product design. These features made AM a competent option in many applications, such as construction, medical field, aerospace and much more [2]. AM technology can process various types of materials such as polymers, ceramics, and metals [3].

One of the rising techniques is the Selective Laser Melting (SLM) process, which is a Powder Bed Fusion technology that uses a high-density and narrow laser beam to fuse the powder particle selectively [4]. SLM processes are capable to produce parts with high resolution, lightweight structure, and internal channels to enhance their mechanical properties [5].

Despite the significant advancements in metal Additive Manufacturing, there are still several challenges and limitations that hinder its ability to fully meet industrial requirements [6]. The AM process is influenced by numerous factors, making it difficult to guarantee consistent quality and repeatability [7].

In most existing processes, including SLM and other AM techniques, process parameters remain constant throughout the printing process [8]–[10]. These parameters are typically determined through trial and error or optimised with the help of expert knowledge and modeling/simulations [11]. However, relying on fixed parameters can lead to issues like heat accumulation that causes irregularities in the melting pool morphology, especially when dealing with complex geometries, resulting in various types of defects.

Over the past two decades, extensive research efforts have been dedicated to improving part quality in metal AM. There is great emphasis in the literature on the importance of online closed-loop controllers in enhancing the performance of the SLM process [7], [12], [13].

However, achieving closed-loop control system for SLM process has two main challenges. First, is the absence of an adequate model to design a controller. Second, is the lack of a suitable simulation platform that can be used to test the controller performance swiftly. Most of the existing software can take several weeks to perform a simple building simulation.

The objective of this study is to expand the existing track-level control-oriented model to a multi-layer and variable shape. Subsequently, a simulation tool based on MATLAB will be proposed, which can accurately capture the thermal behavior of the SLM process and test the input-output control system performance in significantly shorter times than existing approaches. Finally, an exploratory study has been conducted to utilise the online control system to enhance process performance. For the first time in the literature, the implementation of a Fuzzy Logic controller for the SLM process has also been discussed.

1.2. Problem statement

Various research efforts emphasise the importance of establishing an online control system for the SLM process. However, the absence of an adequate model and simulation tool makes achieving it challenging.

There is a great agreement that existing high-fidelity models such as finite element models are computationally intensive and cannot be easily utilised within an on-line closed-loop controller. A control-orientated model presents a valuable option for designing a closed-loop system to compensate for the disturbances that appear during fabrication and enhance the repeatability of the process [8]. Most of the existing models consider simple derivation scenarios (track-level experiments/simulation), making the designed controller performance not robust enough to be used with complex shapes.

Another research gap is the absence of a simulation platform that can be used to test the performance of the design controller before it is practically implemented.

Based on that, the research problem being investigated in this project primarily enquires:

To what extent does a simple control-oriented model improve the controller's design experience and performance, thus improving the product's quality? Furthermore, what will be the best control algorithm that will ensure the repeatability of the process for different printed shapes?

The main research question can be divided into several subsidiary questions for systematic investigation:

- What is the SLM process, and what are the key features and parameters of it?
- What are the existing modelling techniques used to present the SLM process?
- What are the advantages and weaknesses of the control-orientated model?

- What are the key challenges facing the existing and current techniques?
- What will be the effect of simplicity versus the generality of the model in the control system used?
- Why is a closed-loop system required for SLM?
- What will be the best control system for SLM?
- What are the existing simulation platforms for SLM that can be used to test the performance of the control system?
- What are the primary sources of disturbances in the SLM process?
- What is the best way to consider disturbances in the SLM process?

1.3. Research aim and objective

The broad aim of this research project is to find an appropriate answer to the main research question. To achieve that, I intend to fulfill the following objectives:

a) Extend the existing investigation of the control-oriented model from multi-track to full object, thus capture the process's behavior and present the disturbances during the printing of full shapes.

b) Develop a simplified model based on the information collected in objective (a) above.

c) Design a simulation platform that can be utilised for control system implementation and investigation of the control system based on the objectives (a,b).

d) Explore the use of an online closed-loop control system for a selective laser melting process.

e) Explore the advantages of using a fuzzy logic control system to enhance process performance.

By achieving the desired objectives, I believe that the scientific and industrial community would benefit from the proposed model and control algorithm to improve the quality of the produced parts and push the research progress in this area a step ahead.

1.4. Contributions and publications

By the end of this research project, and based on the best of the researcher's knowledge, the research contributions can be summarised as the following:

a) Exploring the field of control system application in the L-PBF process and presenting the current challenges and future opportunities (Chapter Two, section 2.3-2.5). The exploration process was summarised in a conference paper published in 2021 and presented in Appendix A.

   T. Al-Saadi, J. A. Rossiter and G. Panoutsos, "Control of selective laser melting processes: existing efforts, challenges, and future opportunities" 2021 29th Mediterranean Conference on Control and Automation (MED), PUGLIA, Italy, 2021, pp. 89-94, doi: 10.1109/MED51440.2021.9480258.

b) Extending the investigation of physics-based models to multi-layer and different shapes, incorporating the practical considerations and the simplicity of the implementation (Chapter Four). The result was a fast simulation technique that can capture the behaviour of the melt-pool dynamics (temperature and geometry) in a much faster time. With this model one can simulate a shape of 30 tracks of a length of 1cm repeated for 60 layers in 806 seconds whereas this takes around a week to do with a FEM simulator. In collaboration with another research group, we utilised the model and the data generated from it to investigate the application of reinforcement learning in the Selective Laser Melting (SLM) process. Our cooperation resulted in a peer-reviewed paper titled "Multi-layer Process Control in Selective Laser Melting: A Reinforcement Learning Approach," which we plan to submit to the Journal of Intelligent Manufacturing.

c) Based on the extended model investigation, a MATLAB-Based Simulation tool was developed for the control purpose investigation (Chapter Five). The tool is based in SIMULINK, where the designed controller can be placed easily as a block (input-output). The tool simulates the system closed-loop response in matter of seconds. We intend to write a research paper detailing our findings and the tool we developed, which we will share with the research community. The paper's title will be "Selective Laser Melting Matlab-Based Simulation for Control Purposes". This will significantly enhance the impact of our research.

d) Based on the exploratory study conducted at the beginning of the project, a control system design investigation were conducted. The investigation considered for the first time the control implementation during the build of the full object; in-layer, and layer-to-layer control (presented in Chapter 6). Furthermore, the investigation of applying a fuzzy logic controller to establish an online control system for the selective laser melting process was explored. Such a consideration was the first of its kind in the literature. The basic fuzzy logic controller was implemented on a simplified process model and compared with PID and Feedforward control designs. The investigation results showed the superiority of the fuzzy controller over the others for different quantifications of performance (error, settling time, and power usage). The outcomes of the investigation were presented in the following conference papers (copies are provided in the Appendices B-D):

Al-saadi, T.,Rossiter, J.A.and Panoutsos, G. (Accepted: 2023) Analytical comparison between in-situ control strategies for selective laser melting process.In: IFAC-PapersOnLine. 22nd World Congress of the International Federation of Automatic Control (IFAC2023), 09-14 July 2023, Yokohama, Japan. Elsevier.

Al-Saadi, T., Rossiter, J.A. orcid.org/0000-0002-1336-0633 and Panoutsos, G. (2022) Fuzzy logic control in metal additive manufacturing: a literature review and case study. In: Poulin, É., (ed.) IFAC-PapersOnLine. 19th IFAC Symposium on Control, Optimization and Automation in Mining, Mineral and Metal Processing (MMM 2022), 15-18 Aug. 2022, Montreal, Canada. Elsevier , pp. 37-42.

T. Al-Saadi, J. A. Rossiter and G. Panoutsos, Initial Investigation of Online Control System for Selective Laser Melting Process: Multi-layer Level" The 14th United Kingdom Automatic Control Council (UKACC) International Conference on Control (CONTROL 2024), Winchester, UK (Accepted but not yet published)

Furthermore, the findings of Chapter 6, along with additional research, will be documented as a journal paper titled "Advantages of Fuzzy Control in Managing Complex Model Dynamics: Control of SLM Process".

1.5. Thesis outline

The thesis is divided into four parts. The first part includes this chapter and the next two chapters.

- Chapter 1: Briefly introduces the research topic, the aims and objectives of the research field, the key findings and contributions, and the structure of the thesis.
- Chapter 2: Introduces the research topic in more detail, addressing the literature, current challenges, and research opportunities.
- Chapter 3: Overviews the main remit of the investigation, presenting the assumptions considered, system specifications, and the mathematical model of the melting pool.

The second part of the thesis investigates and implements the process model of the SLM process. Our unique approach and research aim to fill a critical gap in the current knowledge of physics-based control-oriented model and simulation.

- Chapter 4: discusses the implementation and the expansion of the SLM model to 3D level and assessment of a model at several levels: i) single-track single layer, ii) multi-track single layer and iii) multi-track multi-layer (two shape).
- Chapter 5: proposes a MATLAB-based simulation tool for control system investigation purposes based on a simplified model of the process.

Part three of our thesis investigates the control system, shedding new light on critical aspects that have not been explored before in closed-loop control system implementation for the SLM porcess.

- Chapter 6: explores and investigates the implementation of a closed-loop control system using classical control approaches and a fuzzy logic control and its impact in enhancing the system performance.

The last part (Chapter 7) summarises the research results and presents future opportunities related to the research topic.

2

Introduction to the Research Problem

This chapter answers the question: why do we need on-line control system for the SLM process? We will begin by introducing additive manufacturing technology and its various applications, focussing on the laser powder bed fusion process, specifically selective laser melting. We will highlight the important production steps, parameters, and quality indicators. Then, we will present a review of the literature on the modelling and control of the SLM process, discussing existing efforts, challenges, and opportunities. The importance of the contributions made in this work can be observed throughout this chapter.

2.1. General introduction additive manufacturing

Based on the American Society for Testing and Materials (ASTM) and International Organization for Standardization (ISO/CD 17296), additive manufacturing, also known as 3d printing, is defined as the following:

> *"A process of joining materials to make objects from 3D model data, usually layer upon layer, as opposed to subtractive manufacturing methodologies."*[1]

The beginning was in the mid-1980s when stereolithography (SLA) technology was introduced to process polymers [2]. At that time, the target was to produce a visualised prototype for marketing purposes before the actual traditional manufacturing process starts. Since the late 1990s, AM technologies have started to process metallic materials such as steel, aluminium, and titanium [3]. Since then, AM has played a vital role in various industrial applications. The applications involve sectors such as toolmaking, medical and aerospace. The following context will briefly present the AM process classification and its applications.

2.1.1 Classification

Based on ASTM and ISO, additive manufacturing technologies are classified into seven categories: VAT photopolymerization, material extrusion, powder bed fusion (PBF), direct energy deposition (DED), binding, material sintering, and sheet lamination processes [1]. The following is a summary of each type.

- VAT photopolymerisation / SLA is considered the earliest technique of AM. The technique uses polymer as a liquid to form the required parts. The building is done layer by layer with the help of ultraviolet light to solidify the materials. The process allows for the production of parts with a high level of precision and a fine finish.

- Material jetting uses the same methodology as the inkjet printer to produce 3d parts. The technique uses a composite of polymer, plastic, and sodium hydroxide as a building material. The material used is spread over the build platform as a droplet [14].

- The Binder Jetting Process (BJP) is a powder-based AM process in which an adhesive is used to bind powder layers. The process uses different kinds of material such as metals, polymers, and ceramics [15].

- Material Extrusion or Fused deposition modelling is considered the most common 3d printer technology known by the public. The method uses a moving nozzle to deposit the material layer by layer. The layers are bonded using a heat source and chemical agent [16].

- Sheet Lamination (SL) is a process that uses sheets to fabricate parts. The sheet could be paper, plastic, or metal. Using a heat source, the sheets are softened and reshaped to the desired shape [17].

- Direct energy deposition (DED) uses a nozzle fixed on a multiaxis arm. Through the nozzle, the melted powder is deposited on the working platform. The method is used to fabricate, fix, and coat existing parts. DED can be subclassified according to the heat source as laser-DED, electron beam-DED, and electric arc-DED [18].

- Powder bed fusion (PBF) is the most widely applied powder-based process among all other Additive Manufacturing systems. The process allows for the use of various materials, such as plastics, glass, and metals. The process requires less or no support because the powder acts as a support structure. The technique can be further classified into Selective Laser Sintering (SLS) and Selective Laser Melting (SLM). The main difference between SLS and SLM is the material used in the processing. The first process is used to fuse plastic, while the second is used for metal powder [19].

Figure (2.1) illustrates the classification of AM processes.

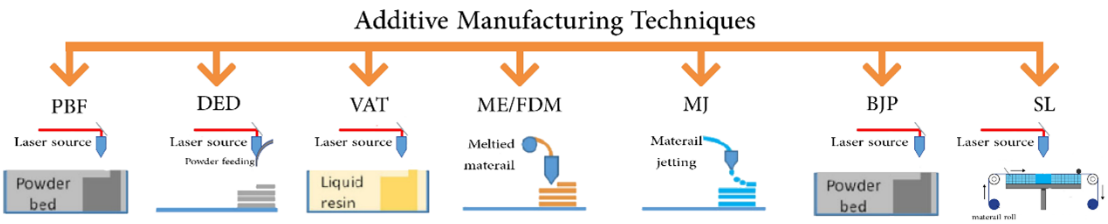


Figure 2.1.: Classification of the AM process.

2.1.2 Application of AM

AM has an enormous range of applications in various industrial sectors. The technique is used to produce a virtual prototype rapidly, which helps in developing new products faster. AM applications are not limited to prototypes; AM can produce manufacturing tools, jigs, and fixtures in a short time with specific features and complex geometries. In addition, AM technology is used to add an extra layer for existing parts (cladding) or fix damaged or cracked components (repairing). Figure (2.2) illustrates the use of different AM techniques in various industries of industrial applications.

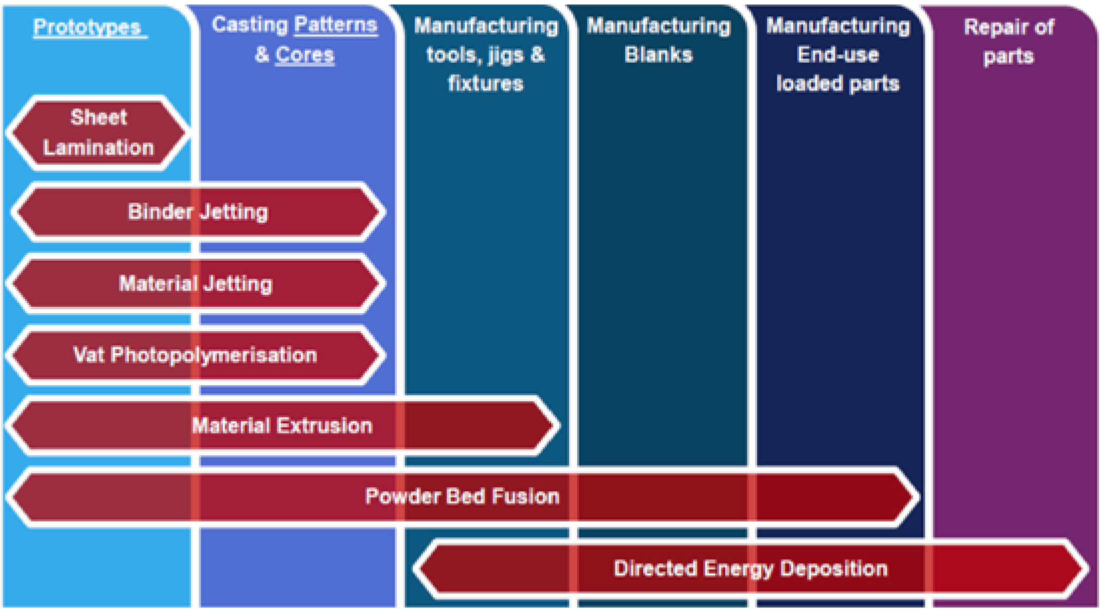


Figure 2.2.: AM process and application[20].

Today AM is widely applied in aerospace, energy, automotive, medical fields, and other industries [21]. The following provides some examples and illustrations of the AM industrial application.

- In construction, AM has been used for more than a decade to build architectural models. With the development of the AM process, the technique is used to print building parts using various building materials such as concrete, metals and polymers (see Figure 2.4. A) [22].

- In the medical field, AM processes play an essential role. The technology is used to develop medical devices and artificial parts. Figure (2.3) illustrates some of these applications.

- The aerospace sector such as Airbus, Boeing and NASA have invested heavily in AM technology research and development. Using AM technology, waste materials, manufacturing time, and design limitations are reduced [20]. Figure (2.4.B) shows a fuel nozzle of an aeroplane produced by an AM process.

- In the energy sector, AM is used to develop a variety of products and parts. An example of one of these applications is the use of AM to produce lightweight components and environmentally friendly windmill blades.

- In the automobile industry, the features of 3D printing were utilised to produce parts with less weight with high durability. Figure (2.4.C) presents a water pump for a car produced by SLM.

Our focus in this work will be on the metallic powder-bed fusion process, particularly the SLM process. Therefore, the following context will introduce this SLM process in more detail.

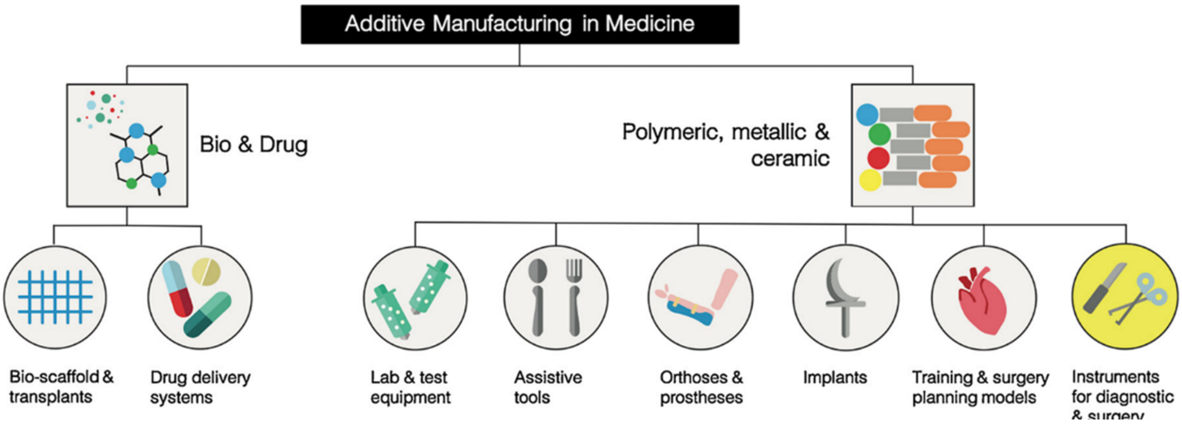


Figure 2.3.: Additive manufacturing application in the medical field [23].

Figure 2.4.: A) Digital Building Platform design at MIT [22], B) Fuel nozzle of Aeroplane produced by AM[24], C) Water pump for a car produced by SLM [25].

2.2. General introduction to selective laser melting process

Selective laser melting is a metallic PBF process that uses a focused laser beam to melt the mounted powder selectively [26]. The process can produce metal parts directly with quality equivalence, or better in some applications, than those produced using traditional manufacturing. The narrow laser source allows selective melting of the powder in the order of microns in thickness and building of parts with satisfactory resolution [8]. The thermal energy produced by the laser system is sufficient to melt the powder at the point of incidence and re-melt the surrounding solidified powder. Thus, the process is capable of producing well-bounded and high-density parts [3]. The following subsections will provide a brief description of the process and its parameters.

2.2.1 Selective laser melting process description

Like all AM process technologies, SLM has many parts and parameters. A good understanding of the process will lead to better utilisation and optimisation of the process to ensure the quality of the product. The basic structure of the SLM process (see Figure (2.5)) can be described as follows [3], [20]:

1. The laser system: the system consists of two units. The first unit is responsible for generating the primary source of the heat, whereas the second is to control the motion of the heat source over the powder.

2. Powder delivery system: a unit to add and compress the material powder uniformly as a layer.

3. Building platform: a place where the part is printed. After completing the scanned layer, an elevator shifts down the building platform and allows the powder delivery system to add the new layer.

4. Collector: a unit to collect the extra powder.

5. Enclosed chamber: a closed space to control the ambient condition.

Due to the significant impact of the laser system on the process, the following subsection will provide further elaboration on it.

2.2.2 Laser source types and its impact

The laser beam is a crucial element in the LPBF process as it acts as the heat source to selectively melt the powder. There are various types that can be used, each with its own characteristics and applications. The choice of laser significantly impacts process efficiency, part quality, and material compatibility. The laser source can be classified based on the

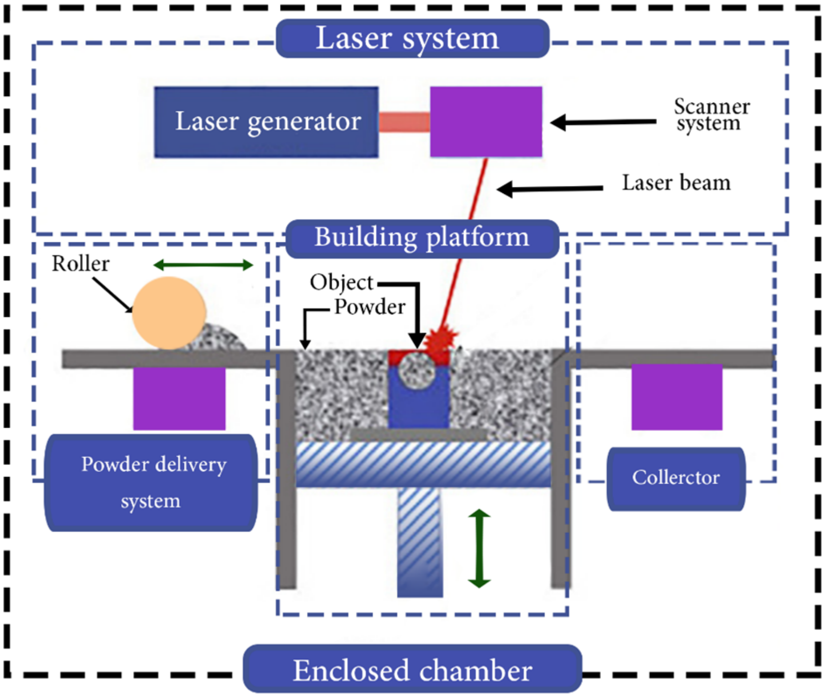


Figure 2.5.: The basic structure of the SLM process.

delivery technique as a continuous wave or modulated source. Table (2.1) provides a brief comparison between the two classes.

Table 2.1.: Comparison between the laser source delivery techniques.

Feature	Continuous Wave	Modulated Laser	Ref.
Beam Emission	Constant uninterrupted beam	Power cycled on and off rapidly	[27]–[29]
Heat Input	High	Lower compared to CW	[27], [28], [30], [31]
Melt Pool Size	Larger	Smaller and more precise	[27], [28], [30], [31]
Surface Quality	Potential for rougher surface	Potentially smoother surface	[27]–[29], [32]
Warping/Cracking	Higher risk	Lower risk	[27], [28], [30], [31]
Material Processing	Efficient for high-melting -point materials	Suitable for finer details and potentially heat-sensitive materials	[27], [28], [30], [31]
Application	Priority is melting efficiency	Priority is detail and heat control	[27], [28], [30], [31]

2.2.3 Production steps in selective laser melting process

The SLM requires a set of steps to produce the desired parts [33]. The beginning is to convert the 3D CAD model into cross-section layers and save it in a suitable file format. One of the commonly used formats is a stereolithographic file (.STL file). Then, the file is loaded to the machine using specific software. Before starting the printing process, a set of parameters will be selected and configured to ensure building quality. The selection of the parameters will be discussed in the coming section. Then, the powder is deposited in the building area, and a focus laser beam with pre-selected power is used to melt the powder based on the data from the file. After fabricating the first layer, the roller spreads a new layer of powder on the platform. The process is repeated until the final product is complete. Finally, the part can be removed and cleaned manually or with the help of another machine. The remaining or unused powder can be reused after a specific preparation. Figure (2.6) illustrates the steps of part fabrication.

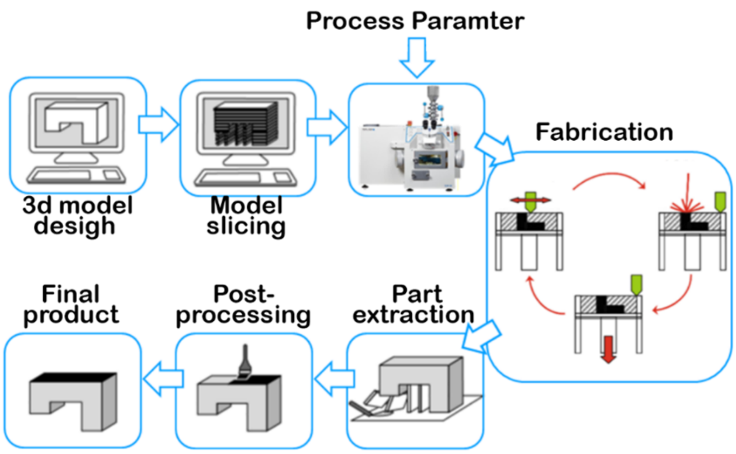


Figure 2.6.: The fabrication procedure using the SLM process [34].

2.2.4 Selective laser process parameter

The SLM process contains more than 150 parameters that have an impact on the process performance [33], [35], [36]. The ones which have a significant effect can be categorised, as shown in Figure (2.7), and they are as follows:

1. Parameters related to the laser system: The laser system is considered to be the most effective part of the SLM process. As mentioned in section (2.2.1), the system is responsible for the primary heat source and how the laser is delivered to the material. The

parameters related to the laser system can be classified into two groups: laser properties (type, power, spot size, and intensity) and scanning methods (scanning strategy, speed, and hatching distance).

2. Parameters related to material properties: There are many parameters related to the powder used in the process. The absorbability property affects the impact of the laser source on the material and how it reacts with the material characteristics. The size, distribution and density of the powder grains are other critical factors that influence the performance of the process and the quality of the product.

3. Parameters related to the process environment: Process environment parameters can be divided into two sections: first, the initial condition of the chamber (the type of gas used, the initial temperature), and second, the current condition of the process (temperature and humidity).

4. Parameters related to the printed part: The dimensions and orientation of the fabricated part affect the building process. It specifies whether support is required or not. Besides, they affect the mechanical properties of the fabricated part (such as residual stress, tensile, and surface quality).

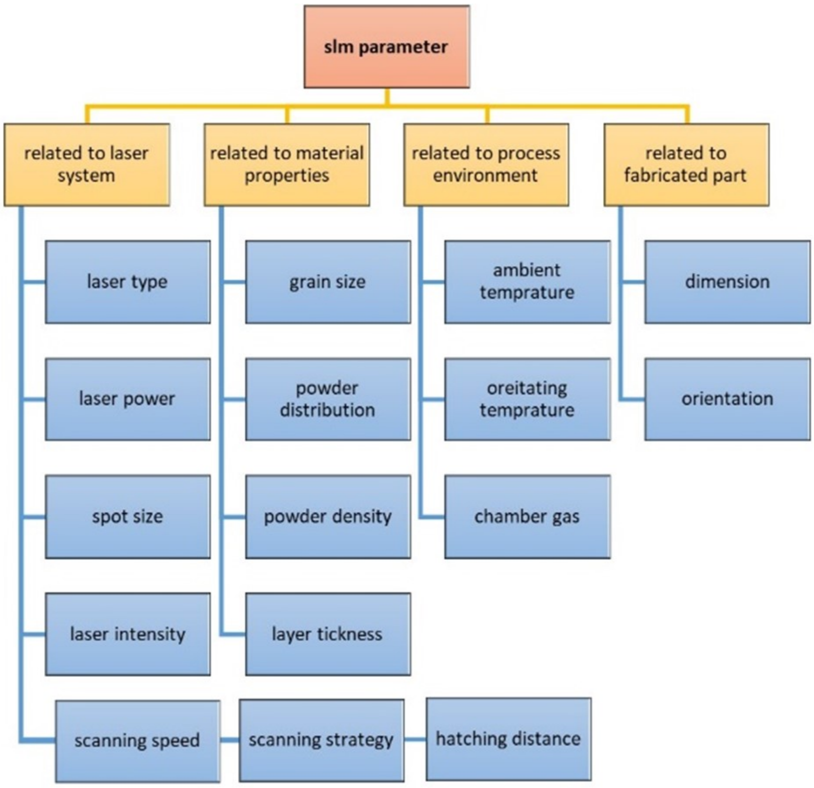


Figure 2.7.: The most significant parameters in the SLM process.

2.2.5 Quality indication of fabricated parts

Additive manufacturing technology's capability usage in industries has reached up to 50 per cent as prototype or end-product [37]. However, to be able to use fabricated parts directly as final products, the process should have the capability to reach the desired industrial requirement of repeatability, reproducibility and reliability. As mentioned before, the process has a wide range of parameters that affect its quality. Nevertheless, some parameters can give an insight into others and have a more significant effect on the process quality. In [2], the product's quality was related to the melt pool dimensions (surface area, width, length, depth, or cross-sectional area). Alternatively, the melt pool temperature was used extensively in the literature to indicate the building quality, residual stress, porosity and surface roughness [8]. A homogeneous temperature field during the fabrication leads to better quality. Therefore, many researchers considered thermal energy (monitoring and control) to be a primary factor that guarantees the final product's quality. From the existing literature, the quality can be assessed from three perspectives:

1. Geometrical (surface area, width, length, depth, or cross-sectional area).
2. Mechanical (strength and fatigue resistance).
3. Physical (defects, residual stress, porosity, and surface roughness).

Unfortunately, most of the assessments are made after the fabrication is completed. This observation points to an active research field, which is the on-line quality assessment of the product processed by such a machine, and this is where the current research work will focus. The coming chapters will present how to relate the quality indications with the process parameters via a mathematical model that helps to understand the process, optimise its parameters and enhance the quality of the final product.

2.3. SLM monitoring system overview

PBF-LB process monitoring is crucial for monitoring the quality of parts and is a milestone in establishing an online control system for the process. Process monitoring for the LPBF process is an active research area because of the complex interplay between process parameters, melt pool dynamics, and final part quality. Although this research focusses on modelling and control, this section will briefly introduce the various techniques that have been explored to gain real-time insight into the PBF-LB process.

Pyrometry is a commonly used technique to monitor the characteristics of the melt pool. This non-invasive method uses electromagnetic radiation to measure temperature and provides absolute temperature data of the melt pool surface. It offers valuable information about heat efficiency and potential overheating. However, challenges arise when the size of the melt pool becomes smaller. In addition, careful calibration of the sensor is required to account for the emissivity of the material.

With the advancement of sensing technology, a spectral emission monitoring technique is used to analyse the light emitted by the melting pool. This technique can provide insight into the process stability and material vaporisation. However, the method requires complex data processing.

Eddy current testing is another monitoring technique used to monitor the quality of the printed part. The method can detect cracks on the surface. The method utilises complex analysis methods that limit its application. The method is limited in its penetration to deeper flaws and in its sensitivity to variation in temperature during the process.

Table (2.2) provides a list of the commonly used sensors in monitoring the LPBF process.

Table 2.2.: Commonly used the sensor to monitor the melt-pool characteristics.

Sensor Type	Measurement Principle	Advantages	Limitations	Applications	References
Pyrometry	Measures thermal radiation emitted from the melt pool to determine the temperature	1. Provides real-time temperature data 2. Non-contact method	1. Sensitive to changes in emissivity 2. Accuracy can be affected by surface conditions 3. Limited to surface temperature measurements	1. Melt pool temperature monitoring 2. Ensuring consistent melting and solidification	[38]
Infrared (IR) Cameras	Captures thermal images to provide a temperature distribution over the powder bed and melt pool	1. Real-time thermal imaging 2. Wide area coverage 3. can detect hotspots and uneven heating	1. Higher cost compared to pyrometers 2. Requires calibration and proper setup 3.Resolution can be limited by pixel size	1. Monitoring temperature distribution 2. Detecting thermal anomalies 3.Ensuring uniform heating and cooling	[39]
Optical Emission	Analyzes the light emitted from the melt pool to determine chemical composition and process quality	Real-time compositional analysis	Complex data interpretation	Monitoring melt pool composition	[39]
High-Speed Cameras	Captures high-frame-rate images or videos of the melt pool and powder bed dynamics	1. Visual feedback on process dynamics 2. Can identify spatter, balling, and incomplete melting 3. Useful for process optimization	1. High data volume for storage and analysis 2. Requires proper lighting and setup 3. Limited to surface observations	1. Monitoring melt pool behavior 2. Observing powder spreading 3.Identifying defects in real-time	[40]
Eddy Current Sensors	Detects changes in electromagnetic properties to identify subsurface defects	1. Effective for non-destructive testing 2. Can identify internal anomalies 3. Useful for quality control	1. Limited to conductive materials 2. Interpretation of data can be complex 3. Sensitive to material properties	1. Detecting cracks and voids 2.Assessing material integrity	[40]
Acoustic Emission	Captures sound waves generated during the melting and solidification process to detect process anomalies	1. Non-contact 2. Non-destructive	Interpretation of acoustic signals can be challenging	1. Identifying defects 2. Irregularities in real-time	[41]

2.4. SLM control system overview

SLM offers a design process with fewer limitations, leading to a revolutionary design in various fields. It allows the production of complex shapes with lightweight internal channels that can improve product performance and meet industrial specifications [5]. Unfortunately, despite all the advantages of SLM, the quality, repeatability, and reliability of metal parts still obstruct their widespread adoption within applicable manufacturing processes. The process contains complex underlying physical phenomena and transformations that occur during the process in a short period of time [7], [42]. These facts mean that the optimisation problem is exceptionally challenging and becomes more complex as the complexity of the designed part increases. In the last two decades, extensive research efforts have been made around the world to model and control AM processes [7], [12], [43]. The investigations emphasise the importance of control systems to enhance product quality. The following subsections present an overview of the control systems applied to the existing SLM machine and the efforts to enhance the quality of the produced part by introducing a control system to the process.

2.4.1 Applied control techniques

Most of the existing SLM and other AM processes are based on constant parameters [8]–[10]. These parameters are determined by trial and error before the process and fixed during fabrication. Research investigations have shown that maintaining the parameters unchanged increases the heat-affected zone [9]. Consequently, heat accumulation causes irregularity in the morphology of the melt pool, excessive dilution, thermal distortion, and cracking. Thus, the properties of the produced parts cannot be guaranteed. The predetermination of an optimal processing set of parameters for specific mechanical properties is used to enhance product quality [44]. However, the technique is neither economical nor robust enough to deal with disturbances.

To address these issues, various process control solutions have been developed and implemented. The following table provides an overview of these solutions used in metal additive manufacturing. It includes the advantages and limitations of each solution, the control level, the companies involved, and the specific parameters or outputs controlled by each method.

In most rescent AM machines various process control solutions have been developed and implemented. The purpose is to ensure consistent part quality and minimise errors. These solutions update to control actions at different levels, such as off-line, on-line, continuous, every track/layer, and off-line optimisation.

The following table (2.3) provides an overview of the process control solutions used in metal additive manufacturing. It includes the advantages and limitations of each solution, the control level, the companies involved, and the specific parameters or outputs controlled by each method.

Table 2.3.: Overview of modern process control solutions in metal additive manufacturing.

Process Control Solution	Advantages	Limitations	Control Level	Companies	Controlled Parameters/Outputs	References
In-situ	1. Real-time data and immediate feedback for adjustments. 2. Quality control, defect reduction, optimization	High cost, complex integration, potential for noise interference	Continuous	EOS, GE Additive, Renishaw, SLM Solutions	Melt pool characteristics, process parameters (laser power, scan speed), defects	[45]–[48]
Ex-situ	1. Less expensive, easier to implement 2. Can be applied to multiple builds. 3. Customization, efficiency, enhanced control	Delayed feedback, the potential for missed issues	Layer-by-layer	Renishaw, Trumpf, Additive Industries	Part geometry, surface quality, mechanical properties	[47], [49], [50]
Process Simulation	1. Predictive capability 2. Optimization potential 3. Cost-effective	Model accuracy depends on input data, computational resource intensive	Offline	FEA, CFD	Process parameters, melt pool characteristics, part geometry, microstructure, mechanical properties	

2.4.2 Efforts in designing on-line control systems

Using an on-line control system can compensate for disturbances and minimise the heat accumulation during the process, thus improving the quality of the produced parts. Different control algorithms were implemented and investigated, varying from classical to most advanced controller techniques. Substantially, most of the researches used the thermodynamic and/or the melt-pool geometry as a key to define the product quality during the fabrication [42], [51]. The first term is related to various defects (porosity, deformation, and cracking) and phenomena (keyhole, rippling, swelling). Whereas the second is related to microstructure evolution and thermo-mechanical properties. Irrespective of the used term, both are related to energy density which can be controlled by varying laser power, scanning speed, and scanning strategies [52]. The following context summarises the previous efforts in on-line control approaches of the SLM process.

Proportional (P) and Proportional-Integral (PI) controllers were used in the first attempts to investigate the controllability of the melt pool size by varying the power of the laser source [53]–[55]. In both attempts, a second-order model of the process is used to select the controller parameters. The model was identified using experimental data using a high-speed CMOS camera and photodiode to capture the system response. The studies presented the effectiveness and importance of the on-line control algorithm. An illustration of the effect of the applied algorithm is present in Figure (2.8).

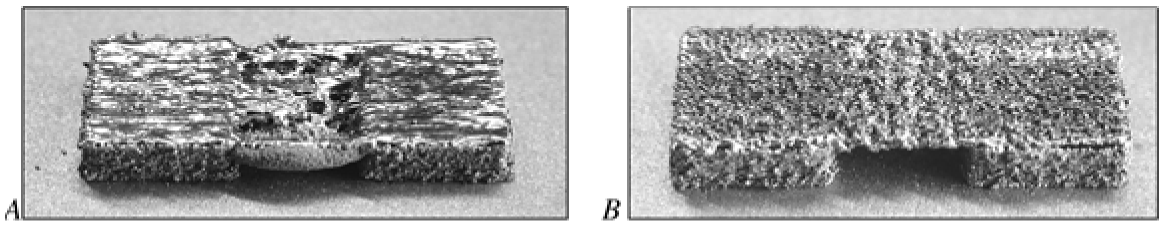


Figure 2.8.: Printing attempts with fixed laser power (A) and with a feedback controller (B).

With the development of measurement and processing equipment, more developed algorithms were investigated. In [10], [56], a combined control system consisting of a feed-forward control and a P-controller was proposed. The designed controller regulates the temperature of the melt pool by varying the input power to the system. The strategy showed a fast response to the change in the temperature and promising results for practical implementation with a reduction of 73% in temperature deviation compared to the open-loop system. Despite that, the experimental implementation was limited to a multi-track scenario. In this work, the advantage of parallel processing was utilised using FPGA.

A few research efforts investigated a particular phenomenon. In [8], a feed-forward (FF) controller was applied to overcome the issue of overmelting and keyhole formation. The approach was used before for DED processes and showed promising results. The controller was based on an analytical control-oriented model that considers the temperature history of the previous track. The experimental result of multi-track-single-layer printing showed a reduction in the over melting and disappearances of keyholes. Additionally, a reduction in the average error rate by 23% was recorded compared to fabrication with a fixed laser power.

Whereas the previous works focused on controlling the melt pool parameters within the scanning vector, a layer-wise control approach was introduced in [5]. In such a method, the previous layer's information is gathered, analysed and then used while processing the following layer to correct the deviation from the desired performance. They measured the melt pool area using a metal-oxide-semiconductor camera. Based on the information provided from the feedback, the energy density was changed in the new layer. The study showed the effectiveness of the approaches to overcome heat accumulation and reduce the swelling phenomenon's effect.

With the various phenomena and the complex physics involved in the SML process, it is very challenging to get an accurate model that can lead to precise control design. Therefore, model-based control systems have limitations in their performance. Various research groups were interested in studying the feasibility of using the Model-Free Control (MFC) system. In [57], [58], an Iterative learning control algorithm (ILC) is used to regulate the power profile within the scanning segment based on live measurement from the coaxial camera. In [59], the same concept was applied in addition to a data-driven model to predict the system's performance and reduce the effect of the complex geometry and temperature history. The deep-learning (DL) and machine learning (ML) concepts were used in [60] to predict the distortion during the process. An area of interest was defined by a cylinder presenting the information near and below the operating point. The suggested approach presented the system as an optimisation problem and solved for best input using an ILC algorithm based on the previous and on-line data. Conclusively, the efforts demonstrated the feasibility of deriving the process using the on-line data only without the need for a mathematical model. However, the repetitive behaviour, which is the base of the suggested algorithm, cannot be held for complex parts.

In [61]–[63], the authors built a controller based on a difference model. The first study proposed a batch model predictive control to temperature of the melt pool. The controller can handle the repetitive and non-repetitive disturbance during the process. The second work utilised state-feedback control to regulate the thermal behaviour of the process. Whereas the two previous works were concerned about in-layer control, the third investigated the use of ILC to update the control signal every layer.

The scope of research was not limited to controlling the laser power or scanning speed. A few groups were interested in studying the effect of scanning speed and scanning path on the melt pool size and temperature, such as [64], [65]. The investigation showed that the residual stress and distortion could be minimised. However, all the existing industrial processes come with pre-sited scanning strategies. In [12], [66], the focus was on monitoring and control of the surface roughness using coherent imaging. The roughness was improved by post-processing using laser pulses and refilling the gaps.

Table (2.4) summarises the control efforts found in the literature and discussed in this chapter.

Table 2.4.: Current Control efforts for SLM processes.

Control Objective	Control strategy	Control variable	Process Signal	Ref
To investigate the controllability of the SLM process using feedback	P and PI control	Laser power	Melt-pool geometry	[53], [67]
To overcome the overheating problem and keyhole formation	FF			[8]
To control melt pool temperature at sufficient time	FF combined with P- controller		Temperature profile	[10], [56]
To avoid heat accumulation	Layer-wise			[5]
To control the temperature profile of the scanning segment	Model-free-ILC			[57]–[59]
To investigate the feasibility of ML control system	ML-ILC			[60]
To improve the surface quality of the product	-		Surface geometry	[12] and [66]
To investigate the effect of scanning path strategy	Open-loop control	Scanning path	Melt-pool geometry	[64], [65]

2.5. SLM Modeling overview

Modelling and simulation of the additive manufacturing process are essential research fields. They play an important role in accelerating the design and production time by reducing (eliminating in some cases) the need for actual trials, in addition to their role in helping with understanding the process underlying physics and the role of different process parameters. Throughout the last twenty years, The interest in such an area grows rapidly, as Figure (2.9) indicates.

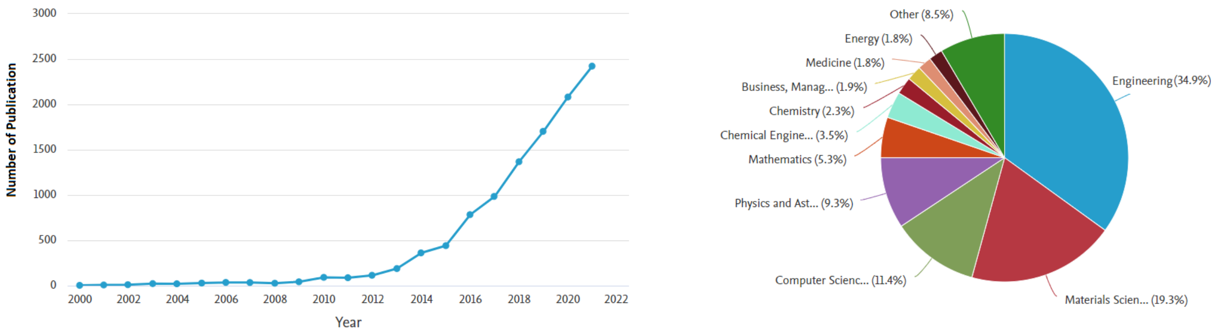


Figure 2.9.: Number of publications regarding modelling and simulation in additive manufacturing per year (left) and the percentage of publications in various research areas (right) [23].

The process encompasses diverse effects from several physics phenomena, which makes the modelling process a challenging task. As was mentioned earlier, there are more than 150 parameters affecting the process during different manufacturing stages. Thus to simplify the investigation, researchers focus on a specific part of the entire process. In [68] the areas of research were classified generally into five categories 1. Process modelling; 2. Microstructure modelling ; 3. Properties modelling; 4. Performance optimization modelling; and 5. Topology and process optimization. Whereas in [8], the authors used the working scale as a classifier for model types. They classified the models into the following: 1. Macroscale: the scale of the part as a whole; 2. Mesoscale: the scale of the powder particles and melt pool and 3. Microscale: the scale of crystalline microstructure. In terms of the number of tracks and layers, the research can be divided into single-track single-layer, single-track multi-layer, multi-track single-layer, and multi-track multi-layer. Single track parameters (width, height, depth) can be used as indicators for the quality geometry accuracy of the building parts. On the other hand, the multi-track and multi-layer model and simulation are used to investigate and enhance the product surface finishing (top, bottom, and sides) and minimize porosity. Each of these classes can be further subdivided to understand the role of specific parameters in certain phenomena.

Since critical phenomena, such as energy deposition, powder fusion, melt pool dynamics and solidification, spattering and denudation, which are responsible for the properties of the fused material, its morphology (pores, cracks, etc.) and part surface quality, occur at the mesoscale [14], the modelling at such a level can be crucial in correctly predicting the properties of the fabricated part. Thus it was chosen that the model investigation in this research belongs to this scope.

There are many modelling efforts that can be found in the literature. The vast majority of the effects were related to modelling the thermal dynamics of the melt pool. That is because many properties are related to the temperature of the substrate during the process. The models were physics-based or -most recently- data-driven based. There are ODE, PDE, linear, non-linear, and empirical models [8], [69]. With all of these existing models with different diversity, unfortunately very few models describe the selective laser melting process, and fewer are control design oriented.

The PDE models were handled using numerical methods such as Finite Element Analysis (FEA), which is not possible to be used for real-time process control due to the higher computation complexity. A data-driven model presents a powerful tool though it also faces challenges. The quality of such models depends on the amount of available or accessible data; the shortage of accurate data is a significant obstacle that questions its accuracy. A physics-based-control-oriented model is considered a valuable alternative that can capture the required specification and be simple enough to design an on-line control.

The idea of using a physics-based model can be traced back to the welding process, where a model was proposed in [70]. The model was used to predict the melt pool geometry while simulating a single-track melt deposition process. The model was extended and reused for different additive manufacturing such as direct energy deposition and a cladding process [71]–[80]. In [8], the concept was accommodated for the SLM process. The target was to develop a control-oriented model that can capture the behaviour of the melt pool and can be used to design a controller.

The previous research work by Wang and his team was the only existing work that described the SLM process using ODEs in a form that a controller can be designed systematically. However, the study was limited to a multi-track, single-layer investigation and a single type of controller utilised to construct a feed-forward control structure. Therefore, one of the goals of this study is to extend the model implementation and investigation to a multi-track and multi-layer level, as the coming section will state.

2.6. Limitations and challenges

With all the advantages that SLM processes have, there are several concerns about the repeatability and reproducibility to adapt the technology worldwide [21], [81]. Almost all the existing research efforts were limited to single-tracks or elementary shapes, which ignored the ability of AM to produce complex parts that cannot be fabricated (or are difficult to be fabricated) using traditional manufacturing technologies. An in-depth investigation of the control systems' performance with complex shapes is required to fulfil SLM's practical application. From the control perspective, the following summarises some of the various challenges and opportunities based on the conducted literature.

2.6.1 Challenges

Based on the literature above, a couple of gaps can be seen, which can be divided into two categories as follows:

- The first is related to the model development, where the second is related to control strategy. The lack of an adequate process model that can be used to design a practical on-line control algorithm was noted. The previous efforts showed that suitable physics-based-control-oriented models barely exist for SLM processes and data-driven models are still underdeveloped. Additionally, since the data-driven model's quality depends on the amount of available or accessible data, a real data shortage is a significant obstacle for any implementation.

- From the control point of view, the literature shows the unavailability of fast enough control systems. The proposed techniques were designed based on simple model that cannot accurately capture the dynamics of the process. The processing speed is considered as a challenge and a limitation to implementation on an on-line control system. That narrowed the control technique options. From the level of control (in-layer, layer-wise, and surface quality) point of view, almost all the efforts targeted a specific scenario without investigating the effect of combining them.

- Since the control system investigation is an emerging aspect in the research field of SLM process, most of the existing software are not equipped with tools that can help in this field, as the literature showed. The existing tools either permit, provide or pre-optimise parameters or allow the use of other software to take care of the control investigation, such as the combination of Matlab with ANSYS. One of the common challenges for most of these software is computation cost, due to the adoption of a numerical methods such as finite element method, finite volume method, finite difference method and molecular dynamics [82].

2.6.2 Future opportunities

With the aforementioned challenges and limitations, the following future opportunities can be seen.

Opportunities in model development

The existing models need to be extended to include the behaviour of the process while producing complex shapes. The model improvement can involve the temperature history of the built tracks and layers. A physics-based-control-oriented model is considered a valuable alternative that can capture the required specification and be simple enough to design an on-line control. Using the leverage of similarity between SLM and other AM process, a model can be developed to fit the process.

Opportunities in control system development:

As can be witnessed from the conducted literature, more investigation is required in this area. In terms of the classical control method, the methods require more investigation to consider the performance of the system in different levels of control (in-layer, layer-wise, and surface quality). Fuzzy logic theory presents a middle ground between the simplicity of the classical controllers and the complexity of the advanced control methods. Thus, it is worth deeply investigating the use of fuzzy controllers to enhance the quality of metallic AM processes and to evaluate the method's strengths and limitations in this context.

Opportunities in developing simulation platform for control purpose:

The literature showed the need of an adequate model for researching and evaluating control systems and simulating their effectiveness. This issue is interconnected with another critical aspect discussed in which concerns about the integration of these technologies into the educational sector. Such integration is crucial for sustaining the advancement of the field and for supplying the industry with skilled professionals in this domain. Therefore, the development of control-orientated models and simulation tools has become an influential factor in advancing our understanding and utilisation of SLM.

Thesis contributions

Our research in this chapter has reviewed the existing literature and identified several gaps in the current efforts. Based on that, our contributions to the field of SLM technology is significant and will advance the state-of-the-art. It also lays a strong foundation for future research and development in control systems for additive manufacturing. The importance of the contribution can be summarised as follows:

1. Exploring control system Applications and identifying challenges: Previous studies have often focused on process optimization and material properties, neglecting the critical role of control systems in ensuring part quality and process reliability. By highlighting the current challenges and future opportunities in this area, we shed light on a crucial aspect of SLM technology that has been underrepresented in the literature.

2. Extension of physics-based models: The extension of physics-based models to multi-layer and different shapes, along with the evidence of a fast simulation technique, addresses a key gap in the SLM process. Previous simulation methods have been time-consuming and computationally intensive, hindering their practical utility for process optimization and control. This work offers evidence of an approach that significantly reduces simulation time while maintaining accuracy, thereby enabling more efficient and scalable analysis of melt-pool dynamics.

3. Development of MATLAB-based simulation tool for control investigations: The development of a MATLAB-based simulation tool for control investigations fills a critical gap in the literature by providing researchers and practitioners with a user-friendly platform for exploring control strategies in the SLM process. Previous studies have lacked accessible and versatile tools for evaluating control algorithms and assessing their impact on process performance. Our tool enables rapid prototyping and evaluation of control systems for SLM applications.

4. Investigation of control implementation during build process and Fuzzy Logic Controller design: Our investigation into control implementation during the build process, including in-layer and layer-to-layer control, represents a significant advancement in the field of SLM technology. Previous control strategies have typically focused on post-processing adjustments or monitoring, neglecting the potential benefits of real-time control during

the printing process itself. Additionally, our exploration of fuzzy logic control represents a novel approach to control system design in the SLM process. Previous studies have primarily focused on conventional control techniques, overlooking the potential advantages of fuzzy logic for handling the inherent complexity and variability of the SLM process.

By addressing these critical gaps in the existing literature, our contributions significantly advance the state-of-the-art in SLM technology and lay the foundation for future research and development in control systems for additive manufacturing.

2.7. Chapter summary

The purpose of this chapter is to provide an overview of the context of the research. It begins by briefly introducing the technology of additive manufacturing, including its classification and various applications. The focus then shifts to the laser powder bed fusion process, specifically the selective laser melting method. The chapter covers the production steps, key parameters, and quality indicators. Moving on from the introductory sections, the chapter goes deep into the core objectives and context of the research: controlling and modelling the process. It discusses existing efforts, ongoing challenges, and potential research opportunities in this area. Finally, we established a connection between the research gaps that exist in the field and our contribution towards filling those gaps.

The following chapters will explore the questions raised in this chapter, which mainly focus on extending the existing physics-based model and achieving an effective online control system.

3

Problem Dimensionality, Assumptions, and Parameters Selection

The purpose of this chapter is to establish the scope of our investigation. We will begin by outlining our general assumptions regarding the process, the level of the model, and the material used. We will also provide a list of the parameters that we will be using during the investigation. Finally, we will present the mathematical model of the process, including its derivation from basic physics, and explain the solution method.

3.1. Process assumptions

As the aforementioned chapters presented, the selective laser melting process has a large number of parameters that affect its performance. Considering all of them in a single model is an infeasible target to achieve. The following context will set out the borders of the current investigation by stating the different assumptions taken into account and how the different process parameters are selected.

3.1.1 General assumptions

The focus of our investigation will be on the thermal behaviour and geometry of the melt pool. The laser power will be considered as the input to the system that influences the desired outcome of the system. During the investigation, the process is assumed to operate under perfect conditions, such as the process environment (controlled chamber temperature, constant humidity, constant pressure, etc.) and the powder used is isotropic [1]. Furthermore, all material properties are assumed to be temperature-independent in order to simplify the model. The assumptions will simplify the consideration of process parameters that have a range of values over the process temperature. In terms of model classification [2], the model that will be used in the investigation is a mesoscale[3] model. The model will relate the laser power as input to the melt-pool geometry as process output. However, part of the investigation will also present the impact of laser power on the melt-pool temperature.

3.1.2 Melt-pool shape assumptions

The melt-pool geometry shape can be divided into two regions, front and rear [83]. The front represents the area with direct exposure to the laser beam, whereas the rear area is outside the laser spot. Thus, the area of interest is the front part which can be estimated to be half an ellipsoid. Figure (3.1) illustrates the schematic diagram of the melt pool where l,w,d are the length, width, and depth of the melt pool, respectively. The area of the interface of the melting pool with the solid below the free surface and to the top of the free surface is denoted as A_s and A_G, respectively. Then volume $V(t)$ and maximum cross-sectional area

[1]Isotropic: homogeneous and the heat is distributed in equal direction
[2]The model's classifications were discussed in chapter one.
[3]A model that is simulated in the scale of powder particle and melt pool.

$A(t)$, A_s, and A_G can be expressed as the following:

$$A(t) = \frac{\pi}{4} w(t) d(t) \tag{3.1}$$

$$V(t) = \frac{\pi}{4} w(t) d(t) l(t) \tag{3.2}$$

$$A_s = \frac{\pi}{\sqrt[3]{2}} (wdl) \tag{3.3}$$

$$A_G = \frac{\pi}{4} (wd) \tag{3.4}$$

Assuming that the melt-pool shape has a fixed value for length-to-width ratio β and a

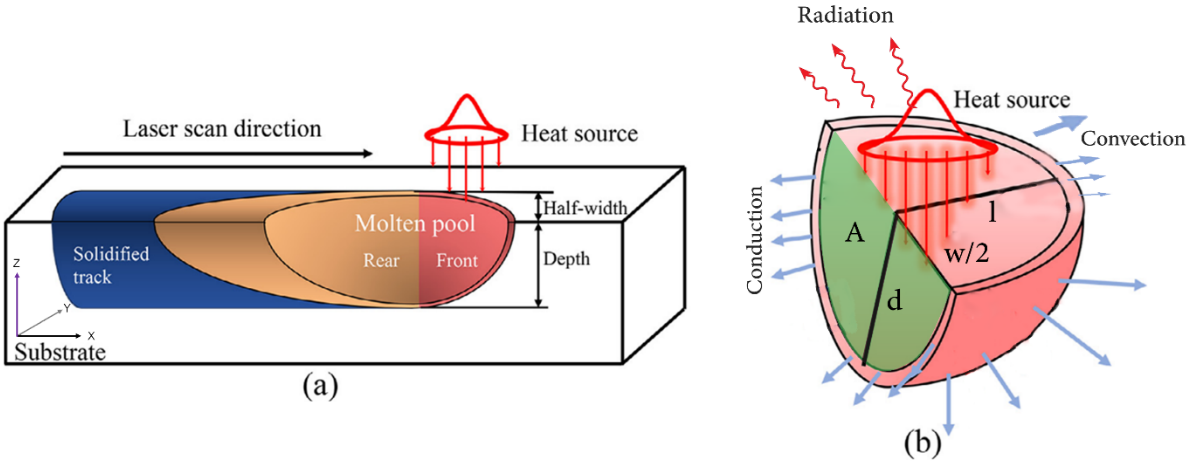


Figure 3.1.: a) The melt pool formation and scanning direction b) The melt pool's front area dimensions.

width-to-depth ratio r, then equations (3.2-3.4) can be rewritten as:

$$V(t) = \lambda A^{3/2}(t) \tag{3.5}$$

$$A_s = \lambda_s A(t) \tag{3.6}$$

$$A_G = \lambda_G A(t) \tag{3.7}$$

where

$$\lambda = \frac{4}{3} (r/\pi)^{1/2} \beta \tag{3.8}$$

$$\lambda_s = 2^{5/3} r^{1/3} \beta^{2/3} \tag{3.9}$$

$$\lambda_G = r\beta \tag{3.10}$$

The assumption of constant dimension ratio helps to distinguish between the melt-pool in its right shape (if r is equal to 2) or it becomes a keyhole (if r is significantly larger than 2) [8].

3.2. Parameters selection

The selection of the process parameters and the material properties that will be used in the model derivation and in the simulation, presented in the next chapter, are based on a mixture of previous investigations and practical considerations of existing machines. The following subsection will introduce the material and the machine used in this research and its parameters.

3.2.1 Material properties

In this research work, the Ti-6Al-4V powder will be used. The titanium alloy is one of the most commonly used alloys in the literature and industry [68]. It has a wide range of applications, including in the aerospace and biomedical fields. The parts manufactured with titanium have the features of being lightweight and having a robust structure [84].

The parameters that will be used in this investigation are listed in Table (3.1). To fulfil the assumption that the parameters of the material are temperature-independent, for the parameters that have a range of values based on their state (solid or liquid), the average value is used.

As we shall see later, the model is sensitive to variations in the selected parameters. Even slight adjustments to these parameters can lead to significant changes in the thermal and geometrical behaviour of the melt pool. For example, when we varied the laser absorptivity (transmission efficiency), the model showed noticeable differences in the dimensions of the melt pool and its temperature distribution. The figures (3.2) and (3.3) illustrate how changing the laser absorptivity ratio clearly influences the behaviour of the melt pool.

This sensitivity emphasises the need for precise selection and control of parameters in the SLM process. Minor deviations can significantly affect the final quality of the construction. Therefore, further refinement of the model is necessary to improve its robustness and ensure consistent performance in a wider range of operating conditions.

3.2.2 Process parameters

There are several L-PBF machines that exist in the industry. However, for industrial research purposes, AconityMINI form Aconity3D is considered a great alternative. The machine is

Table 3.1.: Ti6Al4V powder parameter used in this investigation.

Parameter	Symbol	Value
Material density (kg/m^3)	ρ	4430
Melting temperature (K)	T_m	1923
boiling temperature (K)	T_b	3133
Ambient temperature (K)	T_a	292
Liquid material specific heat (J/kg K)	c_l	700
Solid material specific heat (J/kg K)	c_s	405
Material specific heat (J/kg K)	c_{sp}	694
Thermal conductivity (W/mm K)	k	0.0067
Thermal diffusivity (mm^2/s)	a	2.48
Convection coefficient (W/m^2 k)	α_s	24
Heat transfer coefficient (W/m^2 k)	α_G	20
Surface emissivity	ϵ	0.9
Laser transmission efficiency	η	0.3,0.4
Temperature ratio	μ	0.2
Melt-pool width-to-depth ratio	r	1.75
Melt-pool length-to-width ratio	β	10
Specific latent heat of fusion (J/kg)	h_{SL}	2.84E+05

an open-access machine in such a way that the monitoring units can be modified as the investigation requires. It is equipped with a pyrometer and thermal imaging camera. Table (3.2) presents the process specification.

It is crucial to consider that the selection of machine parameters must yield an adequate energy density to ensure the powder's melting without excessive power input. Assuming fixed parameters except for the laser power and scanning speed, Figure (3.4) depicts the permissible range for the required energy density. Further details on this range can be found in [85]. In our upcoming research, we will be focusing on treating the model/system as a single input single output system. As a result, the speed will be fixed, and the only variable will be the laser speed. This approach will restrict the power range, ensuring that we do not exceed an energy density of 60-240 watts in an ideal case.

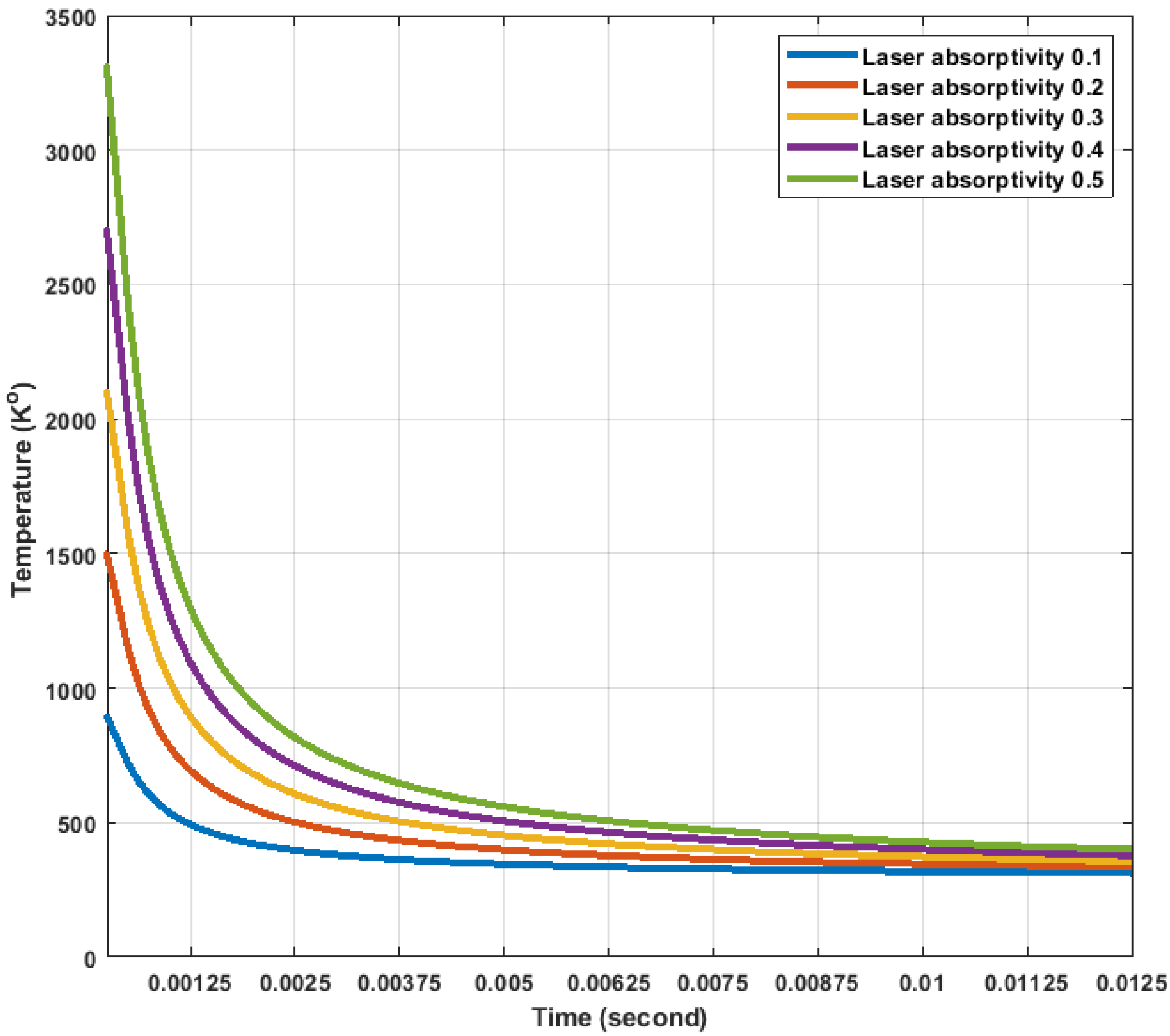


Figure 3.2.: The heat accumulation with respect to various laser absorptivity ration

Another important factor in the machine is the scanning strategy[4]. In this work, the laser is assumed to move back and forth, and all the path segments are not connected. Figure (3.5) illustrates the movement of the heat source during the printing process where the laser source is moving along the x-axis.

3.3. Model of L-PBF process

Generally, numerical and analytical models are used to describe the behaviour of the L-PBF process. Both options are based on solving the heat equations. The following section will introduce the heat equation that will be used in our investigation and the difference between

[4]Scanning strategy: presents how laser source is moving during the process.

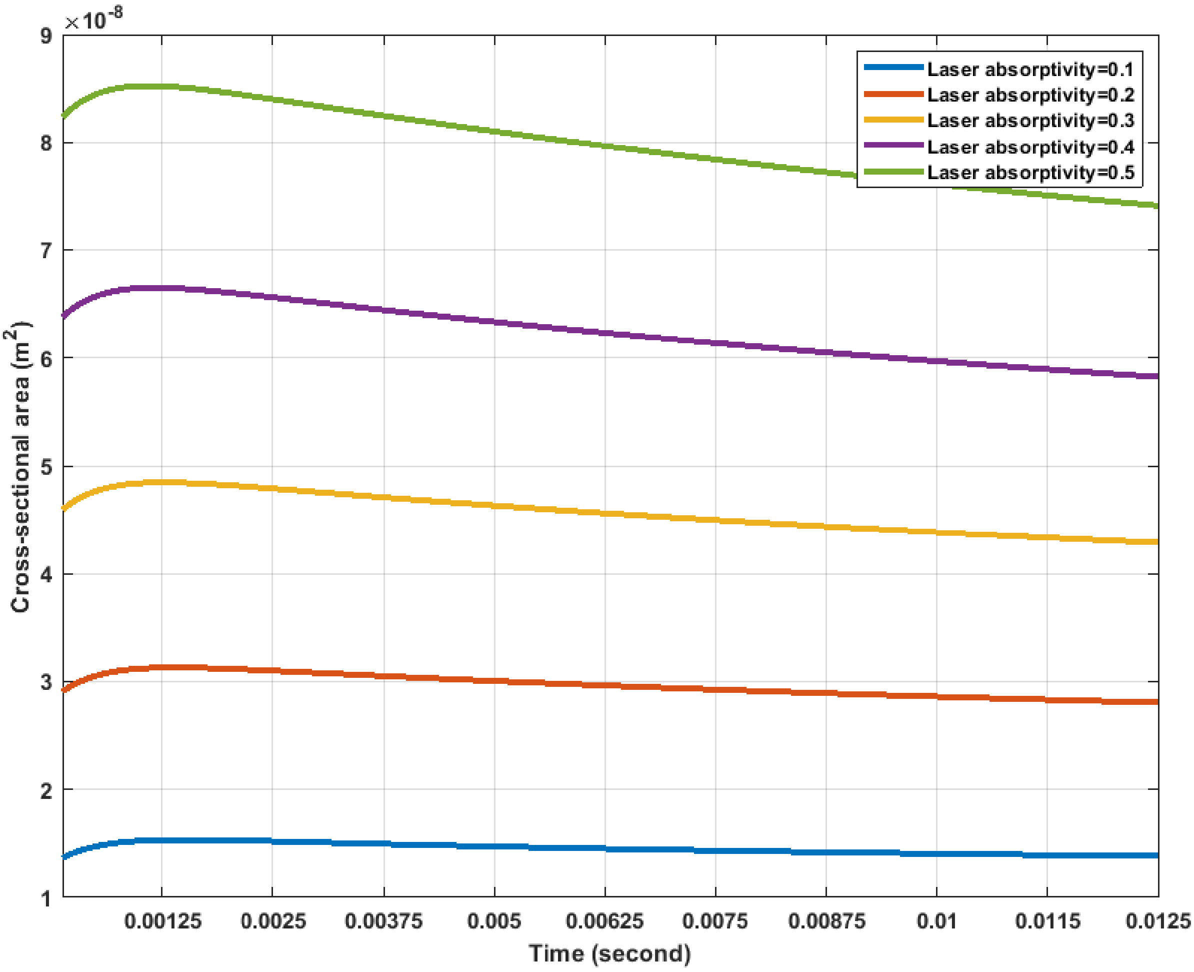


Figure 3.3.: The melt pool corss-sectional area with respect to various laser absorptivity ration

Table 3.2.: AconityMINI basic specification considered in this research.

Parameter	Value
Building space	140mm * 190mm
Laser level	single mode 200W/400W/500W/700W/1000W
spot size	80-500um
monitoring option	coaxial pyrometer/coaxial high speed CMOS
layer thikness	dwon to 10um
scan speed	up to 12m/s

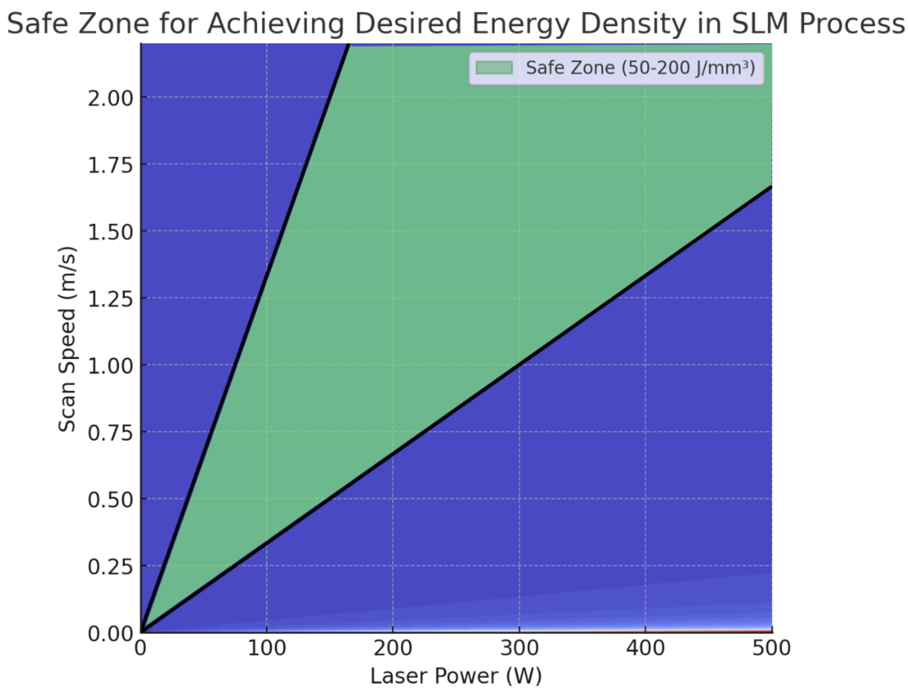


Figure 3.4.: The energy density in relation to scanning speed and laser power.

the two modelling techniques.

3.3.1 Heat balance equation model

Most of the physics-based models for the L-PBF process are based on one of three equations: mass balance, momentum, and heat balance equation [86]. The most suitable form of the equation for the SLM process is the last one since the first two include the powder flow rate, which is not applicable for such a technology [87]. Considering the shape of the melt pool described in the previous section, the energy balance of the melt pool can be given as:

$$\frac{\partial}{\partial t}\left(\rho V\left(t\right) e\left(t\right)\right) = -\rho A\left(t\right) v\left(t\right) e_b + P_s(t) \tag{3.11}$$

where:

ρ is the material density

$e(t)$ is the specific internal energy of the melt pool

$v(t)$ is laser scanning speed

e_b is the specific energy of the solidified bead material

$P_s(t)$ is the total external heat transfer rate from the pool surface.

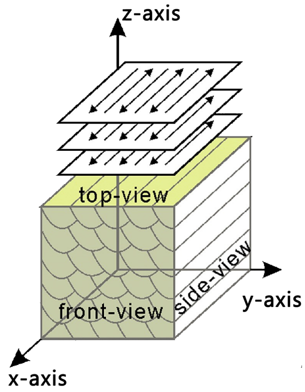


Figure 3.5.: The illustration of the printing process, layer by layer, back and forth in each track.

The left-hand side of the equation represents the rate of change of the stored internal energy. The right-hand side can be divided into two parts; the first represents the energy loss rate to solidify the material, and the second term presents the power absorbed, conducted, convected, and radiated from the pool surface. It is worth mentioning that the convected and radiated power have less impact than the conducted [88]. Thus, in some research, it has been ignored. The specific internal energy of the melt pool $e(t)$ and the specific energy of the solidified bead material e_b can be calculated by:

$$e(t) = c_s(T_m - T_a) + h_{SL} + c_l(T(t) - T_a) \tag{3.12}$$

$$e_b = c_s(T_m - T_{init}) \tag{3.13}$$

where:

c_s is the solid material-specific heat

c_l is the liquid material-specific heat

T_m is the melting temperature of the material

T_a is ambient temperature

$T(t)$ is the average melt-pool temperature

h_{SL} is the specific latent heat of solidification

T_{init} is the initial/ pre-scan temperature.

The total external heat transfer rate from the pool surface $P_s(t)$ is defined as the following:

$$P_s(t) = \eta Q(t) - A_s\alpha_s(T(t) - T_{init}) - A_G\alpha_G(T(t) - T_a) - A_G\epsilon\sigma(T^4(t) - T_a^4) \tag{3.14}$$

where:

η is laser absorption efficiency

$Q(t)$ is the laser power

α_s is the convection coefficient

α_G is the heat transfer efficiency

ϵ is the hemispherical emissivity of the melt surface

σ is the Stefan–Boltzmann constant which is equal to 5.67x10-8

The right-hand terms present the power influx, conductive, convective, and radiative heat loss, respectively. The material and thermal parameters $\rho, c_s, c_l, h_{SL}, \alpha_s, \alpha_G$, and ϵ are assumed to be constant and independent of temperature. Assuming that $T(t)$ reaches much faster to steady-state T_{ss} compared to $V(t)$, and T_{ss} is greater than the T_m by a constant percentage:

$$T \longrightarrow T_{ss} \tag{3.15}$$

$$T_{ss} - T_m = \mu T_m \tag{3.16}$$

where μ depends on the powder material. Then, equation (3.11) can be rewritten as:

$$3/2\lambda e\alpha A^{(1/2)}\frac{\partial}{\partial t}A = -\alpha A(t)v(t)e_b + P_s(t) \tag{3.17}$$

From equations (3.13) and (3.14) it can be noted that $e_b(t)$ and $P_s(t)$ are functions of T_{init}, then the equation can be re-organised as a sum of two functions f and g in compact form as:

$$\frac{\partial}{\partial t}A = f(A(t), T_{init}) + g(A(t))Q(t) \tag{3.18}$$

This equation presents the relationship between the cross-sectional area and the input laser power.

In summary, the model presented by Equation (3.18), considers the material properties of the powder and how it reacts with the heat source (including energy absorption, conduction, convection and radiation factors) in addition to taking into account the initial temperature. The initial temperature presents the heat of the operating point before the laser is applied. It presents the effect of the accumulated heat during the printing process, which can be calculated analytically or numerically, as will be briefly described in the following two subsections.

3.3.2 Solving the model numerically

Numerical models are commonly used to model the L-PBF process [86], [89]. There are various approaches for calculating the temperature and/or the melt-pool dynamic.

One of these approaches is the Finite Element Model (FEM), which simulates the temperature of the melting pool during the process while the heat source is moving. The desired printed part is divided into a set of nodes, and in each simulation step, the heat equation is solved for all the nodes. The nodes are specified by the meshing process of the model. The size and shape of the mesh affect the quality of the simulation result, and there are several ways to select it. However, this choice generally involves a trade-off between simulation quality and computation time. FEA is powerful for complex geometries and material behaviour, but can be computationally expensive for large builds [90].

Another simulation technique is Computational Fluid Dynamics (CFD), which simulates fluid flow phenomena such as melt pool dynamics in laser powder bed fusion (LPBF). CFD uses the finite-volume method (FVM) to discretise the domain and solve governing equations for fluid flow, heat transfer, and species transport. CFD provides insights into melt pool stability, spatter formation, and porosity development. However, CFD models often require empirical data for calibration and may not capture the intricacies of the powder interaction [91].

3.3.3 Solving the model analytically

Analytical models offer closed-form solutions for simplified additive manufacturing (AM) processes, leveraging fundamental physical principles to provide quick estimates of temperature distribution, residual stress, and deformation. These models are advantageous because of their computational efficiency and ability to deliver rapid results. However, their applicability is often constrained to idealised geometries and simplified process conditions, neglecting complexities such as powder packing and detailed laser-material interactions.

One of these approaches to calculating the temperature of the molten point in AM was proposed by Daniel Rosenthal in 1941 [92]. Rosenthal's solution, initially developed for predicting temperature history in welding processes, can be adapted to various AM techniques because of the thermal process similarities. This method extends the applicability of analytical models, offering a balance between computational efficiency and accuracy.

The solution calculates the temperature difference caused by a moving heat source 'i' with constant velocity v on a semi-infinite plate. Considering that the moving source coordinates are (x_i, y_i, z_i), then using the Rosental solution, the temperature at a point of interest (x, y, z) can be calculated as follows:

$$T(x, y, z) = T_a + q_i/(2\pi k R_j)e^{(-v_j(w_j+R_j)/2a)} \tag{3.19}$$

where :

q_i is the source power given by $q_i = \eta Q$

R_i is the distance between the operation point and the heat source

w_i is the distance in the direction of motion between the operation point and the heat source

k is the thermal conductivity constant of the material

and a is the thermal diffusivity constant of the material.
Using the assumption that the material properties are independent of the temperature, Equation (3.19) can be described as a linear equation. Thus if there is more than one source, the superposition principle can be applied. Therefore, for 'n' sources, the initial temperature can be calculated by summing the contribution of all the sources.

$$T(x, y, z) = T_a + \sum_{n}^{j=1} q_i/(2\pi k R_j)e^{(-v_j(w_j+R_j)/2a)} \tag{3.20}$$

Considering the scanning path illustrated in Figure (3.6), the track's endpoint will have a more significant impact on the coming track. Thus, the endpoint of each track will be considered a virtual heat source. Note that the laser path follows a back-and-forth pattern, yet no turn is considered. In other words, the role of the meander is not considered.

To demonstrate the idea, consider the following Figure (3.7). The first virtual source v_1 will be at the end of the first track and will be located at $(s, 0, 0)$, where s presents the length of the track. At any time (t_o) in the second track, the operating point coordinates are $(s - v * t_o, h, 0)$, and the virtual source will be in $(s + v * t_o, 0, 0)$ where h is the hatching distance between the tracks. At the end of the second track, a new virtual source v_2 will be added and will begin to contribute to the initial temperature calculation. The process will continue until the layer is completed. In the next layer, the same process will be repeated; however, the time to add the new layer will be considered, and there will be a change in the z-axis by the value equal to the layer thickness.

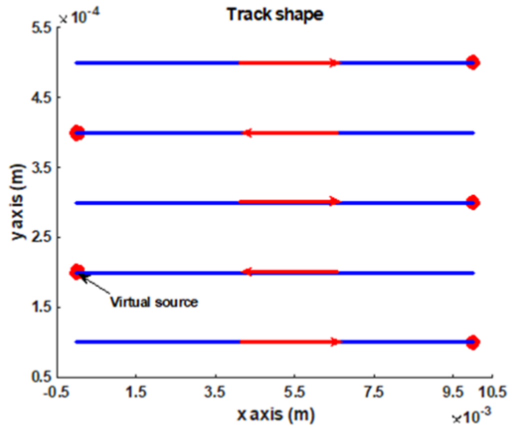


Figure 3.6.: The scanning pattern used in the investigation,where the arrows present the laser scanning direction.

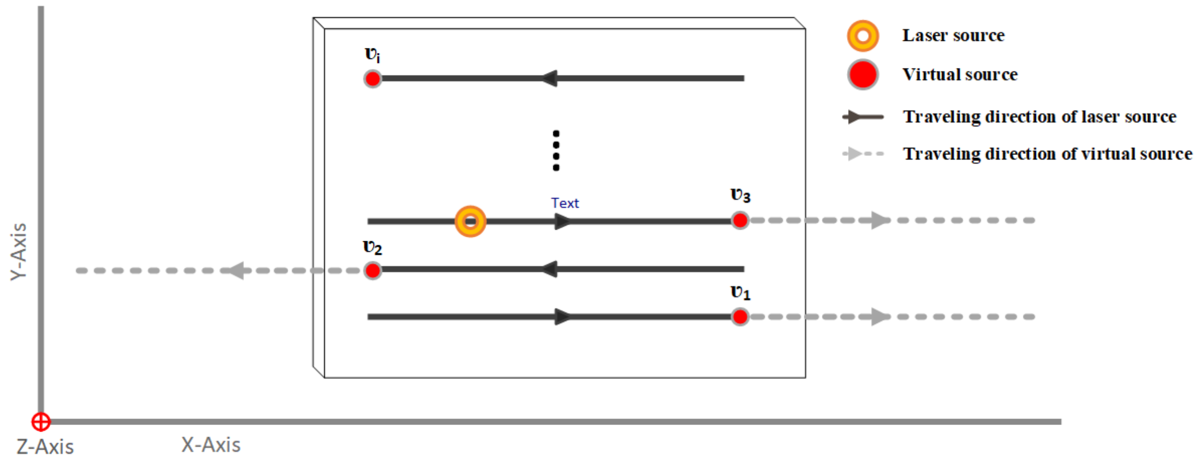


Figure 3.7.: Illustration of laser scanning and the virtual sources location.

3.3.4 The difference between the two computation techniques

As was presented in the two previous subsections, both numerical and analytical methods can be used to predict the behaviour of the melt-pool. Rosenthal's solution provides a quicker solution based on the set assumptions taken into account here. The same assumptions can be considered a drawback of the approach. The effect of the pre-scanned part is simplified and limited to the endpoint of each track. On the other hand, FEM and CFD consider fewer assumptions and provide better estimates. However, the cost is high in terms of computation. From the control perspective, which is part of this project investigation, FEM and CFD are not an applicable candidate to design a controller. Table 3.3 compares the various methods presented in terms of relative speed, computational cost, and accuracy of the solution.

Table 3.3.: A comparison between FEM, CFD and analytical solutions.

Model type	Relative speed	Computational cost	**Accuracy**	Comments
Analytical Solution	10^2 to 10^3 times faster	Low	Medium	Best for quick estimates, limited by assumptions.
FEM	10^3 to 10^4 times slower	High	High	Detailed results, suitable for complex geometries and transient problems.
CFD	Slowest	Very High	Very High	Most detailed, best for melt pool dynamics but highly resource-intensive.

3.3.5 Model linearisation

Linearisation is a widely used technique in the analysis and design of control systems. It simplifies the mathematical representation of a system around a specific operating point. Many real-world systems have highly non-linear relationships between inputs and outputs, making analysing and designing control systems difficult.

Since part of the coming chapter will be tackling the design of classical control systems where the linearised model is required, this section provides the linearised model of the SLM process. Looking back to the derivation of equation 3.18, the source of non-liearity is the area (A). Let the T_{ini} be assumed to be constant,then the model can be rewritten as:

$$\frac{\partial A}{\partial t} = C_1 A(t)^{1/2} + C_2 A(t)^{-1/2} Q(t) \tag{3.21}$$

where the A is the output of the model, the Q is the input and C_i is a constant. The model can be linearised around the A_o and Q_o and expressed as a first-order transfer function in the following form:

$$\frac{A(s)}{Q(s)} = \frac{Ci}{Cj - s} \tag{3.22}$$

3.3.6 Melt-pool temperature estimation

The focus of this research was mainly on the modelling of the cross-sectional area of the melt-pool. However, considering the melt-pool temperature is of great importance. The melt-pool temperature gives an insight into whether area values are realistic or not. If there is a very high temperature (more than 20% above the melting temperature), the area model will still give a value which practically could present the boiling phenomena. The same is applied if the temperature is lower than the melting point.

To estimate the temperature of the melt pool, the basic heat conduction (Fourier's law) is considered. Despite how simple the applied concept is, the model can still capture the required behaviour. The heat conduction equation is given by:

$$Q = mc\frac{dT}{dt} \tag{3.23}$$

where,
Q is the laser power
m is the mass of the material been effected by laser
dT is the temperature difference caused by the applied force
dt is the time that the lase power last in that spot
The total mass affected by the laser source can be deduced from the density (ρ) equation, where the value of the material (V_L) can be calculated by applying the assumption stated in Section 3.1.2. It was assumed that the area under the laser spot is half ellipsoid. Thus, the mass of the material affected by the laser can be estimated by the following equation.

$$m = \rho V_L \tag{3.24}$$

The term $\frac{dT}{dt}$ illustrates the temperature variation resulting from the impact of the laser source on the material for a duration of dt seconds. The temperature difference can be calculated by:

$$dT = T_{new} - Told \tag{3.25}$$

where T_{new} represents the resultant melt-pool temperature (T_{mp}) and T_{old} represents the initial temperature (T_{ini}) calculated by the Rosental solution. The duration in which the laser source remains in the same spot can be calculated by knowing the laser scanning speed (v) and the effective diameter (fi) of the laser source. Thus dt is given by:

$$dt = \frac{fi}{v} \tag{3.26}$$

Combining the previous Equations (3.23) to (3.26) and reorganise them, the melt-pool temperature can be given by the following equation:

$$T_{mp} = \frac{fi.Q}{\rho c v V_L} + T_{ini} \tag{3.27}$$

3.4. Chapter summary

This chapter plays a crucial role in establishing the foundation for our investigation on the selective laser melting process. By defining the scope and objectives with precision, we have ensured a clear and systematic approach towards understanding the process and its subsequent analysis methods. The chapter outlines the model that will be used in the upcoming chapter, taking all assumptions into account.The model was presented by Equation (3.18), along with Equation (3.20), to estimate the geometry of the melt-pool for a given laser power, while taking into account the impact of the temperature of the pre-scanned track, which is regarded as a disturbance to the printing process. The melt pool temperature will be estimated using the heat conduction concept, as Equation (3.27) showed.

In the upcoming chapter, we focus on the steps of the model implementation, present the simulation results, and engage in a comprehensive discussion and analysis of the findings. The objective is to shed light on crucial phenomena and clarify their implications for additive manufacturing.

4

Implementing and Evaluating a L-PBF Process Model: From Single Track to Multi-layer Level

In this chapter, we will implement and simulate the mathematical model presented in the previous chapter. The aim is to demonstrate the capability and limitations of using the Rosenthal solution to model melt-pool dynamics. We will provide a detailed analysis of the model through various simulation scenarios. The chapter will start by introducing the simulation software that can be used to achieve such a task. After the implementation is completed, the model will be used to simulate the performance of the system under several cases: single-track single-layer, multi-track single-layer, and multi-track multi-layer. The results will be analysed to study and illustrate the impact of the laser power on the process performance from various perspectives. By the end of this chapter, we will see that the model introduced in Chapter Three has the potential to reduce the simulation time while maintaining the accuracy significantly. However, it has some limitations when investigating control systems. This observation sets the stage for the next chapter.

4.1. Simulation software and model implementation

There are several choices of software that can be used to build a L-PBF process model and simulate its thermal behaviour and melt pool dynamic, such as MATLAB, ANSYS, ABACUS and COMSOL [86]. One of the research objectives is the design and implementation of a process control system. Thus, MATLAB software will be used as a simulation environment for the process because MATLAB is a powerful and convenient tool for control system engineering. The software is equipped with various engineering and control system toolboxes that help to build mathematical models of complex processes, analyse, and design control systems faster than other simulation software. The model presented in the last chapter will be implemented using MATLAB code and MATLAB SIMULINK, besides many other built-in functions.

The implementation of the SLM process model presented in Chapter 3 can be accomplished through three main steps: first, find the Rosenthal solution using Equation (3.20), second, calculate the geometry of the melt pool using Equation (3.18), and the last step is the estimation of the temperature of the melt pool using the heat conduction Equation (3.27). The first part is calculated using the MATLAB code, whereas the second and third are done in MATLAB SIMULINK. The implementation steps can be summarised in Figure (4.1).

The code begins by defining the dimensions of the object, the parameters of the process, and the material. The dimensions of the object are defined as the length of the tracks, the number of tracks, and the number of layers. The code is developed to capture the required behaviour while simulating the printing process of the equal length tracks. In other words, the simulation generates data assuming that the printed shape is a cube, semicube, or overhang

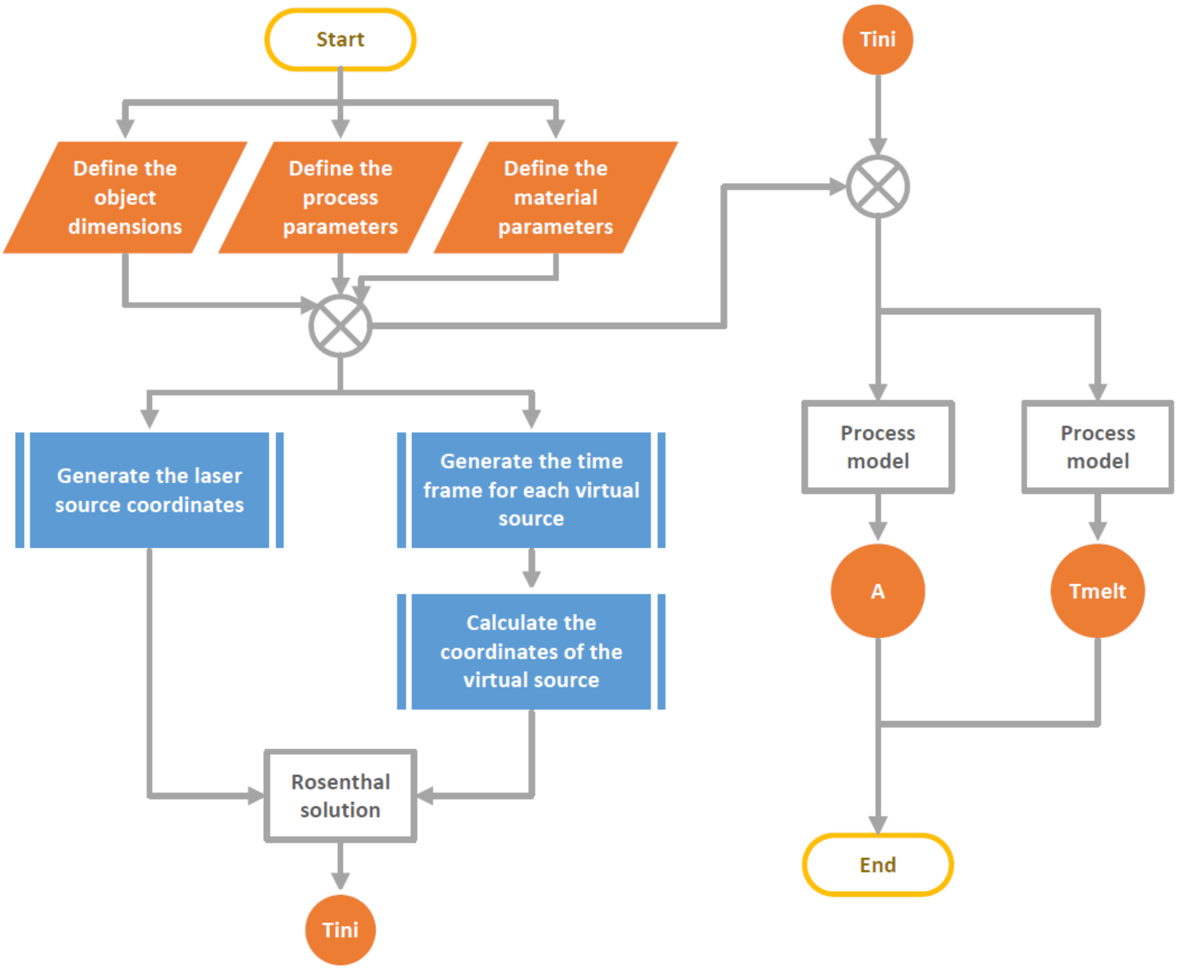


Figure 4.1.: The implementation flow chart for the SLM model outlines the necessary steps and requirements for calculations.

shape. Figure (4.2) illustrates the shapes that can be handled by the code.

The process and material parameters include what was presented in Tables (3.1) and (3.2). Based on the defined variables, the coordinates of the laser source and the virtual sources are calculated. Then, all the generated data are used to calculate the initial temperature. The calculated values of the initial temperature are passed to the Simulink model, where the cross-sectional area and the melt-pool temperature model are defined.

To the best of the researcher's knowledge, no previous studies use MATLAB to simulate the melt-pool behaviour at a multilayer level. In addition to that, the model is implemented in a way that enables the user to change the material and process parameters and test the effect of various process parameters.

The coming section will present a set of simulation scenarios to study the effect of the laser power on the melt-pool behaviour.

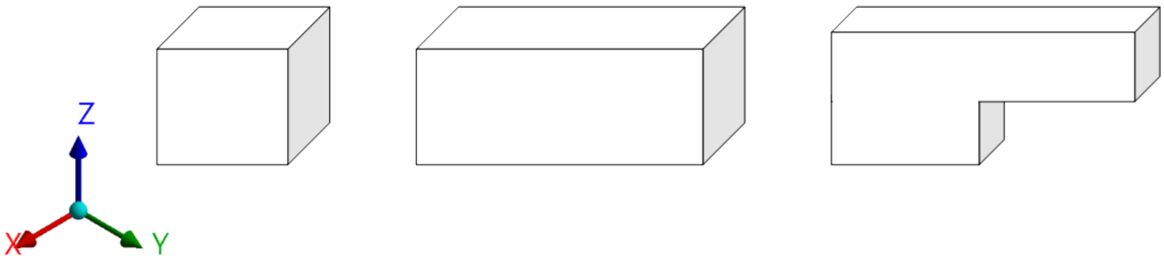


Figure 4.2.: The shapes that can be simulated using the generated code.

4.2. Simulation scenarios

Several simulation sets presented in this section will be studied. The target is to investigate and illustrate the effect of the laser power on the thermal behaviour of the melt-pool and its geometry. The performance of the system will be evaluated by how it responds to different conditions.

The simulation scenarios are divided into three categories based on the number of tracks and layers included in the simulation: single-track single-layer, multi-track single-layer, and multi-track multi-layer. The following subsections describe each category in more detail.

4.2.1 Single-track single-layer

The objective of this part is to simulate the process with a minimal level of disturbance. The code developed in the previous section will be used to calculate the temperature and cross-sectional area of the melt pool. The simulation will be repeated several times under different values of laser power. The laser power will range from 50 to 250 W, providing a safe energy density level given the fixed speed as was shown in Section 3.2.

4.2.2 Multi-track single-layer

In this part, the focus is on studying the impact of a printed line/track on the successive one. The main objective is to study and understand the disturbance caused by heat accumulation during the process. In order to analyse and characterise the disturbance caused by heat accumulation during the fabrication process, a set of tracks will be simulated with different machine setups.

4.2.3 Multi-track multi-layer

This part extends the investigation towards printing full objects. The target of this part is to analyse the heat accumulation inherited from the previous (printed) layers. However, due to the computational cost, the investigation will be limited to two objects and a maximum of 60 layers. The laser parameters will be maintained fixed in both cases. In terms of the code, the difference between this part of the investigation and the two previous sets of trials is the consideration of the time to add a new layer of powder. Based on the Aconity3D machine specification, it takes around 10 seconds to add a new layer of powder.

4.3. Simulation results and discussion

In this section, the results of a set of simulation tasks will be presented. The results will be presented and discussed in the coming three subsections using the same categories as described in the previous section.

4.3.1 Simulation of single-track single-layer

Based on the assumptions made in Chapter Three regarding how the Rosenthal solution is calculated, the initial temperature of the first track at the beginning of the process remains constant until the track is completed. However, the temperature of the second track is changing due to the heat accumulation from the previous printed track. Figure (4.3) shows how the value of the initial temperature changes as the track is printed with different values of laser power. The dotted blue line presents the melting point temperature of Ti6Al4V. For a laser power of 200 watts and above, the melt pool reaches the melting point at the beginning of the track before even applying the laser source. If the assumption is used that the perfect steady state of the melt pool temperature is about 20% more than the melting temperature, a laser power value over 250 watts will lead to over-melting for the substance at the beginning of the track, even without applying the laser source.

Figure (4.4) illustrates the maximum (at the left) and minimum (on the right) initial temperat-

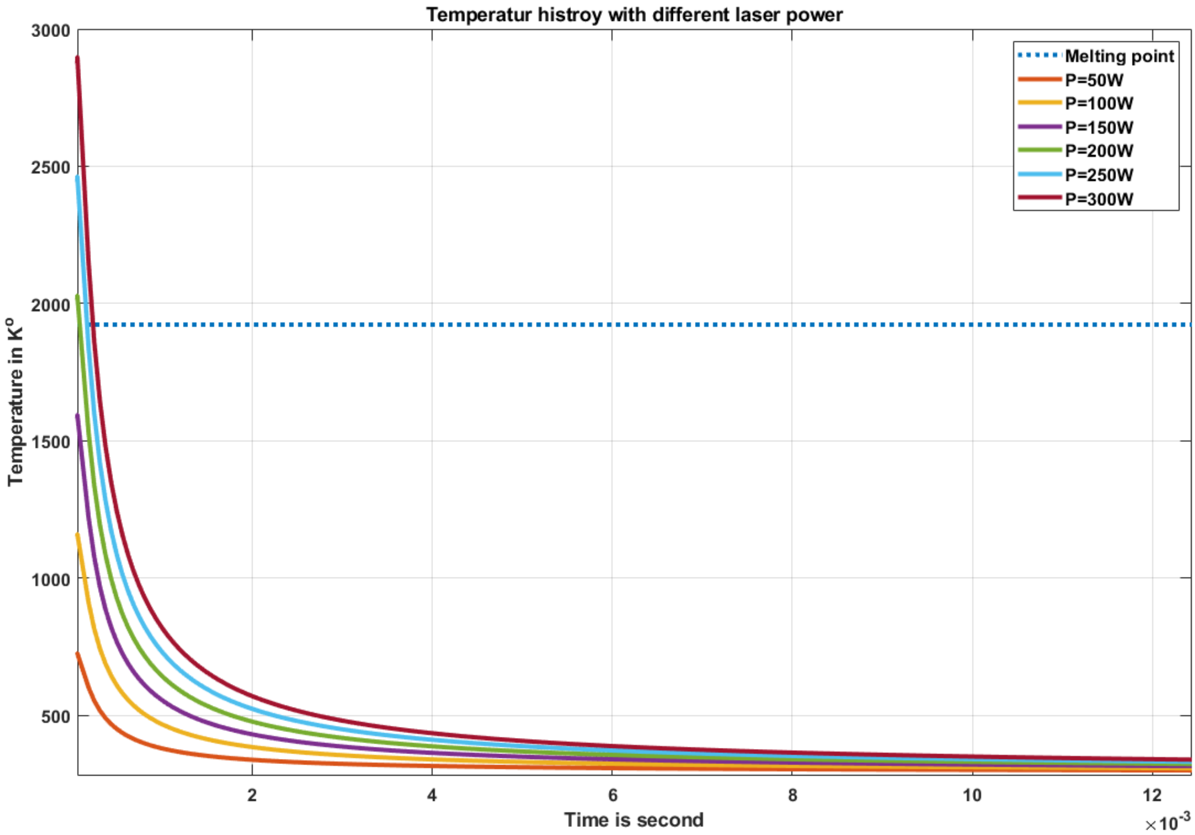


Figure 4.3.: The initial temperature of the melt-pool during printing single track using various levels of laser power.The blue dotted line represents the melting temperature of the material.

ure with respect to the melting temperature (1923 k^o) and the ambient temperature (292 k^o), respectively. The figure is for the printing of the second track where the heat accumulation comes from the previous completed track, since the first track has no change in its initial temperature from the assumption stated.

As can be seen from the figure, the value varies based on the laser power used. The difference between the initial at the end of the track and ambient temperatures presents the inherited heat accumulation passed to the next track. The more power used, the more the heat accumulation passed to the new track. It can be seen that for a laser power of more than 200 watts, the initial temperature reached the melting point before adding more heat from the laser source. This means that the actual melt-pool temperature will be much more than the melting point, leading to practical defects in the building of the component.

The impact of the heat accumulation appears clearly on the temperature of the melt pool, which as Chapter Three showed, was calculated using the basic heat conduction equation. Figure (4.5) demonstrates the temperature profile of the melt pool, while printing the two tracks using different laser power levels. The black dotted vertical line in the middle of

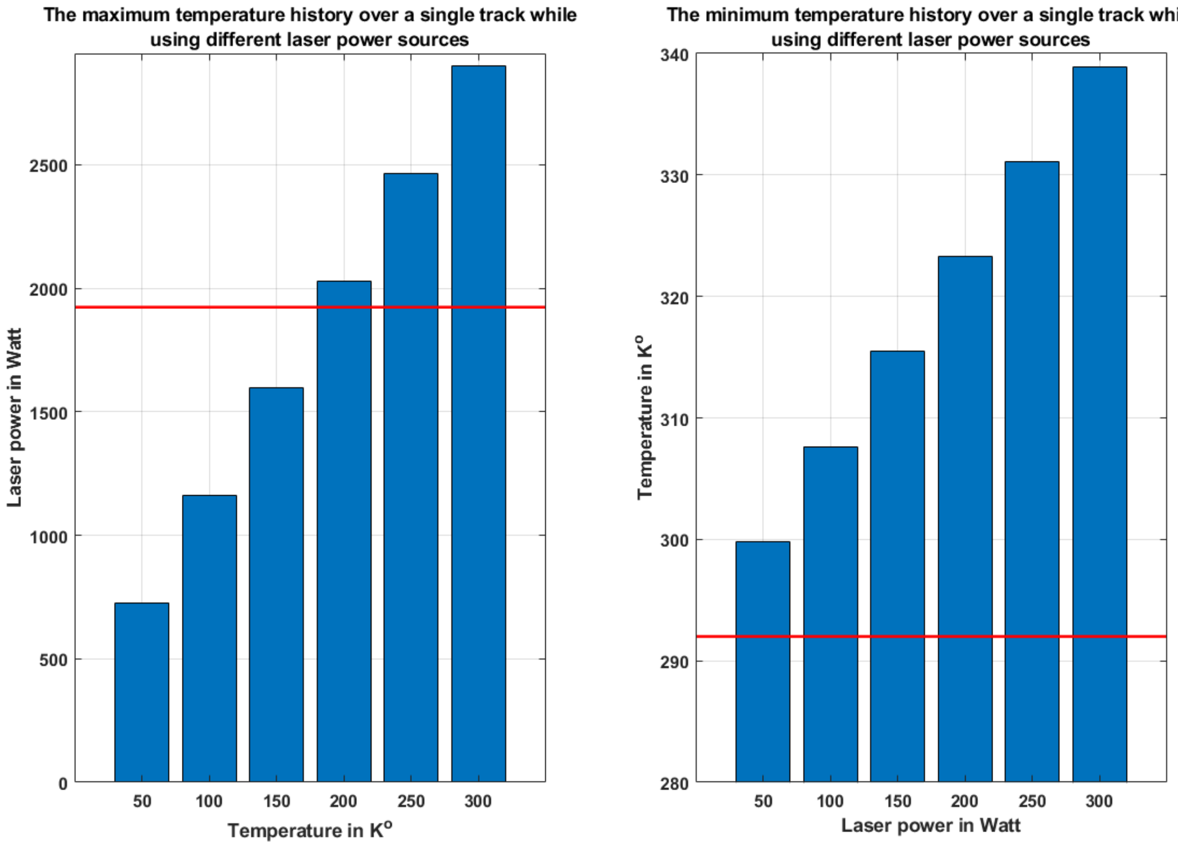


Figure 4.4.: The maximum (at the left) and minimum (on the right) initial temperature while simulating the printing of a single track using different laser power. The red line is the melting point in the figure on the left, where the figure on the right presents the ambient temperature.

the figure represents the starting point of the new track. The figure shows how the heat accumulation raised the melt pool temperature to more than the boiling temperature at the beginning of the new track.

It is important to note that for certain power levels (250 watt and above), the resulting temperature may not be realistic. The calculated temperature may exceed the boiling point. From a computational standpoint, everything is accurate but not practical. In these instances, physics changes, and the numbers have different significance. This note is crucial for modelling representation and for adjustments in the next phase. Therefore, the model we used limits the temperature to a level of boiling. In the coming analysis we will consider any temperature close to or more than the boiling temperature is an indication that the printed object will suffer from defect such as keyhole and swallowing.

Looking back at the figure and focusing this time on the number itself, an important note from the figure is that the melt pool temperature does not return to the previous level at the end of the track. In other words the heat accumulation affects the steady-state temperature

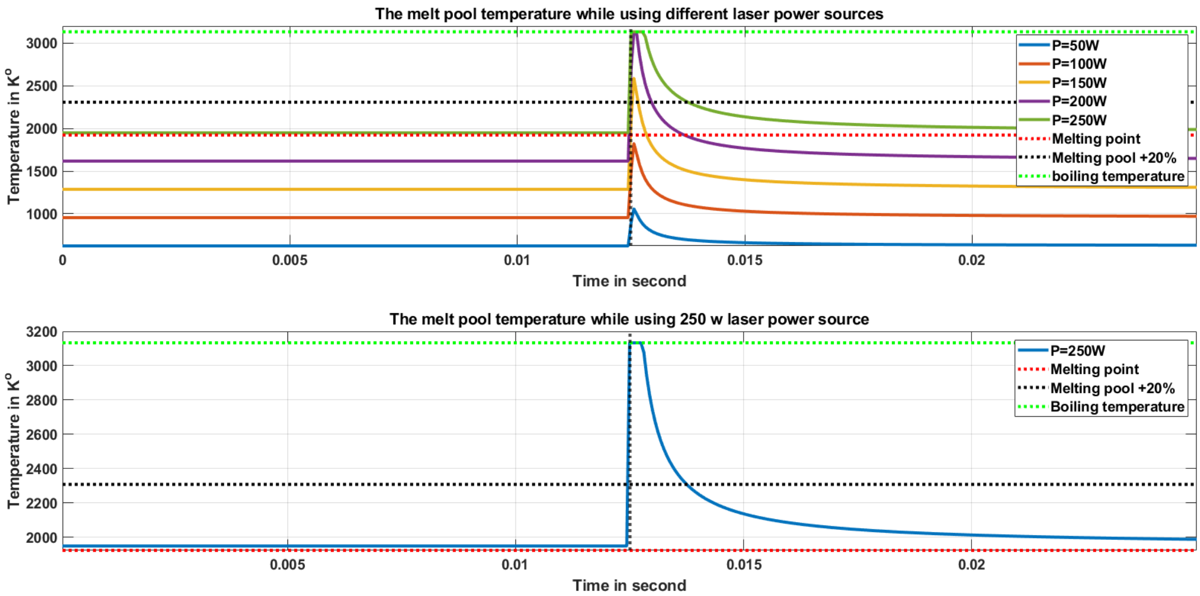


Figure 4.5.: The temperature profile of the melt pool while printing the two tracks using different laser power levels (at the top) and while using 250 watts (at the bottom).

of the melt pool and raises it up as the bottom plot shows clearly. This will lead to the accumulation of the effect on every track as the process continues.

Figure (4.6) presents the maximum and the minimum temperature recorded in the simulation for the different power level. For a laser power less than 100 watts, the material did not reach the melting point, whereas for a power of 200 watts and above, the resultant temperature is away far from the desired range. For the cases where 150 and 200 watts were used, the source at the beginning raised the temperature of the substance more than the desired point and dropped fast to settle below the melting point. For the laser source of power 250 watts, at the start of the second track, the temperature of the melt pool reached more than 112% of the melting point. However, it dropped to settle in the desired range for the reset of the track, which was almost 20% of the total time to complete the track. The previous observations were about the thermal behaviour of the melt pool. From the geometric perspective, Figure (4.7) presents the melt-pool cross-sectional area under the effect of heat accumulation coming from the previous track, where the red dotted horizontal line presents the ideal cross-sectional area. As can be seen from the figure, for the first track the melt pool size is constant despite how far it is from the desired value. The observation is in line with what is expected based on the assumptions and the temperature observation. Once the second track started, the changes appeared. As can be seen from the figure, the melt pool cross-sectional area suffered from irregularity in its shape. With the laser power level less than 200 watts, the melt-pool size is less than the desired value. Reflecting this observation to the reality and with a good understanding to the thermal behaviour, this could mean that

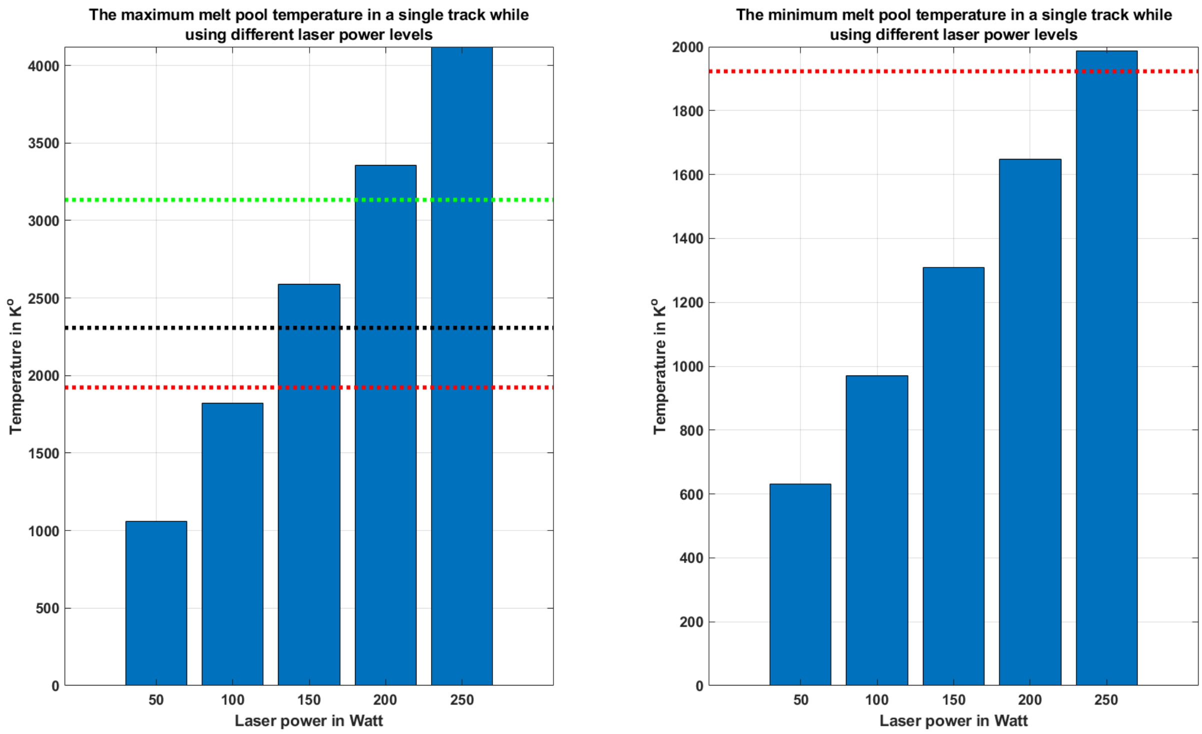


Figure 4.6.: The maximum (left) and the minimum (right) temperature recorded in the simulation of the second track using different power levels. The red, black, and green dotted lines represent the melting temperature, 20% over the melting and boiling temperatures, respectively.

the powder is not melted. On the contrary, where the value of the laser is more than 250 watts, the value was at least more than 11% of the desired value for the lowest value of power. This does not represent practically the real size of the melt pool, but it is an indication of an over melting issue that could lead to many manufacturing defects. For the laser power of 250 watts, the maximum error was around 8% and dropped farther as the process along the track continues.

Figure (4.8) visualises the printed track for three different laser power levels of 50 and 250 watts assuming the length and width relation is fixed as it was assumed in Chapter Three. The red lines specify the borders of the desired size of the track. It can be seen that for the first case, the size of the track is 50% less than the desired width. For the second cases, at the beginning of the track, the deflection from the desired value is at its maximum and as the process progresses, the error is reduced.

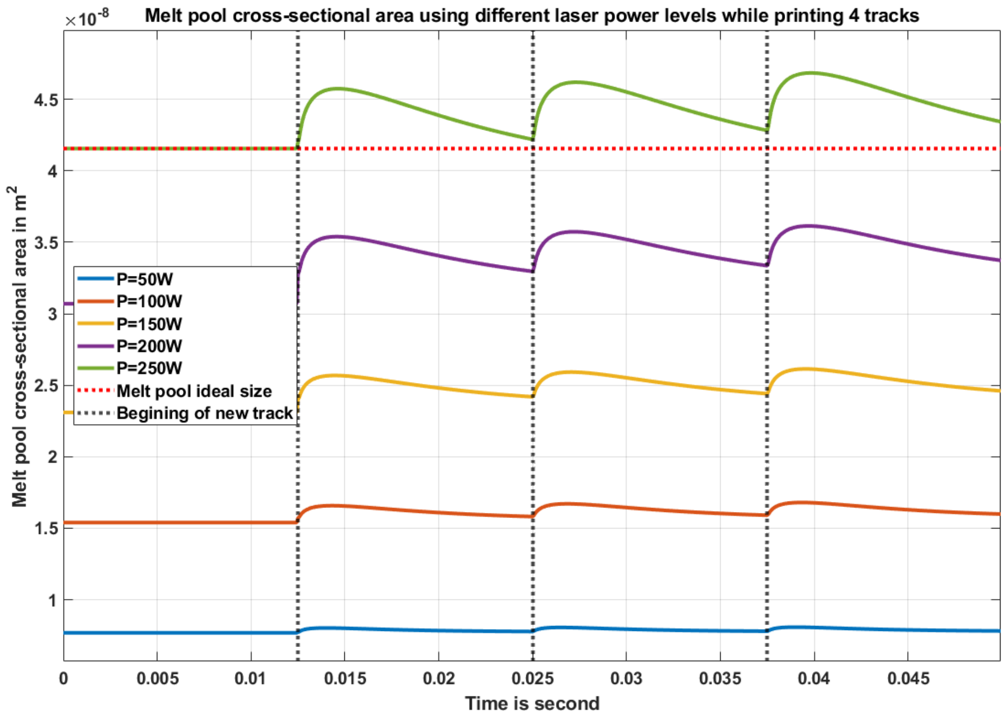


Figure 4.7.: The melt-pool cross-sectional area under the effect of heat accumulation using different laser power levels.

4.3.2 Simulation of multi-track single-layer

This part presents the results of extending the investigation toward multi-track. The results here differ from those of the literature as they consider a more practical case of building a complete layer.

Figure (4.9) represents at the top the initial temperature profile while simulating the building of a set of tracks using different power levels, while the figure at the bottom shows the case for 250 watts. The horizontal dotted line in both plots illustrates the melting point of Ti6Al4V. As was explained before, for the first track the initial temperature is assumed to be constant, as the plot before the first peak shows (the time to complete the first track is 0.0125 s).

The single-track single-layer case presented in the previous subsection can be summarised as follows: the initial temperature starts with ambient temperature, then reaches the maximum at the beginning of the second track, and starts decaying after that until the end of the printed track. The temperature at the end of the track does not reach the ambient temperature level; there are some residuals that affect the starting point of the next track.

If the process is extended to multi-track, the difference in starting point in each track keeps

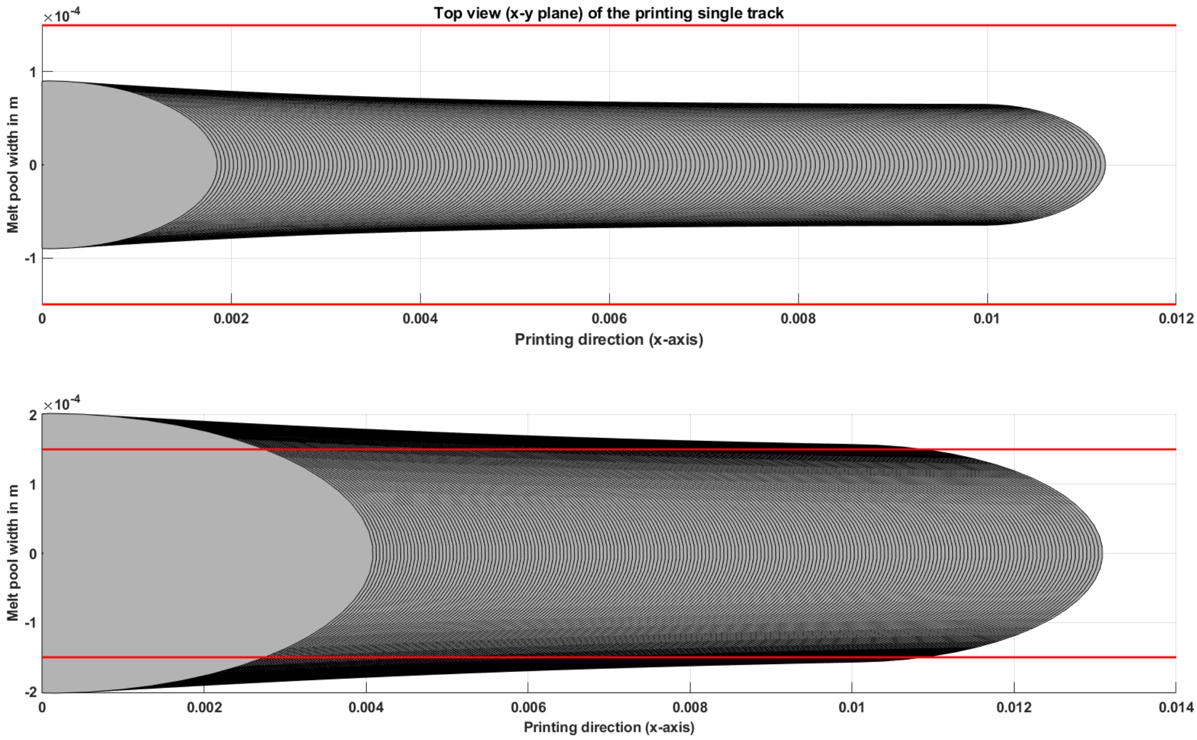


Figure 4.8.: Visualization of the printed track using three different laser power: 50 watts (top) and 250 watts (bottom).

increasing since the starting point consists of the ambient temperature and the residual from the other tracks as Equation (3.20) shows. To illustrate that more, Figure (4.10) presents the effect of three virtual sources and how their effect is added into each other. Looking at any of the points of the total initial temperature, it can be seen that it is a sum of the effects of virtual sources. Take, as an example, the starting point of the fourth track, the total temperature is 2247.07 F^o which is the sum of the contribution of three virtual sources 2171.91+39.1+37.06 F^o.

Another important observation is how the effect of the virtual source diminishes with time. Figure (4.11) presents the effect of the first virtual source. It can be seen that the effect of the source drops significantly as the track is completed. As the process continues, the effect of the source can be ignored; this can help in the future to simplify the thermal model.

Figure (4.12) shows (on the left) the residual temperatures per track caused by different laser power levels and the average temperature residual over a single track (to the right). The initial temperature increases gradually on every track. The figures show also how the power level used in the process increases the value of the residual heat passed to the coming tracks.

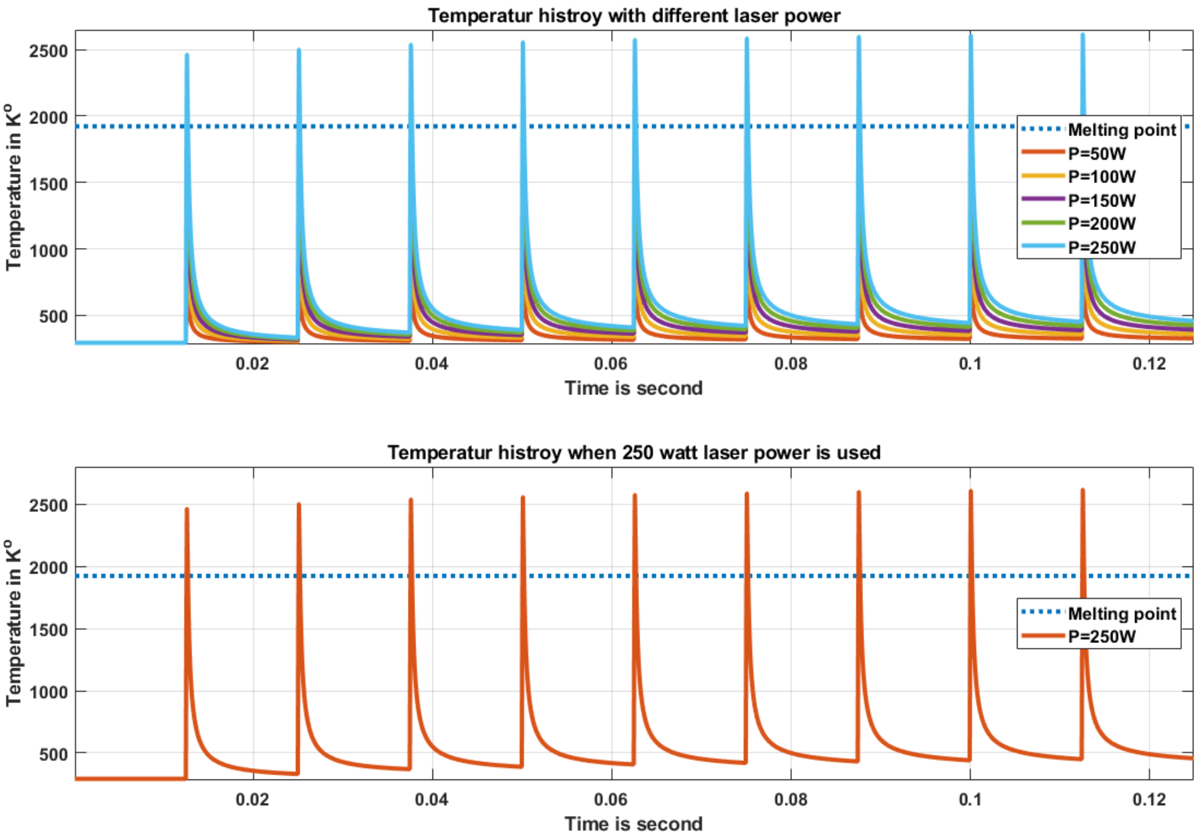


Figure 4.9.: The initial temperature profile while simulating the building of ten tracks using different power levels (top) and using 250 watts (bottom).

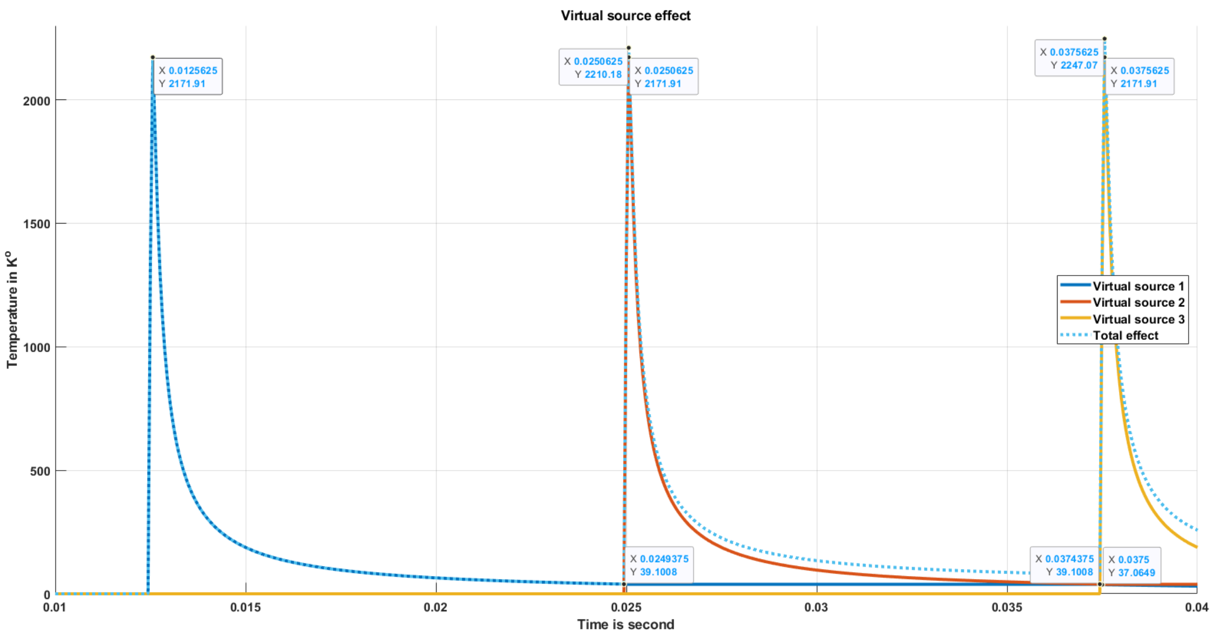


Figure 4.10.: Illustration of heat source contribution to the total initial temperature profile.

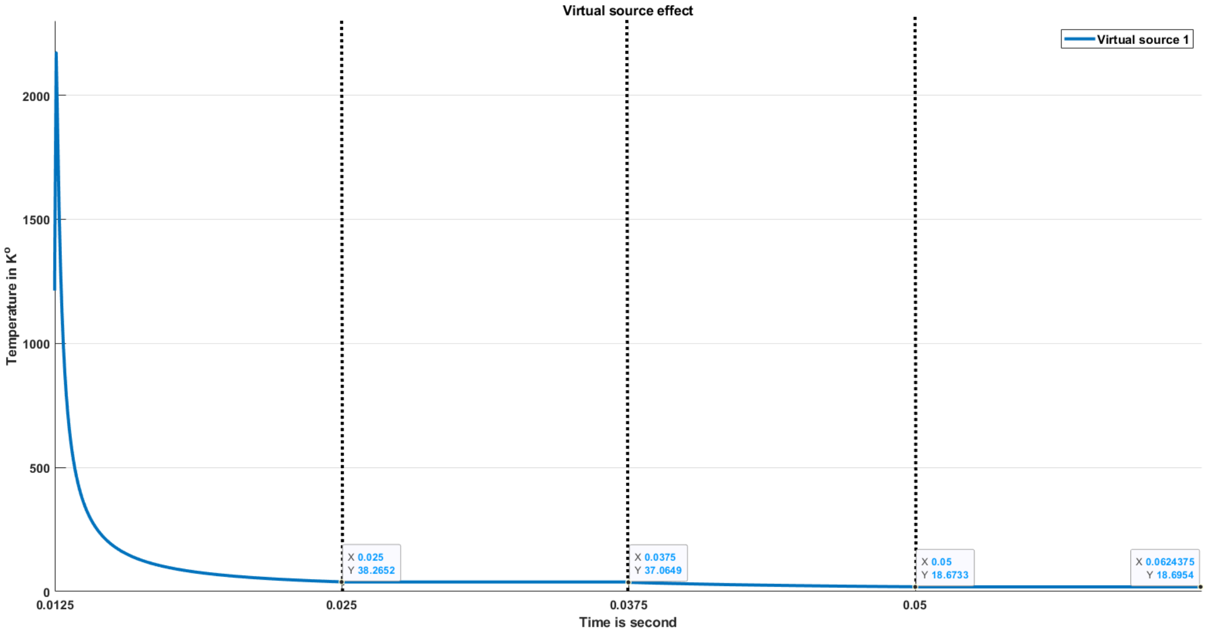


Figure 4.11.: The contribution of a virtual heat source over a set of tracks.

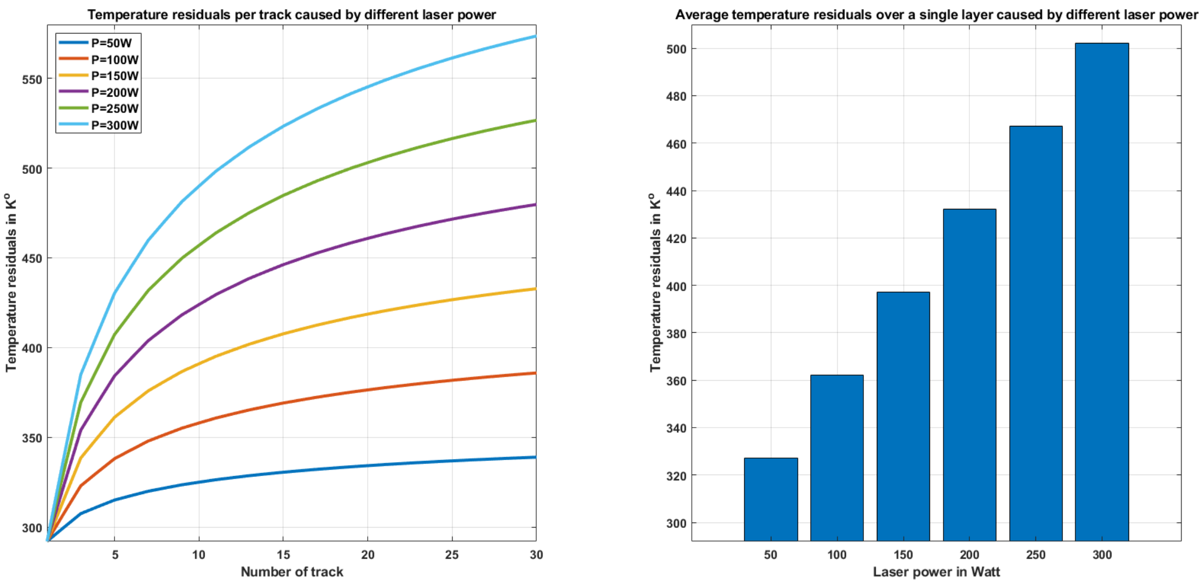


Figure 4.12.: the residual temperatures per track caused by different laser power levels and the average temperature residual over a single track (to the right).

The impact of the change in initial temperature and accumulation of the temperature residual are reflected on the thermal and geometrical behaviour of the melt pool as the simulation results show. Figure (4.13) presents the melt-pool temperature profile during the simulation of ten tracks using different laser power (at the top) and a laser source of 250 watts (at the bottom). The dotted line at the bottom illustrates the melting point of the substance, whereas the top one represents a value of 20% added to the melting temperature. The green line represents the boiling level where it considers that the model reaches saturation level. As explained in Chapter 3, the melt pool conserves its state up to 20% more than the melting temperature.

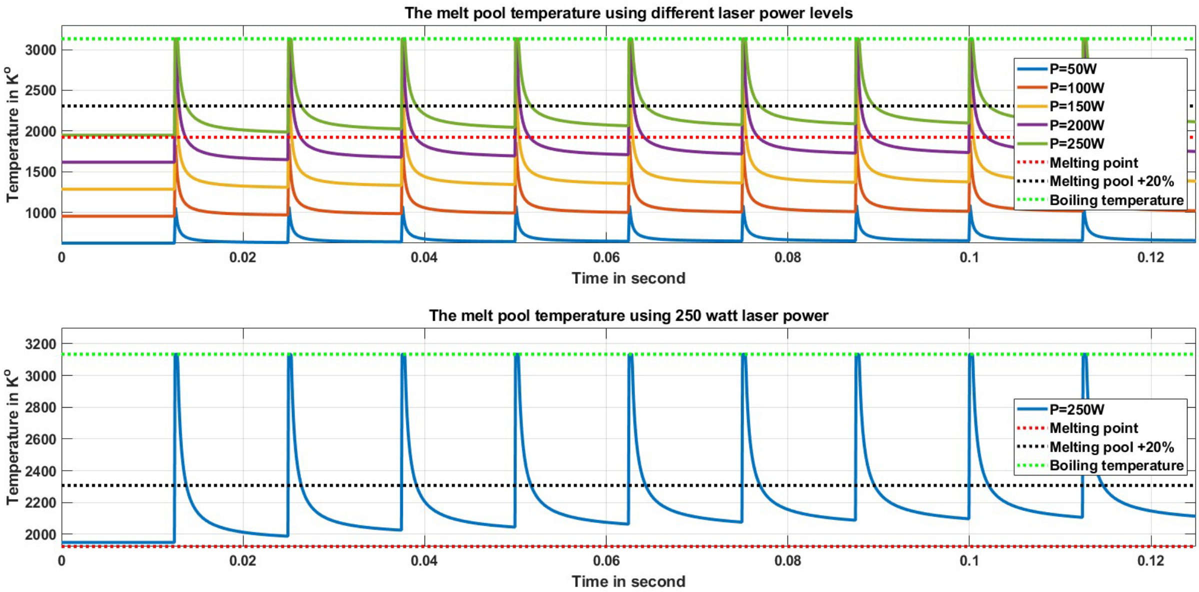


Figure 4.13.: Melt-pool temperature profile during the simulation of ten tracks using different laser power (top) and a laser source of 250 watts (bottom).

Looking at the case where the laser power is 250 watts, it can be observed that in the second track, for almost 10% of its total length, the melt pool temperature was out of the desired range. The percentage increase is due to the process continuing to reach approximately 20% of the last presented track. Another observation that emphasises the effect of the heat accumulation can be seen from the figure (the bottom figure) is that the temperature profile is shifted up (away from the dotted bottom line) as the simulation progresses further. Both observations are applied using different values of laser power, however the more the power the worse the case as it can be seen from the top plot.

The effect of this on the geometry of the melting point is shown by the simulation result presented in Figure (4.14). The red dotted line represents the ideal correctional area of the melt pool, whereas the black line represents the starting point of the track. The ideal value of the melt pool was found by solving Equations (3.18) and (3.20) under the set of assumptions mentioned in Chapter 3.

It is noticed that at the beginning of each track, the cross-sectional area of the melt pool reaches its maximum value on that track due to the maximum effect of the heat accumulation from the previous tracks. Then the size of the melt pool decreases as the effects of the virtual sources fade away. The error in the second track reached 11% at the beginning. The percentage increases at the start reach 18% as the figure shows.

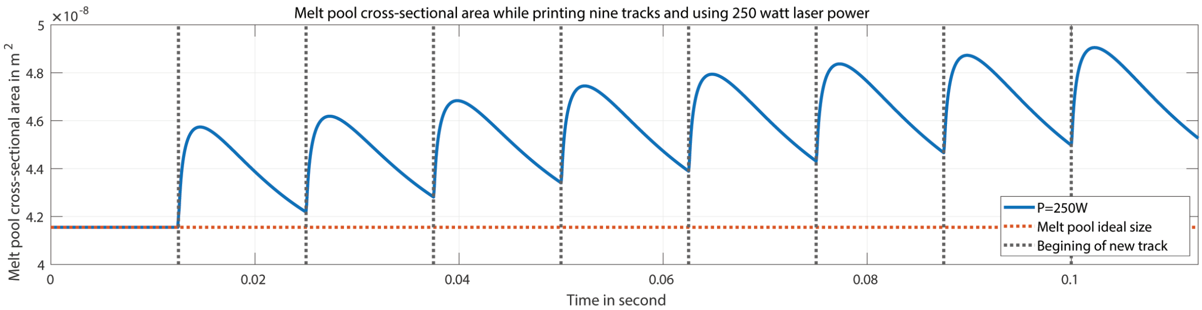


Figure 4.14.: The melt-pool cross-sectional values during the simulation of ten tracks using 250 watts laser source.

The heat accumulation prevents the melt pool from reaching the desired size. The difference between the desired and the actual size of the melt pool increases as the printing process progresses. Figure (4.15) presents the average melt-pool cross-sectional area over a single layer using different laser power level. The variation in the average and the value of the corresponding error can be seen in the figure.

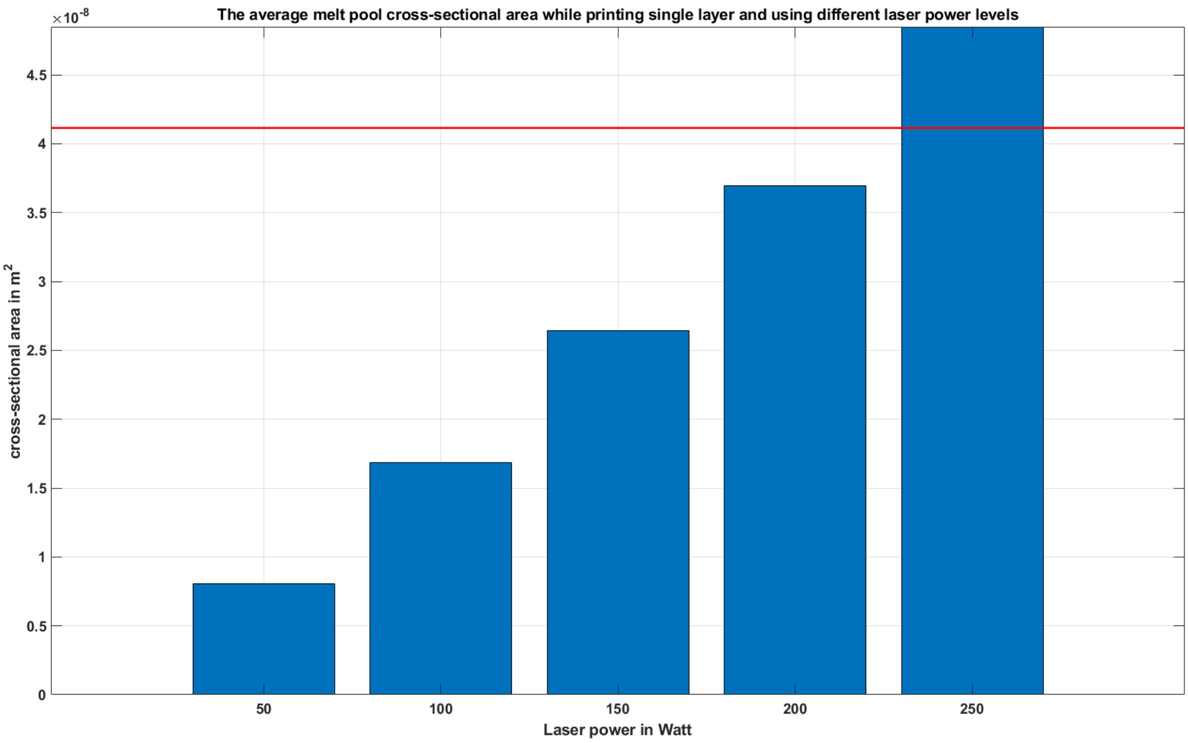


Figure 4.15.: The average melt-pool cross-sectional area over a single layer using different laser power level.

This deflection from the desired operating value, illustrated in the simulation result, presents a defect in the practical case that can lead to an error in the object dimension, porosity, and many other unwanted defects.

4.3.3 Simulation of multi-track multi-layer (cube shape)

The difference between multi-track single-layer and multi-track multi-layer is the consideration of adding a new powder layer. There are several factors that can be considered for such a step, such as the cooling rate of the printed layer, the powder temperature, the overall temperature of the chamber, etc. In this investigation, the time to add a new layer is considered. The effect of the step will be presented as an extra distance added to all previous virtual sources in the pre-printed layer. Thus, heat accumulation (the contribution of the previous virtual sources) is reduced significantly. However, there is still heat accumulation layer after layer.

The simulation in this part considers the case of simulating the printing of a 30 tracks (3 mm object width) by 60 layers (6mm object depth) object. Figure (4.16) presents the graphs of the initial temperature profiles. As can be seen from the top plot, the behaviour of the process is almost periodic. In other words, the dynamic of the melt-pool repeated itself layer after layer. However, there is still a slight increment every layer as bottom plots show. The zoomed plots showed an important observation, as the building continues, the amount of temperature residual decreases in a manner that it will be saturated after a certain time. The amount of temperature inherited from the first layer to the second layer was around 3 F^o, while it reaches not more than 0.5 F^o between the last two layers in the simulation. Practically such a behaviour is expected, because the heat conduction becomes less as the temperature of the substance, chamber, and printed part become closer.

Reflecting that in the melt-pool temperature simulation, the impact is almost the same, Figure (4.17) presents the temperature profile of the melt-pool during the simulation of building two layers. Trackwise, the same observations from the previous subsection are applied. The effect of adding a new layer is witnessed in the middle of the plot, where a drop in temperature appears. As the process (at the same layer) continues, the melt-pool temperature range increases toward the upper limit of temperature stability. Figure (4.18) illustrates how the temperature of the melting pool changes for the same portion of the object through different layers.

From the geometrical point of view, the simulation showed that the building of the part will suffer from having an irregular melt pool size. The error per track as seen in Figure (4.19)

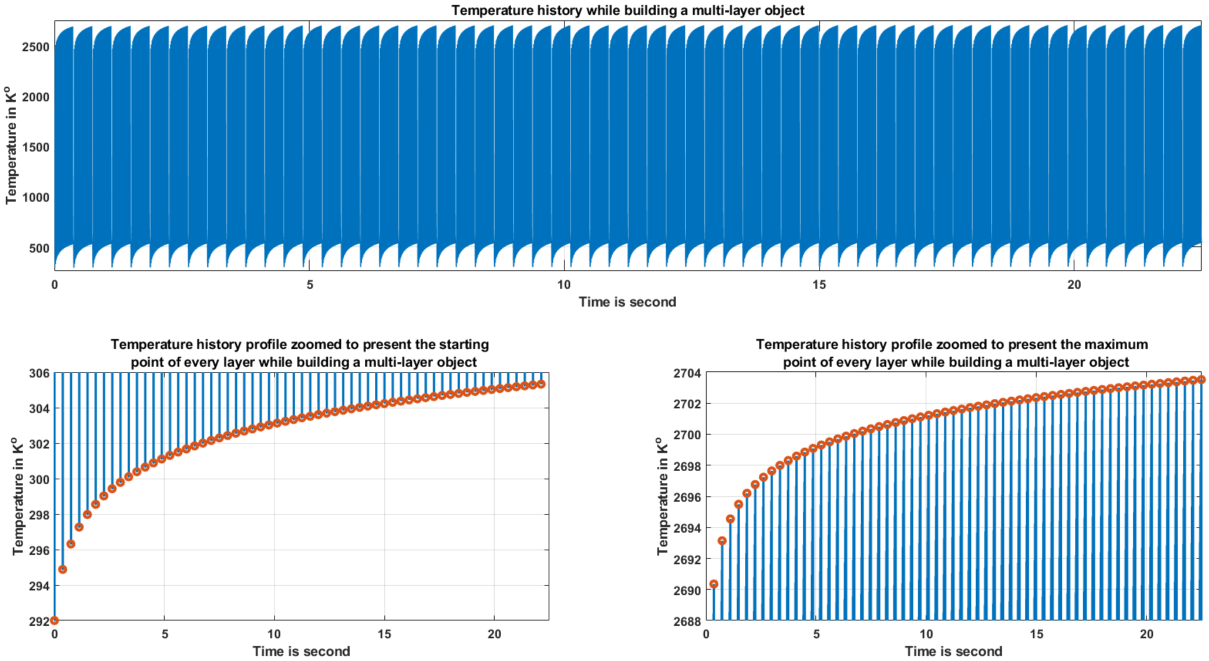


Figure 4.16.: The initial temperature profiles while printing 60 layers, using a laser source of 250 watts.

grows from 10% in the first track to reach around 25% in the last track in the second layer.

For the previous result (melt-pool temperature and size) the presentation was limited to the first two layers to give an insight about what is the impact of the heat accumulation during the process. The impact become worse as the operation progresses to more layers.

4.3.4 Simulation of multi-track multi-layer (overhang shape)

The simulation scenario described above involves a multi-layer configuration in which each layer and track maintains uniformity. However, it is important to note that the actual printing capability of a laser powder-bed machine is far from such an ideal case. Based on the literature and knowledge accumulated until now, any change in the object's dimensions will result in a significant change in the system's behaviour.

To illustrate the profound impact that even minor variations in geometric configuration -particularly- can exert on simulation outcomes, a simulation focused on fabricating an overhang structure was conducted. In this specific scenario, the layers were bifurcated into two distinct sets, with the track lengths of the upper segment designed to be twice as long (20 mm) as those in the base section (10 mm).

This intentional modification to the shape introduces a significant variable into the simu-

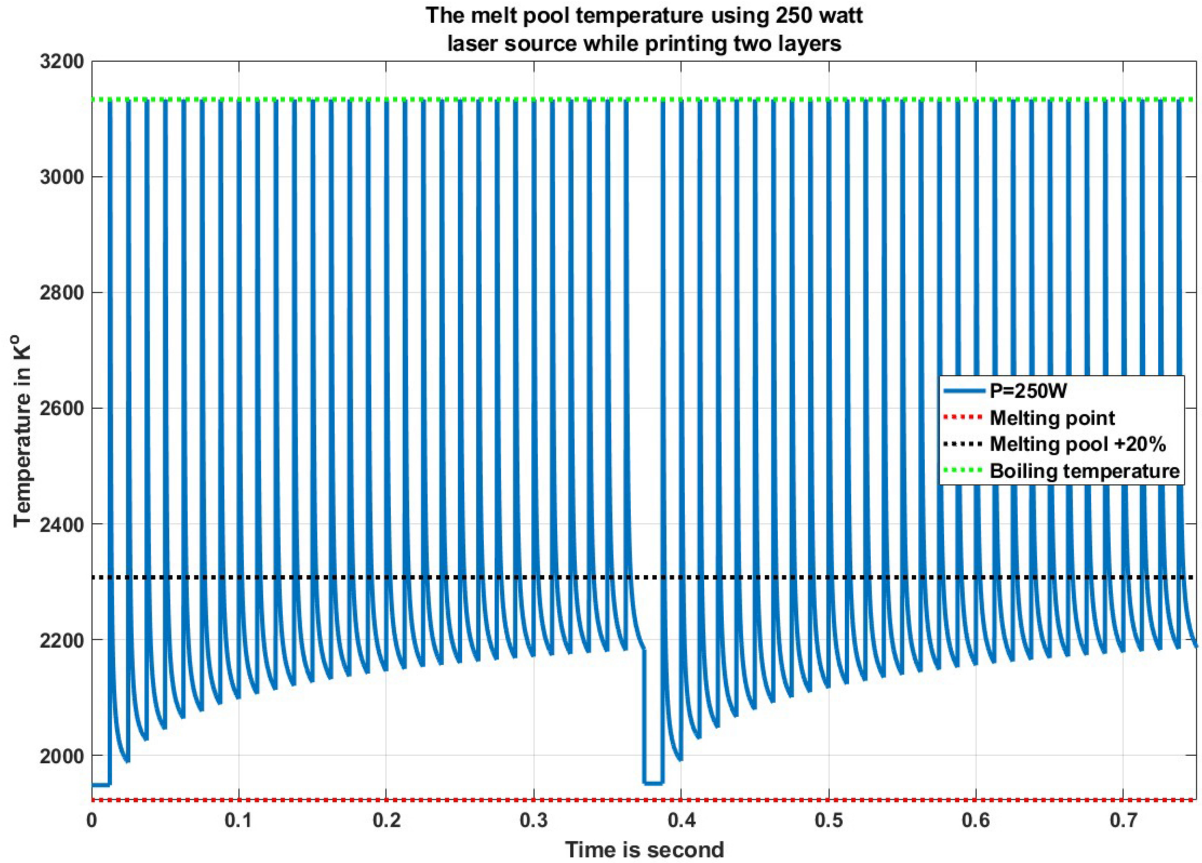


Figure 4.17.: The temperature profile of the melt-pool during the simulation of building two layers using laser source of 250 watts.

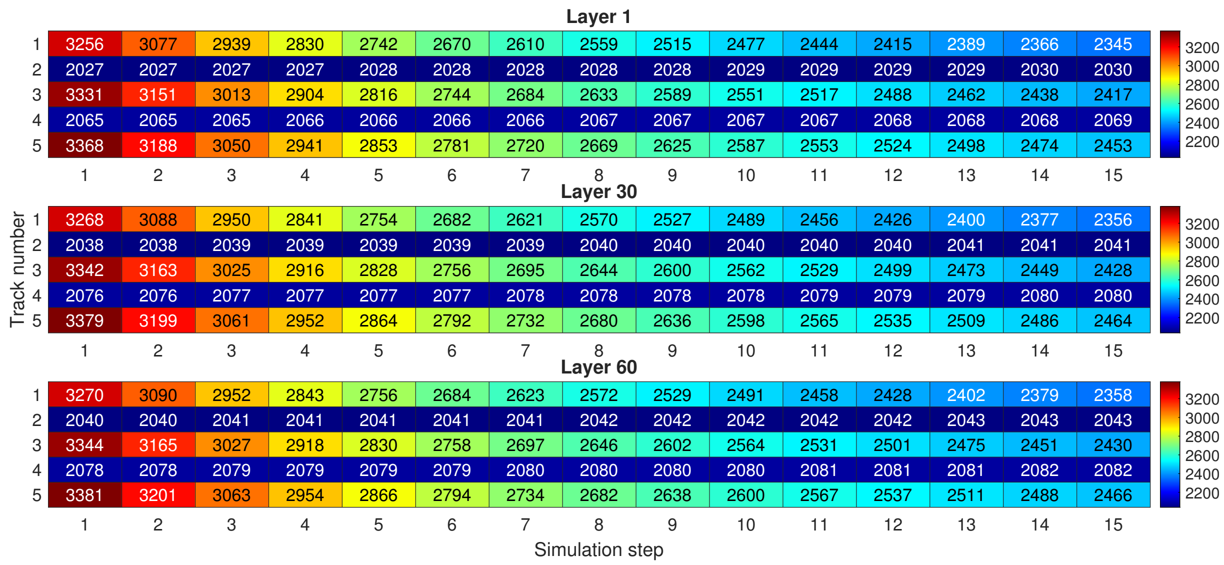


Figure 4.18.: Illustrates how the temperature of the melt pool change for the same portion of objected through layer one, thirty, and sixty.

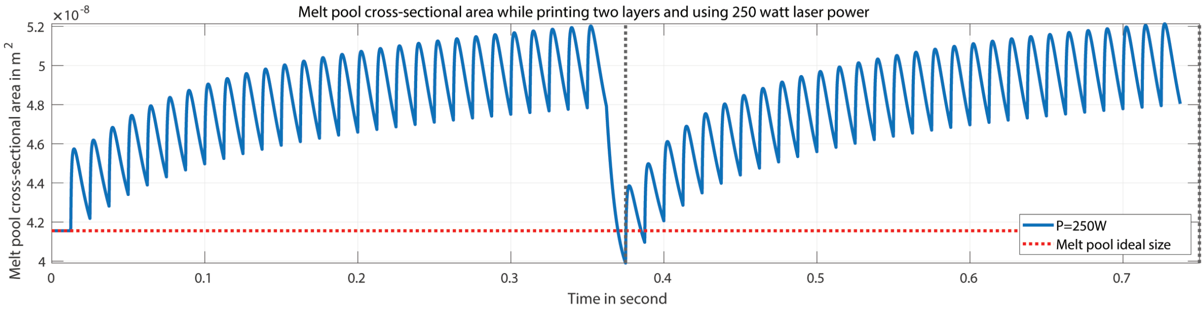


Figure 4.19.: The cross-sectional area during the simulation of building two layers using laser source of 250 watts.

lation that mirrors the challenges encountered in practical additive manufacturing processes, where the dimensions of the objects can vary extensively.

The simulation results are shown in Figure (4.20), showing the minimum, maximum and average initial temperatures per layer for two different cases: a standard cube (top) and a modified overhang shape (bottom). The diagram clearly demonstrates how the adjustment of the dimensions of an object can significantly impact the thermal dynamics and overall performance of the system. The simulation results reveal the complex and often unpredictable nature of thermal behaviour in additive manufacturing processes, particularly when faced with frequent and significant changes in object geometry.

This experiment underscores the necessity for advanced simulation tools capable of accurately predicting the outcomes of such geometric modifications. Understanding the complex interplay between shape changes and system performance is crucial for optimising the additive manufacturing process, ensuring quality, and mitigating potential defects. Our findings suggest that even seemingly minor geometric adjustments can have far-reaching implications on the manufacturing outcome, emphasising the importance of incorporating flexible, dynamic simulation capabilities into the design and planning stages of additive manufacturing. This deeper insight into the relationship between object geometry and system performance paves the way for more sophisticated control strategies and process optimisations, ultimately contributing to the advancement of additive manufacturing technology.

4.3.5 Overall discussion

The aim of this study was to assess the capabilities and limitations of the Rosenthal solution in simulating the dynamics of the meltpool in the field of additive manufacturing. The research findings emphasised various important factors, especially the influence of laser power

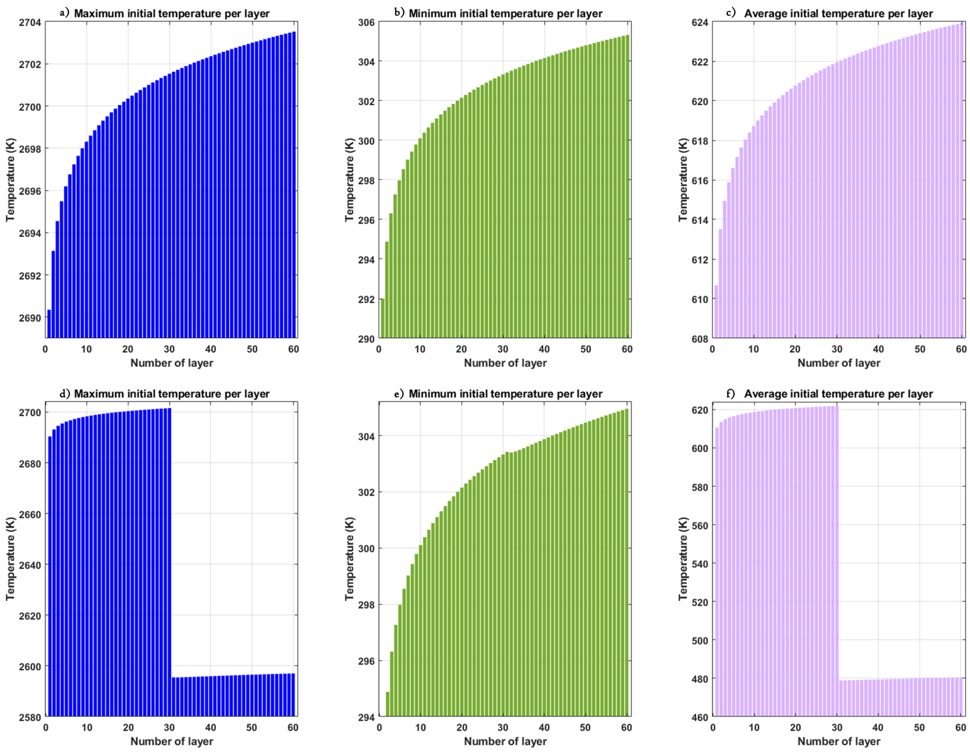


Figure 4.20.: The maximum, minimum and average initial temperature while simulation printing a sim-cube (a,b,c)and overhang shape(d,e,f).

on process efficiency and the considerable efficiency of the Rosenthal model in minimising simulation durations. Furthermore, the results also indicated the limitations of the proposed solution.

Impact of laser power on process performance

Our analysis shows that when using laser powers of 200 watts and above, the melt pool reaches the melting point before the laser is even applied, which causes excessive temperatures. This is a critical issue in high-power laser additive manufacturing because it can lead to the melt pool exceeding optimal temperature ranges, potentially resulting in defects in the manufactured components. Previous studies have also noted similar thermal challenges in additive manufacturing, particularly in relation to heat accumulation and its impact on material properties and structural integrity [93].

The buildup of heat significantly affects the thermal and geometrical behaviour of the melt pool, as predicted by the basic heat conduction equation discussed in Chapter Three. The simulation results confirm that heat accumulation can prevent the melting pool from achieving the desired size, which is consistent with previous research on thermal management in additive manufacturing processes [94].

Implications for advanced simulation tools

This research highlights the importance of creating advanced simulation tools that can accurately predict the effects of geometric changes. Our findings show that even small adjustments in geometry can significantly impact manufacturing outcomes. This aligns with the existing literature, which underscores the importance of adaptable dynamic simulation capabilities in optimising additive manufacturing processes [95].

The knowledge acquired from this study sets the stage for more advanced control strategies and process optimisations. By understanding how object geometry influences system performance, engineers can effectively reduce potential defects and enhance the overall quality of manufactured components.

Performance of the Rosenthal solution vs. traditional FEM simulation

One of the most significant findings of this study is the efficiency of the Rosenthal solution in reducing the simulation time. The Rosenthal model allowed for the simulation of a cube shape (30 tracks, 1 cm each, repeated for 60 layers) in just 806 seconds and an overhang shape in 2781.2 seconds. In contrast, a Finite Element Method (FEM) simulation of similar complexity could take up to a week to complete.

This significant difference in simulation time highlights the potential of the Rosenthal model as a faster alternative to traditional FEM simulations, particularly for preliminary analyses and parameter studies. The ability to produce quicker results without sacrificing accuracy makes this model highly valuable in the iterative design processes commonly used in additive manufacturing [96].

Limitations and future work

Despite its advantages, the Rosenthal model has limitations, particularly in scenarios involving complex thermal interactions and material behaviours that are beyond the scope of its simplified assumptions. Future research should aim to refine the model to address these limitations, possibly through hybrid approaches that integrate FEM and the Rosenthal solution for different stages of the simulation process [97].

Furthermore, exploring adaptive control strategies that consider the dynamic nature of heat accumulation and its impact on the geometry of the melt pool could significantly improve the process reliability and quality of components in additive manufacturing.

4.4. Chapter summary

In this chapter, it was demonstrated how the SLM process model was successfully implemented and used to simulate various scenarios. The Rosenthal solution was employed to extend the model to cover multi-layer analyses and different shapes, resulting in a more comprehensive understanding of the process physics and dynamics. Despite its simplicity, the model captured the thermal and geometric behaviour of the melt pool during the printing process of various shapes. The results show that the model has the potential to significantly reduce simulation time while maintaining accuracy. With this model, one can simulate a shape of 30 tracks of a length of 1cm repeated for 60 layers in 806 seconds, whereas this takes around a week to do with a FEM simulator. In collaboration with another research group, we utilised the model and the data generated from it to investigate the application of reinforcement learning in the Selective Laser Melting (SLM) process. Our cooperation resulted in a peer-reviewed paper titled "Multi-layer Process Control in Selective Laser Melting: A Reinforcement Learning Approach," which we plan to submit to the Journal of Intelligent Manufacturing.

However, the current structure of the model introduces certain limitations, particularly in the context of investigating control systems. This challenge will be addressed in the forthcoming chapter.

Additionally, the simulation results gave clear evidence of the need for a dynamic control strategy to guarantee the quality of the printed part due to the following reasons that was observed through this chapter:

1. Fixing the parameters during the process leads to heat accumulation that causes different types of defects.

2. Changing the system parameter or object dimension significantly changes the system behaviour.

3. The behaviour of the process changes with time; it tends to saturate with time.

Therefore, the upcoming chapters will focus on exploring the use of a closed-loop control system and studying the impact of its use on enhancing the process's performance.

5

Developing a SLM Process Simulation Tool for Control Purpose

Based on the research conducted to this point, the investigation of the control system for the SLM process has faced several obstacles. One major issue is the lack of accessible and versatile simulation tools for evaluating control algorithms and assessing their impact on process performance. Although the model presented earlier was used to build a controller that considers the disturbance caused by heat accumulation, its structure limited the types of controller that could be studied. To fill this gap, a MATLAB-based simulation tool is developed in the chapter to investigate control strategies in the SLM process. The tool is user-friendly and is based on SIMULINK, where the designed controller can be easily placed as a block. The tool simulates the closed-loop response of the system in a matter of seconds. This chapter starts with a brief discussion of the development of simulation tools for additive manufacturing processes and the crucial role of MATLAB in various engineering applications. We will then describe the research methodology used to develop the proposed tool and its architecture. We will also discuss the implementation and integration of the various parts of the tool, evaluate its performance, and compare it with the original model. Finally, we present the limitations and recommendations of the tool. Overall, the proposed platform is powerful and can be used to investigate rapid prototyping and evaluation of control systems for SLM applications, as illustrated in the following chapter.

5.1. Introduction

The revolutionary ability of additive manufacturing techniques makes it an important industrial tool in modern manufacturing. The technology enables us to produce parts with a high level of complexity and precision [8]. Selective Laser Melting (SLM) is one of the AM technologies that has transformed the manufacturing of metallic parts to a higher advanced level.

The narrow laser source used in SLM machines allows the selective melting of powder in the order of microns in thickness and the building of parts with satisfactory resolution [20]. The thermal energy produced by the laser system is sufficient to melt the powder at the point of incidence and re-melt the surrounding solidified powder [3]. Thus, the process is capable of producing well-bounded and high-density parts with better properties and less waste. These manufacturing competencies make it an increasingly vital player in industries ranging from aerospace to biomedical engineering [21].

However, there are numerous challenges that restrict the use of all the advantages of technology. Among these obstacles is the absence of an adequate model for researching and evaluating control systems and simulating their effectiveness [98]. This issue is interconnected with another critical aspect discussed in [21], which concerns the integration of these technologies into the educational sector. This integration is crucial to sustain the advancement of the field and to supply the industry with qualified professionals in this field.

Therefore, the development of control-orientated models and simulation tools has become an influential factor in advancing our understanding and utilisation of SLM.

In this chapter, we present a contribution to the field of SLM research in the form of a Matlab-based simulation tool designed to simulate, study, and implement closed-loop control of the SLM process. Our tool has been engineered with meticulous attention to detail and is capable of providing enough accurate results for control system purposes. This powerful tool has the potential to revolutionise the way we approach SLM research and has already demonstrated its efficacy in enhancing productivity and efficiency. We are confident that our tool will play an important role in advancing the state of the art in SLM research and look forward to its continued use in academic and business settings.

The fusion of Matlab's computational ability with the SLM model introduces a novel paradigm, where researchers can not only simulate the process but also actively manipulate the main process parameters easily. This will serve to bridge the gaps identified previously in both industry and academia, providing an effective solution that addresses these issues. The basic idea of the tool is the utilisation of laser power as a control signal, allowing researchers to test, optimise, and fine-tune their closed-loop controllers with unprecedented ease.

5.2. Simulation tool for SLM process

Computer simulation has become a crucial part of research and higher education due to its cost-effective and time-saving capabilities. The importance of such tools increases significantly when applications become critical, difficult to apply in reality, or include hazards and safety issues [99]. It is worth keeping in mind that the combination of practical experiments and model-based simulation has the potential to significantly improve our understanding.

Reflecting on this in the metallic additive manufacturing process, the machines cost hundreds of thousands of pounds and more, and the preparation of a simple experiment could take several days. Using proper simulation allows users to conduct various experiments virtually in a shorter time and with almost negligible cost.

5.2.1 SLM models

Before discussing the simulation tools used in SLM, it is important to understand that SLM is a multi-scale manufacturing process that encompasses phenomena occurring across various spatial and temporal dimensions [3], [8]. In terms of spatial scale:

1. Macro-scale: The level of the entire produced part. The SLM can fabricate parts with dimensions from millimetres to metres.

2. Meso-scale: The level of melting and solidification of the powder particles, where the dimensions range from 10 to 100 micrometres.

3. Micro-scale: The level of particles where the interaction between the laser beam and powder particles, as well as the formation of the melt pool, occurs at the micrometre level.

Regarding the temporal scale:

1. The millisecond scale: characterises the rapid nature of SLM, where the laser beam scans the powder bed at speeds of several meters per second.

2. The microsecond scale: concerns the melting and solidification of powder particles, taking place within microseconds.

3. The nanosecond scale: concerns how the laser beam interacts with the powder particles and the melt pool in nanoseconds.

The multi-scale nature of the SLM process presents complexity and challenges in modelling and simulating the process. Having a single model to capture the various scales is an unfeasible task. The more detail that is included, the more the computation cost needs to be.

There are many modelling efforts that can be found in the literature. The vast majority of the effects were related to modelling the thermal dynamics of the melt pool. That is because many properties are related to the temperature of the substrate during the process. The models were physics-based or-most recently- data-driven based. There are ODE, PDE, linear, nonlinear, and empirical models [8], [69]. With all of these existing models with different diversity, unfortunately, very few models describe the selective laser melting process, and fewer are control design-oriented.

The PDE models are handled using numerical methods such as Finite Element Analysis (FEA), which it is not possible to use for real-time process control due to the higher computational complexity. A data-driven model presents a powerful tool though it also faces challenges. The quality of such models depends on the amount of available or accessible data; the shortage of accurate data is a significant obstacle that then questions the model accuracy. A physics-based-control-oriented model is considered a valuable alternative that can capture the required specification and be simple enough to use for the design of online control.

The idea of using a physics-based model can be traced back to the welding process, where a model was proposed in [70]. The model was used to predict the melt pool geometry while simulating a single-track melt deposition process. In [8], the concept was adapted for the SLM process. The target was to develop a control-oriented model that can capture the behaviour of the melt pool and can be used to design a controller.

The derived physics model suits an open-loop control system such as a feedforward and AI-based controller. In [100], [101], the research group linearised the model in order to investigate the implementation of feedback control strategies in the SLM process. Linear models are known to be sensitive and could miss many real-world aspects.

Based on this context, this work will focus on mesoscale modelling that will relate the laser power input to the melt-pool cross-sectional area while considering the heat effect from the printed parts.

5.2.2 Common existing simulation

Several simulation tools and software have been developed to simulate the SLM process. The tools utilise different models based on the desired simulation tasks. These tools often focus on specific aspects of the SLM process, such as thermal modelling, powder bed dynamics, or melt pool behavior. The more accurate the simulation (including more physics considerations), the higher it becomes in terms of cost and computation time. The most widely used software in this field is presented in Table 5.1 [102]. The table presents a brief comparison between five common software choices for metallic additive manufacturing. These software are used to simulate different aspects of the LPBF process, including laser scanning, heat transfer, melt-pool dynamic, residual stress and distortion. The most comprehensive is Simufact Additive, whereas the most simple is Netfabb. The FEniCS is an open source FE solver, but requires more programming skills compared to the other. The majority of these software are designed to study the mechanical and thermal behaviour of the desired printed shape. Since the control system investigation is an emerging aspect in the research field of SLM process, most of the existing software are not equipped with tools that can help in this field, as the literature showed. The existing tool either permits to provide pre-optimise parameters or allows the use of other software to take care of the control investigation, such

Table 5.1.: A brief comparison between the most common simulation software used to simulate the SLM process.

Platform	Advantages	Disadvatages
Simufact Additive	Most comprehensive and accurate SLM simulation tool available	Expensive
ANSYS Workbench	Comprehensive and accurate SLM simulation tool	Expensive , limited in resolution
Materialise Magics	Easy to use and affordable	Less comprehensive and accurate
Netfabb	Easy to use and affordable	Less comprehensive and accurate
FEniCS	Flexible and customizable	Requires programming knowledge

as the combination of Matlab with ANSYS. One of the common challenges for most of these software is computational cost, due to the adoption of a numerical methods such as finite element method, finite volume method, finite difference method and molecular dynamics [82].

5.2.3 Why MATLAB-based tool?!

There is a growing need for versatile and user-friendly simulation tools to model SLM processes while providing a platform for closed-loop control experiments. Matlab is a powerful and convenient tool for control system engineering. The software is equipped with various engineering and control system toolboxes that help to build mathematical models of complex processes, analysis, and design control systems faster than other simulation software. It offers the flexibility to integrate various aspects of the SLM process into a single simulation framework. The tool we propose in this research has the following features:

- Flexibility: Each element of the proposed model will be presented as an individual modular/block. This approach makes the combination, modification, and expansion of the system much easier.

- Practical consideration: The proposed tool considers material properties such as thermal conduction, convection and radiation, process parameters such as ambient temperature, scanning speed, and laser power, and control strategies (currently: any singel-input single-output control system).

- User-Friendly Interface: Matlab's graphical interface makes it accessible to a wide range of users, including those without extensive programming experience, enabling them to explore and understand SLM processes more effectively.

- Closed-Loop Control: Matlab-based simulation tools can incorporate closed-loop control mechanisms, allowing researchers to design and test control algorithms for optimizing SLM parameters like laser power in real-time.

- Versatility: Matlab's computational capabilities make it possible to model complex physical phenomena within the SLM process accurately. Researchers can adapt and extend these models to suit their specific research needs.

The computational requirements and main advantages of the proposed model, which include the consideration of the control strategy, are clearly visualised in Figure (5.1).

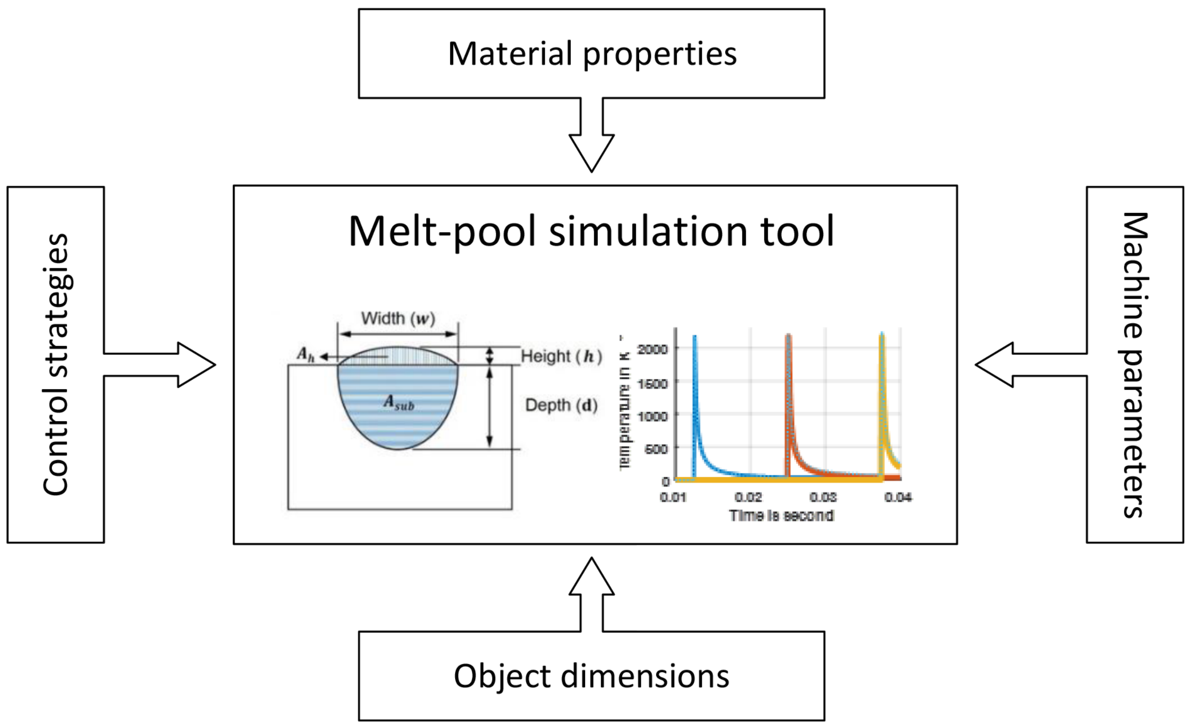


Figure 5.1.: Melt-pool simulation tool: A computational and process requirements.

5.3. Research method

Generally, the fundamental steps to develop a simulation technique are problem formulation, data collection and analysis, model formulation, model validation, and documentation [103]. This research utilises four stages to develop a simulation framework to estimate melt pool geometry and thermal behaviour, as demonstrated in Figure (5.2).

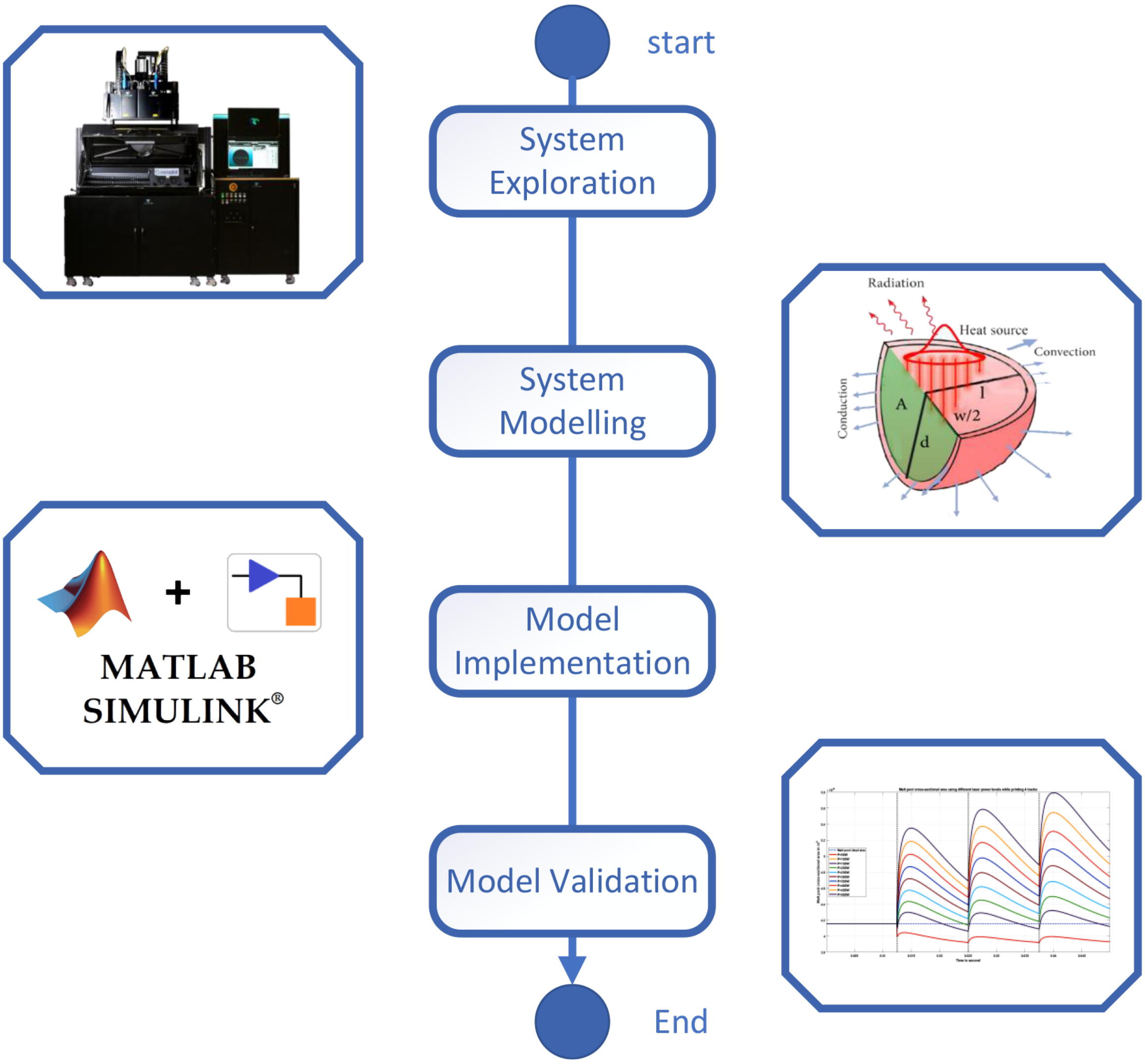


Figure 5.2.: Research method steps.

In the initial stage, the researcher defines the system components and functionalities of the SLM process in general and the AconityMINI (AM) system in specific. These data were collected from intensive research work that covered the existing literature and machine documents. Proceeding to the second stage, a comprehensive analysis of the melt pool model is conducted. The process includes generating various sets of data using physics-based models and analysing them. Based on the produced data, new relations between the machine parameters are deduced using different system identification and curve fitting tools. In the third stage, the finalised model of the melt-pool which includes the temperature history model, the melt-pool temperature estimator, and the melt-pool geometry model are implemented in Matlab software. The implementation will produce a tool that estimates the melt pool temperature and cross-sectional area, considering the heat residuals during the process. Additionally, the tool allows the inclusion of a closed-loop control system and testing of its efficacy. In the last stage, the performance of the model is evaluated. Unfortunately, validation is limited in this research to theoretical validation only. The data generated by the proposed tool will be compared with the original model.

Each stage is discussed in more detail in the subsequent sections, except the first stage, which was discussed in Chapter 3.

5.4. Block modelling and implementation

In this part of the research, the blocks and its model of the proposed tool are discussed. Besides the M-file that initiates the process parameters, the tool consists of five main blocks: melt-pool area, melt-pool temperature, temperature residual, control unit, and process noise. Figure (5.3) illustrates the overall block diagram of the tool. The following context will discuss in more detail each block and its implementation in Matlab.

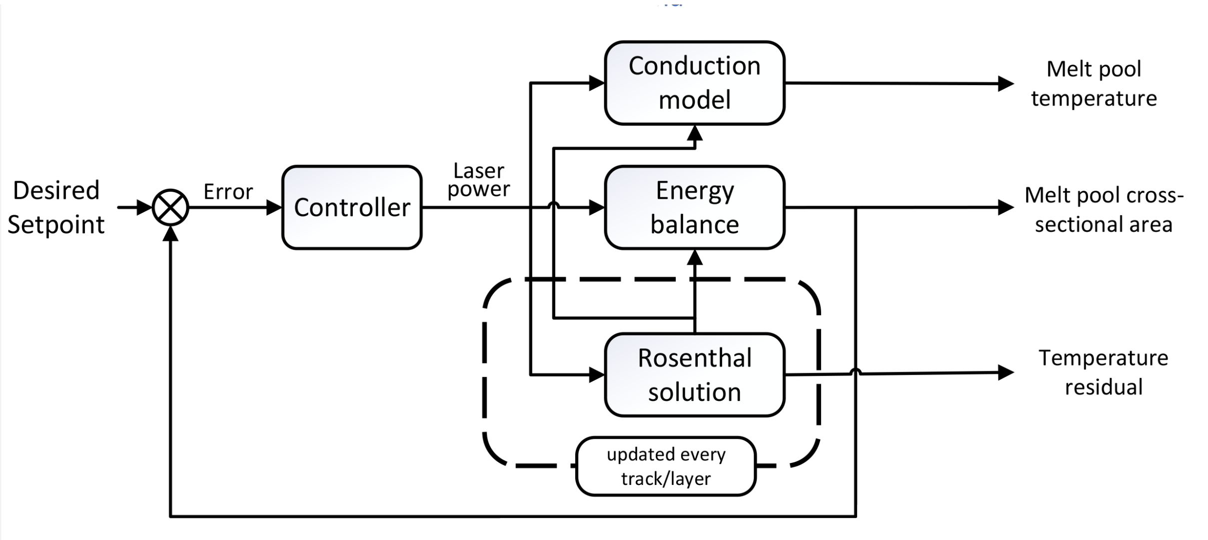


Figure 5.3.: The generic diagram of the overall system.

5.4.1 Model parameters initialisation

At the beginning, the parameters of the machine, material, object, and various model variables are initialised using a Matlab live script. The machine parameter includes the laser power, scanning speed, laser effective area diameter and the powder thickness. The material properties considered in this tool are the ones which were presented in section 3.2.1, Table 3.1. The object dimensions arecurrently the number of tracks and layers to be simulated. From the defined parameters the set of variables are calculated. The time factor is implicitly considered in most of the calculations. The user can easily modify the parameters to assess their influence with just a few straightforward actions. The following Figure (5.4) presents a screenshot of the script. The script is prepared to enable the option of running the Simulink model without opening it. The data generated from the model can be analysed as well as an additional option.

Object dimensions

```
s=10e-3;                % track length
tracks_per_layer=60;    % number of tracks per layer
number_layers=60;       % number of layers
```

Machine parameters

```
Q=250;                  % initial  laser power Watt
v=800e-3;               % scanning  speed m/s
L_thk=30e-6;            % powder layer thickness in m
fi=1e-4;                % effective beam diameter (m)
```

Material properties

```
pro= 4430;              % density kg/m3
Tm=1923;                % melting temperature k
Tinit=292;              % initial  temperature at the beginning k
Ta=292;                 % ambient temperature  k
cl=700;                 %  molten material specific heat J/kg K
cs=405;                 % solid material specific heat J/kg K
csp=694;                % material specific heat J/kg K
k=6.9e+3;               % thermal conductivity  W/mm K
a=2.48e-6;              % thermal diffusivity mm2/s
as=24;                  % convection coefficent W/m2 k
ag=20;                  % heat transfer coefficient  W/m2 k
ep=0.9;                 % surface emissivity
mu=0.2;                 % temperature ratio
r=1.75;                 % width-depth ratio
beta=10;                % length-width
hsl=2e5;                % specific latent heat of fusion
segma=5.67e-8;          % Stefan Boltzmann constant
neff=0.36;              % laser transmission efficiency
qq=neff*Q;              % source power
```

Variable computation for Simulink

```
stepSize=fi/2;          % step size in terms of effective diameter
% specific internal energy  e(t)
et=cs*(Tm-Ta)+hsl+cl*mu*Tm;
% lambda
lumda=(4/3)*sqrt(r/pi)*beta;
lumda_s=((2)^(5/3))*(r^(1/3))*(beta^(2/3));
lumda_g=r*beta;
Coe=((3/2)*lumda*pro*et)^-1;
power_in=pro*v*cs*(Tm-Tinit);
cond=lumda_s*as*((1+mu)*Tm-Tinit);
conv=lumda_g*ag*((1+mu)*Tm-Ta);
radi=lumda_g*ep*segma*(((1+mu)^2)*((Tm)^4)-(Ta)^4);
VolumUnderLaser=0.5*(4/3)*pi*((2.5*fi)^2)*L_thk;
%% To calculate the initial temperature during the process
tcst1=s/v;                        % time to complete on track
tcst2=tracks_per_layer*tcst1; % time to complete on layer / time t
tsampling=0.0000625;              % sampling time of the Simulink  mod
numberOfSamplesPerTrack=single(tcst1/tsampling);    % number of sa
numberOfSamplesPerLayer=numberOfSamplesPerTrack*tracks_per_layer;
TtoSim=tcst2*number_layers-tsampling; % time of simulation
```

Running the Simulink model

```
%sim('SLM_Tini_Simplified_VS',tcst2); % run simulink model
```

Figure 5.4.: Sample of the implemented code.

5.4.2 Melt-pool area estimation

As previously stated in Chapter 3, the melt-pool in the SLM process can be described using a heat balance equation. As detailed in Section 3.3.1, the equation relates the cross-sectional area of the melt pool to the laser power used, while considering the residual temperature

coming from the completed tracks or layer. The model is maintained as is, without linearisation. This will improve the quality of the data generated from the model, enhance the model reliability, and enhance the experience of designing the controller system. Figure (5.5) illustrates how the model is implemented in Matlab Simulink, where table (5.2) contains explanations for the symbols utilised.
The temperature residual input (T_{ini}) that appears in the figure is computed from another block that will be discussed in the coming context. This block can be used alone to investigate the system open-loop response (with or without the temperature accumulation (T_{ini}) only by providing the input laser power (Q).

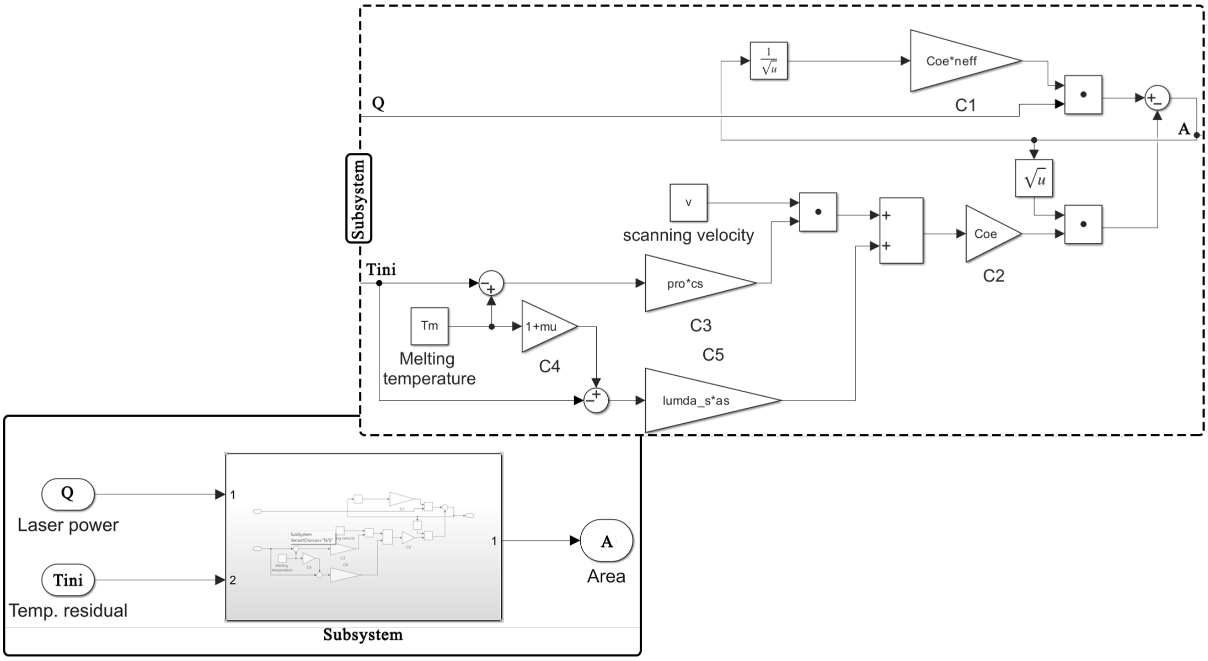


Figure 5.5.: The implementation of the cross-sectional area implementation.

5.4.3 Melt-pool temperature estimation

As stated before the melt-pool temperature gives an insight into whether area values are realistic or not. If there is a very high temperature (more then 20% over the melting temperature) the area model will still give a value, which practically could present the boiling phenomena. The same is applied if the temperature is lower then the melting point.

To estimate the melt-pool temperature, the basic heat conduction described in section 3.3.6 is used to estimate the melt-pool temperature. Figure (5.6) illustrates how the model is implemented in Matlab Simulink.

Table 5.2.: Description of the symbols in model implementation in Simulink.

Symble	Description
lumda	A constant that relates the length-to-width ratio (β) and a width-to-depth ratio (r),$\lambda_s = 2^{5/3}r^{1/3}\beta^{2/3}$
pro	The material density
neff	The Laser absorption efficiency
Coe	A constant coefficient equal to the reciprocal of the 3/2 of the multiplication of lumda density and the specific internal energy (et) of the used material $Coe = ((3/2)\lambda * pro * et^{-1}$
cs	The material-specific heat
Tm	The melting temperature of the material
mu	The percentage of the difference between the steady-state temperature and the melting temperature
v	The scanning velocity of the laser source
as	The material convection coefficient
u	A generic symbel to describe the applied mathematical operation

5.4.4 Temperature history estimation

Temperature history, or the temperature inherited from the printed parts during the process, presents a vital factor that affects the quality of the produced parts.

To model and simulate this factor is a complex process that should consider the effect of the laser source, the temperature of the surroundings and the temperature beneath the substance. Several attempts can be found in this context in the literature, as was presented in Chapters 2 and 3.

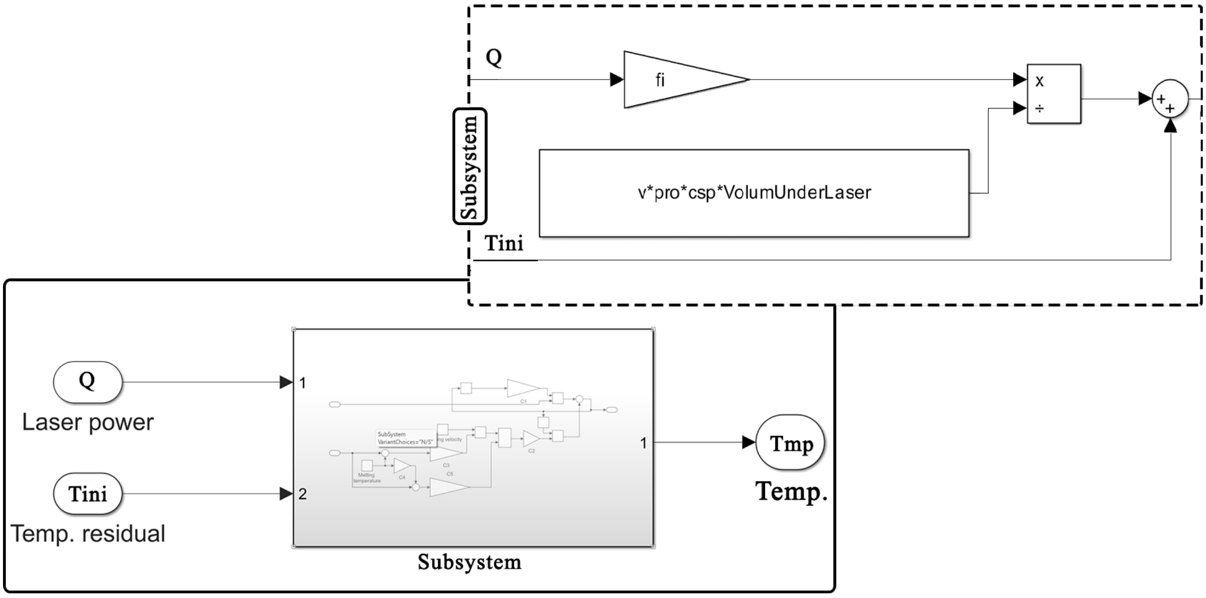


Figure 5.6.: Melt-pool temperature model implementation.

Rosenthal's solution as presented in chapter 4, has been used to model the effect of the printed part. However, using the concept in simulation requires pre-defining all the endpoints of all tracks in the object and computing its effect on the operating point. This significantly increases the computational cost of the simulation task.

For example, if the process parameters presented in Table (3.1) are considered to print a cube with a volume of $1cm^3$, there are approximately 300 tracks in 200 layers. This gives about 60000 virtual sources that need to be considered in every simulation step, which is around 120,000,000 in only $1cm^3$.

In this section, a simplified model based on sets of input-output data was determined. The data sets were generated by solving Rosenthal's equation using the material and process parameters presented in Tables (3.1) and (3.2), different laser power, and different track lengths. Based on the investigation done in Chapater 4, the temperature residuals can be divided into two parts: the temperature coming from the printed tracks and the temperature coming from printed layers. The following subsections illustrate the model derivation and implementation for both types.

Effects coming from previous tracks

According to the simulation results, the initial temperature profile for the same level of laser power exhibits a similar behaviour regardless of the track length, as illustrated in Figure (5.7).

The graph indicates that the longer the track, the lower the temperature at the end. Therefore, there will be no variation in the profile for certain lengths. Due to computational limitations, this research will only investigate track lengths up to 20mm.

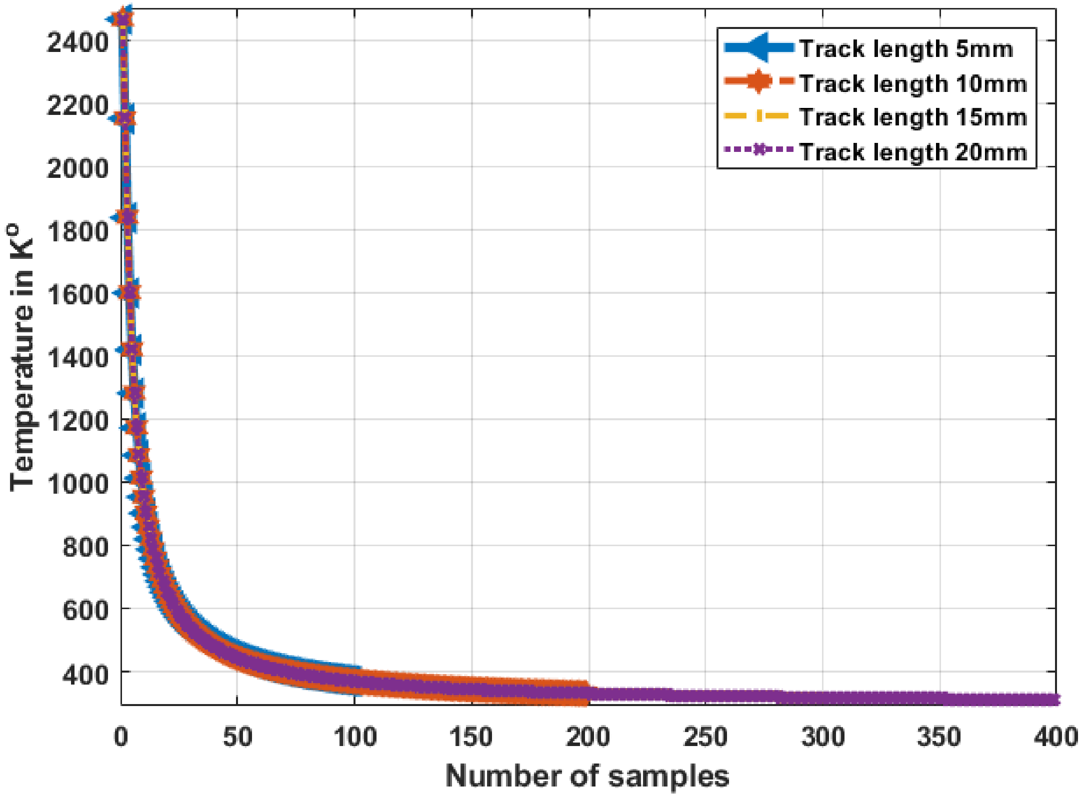


Figure 5.7.: Initial temperature profile using constant process parameters and various track lengths.

The generated data was studied and analysed in order to derive a simpler expression of the virtual source. Using the curve-fitting toolbox in MATLAB, several potential fitting models were explored and evaluated to determine the most suitable one. The best model that could fit the data for each case was a combination of two exponential functions given in the following form:

$$T_{ini}(t) = ae^{-bt} + ce^{-dt} \tag{5.1}$$

Figure (5.8) and (5.9) illustrate the difference between the original data and the fitted curve. The proposed model is consistent with Rosenthal's solution general representation of the virtual source as was shown in Equation (3.20). Table (5.3) presents the values of the coefficients a, b, c and d corresponding to different laser inputs and a track length of 20 mm.

The sum of values of a and c represent the maximum magnitude of the virtual source effect. The values can be correlated to the input laser power using the polynomial with the

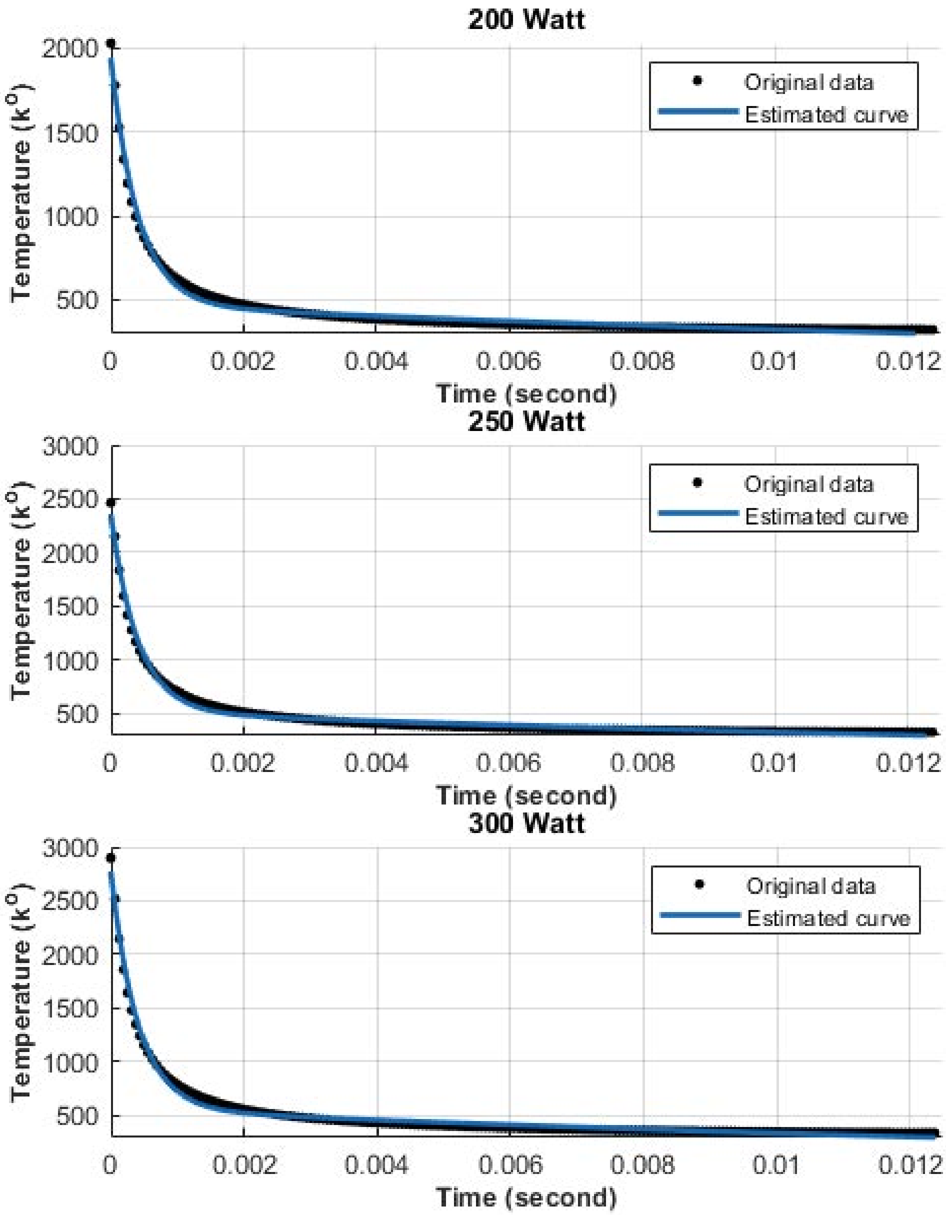


Figure 5.8.: Comparison of original data and curve fitting: The first curve represents the raw data generated from Rosenthal's solution, while the second curve illustrates the result of curve fitting using different laser power.

following expression:

$$Coef(Q) = P_4x^3 + P_3x^2 + P_2x + P_1 \tag{5.2}$$

Table (5.4) presents the coefficients of three different polynomials that can describe a and c as a function of laser power.

The maximum error between the origin value of a and c, and the proposed fitting curve did not exceed 1.7% for all the polynomials. The selection of the best fitting model to be used, will be a trade-off between a better accuracy and computational cost. For our case,

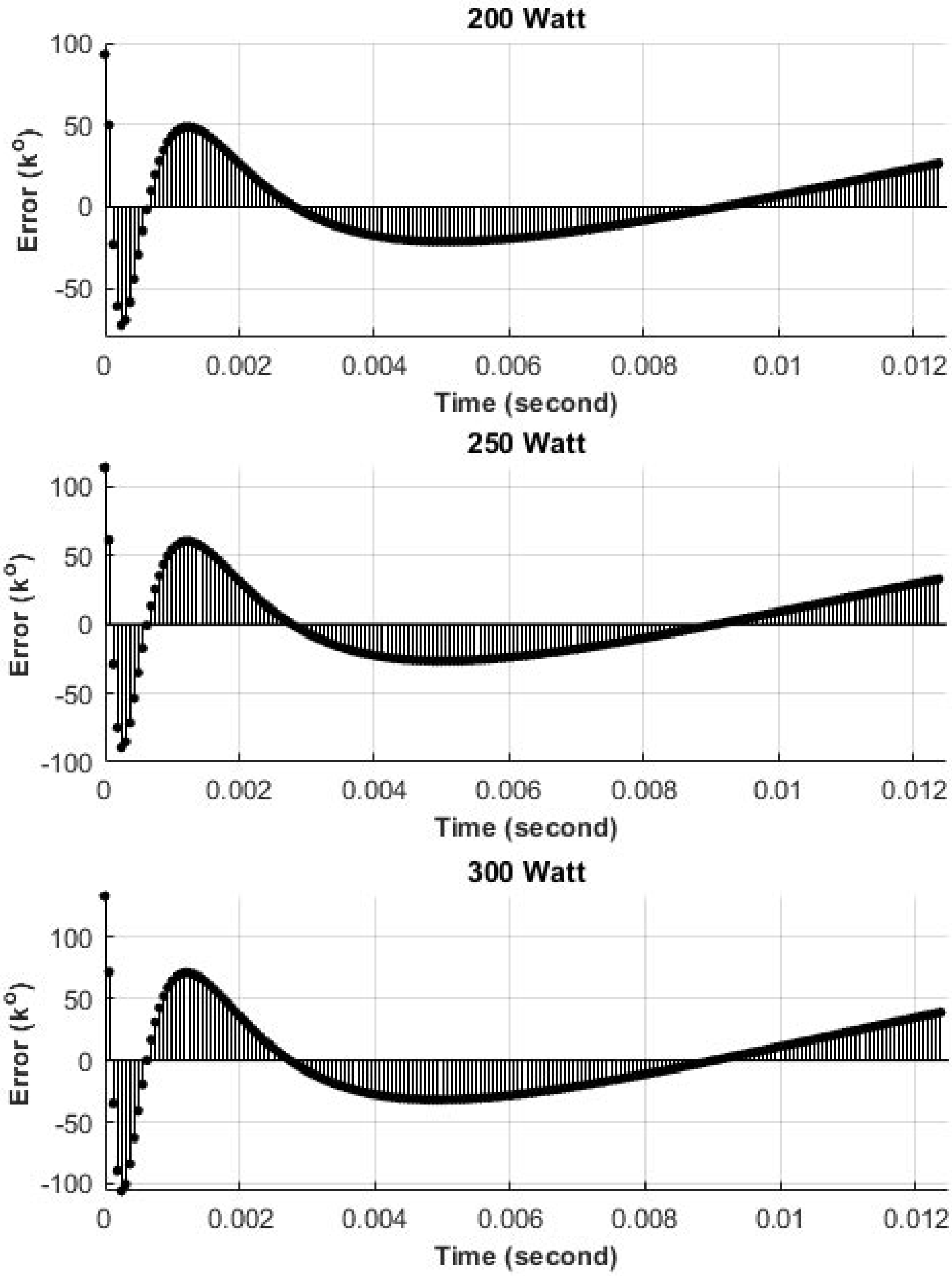


Figure 5.9.: The error between the original data and curve fitting model for the various laser power inputs.

we will select the option with the lowest sum of squared errors (SSE). Figure (5.10) presents the selected fitting model of the coefficients a and c and the corresponding estimation error.

The coefficients b and d represent the cooling rate of the virtual source. Similarly, the coefficients can be related to the applied laser power. However, a linear equation can fit the data with ease. The equations' coefficients are listed in Table (5.5).

Figure (5.11) presents the fitting models for b and d coefficients and the corresponding

Table 5.3.: Coefficients of the estimated model with respect to various laser power in addition to the goodness of fit for each case.

	Coefficient				Goodness of Fit	
Power	a	b	c	d	sse	$r-square$
50	369.3645	-2.01E+03	318.1019	-3.6896	1.49E+04	0.9792
100	738.7627	-2.02E+03	345.2033	-7.2267	5.86E+04	0.9795
150	1.11E+03	-2.03E+03	373.2662	-10.6203	1.30E+05	0.9798
200	1.48E+03	-2.04E+03	402.2535	-13.8789	2.27E+05	0.9802
250	1.85E+03	-2.05E+03	432.1294	-17.0107	3.49E+05	0.9805
300	2.22E+03	-2.06E+03	462.8726	-20.025	4.95E+05	0.9808
350	2.59E+03	-2.07E+03	494.4265	-22.9254	6.64E+05	0.981
400	2.95E+03	-2.08E+03	5.27E+02	-25.7199	8.55E+05	0.9813
450	3.32E+03	-2.09E+03	5.60E+02	-28.4145	1.07E+06	0.9816
500	3.69E+03	-2.10E+03	5.94E+02	-31.015	1.30E+06	0.9818

Table 5.4.: Coefficients of the three different polynomials that can fit to relate the a and c coefficients to the used laser power, in addition to the goodness-of-fit for each case.

	$a(Q)$			$c(Q)$		
Coefficients	1st	2nd	3rd	1st	2nd	3rd
P_1	3.3334	-3.0239	-4.3467	282.1723	291.5643	292.0043
P_2	7.3763	7.4399	7.4633	0.6136	0.5197	0.5119
P_3		-0.0001	-0.0002		0.0002	0.0002
P_4			0			0
sse	84.3868	40.2974	39.5632	96.3306	0.1022	0.021
r-square	1	1	1	0.9988	1	1

residuals for each model. The maximum error between the proposed curves and the data was less than 0.05% in both polynomials.

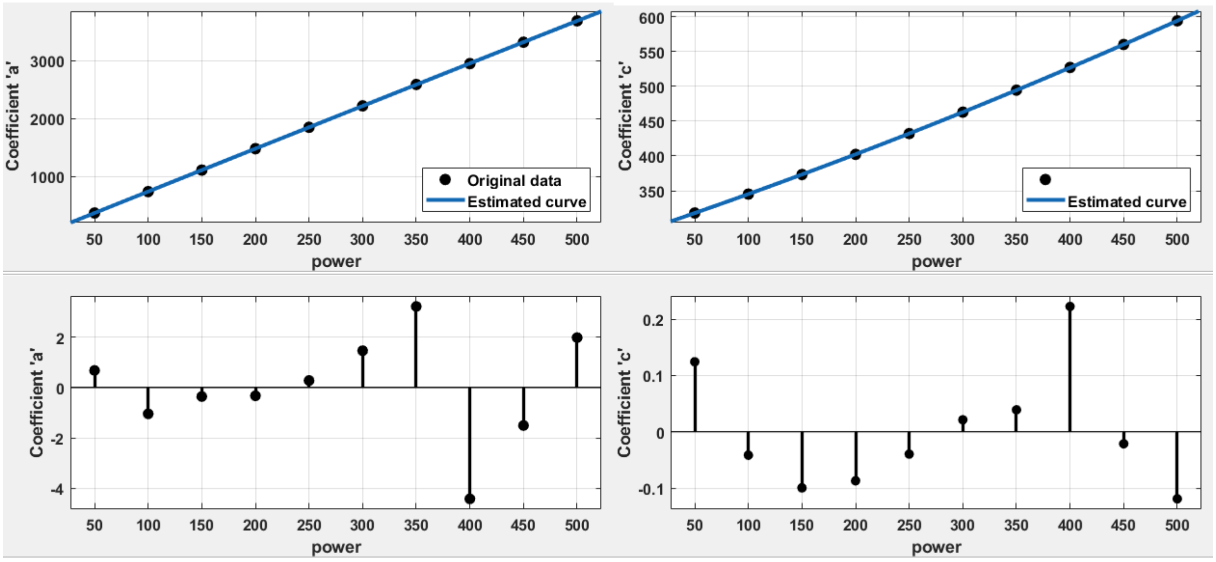


Figure 5.10.: Curve fitting of a and c coefficients and the estimation error.

Table 5.5.: Coefficients of a fitting model that relate the b and d coefficients to the used laser power, in addition to the goodness of fit for each case.

Coefficients	$b(Q)$	$d(Q)$
P_1	-2.00E+03	-0.0083
P_2	-0.2	-0.0752
SSE	0	0
r-square	1	1

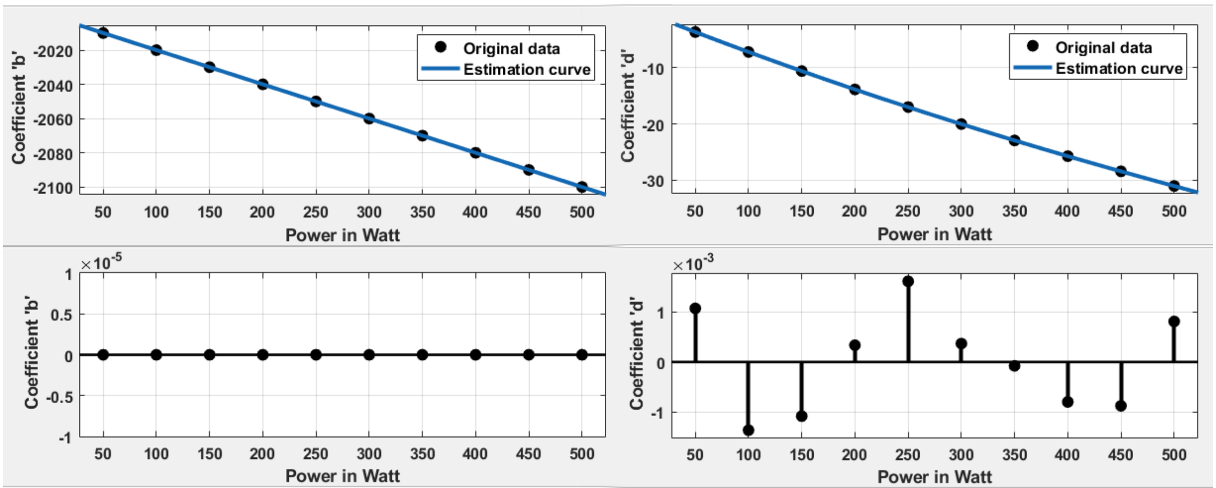


Figure 5.11.: Curve fitting of coefficient b and d and the error estimation corresponding.

The behaviour of the effects coming from previous tracks

Equation (5.1) presents the estimated form of a virtual source effect. Based on the analysis presented in Chapter 3, it has been observed that the source has an impact on the subsequent tracks. In order to mimic this effect, the initial temperature of the end of a track will be fed back and added to the initial temperature of the following track. The impact will gradually decrease exponentially over time as expected in practice.

To quantify the exponential rate of the effect of the virtual source in the new track, several simulation tests were conducted using various track lengths and laser power levels. The best model that can capture the effect behaviour is a combination of two exponential functions similar to the form in equation (5.1). Table (5.6) shows the equation coefficients for the various laser power and track lengths.

The coefficients a and c can be proportionally related to the laser power. Furthermore the proportional factor can be presented as a function of track length. Tables (5.7) and (5.8) present the coefficients of both equations. An important observation that would help in implementing the proposed model later, is the constant ratio between coefficient a and c.

It was observed that the exponential rate is constant regardless of changes in laser power (Figure (5.12) illustrates the observation graphically). However, the rate decreased in magnitude as the track length increased. Both observations are consistent with the heat transfer rules.

The coefficients b and d present the exponential rate that can related to track length and estimated by a third-degree polynomial with zero sse. Table (5.9) presents the polynomial coefficients and the corresponding curve goodness-fitting indices.

In summary, the effects of a coming track will be computed using the equation (5.1) and adding to it the end of the track initial condition.

Effects coming from layers

The heat effect of printed layers is dependent on various factors, including material properties, process parameters, and object dimensions. As shown in Figures (5.13,5.14, and 5.15), changing laser power, track length, or the number of tracks per layer affects the heat value inherited from previous layers.

It is important to note that increasing the track length for the same level of power and

Table 5.6.: Coefficients of a fitting model for different laser power levels and various track lengths, in addition to the goodness of fit for each case.

Track length of 5 mm										
Power	50	100	150	200	250	300	350	400	450	500
a	3.8659	7.7319	11.5978	15.4637	19.3297	23.1956	27.0615	30.9275	34.7932	38.6592
b	-351.714	-351.714	-351.714	-351.714	-351.714	-351.714	-351.714	-351.714	-351.715	-351.715
c	10.0981	20.1962	30.2943	40.3924	50.4905	60.5886	70.6866	80.7847	90.883	100.9811
d	-59.4792	-59.4792	-59.4792	-59.4792	-59.4792	-59.4792	-59.4792	-59.4792	-59.4793	-59.4793
Track length of 10 mm										
Power	50	100	150	200	250	300	350	400	450	500
a	2.0891	4.1781	6.2672	8.3562	10.4453	12.5344	14.6233	16.7124	18.8014	20.8905
b	-185.268	-185.268	-185.268	-185.268	-185.268	-185.268	-185.269	-185.269	-185.269	-185.269
c	5.3213	10.6425	15.9638	21.285	26.6063	31.9275	37.2488	42.5701	47.8914	53.2126
d	-31.1258	-31.1258	-31.1258	-31.1258	-31.1258	-31.1258	-31.1259	-31.1259	-31.1259	-31.1259
Track length of 15 mm										
Power	50	100	150	200	250	300	350	400	450	500
a	1.4311	2.8623	4.2934	5.7246	7.1557	8.5868	10.0179	11.449	12.8802	14.3113
b	-125.454	-125.454	-125.454	-125.454	-125.454	-125.455	-125.455	-125.455	-125.455	-125.455
c	3.6083	7.2167	10.825	14.4334	18.0417	21.6501	25.2585	28.8669	32.4752	36.0836
d	-21.0465	-21.0465	-21.0465	-21.0465	-21.0465	-21.0466	-21.0466	-21.0466	-21.0466	-21.0466
Track length of 20 mm										
Power	50	100	150	200	250	300	350	400	450	500
a	1.0883	2.1765	3.2648	4.3531	5.4413	6.5296	7.6178	8.7061	9.7943	10.8826
b	-94.8	-94.8	-94.8	-94.8	-94.8	-94.8004	-94.8004	-94.8004	-94.8004	-94.8004
c	2.7292	5.4583	8.1875	10.9167	13.6459	16.3751	19.1043	21.8334	24.5626	27.2918
d	-15.8945	-15.8945	-15.8945	-15.8945	-15.8945	-15.8945	-15.8945	-15.8945	-15.8945	-15.8945

number of tracks per layer will reduce the amount of heat accumulation. Contrarily, maintiang the track length and laser power while increasing the number of tracks per layer will increase the amount of heat accumulated between the layers. A similar effect is observed when the track length and number of tracks per layer are maintained while increasing the laser power.

For the case illustrated in the figures (5.13, 5.14, and 5.15), the difference appears very small (a few degrees or a fraction of a degree in the track case), yet it not always the case.

To develop practical intuition, three distinct geometries were constructed to illustrate the

Table 5.7.: Coefficients of a fitting model that relate the a and c coefficients to used laser power for the various track lengths, in addition to the goodness of fit for each case.

Track length /Coefficients	5mm	10mm	15mm	20mm
a	0.0773	0.0418	0.0286	0.0218
c	0.202	0.1064	0.0722	0.0546
sse	0	0	0	0
r-square	1	1	1	1

Table 5.8.: Coefficients of a fitting model that relate the a and c coefficients to the track length, in addition to the goodness of fit for each case.

Coefficients	a	c
P_1	0.151	0.4038
P_2	-0.0196	-0.054
P_3	0.0011	0.003
P_4	0	-0.0001
sse	0	0
r-square	1	1

Table 5.9.: Coefficients of a fitting model that relate the b and d coefficients to the track length, in addition to the goodness of fit for each case.

Coefficients	b	d
P_1	-702.261	-119.454
P_2	93.6843	16.0467
P_3	-5.2314	-0.8994
P_4	0.1033	0.0178
sse	0	0
r-square	1	1

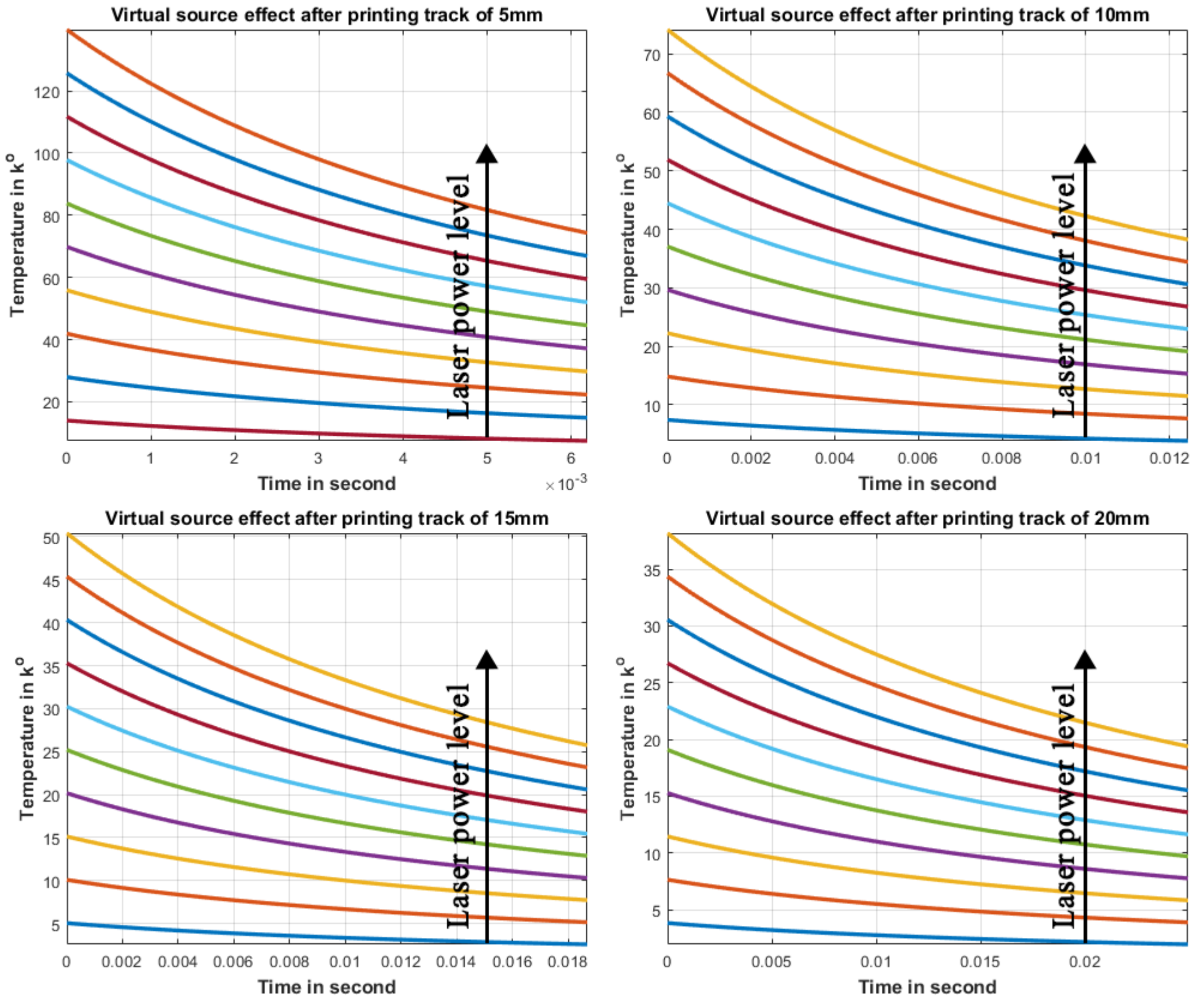


Figure 5.12.: The effect of virtual source after one track for various track length and laser power.

temperature range variation resulting from changes in the object's geometry. These geometries are differentiated by the dimensions of the build layer, namely "bigplate" (40 tracks, 10mm each), "rectangle" (18 tracks, 5mm each), and "thinwall" (4 tracks, 10mm each). Figures 5.16 and 5.17 illustrate the average temperature of the various cases.

Throughout the build process, it is evident that the average temperature of each layer increases as additional layers are added, attributed to heat accumulation. In all three scenarios, the simulation includes an adequate number of layers to demonstrate the saturation point of heat accumulation. This comprehensive analysis facilitates an understanding of the substantial influence of the geometry of the object on heat accumulation issues.

The heat accumulation in the "bigplate" geometry saturates after 25 layers, while the "rectangle" geometry saturates after 100 layers, and the "thinwall" geometry saturates after 200 layers. Additionally, the average temperature difference between the initial layer and

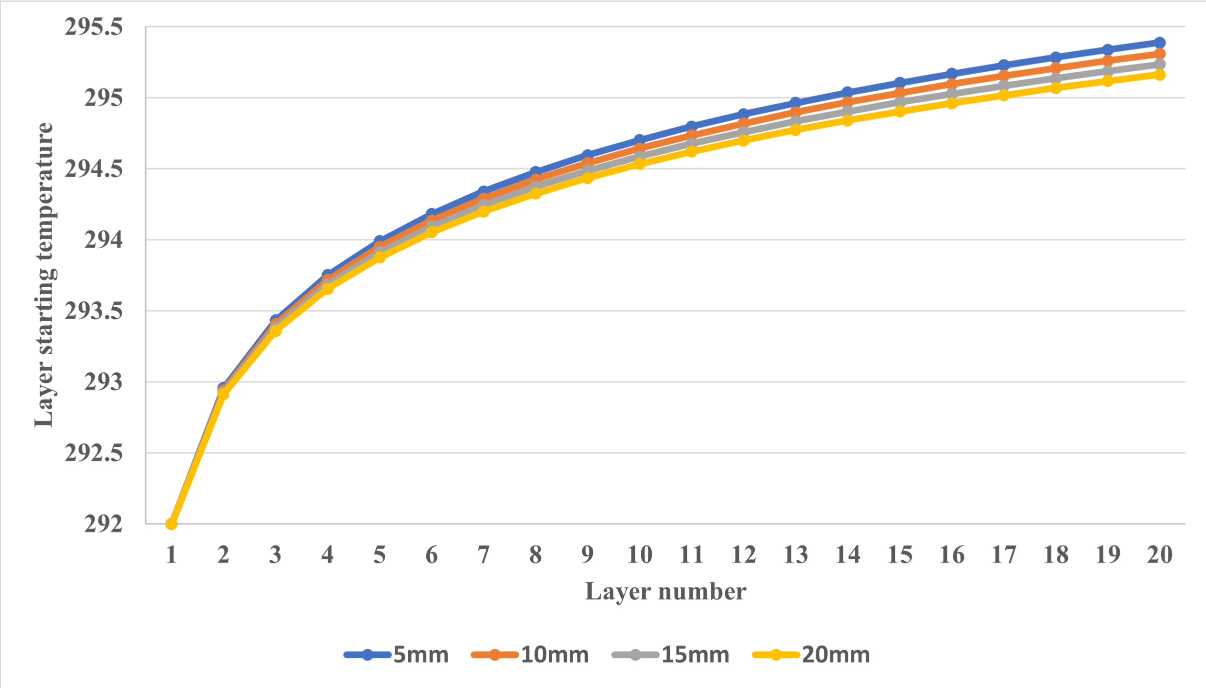


Figure 5.13.: The stating temperature in K^o per layer when the laser power and number of tracks are fixed and varying the track length.

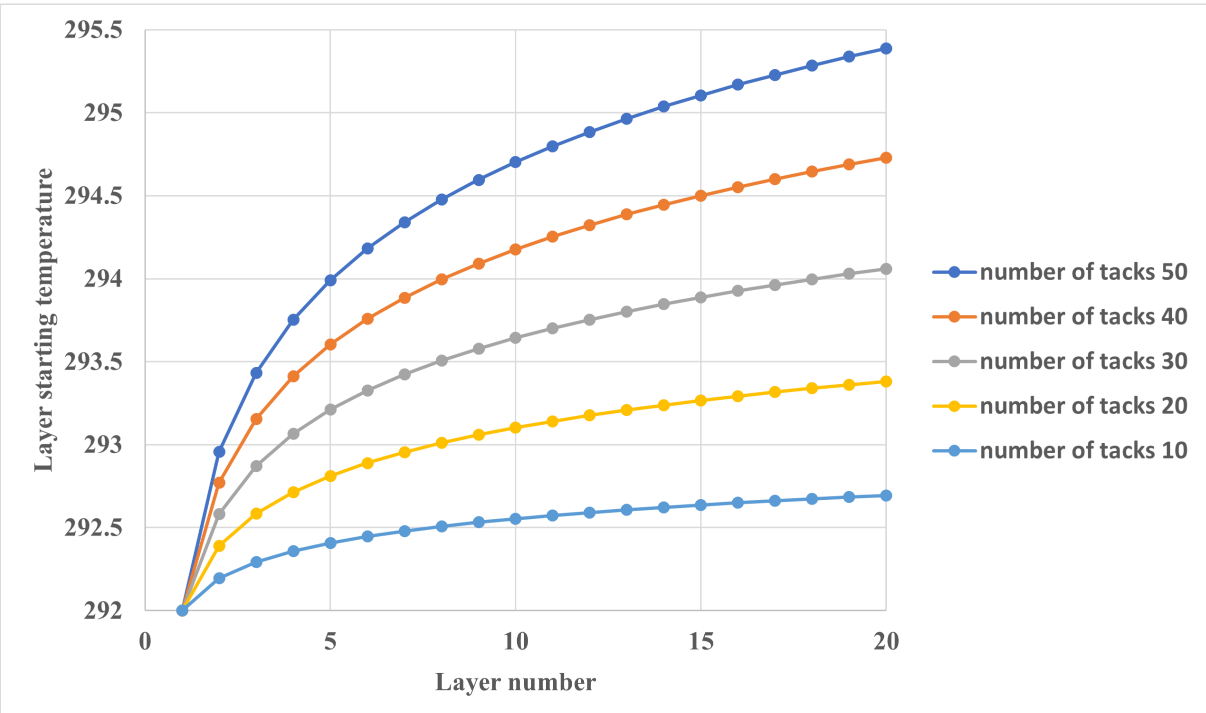


Figure 5.14.: The stating temperature in K^o per layer when the laser power and the track length were fixed and varying the number of tracks per layer.

the saturation layer is 10K for the "bigplate" geometry, 36K for the "rectangle" geometry, and 115K for the "thinwall" geometry. Consequently, it can be inferred that the "thinwall"

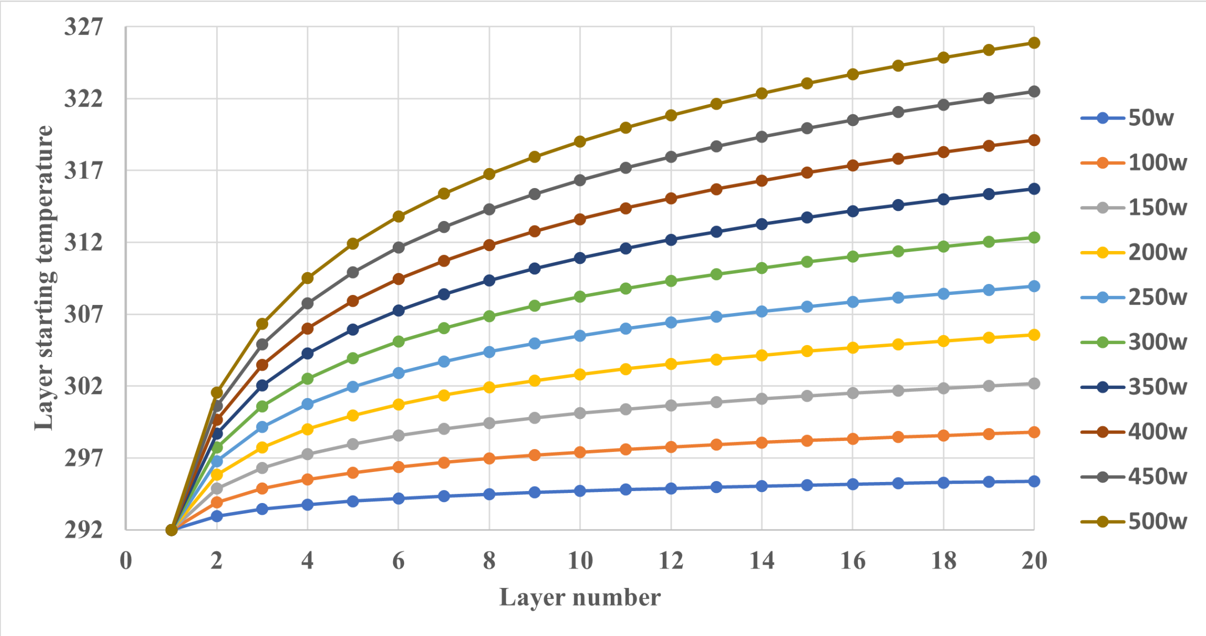


Figure 5.15.: The stating temperature in K^o per layer when the laser power is varying and the tracks number and length are fixed.

geometry presents the most significant challenges in terms of layer-wise heat accumulation.

Given the various factors that can affect the heat accumulation from printed layers, the curve fitting toolbox is not suitable for generating a simplified model. Instead, the regression learner app from Matlab is the ideal tool for creating a multivariate model. The Rosenthal solution is used to generate 200 data sets for the model, and each set changes one parameter while keeping the others fixed. Each simulation generates data for printing 20 layers. By providing data about the number of tracks per layer, track length, and the value of power source at the end of the layer, the tool provides an estimate of the maximum effect of the previous printed layer.

The tool produced a series of models using different regression techniques. We have chosen the model with the lowest root mean square error, which happened to be the Gaussian process regression model. Figure (5.19 and 5.18) provides a comparison between the actual and estimated data, as well as the prediction error.

The behaviour of the effects coming from previous layers

Similarly, the behaviour of the impact coming form the previous layer was derived. The regression learner were fed with the different sets of data (lasers, number of tracks,length) to determine the coefficients of the polynomial that can capture the effect behaviour and how

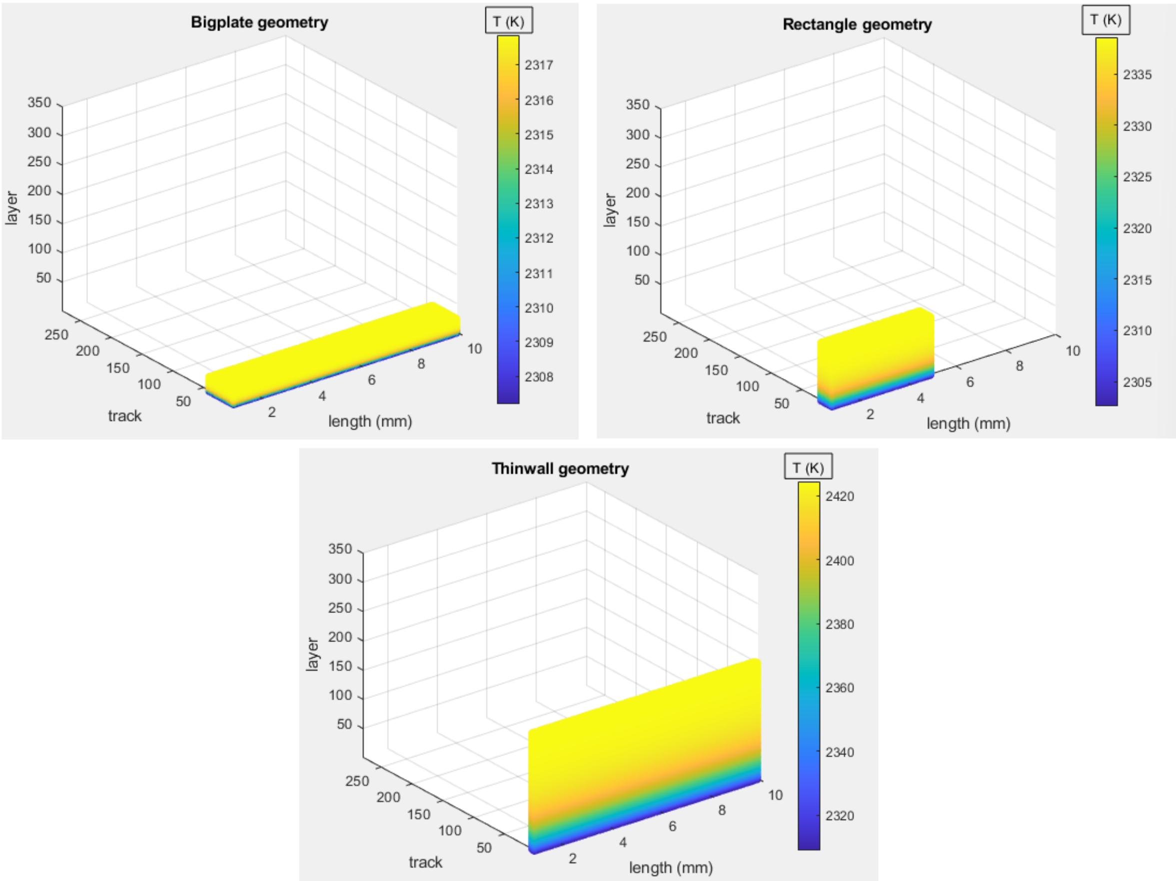


Figure 5.16.: Visual representation of heat accumulation among the layers using colormaps. Each point is labeled with the average temperature of its respective layer. The axes are scaled to accurately reflect the dimensional differences among the three geometries.

it decays with time.

The laser power (Q) in this model will be updated on every track to mimic Rosenthal's solution computation concept and reduce the computational cost significantly. The total effect (temperature history) can be calculated by adding the two parts (effect from tracks and effect from layers). Figure (5.20) presents the implementation of various functions needed to implement the initial temperature estimation model in SIMULINK. The figure presents the main subsystems used. However, there are many other functions embedded in these subsystems.

The virtual source power block is developed to hold the laser power (Q_{hold}) until the track/layer is completed. The time cycle synchronisation block is designed to ensure synchronisation between the various blocks during these simulations. The block generates four signals: track time cycle, layer cycle, completed track number, and completed layer number. The blocks 'Complete track effect calculation' and 'Complete track effect calculation' are the

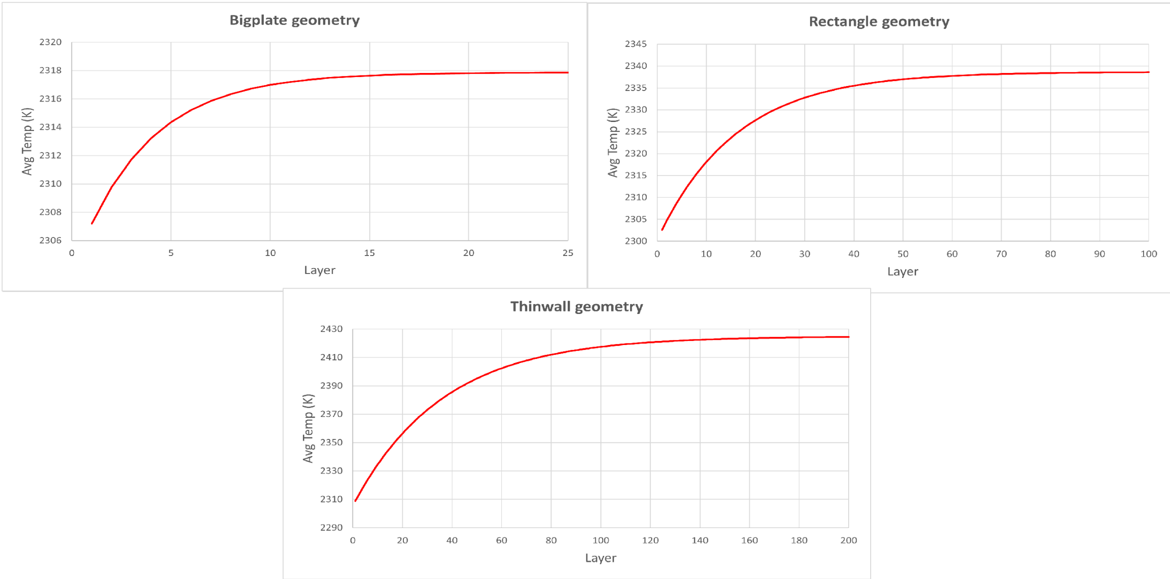


Figure 5.17.: Average layer temperature graphs are used to represent heat accumulation among the layers. These graphs correspond to the respective colormaps in the Figure 5.16

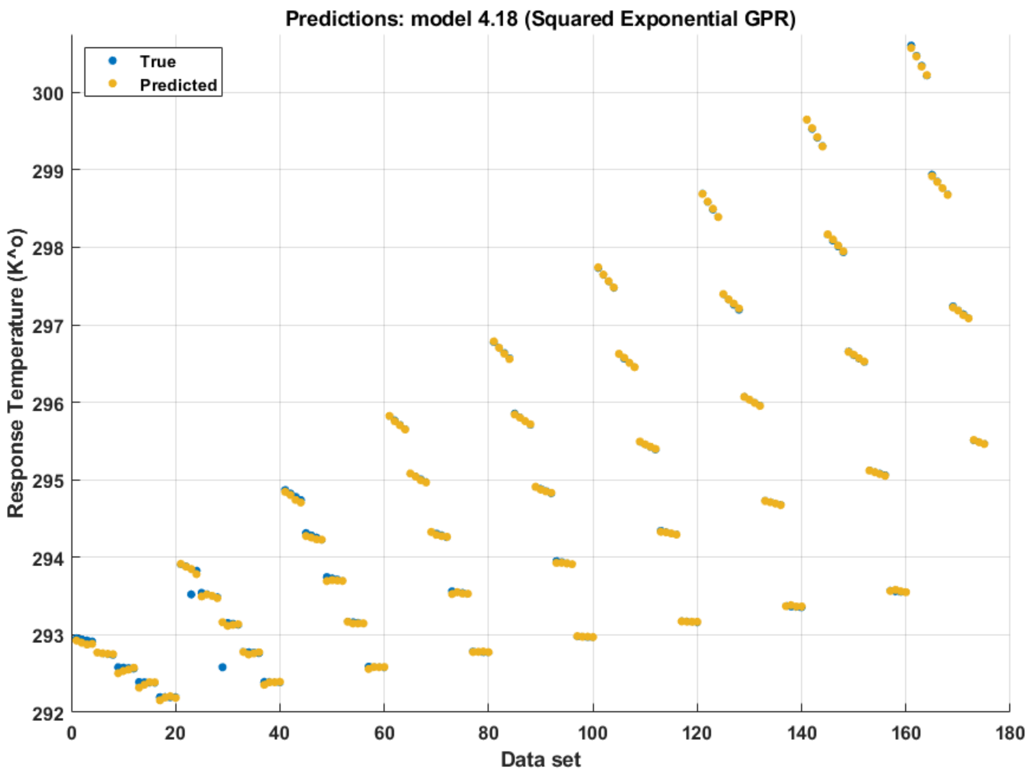


Figure 5.18.: The stating temperature in K^o per layer when the laser power is varying and the tracks number and length are fixed.

implementation of equation 5.1.

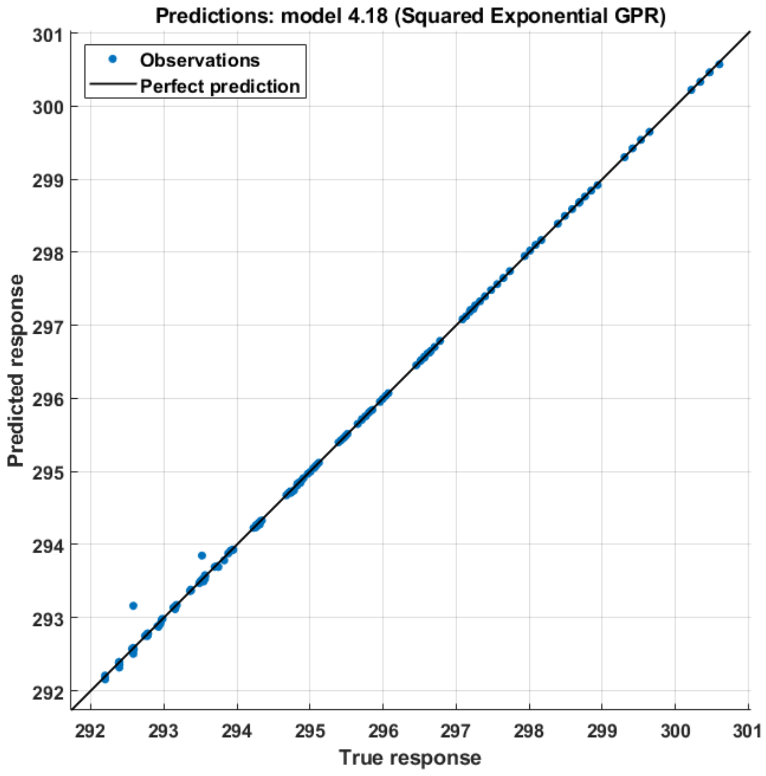


Figure 5.19.: The stating temperature in K^o per layer when the laser power is varying and the tracks number and length are fixed.

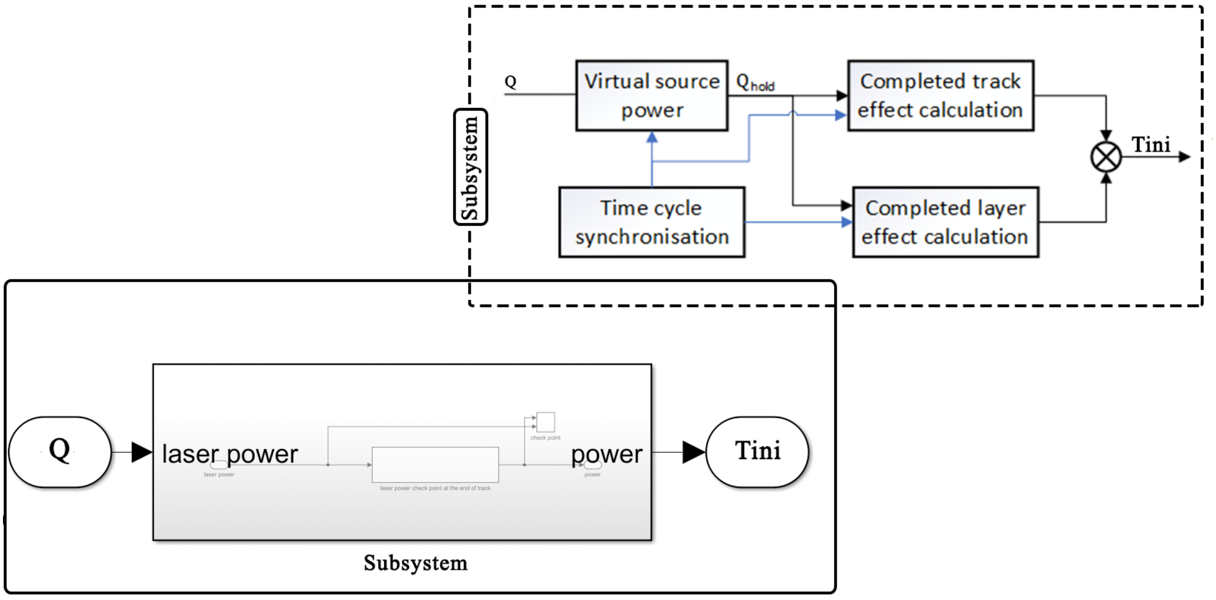


Figure 5.20.: Melt-pool initial temperature model main blocks and how its integration

5.5. Model evaluation and comparison

In this investigation, we encountered a notable limitation in the validation process. This prevents optimal achievement of having the highest level of accuracy and reliability in our findings. However, we believe that our findings still provide valuable insights and directions for future research in this area. In this section, the initial temperature computed using Rosenthal's solution and the proposed model are compared. Figures (5.21 and 5.22) present the initial temperature profile generated using the proposed model and the Rosenthal solution, and the difference between them for the first and the 60th layers. The following observations can be noticed:

- The heat accumulation from one track to another in the proposed model has a slower growth rate compared to the Rosenthal's solution.
- The difference between the two figures shows that the layer-to-layer accumulation is also subject to the same observation.
- In the first layer, the error increases with each track, whereas in the final layer, the opposite behaviour can be observed.

Table (5.10) presents the difference in percentage between the two models in four cases: first and last track in the first layer, and first and last track in the last layer. This explains the difference in the heat accumulation rate between the two models. The error within the track is expected due to the simplification of the computation process. Figures (5.23) and 5.24 graphically present the percentage of error in the first case.

The melt-pool temperature behaves exactly the same and has the same error percentage as the initial temperature due to the linear correlation between both variables. The variation between the two models for the cross-sectional area differs based on the laser power used and the number of completed tracks. The data of the proposed model tend to stall more faster after fee tracks than the original model, as can be seen in Figure (5.25).

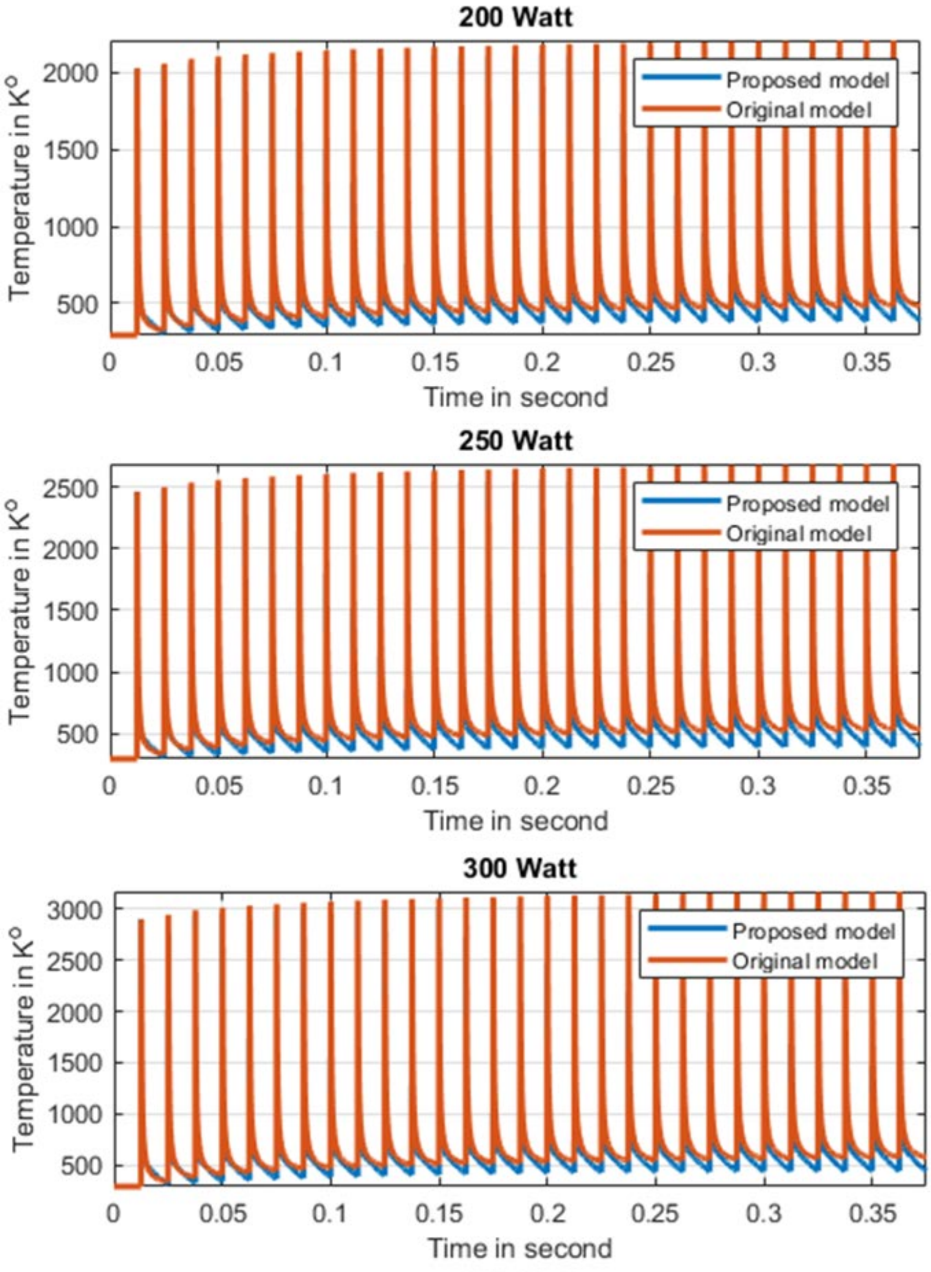


Figure 5.21.: The initial temperature profile generated using the proposed model and the Rosenthal's solution for the first layer.

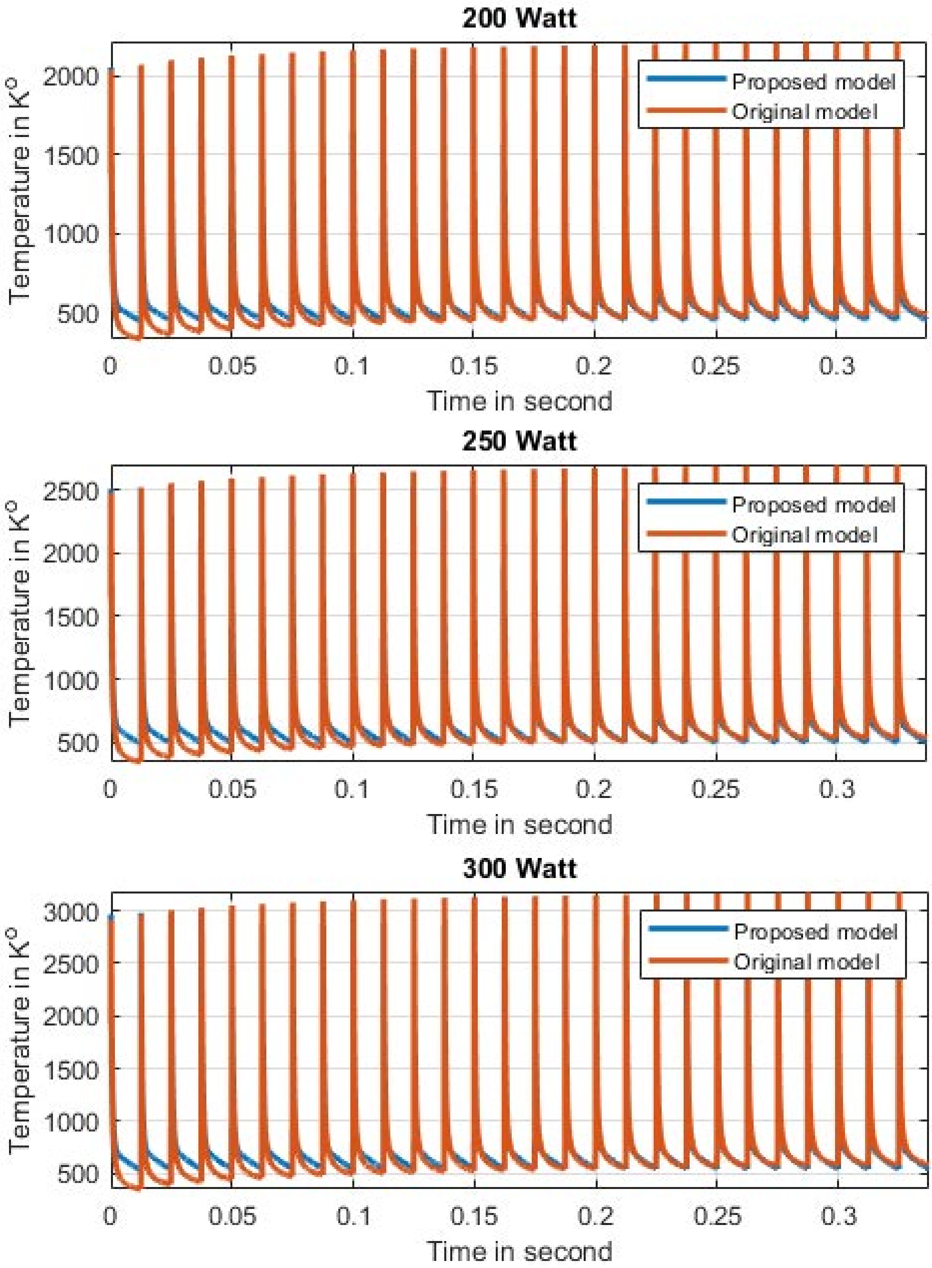


Figure 5.22.: The initial temperature profile generated using the proposed model and the Rosenthal's solution for the last layer.

Table 5.10.: The maximum, minimum, and average percentage of error between the proposed and original model for the first and last track in the first and last layer.

First layer first track										
Power	50	100	150	200	250	300	350	400	450	500
Max. %	22.8079	31.7346	36.5686	39.7226	42.0244	43.8346	45.3355	46.6292	47.7774	51.6581
Min. %	-11.2918	-13.5702	-14.4389	-14.8032	-14.9298	-14.9256	-14.8419	-14.7061	-14.5344	-14.3369
Avg. %	0.3488	1.6146	3.4714	5.7498	8.326	11.1059	14.0164	16.9999	20.0107	23.0126
Last layer first track										
Power	50	100	150	200	250	300	350	400	450	500
Max. %	18.1058	25.0845	29.0088	31.6933	33.7327	35.3814	36.7679	37.9651	39.0181	39.9569
Min. %	-12.9881	-15.1854	-15.8305	-15.9641	-15.8822	-15.6995	-15.4688	-15.2171	-14.9591	-14.7031
Avg. %	-5.9702	-8.7598	-9.9086	-10.1188	-9.7815	-9.1309	-8.3137	-7.4245	-6.5254	-5.6573
First layer last track										
Power	50	100	150	200	250	300	350	400	450	500
Max. %	27.5888	37.4582	42.9786	46.6884	49.4514	51.644	53.4582	55.003	59.2893	64.5351
Min. %	-7.128	-8.6871	-9.0483	-9.0142	-8.8174	-8.5488	-8.25	-7.9422	-7.6368	-7.3399
Avg. %	6.9097	11.8902	17.2082	22.6426	28.0418	33.3016	38.3507	43.141	47.6412	51.8323
Last layer last track										
Power	50	100	150	200	250	300	350	400	450	500
Max. %	19.9957	26.7629	30.5798	33.1988	35.193	36.8078	38.1667	39.3401	40.3715	41.2897
Min. %	-11.4294	-13.8321	-14.5664	-14.7499	-14.7003	-14.5409	-14.3285	-14.0922	-13.8479	-13.6048
Avg. %	-2.7086	-4.9031	-5.5943	-5.4488	-4.8322	-3.9611	-2.9695	-1.9427	-0.9362	0.0142

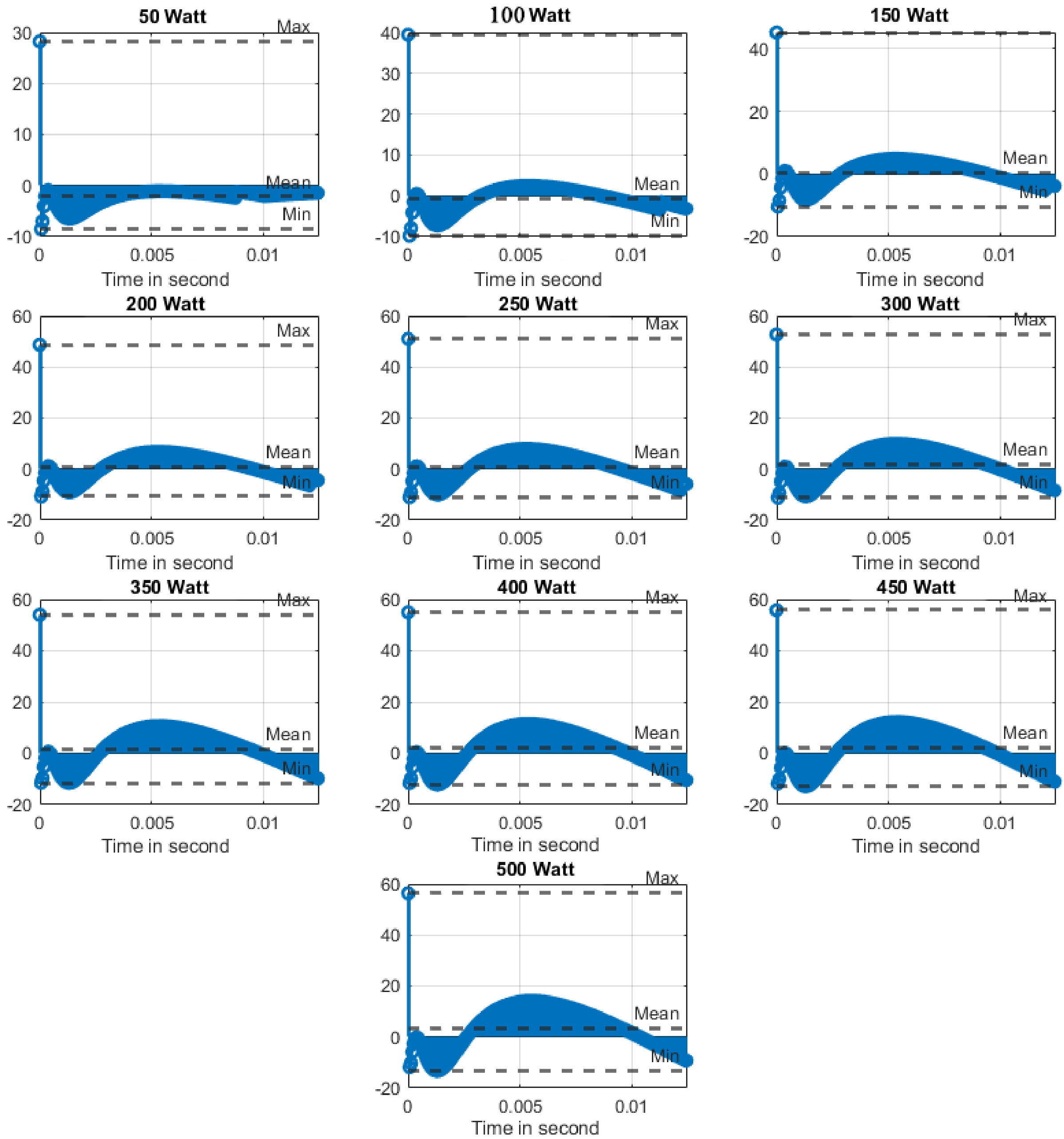


Figure 5.23.: The difference in percentage between the initial temperature profile generated using the proposed model and the Rosenthal's solution for the first track.

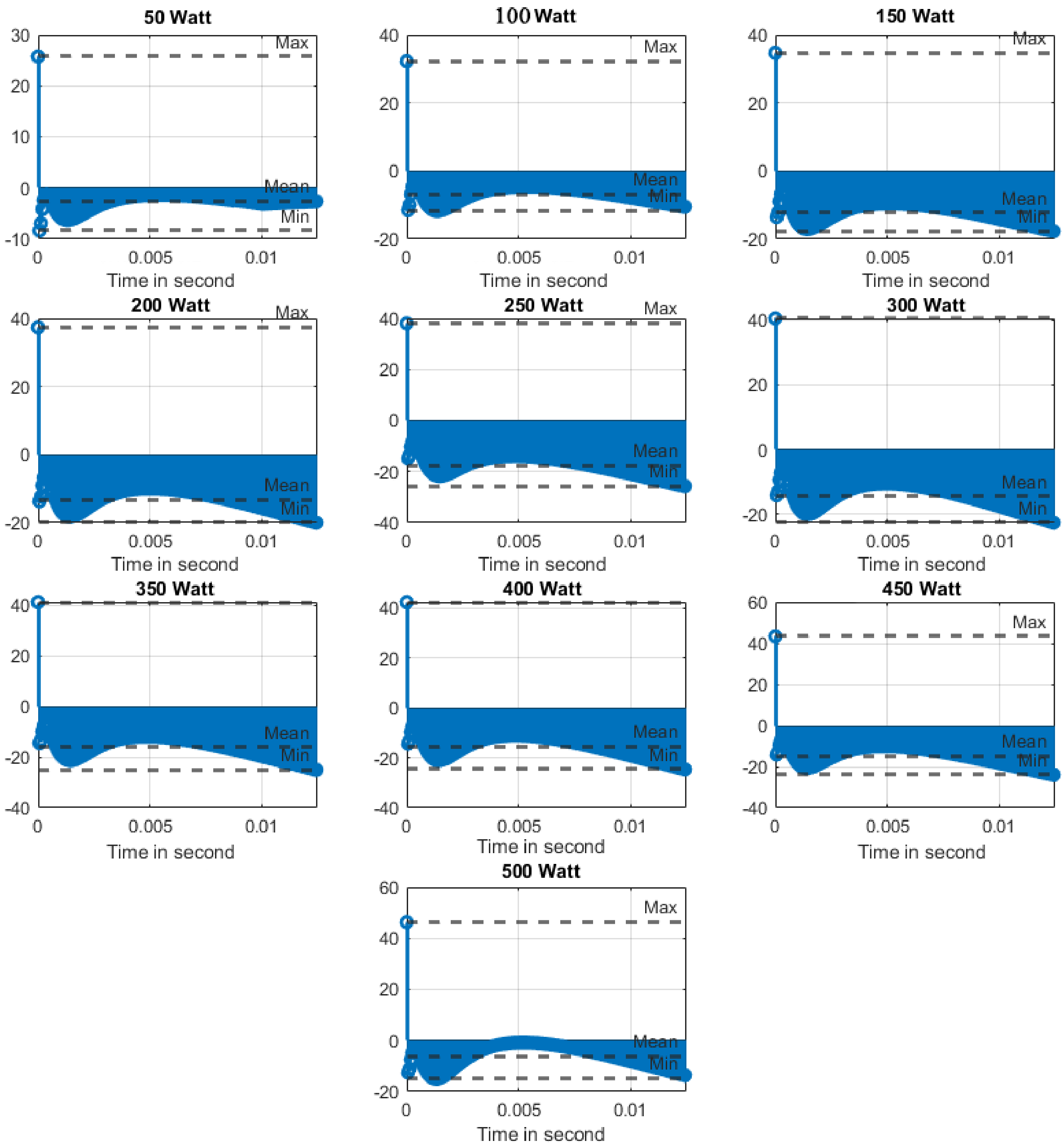


Figure 5.24.: The difference in percentage between the initial temperature profile generated using the proposed model and the Rosenthal's solution for the 30th track.

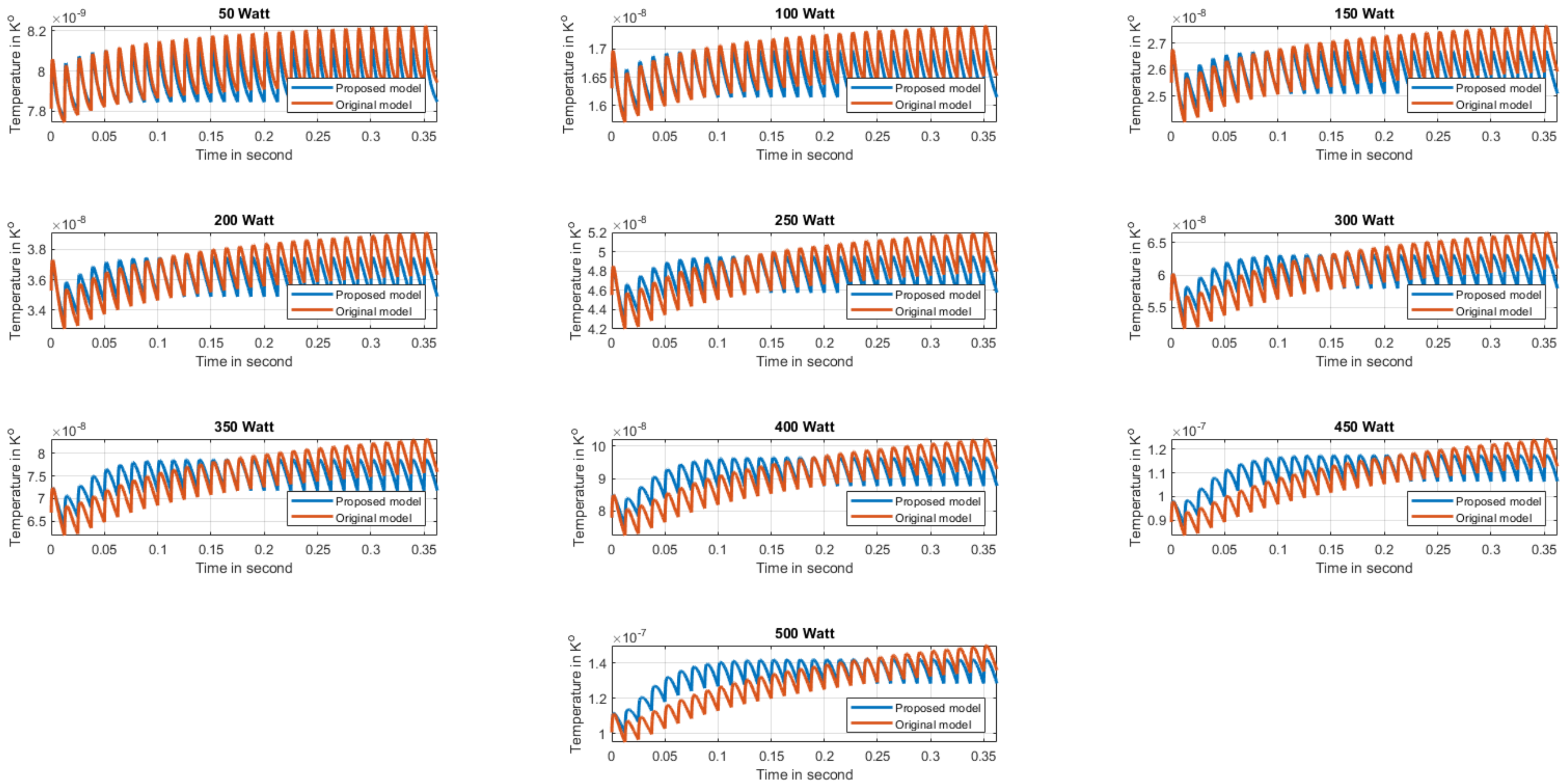


Figure 5.25.: The cross-sectional profile generated using the proposed model and the original model for the first layer.

5.6. Discussion

The development of a MATLAB-based simulation tool for investigating control strategies in the Selective Laser Melting (SLM) process represents a significant advancement in the field of additive manufacturing. This tool, built within the SIMULINK environment, offers a user-friendly interface where controllers can be easily integrated as blocks, allowing for rapid simulation of closed-loop system responses. Despite its advantages, this study also revealed several limitations and areas for further development, which are discussed below.

Comparison of Initial Temperature Profiles

The comparison between the initial temperature profiles generated using the proposed model and the Rosenthal solution revealed significant differences in heat accumulation. The proposed model showed a slower growth rate of heat accumulation from one track to another compared to the Rosenthal solution. This difference was observed within individual layers as well as across multiple layers. Specifically, in the first layer, the error increased with each track, while in the final layer the opposite behaviour was observed. This error within the track can be attributed to the simplifications made in the computation process, highlighting the trade-off between model complexity and computational efficiency.

These findings suggest that, while the proposed model effectively captures the overall behaviour of the system, it introduces a systematic error that must be considered in further developments. The observation that the error increases or decreases based on the position of the layer also emphasises the importance of layer-to-layer heat accumulation in the accuracy of SLM simulations. Previous research has similarly emphasised the challenges of accurately modelling thermal behaviours in SLM, especially when considering cumulative effects over multiple layers [104].

Limitations of the Current Study

It is important to acknowledge the limitations of this study, as they have the potential to significantly impact the generalisability and reliability of the findings. Therefore, it is crucial to take into account the following limitations:

1. Experimental validation:

   In this investigation, we encountered a notable limitation in the validation process. This prevents optimal achievement of having the highest level of accuracy and reliability in our findings. Experimental data is critical to accurately assess the proposed model and determine its capabilities and limitations. However, our findings still provide valuable insight and directions for future research in this area.

2. Scanning technique:

   Our investigation utilises a single scanning strategy, which has been employed in numerous industrial machines and research studies. Nonetheless, the literature reveals a growing trend towards exploring various scanning techniques that can significantly affect the thermal behaviour of the build object [105], [106].

3. Complex shapes and support:

   The investigation conclusively demonstrated that the proposed model has the capability to accurately capture the behaviour of the actual process. However, it is important to note that the investigation was limited to imitating the behaviour during the printing of simple shapes. Practically, the application of metallic additive manufacturing includes complex shapes and support structures that affect the overall performance of the printing process. Thus, extending the invitation beyond regular shapes is a vital step toward achieving our goals [106].

4. Multi-input multi-output:

   Despite the system's capability to capture behaviour, considering a multi-input multi-output case can provide better control investigation and a wider research spectrum for a more practical and accurate system.

Implications for Future Research

The findings of this study emphasise the need for more adaptable and experimentally validated simulation tools for SLM control systems. Future research should prioritise addressing the identified limitations, particularly through experimental validation, exploring different scanning techniques, and accommodating complex geometries and MIMO systems. These developments would greatly improve the reliability, efficiency, and quality of the SLM process, paving the way for more advanced and effective control strategies.

The next chapter will illustrate how the developed tool can serve as a valuable platform for further exploration and evaluation of various control strategies. The potential of this tool to facilitate future advancements in SLM control systems is significant, ultimately leading to improved build quality, process efficiency, and system reliability.

5.7. Chapter summary

While several simulation tools exist for the SLM process, limitations and gaps remain when specifically focussing on the investigation of the control system. This chapter presents an initial proposal for an SLM simulator for controller purposes. The tool is user-friendly and is based on SIMULINK, where the designed controller can be easily placed as a block. The derived model used in this tool is based on a deep understanding of the process and hundreds of data sets generated form open-loop model under various simulation conditions. The proposed model effectively captures the overall behaviour of the system. However, it exhibits a systematic error that grows larger as we move further away from this range. Further investigation is required to address the limitations that we had in this investigation and to expand the tool's capabilities; future research can pave the way for even more effective control systems in the SLM process, ultimately leading to improved build quality, efficiency, and reliability. The next chapter will demonstrate how this tool serves as a valuable platform for exploring and evaluating various control strategies, further highlighting its potential and opening doors for future advancements in SLM control systems.

6

Control System for SLM Process: Design, Implementation, and Assessment

Heat accumulation during Selective Laser Melting (SLM) significantly deteriorates part quality, hampering its widespread adoption. Although previous control strategies focused primarily on post-processing adjustments or monitoring, they missed the opportunity for real-time control during printing itself. This chapter addresses this by exploring novel online control systems for SLM. Our work represents a significant advancement in two key ways:

1. Multi-layer, In-Situ Control: We explore both in-layer and layer-to-layer control strategies, going beyond previous approaches focused solely on single-layer or post-processing. This enables proactive adjustments throughout the build process, leading to potentially superior quality and consistency.

2. Fuzzy Logic Control Exploration: For the first time in SLM control, we investigate the application of fuzzy logic. This technique leverages human experience and excels in handling inherent uncertainties and nonlinearities, common challenges in SLM.

In addition to the main contribution, this chapter effectively showcases the potential of the tool proposed in the previous chapter by utilising it successfully in implementing a range of simulation scenarios swiftly.

This chapter starts by introducing the control problem and its significant impact on the performance of the SLM process. The chapter will then investigate three commonly used industrial control strategies. The control candidates will be designed and implemented using the tool developed in Chapter 5. The control system will be investigated from four different perspectives: the ideal case, including noise, delay, and tracking performance. Finally, we thoroughly evaluate and discuss the advantages and limitations of each proposed system, providing valuable insights for future research and applications.

6.1. Introduction

The growing need for sustainable, durable, and environmentally friendly manufacturing processes drives the continued development of advanced techniques. In response, metal additive manufacturing technologies, including selective laser melting (SLM), have received substantial interest over the past three decades. This technology offers numerous advantages, including reduced manufacturing steps, reduced material waste, and greater flexibility in design compared to traditional methods [4], [2]. As a result, SLM has become increasingly adopted in various sectors such as aerospace, automotive, and healthcare, where high-performance materials and complex geometries are crucial.

However, despite its potential to revolutionise production across these industries, SLM faces a significant challenge: heat accumulation during the printing process. This excessive heat can lead to part distortion, residual stresses, and material property degradation, ultimately compromising the quality and consistency of the final product. Addressing this challenge is crucial for the broader adoption and advancement of SLM technology.

The AM process is complex and influenced by several factors, which makes it difficult to ensure consistent quality and repeatability [7]. In widely used techniques such as the SLM and other AM processes, constant process parameters are typically maintained throughout the 3D printing process [8]–[10]. These parameters are usually determined through trial and error, optimisation with expert knowledge, and modeling/simulations [11]. However, using fixed parameters can lead to issues such as heat accumulation, resulting in irregularities in the melting-pool morphology, particularly in complex geometries, and leading to various types of defects. Recognising this limitation, researchers increasingly advocate for real-time, in-situ control mechanisms (as detailed in Chapter 2). These mechanisms offer dynamic adjustments to the process parameters based on evolving thermal conditions within the construction environment, allowing proactive management of heat accumulation and potentially leading to better quality and consistency of parts[7], [12], [13].

This chapter seeks to address this gap by exploring novel online control systems designed specifically for the SLM process. Our research contributes to the field in two significant ways:

1. Multi-layer, In-Situ Control: We propose and investigate control strategies that operate both within individual layers and across successive layers. This approach marks a departure from conventional methods, allowing proactive adjustments that can significantly enhance part quality and process consistency.

2. Fuzzy Logic Control Exploration: We introduce the application of fuzzy logic control (FLC) to SLM, a novel undertaking in this context. FLC's ability to handle uncertainty and non-linearity makes it particularly suited to managing the complex thermal dynamics of SLM, offering a promising avenue for improving control precision and part outcomes.

This chapter serves as a pivotal exploration of the control systems that are paramount to optimising the selective laser melting (SLM) process. The efficacy of these systems is not only a matter of theoretical interest but is crucially important for the practical application of SLM in producing high-quality, precise parts.

The chapter begins with a discussion of the control problem and its implications for SLM performance. We then review three industrial control strategies commonly employed in manufacturing: PID, Feedforward, and fuzzy logic. Using the tool developed in Chapter 5, we design, implement and rigorously evaluate each proposed control system.

This chapter presents a comprehensive analysis conducted in four distinct scenarios, each thoughtfully designed to test the resilience, adaptability, and precision of the proposed control system under varying conditions.

Starting with an ideal scenario, we establish a baseline for performance, free from the complexities and imperfections of real-world manufacturing. This idealised setting provides a benchmark against which the impacts of additional realistic challenges can be measured. We progressively introduce noise and delays into the system, reflecting common disturbances and imperfections encountered in industrial settings. These steps are crucial for understanding how external and internal factors affect the control system's performance and, by extension, the quality of the SLM process.

Moreover, the investigation delves into the control system's tracking performance, a critical capability for adapting to the dynamic conditions of SLM. This analysis not only highlights the system's responsiveness, but also its potential for real-time adjustments, a necessity for achieving consistent outcomes in additive manufacturing.

By situating our work within the broader landscape of SLM research and highlighting the contributions of our investigation, this introduction sets the stage for a detailed exploration of a critical boundary in additive manufacturing technology.

6.2. Control system problem statement

As noted in the earlier research finding, heat accumulation poses a significant challenge that affects the quality of the resulting component. Consequently, the objective of the control system is to regulate the cross-sectional area of the melt pool $A(t)$ under various cases-noise, delay, and change in the reference value-by controlling the laser power input value $Q(t)$, to minimise heat build-up. The control design is established with the assumption that all process settings remain constant and the only variable under control is the laser power level. Figure (6.1) illustrates the generic block diagram of the process with the feedback control system.

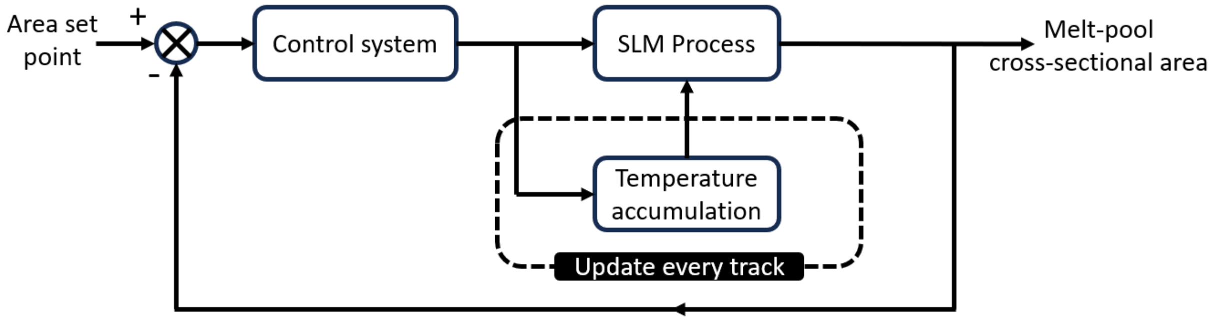


Figure 6.1.: Generic block diagram of control system implementation for the SLM process.

6.3. Control system candidates

The unavailability of fast enough control system to capture the dynamics of the process and respond to any perturbation in an appropriate time was indicated by many researchers. Processing speed is considered a challenge and a limitation in implementing an online control system. From the level of control (in-layer, layer-wise, and surface quality) point of view, almost all the efforts targeted a specific scenario without investigating the effect of combining them.

The main focus of this research is to explore and develop an efficient online control system for the SLM process. The controller's primary objective is to regulate the output and control the necessary parameters for optimal performance in SLM. This is important as it aligns with the precision demands of additive manufacturing processes.

An SLM process is characterised as a complex and non-linear system, which makes the design of a control system capable of handling the complex intricacies of the SLM process a significant challenge. The crucial challenge lies in formulating a control strategy for a system as complex as SLM. The fundamental characteristics of the SLM process involve the delivery of a precise amount of energy to compensate for material deficiencies, the maintenance of optimal melting and solidification, and the maintenance of stability and safety measures to prevent defects and guarantee quality in manufactured parts.

Several different control approaches have been proposed to solve the SLM control problem. The approaches vary from vary basic structures to the ones which include artificial intelligence (AI) aspects. This work excludes discussion of AI-based controllers because such controllers require a lot of data and are computationally expensive, which makes the implementation an infeasible task with the existing processing capability and indeed available data.

This work focuses on three control structures: Proportional Integral Derivative (PID), feed-forward and fuzzy logic. The first two represent the most well-known and used control approaches in the industry, whereas the last has some features of AI but with a fast computational capability. The following sections give a brief review of the three approaches.

6.3.1 PID

The Proportional-Integral-Derivative control algorithm is widely used in industrial systems for its simplicity, reliability, and ease of tuning [107] and [108]. It excels in situations where the controlled system lacks a simple mathematical representation or model and is known for its robust performance, even in the face of uncertainties [109], [110]. The fundamental principle of the PID control algorithm involves measuring the difference between the actual and desired system output signals [111], [112]. This error is then inputted into the control system, which generates a control action to minimise the error until it is almost zero [109], [110]. The PID controller is made up of three adjustable parameters:

- Proportional (K_p): Amplifies the error signal, providing a quick response to changes in the system.
- Integral (K_i): Eliminates steady-state errors by accumulating past errors over time.
- Derivative (K_d): Anticipates future errors by considering the rate of change of the error signal, improving stability, and reducing overshoot.

Table (6.1) summarises the key characteristics of each part. The controller can be presented mathematically as follows:

$$u(t) = K_p e(t) + K_i \int e(t) + K_d \frac{de}{dt} \tag{6.1}$$

Table 6.1.: The function of PID various parts and its advantages and disadvantages.

Component	Function	Advantages	Disadvantages
Proportional (P)	Amplifies error signal proportionally	Quick response to errors Simple to understand and implement	Can lead to steady-state error Overshoot and oscillations if gain is too high
Integral (I)	Eliminates steady-state error by accumulating past errors	Eliminates steady-state error Improves accuracy	Can slow down system response May cause instability if not properly tuned
Derivative (D)	Anticipates future errors by considering rate of change of error signal	Improves stability and reduces overshoot Reduces settling time	Sensitive to noise and disturbances Can be difficult to tune

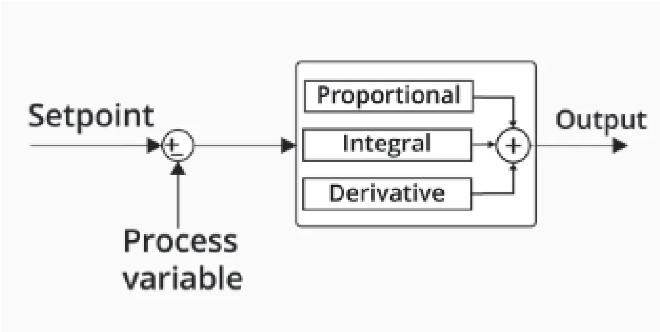


Figure 6.2.: The basic structure of PID controller

In this context, $e(t)$ denotes the variation between the input of the set point and the plant output, while $u(t)$ represents the control output signal influenced by the proportional, integral, and derivative parameters [109], [110]. The complete PID controller is explained in detail by Ogata (2010) and provides an effective means of regulating systems by balancing the contributions of the proportional, integral, and derivative components to ensure optimal performance under various dynamic conditions [111].

The literature abounds with alternative algorithms to derive proportional-integral-derived (PID) gains. The approaches range from very basic techniques to those that include aspects of artificial intelligence.

In this study, the automatic tuning toolbox available in MATLAB is utilised for this purpose, as it is widely acknowledged as a best practice approach to start with and uses accurate optimisation and selection criteria. In addition to that, the trial-and-error tuning method will be utilised to fine-tune the controller.

To achieve successful trial-and-error parameter tuning, it is crucial to inspect the effects of the parameters on the controller output behaviours. The following dynamic behaviours demonstrate the typical impact of tuning parameters on the PID controller output for step set-point changes [113]:

- If the control output signal shows significant oscillation, it indicates that the proportional gain is too high.
- If the control output signal displays an overdamped response, it means that the proportional gain is too small.
- If the control output signal oscillates more above the set-point than below it, it indicates strong integral action.

- If the control output signal oscillates more below the set-point than above it, it indicates a weak integral action.

- If the controller output signal includes several oscillation peaks from the beginning to the steady-state phase, then the derivative time is too high. This is due to the amplification effect on the signal from a strong derivative part.

6.3.2 Feedforward control

Feedforward control is a powerful strategy used in control systems to manage disturbances, or indeed set point changes, that are measurable or well-known [114]. This approach involves defining an input perturbation that corresponds to the measured disturbance, which helps counteract its impact on the system's performance through effective mathematical modeling. The success of the feedforward control scheme depends on the accuracy of the disturbance model and the reliability of the measuring system used.

The integration of feedforward and feedback control is a widely used method to create a comprehensive control system that can efficiently handle disturbances and broader system behaviour. The basic structure of this integration is illustrated in Figure (6.3), where the feedforward controller (C_{ff}) mathematically counters the dynamic relationship between the disturbance and the output (P_d). Meanwhile, the feedback controller tackles the dynamic interplay between the control signal and the process output (y). This mathematical integration is a crucial design method that guarantees a holistic control approach. The utilisation of

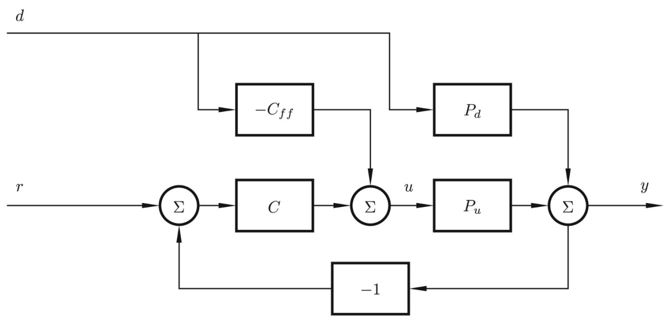


Figure 6.3.: The basic structure of feed-forward control

a combined feedforward and feedback strategy offers numerous advantages, notably its capacity to rapidly and precisely address specific disruptions. The feedforward element delivers swift correction by leveraging mathematical principles of disturbance modeling, while the feedback controller addresses broader system behaviour. This dual approach leads to improved control performance overall, particularly in situations where precise mathematical calculations are essential for optimal control.

It is crucial to note that feedforward control has certain limitations. Its efficacy is contingent on the accuracy of the mathematical model and the reliability of the measurement system for the disturbance signal. Any inconsistencies or uncertainties in either of these variables could potentially impact the control's performance. Additionally, feedforward control may face challenges when it comes to handling unpredictable or complicated disturbances that cannot be precisely depicted mathematically.

There are several feedforward control design techniques. The selection of the best approach depends on disturbance characteristics, system dynamics, sensor availability, and computational resources.

Inverse dynamics-based approaches, as highlighted by [115], directly calculate the counteracting control input from a precise system model. This excels for predictable disturbances in well-defined systems, but sensitivity to model inaccuracies and complex dynamics can be drawbacks.

Disturbance model reference control, explored by [116], employs a separate disturbance model that predicts its future impact on the output. The control system then generates an input to cancel this effect, proving effective for measurable disturbances with known dynamics but requiring accurate disturbance models.

The Smith predictor, detailed in [117] , uses a time-delayed disturbance signal to anticipate its future influence and generate a counteracting input. This robustness to model uncertainties makes it suitable for time-delayed disturbances, but the complexity increases with multiple disturbances.

For complex systems and disturbances, model predictive control (MPC) shines. As outlined in [118] , MPC leverages an internal model to predict future behaviour and optimize the control sequence based on disturbance predictions. This flexibility comes at the cost of high computational demands.

Finally, adaptive feedforward control, discussed in [119], adapts the disturbance model or control law in real-time based on system changes. This handles slowly changing disturbances or uncertain dynamics well, but requires robust adaptation algorithms.

Table (6.2) summarise the advantages and limitations of each method.

Table 6.2.: Summary of commonly used feed-forward strategies.

Method	Advantages	Limitations
Inverse dynamics-based	Precise control, fast response	Model sensitivity, complex dynamics
Disturbance model reference	Effective for measurable disturbances, independent model	Model accuracy, multiple disturbances
Smith predictor	Robust to time-delayed disturbances, simple implementation	Multiple disturbances, tuning complexity
Model predictive control (MPC)	Handles complex systems, optimization capability	Computational cost, model complexity
Adaptive feedforward control	Adaptability to changing disturbances, robustness	Design complexity, performance guarantees

6.3.3 Fuzzy logic control

In the 1960s, when the Fuzzy Logic (FL) theory was initiated by Lotfi A. Zadeh [120], it was challenging to appreciate its merits due to the absence of a practical application. It took almost a decade to see the first FL controller for an actual industrial application, which Mamdani and Assilian proposed in 1975 for steam engines [121]. After that, the application of the FL grows rapidly to cover different aspects. The approach helps in reducing the gaps between the theoretical (ideal) side and the practical (uncertain) side by considering the uncertainty and the inaccuracy of the models [122].

The FL theory is a non-linear representation of the engineering problem, including the human factor and statistical information in evaluating the process [123]. It allows treatment of system variables in gradient logic rather than binary logic (e.g. 0 or 1) [124], which is closer to the practical world where the relationship between the variables includes complex categorisation of the membership status. The strength of FL can be seen in three main points:

1. FL formulate and consider the human expertise and knowledge to define the objective problem and the decision variables [125], [126].
2. FL can be suitable for systems that have no accurate description [121], [122].
3. FL can be an economical alternative compared to other intelligent systems [126].

FL theory presents a middle ground between the simplicity of classical controllers and the complexity of the advanced control methods. Thus, it is worth deeply investigating the use of fuzzy controllers to enhance the quality of metallic AM processes and to evaluate the strengths and limitations of the method in this context.

Based on the best of the authors' knowledge, using a fuzzy logic controller in the L-PBF process has not been yet investigated. However, there are few attempts to apply it with other metallic AM processes, that can be further developed and investigated towards building a FLC for L-PBF.

The idea was investigated first in [127], where an FLC is designed and implemented for the direct metal deposition process. The purpose of the controller was to manipulate the input power to achieve the desired bead height. Theoretically, under the assumption of linearity, the controller shows promising results compared to the conventional control algorithm. However, the controller's performance in the actual experiment was limited due to the sensor capability.

In [126], a neuro-fuzzy (NF) algorithm was used to identify and control a cladding process.

The model was first identified using the NF system based on experimental data and then using the same technique, a controller was designed to vary the processing speed to control the height of the deposition. Generally, the obtained result showed promising results for the system performance.

Another investigation was recently done in [128]. The FLC was used to control the deposition height in the wire and arc process by varying the speed. The proposed control system used the data of the previous layer to update the speed for the coming layer. The investigation shows better accuracy in the geometry of the printed sample.

The previous studies focused on the metallic AM process; however, other research efforts were conducted on polymers printers. In [129], the FL was used to enhance the quality of the product by detecting defects and correcting the process parameters. The proposed system scans the printed part and compares it with the CAD model. In [130], the FLC was used to control the working environment temperature to overcome the warping problem. Compared with the PID controller, the system has 22% less warping. The use of an adaptive fuzzy-PID controller to control the temperature of the process (bed, nozzle, ambient temperature) was investigated in [131]. The research shows an enhancement in system performance in terms of overshoot percentage and tracking performance.

The FLC system consists of five main parts; the following is a brief about each part:

Membership function: A function that defines the degree of membership of an input to different fuzzy sets. It can be featured by the following set of features:

1. Core: all the elements x in the fuzzy set 'A' have the full membership function. Mathematically, it is defined as:

$$\forall x \in \tilde{A}, \quad \text{where} \quad u_{\tilde{A}}(x) = 1$$

2. Support: all the elements in fuzzy set A that have a nonzero membership value.

$$\forall x \in \tilde{A}, \quad \text{where} \quad u_{\tilde{A}}(x) > 1$$

There are several representations of the membership function. Table (6.3) presents the most common fuzzy membership functions, their advantages and limitations.

Fuzzification: This stage acts as the bridge between the physical world and the fuzzy domain. Crisp input values from sensors or measurements are mapped onto fuzzy sets using membership functions.

Table 6.3.: The most commonly used fuzzy membership functions, their advantages, and limitations.

Fuzzy Membership Function	Shape	Parameters	Advantages	Limitations
Triangular	triangular	3	Simple and intuitive, Suitable for clear boundaries and peaks	Less flexible for gradual transitions, May not accurately represent complex concepts
Trapezoidal	trapezoidal	4	More flexible than triangular MFs, Useful for less distinct boundaries or plateaus	More complex to define and interpret, May not be as smooth as Gaussian or sigmoid MFs
Gaussian	bell-shaped	2	Smooth and continuous, Natural spread for linguistic terms, Easy to tune with mean and standard deviation	May not be suitable for sharp transitions, Can be computationally expensive for large datasets
Sigmoid	S-shaped	2	Smooth transitions, Asymptotic approach to 0 and 1, Useful for gradual changes	Less intuitive than other MFs, May not accurately represent certain concepts

Fuzzy Rule Base: This is the knowledge base of the FLC, it consists of a set of if-then rules that relate the input variables and the output. Rules are typically designed by experts or derived from training data.

Fuzzy Inference Engine: This represents the brain of the FLC. Apply the fuzzy rules to the current input values, by activating the relevant rules and determining the degree of activation for each. There are two common inference methods: Mamdani or Sugeno. Based on the method used, the fuzzy output set is generated.

Defuzzification: This process is done by converting the fuzzy output set from the fuzzy inference engine to a crisp value. There are many techniques to achieve this. The most commonly used are center of gravity, mean of maxima, and largest of maxima.

6.4. Control system simulation cases

To thoroughly assess the control systems suggested, various scenarios were created. Each scenario consisted of a different control situation. The first scenario was the ideal case, which established the baseline for the system's overall performance under optimal conditions. The subsequent scenarios introduced noise, delay, and finally tracking of the desired reference value. These scenarios were designed to test and evaluate the proposed control system in a comprehensive way. The next subsection will briefly introduce each scenario.

6.4.1 Ideal case- nothing but the original theoretical model

In the context of developing control systems for the SLM process, it is imperative to analyse an ideal scenario that is free from the influence of external disturbances and internal imperfections. The proposed control systems will be tested under ideal conditions where nothing is counted but the dynamics of the system. By establishing a baseline of the system's peak performance, we can subsequently compare the control system's performance later with more practical conditions.

The establishment of the baseline is not just an academic exercise, but rather a crucial step in understanding the impact of various practical industrial challenges on control system performance. Through rigorous simulations, we can explore control precision, response dynamics, and stability, which are essential to the SLM process. This exploration will enable us to optimise the control system to enhance the efficacy of selective laser melting, setting the foundation for efficient control in a complex manufacturing landscape.

6.4.2 With noise in the output

Moving beyond the theoretical ideal, this subsection shifts our focus to a scenario that mirrors the inherent unpredictability of real-world manufacturing environments: the introduction of noise into the selective laser melting process. In this case, we investigate how well the proposed control systems can handle the noise factors that occur in actual manufacturing conditions. There are several sources of noise that can affect different parts of the process, but for this investigation, a random noise of the maximum value of 1% of the reference value is added to the output signal of the process model. Our focus is to examine the system's ability to adapt and remain resilient when it is faced with such complexities rather than just in an idealised context.

The integration of noise into the simulations serves two main purposes. Firstly, it enables the evaluation of the robustness of the control system against disturbances that could affect the precision of the SLM process. Secondly, it provides insights into the adaptability of the proposed control systems, namely its ability to maintain high levels of accuracy despite the presence of noise. These qualities are indispensable to ensure the reliability and consistency of additive manufacturing outputs. Therefore, the inclusion of noise in simulations is a crucial step toward achieving high-quality additive manufacturing processes.

6.4.3 With a delay in the feedback

Delays are often found in industrial plants and can pose significant challenges to the effectiveness of control systems. In the SLM process, delays can occur in the laser system, where it takes microseconds to respond to changes. Furthermore, the feedback system may cause a delay, the delay amount potentially reaching 65 microseconds, as reported in [56]. This section aims to investigate the impact of delays on the performance of proposed control systems where the delay is placed in the feedback loop.

Understanding these effects is critical to developing strategies to counteract or compensate for delays, ensuring that the SLM process remains stable and efficient. By quantifying the responsiveness and adaptability of the control system in the face of such challenges, we can offer valuable perspectives on its potential for real-world applications, where timing and precision are essential.

6.4.4 Tracking the change in the reference value

In control system engineering, tracking is a crucial aspect that determines how accurately a system can follow the desired output. It is essential to achieve effective tracking to maintain system performance, which includes stability, accuracy, and responsiveness across diverse applications.

The selective laser melting process requires precise control to achieve the desired microstructure in the fabricated object [132]. During this investigation, we will demonstrate the tracking performance of the control systems while varying the desired reference cross-sectional area. Accurate tracking is critical to ensure the quality and consistency of manufactured parts, from adapting to changes in material properties to responding to layer-by-layer, track-by-track and point-by-point adjustments.

By evaluating the system's tracking accuracy and response dynamics, we aim to highlight its capacity for real-time adaptation and optimisation. This underscores the potential for advancements in additive manufacturing technology.

6.5. Assessment parameters

Several assessment indices can be selected to evaluate and compare the performance of various designed control systems. Each of the indices provides insight into different aspects of the behaviour of the system. In this work, we will limit our consideration to the settling time, steady-state error, the integral of absolute error (IAE), and the average consumed power. Here is some brief information about each of them:

1. Settling Time: This is the duration required for a system to respond and reach close to a steady-state value after an input change. The shorter the settling time, the more responsive the system, which is important for applications requiring rapid changes.

2. Steady-State Error: This is the difference between the desired and actual values when the system is in steady state.

3. Integral of Absolute Error (IAE): This is the accumulation of the magnitude of the absolute error over time, which can be expressed mathematically as the integration of $|e(t)|$ with respect to time.

The utilisation of these indices presents a comprehensive and robust framework to evaluate the performance of control systems in SLM.

6.6. The models required for control system design

Before starting the design process, it is worth recalling the model used in this part of the investigation. Initially, the plan was to use the linearised model of Chapter 3, which is presented by Equation 3.22, for the PID and FF controller design. However, during the investigation conducted in Chapter 4, it was noted that the initial temperature range was wide. As the initial temperature is a linearised variable, this would affect the quality of the model. Thus, another model was determined using the $MATLAB$ system identification toolbox. The model can be presented as the following transfer function:

$$\frac{A(s)}{P(s)} = \frac{0.00019}{s^2 + 3.153x10^{-3}s + 1.2x10^6} \tag{6.2}$$

where the disturbance transfer function is given by

$$\frac{A(s)}{D(s)} = \frac{5.046x10^{-}9s + 6.04x10^{-}7}{s^2 + 7.216x10^2 s + 3.465x10^4} \tag{6.3}$$

These models are intended for control purpose design. However, during the implementation, testing, and tuning phases, the models will consist of Equations (3.20) and (3.18). These equations have been selected on the basis of their ability to accurately represent the system dynamics and provide the necessary control inputs to achieve the desired outcomes. For FLC system, the design, implementation, testing, and tuning will be based on the original system (Equations (3.20) and (3.18)).

6.7. Control system design

In this section, the design steps of the proposed control systems specially customised for the selective laser melting process are discussed. The main objective is to outline the methodology and key considerations that have been implemented to improve the efficiency and accuracy of the SLM process. By employing a systematic approach, we aim to ensure that the control system meets the intricate demands of SLM technology.

For the evaluation of the proposed control candidates, the basic structure of the proposed control system is selected to be used for all the selected candidates. This approach guarantees a fair comparison and allows us to establish the results as a baseline for future investigations. By maintaining consistency in the fundamental architecture of each control system, we ensure that differences in performance are attributable to the control strategies themselves rather than variances in design setup. This methodology not only improves the credibility of our comparative analysis, but also sets a solid foundation for future research, facilitating a clear understanding of progress and improvements in control systems for SLM technology.

The following subsection will report the design procedure of the proposed control systems.

6.7.1 PID control desing

The design of the PID controller is achieved by selecting three values: proportional gain (K_p), integral gain (K_i), and derivative gain (K_d). The literature describes numerous alternative algorithms to select the PID gains; however, in this work, the automatic tuning toolbox in $MATLAB$ will be used for such a purpose as this represents an accepted good-practice approach. The design process started with setting the characteristics of the desired performance. The main target is to have a fast, stable, and minimum error.

It is important to note that the selection process was based on a simplified second-order system linearised model, which was presented in the previous section by Equation 6.2. However, since the design was based on a simplified model, the system's performance was not optimal. To improve system performance, the set of tuning rules presented in Section 6.3.1 were used. The final list of PID gains used is presented in Table (6.4).

Table 6.4.: The PID gains used in the simulation

Variable	Value
K_p	5.58e-10
K_i	1.01e-13
K_d	-1.9e1

6.7.2 FF control desing

In the field of control system design, a combination of feedforward control and a PID controller is used to create a robust mechanism to manage complex processes. The FF control anticipates system disturbances and compensates for them before they can affect the system. On the other hand, the PID controller adjusts the output according to the error between the desired and actual state of the system. This combination of controllers ensures that the system is operating optimally, even in the presence of disturbances. For the PID part, the gains will be kept the same as in the previous section. However, the inverse dynamics-based approach will be used for the FF controller. The approach is simple and has been selected to ensure a fair comparison with other controller designs. In such a method, the compensator model is described by a transfer function that relates the disturbance (in this case, the heat accumulation) transfer function to the system transfer function as following:

$$C_{ff}(s) = \frac{A(s)/D(s)}{A(s)/P(s)} \tag{6.4}$$

Theroitically, by substituting Equations (6.2) and (6.3) into (6.4), the disturbance signal is completely eliminated, preventing it from affecting the process output. The transfer function of the feedforward control can be described as follows:

$$C_{ff}(s) = \frac{-7x10^{-7}s^2 - 0.002s - 0.84}{0.00019s^2 + 0.137104s + 6.5835} \tag{6.5}$$

6.7.3 FLC desing

While PID and FF controllers offer a simple and widely used approach for control systems, fuzzy logic control presents a more sophisticated alternative, especially for processes with complex dynamics like selective laser melting. However, FLC design involves a more complex process compared to other controllers. As mentioned earlier, FLC requires a series of well-defined steps, which include:

Step 1:Identifying the variables (inputs, states, and outputs) for the fuzzy inference system.

As a start, the error on the cross-sectional area $e(t)$ and the rate of change on the error $\dot{e}(t)$ are selected to be the fuzzy inputs. Based on the simulation of the model and the data collected from the literature and experiments, the error range varies between -3.35e-8 to 2.21e-9, where the rate of change in the error was between -5.05e-10 to 2.632e-10. It is important to know about these ranges as they play an important role in the coming steps and in selecting the gains of the FLC system. On the other end of the fuzzy inference system, the output of the fuzzy controller is selected to be the control signal $u(t)$. Similarly, the scaling factor is selected to be a proportional gain that relates the fuzzy output with the control variable, which is the laser power $Q(t)$in this case.

Step 2: Dividing the range of each variable and assigning a membership function to each subset.

In this step, the range of variables will be broken down into different subsets. After that, a linguistic variable will be assigned for each subset. Both signals were divided into five subsets (linguistic variables): high negative (HN), negative (N), zero (Z), positive (P), and high positive (HP). The FLC output 'the laser power' was divided into five linguistic levels: very negative (VN), negative (N), zero (Z), positive (P) and very positive (VP).

Step 3: Forming the Fuzzy rule-base.

Based on the model simulation and knowledge constructed from the literature and experiment data, a set of if-then rules are formed to relate the input variables and the output. Tables (6.5) summarises the set of rules for the different cases.

Step 4: Reasoning and aggregation. In this step, the fuzzy inference engine used the defined set of rules and the input fuzzy sets to produce the output fuzzy set. In this work the Mamdani inference is used as a fuzzy inference system, and OR operations are used to combine the two fuzzy inputs.

Step 5:Defuzzifying the control output Here step 3 is reversed. The fuzzy output set produced by the fuzzy inference system is converted to a precise value that represents the

Table 6.5.: Fuzzy logic set of rules.

Input Variable		Change in error ($\frac{\mathrm{d}}{\mathrm{d}t}e(t)$)				
		HP	P	Z	N	HN
Error ($e(t)$)	HP	VP	VP	VP	VP	VP
	P	VP	P	P	P	VP
	Z	VP	Z	Z	Z	VN
	N	VN	N	N	N	VN
	HN	VN	VN	VN	VN	VN

control action that will derive the process. In this stage, the defuzzification is done using centroid method.

Figure(6.4) illustrates the membership function of the input and output signal, and the response surface. It is important to note that the choice of linguistic variables, membership

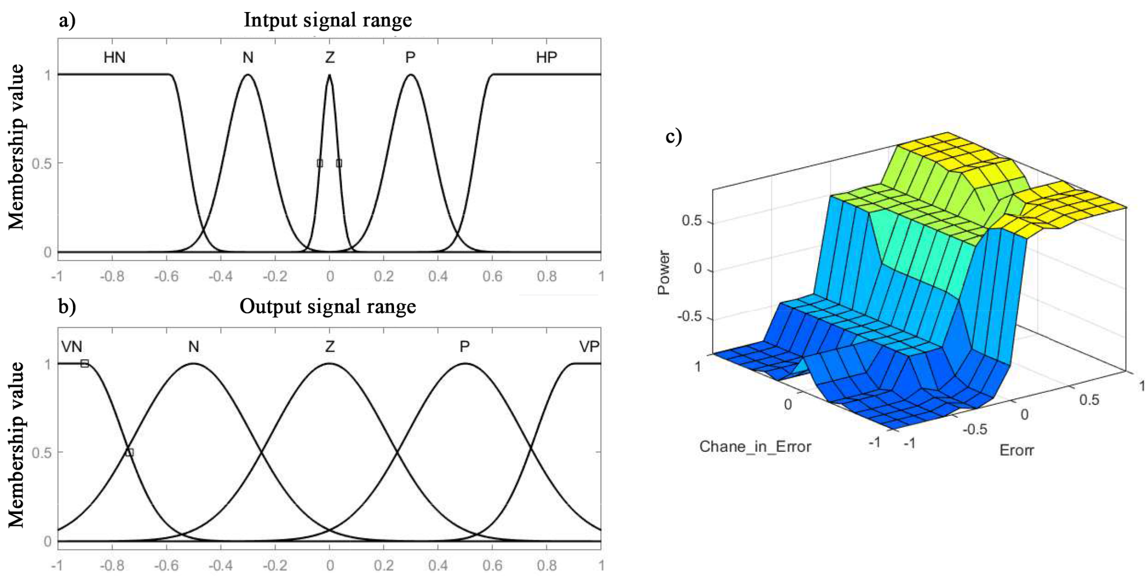


Figure 6.4.: The membership function of the input and output signal and the response surface of the design FLC system.

functions, and fuzzy rules is a research area that requires more investigation and is part of future work.

6.8. Control system implementation and results

This section takes a comprehensive look at the performance of various control strategies designed specifically for the selective laser melting process, employing a range of simulation scenarios to thoroughly assess their effectiveness. The evaluation begins with a straightforward scenario, an ideal condition in which the control system is applied directly to the process without any complicating factors such as noise, delays, or variations in the desired output. This baseline scenario provides a clear picture of how control systems are intended to function under perfect conditions.

Continuing from the ideal, the analysis introduces a layer of complexity by incorporating noise into the output signal. This step is designed to simulate the kind of environmental disturbance that might occur in a typical manufacturing setting, challenging the control system's ability to maintain process quality despite external fluctuations.

The exploration then moves on to examine the impact of delays on system performance. Delays, whether in processing, response, or communication, are common in practical applications and can significantly affect the timeliness and accuracy of control actions. This scenario tests the resilience and adaptability of the control systems to handle these inevitable lags.

Furthermore, the study addresses variability in the desired output, reflecting the dynamic nature of manufacturing demands. This scenario tests the flexibility of control systems to accurately track and respond to changes, ensuring that the output of the process satisfies varying specifications over time.

For implementing and testing each scenario, the simulation tool introduced in Chapter 5 plays a crucial role. This tool facilitates the straightforward application of each control strategy to the respective scenarios, requiring minimal steps for setup and execution. This simplicity in implementation emphasises the tool's effectiveness and user-friendliness, making it a valuable asset for investigating the intricacies of online control systems in the context of selective laser melting.

The simulation will present the behaviour of the melt pool while printing an object that is composed of 60 layers, each containing 30 tracks of length of 1 cm of Ti6Al4V powder.
The following context presents the simulation results of applying the control candidates for each case under consideration.

6.8.1 Ideal case

Figure (6.5) presents the response of the SLM control system under ideal conditions (no noise, no delay) with and without the use of a control system. The figure picture a part of the overall response- three tracks. The blue curve illustrates the system response without a controller. As can be seen in the figure, the worst case occurred at the return end. The cross-sectional area without a controller did not reach the desired value nor maintain a constant level. The maximum value recorded for every track increased as a result of the heat accumulation from a track to another. The inconsistency in the melt-pool area leads to the aforementioned building defects. The introduction of a control system significantly enhanced the system's

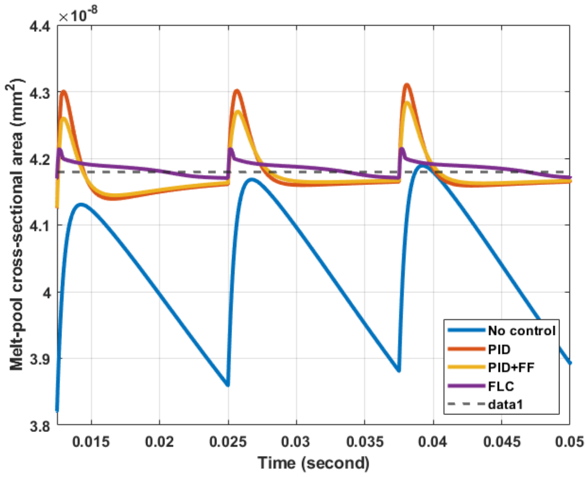


Figure 6.5.: The system responses of the model using the various control systems (cross-sectional area of the melt pool).

transient and steady-state responses, as evidenced by the improved performance across all control strategies compared to the uncontrolled case as seen in figure (6.5). As expected, all controlled scenarios exhibited stable behaviour with less deviation from the desired melt-pool cross-sectional area setpoint. However, the controllers demonstrated varying degrees of effectiveness.

The PID and the combined PID-FF controller displayed similar performance, except at the start of each laser track. Here, the feedforward element provided a slight advantage due to its ability to anticipate and counteract disturbances before they significantly impact the system. This highlights the benefit of FF control in rejecting predictable transients.

However, fuzzy logic control stood out by offering a significant improvement in overall system behaviour. The PID and FF control strategies are sensitive to limitations due to the inherent nonlinearities of the SLM process and potential model inaccuracies. In contrast, FLC can effectively handle these complexities by incorporating human-like reasoning and fuzzy sets. This allows the FLC to adapt to nonlinear relationships and compensate for uncertainties in the model, leading to superior control performance in SLM.

The effectiveness of the control system is evident in its ability to reduce the accumulation of heat and regulate the initial temperature of the melt pool, as illustrated in Figure 6.6. Compared to an uncontrolled scenario (blue curve), the implementation of a controller significantly mitigates temperature spikes at the end of each laser track (return point) by at least 20%. This reduction helps maintain a more uniform thermal profile throughout the melt pool, minimising the risk of overheating and potential defects in the final product.

Furthermore, FLC; demonstrates a clear advantage in managing initial melt-pool temperature. While other control strategies achieve a 20% reduction at the return point, FLC surpasses this performance by achieving a remarkable 36% reduction in the initial temperature itself. This signifies FLC's ability to proactively address thermal transients and establish a more stable starting point for each laser track. This improved temperature control can lead to superior quality and consistency in fabricated parts.

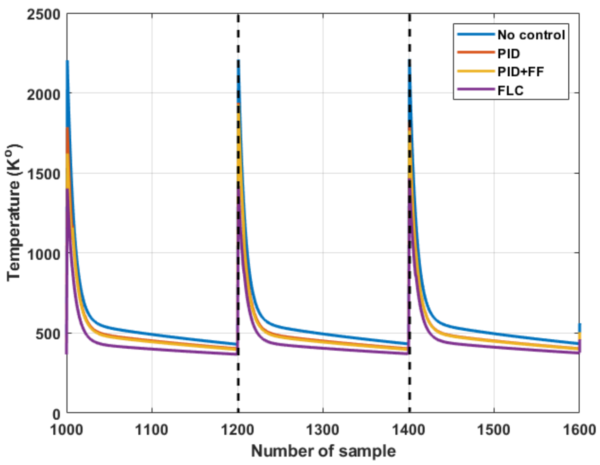
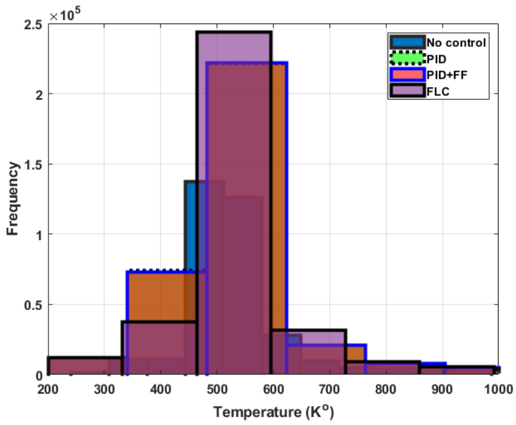
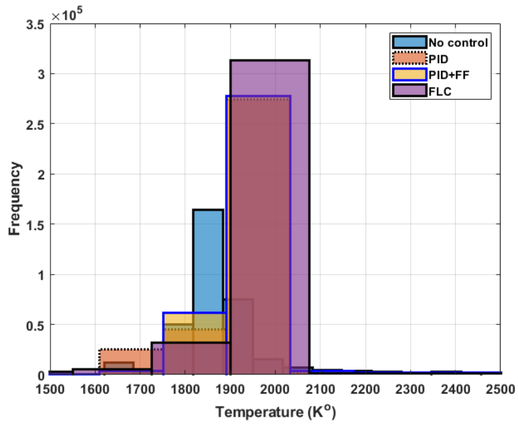


Figure 6.6.: The initial temperature of the melt-pool using the various control systems.

Examining the thermal distribution for the melt pool, histograms (like Figure 6.7) offer valuable insights. These plots depict the distribution of initial and melt pool temperatures throughout the simulation of the object. Ideally, these values should be centred around 292K (ambient temperature) and 1923K (melting temperature), respectively, for optimal process stability and material properties. As evident from the histograms, the designed FLC system achieves this desired temperature distribution more effectively compared to other investigated controllers.



(a) Initial temperature histogram.



(b) Melt temperature histogram.

Figure 6.7.: The histogram of the initial and melt temperature of the system with and without a controller for the entire object simulation.

While the implemented controllers demonstrably reduced heat accumulation within the melt pool (as seen in Figure6.6), it is important to note that heat does not completely disappear. Figure (6.8) illustrates how heat accumulation still progresses gradually as the building progresses. This encourages further investigation and analysis for the design of the control system in the future.

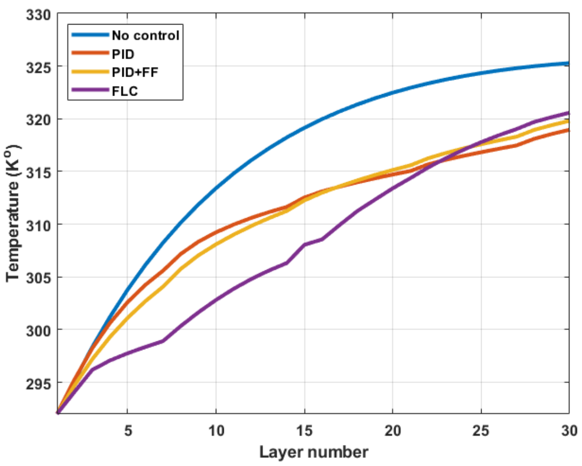


Figure 6.8.: The minimum initial temperature using the various control system.

From the control signal point of view, the control signal, represented by laser power, reveals a key advantage of FLC. As shown in Figure (6.9), FLC exhibits a faster response to sudden disturbances experienced at the end of each laser track compared to other control strategies. This faster reaction time allows FLC to more effectively mitigate these transients and maintain a stable melt-pool temperature.

However, when examining the overall power consumption in the simulation of the entire object build (as illustrated in Figure 6.10), the differences between the control systems are not significant.

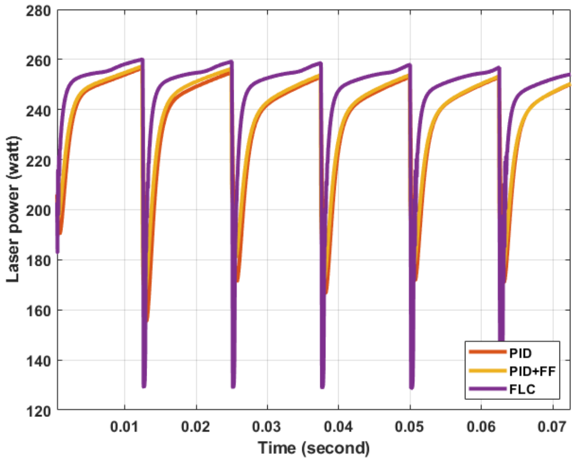


Figure 6.9.: Laser power (control signal) while simulating a couple of tracks for the various control systems.

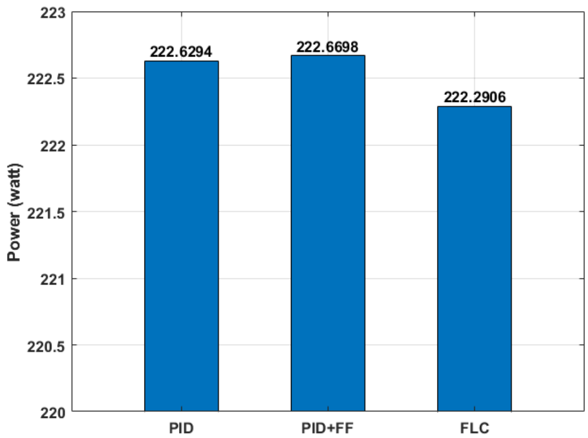


Figure 6.10.: The average usage power during the full simulation using the various control system.

In terms of the effect of the control system on reducing error, the FLC system achieves a remarkable reduction in AIE compared to other controllers. This translates to approximately 50% lower overall error throughout the entire process. This significant improvement highlights FLC's superior ability to maintain the desired melt-pool characteristics and minimise deviations from the setpoint as shown in figure (6.11).

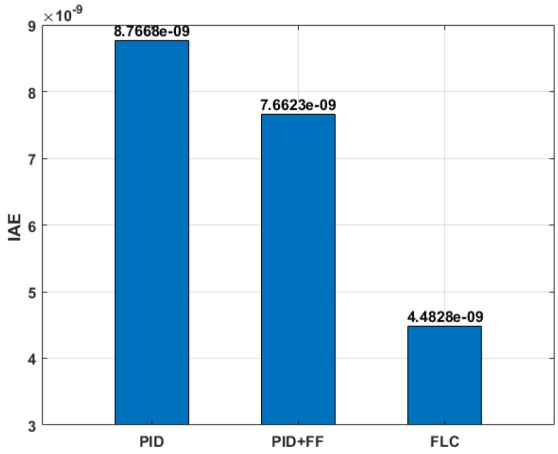


Figure 6.11.: The Absolute integral error using the various control system.

6.8.2 Introducing noise

Adding a random noise has challenged the proposed controllers. Figure (6.12) shows the system response under noisy conditions. Compared to the ideal case, the cross-sectional area of the melt pool exhibits fluctuations around the setpoint as a result of the influence of noise. However, the control system remains stable and effectively mitigates the noise to a certain extent. The control effort shows higher variations compared to the ideal case, indicating continuous adjustments to compensate for noise-induced errors.

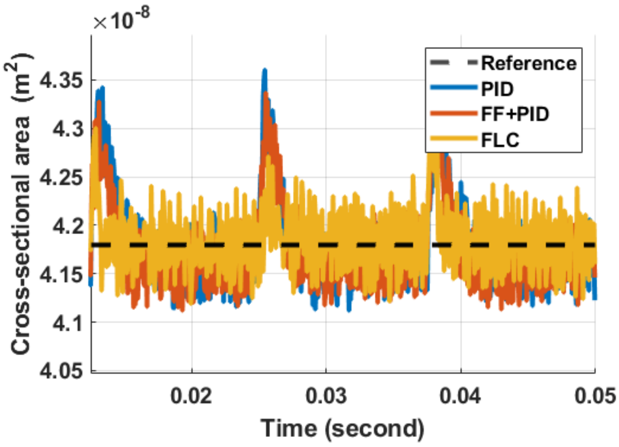


Figure 6.12.: The system responses of the model using the various control systems (cross-sectional area of the melt pool) under the effect of random noise.

The FLC system was found to be more effective in suppressing noise compared to other control systems. This is further evident in the value of the IAE for each proposed system. Figure (6.13) provides a comparison of the IAE values for the various control systems, highlighting the impact of noise by comparing them with the ideal scenario. By examining the

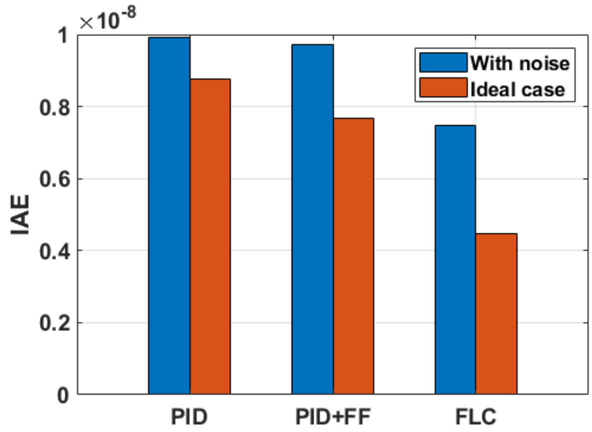


Figure 6.13.: The Absolute integral error using the various control systems under the effect of random noise compared to the ideal case.

control signal for each system as shown in Figure (6.14), it is notable that the control signal produced by FLC exhibits significant fluctuations. In theory, this indicates that the controller has the ability to respond to changes quickly. However, in practice, it may pose a challenge for the actuation system. These results highlight the importance of considering noise

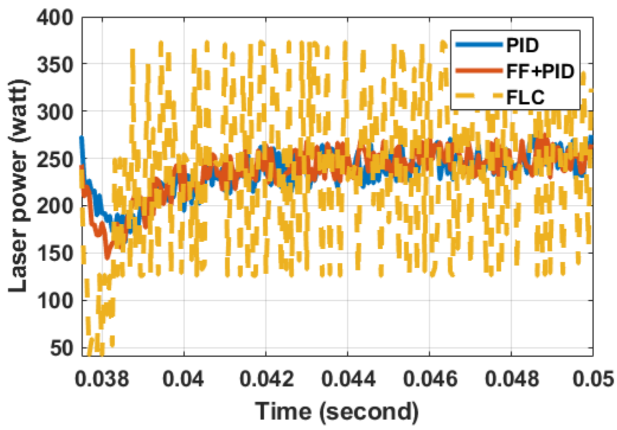


Figure 6.14.: Laser power (control signal) under the effect of the random noise while simulating a couple of tracks for the various control systems.

in control system design. Although the system maintains stability under noisy conditions, the performance is degraded compared to the ideal case. This emphasizes the need for robust control algorithms and noise filtering techniques to ensure consistent and accurate performance in a real SLM environment

6.8.3 Introducing delay

In order to simulate communication delays between sensors, actuators, and the controller, a time delay was added to the control loop. The system response with a time delay is illustrated in Figure (6.15). The overall performance of the system using different control systems showed

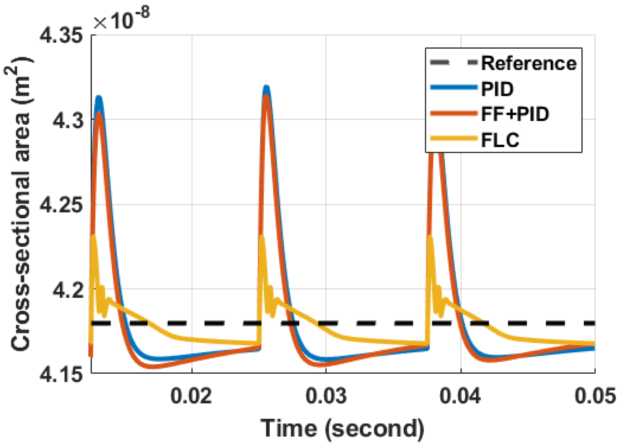


Figure 6.15.: The system responses of the model using the various control systems (cross-sectional area of the melt pool) under the effect of a delay in the feedback loop.

a slight variation compared to the ideal scenario. Even with the calculation of IAE, the same observation is maintained. Figure (6.16) provides a comparison of IAE values for different control systems, highlighting the impact of introducing a delay in the system's performance and comparing it to the ideal scenario.

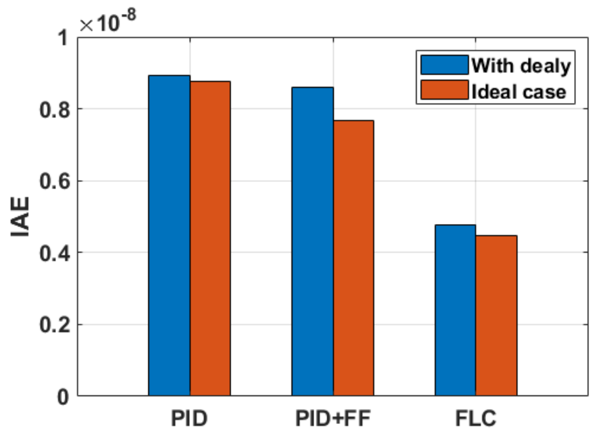


Figure 6.16.: The Absolute integral error using the various control systems under the effect of a delay on the feedback loop compared to the ideal case.

However, when examining the system performance in terms of control signal, the control effort shows a characteristic oscillatory behaviour as the system tries to compensate for the

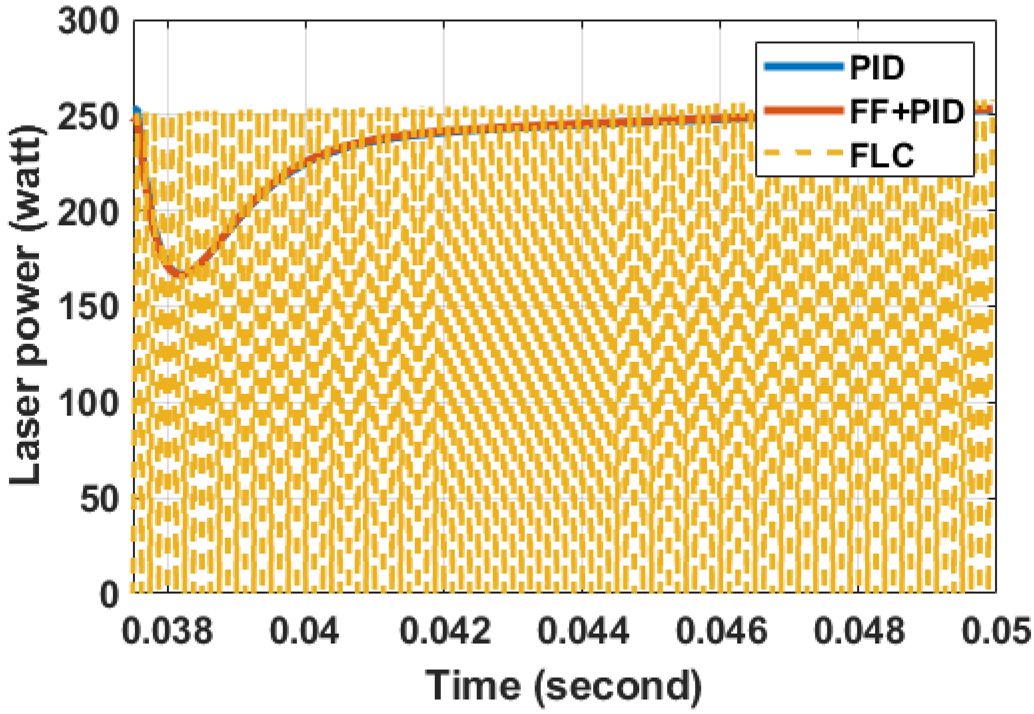


Figure 6.17.: Control signal under the effect of adding a delay on the feedback loop while simulating a couple of tracks for the various control systems.

delayed information about the melt pool cross-sectional area (as shown in Figure (6.17)). This oscillation is very clear when using FLC.

In extreme delay scenarios, this oscillation can lead to instability, emphasising the critical importance of minimising communication delays in real-time control systems.

The results highlight the need to consider time delays during the design of the control system. Delays can significantly degrade performance and even lead to instability. Techniques such as model predictive control or Smith predictors can be employed to mitigate the effects of delays and ensure accurate control behaviour.

6.8.4 Tracking problem

This investigation evaluated the control system's ability to track a change in the set point for the cross-sectional area of the melt pool. A reference trajectory was implemented that simulates the desired melt pool cross-sectional area profile. As shown in Figure (6.18), the melting pool area successfully follows the reference with minimal tracking error. The control effort adjusts dynamically (Figure6.19), demonstrating the effectiveness of the implemented

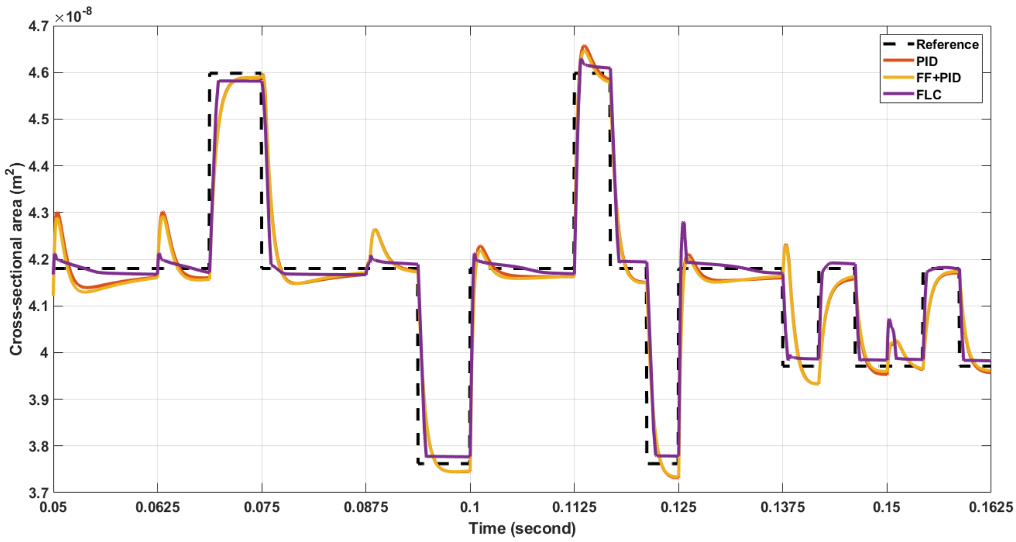


Figure 6.18.: The system response using the various control systems (cross-sectional area of the melt pool) while tracking the desired melt pool cross-sectional area profile.

tracking control strategy. In particular, FLC exhibits a clear advantage in tracking the desired characteristics of the melting pool, as evidenced by a lower total error accumulation (IEA) in Figure 6.20.

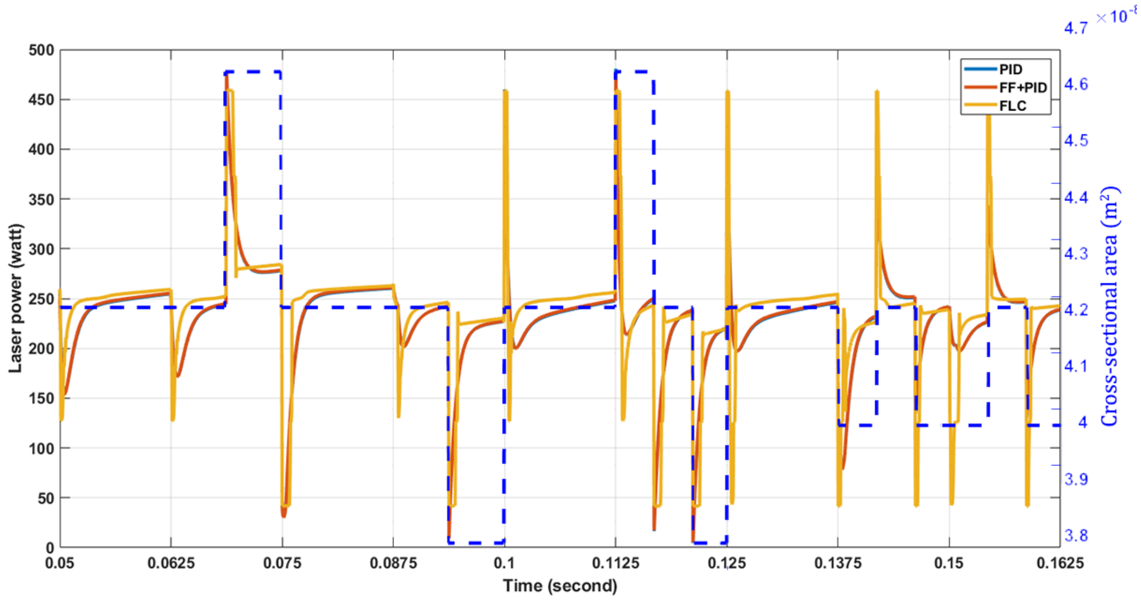


Figure 6.19.: Laser power (control signal) while tracking the desired melt pool cross-sectional area profile using various control systems.

From a thermal perspective, Figure (6.21) illustrates how the melt pool temperature responds to the manipulation of the reference value. Interestingly, adjustment of the cross-sectional

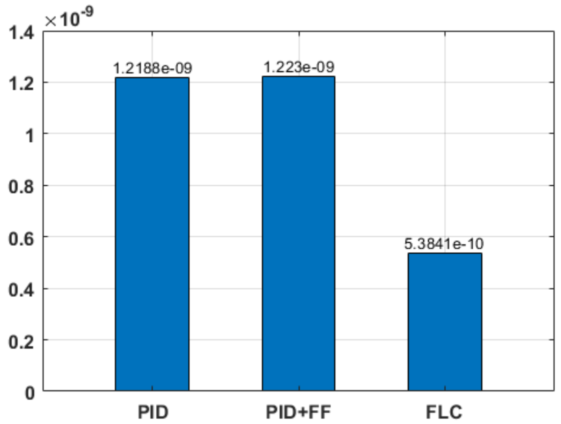


Figure 6.20.: The Absolute integral error using the various control systems while tracking the desired profile.

area also influences heat accumulation, potentially affecting the final microstructure. This highlights the interconnected nature of the process parameters in SLM.

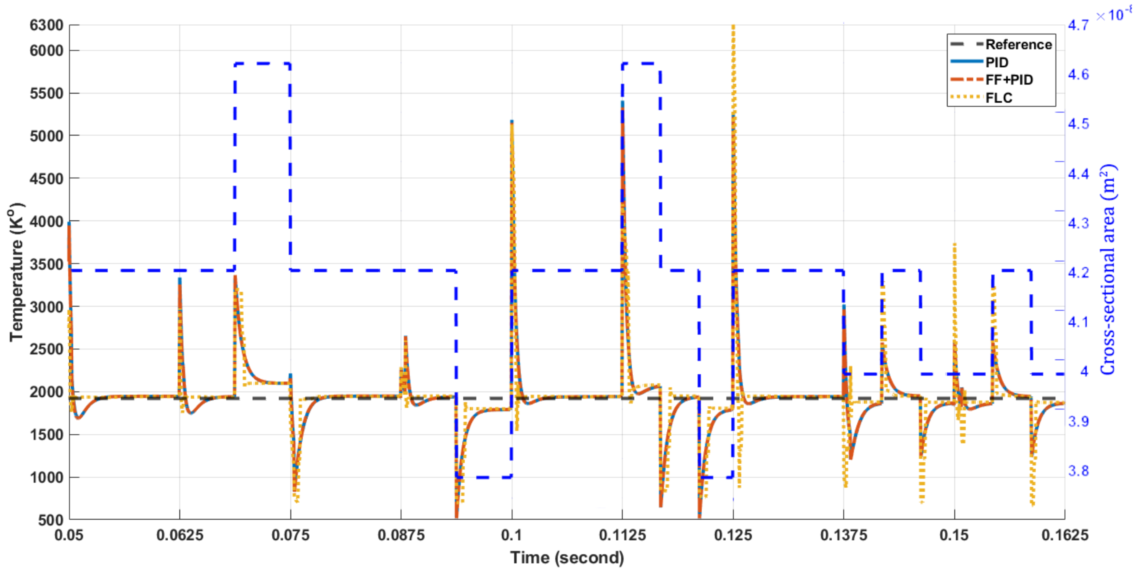


Figure 6.21.: The melt-pool temperature using the various control systems while tracking the desired melt pool cross-sectional area profile (demonstrated in the blue dotted line).

Overall, these results showcase the control system's ability to adapt to varying demands. Tracking control allows for precise manipulation of the melt pool during the SLM process, enabling the creation of complex geometries with tailored melt pool characteristics.

6.9. Summary of control systems performance

The investigation aim of this chapter was to assess and compare the effectiveness of various control systems for the selective laser melting process under different operating conditions. To achieve this, we simulated SLM processes with and without control systems, taking into account factors such as noise, time delays, and tracking issues. Based on the several simulation scenarios conducted in the previous section, the performance of the proposed control systems can be summarised in the following points:

1. Implementing a control system significantly enhances response compared to no control, leading to a more stable melt pool with minimal deviation from the desired cross-sectional area.

2. Dispute the fact that the use of controllers has a slight improvement in average power consumption; the power manipulation during the building resulted in a better thermal and geometrical behaviour of the melt pool.

3. Fuzzy Logic Control (FLC) consistently demonstrates superiority over the other control systems due to its ability to handle nonlinearities and model uncertainties present in the SLM process. This translates to:

    - Reduced Heat Accumulation and Initial Temperature: FLC effectively minimises heat build-up and initial melt-pool temperature, leading to improved product quality.

    - Superior Noise Suppression: FLC exhibits greater effectiveness in suppressing noise disturbances than other control strategies.

    - Faster Response and Tracking: FLC shows a quicker response to transient disturbances and superior tracking of changing setpoints for the melt-pool area.

4. Dispute the amount of improvement caused by introducing the online control system to the SLM process, there is still a list of challenges and considerations that need to be addressed in more detail. Here are the commonly observed ones:

    - Heat Accumulation: Although controllers reduce heat buildup, it is not completely eliminated and requires further investigation for long-term control strategies.

    - Actuation Challenges: Rapid response to disturbances that were observed spicily with FLC could lead to significant control signal fluctuations, potentially posing challenges to the actuation system.

- Communication Delays: Delays in the control loop can introduce oscillatory behaviour, particularly with FLC. More research is required to develop techniques to mitigate the delay effect and ensure stability.

Overall, this investigation demonstrates the significant advantages of using an online control system - practically the FLC- to regulate the melt pool characteristics in the SLM process.

6.10. Discussion

The research presented in this chapter marks a substantial advancement in the field of Selective Laser Melting (SLM), particularly in addressing the challenges posed by heat accumulation during the additive manufacturing process. By shifting the focus from post-processing adjustments and monitoring to real-time, in-situ control strategies, this study introduces a novel approach to enhancing the quality and consistency of SLM-produced parts.

Multi-Layer, In-Situ Control Strategies

One of the most significant contributions of this work is the exploration of multi-layer, in-situ control strategies. Unlike previous studies that have predominantly focused on single-layer control or post-process corrections, this research delves into both in-layer and layer-to-layer control mechanisms. This proactive approach allows for continuous adjustments throughout the build process, thereby maintaining a more stable melt pool and ensuring that the cross-sectional area of each layer closely adheres to the desired specifications. The implementation of such control systems resulted in notable improvements in process stability, as evidenced by the reduced deviation in the melt-pool geometry and the more consistent thermal behaviour.

This shift towards real-time control is aligned with the growing need for more sophisticated and responsive systems in additive manufacturing. As highlighted in previous studies, the ability to make adjustments on-the-fly can significantly improve the quality of the final product, reduce waste, and improve process efficiency [104]. However, the success of such systems depends on their ability to effectively manage the complex dynamics of the SLM process, including the challenges posed by heat accumulation, noise, and time delays.

Fuzzy Logic Control: A Novel Approach

The introduction of Fuzzy Logic Control (FLC) as a control strategy in SLM represents a pioneering step forward. Fuzzy logic is particularly well suited to the SLM process because of its ability to handle the inherent non-linearities and uncertainties that characterise additive manufacturing. Unlike traditional control systems, FLC does not require a precise mathematical model of the process, making it highly adaptable to the complex and often unpredictable nature of SLM.

The results from this study underscore the superiority of FLC over other control strategies in several key areas:

- Heat Accumulation and Initial Temperature: FLC demonstrated a significant reduction in heat build-up and initial melt-pool temperature, directly contributing to improved part quality.
- Noise Suppression: The FLC system was more effective at suppressing noise disturbances, which are common in the SLM process due to the variability in material properties and environmental conditions.
- Response and Tracking: FLC showed faster response times to transient disturbances and superior tracking of changing setpoints for the melt-pool area, ensuring that the desired melt-pool geometry was maintained throughout the build process.

These findings are consistent with the broader literature on fuzzy logic, which has been shown to excel in applications requiring robust performance in the face of uncertainty and complex dynamics [105], [133].

Challenges and Future Considerations

While the introduction of online control systems, particularly FLC, offers significant improvements in SLM, several challenges remain that require further investigation:

- Heat Accumulation: Although the controllers reduced heat accumulation, it was not completely eliminated. This persistent issue suggests that additional strategies, possibly involving hybrid control systems or advanced cooling techniques, may be necessary to achieve long-term stability.
- Actuation Challenges: The rapid response of the FLC system, while beneficial in many respects, can lead to significant fluctuations in the control signal. These fluctuations pose challenges for the actuation system, which must respond quickly and accurately to maintain control. Future work should explore methods to smooth these control signals

without compromising response time.

- Communication Delays: Communication delays in the control loop were found to introduce oscillatory behaviour, particularly in the FLC system. This highlights the need for further research on delay compensation techniques to ensure that the control system remains stable under all operating conditions.

In general, this study demonstrates the substantial advantages of incorporating online control systems into the SLM process. The ability to regulate melt-pool characteristics in real-time, particularly through the use of FLC, represents a significant step forward in additive manufacturing technology. However, addressing the challenges identified in this study will be crucial for further advancing these systems and fully recognising their potential in industrial applications.

6.11. Chapter summary

This chapter discussed the design of online control systems for optimising the selective laser melting process. Specifically, the chapter focused on the issue of heat accumulation, which can affect the quality of the manufactured product. To overcome this challenge, the chapter introduced online control strategies that operate on multiple levels within the SLM process, allowing for instantaneous adjustments and improved part quality and consistency.

One of the most important points in this chapter is the examination of fuzzy logic control in the context of selective laser melting, an innovative application in this field. FLC is highly capable of dealing with uncertainties and the non-linear dynamics of SLM, making it an ideal choice for improving control accuracy and, thus, the results of the manufacturing process.

The chapter begins by discussing the challenges that arise due to heat accumulation in the SLM process and the need for real-time control mechanisms that can address them. The control problem is then defined as regulating the cross-sectional area of the melt pool to minimise the accumulation of heat. After that, it reviews various control system candidates, including PID, Feedforward, and Fuzzy Logic. Each control approach is evaluated for its ability to address the complexities of the SLM process, with a special emphasis on FLC due to its potential to handle the process's inherent uncertainties and non-linearities.

In addition, the chapter provides an overview of a set of simulation scenarios that are developed to evaluate control systems under different conditions. These conditions range from ideal environments to those filled with noise, delays, and various desired outputs. The purpose of these scenarios is not only to showcase the capabilities of the proposed control strategies but also to establish a foundation for further research into optimising the SLM process.

This chapter makes a significant contribution to the field of additive manufacturing. It proposes advanced control strategies for the SLM process, which improves the quality of parts and the efficiency of the process. The introduction of fuzzy logic control as a practicable solution for the optimisation of SLM processes represents a promising direction for future research. It offers insights into the performance of the control systems under various realistic conditions and sets the stage for further advancement of the SLM technology. By strategically managing heat accumulation, these control systems prepare the way for the broader adoption and improvement of SLM. This emphasises the significance of the chapter in pushing forward the boundaries of manufacturing technology.

7

Conclusion and Future recommendation

This chapter serves as a conclusion to the thesis and focuses on outlining future research directions to expand upon the current findings and push the field of SLM control systems forward. We suggest specific recommendations to address limitations, optimise outcomes, and guide further exploration. Following these recommendations will help improve the understanding and application of online control systems, leading to better performance in Selective Laser Melting. Furthermore, we provide a brief summary of the critical contributions of this research and its broader impact on metal additive manufacturing.

7.1. Future recommendation

This section provides set recommendations for future research to improve current research findings and push research forward. The suggestions aim to address current research limitations, optimise findings, and guide future research. Based on a comprehensive analysis, trends, and gaps, the recommendations aim to foster innovation in the field and contribute to its progress. The recommendations can be listed as follows:

1. **Validation and expansion of the simulation model:**

Firstly, it is essential to validate the model with real data to determine its realism and identify necessary improvements. This step will provide valuable information on the performance of the model in practical scenarios. Secondly, it is crucial to expand the investigation to different materials. The current model concentrates on a specific material, but it is essential to explore its application across various materials that are commonly used in SLM to test its adaptability and robustness. Lastly, it is recommended to conduct a comparative analysis with existing models, especially benchmarking against established methods such as Finite Element Method (FEM) simulations. Such a comparison will not only highlight the strengths and weaknesses of the fast simulation model but will also guide its further development.

2. **Explore the industrial feasibility of the control strategies:**
   It is essential to validate the control strategies developed in this study through laboratory experiments. Practical validation is necessary to establish the potential effectiveness of strategies in actual SLM systems despite the potential shown by simulations. This step will bridge the gap between theoretical models and their practical applications, ensuring that the strategies are feasible for real-world operations. It is crucial to address the practical challenges associated with applying these strategies in real-world industrial environments. This involves overcoming the limitations related to sensors, ensuring computational feasibility, and integrating the strategies with existing control systems. Understanding these challenges is essential to successfully adopt these control strategies in industrial settings, which will pave the way for their widespread use and ultimately contribute to the advancement of SLM technology.

3. **Further develop in MATLAB-based simulation tool:**
   Further investigations and developments of the proposed simulation tool is necessary. The development process should take into consideration the ability to adjust the dimensions of the object and handle more complex shapes. Furthermore, creating a user-friendly interface would make the tool more accessible and intuitive for a wider range of users. These improvements would significantly increase the versatility and effectiveness of the tool in optimising and analysing control systems for various applications.

4. **Refine the fuzzy logic control approach:**
   The consideration of investigating advanced fuzzy logic structures such as type-2 fuzzy logic or adaptive neuro-fuzzy inference systems which may lead to enhanced control performance. Additionally, implementing automated optimisation algorithms that can find the optimal settings for the membership functions and rules within your fuzzy logic

controller will further improve its effectiveness.

5. **Explore different control techniques:**
   While research concentrates on classical and fuzzy logic control, consider investigating other control approaches like model predictive control to see if they offer better performance or suitability for specific scenarios. In addition, hybrid control strategies should be considered to handle the endpoint of the tracks and the rest of the printed part.

These recommendations offer a roadmap for enhancing the investigation findings on the use of an on-line control system for the selective laser melting process and pushing the research forward.

7.2. Conclusion

This thesis thoroughly investigates the application of an online control system to the selective laser melting. The study explores the complexities of the SLM process and its potential as a revolutionary technology for fast and precise production of intricate components from digital models. It provides a comprehensive understanding of SLM and its transformative role in additive manufacturing.

Our thesis aimed to address the problems associated with the SLM process, such as the deterioration of part quality due to thermal behaviour during the process, which has hindered its widespread implementation.

We made four important contributions to the field through our research:

- Exploring the field of control system application in the SLM process and presenting the current challenges and future opportunities.

- Extending the existing model to go beyond the traditional track-level representation. We have a new comprehensive approach that enables a more efficient understanding of the SLM process with a multi-layer, variable-shape framework.

- A MATLAB tool was developed to reduce the simulation time while accurately capturing the process behaviour. This tool enables fast design and testing of control systems and offers practical solutions to overcome dynamic challenges.

- Investigating the implementation of three commonly used control strategies in industry in several practical cases. The use of fuzzy logic in controlling multilayer SLM is a pioneering contribution. It provides an effective way of handling uncertainties and seamlessly integrates with the multi-layer model.

This research provides valuable insights for additive manufacturing beyond traditional processes. Improve SLM technology by addressing challenges of heat accumulation and enhancing part quality through on-line control systems. The work advances academic knowledge and holds practical implications for metal additive manufacturing. This thesis contributes to the growth and optimisation of SLM and marks a significant contribution to the field of additive manufacturing.

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Appendices

A

Paper 1

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Control of selective laser melting processes: existing efforts, challenges, and future opportunities

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***Abstract*— Additive Manufacturing (AM) or widely known as 3D printing is a technology for producing parts directly from the computer without the need for traditional tools. The technology provides fast production for complex shapes with higher properties. Selective Laser Melting (SLM) is one of AM technologies that is used to produce metallic parts. For the last twenty years, the technique attracted the attention of both industry and academia. The complexity of the underlying physics and the fast dynamics during the process degraded the quality of the produced parts and hampered widespread adoption of the technology. A significant emphasis on the importance of on-line control systems to achieve higher levels of quality and repeatability can be found in the literature. In this review paper, we fill an important gap in the literature represented by the absence of one single source that describes what has been accomplished and gives an insight into what still needs to be achieved in the field of process control for metal-based AM processes. The article ends by discussing future opportunities in the associated on-line control system development.**

I. INTRODUCTION

A new industrial era has been motivated by the development of manufacturing processes. The advanced techniques facilitate the response to the world's requirements in a faster and more effective manner. Additive Manufacturing (AM) is a process that provides rapid manufacturing with optimised use of energy, labour, and materials. The process fabricates parts layer-by-layer directly from the computer. The diversity of materials that can be processed by the different types of AM processes expand the range of applications. The applications involve tool making, aerospace engineering, energy technologies, automotive manufacturing, and medical engineering [1]. AM is classified into seven categories, five of them apply to process metals which are powder bed fusion (PBF), directed energy deposition (DED), binder jetting, material jetting, and sheet lamination processes [2]. This paper focuses on a Selective Laser Melting (SLM) process, which is a specific PBF method, which uses a high power-density laser to melt and fuse metallic powders to fabricate parts. The technology does not only provide prototypes but also produces products ready to be used in different fields [3-6]. SLM offers a design process with fewer limitations, leading to a revolutionary design in different fields. It allows production of complex geometries, lightweight structures, and internal channels to improve product performance and to meet the industrial specifications [7]. Unfortunately, with all advantages offered by SLM and other AM processes, the quality and repeatability of metal parts still hamper significantly their widespread adoption as viable manufacturing processes [6]. The process contains complex underlying physical phenomena and transformations occurring during the process in a short time [8] and [9]. In particular for complex materials, just as titanium alloys used in the aerospace sector. Over 150 parameters affect the SLM process [10]. The facts above mean the optimisation problem is exceptionally challenging and becomes more complex as the complexity of the designed part increases. There are extensive research efforts over the world in the last two decades in modelling and control of AM processes [5],[8], and [11]. The investigations emphasise the importance of control systems to enhance product quality. Figure 1 presents the number of published papers in the area of control and modelling over the last twenty years. In this review paper, we focus on the existing efforts applied in SLM and promising algorithms that show encouraging results on other AM types. In addition to the gaps and future opportunities in the field of the on-line control system. After this section, the paper is organised as follows: section II considers the SLM process description, section III discusses the control effort in SLM, section IV introduces a promising algorithm, section V discusses gaps and future opportunities for improvement and the paper finishes in section VI with some conclusions.

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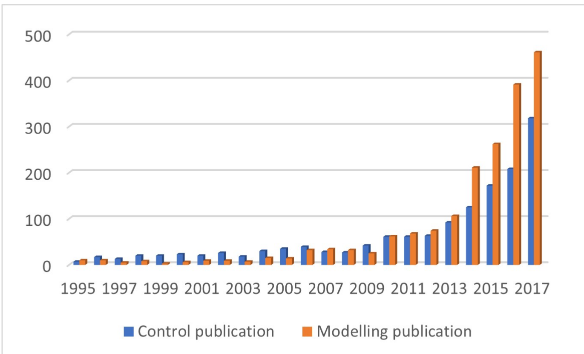

Fig. 1: The published papers in control and modelling over the last twenty years[12]

II. Selective laser melting process overview

A good understanding of the process is required for better utilisation and optimisation of the process inputs to ensure product quality. The fundamental elements of the SLM process are shown in figure 2. The parts can be described as follows [13]:

1) The laser source is considered as the primary source of the heat in the process. The laser power, type, spot size, and other parameters related to laser source have a significant impact on system performance.
2) The scanning motion device is the part that controls the scanning speed, hatching distance and the scanning strategy of the laser source over the powder.
3) The powder feeder and roller/reactor are responsible for adding the new layer after the previous layer is fabricated. The performance of the roller will affect the powder distribution in the newly added layer, thus the quality of the layer.
4) The elevator to lower down the scanned layer to allow the feeder to add the new layer.
5) The enclosed chamber provides a specific feature for the ambient to ensure the quality of the end-product.

More information about the process and its parameters can be found in [14]–[16].

III. Efforts in on-line control for SLM process

Most of the existing SLM and other AM processes are based on constant parameters [17]–[19]. These parameters are determined by trial and error at the beginning and fixed during the fabrication process. Research investigations showed that maintaining the parameters unchanged increases the heat affect zone [19]. Consequently, the heat accumulation produces irregular morphology of the melting pool, excessive dilution, thermal distortion and cracking. Other process uncertainties also add to the complexity of optimising the process, for example, powder batch-to-batch variability and recoater degradation, which further complicate the control requirements. Therefore, the properties of the produced parts cannot be guaranteed. The predetermination of an optimal processing set of parameters for specific mechanical properties is a commonly used method to enhance product quality or printability [20] and [21]. However, such an approach is neither economical nor robust enough to deal with perturbations.

On the contrary, using an on-line control system can compensate for the disturbances and improve the quality of the produced parts. Different control algorithms have been implemented and investigated, varying from classical to advanced controller techniques. Significantly, most of the researchers used the thermodynamic and/or the melt-pool geometry as a key to define the product quality during the fabrication [9] and [22]. The first term can introduce different kinds of defects (porosity, deformation, and cracking) and phenomena (keyhole, rippling, swelling), whereas, the second is related to microstructure evolution and thermo-mechanical properties. Irrespective of the used term, both are related to energy density which can be controlled by varying laser power, scanning speed, and scanning strategies [23]. The following content summarises the previous efforts in on-line control approaches for the SLM process.

Proportional (P) and Proportional-Integral (PI) controllers were used in the first attempts to investigate the controllability of the melt pool size by manipulating the laser power [24]–[26]. In these attempts, the designed controller was based on a second-order model which was identified using experimental data collected from a high-speed CMOS camera and photodiode. The studies presented the effectiveness and importance of the on-line control algorithm. An illustration of the effect of the applied algorithm is presented in figure 3.

With the development of measurement and processing equipment, more developed algorithms were investigated. In [18] and [27], a combined control system consisting of a feed-forward control and a P-controller was proposed. The temperature of the melt pool was controlled by changing the input laser power. The strategy showed a fast response to the change in the temperature and promising results for practical implementation with a reduction of 73% in the temperature deviation compared to the open-loop system. Despite that, the experimental implementation was limited to multi-track. In this work, the advantage of parallel processing was utilised using FPGA.

Some of the research efforts investigated a particular phenomenon. In [17], a feed-forward (FF) controller was applied to overcome the issue of over melting and keyhole formation. The approach was used successfully for DED processes. The controller was based on an analytical control-oriented model that considers the temperature history of the previous track. The experimental result of multi-track-single-layer printing showed a reduction on the over melting and disappearances of the keyhole. Additionally, a reduction in the average error rate by 23% was recorded compared to the fabrication with fixed laser power.

Whereas all of the previous works focus on controlling the

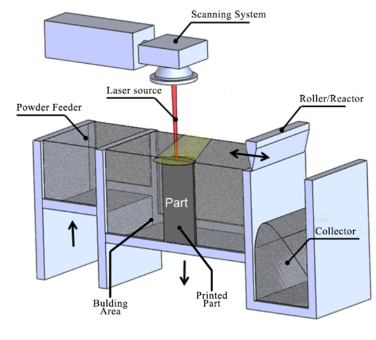

Fig. 2: The basic structure of the SLM process [15].

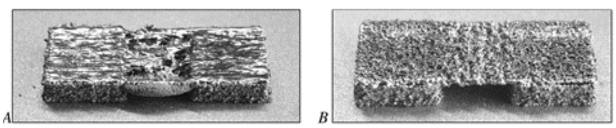

Fig. 3: Printing attempts with fixed laser power (A) and with a feedback controller (B) [25].

melt pool parameters within the scanning vector, a layer-wise control approach was introduced in [7]. In such a method, the information of the previous layer is gathered and analysed then used in the following layer to correct the deviation from the desired performance. The authors measured the melt pool area using a metal-oxide-semiconductor camera. Based on the information provided from the feedback, the energy density was changed in the new layer. The study showed the effectiveness of the approach to overcome heat accumulation and reduce the effect of the swelling phenomenon.

With the highly complex phenomena and complex physics involved in the SLM process, it is very challenging to get an accurate model that can lead to precise control design. Therefore, model-based control systems have limitations in their performance. Different research groups were interested in studying the feasibility of using a Model-Free Control (MFC) system. In [28] and [29] an Iterative learning control algorithm (ILC) is used to regulate the power profile within the scanning segment based on live measurement from the coaxial camera. In [30], the same concept was applied in addition to a data-driven model to predict the performance of the system and reduce the effect of the complex geometry and temperature history. The machine learning (ML) concepts such as deep-learning (DL) were used in [31] to predict the distortion during the process. An area of interest was defined by cylinder, presenting the information near and below the operating point. The suggested approach presented the system as an optimisation problem and solved for the best input using an ILC algorithm based on the previous and on-line data. Conclusively, the efforts demonstrated the feasibility of deriving process decisions using the on-line data only without the need for a mathematical model. The scope of research was not limited to controlling the laser power or scanning speed. A few groups were interested in studying the effect of scanning path and scanning strategy on the melt pool size and temperature, such as [32] and [33]. The investigations showed that the residual stress and distortion could be minimised. However, all the existing industrial processes come with pre-sited scanning strategies.

In [11] and [34] the focus was directed to monitoring and control of the surface roughness using coherent imaging. The roughness was improved by post-processing using laser pulses and refilling the gaps. In [35], a backstepping control was designed for a nonlinear partial derivative equation model. The model was developed to capture the thermodynamics of the phase change of the melt pool. The investigation was limited to proving the Lyapunov stability of the controller. Table I below summarises the control efforts found in the literature.

IV. Promising Control Methods Used for Other AM Process

Most of the metallic AM systems are based on the same concept and melting requirement. Therefore, many efforts that were investigated or implemented in other AM process can be adequate for the SLM process. An example of such attempts can be found in [17] and [36]–[38]. The following context presents promising techniques that were applied with the DED AM process but not yet investigated with SLM technology. Table II below summarises several different approaches, discussed next, which were investigated to control the different AM process.

A. Simulated feedback

In [36], the implementation of a feed-forward and a model-based simulated output feedback controller was investigated. The method aids to overcome the issue of real measurement. The simulation results demonstrated up to 50% enhancement in the accuracy of the deposition geometry. However, the main challenge for practical implementation is the absence of a high-fidelity model simulator.

B. Model predictive control

With the constraints included in the DED process, model predictive control (MPC) attracted the attention of a few groups. In [39] a generalised model predictive control (GPC) law was proposed to track the temperature of the melt-pool. A higher level of MPC was investigated in [40] and [41]. They applied a multivariable predictive control to control the multi-input-multi-output (MIMO) control-oriented model for the cladding laser aided power deposition process. The approaches try to control the geometry and temperature profile of the melt pool by varying the laser power and scanning speed.

C. Feedback linearisation

In [42], a MIMO reduced-order model was derived and controlled using a feedback linearisation method. The simulation results for a single layer deposition showed the effectiveness of the control technique.

D. Model-free adaptive iterative learning control

The performance of the model-free adaptive iterative learning control (MFAILC) algorithm was investigated to overcome the complicity and uncertainty of the model [43]. The algorithm is used to control the width of the melt pool in wire arc DED AM process by moderating the laser power. The results showed good tracking performance and robustness against disturbance in welding speed and stick-out length.

V. Challenges and Future Opportunities

With all the advantages that SLM processes have, there are several concerns about the repeatability and reproducibility to adapt the technology worldwide [44,45]. Almost all research efforts focused on single-tracks or elementary geometries, such as thin walls and cubes which ignored the ability of AM to produce arbitrarily complex geometries that cannot be produced (or are very difficult to) using traditional manufacturing technologies such as subtractive, casting, forming etc. The in-depth investigation of the performance of the control systems with complex shapes is required to fulfil the practical application of SLM. Besides that, there are few efforts investigating the phenomena that could appear during the building process. From the control perspective,

TABLE I: Current Control efforts for SLM processes

Control Objective	Control strategy	Control variable	Process Signal	Ref
To investigate the controllability of the SLM process using feedback	P and PI control	Laser power	Melt-pool geometry	[24]-[25]
To overcome the overheating problem and keyhole formation	FF			[17]
To control melt pool temperature at sufficient time	FF combined with P- controller		Temperature profile	[18],[26]
To avoid heat accumulation	Layer-wise			[7]
To control the temperature profile of the scanning segment	Model-free-ILC			[28]-[30]
To investigate the feasibility of ML control system	ML-ILC			[31]
To improve the surface quality of the product	-		Surface geometry	[11],[34]
To investigate the effect of scanning path strategy	Open-loop control	Scanning path	Melt-pool geometry	[31],[32]
To investigate the Lyapunov stability	Backstepping	Laser power		[35]

TABLE II: Promising techniques applied for other AM process

Method	Objective	Control Variable	Process signal	Achievement	Ref
Simulated feed	To overcome the issue of real measurement	Laser power	Height of the decomposition	Feasibility of the control algorithm	[36]
GPC	To Compensate of the lack of deposition		Melt pool temperature	Good tracking performance and robustness algorithm	[39]
Multi-variable predictive control	To control the geometry and temperature of the melt pool	Laser power and Scanning speed	Melt pool and temperature profile	Prove the feasibility of the control algorithm	[40],[41]
Feedback linearization	To reduce the residual stress			Simulation Investigation about the proposed algorithm	[42]
MFAILC	To regulate the melt pool temperature	Laser power		Good tracking performance	[43]

the following summarises some of the various challenges and opportunities from the literature.

A. Challenges

1) Challenges and limitations regarding the used model: The lack of an adequate process model that can be used to design a practical on-line control algorithm was noted. The previous efforts showed that suitable physics-based control-oriented models barely exist for SLM processes and data-driven models are still underdeveloped. Additionally, since the quality of the data-driven model depends on the amount of available or accessible data, the shortage of real data is a significant obstacle for any implementation.

2) Challenges and limitations regarding control technique and data processing: The unavailability of fast enough control systems to capture the dynamics of the process and respond to any perturbation in an appropriate time was indicated by many researchers. Processing speed is considered as a challenge and a limitation to implement an on-line control system. Apart from that, most of the research studies did not address the stability, uncertainty and robustness in any significant depth. From the level of control (in-layer, layer-wise, and surface quality) point of view, almost all the efforts targeted a specific scenario without investigating the effect of combining them. Although the model-free control algorithm helps to overcome the need for a mathematical model, the technique requires exact repetition from iteration to iteration. However, this is not applied in most of the shapes.

B. Future Opportunities

With the aforementioned challenges and limitation, the following future opportunities can be seen:

1) Opportunities in model development: The existing model needs to be extended to be able to include the behaviour of the process while producing complex shapes. The model improvement can involve the temperature history of the built tracks and layers in addition to the formation phenomena. The following approaches look promising to develop a control-oriented model for selective laser melting processes:

- Using the leverage of similarity between SLM and other AM process, a model can be developed to fit the process.
- Develop a physics-based model that can capture the required specification and be simple enough to design an on-line controller.
- Using ML and data-driven concepts, that can capture different information about phenomena included in the SLM process, in order to design a tailored control approach.

2) Opportunities in control system development: As it was mentioned in section V.A.2, the majority of the proposed methods did not take into consideration the control issues such as stability, robustness, and uncertainty. Therefore, more investigation is required in this area. In terms of an on-line predictive control system, to the best of our knowledge, the implementability of model predictive control (MPC) is not yet investigated for SLM process. Using MPC can compensate for the uncertainty of the derived model. Likewise, a multi-level control system that links the different level of control (in-layer, layer-wise, and surface quality). Such a technique can improve product quality by ensuring the quality of building in different stages. A model-free control concept can play an essential role in overcoming the issue of modelling; however, more investigation is required.

VI. Conclusion:

This work is aimed to gather the previous works on on-line control for Selective Laser Melting (SLM) processes. The investigation emphasised the importance of the control system. The work demonstrates how the control system affects the production time, mechanical properties, microstructure, defects, geometry accuracy, and disturbance compensation, therefore, enhancing the overall performance of the system and the quality of the produced parts. Different efforts were presented besides some other promising algorithms. The challenges and limitations that face the current works were highlighted. Based on that, future opportunities were presented. To ensure the quality of the produced parts from SLM process, further investigation in the on-line control system is indispensable.

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Paper 2

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Fuzzy Logic Control in Metal Additive Manufacturing: A Literature Review and Case Study

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Abstract: Since the development of the Fuzzy Logic theory by Zadah (1965), motivated by the human-level understanding of systems for the development of computational and mathematical frameworks, it has become an active research field for a broad spectrum of research in academia and the industry, from systems modelling to systems monitoring and control. In this research, the authors intend to highlight the use of Fuzzy Logic theory in metal additive manufacturing processes. The modelling of such processes has a lot of uncertainties due to the large underlying physics during the operation, which makes the Fuzzy Logic Controller a promising tool to deal with such a process. This work will provide a survey of the previous efforts and a case study to illustrate the approach's effectiveness in such a complex manufacturing technique.

Keywords: metallic additive manufacturing,laser powder bed fusion, control, fuzzy logic

1. INTRODUCTION

In the 1960s, when the Fuzzy Logic (FL) theory was initiated by Lotfi A. Zadeh (Zadeh (1965)), it was challenging to appreciate its merits due to the absence of a practical application. It took almost a decade to see the first FL controller for an actual industrial application, which Mamdani and Assilian proposed in 1975 for steam engines (Tan (1998)). After that, the application of the FL grows rapidly to cover different aspects. The approach helps in reducing the gaps between the theoretical (ideal) side and the practical (uncertain) side by considering the uncertainty and the inaccuracy of the models (Lhachemi et al. (2019)).

The FL theory is a non-linear representation of the engineering problem, including the human factor and statistical information in evaluating the process (Jing et al. (2021)). It allows treatment of system variables in gradient logic rather than binary logic (e.g. 0 or 1) (Wang (1997)), which is closer to the practical world where the relationship between the variables includes complex categorisation of the membership status. The strength of FL can be seen in three main points:

(1) FL formulate and consider the human expertise and knowledge to define the objective problem and the decision variables (Elkaseer et al. (2018); Farshidianfar et al. (2013)).
(2) FL can be suitable for systems that have no accurate description (Lhachemi et al. (2019); Tan (1998)).
(3) FL can be an economical alternative compared to other intelligent systems (Farshidianfar et al. (2013)).

FL applications include many sectors in the fourth industrial revolution. Among these are 3D printing or what is known scientifically as additive manufacturing (AM). AM is an advanced technique of producing parts using layer by layer fabrication (Al-Saadi et al. (2021)). It has the power to produce parts with customised properties and shapes without going through traditional manufacturing steps. This gives the AM processes the ability to offer revolutionary design in various fields in the industry such as aerospace, energy, automotive and tooling (Tapia and Elwany (2014)).

AM has seven main categories (Seifi et al. (2017)) that can process various types of material (plastic, metal, ceramic, etc.) in different formats (liquid, wire, and powder) using different techniques. A promising technique of AM process is the selective laser melting (SLM) process. SLM is a laser powder bed fusion AM method, where a metallic powder is melted selectively in high resolution using a high power-density laser source to fabricate parts and build it layer by layer (Gupta (2017); Mercado Rivera and Rojas Arciniegas (2020)). As a result, it can produce parts with complex geometries, lightweight structures, and internal channels, improving product performance and industrial specifications (Vasileska et al. (2020)).

However, the level of development of metallic processes still hampers their widespread adoption. The quality and repeatability of the metal parts produced by the process continue to face many challenges. The process contains complex underlying physical phenomena, a large number of parameters, and transformations occurring during the process in a short time (Druzgalski et al. (2020)). There have been extensive research efforts over the world in

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the last two decades in modelling and control of AM processes (Gupta (2017)). The investigations emphasise the importance of a control-oriented model and the control strategies to enhance product quality. Nevertheless, more research is required to attain efficient online closed-loop controllers that can compensate for the perturbations during the process. Since most control-oriented models are based on simplification and reduction, the classical controller can face many limitations and drawbacks.

Motivated by the ability of FL theory to handle complex and uncertain models, this research work will provide a brief literature review about the use of the fuzzy logic theory (modelling and control) in the field of metal additive manufacturing in general. In addition, a case study of designing a fuzzy controller for an L-PBF process, which will be used to illustrate the advantages of FL-based control over classical PID control (the compassion is limited due to publication size).

The paper after this section will be organised as follows: Section 2 will consider why we need to consider FL in AM, section 3 discusses a fuzzy logic application in AM, section 4 presents a case study, section 5 contains a discussion including a review of future opportunities and section 6 finishes the paper with a conclusion and future work.

2. WHY DO WE NEED TO CONSIDER FUZZY LOGIC IN METALLIC AM

With all the advantages that metallic AM processes have, there are several concerns about the repeatability and reproducibility to adapt the technology worldwide (DebRoy et al. (2019); Dowling et al. (2020). The research investigations presented in the literature show that the system dynamics vary continuously during the process. The variation depends on how the heat has accumulated during the fabrication of the object, which depends on the object geometry. Consequently, the operation parameters for most existing metallic AM processes are determined by trial and error in advance, or via the heuristic use of offline numerical and analytical models. Such process paramteres, are then 'fixed' during the fabrication (Tang and Landers (2009); Wang et al. (2020)). Such a method works well with regular shapes but not with complex geometry. Research investigations showed that maintaining the parameters unchanged increases the heat affect zone (Tang and Landers (2009)). Consequently, heat accumulation and other complexities cause irregular melting pool morphology, excessive dilution, leading to various defects such as thermal distortion, lack of fusion, and cracking. Thus, the properties of the produced parts cannot be reliably guaranteed, which is a major barrier for critical applications.

Another approach predetermined the optimal processing set of parameters for specific mechanical properties to enhance product quality using thermal models (Fox et al. (2016)). However, the approach is not economical nor robust enough to deal with perturbations.

Using an online control system can compensate for disturbances and minimise heat accumulation during the process, thus improving the quality of the produced parts(Gupta (2017); Fleming et al. (2020)). Proportional (P) and Proportional-Integral (PI) controllers were used in the first attempts to investigate the controllability of the melt pool size by manipulating the laser power Craeghs et al. (2010). The studies presented the effectiveness and importance of the online control algorithm. However, the controller's performance was limited because the designed controller was based on a simplified second-order model.

Different control algorithms were implemented and investigated, varying from classical to more advanced controller techniques. From the previous author work (Al-Saadi et al. (2021)) the lack of an adequate process model that can be used to design a practical online control algorithm was noted. Furthermore, it will be very challenging to find such a model without linearisation in order to apply classical control theory. Unfortunately, the linearisation of the process can exclude a part from its featurethat could challenge control performance (Ibrra and Webb (2016)). Thus applying classical approaches is not the optimal solution in such a case.

Modern control systems such as ones that include artificial intelligence can provide a solution to enhance complex performance without needing an accurate model (or even any model). However, since such techniques are data-driven, their quality depends on the amount of available or accessible data; a real data shortage is a significant obstacle for any implementation. Based on the aforementioned section, FL theory presents a middle ground between the simplicity of the classical controllers and the complexity of the advanced control methods. Thus, it is worth deeply investigating the use of fuzzy controllers to enhance the quality of metallic AM processes and to evaluate the method's strengths and limitations in this context.

3. FUZZY LOGIC CNTROLLER (FLC) APPLICATION IN AM

Based on the best of the authors' knowledge, using a fuzzy logic controller in the L-PBF process has not been yet investigated. However, there are few attempts to apply it with other metallic AM processes, that can be further developed and investigated towards building a FLC for L-PBF.

The idea was investigated first in Hua and Choi (2005), where an FLC is designed and implemented for the direct metal deposition process. The purpose of the controller was to manipulate the input power to achieve the desired bead height. Theoretically, under the assumption of linearity, the controller shows promising results compared to the conventional control algorithm. However, the controller's performance in the actual experiment was limited due to the sensor capability.

In Farshidianfar et al. (2013), a neuro-fuzzy (NF) algorithm was used to identify and control a cladding process. The model was first identified using the NF system based on experimental data and then using the same technique, a controller was designed to vary the processing speed to control the height of the deposition. Generally, the obtained result showed promising results for the system performance.

Another investigation was recently done in Li et al. (2020). The FLC was used to control the deposition height in the wire and arc process by varying the speed. The proposed control system used the data of the previous layer to update the speed for the coming layer. The investigation shows better accuracy in the geometry of the printed sample.

The previous studies focused on the metallic AM process; however, other research efforts were conducted on polymers printers. In Moor et al. (2018), the FL was used to enhance the quality of the product by detecting defects and correcting the process parameters. The proposed system scans the printed part and compares it with the CAD model. In Keskekci Abdullah Burak ,Senol Ramazan (2020), the FLC was used to control the working environment temperature to overcome the warping problem. Compared with the PID controller, the system has 22% less warping. The use of an adaptive fuzzy-PID controller to control the temperature of the process (bed, nozzle, ambient temperature) was investigated in Liang et al. (2019). The research shows an enhancement in system performance in terms of overshoot percentage and tracking performance.

4. CASE STUDY

In this section, the FL controller effectiveness is shown using a case study example. It is worth mentioning that there is no previous investigation of using FLC on a L-PBF process. The section will start with a brief description of the L-PBF process, followed by the formulation of the control problem, controller design and simulation results.

4.1 System overview

Selective laser melting is a metallic PBF process that uses a focused laser beam to melt the mounted powder selectively (Nematollahi et al. (2019)). The process can produce metal parts directly with quality equivalence, or better in some applications, to the ones produced using traditional manufacturing. The narrow laser source allows selective melting of the powder in the order of tens of microns in thickness and building of parts with a significantly satisfactory resolution (Wang et al. (2020)). The thermal energy produced by the laser system is sufficient to melt the powder at the point of incidence and re-melt the surrounding solidified powder. Thus, the process can produce well-bonded and high-density parts (Gibson Rosen, David W., Stucker, Brent. (2010)).

The SLM requires a set of steps to produce the desired parts (Gunasekaran et al. (2020)). The beginning is to convert the 3D CAD model into cross-section layers and save it in a suitable file format. Then, the file is loaded to the machine using specific software. Before starting the printing process, a set of parameters will be selected and configured to ensure building quality. The selection of the parameters will be discussed in the coming section. Then, the powder is deposited in the building area, and a focus laser beam with pre-selected power is used to melt the powder based on the data from the file. After fabricating the first layer, the roller spreads a new layer of powder on the platform. The process is repeated until the final product is completed. Finally, the part can be removed and cleaned manually or with the help of another machine. The remaining or unused powder can be reused after specific preparation.

4.2 Problem formulation

Using the L-PBF process, the part quality depends on the melt pool dimensions and the thermal behaviour during the fabrication. The heat accumulation during the process causes irregularities in melting pool morphology, excessive dilution, thermal distortion, and cracking. Thus, the properties of the produced parts cannot be guaranteed. Therefore, maintaining the melt pool size is essential to ensure quality. In order to achieve that, a fuzzy control system will be designed to regulate the melt pool dimension by manipulating the laser power to reduce the impact of the temperature accumulation during the fabrication.

The controller will be designed based on the knowledge gained from the literature and the process model simulation presented in Wang et al. (2020). Then the controller's performance will be tested on a linearized version of the model and compared with the performance of the PID controller.

4.3 Fuzzy control system design

The basic structure of the fuzzy controller:
A fuzzy logic controller (FLC) is like any other conventional controller. It has inputs from the system and outputs that control the plant. However, the main difference appears in the decision making of the control signal. The control signal is based on human or/and statistical knowledge. Figure (1) presents the basic structure of the FLC. The input could be the system output, states, or error signal. On the other side, the output of the fuzzy system will be the control signal. The fuzzifier block converts the crisp input from the system to fuzzy sets using membership functions. The inference block presents the heart of the fuzzy system, where the predefined set of rules, membership function, and the input sets are used to assign the output sets. Finally, the output sets are converted to crisp values through defuzzification.

Generally, the FLC can be classified into two main classes, non-adaptive and adaptive fuzzy control (J.Ross (2010); Wang (1997)). In the first class, the controller parameters and structure are maintained fixed during the process. The main advantages of such an alternative are the simplicity of configuration and implementation. Nevertheless, it could have limitations with a complex system. Contrariwise, the adaptive fuzzy controller provides better handling for a complex system in the cost of complexity of the control structure. In such a category, the parameters or/and structure can change based on the input and output information. This particular work will focus on the primary non-adaptive fuzzy controller.

Fuzzy logic control design:
In order to enhance the product quality produced by the SLM process, most of the research efforts emphasise controlling the geometry or temperature of the melt pool during fabrication. Thus a closed-loop control system is required. Figure(2) illustrates the basic schematic diagram of the closed-loop system of the SLM process. The desired

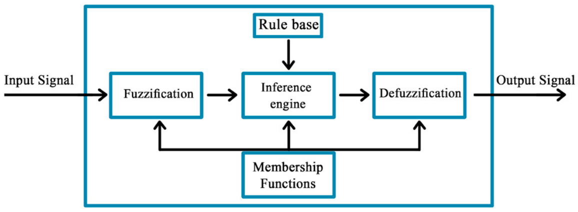

Fig. 1. The fabrication procedure using the SLM process

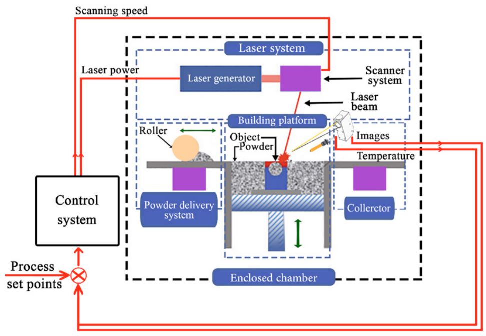

Fig. 2. The basic schematic diagram of the closed-loop system of the SLM process

output could be either melt-pool geometry or temperature, where the control variable is the laser scanning speed or power. This work investigates the control of the melt-pool area by varying the laser power. The inputs to the FLC are selected to be the error signal and the rate of change of the error. The input signals are divided into five linguistic levels: high negative (HN), negative (N), zero (Z), positive (P), and high positive (HP), where the controller output "the laser power" is split into five levels: very negative (VN), negative (N), zero (Z), positive (P), and very positive(VP). The input and output signals' membership functions are selected to be gaussian functions and illustrated in figure(3). Tables (1) and (2) summarise the range of the signals and the fuzzy rules used in the simulation. It is worth mentioning that the selection of the linguistic variables, membership functions and fuzzy rules is a research area that requires more investigation, which will be a part of future work.

Table 1. The range of the input and output signal, that's used in designing the FLC

Variable name	Range
Error (m)	$(-10 \text{ to } 10)\text{x}10^{-9}$
Change of error (m)	$(-3 \text{ to } 3)\text{x}10^{-6}$
Laser power (W)	0-500

Table 2. Fuzzy rules

Variable		Change in error				
		HP	P	Z	N	HN
Error	HP	VP	VP	VP	VP	VP
	P	VP	P	P	P	VP
	Z	VP	Z	Z	Z	VN
	N	VN	N	N	N	VN
	HN	VN	VN	VN	VN	VN

4.4 Simulation and Analysis

The designed FLC in the previous section was simulated and compared with the PID controller. The PID controller parameters were selected using the auto-tune toolbox in MatLab using the same assumptions and model information used to design the FLC. The reference value was selected to be $11\text{x}10^{-9}$ mm^2. This value represents the steady-state value of the melt-pool cross-sectional area, which is computed using the model presented in Wang et al. (2020). Both controllers' performance was evaluated in responding to a step-change and disturbance rejection. The disturbance rejection is selected to mimic the worst case of heat accumulation during the process. The simulation results are presented in figure (4). Generally using a closed-loop controller improved the system response, thus enhancing the building quality. Comparing the system performance using the PID controller and the fuzzy logic controller, the following points can be noted:

- The PID controller suffered from overshoot and undershoot at the beginning of the simulation and when the disturbance signal was introduced. Reflecting this into reality, a geometrical error and defects will be presented, and it will be obvious in the edges of the printed item. On the other hand, the FLC showed significant effectiveness in achieving the desired geometry and reducing the effect of the heat accumulation to a negligible level.
- The system with FLC was two times faster than the system with the PID controller. Such a result is expected due to the way of defining the two controller structure. Practically, having a fast control system has a significant impact on capturing the dynamics of the process and responding to perturbations in a sufficient time.
- The PID controller produced a zero steady-state error, whereas the FLC records an error around 1 % of the desired value.

Table (3) summarises the system's key performance indices using both controllers.

5. DISCUSSION AND FUTURE OPPORTUNITIES

Many research questions can be raised based on the presented literature and the case study. These questions present future research opportunities, which can be listed as follows

- What will be the controller's performance with the nonlinear model? In the presented case study, the controller was simulated based on a linearized model of the SLM process. However, the real system, as mentioned before, is highly nonlinear. The questions

Table 3. Key performance indices of the system using both controllers

	Controller type	
Performance index	PID	Fuzzy
Overshoot	9%	0%
Settling time	0.003	0.0055
Error	0	1%
Disturbance rejection	Caused an overshoot	Barely affected the system

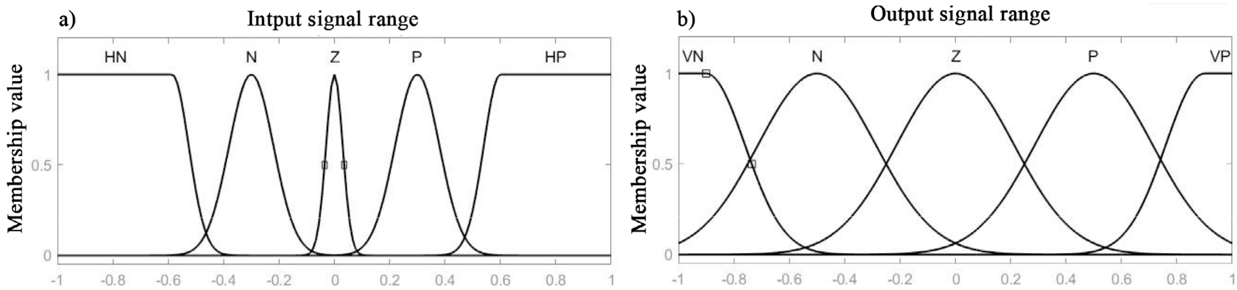

Fig. 3. Input membership function (a) nad Output membership function (b)

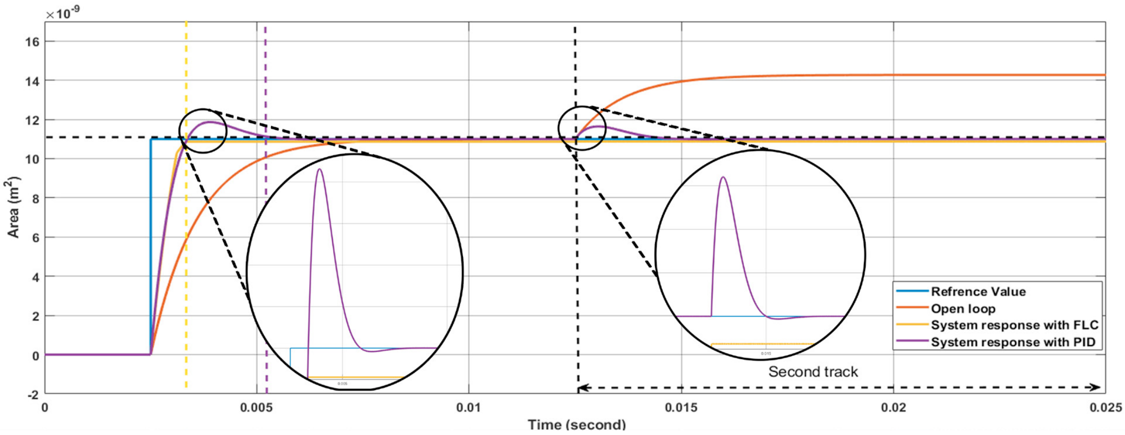

Fig. 4. System response under different conditions: open-loop, using FLC, and using a PID controller.

here are: to what extent can the fuzzy controller cope with the system's nonlinearity? Will the basic fuzzy inference system perform well, or there will be a need to use a more complex fuzzy structure?

- What will be the cost of guaranteeing stability, optimality, and robustness? The presented simulation of the fuzzy controller was achieved after trial and error tuning. However, although it gives good results, it misses considering the issues and the analysis of stability, optimality, and robustness. As mentioned in Al-Saadi et al. (2021), these issues were not investigated even for the classical controllers.
- What will be the advantages and the limitations of the Adaptive Fuzzy controller? In section 4, the adaptive fuzzy controller is mentioned as another class of FLC. Such a type could be a powerful tool when the system is extended to MIMO level or when the controller is required to modify the process parameters in and between the layers. On the other hand, it could affect the performance of the system response.
- How effective will the fuzzy controller be in practice? Although the theoretical investigations showed a promising result, there could be practical limitations. Based on the existing literature, the feedback signal is a noisy signal with a delay because of sensory issues. Thus it is crucial to investigate the performance of the FLC under these conditions and analyze the limitations in a practical implementation.

The above questions require more investigation and analysis and present future research opportunities.

6. CONCLUSION

This research work was aimed to highlight the use of fuzzy logic theory in the field of metallic additive manufacturing. In addition to the literature, a case study of designing a fuzzy controller for a selective laser melting process was presented. The investigation illustrates the effectiveness of such a control algorithm. The conducted literature review and the simulation of the case study showed promising results for the use of FLC and emphasised its capability of improving the performance of metallic additive manufacturing. However, more investigation and analysis are required to determine the applicability of the controller as well as some applications on real hardware.

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Paper 3

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In-situ proces control strategies for selective laser melting

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Abstract: Selective Laser Melting (SLM) is an additive manufacturing process that has been attracting the attention of researchers and developers in academia and industry over the last two decades. The SLM manufacturing process is capable of producing sophisticated industrial tools and geometrically complex parts in fewer steps (near net-shape), thus saving resources compared to subtractive manufacturing processes. However, the current industry-scale platforms for manufacturing metal parts via SLM do not sufficiently exploit online feedback control strategies. There is still significant potential for advanced process control which can enhance the overall performance of the system, as well as enable sophisticated manufacture, for example via active control of microstructure to enhance part performance in geometrically complex parts. This paper presents a comparison between the performance of three well-known industrial control strategies, to illustrate strengths and weaknesses in addition to addressing the key challenges and identifying some research opportunities in the field.

Keywords: Metallic additive manufacturing, selective laser melting, powder bed fusion, feedback control, fuzzy logic, PID, feed-forward.

1 Introduction

With the recent global requirements (sustainability, durability, and environmental-friendly) for most industrial applications, the need for advanced manufacturing techniques is increasing. During the last three decades, the world witnessed an increasing focus on using additive manufacturing (AM) technologies for metals (Al-Saadi et al. (2021)). AM is a manufacturing process for building 3D objects directly from the digital design using a layer-by-layer approach (Seifi et al. (2017)) without the need for traditional manufacturing steps (e.g. subtractive manufacturing). The technology offers many advantages such as a reduction in the number of manufacturing steps, better utilisation of the manufacturing material, and fewer design limitations (Tapia and Elwany (2014)).

AM constitutes several different manufacturing techniques that can handle a wide range of materials and it is used in different industrial sectors such as aerospace, energy, medical, and many more (Guo and Leu (2013)). Among these technologies this paper focuses on the selective laser melting process (SLM), which is classified under the laser powder bed fusion (L-PBF) AM methods. SLM is used to manufacture metallic parts by fusing the powder particles selectively to build the required objects (Duda and Raghavan (2016)). The technique provides a substantial solution to design and fabrication of complex metallic parts requiring a lightweight and solid structure, and specific mechanical features (Vasileska et al. (2020)).

The SLM process generally consists of five main units, that can be described as follows:

(1) The laser unit: the unit responsible for generating the laser beam and controlling its movement over the powder.
(2) Powder delivery unit: this part is responsible for adding new layers. It adds and compresses the material powder uniformly as a layer.
(3) Building platform: the unit presents the working space where the part is printed. After completing each layer, the unit shifts down and allows the powder delivery unit to add a new layer.
(4) Collector unit: a unit to collect the extra powder.
(5) Enclosed chamber: a closed space to control the ambient conditions.

In addition to these units, a monitoring unit could also exist in an industrial machine to monitor the ambient temperature, machine performance and manufactured part. Figure (1) illustrates the basic structure of the SLM process.

The production process of a 3D part goes through a set of steps (Gunasekaran et al. (2021)). It begins with converting the 3D CAD model into cross-sectional layers and saving it in a suitable format (e.g. an .STL file). The machine parameters will be configured which make the process ready to start. The process fabricates one layer after another untill the part is completed. Lastly, the part is removed and cleaned manually or with the help of another machine.

There are still challenges and limitations to fully meet the industrial requirements in metal AM (Mercado Rivera and Rojas Arciniegas (2020)). The process has numerous

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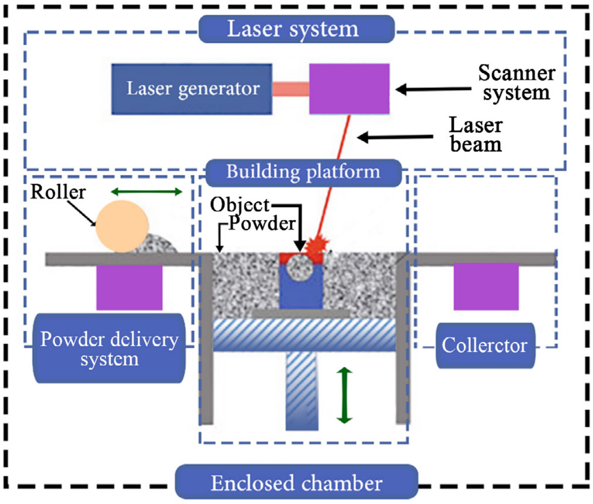

Fig. 1. The basic structure of SLM process

factors that affect its performance which means the quality and the repeatability of the process can not be guaranteed (Druzgalski et al. (2020)). In most of the existing SLM and other AM processes, the process parameters are kept constant Wang et al. (2020); Tang and Landers (2009); Volker et al. (2018) throughout the 3D printing process. The parameters are predetermined by trial and error or optimised before production via the use of expert knowledge and modelling/simulations . The use of fixed parameters can lead to heat accumulation and cause irregularity in the melting pool morphology, in particular for complex geometries, which leads to many defects (Tang and Landers (2009)).

Over the last twenty years, extensive research work has focused on enhancing part quality. There is a general agreement that using an online control system will improve process performance (Fleming et al. (2020); Druzgalski et al. (2020); Duda and Raghavan (2016)), thus in the literature, there are several attempts to design a control system for the SLM process. To illustrate the strengths and weaknesses of various control approaches in controlling the SLM process, this work evaluates the efforts that are suitable to establish an online control system for the process. In addition this paper provides a comparison between several control strategies and makes proposals.Based on the best of the authors' knowledge, such comparison and analysis about control systems for SLM were not covered before in the literature.

After this section, the paper will be organised as follows: Section 2 provides a brief survey of the online control effort in the SLM process. Sections 3 and 4 address the control problem, and control design, and simulation case studies. Section 5 discusses the simulation results and points to some research opportunities in the field of online control system of the SLM process. Section 6 sums up the investigation conclusions and future work.

2 Efforts in Online Control for SLM

As emphasised in the literature, using an online control system presents a promising solution to overcome the process perturbations and reduce the effect of meltpool abnormalities during the part building process (Fleming et al., 2020; Gupta, 2017). Several control systems were proposed and studied in the literature. In most of the studies, the melt-pool geometry and/or its thermodynamics were considered as an indication of the process quality (Lee et al. (2019); Holder et al. (2020)). Regulating the melt-pool geometry produces a better microstructure and better mechanical properties. Conversely, controlling the melt-pool temperature prevents porosity, deformation and cracking, in addition to many manufacturing phenomena such as a keyhole and swelling.

Regardless of the controlled variable, paths are correlated to the process energy density that can be controlled by manipulating the effective laser power, scanning speed and scanning strategies (Reutzel and Nassar (2015)). The efforts of controlling the SLM process can be classified into two groups: classical approaches and data-driven based. Proportional (P) and Proportional-Integral (PI) controllers were the first classical online system investigated in (Kruth et al. (2007b,a); Craeghs et al. (2010)). The studies present the first control attempts to control the melt-pool geometry by varying laser power. The controllers were designed based on a second-order empirical model. The investigations showed how effective the online control system could be to enhance the process quality.

Many years after, the advantage of new emerging machines and process mechanisms encouraged researchers to address the control problem in the SLM process again. In (Volker et al. (2018); Renken et al. (2019)), the capability of the Field-Programmable Gate Array (FPGA) board was used to implement a combined control system including a P-controller and feedforward (FF) controller. The proposed control structure is designed to control the temperature of the melt pool by adjusting the laser power. The experiments showed a reduction in system temperature error by 73% compared to the open-loop response. Unfortunately, the study was limited to a few well separated multi-tracks.

In the previous works, the control systems are based on observations and experimental trials. In Wang et al. (2020), the FF controller was designed based on a control-oriented model. The investigation showed the designed controller managed to regulate the melt-pool geometry during the process and reduced the error to 23% compared to operation with a fixed laser power. The use of data-driven approaches in the SLM process started with a feasibility study of using model-free control system presented by Latipova and Baitimerov (2018); Kim et al. (2018). Iterative learning control (ILC) concepts were used to maintain the power input within the scanning portion based on the actual reading from the imaging system. In Ahrari et al. (2017), the same concept was applied combined with a data-driven model to predict the system's performance and reduce the effect of temperature history. The deep-learning and machine learning concepts were also used in (Holder et al. (2020)) to anticipate the disturbance during the process in a specified area. The area of interest was defined by a cylinder that captures the surrounding condition of the operating point. The author presented the system as an optimisation problem that can be solved using an ILC algorithm based on the previous and online data. The research illustrated the feasibility of controlling the process using the online data only. However, the repetitive behaviour, which is the base of the suggested algorithm, cannot be applied to geometrically complex parts.

Based on a recent authors' investigation presented in (Al-Saadi et al. (2022)), a fuzzy logic control (FLC) algorithm is presented as a control candidate for the SLM process. A basic FLC was designed to overcome the heat accumulation issue during printing a single layer of metal. The result showed a significant reduction in the error signal. However, the work is limited to theoretical investigations only.

3 Controller Design

3.1 Control problem statement

The objective of the control system is set to manipulate the laser power input Q(t) to regulate the melt-pool cross-sectional area A(t) and reduce the effect of heat accumulation (or lack of heat) during the building process. The heat accumulation causes a variation in the initial temperature (T_{init}) as the layers and tracks change. It is assumed that all the process parameters are constant and independent of the temperature.

Several different control approaches have been proposed to solve the stated control problem. The approaches vary from vary basic structures to the ones which include artificial intelligence (AI) aspects. This paper excludes discussion of AI based controllers because such controllers require a lot of data and are computationally expensive which makes the implementation an unfeasible task with the existing processing capability.

Three control structures are presented in this paper: Proportional Integral Derivative (PID), feed-forward and fuzzy logic. The first two represent the most well-known and used control approaches in the industry, whereas the last has some features of AI but with a fast computational capability. The following sections gives a quick review of the three approaches.

3.2 PID controller design

One of the most commonly used feedback controllers in the industry is the PID controller (Nise (2011)). Despite the fact that it is considered one of the simplest closed-loop controllers, it has a great impact on the system performance and simple tuning method. The design of the PID controller is achieved by selecting three values: proportional gain (k_p), integral gain (k_i), and derivative gain (k_d). The first part increases the system's overall gain, whereas the second and third are used to improve the steady-state error/convergence speed and the transient response respectively. The literature describes numerous alternative algorithms to select the PID gains, however in this work the automatic tuning toolbox in $MATLAB$ will be used for such a purpose as this represents an accepted good practice approach.

3.3 Feedforward controller design

Feedforward control is an effective control scheme to handle measurable or well-known disturbances (Guzmán and Hägglund (2021)) where the impact can be modelled effectively. It is based on an defining an input perturbation linked to the measured disturbance; this input perturbation counteracts the impact of the disturbance on the system's performance. Consequently, the controller performance depends on both the accuracy of the model and the disturbance measuring system. The feed-forward controller is commonly used in conjunction with a feedback controller, the first to give rapid compensation for the disturbance and the second to handle general system behaviour, uncertainty and so forth. Figure (2) presents the basic structure of feed-forward combined with a feedback controller, where the feed-forward controller (C_{ff}) counteracts the dynamic between the disturbance and the output (P_d);d the dynamic between the control signal and the process output is P_u.

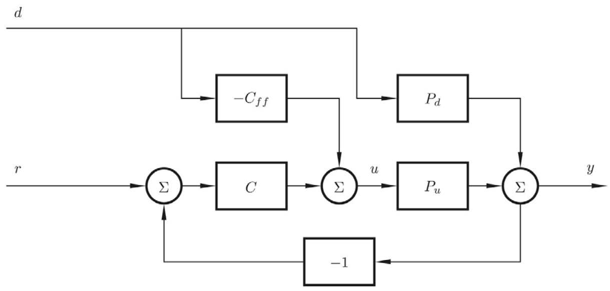

Fig. 2. The basic structure of feed-forward control

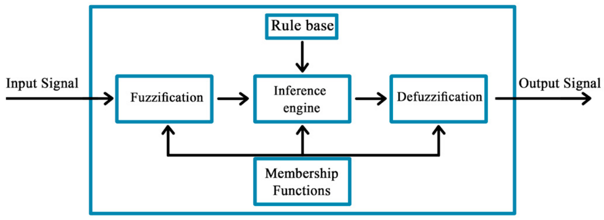

Fig. 3. The basic structure of the FLC system

3.4 Fuzzy logic controller design

Fuzzy logic control (FLC) theory offers a convenient control solution for systems that can not be described accurately (Lhachemi et al. (2019)). The technique exploits human experiences, general knowledge and observation to formulate control frameworks. The controller consists of a fuzzifier, defuzzifer, set of rules, set of membership functions, and inference system. The first two, convert the signal value from crisp to fuzzy and vice versa. The input can be presented by the actual system output, states, or offset signal. The control decision is made by the inference system based on the predefined rules and membership functions.

Figure (3) presents the basic structure of an FLC system. In this work, the input signals are selected to be the error $e(t)$ in the desired cross-sectional area and its derivative $\frac{\mathrm{d}}{\mathrm{d}t}e(t)$. Both signals were divided into five subsets (linguistic variables): high negative (HN), negative (N), zero (Z), positive (P), and high positive (HP). The output of the FLC was selected to present the control signal "the laser power" and it was divided into five linguistic levels: very negative (VN), negative (N), zero (Z), positive (P), and very positive(VP). Table (1) presents the designed fuzzy rules. It is important to note that the design process of

FLC for SLM, including the choice of linguistic variables, membership functions and fuzzy rules is a research area that requires more investigation and is part of future work.

4 Process Model and Simulation Result

Modelling and simulation of the additive manufacturing process are essential research fields. They play an important role in accelerating the design and production time by reducing (eliminating in some cases) the need for the actual trials. Many modelling efforts can be found in the literature. The vast majority of the efforts are related to modelling thermal dynamics in the melt pool. That is because many properties are related to the temperature of the substrate during the process. The model used in this work is an extension of the model presented in Wang et al. (2020). The model combines the heat energy equation and the Rosenthal solution to estimate the cross-sectional area $A(t)$ of the melt-pool with respect to the laser input power $Q(t)$ and the $T_{init}(t)$ initial temperature. The heat equation, the system, model and the initial temperature are given by equations (1) to (3).

$$\frac{d}{dt}(\rho V(t)e(t)) = -\rho A(t)v(t)e_b + P_s(t) \tag{1}$$

$$\frac{dA(t)}{dt} = f(A(t), T_{init}) + g(A(t))Q(t) \tag{2}$$

$$T_{init}(x, y, z) = T_a + \Sigma_{j=1}^{i-1} \frac{q_i}{2\pi k R_j} e^{-v_j(w_j R_j)/2a} \tag{3}$$

where ρ,e_b, $e(t)$, k, a are the material density, the specific energy, the specific internal energy, the thermal conductivity constant, and the thermal diffusivity of the material respectively. $P_s(t)$ and $v(t)$ presents the power delivered and the scanning speed of the laser system. The symbols q_i , R_j and w_j presents the virtual source power 'the power of the end point of the track', the distance between the operation point and the virtual source and the distance in the x-direction between the operation point and the virtual, where i is the number of printed tracks. The derivations of equation (2) and the melt-pool volume $V(t)$ calculations are shown in Wang et al. (2020).

The model presented by equations (2, 3) is used to simulate printing four tracks with length of 1 cm using Ti6Al4V powder parameters. The scanning strategy is illustrated in figure (4). Two simulations cases were conducted, first with an ideal implementation of the Rosenthal solution to compute T_{init} using equation (3) and the second a random variation in the temperature signal is introduced to mimic the actual situation during the process. Figure (5.a) presents the initial temperature before every time step for two simulation cases. The system response is illustrated in figure (5.b).

Table 1. Fuzzy logic set of rules

Input Variable		Change in error ($\frac{d}{dt}e(t)$)				
		HP	P	Z	N	HN
Error ($e(t)$)	HP	VP	VP	VP	VP	VP
	P	VP	P	P	P	VP
	Z	VP	Z	Z	Z	VN
	N	VN	N	N	N	VN
	HN	VN	VN	VN	VN	VN

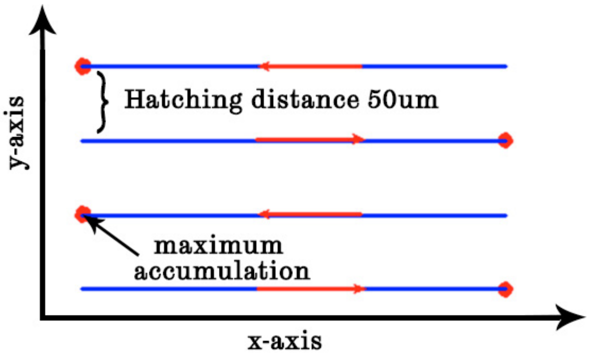

Fig. 4. The scanning pattern used in the investigation, where the arrows present the laser scanning direction.

5 Discussion and Future Opportunities

As can be seen from figure (5.a), the worst case occurred at the return end. The initial temperature which presents the heat accumulation effect the system response as shown in the figure (5.b). The cross-sectional area drifts away from the desired size and the error worsens in every track leading to the aforementioned building defects.

Introducing the control system enhanced the transient and steady-state responses of the system in general as seen in the green/yellow plots in figure (5.a). The PID and the FF controller combined with PID perform almost the same, except at the beginning of each track where the controller with feed-forward acts slightly better due to its capability to anticipate and reject the disturbance before it effect the system. By comparison, the fuzzy logic controller significantly improves the system's behaviour. The PID and the FF control strategies suffer from many limitations due to the non-linearity of the process and the inaccuracy of the model, whereas the FLC is better able to deal with such problems. Table (2) presents the numerical comparison of performance in terms of maximum error, integral absolute error (IAE), and the settling time. The presented values shows the superiority of the fuzzy logic controller over the other two approaches.

In the second simulation case where the random variation in the initial temperature signal was introduced, all the controllers' performances are affected. The settling time in such case is difficult to measure, however the IAE value could illustrate the change in the system performance. Figure (6) presents a comparison of the IAE before and after adding the random variation and again FLC is seen to be the best.

Despite the promising potential shown when using an online control system, the implementation faces some challenges, recommendations and future opportunities.

Table 2. Performance indices of the designed control systems

Performance index/ Control strategy	Settling time 'second'	Maximum error in %	IAE
PID control	0.0027	6.5	3.30E-06
Fuzzy logic control	0.0013	3.7	2.80E-06
Feed-forward control	0.0023	6	3.29E-06

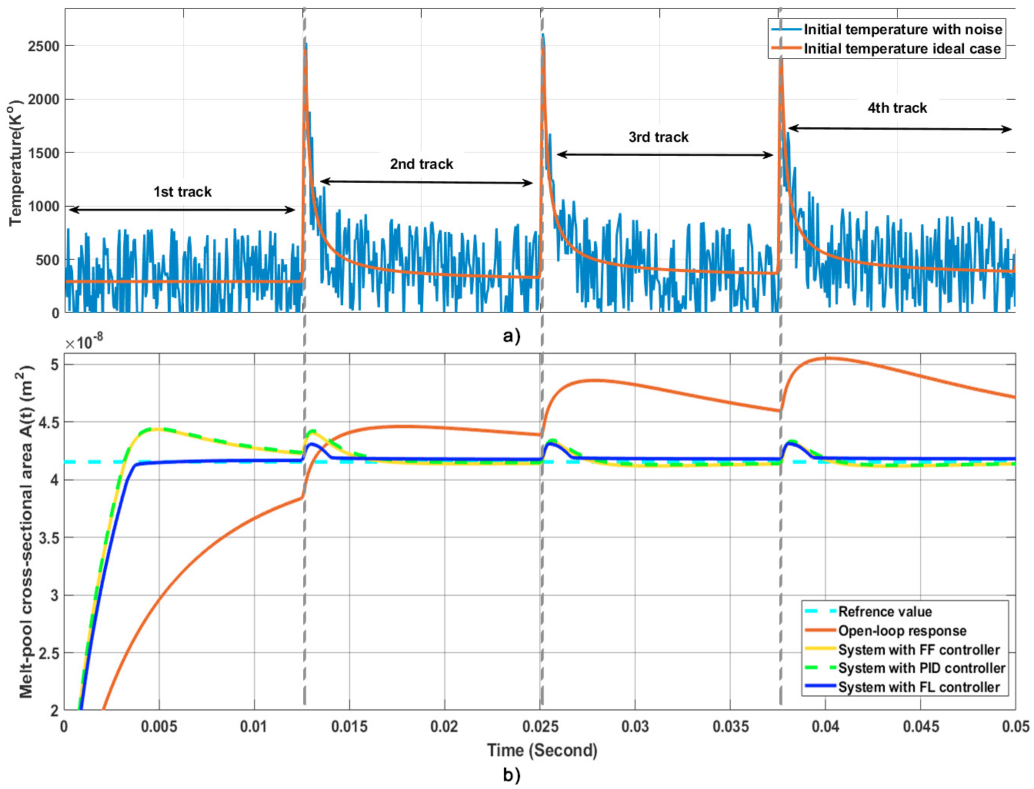

Fig. 5. a) The initial temperature profile in both cases. b) the system responses with different control systems.

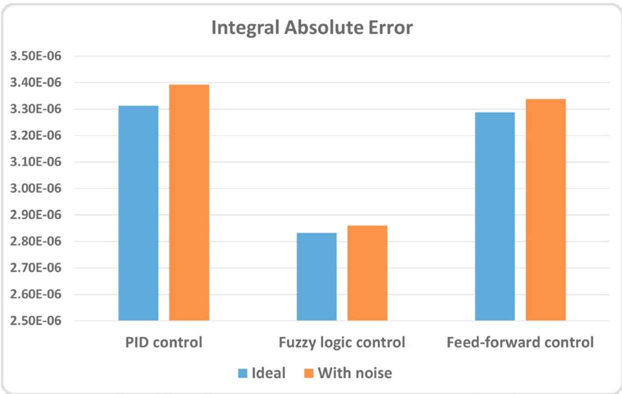

Fig. 6. A comparison between the IAE value for the control systems before and after adding the random variation in the temperature signal.

- A practical validation for the model and control system is outstanding. Using Rosenthal solutions has a limitation in presenting the heat accumulation. The method considers the source of disturbance is the end of each track. Practically the disturbance could occur from the point before, the underneath layer and/or the surrounding environment.
- Most of the existing effort, including this work, tested the control system performance in the process of printing or building simple shapes (identical tracks/layers). In order to show the effectiveness of the control system, a complex building process needs to be included in the investigation and the evaluation.
- The tuning method used in this work are limited to the classical approach. It is worth investigating how modern tuning (adaptive for example) methods could enhance the system performance, especially when the investigation considers complex shapes.
- There are many research investigations about the best control algorithms that can be used in the SLM process. However, in most cases, practical implementations are missing due to manufacturers blocking sensor/actuator access; more accesible equipment is needed to investigate the potential fully.
- There is a research opportunity to study the impact of the control system on the morphological structure of the parts. Will better consistency in the melt pool improve mechanical and structural properties?

6 Conclusion

This research work provides a comparison and evaluation of three common industrial online control strategies applied to a selective laser melting process. The work reiterates the observations of previous investigations about the potential of online control to significantly improve behaviour. This in itself should serve as a motivation for equipment manufacturers to allow better access to the sensor/actuator architecture to allow proper practical investigations. Moreover, the comparison of different control approaches demonstrates an advantage in pursuing intelligent control methods, such as fuzzy logic controllers as compared to more classical control strategies, an observation that is perhaps unsurprising given the number of non-linear and hybrid characteristics that are present. Certainly this merits further investigation and proposals for systematic tuning rules to deal with the more complex shapes which are common in AM. One can also investigate more advanced feedback control methods, using more sophisticated control theory as well as intelligent-based control methods, while balancing the need for simple systems that could be realised in an industrial setting.

Acknowledgements

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- Sultan Qaboos University for their financial support.

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Paper 4

Initial Investigation of Online Control System for Selective Laser Melting Process: Multi-layer Level

Taha Al-Saadi* [1] J. Anthony Rossiter* [2] and George Panoutsos * [3]

***Abstract*—Selective Laser Melting (SLM), an additive manufacturing process, has attracted significant attention from academia and industry over the past two decades. SLM is a productive technique for creating complex industrial components and tools with fewer stages, resulting in resource conservation in contrast to conventional manufacturing methods. Nonetheless, the current platforms employed in SLM metal part production lack the efficient utilisation of an online closed-loop system. The literature showed a significant place for utilising advanced control systems to improve overall performance. Such enhancement will enable the process to be used to fabricate more sophisticated parts. Introducing an online control system could also empower part production with better internal microstructure characteristics. This research reports an initial investigation of applying a closed-loop system to reduce the effect of heat accumulation while building a multi-layer object, thus improving the system. The controller changes the laser input in the track and considers the temperature residuals for the completed layers. The simulation results presented a significant improvement in disturbance rejection and better control of the melt-pool characteristics.**

***Index Terms*—Metal additive manufacturing, selective laser melting, laser powder bed fusion, feedback control, PID, mlti-layer.**

I. Introduction

Additive manufacturing (AM) is a group of manufacturing techniques to build 3D parts directly from a digital design. The building is achieved by printing one layer after another until the full product is completed [1]. The technology is a fast manufacturing tool since it reduces many traditional fabrication steps. It provides more flexibility and freedom in product design. These features made AM a competent option in many applications, such as construction, medical field, aerospace and much more [2]. AM technology can use various types of materials such as polymers, ceramics, and metals to fabricate the desired object [3]. The technology is divided into seven groups based on the heat source, the material that it can process, and the form of the material (wire, powder, and liquid): photopolymerisation, material jetting, binder jetting, material extrusion, sheet lamination, direct energy deposition (DED), powder bed fusion (PBF) [1].

One of the rising techniques is the selective laser melting (SLM) process, which is a laser PBF technology that uses a high density and narrow laser source to fuse the powder particle selectively [4]. SLM processes are capable to produce parts with high resolution, lightweight structure, and internal channels to enhance their mechanical properties [5]. The process consists of five primary parts, here is a brief description of each one:

1) Laser Unit: This part controls the laser beam power, speed, and scanning pattern across the building platform.
2) Powder Delivery system: The unit uniformly deposits and compresses the material powder to add a new layer.
3) Building Platform: This is where the object is fabricated. The platform lowers after each layer to add a new one.
4) Collector Unit: This unit collects excess powder.
5) Enclosed Chamber: A sealed space that regulates ambient conditions.

In addition to these components, an industrial machine may include a monitoring unit to control ambient temperature, machine characteristics, and part production. Figure (1) demonstrates the main units of the SLM process. The production process of the 3D object using SLM process involves several steps [6]. It starts with transforming the 3D model to a set of slices and stores it in an appropriate file format, such as an .STL file. Then the machine parameters are configured to prepare for the production. The manufacturing process constructs each layer on top of the previous one until the part is complete. Finally, the completed part is moved out from the building platform and cleaned.

Despite the significant advancements in metal Additive Manufacturing, there are still several challenges and limita-

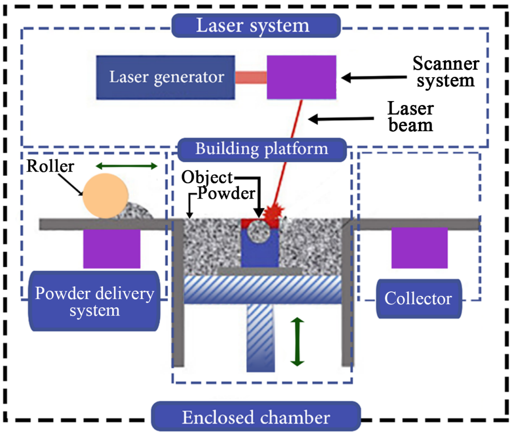

Fig. 1. The basic structure of SLM process

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tions that hinder its ability to fully meet industrial requirements [7]. The AM process is influenced by numerous factors, making it difficult to guarantee consistent quality and repeatability [8]. In most existing processes, including SLM and other AM techniques, process parameters remain constant throughout the printing process [9]–[11]. These parameters are typically selected through trial and error or optimised with the help of expert knowledge and modeling/simulations [12]. However, relying on fixed parameters can cause issues like heat accumulation, leading to irregularities in the melting pool morphology, especially when dealing with complex geometries, resulting in various defects.

Through the past twenty years, extensive research efforts have been dedicated to improving part quality in metal AM. There is great emphasis in the literature on the importance of introducing an online control system to enhance the performance of the SLM process [8], [13], [14]. There have been multiple attempts in the literature to design control systems for the SLM process. The existing control efforts in the literature can be classified into two groups: in-layer and layer-to-layer control systems. The first type variates the control variables (laser parameters) continuously during the process, while the second updates the process parameters once every layer. The in-layer control strategy requires a rapid sensing and processing system to respond to any deviation in the process, which could be a practical limitation. However, achieving such a control system will guarantee the accuracy of the building. The existing efforts ignored the inherited heat from the printed layer. On the contrary, the layer-to-layer control system approaches update the control signal once every layer. Thus, it cannot handle the errors that occur during the layer.

This study aims to demonstrate the impact of using online feedback system for the SLM process while fabricating a multi-layer object. In other words, the controller will react to the changes occurring during the whole process in layer and while adding a new layer. The control system will regulate the geometry of the melt-pool and reduce heat accumulation during the process. Based on the best of the authors' knowledge, the absence of such investigation in the literature is a clear research gap that is an important step towards automating the SLM process.

In the upcoming sections of the paper, will cover the following topics. Firstly, Section II, will provide a quick survey of the control effort in the SLM process. After that, in Section III, the physics model that is used in this investigation will be presented. Subsequently, in Section IV, the control problem and the control system design will be addesed. Section V will present and discuss the simulation results and highlight research opportunities in the online control system of the SLM process. Finally, Section VI, summarises the findings of the investigation and outline the future work.

II. Effort in online control system for SLM process

As highlighted in various academic works, the utilisation of an online control system offers a promising solution for addressing disruptions in the manufacturing process and mitigating the adverse effects of irregularities in the molten pool during the component fabrication procedure [13], [15]. Numerous control systems have been proposed and examined within the scholarly literature. In most of these research studies, special attention has been given to the geometry and thermodynamics of the molten pool as indicators of process quality [16], [17] . The regulation of the molten pool's geometry and temperature has been shown to yield improved microstructural characteristics and enhanced mechanical properties. The implementation of a control system serves to prevent issues such as porosity, distortion, cracking, as well as various manufacturing anomalies like keyhole formation and swelling.

Irrespective of the metric used to assess quality, both are intrinsically linked to the energy density allied in the process, which is a parameter that can be adjusted through manipulation of key variables such as laser power, scanning speed, and scanning strategies [18]. The existing effort in regulating the performance of the SLM process can be categorised generally into two groups: classical control and data-driven approaches. Proportional (P) and Proportional-Integral (PI) controllers were the first types of controller that have been investigated to improve the geometry of the produced part by the controller in the laser source power [19]–[21]. It is important to mention that the control system was designed on the basis of a second-order empirical model. The findings showed the potential effectiveness of an online control system in improving the overall quality of the process.

Years later, with the advent of new and advanced machines along with innovative process mechanisms, researchers were once again motivated to tackle the control challenges within the SLM process. Researchers in the studies [11], [22], utilized a Field-Programmable Gate Array board to develop an integrated control system that combined a P controller and a feedforward controller. The control structure was designed to regulate the temperature of the melt pool by controlling the laser power. The results showed a 73% reduction in temperature error compared to the open-loop response.However, it is worth noting that this study had limitations as it focused on a small number of well-separated multi-tracks.

In prior studies, the control systems relied on observations and empirical experimentation models. However, in [9], a feedforward (FF) controller was developed using a control-oriented model. The research findings demonstrated that this designed controller effectively maintained control over the melt-pool geometry throughout the process, resulting in a substantial 23% reduction in error when compared to operating with a constant laser power setting.

The use of data-driven techniques in the SLM process began with a preliminary investigation, as described in [23], [24]. This investigation introduced a model-free control system that utilised Iterative Learning Control (ILC) principles. The control system aimed to adjust the power input within the scanning segment based on real-time data from the monitoring system. In another study, a data-driven model was used to predict system performance and reduce the influence of temperature history [25].

In a recent study [17], the authors used deep learning and machine learning techniques to predict disturbances that may occur during a process within a specific area. The area of interest was defined by a cylinder that encompasses the environmental conditions around the operational point. The researchers formulated the system as an optimisation problem that can be solved using an ILC algorithm by analysing both past and current data. These research efforts demonstrated the viability of controlling the SLM process exclusively using real-time data. However, it's important to note that the proposed algorithm, which relies on repetitive behaviour, may not be suitable for geometrically complex components.

In [26]–[28], the authors built a controller based on a difference model. The first study proposed a batch model predictive control to the temperature of the melt pool. The controller can handle the repetitive and non-repetitive disturbance during the process. The second work utilised state-feedback control to regulate the thermal behaviour of the process. Whereas the two previous works were concerned about in-layer control, the third investigated the use of ILC to update the control signal every layer. The authors of this article investigated recently conducted research on the use of a fuzzy logic control (FLC) algorithm as a potential control method for the SLM process [29]. They developed a basic FLC to address the problem of heat buildup while printing a single layer of metal. The results demonstrated a substantial decrease in the error values. In summary, all the highlighted efforts tackle either in layer or layer-to-layer control problems. From the used model point of view, the models varied between: experimentally based, difference model, or physics-based model.

In this work we present simulation results of building 3D part under the use of PID controller to regulate the melt-pool area and, a specific novelty is the consideration of the heat accumulation from track to track and layer to layer.

III. Process Model

The modeling and simulation of additive manufacturing processes are essential in accelerating the design and the production process by minimizing actual trials. Moreover, these fields help us to understand the underlying physics of the process and the impact of different process parameters. There are many modeling studies available in the scientific literature, but most of them concentrate on the impacts related to thermal dynamics in the melt pool [9]. This is because the temperature of the substrate during the process affects many properties. Models can be based on physics or data-driven approaches [30]. There are ODE, PDE, linear, nonlinear, and empirical models [31]. Within all of these existing and diverse models, unfortunately, there are very few models that describe the selective laser melting process and fewer which are control design oriented.

This research investigation used the model presented in [9]. It is a physics-based model that takes into consideration the material properties and process parameters. The model

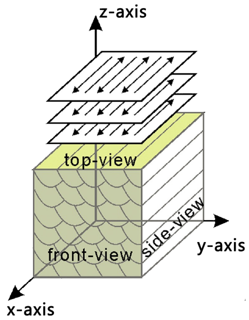

Fig. 2. The illustration of the printing process, layer by layer, back and forth in each layer

assumes that the laser path is a set of parallel tracks that move back and forth in every layer as shown in Figure (2). The model includes the effects of the completed tracks on the upcoming ones. The impact is considered as a disturbance to the process.

The model integrates the heat balance equation and the Rosenthal solution to calculate the melt-pool's cross-sectional area $A(t)$. The model starts from the energy balance equation that can be presented as follows:

$$\frac{d}{dt}(\rho V(t)e(t)) = -\rho A(t)v(t)e_b + P_s(t) \tag{1}$$

where ρ,e_b, $e(t)$, are the material density, the specific energy, and the specific internal energy. $P_s(t)$ and $V(t)$ present the power delivered and the melt-pool volume. Applying the set of assumptions related to the shape of the melt-pool, the temperature of the steady-state melt-pool, and the material properties that is described in more details in [9] Equation 1 can be rewritten as

$$\frac{dA(t)}{dt} = f(A(t), T_{init}) + g(A(t))Q(t) \tag{2}$$

where $T_{init}(t)$ is the initial temperature that can be give as

$$T_{init}(x, y, z) = T_a + \Sigma_{j=1}^{i-1} \frac{q_i}{2\pi k R_j} e^{-v_j(w_j R_j)/2a} \tag{3}$$

and $Q(t)$ is the laser input power. The parameters k, a in Equation 3 are the thermal conductivity constant and the thermal diffusivity of the material, respectively. The symbols q_i and $v(t)$ represent the virtual source power, which is the power at the return end of the track, and the scanning speed of the laser beam. Meanwhile, the symbols R_j and w_j denote the distance between the operation point and the virtual source, and the distance in the x-direction between the operation point and the virtual source. Here, i is the number of printed tracks. In this work the process parameters are selected to present what is actually used in practice. Furthermore, the Rosenthal solution presented in Equation 3 was applied to estimate the heat residual passed to the next layer. Despite the fact that the model was able to generally capture the behaviour of process, and the model is not yet verified with the given modification.

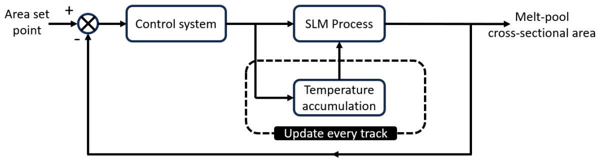

Fig. 3. Generic block diagram of control system implementation for the SLM process

IV. Controller Design

A. Problem statement

As noted in the earlier sections, heat accumulation poses a significant challenge that affects the quality of the resulting component. Consequently, the objective of the control system is to regulate the cross-sectional area of the melt pool A(t), by controlling the laser power input value Q(t), to minimise heat buildup. The control design is established with the assumption that all process settings remain constant and the only variable under control is the laser power level. Figure (3) illustrates the generic block diagram of the process with the feedback control system.

B. Controller design

The proportional-integral-derivative (PID) controller is the most used controller in the industry; almost 90% of used controllers in various industrial applications are based on PID [32]. It provides a simple yet efficient solution for the control problem. From its name, the PID control consists of the main parameters. The P term responds proportionally to the error signal, where the second integral part corrects the control signal based on integrating the error signal over time. The effect of an integral part appears in reducing the steady-state error. The derivative part is responsible of improving the transient response of the system based on the rate of change of the error signal.

The selection of the control variables are achieved through various tuning method varied in their simplicity, such as Ziegler-Nichols, Cohen-Coon, particle swarm optimisation or genetic algorithms, model predictive control and many more [33]. The method used depends on several factors, such as the nature of the process, the level of accuracy required, the accessibility of data, etc.

Since this work is more interested in providing evidence of the effect of PID control on the SLM process performance, $MATLAB$ auto-tuning toolbox was used to select the PID gains: proportional gain (k_p), integral gain (k_i), and derivative gain (k_d). The toolbox was fed with a linearised model of the process. The linearisation was done around the desired cross-sectional area with the crossponding initial temperature. The used PID structure can be described by the following equation:

$$u(t) = k_p e(t) + k_i \int e dt + k \dot{e}(t) \tag{4}$$

Assuming there is a sensor that can provide the required data, a fast processer to handle them, and an actuator that respond fat to the changes ,the controller will provide continually the control signal $u(t)$ based on the calculated error value.

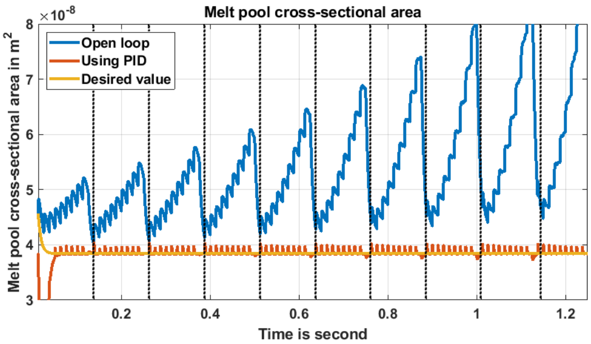

Fig. 4. The simulation result of the melt-pool cross-sectional area with and without a controller .

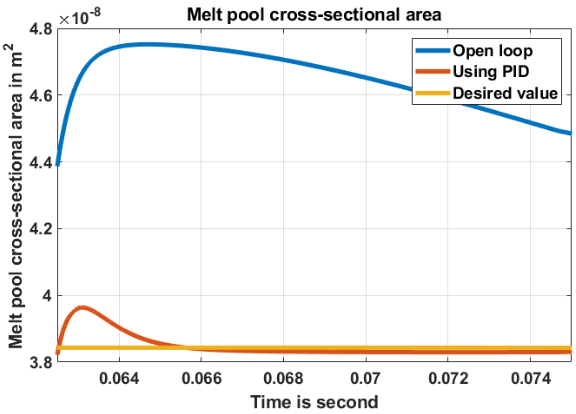

Fig. 5. The simulation result of the melt-pool cross-sectional area for a single track with and without a controller

V. Simulation and Discussion

The process model presented in the previous section III is used to simulate the behaviour of the melt pool while printing a part of ten layers that consists of ten tracks of length of 1 cm of Ti6Al4V powder. The reference value was selected to be 3.8e-8 mm^2. This value is computed using the model under perfect conditions and without heat accumulation. Figures (4-6) demonstrate the system response, the initial temperature, and melt-pool temperature during the process.

Figure (4) shows the cross-sectional area of the melt pool during the process. The black dotted line presents the start of a new layer. Looking into the system response without controller presented by the blue curve, the value of the cross-sectional area operates away from the desired size, and the deference becomes worse on every track. The drop at the start of each layer is due to the effects of adding a new layer. As it was explained in the previous sections, adding a new layer cools down the process, however there is still

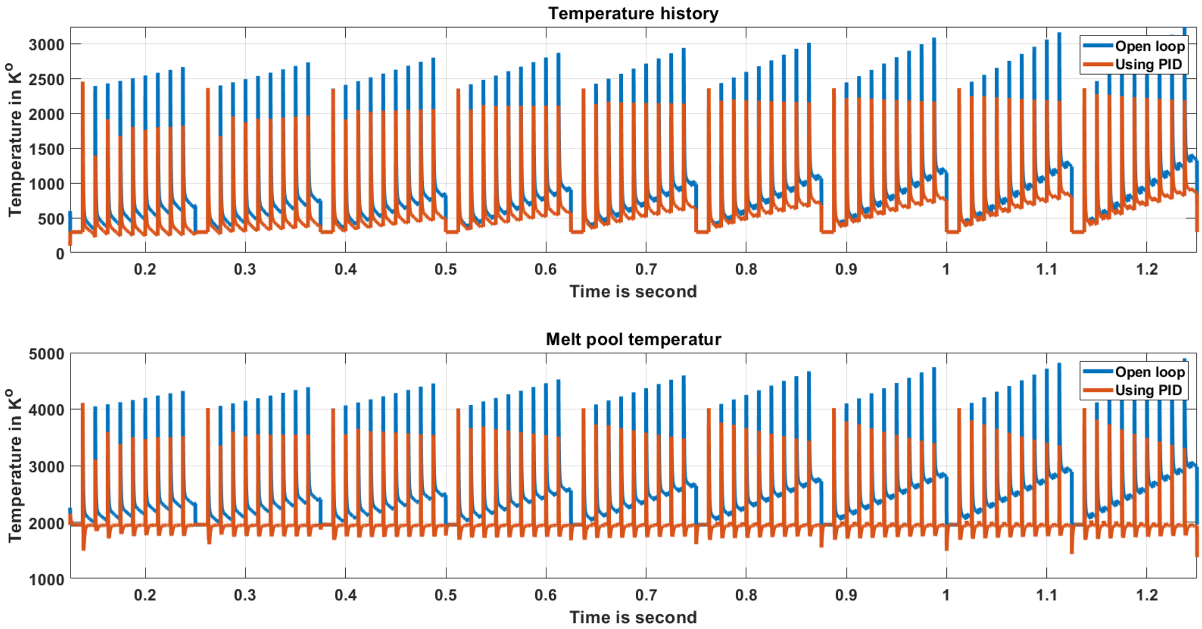

Fig. 6. The initial temperature and melt-pool temperature profile during the process simulation with and without a controller.

some temperature residual that is past from the completed layer to the new one. Introducing the control system resulted in an enhancement of the system's transient and steady-state responses, as demonstrated by the red curve.

Figure (5) demonstrate the huge difference between the open-loop and closed-loop performance during the simulation of one of the tracks. Looking into the initial temperature profile presented in the top plot in figure (6), it can be seen clearly the reduction of disturbance level. The controller helps to regulate the melt-pool temperature area. As it can be seen from the bottom plot in figure (6), the temperature keep operating around the melting point. Regulating the melt pool temperature during the printing process enhances the quality of the produced part as many of investigations indicates. [34]. Figure (7) presented the IEA and the average used power during the simulation. As it can be seen, that using controller reduce the IEA to more than 58 % and save around 18 % of power. Despite the promising potential demonstrated by the use of an online control system, further research is required in various areas. The following research opportunities have been identified during this study:

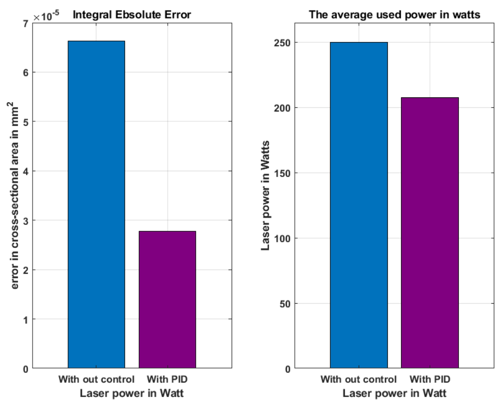

Fig. 7. A comparison between the open-loop and closed-loop performance in terms of IAE and average power consumption

1) Practical Validation: There is a need for practical validation of the model and control system performance. Current limitations exist when using Rosenthal solutions to represent heat accumulation, as it assumes that disturbances originate only from the end of each track. In practise, disturbances could arise from points before, the underlying layers, and/or the surrounding environment.
2) Complex Building Processes: Most studies, including this one, test control systems during simple printing or construction. Testing them in complex building processes is important to evaluate practical effectiveness.
3) Modern Tuning Methods: Investigating modern tuning methods, such as adaptive approaches, could enhance system performance, especially when dealing with complex shapes.
4) Accessible Equipment: SLM control algorithms need more accessible equipment for practical implementation due to manufacturer restrictions on sensor and actuator access.

VI. Conclusion

This research work presents preliminary findings regarding a common industrial online control strategy for the Selective Laser Melting (SLM) process. It reaffirms the observations made in previous studies about the substantial potential of online control to significantly enhance process behavior. This, in itself, should encourage equipment manufacturers to facilitate greater access to sensor and actuator architecture, enabling more comprehensive practical investigations. Furthermore, this study introduces a level of investigation that, up until now, has not been thoroughly explored in the literature. The analysis of a control system in a multi-layer process represents a notable research gap. Despite the accuracy of the used model, the initial investigation provides evidence of the effectiveness of the online control system in enhancing the performance of the SLM process. Certainly, this topic requires more research and development of systematic tuning rules to handle complex conditions that occur in SLM. Additionally, exploring advanced feedback control methods that utilise more sophisticated control theory and intelligent-based control methods would be beneficial. However, it is important to balance the need for simple systems that can be implemented in an industrial setting.

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